ECOFRAM Terrestrial *Draft* Report

Ecological Committee on FIFRA Risk Assessment Methods (ECOFRAM)

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1.0 INTRODUCTION

1.1 BACKGROUND

In May 1996, the U.S. Environmental Protection Agency's (EPA) Office of Pesticide Programs (OPP) presented two ecological risk assessment case studies to the FIFRA Scientific Advisory Panel (SAP) for comment on its methods and procedures. While recognizing and generally reaffirming the utility of the current ecological assessment process for screening purposes, the Panel offered a number of suggestions for improving the process. Foremost among the suggestions was that OPP move beyond the present single point deterministic assessment process and develop the tools and methodologies necessary to do probabilistic assessments of risk. Such assessments would address the magnitude of the expected impact as well as the uncertainty and variation involved in the estimates. In addition, the SAP identified several areas in the assessments that could be expanded to present a more complete perspective or characterization of the potential environmental risk for the pesticides examined.

Following the recommendations of the SAP and building on previous efforts, the Environmental Fate and Effects Division (EFED) within OPP began a new initiative in 1997 to revise the assessment process. The purpose of this initiative is to strengthen the core elements of the ecological assessment process by identifying, developing, and validating tools and methodologies to conduct probabilistic assessments and to improve risk characterization. These methodologies are intended for use by OPP to evaluate the effects of pesticides on terrestrial and aquatic species. Thus, they need to be developed within the context of the FIFRA regulatory framework and consider OPP resource and time constraints.

In recognition of the importance of involving stakeholders in redesigning its ecological assessment process, OPP initiated several channels for external involvement. This led to the formation of the Ecological Committee on FIFRA Risk Assessment Methods (ECOFRAM), who was charged with conducting the primary review of the current assessment process and

developing new tools and methodologies for aquatic and terrestrial assessments. ECOFRAM is comprised of scientific experts drawn from government agencies, academia, contract laboratories, environmental advocacy groups, and industry. Participants were selected based on expertise, affiliation, and availability to ensure that the appropriate disciplines were represented along with a cross-section of affiliations.

ECOFRAM was divided into Aquatic and Terrestrial Workgroups. This report reflects the work of ECOFRAM's Terrestrial Workgroup, which has been developing methods and tools that could be used for revising the assessment process for evaluating pesticide impacts on terrestrial species. The report also identifies research areas and validation needs.

1.2 THE CHARGE TO ECOFRAM

The Charge to ECOFRAM, which outlines the scope of the initiative, was as follows:

> "The ultimate goal of this initiative is to develop and validate risk assessment tools and processes that address increasing levels of biological organization (e.g., individuals, populations, communities, ecosystems), accounting for direct and indirect effects that pesticides may cause. Achieving this goal may require more than the limited resources and time available for the initial effort. Therefore, work groups will first address direct acute and chronic effects of pesticides on individuals and populations of high-risk species. The species considered first will be terrestrial vertebrates and aquatic vertebrates and invertebrates. Terrestrial invertebrates and terrestrial and aquatic plant species will be addressed subsequently, as resources permit.
>
> Work groups are charged with developing a process and tools for predicting the magnitude and probabilities of adverse effects to non-target aquatic and terrestrial species resulting from the introduction of pesticides into their environment. The

methods developed should consist of standardized procedures that integrate estimates of pesticide exposure with knowledge about the potential adverse effects. The methods should account for sources of uncertainty. In addition, the methods must be developed within the context of the FIFRA regulatory perspective and follow the outline provided by the Framework for Ecological Risk Assessment (U.S. EPA, 1992).

The tools that are developed need to have reasonable scientific certainty and be capable of acceptable validation within a reasonable time frame. Nevertheless, model development, as a primary tool, may be limited by a less- than-complete understanding of ecological systems and by the ways that various direct and indirect effects of pesticides may be expressed at higher levels of biological organization. Probabilistic techniques developed should use existing fate and effects data where possible. However, in developing new methodologies and improving risk estimates, it may be necessary to modify or discontinue current tests or to develop new ones.

Methods developed for risk estimates should reflect a solid foundation in environmental toxicology and account for species sensitivity, environmental fate (including the transport, degradation, and accumulation of pesticides in the environment), and other variables. The type of pesticide formulation, application techniques, habitat types (e.g., estuary, pond, stream, field, forest), and species associated with these habitats need to be considered. The translation of residue estimates into exposure estimates and routes of exposure should be incorporated into the methodology.

Methods should be specific enough to allow different risk assessors supplied with the same information to estimate similar values of risk. The rationale for the choice of scenarios needs to be clearly stated. Assumptions and extrapolations

need to be specified and explained so the significance of the ecological risk estimates provided by the methods is easily understood.

Finally, the workgroups are asked to define any additional developmental or validation efforts that are needed for the probabilistic methods developed. This will provide a firm scientific basis for use of the risk estimates by environmental decision makers."

1.3 FOCUS OF THE REPORT

The Terrestrial Workgroup met approximately monthly for a year and a half to take up the Charge to ECOFRAM. They began their deliberations by discussing the focus described by the Charge. They agreed to first address direct acute and chronic effects of pesticides to birds and mammals. The Workgroup also discussed the importance of indirect effects and concluded that they are a significant issue. However, assessments of direct toxicity drive the current pesticide registration process and are more tractable than addressing indirect effects. Also, it was generally felt that indirect effects were too complex to adequately address within the time frame of ECOFRAM. As a result, the Workgroup concluded that a focus on direct acute and chronic effects to birds and mammals was appropriate.

The Terrestrial Workgroup also discussed the consideration of species other than or in addition to birds and mammals. However, the larger databases of toxicity and life history information for birds and mammals make them more amenable for developing a new process for risk assessment than other species. Again, the Workgroup concluded that the focus as directed in the Charge was appropriate.

1.4 ROLE OF THE NEW EPA GUIDELINES

The Terrestrial Workgroup, as specified in the Charge, followed the outline provided by the

Framework for Ecological Risk Assessment (U.S. EPA 1992) for developing ecological risk assessments. The Framework was later expanded and replaced by Guidelines for Ecological Risk Assessment (U.S. EPA 1998).

The Guidelines for Ecological Risk Assessment base the ecological risk assessment process on integrating two major elements, characterization of exposure and characterization of effects (toxicity). These elements provide the focus for conducting the three phases of risk assessment, which are described in Sections 1.4.1 - 1.4.3.

1.4.1 Problem Formulation

Problem formulation is the first phase of the ecological risk assessment process. In problem formulation, the purpose for the assessment is articulated, the problem is defined, and a plan for analyzing and characterizing risk is determined. This phase begins by addressing the available information on stressor (chemical), sources of the stressor, and the characteristics of the non-target wildlife and ecosystem at risk. This results in assessment endpoints and conceptual models, which are used to complete an analysis plan, the final step in problem formulation.

1.4.2 Analysis of Exposure and Effects (Toxicity)

The second phase of the assessment process is analysis of exposure and effects (toxicity). This phase provides an exposure characterization, which includes estimates of dose and/or dose distributions. This phase also provides an effects (toxicity) characterization, which includes the determination of dose-response factors, such as the LD50 or EC50 and dose-response slope, and/or distributions of dose-response factors.

The initial step in this phase is identifying the strengths and limitations of the data on exposure, effects, the ecosystem, and animal life history. Data are then analyzed to characterize the nature

of potential or actual exposure and the ecological response under the circumstances defined in the conceptual model.

1.4.3 Risk Characterization

The third phase is risk characterization. This phase integrates the exposure and effects characterizations through the risk estimation process. It includes a summary of assumptions, scientific uncertainties, and the strengths and limitations of the analyses. Output of the risk characterization phase include the results of integrating the exposure and effects characterizations, discussed the ecological effects that are predicted, and the uncertainties and lines of evidence that were involved.

1.5. TERRESTRIAL WORKGROUP'S APPROACH TO ADDRESSING THE CHARGE

Using the above outline as specified in the Charge, the Workgroup developed the following steps to address the tools, methods, and data needs for conducting probabilistic assessments for pesticides:

- Defined and developed assessment questions (endpoints) and conceptual models.
- Defined the scope of the initial model development given time and resource constraints.
- Identified major variables that influence pesticide exposure and effects to non-target terrestrial species.
- Developed the structure of the risk assessment models.
- Defined distributions for these variables or how to estimate them.
- Defined the uncertainties associated with available data and additional data needed to support methods identified or were being developed.
- Tested the models using three of four case studies scenarios.
- Defined additional developmental and validation work required.

- Developed suggestions on how these new tools and models could be incorporated into the pesticide registration assessment process.

As the Terrestrial Workgroup began to move through these steps, they realized that not enough time or resources were available to adequately address all of them. While most steps were addressed and are discussed in this report, it became obvious that developing probabilistic models and refining them to a stage that could be applied to case studies would not be feasible. They were also unable to develop the associated case studies and thus limited their efforts to developing examples of concepts identified and how they could be applied. It should be noted that Chapter 7 provides recommendations regarding the steps that were not fully developed. It also provides key concepts and conclusions based on the discussions of the steps that were fully addressed.

In this report, the Terrestrial Workgroup presents their findings based on their discussions as they worked through this approach. It proposes a sequential organization to probabilistic assessments, includes relatively simple assessments that may be broadly applicable, and identifies more complex case-specific assessments designed for the unique features of each pesticide use scenario. Each probabilistic approach is demonstrated through the use of examples.

1.6 ORGANIZATION OF REPORT

The report begins with this introductory chapter, which provides background information, including a discussion of the charge to ECOFRAM, the focus of the report, the role of the EPA Guidelines, and the Terrestrial Workgroup's approach to addressing the Charge. It also provides a brief overview on probabilistic assessments and other assessment methods and the basic model structure for probabilistic assessments.

Chapters 2 - 5 follow the basic elements of EPA's guidelines as described in sections 1.4. Chapter 2 presents problem formulation, including a discussion of assessment endpoints,

conceptual models, questions often posed by risk managers, and additional considerations. Chapters 3 and 4 present the findings of the Terrestrial Workgroup regarding Exposure and Effects, respectively. Chapter 3 provides an introduction and a discussion of the factors affecting exposure pathways. It also presents discussions regarding the dose resulting from various routes of exposure. Chapter 4 discusses the scope of the effects assessment, the suitability of current toxicity tests, indirect and sub-lethal effects, and provides a discussion of intra- and interspecies methods and variability.

Risk assessment methods are presented in Chapter 5. The focus of this chapter is to present various methods for integrating the exposure and effects characterization into estimates of risk.

Chapter 6 provides levels of refinement for the assessment process and discusses ways to implement probabilistic risk assessments into the pesticide registration process. Chapter 7 provides the Terrestrial Workgroup's recommendations and conclusions. This includes recommendations for further development of approaches, data needs, and research needs to address the limitations in the understanding of the effects of pesticides in the environment. The report concludes with references and the appendices in Chapter 8 and 9, respectively.

1.7 A BRIEF OVERVIEW ON PROBABILISTIC ECOLOGICAL RISK ASSESSMENT

1.7.1 Why Do A Probabilistic Ecological Risk Assessment?

The SAP stated that the methodologies and specific endpoints used by OPP have several limitations in relation to their utility in risk assessment. Consequently, they recommended that OPP develop the necessary databases and methodologies to conduct probabilistic assessments of risk.

> "OPP believes that its current procedures for ecological risk assessment generally provide a cautious and protective evaluation of the potential for widespread damage to non-target fish and animals from use of pesticides according to label directions. However, while

> these current procedures can serve as a screen to identify possible environmental damage, they often provide less information on the likelihood of damage and the uncertainty in such estimates as is desirable in balancing risks and benefits as required under FIFRA" (US EPA 1997).

The current use of deterministic quotients provides an assessment that the estimated risk, in the form of an index value, would be less than or greater than a defined level of concern. However, the index value provides no information about the probability of an unacceptable risk or the magnitude of risk. Although a quotient value of 10 is several times higher than most numerical levels of concern, the relationship between risk quotient values and the risk to the environment is unknown, so it is not possible to determine the significance of an index value of 10. Nor is there sufficient understanding to compare the relative risk between quotient values of 10 and 50. Theoretically, a value of 50 means greater risk than a value of 10, but it is not possible to determine if the real risk between the two quotient values is substantial or negligible. Addressing issues of the probability or magnitude of risk requires alternative approaches that incorporate what we know about measured or estimated parameters and their associated uncertainty.

Suter (1993) states that the

> "uses of probabilistic analysis can help to clarify the relationship between decision making and uncertainty. They can be used to justify a particular degree of conservatism in the face of uncertainty or can be used to justify making additional measurements or conduct additional tests to reduce uncertainty. ... Thus this approach provides a means of determining the need for more data, and for prioritizing data needs. One would do the research that would do the most to decrease the total uncertainty within the restraints of time and money. In addition, these curves [probability density functions] make clear the advantage of estimating the expected effects and associated uncertainties, rather than using worst case assumptions or arbitrary safety factors. Because there is no objective

scale of badness or safety, there is no objective way to compare the defensibility of safety factors or to justify how bad a worst-case must be. Probabilistic analysis provides a means of comparing assumptions, models, and data put forth by the parties in an environmental dispute."

Consequently, probabilistic assessments provide a means to go beyond ambiguous qualitative narrative assessments to more explicitly quantify what is quantifiable and to state specifically the assumptions made in the assessment.

1.7.2 What is Probabilistic Ecological Risk Assessment?

There is no unified term that is used to designate assessments that quantitatively characterize the uncertain variables in estimates of ecological effects. Various terms are used in the literature to delineate this type of an assessment. While ECOFRAM used the term "Probabilistic Risk Assessment", as mentioned in the Charge, other terms can be used to identify similar types of assessments. These include risk assessment (Suter 1993), quantitative policy analysis (Morgan and Henrion 1992), quantitative risk analysis (Vose 1996), stochastic modeling (Ott 1995), probabilistic analysis (EPA, 1997), and Monte Carlo Analysis (EPA 1997). These terms all are used to delineate assessments that predict the magnitude and probability of effects, where probability is the characterization, quantitatively, of the uncertain variables.

Probabilistic risk assessments are not new. They have been performed to predict the probability of nuclear accidents (Covello and Merkhofer 1993), traffic accidents (Fischhoff et al. 1981), weather events, food safety (Covello and Merkhofer 1993), and risk of acidification of lakes (Linthurst et al. 1986, Baker and Harvey 1984). However, there is a growing awareness among scientists and decision makers of the value of integrating these uncertainties into the characterization of ecological risks from the use of pesticides. The proliferation of user-friendly software packages that can incorporate parameter variability and uncertainty has greatly

increased the number of scientists with direct access to the tools for conducting probabilistic assessments.

The basis for probabilistic risk assessment is relatively simple. The major uncertain variables that influence the risk of concern are identified and their parameters (e.g., distribution type, mean, variance, and correlation to other uncertain variables) are defined or estimated. Using the laws of mathematical statistics, the uncertain variables are combined to estimate the parameters of the distribution of the risk of concern. For simple additive or multiplicative models the math is relatively straightforward. However, the math can quickly become relatively complex and tedious. With the advent of powerful desktop computers, commercial software packages have been developed that can perform the mathematical operations through Monte Carlo sampling of the input variable distributions to estimate the output distribution of risk with relative ease. The underlying theory of Monte Carlo sampling is grounded in the frequency interpretation of statistics. In Monte Carlo methods, samples are randomly drawn from a defined distribution.

1.7.3 Uncertainty and Probabilistic Risk Assessment

The three major types of uncertainty variables addressed in current risk assessment literature are natural variability, lack of knowledge, and model error. Natural variability is defined as the true heterogeneity or natural variation in the risk estimate and may be better defined though increased sampling to approach the true variability (bounds) in the population. Uncertainty is defined as ignorance or lack of knowledge about the estimate of risk due to absence of data or incomplete knowledge of important variables or their relationships. Uncertainty may be reduced through further research. Model error results from the chosen model failing to adequately mimic the system in question. In practice, it is often difficult to completely separate the 3 major types of uncertainty, because they are somewhat inter-related.

Several techniques have been developed to address the absence of knowledge in assessing risk. While the Terrestrial ECOFRAM Workgroup did not discuss these techniques in depth due to

time limitations, they were briefly discussed and will need further attention as the Agency moves to probabilistic risk assessments of pesticides. (See Chapter 7.) Briefly, two of the more common methods employed entail the use of conservative models or subjective judgement. While not without limitations, they provide methods which can be used to provide a "best estimate of risk" given the state of knowledge and can provide separate estimates of the uncertainty from natural variability and lack of knowledge.

The use of conservative models to represent reasonable worst case scenarios (e.g., 100% of diet contaminated, residues levels measured immediately after application) is an approach that has been used to compensate for the absence of empirical information. An alternative is to use conservative estimates of input distributions. Maximum entropy inference (MEI) uses a formal set of rules to specify input distributions according to the amount of information available (Lee and Wright, 1964). This maximizes the uncertainty in input distributions that can be assigned based on the lack of knowledge. The MEI approach has several advantages compared to subjective judgements by individuals. It avoids human bias and helps mitigate against unfounded confidence in our predictive skills (Moore 1996). These approaches could be viewed as a reasonable way to minimize type two error, that is, missing effects that are occurring or could occur.

Subjective or Bayesian statistical methods incorporate the absence of knowledge into risk assessment through subjective judgement. Actually, the probability theory used for the Bayesian approach is identical to the classical approach, but the underlying philosophy is different. Warren-Hicks and Butcher (1996) point that out the major difference between a Bayesian and classical approach is the concept of probability employed. For the classical case, probability is regarded as representing the frequency with which an event would occur in repeated trials. For the Bayesian case, probability is regarded as representing a degree of reasonable belief based on existing information. Bayesians do not require assumptions about repeated trials to make inferences about output, but rather the inferences are made based on the available data. This information takes on two forms: sample information and prior information. Each must be available for the Bayesian

paradigm to be implemented and probability statements about the risk are made based only on these two sets of information.

Numerous publications are available which discuss extensively the approaches to developing probabilistic risk assessments and potential sources of errors and biases that can be introduced into the analysis (Vose 1996, Morgan and Henrion 1990, Hammersley and Handscomb 1964, Kloek and Van Dijk 1978, Hammersley and Mortan 1956, Wilson 1984). The reader is referred to these publications for an in-depth review.

It is assumed that probabilistic assessments will reduce uncertainty in decision-making by interactively refining our models to reflect new data and understanding of ecological relationships. We may thus achieve greater certainty that our model predictions are a reasonable reflection of field responses. However, by acknowledging the natural variation in the numerous measures of exposure and effects rather than using worst-case assumptions, model predictions of risk will reflect the tremendous variability in risks to individuals that exist in terrestrial systems. Consequently, as we reduce the uncertainty in our model(s) of the environment, we are simultaneously and increasingly acknowledging the variation in risks at the level of the individual within a population or a landscape.

1.7.4 EPA Guidance on Probabilistic Risk Assessment

The U.S. Environmental Protection Agency has also developed guidance on the basic principles of probabilistic risk assessment, which includes 16 guiding principles for developing probabilistic risk assessments (Appendix A1). These principles help to ensure good scientific practices when developing these type of assessments (US EPA 1997). Although all 16 principles are important, two warrant special attention.

The first principle is that the assessor needs to pay particular attention to the difficulty of developing and justifying input distributions. While the limitations induced by these components

of developing probabilistic risk assessments are generally acknowledged, often their consequences are given insufficient attention (Ferson 1995).

Mis-specification of the sampling distribution can drastically change the shape of the out put distributions. In probabilistic risk assessments, the distribution from which the samples are drawn is assumed to be the true distribution or, when information is scant or nonexistent, a distribution of the parameter of interest is assumed. The degree that the sample distribution or the assumed distribution differs from the true distribution can significantly influence the results, particularly if the mis-specified distribution occurs for a sensitive parameter in a multi-parameter model. Before attempting to fit probability distributions to a set of observed data, the properties of the observed data should be considered. Vose (1996) points out,

> ”The properties of the distribution or distributions chosen to be fitted to the data should match those of the variables of interest. Software like BestFit has made fitting distributions to data very easy and removes the need for any in-depth statistical knowledge. These products are generally extremely useful but, through their automation and ease of use, inadvertently encourage the user to attempt fits to wholly inappropriate distributions.”

Vose (1996) as well as the other reference text above on probabilistic risk assessment review in-depth various statistical methods for fitting distribution to data.

While there are numerous references for estimating distributions from empirical data, these standard approaches are of limited value when few data exist. Where data are severely limited, several methods have been advanced to define the “best” estimate of the distribution in question. These include (1) employing maximum entropy criteria to select distributions from a priori constraints (Lee and Wright 1994), (2) focusing on extreme value distributions when the tails are of interest (Lambert et al. 1964), (3) gathering empirically fitted distributions (Haimes et al.

1994), and (4) using default distributions such as the triangular or exponential (Bartley et al. 1983, Finley et al. 1994, Haimes et al. 1994). Ferson (1995) points out, however, that

> "in the absence of a complete empirical base, all of these methods for selecting input distributions require assumptions that cannot be justified by appeal to evidence and therefore may be false. These unsubstantiated assumptions can make a difference in the results. As Bukowski et al (1995) showed, the choice about distribution shape can have a sizable effect on the risk analysis, again especially in the tails."

Ferson (1995) believes that this can be overcome using probability bounds and reviews some computational methods to estimate probability bounds dependent on the amount of empirical data available. He further suggests that in all cases, the bounds will enclose the true probability distributions and provide a conservative expression of the potential risk. While it is beyond the scope of this report to review these methods in depth, assessors should become familiar with these various methods for estimating distribution shapes and their limitations.

The second guiding principle that needs to be emphasized is falsely assuming statistical independence and/or inadequately accounting for correlation between input variables. In the absence of understanding or accounting for variable dependancy or correlation, the potential to underestimate potential effects can be significant. If the assessor assumes that input variables are independent, principles of probability will lead to the conclusion that the potential for the dependent output is a multiple of the input variable, which results in a much lower probability of occurrence than for any of the input variables. However, if the input variables are dependent, but highly correlated, the probability of occurrence of the output variable may be close to the probability of any one of the input variables. If the correlations are small to moderate in strength, the central tendencies are generally not greatly influenced, but the tails of the distribution can be extremely sensitive, leading to under estimation of the probability of rare events. This can be extremely critical in estimates of risk to endangered species or other populations where a threshold may exist, which if exceeded, result in a low potential for recovery. Not accounting for

correlation, that is assuming independence among input variables, or inadequately accounting for correlations can lead to such an underestimate and an erroneous conclusion of potential effects. Also, the type of correlation is critical. As Ferson (1995) points out,

> "linear correlation is not the only form of statistical dependence, which is the reason, of course, that uncorrelatedness does not guarantee independence. And pair wise independence does not imply mutual independence in the general multi variate case. In short, there are more things in the heaven of arithmetic on random variables than have been dreamt of by practicing risk analysts."

Numerous publications, including the ones referenced above, are available that outline statistical techniques to determine dependency and correlation of variables and methods to incorporate the relationships into assessment models. However, these techniques are dependent on the available data. In cases when the relationships of the variables are not known, these methods and techniques maybe of little value.

1.7.5 Application of Probabilistic Risk Assessment to Terrestrial Ecotoxicology

Implementation of probabilistic approaches will necessitate several changes in the ecological risk assessment process for pesticides. The greatest change is the increase in supporting data when refinements of assessments are needed to reduce the uncertainty in the predicted effects. The point estimates for toxicity (e.g., LC50, LD50, NOEC) and exposure (e.g., maximum residue concentration on food types) would be replaced by distributions of values that capture the natural variability in these parameters and our uncertainty due to measurement error or lack of knowledge about the biological or chemical system in question. The distributions of exposure would have to express the variability of parameters both spatially (e.g., heterogeneity of residues throughout fields) and temporally (e.g., degradation of residues over time). The results of toxicity tests would be expressed as the complete dose-response relationship, including the slope and

confidence limits of the relationship. Instead of focusing on the species with the lowest toxicity values, the measured or estimated distribution of toxicity values among all species would be used.

In expressing the uncertainty in the estimates of exposure and toxicity, there are several additional parameters that may need to be considered to more completely characterize the risk. For example, the exposure profile may be refined by information about the specific characteristics of the pesticide, such as degradation rates, movement in the environment, timing of applications, and application methods. The effects profile may be refined by information about mode of action, temporal development of effects, intra- and interspecific differences in toxicity, and behavioral responses to exposure. The incorporation of additional explanatory parameters is intended to address the many shortcomings of the simplistic risk quotients.

To better estimate the exposure of wildlife to agricultural pesticides, it will be necessary to estimate the dose received by individual animals via the various routes of exposure rather than simply using environmental concentrations (e.g., residues concentrations on food) as a surrogate for exposure. Consequently, current dietary tests that report a toxicity endpoint in units of concentration in the food may have to be revised to express test endpoints as the ingested dose producing a response.

The changes implicit in a probabilistic risk assessment process also require changes in the interaction between risk assessors and risk managers. Ultimately, the output of ecological risk assessments will be presented as the probability that a specific risk may occur or the probability of a specified magnitude of risk may occur. These probabilities also will be associated with quantifiable uncertainties related to stochastic variability, measurement error, and model error that can be used to assess the level of confidence in the model predictions. A dialogue between risk assessors and risk managers will be necessary to define specifically the goals of the assessment, the degree of certainty required for acceptable model output, the conservativeness of model assumptions, and the magnitude of risk that is acceptable. While it is implicitly understood that conservative assumptions are part of a screening assessment, at higher tier

assessments the use of conservative assumptions needs to be clearly identified and their potential influence on the assessment acknowledged by both risk assessors and managers. Conservatism is a value judgement deliberately introduced to account for uncertainty. It requires the involvement of risk managers so that risk assessors are not forced to go beyond their role as providers of assessments. Risk managers need to understand the potential for distortions of the assessment due to cascading of biases from conservative assumptions.

1.7.6 Potential Problems in Applying Probabilistic Risk Assessment to Ecological Systems

As suggested, the theory and tools exist to properly specify the structure and input probability distributions for probabilistic risk assessments. However, the appropriate representations of the model equations in relation to the true environmental interactions, the identification of the appropriate variables, their distribution and the relationship between them remains a serious challenge in probabilistic ecological risk assessment. Ecological complexities suggest obvious questions about the ease with which probabilities can be attached to the immeasurable states of nature likely to occur. The simplest information on chemical specific residues and fate data in the environment is often scant, and chemical specific toxicity data on species likely to be exposed is rarely available. Further, life history data on the numerous species potentially at risk from the use of pesticides is limited and where available, is confined in space and time. A large proportion of the discussions in this report address the limitations in the available data and suggest ways to estimate or collect additional data to reduce the associated uncertainty.

Ideally, to reduce the uncertainty to a minimum, each of the critical variable distributions should be defined through rigorous scientific investigation. Then through the systematic integration of these distributions, using appropriate probability theory, a clear delineation of the potential ecological risk could be made. However, when attempting to assess the possible consequence of a pesticide application under the infinite conditions in the environment, one cannot enumerate the complete set of input variables or outcomes nor repeat the experiment often enough to be able to reasonably estimate the probabilities of each critical input variable or outcome occurring. The

practical constraints and our less than perfect understanding of natural systems and their interaction with pesticides suggest that developing probabilistic ecological risk assessments for pesticides will require a substantial commitment of time and resources.

1.8 OVERVIEW OF METHODS CONSIDERED FOR PERFORMING ECOLOGICAL PESTICIDE ASSESSMENTS AND INTEGRATION INTO THE REGULATORY PROCESS

While the Terrestrial ECOFRAM Workgroup mainly addressed assessment methods that predicted the magnitude and probability of effects, other methods were also discussed. In the discussions, particularly when addressing the integration of probabilistic tools into the regulatory process, it became apparent that not every assessment requires or warrants a quantitative estimate of the magnitude and probability of effects. In some circumstances, a quantitative assessment may be warranted, but the limitations in data and/or the understanding of the system requires assumptions which introduce such large uncertainty in the predicted effects that the assessments would not be scientifically defensible. Therefore, the Workgroup believed there was a need to explore or at least identify assessment methods that could be used as screening tools when data limitations imposed restrictions on full probabilistic techniques.

The options for performing ecological pesticide assessments are outlined below in order of increasing complexity and potential realism:

- Deterministic quotients (a ratio of single values of exposure divided by toxicity),
- Assessment methods that involve a comparison of the exposure distribution to an effects value (fixed value), and
- Methods that incorporate functions to integrate exposure and effects distributions.

All of these methods have their value and can be applicable to ecological risk assessments. The simplest methods can be used for screening in order to scope the risk assessment. As additional

refinements of the assessment are required, the more complex tools and methods can be implemented to better define the associated uncertainties in the assessment and with additional data they may be reduced. This approach to the risk assessment process discussed by the workgroup was labeled “levels of refinement” and Figure 1.8-1 illustrates the general approach. As previously indicated, not all assessments require or warrant a quantitative estimate of the variability and uncertainty. It may be unnecessary to perform a probabilistic assessment when screening calculations clearly show the potential for adverse effects are minimal. If the inputs into the screening calculations have been established based on conservative assumptions, the certainty of the estimate of minimal risk should be, while maybe not quantified, relatively high. In cases where the potential for adverse effects is high long with a high level of certainty, further assessment may need to be considered.

Level 1 in Figure 1.8-1 involves simple models with deterministic inputs and outputs. An assessment at this level uses conservative assumptions, ignores minor pathways and effects and utilizes the standard laboratory studies and existing data. However, it should be noted that the conservative input is established based on distributions or conservative estimations of distributions for both exposure and effects. Depending upon the potential for effects and the quantity and quality of data, additional refinements of the assessment may be appropriate.

An assessment at the higher levels of refinement (Levels 2 - 4) uses more complex models with inputs being the distribution of the major variables and probabilistic output. Additionally, conservative assumptions are replaced by data and would include an analysis for all significant pathways and direct effects. The highest level of refinement would involve special studies or focused field studies and would be defined through sensitivity analysis of the model to help determine which variables are contributing to the uncertainty the most. These additional studies could include toxicity studies on species that may be at the highest risk, foliar dissipation studies to define residues distributions in space and time more accurately, or wildlife monitoring studies to better estimate the use of contaminated areas.

Figure 1.8-1. The concept of Levels of Refinement. The Terrestrial ECOFRAM developed the concept of Levels of Refinement as a means of organizing the variety of tools available for probabilistic risk assessments. The Levels are not intended to imply a rigidly tiered assessment process (see Chapter 6). Instead, there is a continuum between the lowest and highest Levels and tools from different levels may be used for different parameters, according to the needs of each assessment.

Level 1	Level 2	Level 3	Level 4
•Deterministic inputs			•Probabilistic inputs
•Deterministic outputs			•Probabilistic outputs
•Simple models			•Complex models
•Conservative assumptions			•Assumptions replaced by data
•Ignore minor pathways and effects			•Include all significant pathways and effects
•Use only standard studies			•Include special studies where needed
•Use only existing field data			•Include focussed field studies where needed

These four levels of refinement are not rigid steps from one level to the next. They are intended to be a flexible path to refine assessments as needed and may include various levels of refinement of the variables and assumptions in a single assessment. Chapter 6 address the level of refinement approach in greater detail.

An important point to understand as assessments are refined is the difference in defining uncertainty and reducing uncertainty. As the more sophisticated probabilistic methods are used, the uncertainty in the estimates should become better defined. However, to lower uncertainty requires additional information or data. For example, the basic toxicity studies, the LC_{50} or the LD_{50} provide only a point estimate of the toxicity value. The 95% confidence limits that are usually reported do not give information about the precision of the median lethal dose or concentration estimate. These limits define an interval such that if all possible replicate 95% confidence intervals were determined for the sampled individuals under the same conditions, 95% of them would include the true median lethal dose of the population. The LC_{50} or the LD_{50} and the reported confidence limits describe the distribution of the susceptibilities of the individual test organisms in that test, but gives no indication of the reproducibility or repeatability of the test. To obtain the precision of the estimated median lethal dose or concentration, replicate tests must be conducted (Stephan 1977). The number of replicates required is dependent on the precision wanted and the natural variation in the population for the chemical being tested. For a number of the variables which are identified, current testing provides only point estimates. Depending on the sensitivity of the assessment results to a particular variable, further replication may be required to provide better estimates of the potential effects.

1.9 BASIC MODEL STRUCTURE FOR PROBABILISTIC RISK ASSESSMENT

The basic structure of the model for estimating the magnitude and probability of pesticide effects to non-target species can be expressed in the familiar, general equation outlined in the Ecological Risk Assessment Guidelines:

$$\text{Risk} = f(\text{exposure, toxicity}).$$

Risk is a function of exposure and toxicity, and therefore assessments of risk are based on the characterization of exposure and effects. Whether, the risk assessment is deterministic or probabilistic, it is based on an exposure and a toxicity (effects) assessment. The major difference is that in probabilistic assessments, you define and use distributions of one or more variables instead of point estimates of the variables and combine the distributions to estimate the probability and magnitude of effects.

There are alternative, and in some cases more complete, definitions of probabilistic risk assessments. However, we will define probabilistic assessments as those that estimate the cumulative percentage probability that the percentage of non-target organisms adversely affected by pesticides will be (1) less than or equal to or (2) greater than any given percentage of concern.

Probabilistic risk assessments are generated by integrating estimated distributions of dose (which constitute an exposure assessment) with distributions of experimental dose-response factors such as the LD50 or EC50 and the dose-response slope (which constitute an effects assessment). This section contains a brief discussion on how to generate Monte-Carlo based probabilistic risk assessments as defined previously.

1.9.1 PDFs, Normal and Lognormal PDFs, and CDFs

Distributions for the independent (input) variables or dependent (output) variables for any equation can be presented as probability density functions (PDFs) and/or as cumulative distribution functions (CDFs). PDFs are statistical distributions that give the fractional probability (as a function of a random variable x) that any randomly selected value from the distribution will be equal to x. Examples of two types of PDFs that are commonly used in environmental assessments are the normal and lognormal distributions (Ott 1995):

Normal: $$f_N(x) = \left[1/\left(2p\, s_x^{\,2}\right)^{0.5}\right]\exp\left[-\left(x - m_x\right)^2 / 2s_x^{\,2}\right], \quad \infty < x < \infty \quad \text{(Eq. 1.9-1)}$$

Lognormal: The lognormal distribution is normal for the transformed variable y = ln x. For the

untransformed variable x, the lognormal distribution is given by:

$$f_{LN}(x) = \left[1/x\left(2p\,s_y^{\,2}\right)^{0.5}\right]\exp\left[-\left(\ln x - m_y\right)^2 / 2s_y^{\,2}\right], \quad 0 \le x < \infty \qquad \text{(Eq. 1.9-2)}$$

where

σ_y^2 = variance for the transformed variable y

μ_y = mean of the transformed variable y

Estimates of the variance and the mean of the ln transformed variable y (s_y^2 and m_y) can be computed from estimates of the variance and mean of the untransformed variable x (s_x^2 and m_x) with the following equations (PRZM3 Manual):

$$s_y^2 = \ln\left[1 + \left(s_x^2 / m_x^2\right)\right] \qquad \text{(Eq. 1.9-3)}$$

$$m_y = \ln m_x - 0.5 \bullet \ln\left[1 + \left(s_x^2 / m_x^2\right)\right] \qquad \text{(Eq. 1.9-4)}$$

Note that even though y = ln x, m_y is not equal to ln m_x and that exp m_y = geometric mean of x, not the arithmetic mean m_x.

CDFs are integrals of the PDFs from the lower bound "a" of the PDF to any value of the random variable v ≤ to the upper bound "b" of the PDF (Ott 1995):

$$F(v) = \int_a^v f(x)dx \qquad \text{(Eq. 1.9-5)}$$

where F(v) is the area under the PDF from a to v

As v —> the upper bound "b" of the distribution, F(v) —> 1 such that the complete area under the PDF from a to b is given by:

$$\int_a^b f(x)dx = 1 \qquad \text{(Eq. 1.9-6)}$$

where

a = lower bound of the distribution

b = upper bound of the distribution

The cumulative probability that any value x randomly selected from the PDF will be $\leq$ to some specific value of the random variables v is given by the CDF (Ott 1995):

$$\text{Cumulative Probability}(x \leq v) = F(v) = \int_{a}^{v} f(x)dx \qquad \text{(Eq. 1.9-7)}$$

From equations 1.9-5 and 1.9-7, it can be seen that the cumulative probability that any value x randomly selected from the PDF will be greater than some specific value v or be within some interval c to d are given respectively by (Ott 1995):

$$\text{Cumulative Probability}(x > v) = 1 - F(v) \qquad \text{(Eq. 1.9-8)}$$

$$\text{Probability}(c \leq x \leq d) = F(v = d) - F(v = c) = \int_{c}^{d} f(x)dx \qquad \text{(Eq. 1.9-9)}$$

1.9.2 Monte Carlo Simulations

Equations giving an output (dependent) variable as a mathematical function of other input (independent) variables (such as equations for estimating pesticide concentrations, dose or effects in the environment) can be used deterministically or probabilistically. An equation being used deterministically estimates a single value for the output (dependent) variable based upon single values being substituted for each of the input (independent) variable in the equation. An equation being used probabilistically generates a distribution of values for the output variable based upon a distribution of values being substituted for one or more of the input variables in the equation.

Distributions of values for the output variable of an equation are generally obtained by performing

Monte Carlo simulations. In Monte Carlo simulations, statistical distributions in the form of probability density functions are assigned to one or more of the input variables. The computer algorithm generating estimated values of the output variable is then run numerous (generally thousands of) times. For each of the runs, the values of the input variables for which statistical distributions are assigned are randomly selected from their distributions.

The random selection of input values for each run gives different combinations of input values and a different resulting estimated output value for each run. The thousands of runs result in a distribution of estimated output values.

In performing a Monte Carlo simulation, any significant correlations between any of the input variables must be accounted for to avoid randomly generating nonsensical combinations of values for the input variables for some of the runs that would not actually occur (Vose 1996). The correlation between any two variables is generally represented by the magnitude of the linear or rank order correlation coefficient depending upon the requirements of the Monte Carlo software being used.

Correlations among all of the input variables can be represented by a correlation matrix in which element ij is equal to the linear or rank order correlation coefficient between the variable representing row i and the variable representing column j (Farrar 1997). If the variables are not correlated, the element is set equal to zero. Computations with the correlation matrix vary depending upon the software being used and whether linear or rank correlation coefficients are used. However, in each case, the correlation matrix is used to ensure that correlations between input variables are maintained during the random selection of input values.

In performing a Monte Carlo simulation, the scale and location of the input distributions should be comparable to the scale and location of the simulation. For example, if the scale and location of the simulation is Iowa, distributions of input variables for the entire United States or for Florida should not be used.

1.9.3 Functional Relationships Between Risks, Dose, and Dose-Response Parameters

Risk is a function of dose and dose-response parameters such as the LD50 or EC50 and the dose-response slope. Alternatively, risk can be viewed as a function of dose and the sensitivities (tolerances) of non-target organisms where the sensitivity (tolerance) of an individual organism is defined as the threshold dose required to cause the organism to exhibit an adverse effect such as death, growth or reproductive effects. Dose-response functions (equations defined by dose-response parameters) and sensitivities are closely related because a dose-response function represents the CDF of a sensitivity PDF (Finney 1962).

Dose is a function of animal behavior or other animal characteristics (such as food and water ingestion rates, inhalation rates, diet, and body weight) and of pesticide concentrations in environmental media . Pesticide concentrations in environmental media are functions of numerous parameters including the application rate (which helps to determine the initial concentration), characteristics of the environmental media (such as plant biomass) and dissipation rate constants.

1.9.4 Basic Steps in Generating a Probabilistic Risk Assessment

There are 4 basic steps in generating a probabilistic risk assessment for a single non-target species foraging over a single defined pesticide use area for a specified time interval. The steps can be repeated for the same species in other use areas or for other species in the same use area. The steps are discussed below and are graphically presented in Figures 1.9-1 through 1.9-5.

The normal looking PDFs represented in Figures 1.9-1 through 1.9-5 are only for illustrative purposes and are not meant to imply that all of the distributions are normal. In fact, environmental data often follow lognormal or other types of skewed distributions (Ott 1995).

1.9.4.1 Step 1: Exposure Assessment

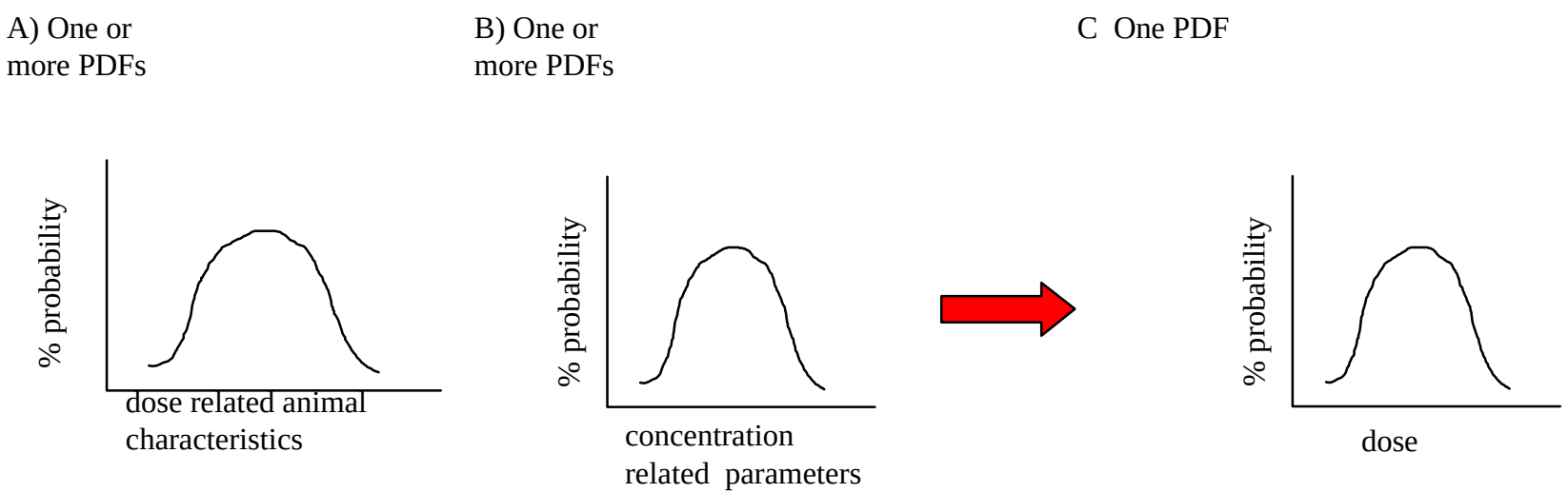
A dose distribution is generated using a Monte Carlo simulation consisting of numerous individual runs. Statistical distributions in the form of PDFs are assigned to one or more of the input variables affecting dose such as food ingestion rate, initial residue concentrations, and dissipation rate constants. The computer algorithm generating estimated values of the dose is then run numerous (generally thousands of) times. For each run, the values of the one or more input variables for which statistical distributions are assigned are randomly selected from their distributions.

The random selection of input values for each run gives different combinations of input values and a different resulting estimated dose for each run. The thousands of runs result in a distribution of estimated doses in the form of a PDF. The exposure assessment process is graphically represented by Figure 1.9-1. Sub-figure A represents one or more input PDFs for dose related animal characteristics such as the ingestion rate, body weight, and percent diet for different types of food. Sub-figure B represents one or more input PDFs for concentration related parameters that are used to estimate concentration versus time series in environmental media such as the initial concentration, plant biomass, and dissipation rate constants. Sub-figure C represents the dose PDF output of an exposure assessment

1.9.4.2 Step 2: Effects Assessment

In a laboratory dose-response study, regression is used to estimate the values of dose-response parameters (such as the LD50 or EC50 and the dose-response slope) that best fit dose-response data to a dose-response equation (such as the probit) and its associated dose-response curve. The dose-response equation and its associated dose-response curve give the percentage (or some transformation of the percentage) of experimental organisms affected as a function of experimental dose (or some transformation of the dose). Each dose-response experiment will

Figure 1.9-1Exposure Assessment. Step 1: Probabilistic Exposure Assessment



generate a single LD50 or EC50, a single dose-response slope, a single dose-response equation, and a single dose-response curve. Based on repeated dose-response experiments, distributions of dose-response parameters such as the LD50 or EC50 and the dose-response slope can be generated. Depending upon the quantity of dose-response data available, such distributions can be best fit PDFs, hypothetical PDFs generated by selecting a distribution type based on the literature and computations of the mean and standard deviation of the available data or empirical non-parametric distributions.

Recall that the sensitivity (tolerance) of an individual is the threshold dose required for the organism to exhibit an adverse effect and that a dose-response equation is the CDF for a sensitivity PDF. Each dose-response equation (defined by a LD50 or EC50 and a slope) has an associated sensitivity PDF. If the PDFs for dose-response parameters (such as the LD50 or EC50 and the slope) can be assumed to be independent, a set of n random selections from each dose-response parameter PDF will result in n dose-response equations and n corresponding sensitivity PDFs.

One or more dose-response equations (each defined by a specific value of the LD50 or EC50 and the slope) can be used to generate one or more sensitivity (tolerance) PDFs for use in Method A of Step 3 (section 1.9.4.3) to help generate a risk PDF. Alternatively, one or more dose-response equations can be used more directly in Methods B and C of Step 3 to help generate a risk PDF.

The effects assessment process is graphically represented in Figure 1.9-2. Sub-figure A represents the frequent case where only a single dose-response equation (represented by its associated dose-response curve) is available. Nevertheless, the single dose-response equation is sufficient to generate an associated sensitivity (tolerance) PDF as represented by Sub-figure B. Sub-figure C represents the much less frequent case where multiple dose-response equations (represented by their associated dose-response curves) are available. In such cases, single PDFs can be generated for the various dose-response parameters such as the LD50 or EC50 (Sub-figure D) and the dose-response slope (Sub-figure E).

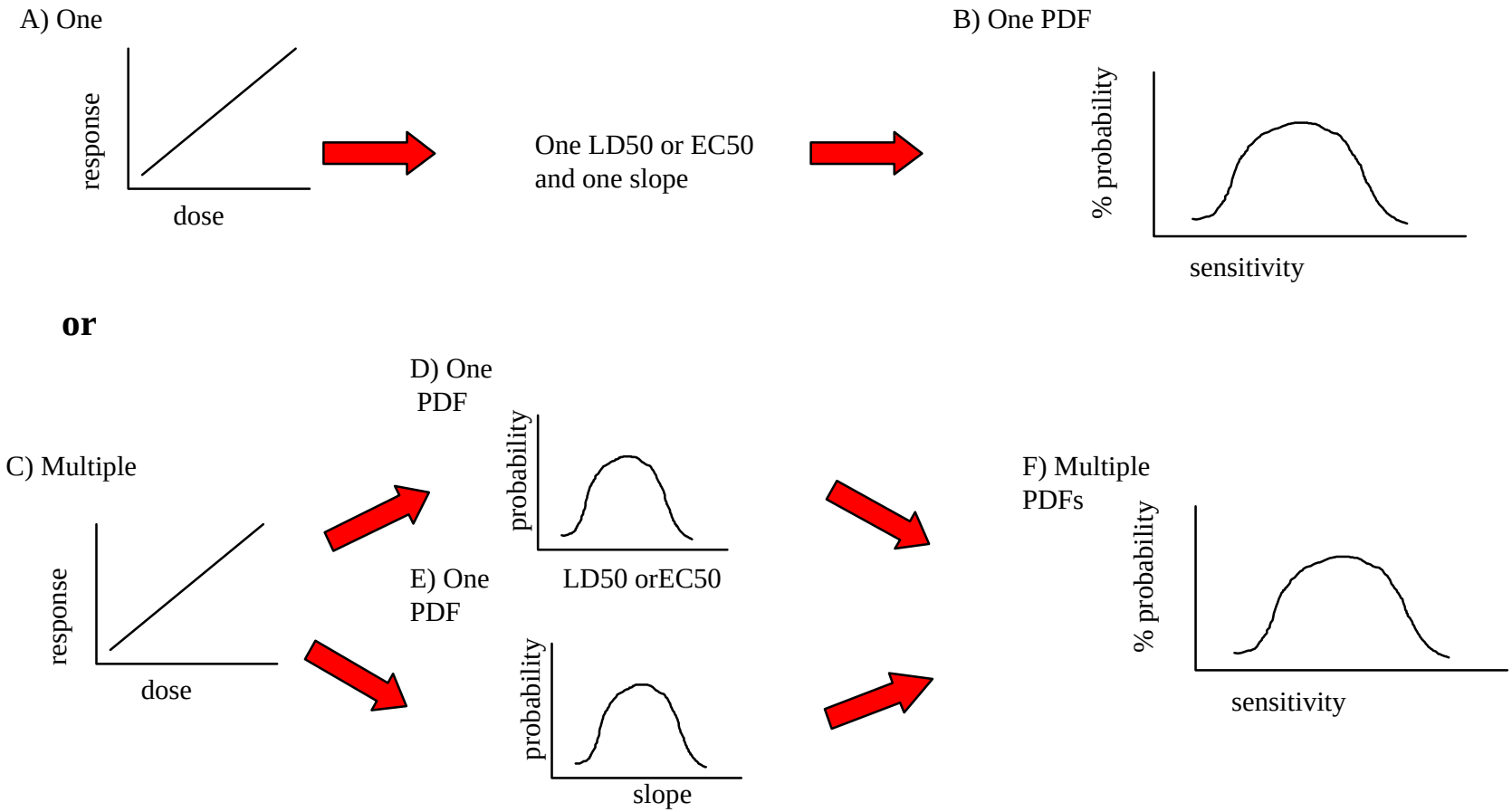
Assuming that the PDFs for the LD50 or EC50 and the dose-response slope are independent, multiple dose-response equations (defined by the LD50 or EC50 and the slope) can be generated by randomly sampling from both their distributions. Therefore, because a sensitivity (tolerance) distribution is associated with each dose-response function, multiple sensitivity (tolerance) PDFs can be generated from the LD50 or EC50 and dose-response slope PDFs as represented by the arrow going from Sub-figures D and E to Sub-figure F.

1.9.4.3 Step 3: Generation of a Risk PDF

A risk PDF gives the probability of the percent of organisms affected being equal to any given value of the random variable x as a function of x. There are various methods for generating a risk PDF from the outputs of the exposure and effects assessments. Three methods are as follows:

Method A of Generating a Risk PDF: This method uses the dose PDF and one or more sensitivity PDFs generated in steps 1 and 2, respectively. The simulation consists of N groups of n runs each. Each run represents a different single individual and results in the individual being classified as adversely affected or not affected. The classification is based upon a comparison of the individual's randomly selected dose (from the dose PDF) to its randomly selected sensitivity (from a sensitivity PDF). Recall that an individual's sensitivity (tolerance) is the threshold dose necessary for the organism to exhibit an adverse effect (death, reduced reproduction, reduced growth, etc.). If an individual's randomly selected dose (from the dose PDF) is greater than or equal to its randomly selected sensitivity (from the sensitivity PDF), the individual is classified as being adversely affected. If an individual's randomly selected dose is less than its randomly selected sensitivity, the individual is classified as not being adversely affected. In the case where there are PDFs for the LD50 or EC50 and the slope, the sensitivity distribution for a given run (from which the sensitivity is randomly selected) is generated from a dose-response equation defined by randomly selected values of the LD50 or EC50 and the slope from their PDFs.

Figure 1.9-2 Effects Assessment. Step 2: Probabilistic Effects Assessment



Each set of n runs only generates a single point (percent of organisms adversely affected) on the risk PDF. However, N sets of n runs each generates N points (percent of organisms adversely affected) on the risk PDF.

Method A is graphically represented in Figure 1.9-3. Sub-figure A represents the Dose PDF generated in Step 1. Sub-figure B represents one or more sensitivity PDFs generated from a single dose-response equation or from multiple dose-response equations derived from the random selection of LD50 or EC50 and slope values from their PDFs. The arrow to Sub-figure C represents the generation of the risk PDF (Sub-figure C) from the dose and sensitivity PDFs

Method A is used in an example model (Paret) discussed in Chapter 5 and Appendix A2.

Method B of Generating a Risk PDF: This method uses the dose PDF generated in step 1 and either a single dose-response equation or the LD50 or EC50 and slope PDFs generated in step 2. The simulation consists of N groups of n runs each. Each run represents a different single individual and results in the individual being classified as adversely affected or not affected. The classification is based upon a comparison of the individual's percent probability of being affected to a randomly selected percent from the uniform distribution. If an individual's probability of being affected is greater than or equal to the percent randomly selected from the uniform distribution, the individual is classified as being adversely affected. If an individual's probability of being affected is less than the percent randomly selected from the uniform distribution, the individual is classified as not being adversely affected.

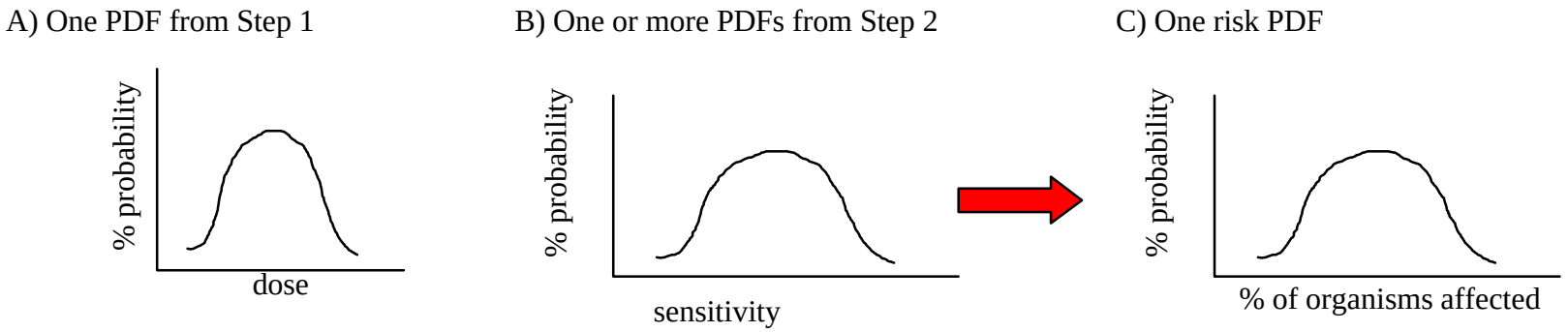
The individual's percent probability of being adversely affected is determined by substituting a randomly selected dose (from the dose PDF) into the dose-response equation for the given run. Although the response in a dose-response equation is experimentally expressed as the percent of organisms adversely affected at a given experimental dose, it is also equivalent to the percent

Figure 1.9-3 Method A Step 3 Generation of a Risk PDF

Method A: Simulation consists of N sets of n runs each.

Each run represents an individual and results in classifying the individual as affected or not affected based on a comparison of the individual's randomly selected dose and its randomly selected sensitivity (the threshold dose for the organism to exhibit an affects).

Each set of n runs generates a single point for the percent organisms affected on the risk PDF. N sets of n runs each generates N points of the % of organisms affected on the risk PDF.



Note: The risk PDF depicted byC gives the percent probability that the percent organisms affected is equal to any given value x on the x axis as a function of x.

probability that an organism randomly selected from the population will be affected by the given dose.

In the case where there are PDFs for the LD50 or EC50 and the slope available, the dose-response equation for a given run (in which a randomly selected dose is substituted to determine the percent probability that the organism will be adversely affected) is defined by randomly selected values of the LD50 or EC50 and the slope from their PDFs.

Each set of n runs only generates a single point (of percent of organisms adversely affected) on the risk PDF. However, N sets of n runs each generates N points (of percent of organisms adversely affected) on the risk PDF.

Method B is graphically represented in Figure 1.9-4. The top row of Sub-figures represent the case where there is only one dose-response function available. The dose PDF (Sub-figure A) generated in Step 1, a single dose-response function (Sub-figure B) generated in step 2 are combined to generate a risk PDF (Sub-figure C). The second row of Sub-figures represent the case where LD50 or EC50 and slope PDFs are available. The dose PDF (Sub-figure D) generated in Step 1, the LD50 or EC50 PDF (Sub-figure E) and the slope PDF (Sub-figure F) generated in step 2 are combined to generate a risk PDF (Sub-figure G).

Method B is used in the Dixon Granule Model (see Appendix A3). Method B should give identical results to those of Method A when applied to the same data using the same number N of sets and the same number n of runs per set in the simulation.

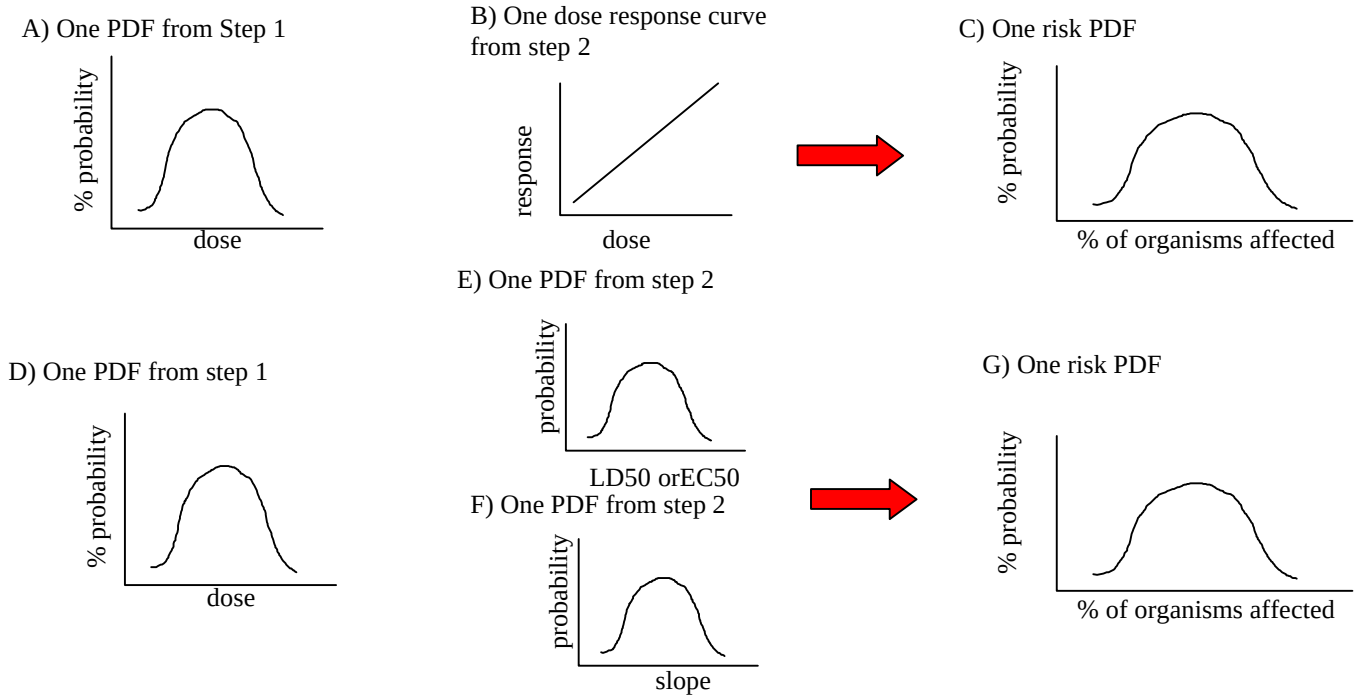
Method C of Generating a Risk PDF: This method uses the dose PDF generated in step 1 and either a single dose-response function or the LD50 or EC50 and slope PDFs generated in step 2. The simulation consists of N runs. Each run represents a different subpopulation of an unspecified large number of organisms. All individuals within the subpopulation are assumed to receive the

Figure 19-4 Methods B and C Step 3: Generation of A Risk PDF

Method B: Simulation consists of N sets of n runs each.

Each run represents an individual and results in classifying the individual as affected or not affected (based on a comparison of the individual's randomly selected percent probability of being affected with a randomly selected Percent from the uniform distribution).

Each set of n runs generates a single point of the percent of organisms affected on the risk PDF. The N sets of n runs each generates N points of the % of organisms affected on the risk PDF.



Method C: Simulation consists of N runs.
Each run represents an unspecified large number of individuals and generates a single percent of organisms affected point on the risk PDF. N runs generates N% of organisms affected points on the risk PDF. The figures for method C are identical to those for method B.

same randomly selected dose and to respond according to the same dose-response function. In the case where there are PDFs for the LD50 or EC50 and the slope available, the dose-response equation for a given run is defined by randomly selected values of the LD50 or EC50 and the slope from their PDFs.

Each run generates a single point (percent of organisms adversely affected) on the risk PDF. A total of N runs generates N points (percent of organisms adversely affected) on the risk PDF.

Figure 1.9-4 is applicable to Method B and also applicable to Method C.

Method C is simpler than Methods A and B, because it eliminates the additional step of classifying each individual as being adversely affected or non-affected. Therefore by using Method C, it is not necessary for the simulation to consist of N sets of n runs each where each run represents a different single individual instead of a different single subpopulation. Instead the simulation can consist of N runs where each run represents a different single subpopulation.

Although method C is simpler than Methods A and B, Method C does not account for the sampling error associated with small populations like Methods A and B do. Therefore as discussed in Appendix D1, Method C is probably only applicable to large populations.

1.9.4.4 Step 4: Generation of a Risk CDF and (1 - CDF) from the Risk PDF

The risk PDF generated in Step 3 should be included in a risk assessment to graphically show the estimated distribution of percentages of organisms adversely affected. However, the quantitative information a risk PDF provides is of limited value for assessing risk because it gives the percent probability that the percentage of organisms adversely affected is equal to any given value x on the x axis as a function of x.

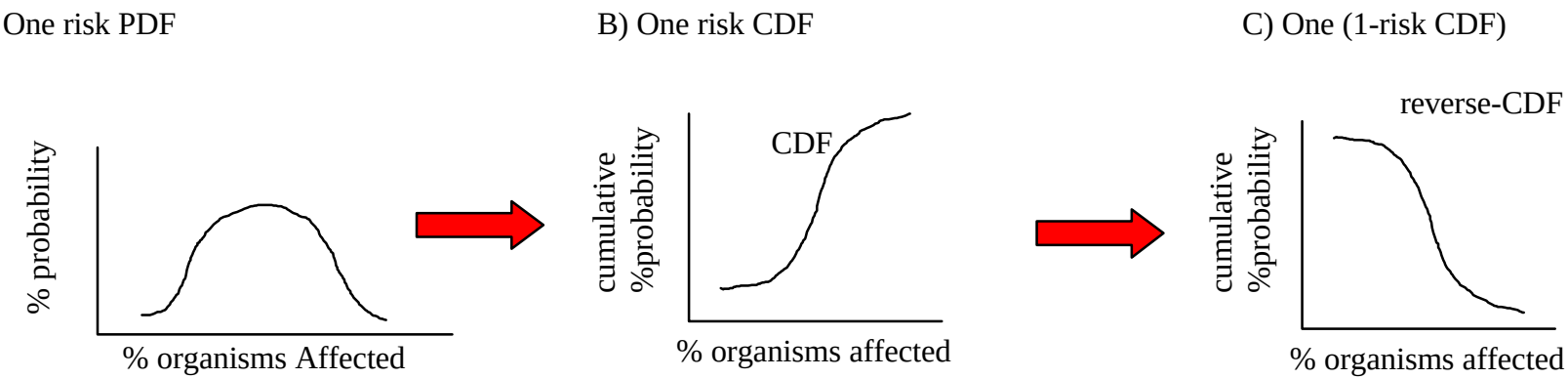
From a risk assessment standpoint, the risk CDF and (1 - risk CDF) provide more useable

information than the risk PDF. The risk CDF gives the cumulative probability that the percent of affected organisms is $\leq$ any given value v on the x axis as a function of v. The (1 - risk CDF) function gives the cumulative probability that the percentage of organisms affected is > than any given value v on the x axis. Therefore, the risk CDF and (1 - risk CDF) should also be provided along with the risk PDF.

As previously indicated, the CDF is obtained by integrating the PDF from the lower bound of the PDF to any value of the random variable v $\leq$ upper bound of the PDF as shown by equation 1.9-7. Only the simplest PDFs such as the exponential or triangular can be integrated analytically. However, tables reflecting numerical integration are available for all standard PDFs. In addition, off the shelf Monte Carlo software such as @RISK and CRYSTAL BALL readily generate CDFs from their corresponding PDFs.

The differences between a PDF, a CDF, and 1 - CDF are graphically represented in Figure 1.9-5 by Sub-figures A, B, and C, respectively.

Figure 1.9-5 Step 4 Generate A Risk CDF and (1-Risk CDF)



The risk PDF depicted by A gives the percent probability that the percent of organisms affected are equal to any given value x on the x axis as a function of x.

The risk CDF depicted by B gives the cumulative percent probability that the percent of organisms affected is less than or equal to any given value v on the x axis as a function of v.

The (1-risk CDF) depicted by C gives the cumulative percent probability that the percent of organisms affected is greater than any given value v on the x axis as a function of v.

2.0 PROBLEM FORMULATION

2.1 ASSESSMENT QUESTION (ENDPOINTS) AND CONCEPTUAL MODELS

The initial discussions of the Terrestrial Workgroup focused on defining the assessment questions or endpoints (problem formulation). According to the EPA Guidelines for Ecological Risk Assessment, assessment endpoints are explicit expressions of the actual environmental value that is to be protected and is directly related to a characteristic of an ecological component that may be affected by exposure to a stressor. There are several criteria for selecting assessment endpoints, which include ecological relevance, susceptibility to the stressor, and the relationship of the assessment endpoints to management goals and societal value. Each assessment endpoint must contain two elements, the valued ecological entity and the characteristic of that entity which is potentially at risk and is important to protect.

The Guidelines for Ecological Assessment indicate that assessment endpoints are critical to problem formulation because they direct the assessment to address management concerns and are central to conceptual model development. Their relevance is determined by how well they target susceptible ecological entities. The Guidelines indicate that the ability of assessment endpoints to support risk management decisions depends on whether they are measurable ecosystem characteristics that adequately represent management goals. Therefore, the interaction among risk assessors, risk managers, and other interested parties are extremely important in the development of the risk assessment. The Guidelines also emphasize that risk assessment and risk management are two distinct activities. The former is the evaluation of the likelihood of adverse effect, while the latter is the selection of a course of action in response to an identified risk. Risk management is based on many factors in addition to the risk assessment, including social, legal, political, and/or economical considerations.

The scope of the ECOFRAM's charge includes the development of probabilistic risk assessment methods to address the array of pesticide uses now and in the future, including all application

methods and crops in all environments throughout the United States. Clearly this task is too broad to define specific assessment endpoints for all assessments. The ecological entities concern in Florida avocado fields treated with foliar insecticides will be different from one in a California strawberry field treated with a soil fumigant. The risk assessment must be tailored for each unique situation. However, the Workgroup believed that generalized assessment endpoints could be drawn which would be applicable for developing probabilistic methods. These methods should be adaptable for use in a large majority of ecological pesticide risk assessments.

In defining the assessment endpoints, the Workgroup, as previously indicated, followed the outline presented in the Guidelines for Ecological Risk Assessments. The Guidelines indicate that the initial work in problem formulation includes integration of available information on the pesticide and its use, identifying the species and ecosystem at risk, and the important variables that influence exposure and effects. From this information, the guidelines indicate two products are generated from the problem formulation, assessment endpoints and conceptual models. In developing the general assessment endpoints and conceptual models, the Workgroup focused on the following points:

- Risk management questions,
- Potential ecological effects of pesticides, and
- The major variables that influence these effects.

2.2 RISK MANAGEMENT QUESTIONS

In defining the ecological risk assessment questions or endpoints, the Workgroup believed it was extremely important to consider the questions often posed by risk managers. For the assessment to be useful in the decision-making process, they must address questions which are both understood and believed relevant to the regulatory decision by the risk manager. If the questions addressed in an assessment are not considered relevant or understood by the risk manager, they

would contribute little to the regulatory decision. Therefore, risk assessments should address clear, predetermined questions (US EPA 1992).

In 1997 a workshop was held to begin this initiative. It included a presentation by Steve Johnson, then the Acting Deputy Office Director of OPP, summarizing the questions often posed by risk managers. In Mr. Johnson's presentation, he identified the questions most often posed by risk managers:

- What are the effects of concern?
- Why are they of concern?
- What is the magnitude and probability of these effects?
- Will there be population(s) impacts?
- Will the population(s) recover?
- Are the effects seen across different species?
- Will the effects influence the density and diversity of the species?
- How confident are we in our estimate of the effects?
- What models did we use? Have they been validated?
- Are the models widely accepted and scientifically sound?
- How predictive and confident are we in using the models?
- Have you completed a comparative analysis of the potential environmental effects with similar compounds and/or alternatives?
- Is there any monitoring data? How have you factored the monitoring data into your assessment?
- If there are unresolved scientific issues, can data be developed/studies conducted to answer these questions?
- How long will it take to conduct the studies and how much will they cost?
- Have other agencies and/or countries assessed the environmental risks?
- How do our assessments compare with those of other agencies and/or countries?
- For each question already mentioned are there any mitigation measures (i.e. buffer zones,

filter strips, use reduction, etc.) that will eliminate or reduce the calculated risk?

- Can we measure/monitor to determine if our mitigation measures are working?
- In summary, help me put this pesticide and its potential environmental risk in perspective.

In addition, several risk managers participated in the initial ECOFRAM meeting that followed the workshop. The risk managers emphasized that bright lines could not be specified to guide risk management decisions involving ecological risk. They also indicated they wanted as complete a picture as possible of the potential ecological impacts from pesticides, including a clear understanding of the uncertainties associated with the assessment. They also indicated that they were interested in estimates of risk at the individual, population, community, and ecosystem levels, accounting for direct and indirect effects. They acknowledged assessment limitations, but believed that assessments should provide the most complete picture of ecological riska that is scientifically defensible.

2.3 TYPES OF ECOLOGICAL EFFECTS

In defining the assessment questions (endpoints), the Workgroup discussed the potential risk the use of pesticides pose to non-target species. These include direct poisoning and death by ingestion, dermal exposure, and\or inhalation; sub-lethal toxic effects indirectly causing death by reducing resistance to other environmental stresses such as diseases, weather, or predators; indirect effects through reduced food resources or alteration of habitat; altered behavior such as abandonment of nest or young, change in parental care, or reduction in food consumption; or lowered productivity through fewer eggs laid, reduced litter size, or reduced fertility. These effects will manifest themselves in wildlife through reduced survival and/or lower reproduction success.

The major emphasis in assessing pesticide impacts to non-target wildlife has been direct lethal effects. This emphasis has been driven by the type of laboratory toxicity data that is generally the most prevalent. While certainly of concern, the workgroup believed limiting the assessment to the

magnitude of toxicity might miss the more subtle, but equally disruptive sub-lethal or indirect effects. Not all exposure to pesticides result in the immediate death of an animal. Sub-lethal doses of some pesticides can lead to changes in behavior, weight loss, impaired ability to reproduce, inability to avoid predators, and lower tolerance to extreme temperature and other environmental conditions.

These lethal and sub-lethal effects can be further aggravated by the intended effects of the pesticides through reduced food supplies or altered habitat. Pesticides are intended to alter the agro- or other ecosystems on which they are used, and therefore by their vary nature, have the potential to disrupt the system to which they are introduced. Wildlife food sources can be reduced by both herbicides and insecticide applications and can have significant effects on individual animals and local populations. Insect-eating animals lose a portion of their food supply when insecticides are applied within their home range. Herbicides can reduce availability of both plants and insects as food supplies. Spraying herbicides on weedy areas destroys insect habitat, leading to less abundant and diverse insect populations available as wildlife food sources. Loss of seed producing weed species from repeated herbicide use results in an additional decline in food resource and habitat alteration.

As previously indicated, the application of pesticides may have indirect effects on non-target species by altering food supply or habitat integrity. While establishing a causal relationship between such ecosystem alterations and wildlife effects is difficult to demonstrate, it is clear that indirect effects are possible because of the interdependency of species within an ecosystem. Therefore, in defining the assessment endpoints and understanding management goals, the interrelationships existing among the various components of the ecosystem needs to be considered.

2.4 MAJOR VARIABLES

In defining the assessment endpoints and in developing conceptual models, major variables that

influence exposure and effects were identified and discussed. As indicated in the previous chapter, the basic structure of the risk assessment model is divided into exposure characterization, effects characterization, and integration of exposure and effects to generate a risk characterization. The results are integrated into a characterization of the risk.

The main objective of the exposure part of the risk assessment process is to estimate the distributions of dose to non-targets. Dose is the amount of pesticide introduced into or taken up by an organism. The variables that influence dose can be separated into two components, the chemical/physical component and the biological component. The chemical/physical component of estimating the dose are the environmental and chemical variables that influence the distribution of residues levels in time and space in environmental media (e.g., air water, soil, food). The biological component addresses the animal behavior attributes that affect the frequency and intensity of the contact with the various environmental media.

For terrestrial wildlife there are three major routes of exposure: oral, dermal, and inhalation. The major chemical/physical variables that influence dose for such exposure routes include:

- The chemical/fate properties of the pesticide,
- Plant/crop characteristic and agricultural properties,
- Meteorological conditions,
- Soil properties, and
- Wildlife water source properties.

For the biological component, the major variables that influence dose for such routes of exposure is species dependent and include:

- Food, water, and soil ingestion rates,
- Inhalation rates,
- Dietary diversity,

- Habitat requirements and spacial movement,
- Direct ingestion rates (granular formulation), and
- Dermal and inhalation absorption rates.

The objective of the effects part of the risk assessment process is to estimate the distributions of specific effects to non-target species at a given distribution of exposure, the dose-response relationship. The major variables that influence the response of individual animals includes:

- Toxicity (intra- and inter-species variability),
- Age and sex,
- Nutritional status,
- Breeding status,
- Environmental conditions, and
- Duration and extent of exposure.

A number of the variables that influence exposure and effects are discussed in Chapters 3 and 4. Ways to estimate their distributions and some of the uncertainties associated with these techniques are also discussed, although not all are explored in the same depth due to the absence of data and/or time. Chapter 5 provides a skeleton structure for integrating some of the important variables to estimate the probability and magnitude of effects. While additional developmental work will be required to establish working assessment tools and research will be needed to define or better define the major variables and their influence on effects, these tools and methods provide a basis for advancing ecological risk assessments of pesticides.

2.5 CONCEPTUAL MODEL AND ASSESSMENT ENDPOINTS

From the discussions of the potential exposure pathways and effects of pesticides to non-target species, the identification of the major variables that could influence these exposure and effects, and the input from the risk managers, the Workgroup developed several conceptual models.

Figure 2.5-1 shows the initial model developed by the Workgroup. It includes a large number of potential exposure and effect routes for a variety of organisms under varying combinations of site and application combinations and as well as consideration of indirect effects. Other conceptual models were also developed and are presented in following chapters as well as in the appendixes.

Based on the input from the risk managers and the Workgroup discussions of the potential effects of pesticides to non-target species and the major variables that influence these effects, the following general list of assessment endpoints were defined for ecological risk assessments of pesticides:

INDIVIDUAL ENDPOINTS

- Survival of valued ecological entity*
- Reproduction of valued ecological entity*
- Growth and development of ecological entity
- Morbidity of valued ecological entity

POPULATION LEVEL EFFECTS

- Population size of valued ecological entity*
- Persistence of valued ecological entity*
- Demographics of valued ecological entity

COMMUNITY AND SYSTEM VALUES

- Patterns of taxonomic diversity
- Patterns of functional diversity
- Changes in compositional integrity
- Nutrient cycling
- Energetics

(*) Primary endpoints considered by ECOFRAM

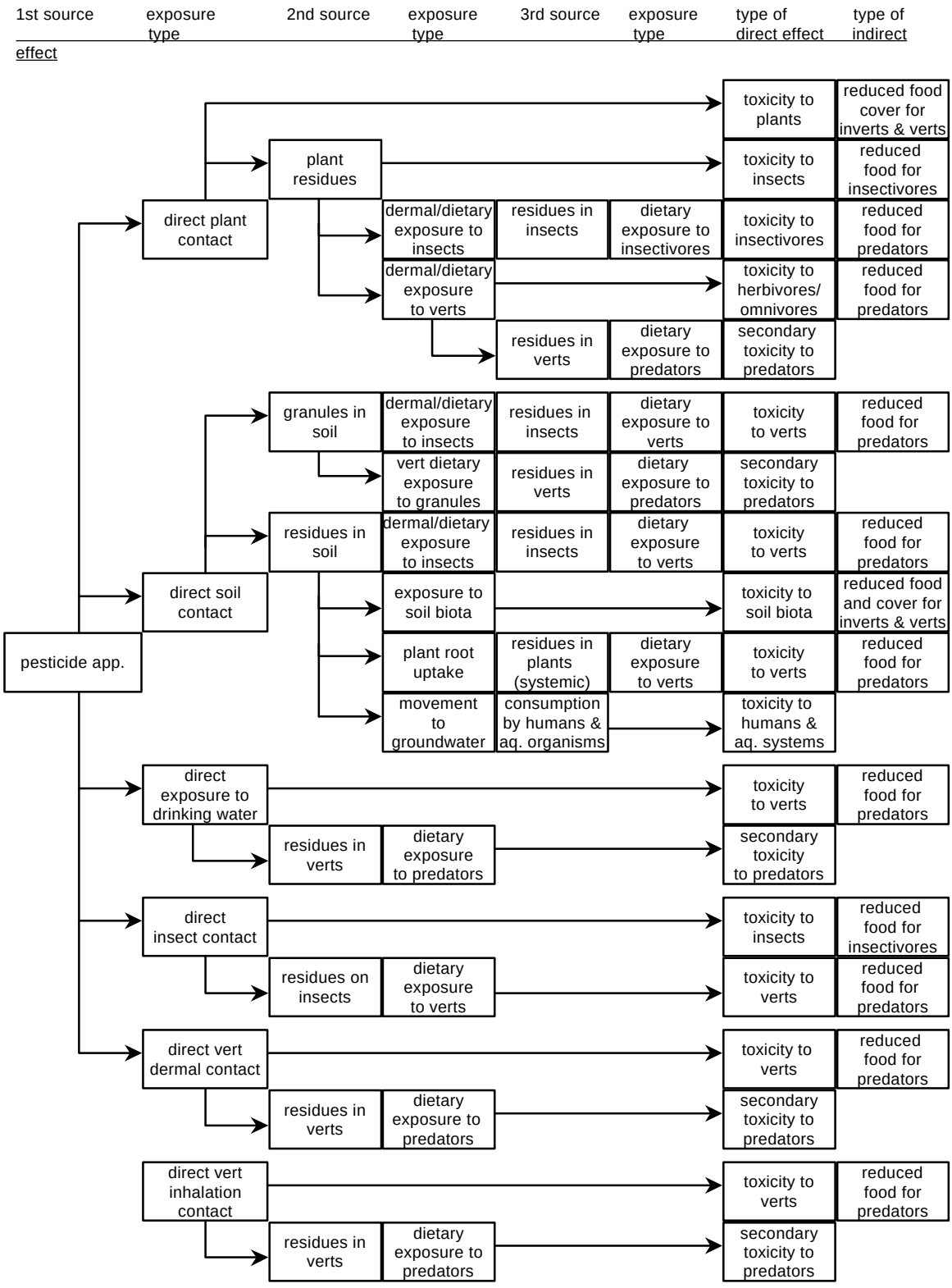


Figure 2.5-1 Generic conceptual model emphasizing exposure characteristics.

As specified in the Charge and as agreed upon by the majority of the Workgroup, direct acute and chronic effects of pesticides to birds and mammals at the individual and population levels would be addressed first. As previously indicated, the focus on direct toxicity does not imply it is the more important than other effects. However, the Workgroup felt the assessment of direct toxicity drives the current pesticide assessment process and is more tractable than addressing other, more complex interactions. Also, given the time frame of ECOFRAM, the scope of the questions potential effects addressed needed to be limited. And, in fact, even narrowing the scope to direct effects at the individual and population levels was believed by some as an ambitious goal.

Similarly, the focus on birds and mammals does not imply they are the most important taxonomic groups. As indicated in Chapter 1, the larger databases of toxicity and life history information on these species was believed to make them more amenable for developing a new process for pesticide risk assessment. As the process developed, birds received the majority of the emphasis because of the emphasis of current assessment process on avian species and the expertise of Workgroup members. However, the methods developed could easily be applied to mammalian and other vertebrate species.

Also, as discussed in later sections, the hope to address population level effects was limited by the available data. The Workgroup felt that a complete probabilistic assessment of pesticides to non-target species should consider other groups of non-target vertebrates, invertebrates, microorganisms, and plants. Thus, they concluded that the developmental effort needs to be continued beyond this initiative and be expanded to include other types of species as well as population and overall ecosystem effects. Appendix B1 discusses further the development of the assessment endpoints.

2.6 ADDITIONAL CONSIDERATIONS FOR PROBLEM FORMULATION FOR PESTICIDES

The task of defining specific endpoints for all assessments is difficult due to the numerous conditions and areas where pesticides are used. However, there are some special considerations that appear appropriate to factor into the problem formulation phase of the assessment for chemical specific assessments. These include pesticide formulation and use patterns, defining the agro-ecosystem at risk, identifying the time scale to be considered, and identifying high risk species in the agro-ecosystem of concern.

2.6.1 Formulation and Use Patterns

All pesticides registered under FIFRA are required to have a label which provides specific instructions and information for users. The label also provides important information for the problem formulation and risk characterization phases. The label, for example, identifies the formulation type. These include liquids (emulsifiable concentrates, suspension concentrates, and suspo-emulsions), solids (water dispersible granules, wettable powders, water soluble powders, tablets, granules, pellets, and baits) and others (water soluble bags, gels, pastes, water-based solutions). It also provides information on use patterns which are defined by the formulation type, carrier type, crop and region, pest complex, application method and rates, number, and frequency of application.

This information is important when considering the risk posed by pesticides. For example, the application method (aerial, ground-directed boom spray, in furrow granular application) will affect route and probability of exposure. The application rates, number and frequency of applications will contribute to exposure estimates. Dry applications present a special case for terrestrial exposure and will require special risk assessment methodology. (See Chapter 3, granular applications.) Thus, it is of primary importance to consult the current or proposed label

for each product to establish potential exposure issues that need to be factored into the problem formulation.

2.6.2 Defining the Ecosystem at Risk

In the problem formulation phase, it is important to define the ecosystem at risk. Meaningful definitions of any ecosystem are elusive because it is difficult to precisely define their spatial and temporal scales. To circumvent this difficulty, at least in initial assessments, the term agro-ecological scenario will be defined as the agricultural land, for example a field orchard, capable of supporting commercial crop production and its border area. This definition is suggested because it describes the habitat used by the species at risk and represents the area that will receive the vast majority of residues by direct application or drift. Operationally, the individual agricultural field is the basic spatial unit for pest management because recommendations for treatments will be made at that spatial level.

The particulars about an agro-ecological scenario that should be considered during problem formulation include (1) cultural practices, including annual pattern of planting, (2) cultivation and harvest, (3) irrigation, (4) weed management, and (5) insect management. Each of these facets of production agriculture can affect risk. Another consideration is that not all of the border will be a non-crop. Often agricultural fields are adjacent to other agricultural fields. Finally, the body of data on pesticide drift indicates that the levels of pesticide residues in the border will be much lower than the residue levels in the target crop fields.

When initiating a risk assessment, the assessor would first identify the range of agro-ecological scenarios for the pesticide. Each scenario would then be characterized in terms of the variables which affect exposure, either deterministically or probabilistically. A risk assessment could then be conducted separately for each scenario. The results could then be combined, taking into account the relative frequency of each scenario, to arrive at an overall assessment of the magnitude and probability of adverse effects for a given region.

The border area surrounding the specific crop is often a more suitable habitat for terrestrial vertebrates than the treated field itself. This border comprises a wide variety of vegetation types and associated ecotones surrounding the cultivated field edge. It is possible to derive estimates for the maximum areas of crop field borders that have potential to contain residues. These depend on the area of the crop, field size, and field shape.

For the purpose of preliminary or screening-level assessments, it would be preferable to avoid evaluating the full range of relevant scenarios and to identify which of the relevant scenarios are most likely to generate a high risk for wildlife. This scenario would be used for screening purposes.

Initially, the task of identifying and defining the scenarios will be onerous. However, much of the information will be generic, applying equally to the assessments for many pesticides used on a particular crop. Over time, an increasingly comprehensive set of scenarios would be accumulated, in effect a large database of 'model environments'. If this database is computerized and designed to sort variables by frequency and geographic distribution, the effort required to select the scenarios and many of the computations for risk assessment could be strongly facilitated. Such a database could become the basis for landscape level assessments of risk.

The primary variable in defining an agro-ecological scenario is the type of crop (e.g., corn, cotton, etc.) or at least a general category of similar crop types (e.g., forage, grain, etc.) because the crop defines the invertebrate pest problems which in turn determine the pesticide use scenarios. Another important variable or group of variables is the characteristic of the non-crop habitat adjacent to, and interspersed among, fields of the crop of interest. In many cases, identifying the state or local region will establish the general nature and plant species range of the non-crop habitat that might be associated with the crop. This is important because these habitats influence the kinds and numbers of wild species inhabiting the region.

Geographic regions also generally define meteorological conditions that determine the need for irrigation. Irrigated crops and habitats in otherwise semi-arid conditions usually support very different wildlife populations, even populations that would not occur in that location under natural conditions. Additional important geographic variables include soil type, terrain, and temperature regime. Four examples of important agro-ecological scenarios and brief discussions of some of their ecological characteristics that would need to be considered are provided in Appendix B2.

The agro-ecosystem concept developed above is a very useful vehicle for real-world application of the generalized exposure model developed in Chapter 3. Ecological risk assessment for pesticides do not often attempt to include a realistic treatment of spatial relationships. The extent of the growing area of a particular crop, the timing of crop production, the relationship of the crop agro-ecosystem to other ecosystems, and market share are given limited attention. Explicit identification of terrestrial vertebrate species at risk are often not attempted, and the relationship of these species with the agro-ecosystem are often not specified.

The agro-ecosystem concept, with its spatially explicit scale and identification of focal species, can provide greater understanding of potential impacts of pesticides to non-targets. One can readily see the value of the concept and how it can be applied in simulation models such as those illustrated in Appendix A2 (e.g., PARET). Yet certain elements of risk, such as the likelihood and magnitude of effects and the likelihood of recovery, are in some situations inextricably related to even larger spatio-temporal characteristics of the crop agro-ecosystem in question. These characteristics may not be appropriate for lower levels of refinement, but may be considered in certain cases where additional refinements of the assessment are appropriate. (See Chapter 6.)

For the purposes of this section, information on the spatial and temporal relationship of the agro-ecosystem with other ecosystems or agro-ecosystems would form the basis for a higher level assessment. In the Guidance Document for Ecological Risk Assessment, such information falls into the category “Measures of Ecosystem and Receptor Characteristics”. The important characteristics will depend on the stressor and the crop. These characteristics could include,

among other things, field size, spatial extent and patchiness, proximity to the same or other crop agro-ecosystems, proximity to other ecosystems, the composition of the field border, terrestrial vertebrate species that actually use the crop agroecosystem, timing of crop production, timing of pesticide application, and so on. Because such information would be relevant only at the higher levels of refinement, specific information would only be presented on a case-by-case basis.

Technology has advanced and the inclusion of larger spatial and temporal scale information in ecological risk assessments is feasible. These advances include access to satellite imagery, more powerful computers, Geographical Information Systems, suitable radiotracking equipment, Global Positioning Systems, and readily available public databases. The challenges in making use of this information in probabilistic assessments at scales larger than the agro-ecosystem will be to reach agreement about when such information should be included in an assessment, how the information will be used, and how the results will be interpreted.

As the discussion above indicates, there have been few ecological risk assessments that have considered the spatial scale of an agro-ecosystem. However, as pesticide risk assessments are refined, spatio-temporal data based on the agro-ecosystems of interest need to be factored into the assessment.

2.6.3 Time Scale

Time-related processes have an important influence on risk. The most familiar example is the dissipation of residues. Dissipation rates vary widely between pesticides and, if the half-life is short, risk may be greatly reduced. Depuration rates have a critical influence because it is the balance between intake, internal metabolism, and depuration which determines whether a significant internal dose will accumulate. Depuration is rarely explicitly considered in current assessment procedures, although it occurs in toxicity tests and therefore is accounted for implicitly. The balance between intake and depuration may also be affected by short-term variations in feeding rate, especially in situations where animals consume most or all of their daily requirement in a few minutes or hours (gorging behavior). Also, timescale is important for pesticides exhibiting delayed or cumulative effects (e.g. anticoagulants, organochlorines).

If risk a assessment is to take account of these types of temporal variation, it is necessary to express dose per unit of time (i.e. mg pesticide per kg bodyweight per unit time) as a function of time, and for the time unit (e.g., days, hours, etc.) to be sufficiently small that any significant peaks and troughs are represented. For chronic assessments, it is also necessary to compute total and average doses over multiple time units, possibly extending over several days to weeks. This is relatively straightforward provided changes in residues, behavior, and other factors can be modeled on the appropriate timescale. The difficulty lies in measuring effects on a comparable timescale. Three options were considered:

Option 1: Base the entire effects assessment around internal dose (body burdens) rather than external dose. This requires measurement or estimation of depuration, and the measurement or estimation of effects in relation to body burden rather than external dose. Substantial research would be required to develop this approach, and it would probably require new types of routine testing.

Option 2: Estimate an exposure/time profile first, then use it to customize the exposure profile in effects tests. This would be impractical for routine use, as the studies would be significantly more complex and would be relevant only to a very narrow range of scenarios. However, it might be a useful option in special cases, for scenarios where temporal variation appeared critical to the assessment outcome.

Option 3: Identify a limited number of key time scales and carry out matched exposure and effects assessments for each in turn. This may enable the retention of constant exposure profiles as a reasonable approximation in effects tests, combined with the use of time-weighted averages in the exposure assessment when appropriate. This is probably the most practical option for routine use.

Option 3 is the simplest, providing suitable time scales can be identified. There would be enormous advantage in using time scales similar to existing effects tests, if possible, to maintain the usefulness of existing data. In the acute oral test, the dose is administered in one or a few minutes; in the dietary test birds are exposed for 5 days and in the current avian reproduction

study for 20 weeks.

Consideration of the existing test time scales, the processes mentioned at the start of this section and historical examples of pesticide impacts suggests the definition of three time scales as follows:

Short Term: Minutes to hours, representing gorging behavior, diurnal peaks in feeding (e.g. dawn and dusk), and pesticides which depurate or dissipate very rapidly. Relevant existing effects test, LD50.

Medium Term: Hours to days, representing scenarios with relatively high exposures over several days. Also appropriate for acutely toxic pesticides with delayed effects (e.g. rodenticides). Relevant existing effects test, avian LC50.

Long Term: Days to weeks, representing long-term, low level exposures. Especially relevant to pesticides with bioaccumulative effects (e.g. organochlorines). Relevant existing effects test, avian reproduction study.

These time scales are illustrated conceptually in Figure 2.6-1.

In the following sections, the three standard time scales defined above are used as the general basis for both exposure and effects assessments. In screening assessments, exposure will be estimated over the three standard time scales and compared to the corresponding effects tests which use constant exposure levels over time. All three time scales should be considered for every pesticide. In some cases the screening assessment may indicate that one or more of the

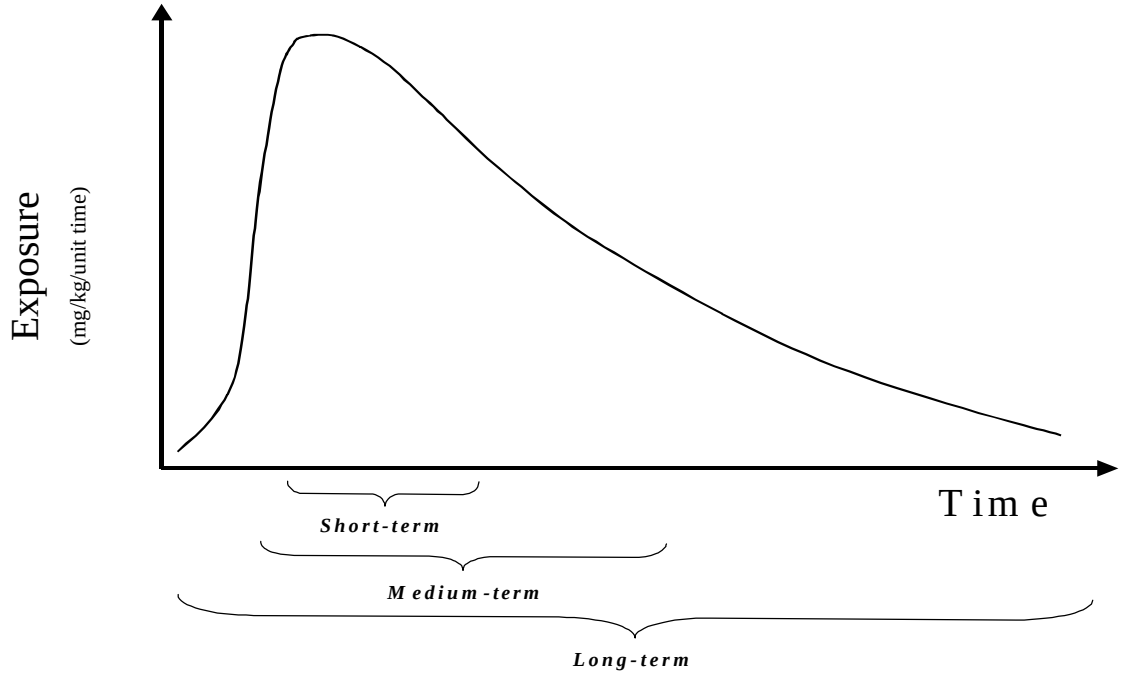


Figure 2.6-1. The exposure analysis produces a profile of exposure over time, usually starting at the time of pesticide application. In screening assessments, this profile will be used to generate three estimates of exposure, integrated over the three *standard time scales* (short, medium and long-term). These will usually correspond to the exposure periods used in the standard effects tests (currently <1 day, 5 days, and 20 weeks for birds). In refined assessments, special effects tests may be conducted to reflect the predicted exposure profile more closely.

time scales is sufficiently unlikely to cause significant exposure and further assessment is not required. When a refined assessment is required, exposure should be examined in more detail (as a continuous trend over time) to identify the magnitude and duration of potentially significant peaks. If this suggests that non-standard time scales and varying exposure over time may be critical to understanding risk, the use of special effects studies may be considered.

2.6.4 Identification of Species at Risk

Another important consideration in problem formulation and the analysis phase of the assessment process is the identification of the species to be addressed. Most agro-ecological scenarios provide habitat for numerous species of birds and mammals. These species utilize the crop and surrounding environment in different ways and in different intensities. It is impractical to attempt to develop a risk assessment that would include all bird species in a given region. Additionally, some of these species may utilize their environment so they are rarely at risk of exposure to pesticide applications. Thus, little value would be added to the risk assessment by considering these species.

The concept of concentrating a risk assessment on a few key species stems from the awareness of these circumstances and an understanding of the extreme cost of conducting a comprehensive risk assessment. The proper use of key species in risk assessments can result in an assessment based on the species most sensitive to the test substance and ecologically most susceptible to exposure. Thus, an assessment based on elected key species provides safety considerations for a much broader array of species. However, this concept is only effective when appropriate consideration is given to the selection of the key species.

Behavior is a major factor used to help identify key species. Certain species may utilize agricultural habitat for foraging, nesting, or both and, by the nature of their behavior, be at much greater risk of pesticide exposure. A species which (1) spends a large proportion of its time in the treated crop and (2) has a foraging technique and preferred food (e.g., ground-gleaning invertebrate eaters) that maximizes the risk of exposure would be an ideal key species. The combination of foraging technique and food preference are characteristics by which birds and

mammals may be broadly grouped for the purpose of risk assessment. Thus, by identifying specific ecological characteristics, such as if and how much it forages and/or nests in or near the crop of interest, one can estimate the probability and degree of exposure. Additionally, the sensitivity of the species to the pesticide is important in the risk determination of acute or chronic effects. Taxonomic considerations may also be important when selecting key species because of varying sensitivity among species.

The use of key species provides several advantages when conducting a risk assessment. These include narrowing the focus of the investigation, increasing the efficiency and sensitivity of the assessment, and increasing the tractability of the assessment while reducing the cost. Unfortunately, there are major data gaps in our knowledge of some of the parameters mentioned above for wild avian species. Little data is available on comparative sensitivity to pesticides among wild bird species. Some information may be found in published acute toxicity tests and through pesticide incident databases. Also, in most cases, we do not know what proportion of avian species' diets comes from pesticide treated habitats.

In the risk assessment process, the initial assessment may want to consider the substitution of hypothetical "generic birds" and mammals in place of specific key species, which may provide adequate sensitivity while also facilitating an efficient and less costly assessment. The hypothetical birds and mammals would have defined body size, life history strategy, foraging technique and food selection that make them representative of three primary avian groups. These are (1) small, granivorous passerine birds or small mammals, (2) small, insectivorous passerine birds or small mammals, and (3) a bird of prey that consumes passerine birds and small mammals. Physiological and ecological characteristics can be assigned to these hypothetical birds which characterize them as having high medium or low probability of pesticide exposure.

A dose-response equation (curve) defined by the LD50 and dose-response slope can be developed for the hypothetical bird species. The LD50 for the hypothetical bird species can be estimated from the LD50 of one or more experimental bird species by using the extrapolation factors discussed in Chapter 4. Theoretically, similar extrapolation methods could be used to estimate the dose-response slope for the hypothetical bird species from the dose-response slope(s) of one or

more experimental bird species. However, because the dose-response slope database is currently inadequate for extrapolation purposes, it will be assumed that the dose-response slope for the hypothetical bird species is equivalent to that of the experimental bird species.

If during the regulatory process, the screening level assessment uses (1) the hypothetical animals with high probability of exposure and (2) the risk of negative effects is determined to be low, further assessment may not be needed. If such a risk assessment indicates potential for higher risk, a more refined assessment may be conducted to more definitively characterize the risk. Recommended criteria for the screening-level assessments, hypothetical bird and mammal species are given in Appendix B3.

In cases where further refinement of the risk assessment is required, it may be appropriate to use species that occur in the areas of or proposed use of the pesticide and may require additional laboratory or field studies beyond those considered in the initial risk assessment. Since it may be impractical to address all species potentially at risk, careful selection of key species will help ensure the assessment provides a reasonable estimate of the potential risk to the more sensitive species. A proposed set of criteria for key species selection follows:

Criteria 1: The species are commonly nesting and foraging in and/or adjacent to (within the drift zone) the agro-ecological scenario. The greater the proportion of time spent on the treated field (PT), the stronger the justification for selection as a key species.

Criteria 2: Their foraging techniques render the species subject to exposure.

Criteria 3: The species obtain a substantial portion of their diet from the treated field or adjacent habitat within the drift zone. The greater the proportion of diet obtained on the treated field (PD), the stronger the justification for selection as a key species.

Criteria 4: The species is sensitive to the test substance.

Criteria 5: Data verifying criteria 1 - 3 are available or obtainable.

- Acute toxicity data is available for the selected species or data are available from other species that can be scaled to represent the sensitivity of the selected species
- Data are available on PD and PT (see Section 4.2 for discussion of PD and PT) or can be obtained for the selected species from field studies of the selected species.

Criteria 6: Appropriate measurement and assessment endpoints can be evaluated in the field or laboratory for the selected species. (See Section 3.5 for discussion of measurement and assessment end points.)

Appendix B3 provides further information and example for selecting key species.

3.0 EXPOSURE ASSESSMENT

3.1 INTRODUCTION

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3.1.1 Objective of an Exposure Assessment

The objective of the exposure assessment portion of a terrestrial ecological risk assessment of pesticides is to estimate PDFs of pesticide intake or dose to non-target terrestrial organisms. What is meant here by the term "dose" is a quantifiable amount of material introduced into or taken up by an organism. For the dose estimate to be useful in the estimation of ecological risk, it should be expressed in terms of pesticide weight per organism body weight per unit time, i.e. mg/kg/day. While environmental concentrations, such as ppm on wildlife food sources, have been used to estimate exposure to wildlife, they do not directly address the amount of chemical ingested by the individual, the critical quantity producing the response. Unlike exposure concentrations, estimates of dose take into account biological factors affecting exposure such as ingestion rates, foraging patterns, and percentage of diet represented by different food types. As further discussed in the effects section, current wildlife toxicological tests may have to be modified so exposure estimates in weight of pesticide per body weight per time can be directly compared to results of wildlife toxicological test endpoints.

A caveat must be noted concerning the relationship of toxicant dose to the quantity of toxicant actually reaching a site or sites of action within the organism. The relationship was not explicitly considered in the Terrestrial Workgroup discussions. To produce an effect, an ingested compound must first be absorbed, for example in the gastrointestinal system. The compound is then circulated to the site of action via blood plasma. Toxicants are delivered to most organs and tissues (other than the gut and liver) by systemic blood circulation. The proportion of a chemical dose reaching the blood along with the toxicity of the chemical will determine how much dose an

organism can receive before its exhibits an adverse effect.. Bioavailability is defined as the ratio of a compound in the plasma to that consumed by oral ingestion (Amdur et al., 1994). Systemic availability may be modified by reduced absorption after oral ingestion, intestinal biotransformation, hepatic biotransformation, and formulation ingredients that modify solubility, particle size, or uptake of compounds.

Bioavailability could sometimes be determined in higher tier risk assessments for special cases in which prior information indicates bioavailability could be an issue. However, in most cases it will sufficient to base the assessment on the external dose, i.e. the total toxicant entering the organism and external dose response curves. The methods proposed in this chapter therefore focus on estimating external dose.

3.1.2 Conceptual Model of Exposure Pathways

The initial step in an exposure assessment is identifying routes of exposure and the major variables that potentially could influence the distribution of doses. Terrestrial wildlife can be exposed to pesticides through multiple pathways (Fig 3.1-1). They may ingest contaminated food or soil, drink or swim in contaminated water, and breathe contaminated air. They may also directly ingest granular formulated pesticides mistaking them for grit or seeds. Dermal exposure may occur if the animal's skin contacts spray particles or contaminated vegetation, water or soil. Residues deposited on skin, fur and/or feathers may become a source of oral exposure during grooming, preening or other activities. Because wildlife species are mobile, moving among and within various habitats, exposure can vary depending on habitat use and the extent of contamination of its components. As a consequence, estimation of wildlife exposure requires the consideration of a number of variables including environmental residues, routes of exposure, habitat requirements and spatial movements for the species associated with the pesticide use area.

For terrestrial wildlife, three major exposure pathways can be identified (Figure 3.1-1). They are oral, dermal, and inhalation. Oral exposure occurs through the consumption of

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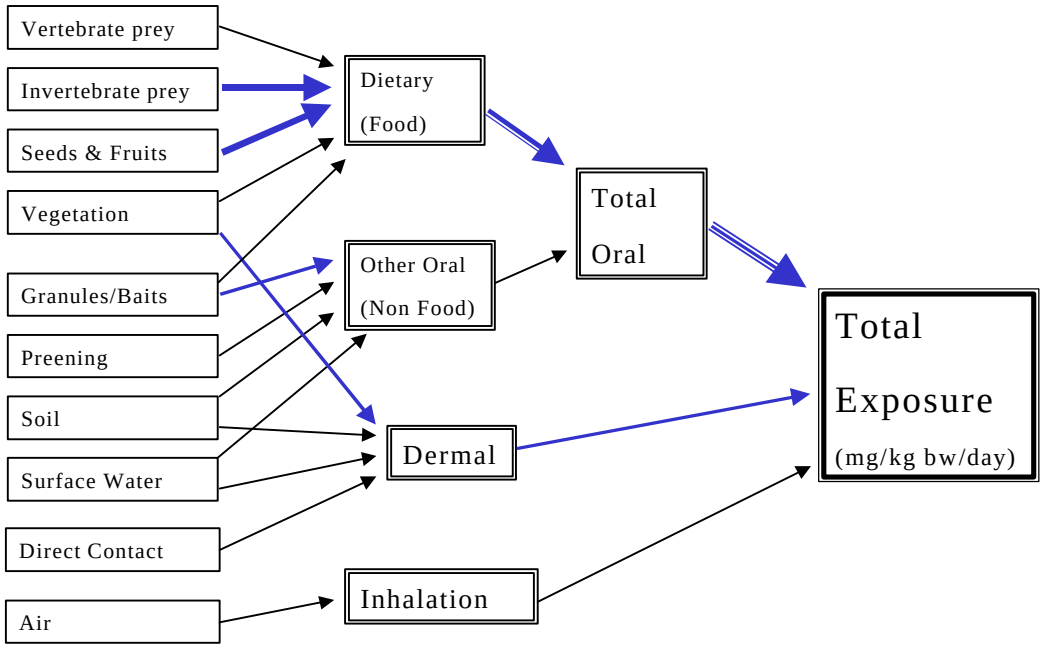


Figure 3.1-1. Conceptual model of exposure pathways for birds and mammals. Thickness of arrows denotes relative importance of pathways.

contaminated food, water, or soil and direct ingestion of granular products mistaken as grit or a food source. Dermal exposure occurs when pesticides are absorbed directly through the skin when the animal contacts spray particles directly or contacts contaminated biotic or abiotic components of the habitat. Exposure from inhalation occurs when volatile pesticides or fine particulates or droplets are respired into the lungs.

3.1.3 Content of the Exposure Assessment Chapter

The following sections of the Exposure Assessment Chapter explore various aspects of estimating dose distributions to non-target terrestrial organisms. Descriptions of the factors affecting dose and information applicable to all dose equations are provided in Section 3.2. Dose equations and discussions on estimating dose equation variables are provided for different exposure pathways and associated environmental media in Sections 3.3 (ingestion of food), 3.4 (ingestion of water), 3.5 (ingestion of granules), 3.6 (ingestion of soil), 3.7 (overall ingestion), 3.8 (inhalation of air), and 3.9 (dermal contact with various environmental media). Estimating pesticide concentrations in environmental media, outputs from and inputs to exposure assessments, and different proposed levels of exposure assessment are discussed in Sections 3.10, 3.11, and 3.12, respectively.

3.2 FACTORS AFFECTING DOSE

The pesticide dose non-target organisms receive will depend upon pesticide concentrations in environmental media and the frequency and magnitude of the ingestion of, inhalation of, and dermal contact with the pesticide contaminated environmental media (food, water, granules, soil, and air).

3.2.1 Physical Chemical and Biological Components of Dose

The numerous factors affecting dose can be divided into two types or components, a physical chemical component and a biological component. The physical chemical component consists of

physical chemical properties of the pesticide and environmental media that influence the concentrations of pesticides in pertinent environmental media (e.g., food, water, granules, soil, and air) as a function of time and location within each medium. The biological component consists of animal behavior/attribute factors (which along with various properties of the environmental media) affect the frequency and magnitude of the ingestion of, inhalation of, and dermal contact with pesticide contaminated environmental media.

Some variables described below such as the food ingestion rate are explicitly included in the dose equations provided in Sections 3.3 through 3.9. Others variables such as dissipation rate constants are not explicitly included in the dose equations, but are used to estimate the variables which are explicitly included in the dose equations such as the pesticide concentrations in environmental media.

For each of the exposure pathways depicted in Figure 3.1-1, a number of physical, chemical and biological variables influence the extent of exposure. The major **physical chemical variables** that influence dose for each of the routes of exposure include the following:

Pesticide and Degradate Properties: Aqueous solubility, acid/base (pK_as), Henry's constant, octanol/water partition coefficient, diffusivities, soil/water partition coefficients, plant/water partition coefficients, foliar washoff, overall and process specific dissipation rate constants in various environmental media, and (for degradates) formation rate constants.

Plant/Crop Characteristics and Agricultural Practices: Dates of planting, emergence and muturity of wildlife food sources; crop, crop and field edge cover; foliar interception, field vegetative residue cover, root depth, soil incorporation depth, tillage practices, irrigation practices, spray elevation, spray nozzle size, droplet size spectrum and number, dates, rates, and method of pesticide applications.

Meteorological Conditions: Precipitation, temperature, solar irradiation, relative humidity, wind

speed, and wind direction.

Soil Properties: Organic content, pH, soil texture, initial soil moisture, field capacity, wilting point, saturated hydraulic conductivity, slope, temperature, bulk density and porosity as a function of vertical and/or horizontal segmentation.

Wildlife Water Source Properties(Dew and Surface Water): Pesticide loading due to direct application, runoff, soil erosion and spray drift, size of water source, pH, temperature, suspended sediment concentration, dissolved natural organic concentration, redox potential, base flow, depth and width of water source, and dispersion coefficients.

For the biological component the major **biological variables** that influence dose for each of the routes of exposure is species dependent and include the following:

Food, Water and Soil Ingestion Rates: Food type or types and availability, feeding strategy, developmental stage, reproduction status, sex, environmental conditions, individual weight, food and water requirements related to metabolic strategies of species, availability of water sources, and acceptability of contaminated food or water.

Dietary Diversity: Total number of ingested media, and the proportional ingestion rate of each media.

Habitat Requirements and Spatial Movements: Home range, spatial arrangements of habitat components, quantity and quality of habitat components, habitat use in time and space and portion of habitat that is contaminated.

Direct Ingestion (Granular Formulations): Granular size, granular shape, carrier, color, natural grit availability, and species grit use.

Inhalation and Dermal Absorption Rates: Inhalation rate, preening/grooming behavior, dust-bathing behavior, locomotory behavior and its effects on the frequency and degree of contact with contaminated soil, water, foliage etc., physico-chemical properties affecting uptake across membranes.

While it's impossible to include all of the variables and their possible interactions which may affect the distribution of dose, it is possible to address most of the important variable distributions that are believed to contribute most to the variation in dose to non-target terrestrial species. There are literally thousands of variables that can influence the extent of exposure. A number of these are inter-dependent and they can vary spatially and temporally. These facts make it a challenge to accurately estimate dose to non-target species. However, if advancements in estimating ecological risk are to be made, these challenges must be addressed and through time, if the resources are committed to research, the uncertainties in risk estimates will be better defined and reduced.

3.2.2 Information Applicable to all Dose Equations in Sections 3.3 through 3.9

Equations for estimating the pesticide doses (to birds or mammals) associated with the various exposure pathways and associated environmental media discussed in Section 3.2 are provided below in Sections 3.3 through 3.9. The equations give the one day dose on any given day i (in mg/kg body weight*day), the cumulative dose over multiple days N_i (in mg/kg BW), and the average daily dose (in mg/kg BW*day) as a function of pesticide concentrations in various environmental media.

For purposes of illustration, we have chosen to base the dose equations provided below in Sections 3.3 through 3.9 on a daily time step. However, the same equations would be applicable to a different time step such as a hourly one as long as the variables were defined in terms of the different time step instead of a daily time step.

The dose equations provided in Sections 3.3 through 3.9 imply a 'cell' model of habitat structure

and animal movement. The environment is divided into a number of fields, some of which may be treated with pesticide while others are untreated or receive only spray drift. Animals move from one field to another, accumulating exposure via the various routes (dietary, dermal etc.) as they go. Note that although the spatial unit used in the dose equations is described as 'field', in practice other habitat types such as hedgerows and wetlands may also need to be considered. In this case, the subscript j in the equations will refer not just to fields, but to all of the different habitat cells which are considered in the assessment. The equations do not preclude the bird or mammal foraging over more than one field or other habitat unit in each time unit (e.g. more than one field or habitat unit per day).

In the dose equations provided below in Sections 3.3 through 3.9, the pesticide exposure concentration C_{ijk} in environmental medium k within field j on day i should theoretically be the time averaged concentration over the period in which the organism is exposed to environmental medium k in field j on day i:

$$\overline{C_{ijk}} = \frac{\int_{t_{ij1}}^{t_{ij2}} C_{ijk}(t)\,dt}{\left(t_{ij2} - t_{ij1}\right)} \qquad \text{(Eq. 3.2-1)}$$

where,

t_{ij1} = beginning of the exposure period in field j on day i (hr)

t_{ij2} = end of the exposure period in field j on day i (hr)

$C_{ijk}(t)$ = pesticide concentration in medium k in field j during day i as a function of time

Assigning ij subscripts to the beginning and end of exposure periods within a given field j on a given day i is necessary because a bird can be in more than one field on a given day and may revisit the same field on one or more additional days.

If the organism is in field j all of day i, $(t_{ij2} - t_{ij1}) = (t_{i+1} - t_i) = 1$ day and $C_{ijk(avg)}$ will be the average concentration over the whole day. However, if the organism is not in field j for the entire day, the time averaged concentration over the exposure period $(t_{ij2} - t_{ij1})$ will be either greater than or less than the time averaged concentration over the entire day depending on whether the organism is in field j early or later on day i. To be conservative and to simplify computations, C_{ijk} for the entire day can alternatively be assumed to be equal to the initial pesticide concentration in media k within field j at the start of day i at $t=t_i$: $C_{jk}(t=t_i)$. Such an assumption also works well with a daily time step model which provides a different estimated concentration for each succeeding day.

3.3 DOSE RESULTING FROM INGESTION OF CONTAMINATED FOOD

3.3.1 Detailed Equations for Dose Through Food

The detailed equations below for dose through food are similar to simpler ones provided by Pastorok et al. (1996) and Sample et al. (1997) except they are summed over different fields or different fields and days. The one day dietary dose for any foraging day i, the cumulative dietary dose over N_i foraging days and the average daily dietary dose over N_i foraging days a bird or mammal receives through ingestion of pesticide contaminated foods (k) from foraging over one or more fields (j) per day are given respectively by:

$$\text{One Day Dose}_{\text{dietary(day i)}}\,(\text{in mg / kg body Wt} * \text{day}) = \sum_{j=1}^{j=N_j} \sum_{k=1}^{k=N_k} FIR_{ijk} \bullet C_{ijk} \;/\; W$$

(Eq. 3.3-1)

$$\text{Cumulative Dose}_{\text{diet}}\,(\,\text{N}_\text{i}\,\text{days in mg / kg body Wt}) = \sum_{i=1}^{i=N_i} \sum_{j=1}^{j=N_j} \sum_{k=1}^{k=N_k} FIR_{ijk} \bullet C_{ijk} \;/\; W$$

(Eq. 3.3-2)

Average Daily $Dose_{dietary}$ in mg/kg BW*day = Cumulative $Dose_{dietary}/N_i$ (Eq. 3.3-3)

where,

k = index for different food types (e.g., short grass, long grass, insects, fruits, seeds , soil, etc.)
N_k = maximum number of different food types consumed by the bird or mammal
j = index for different foraging fields
N_j = maximum number of fields foraged by the bird or mammal over the foraging period of interest
i = index for different foraging days
N_i = number of days during the foraging period of interest for which a dose is to be computed
FIR_{ijk} = food intake rate (kg fresh weight/day) of food type k by the bird or mammal in field j on day i (FIR_{ijk} = 0 if the bird or mammal is not in field j on day i or if food type k is not in field j)
C_{ijk} = initial or average pesticide concentration on/in food type k in field j on day i (mg pesticide/kg fresh weight food mass). If the field j has not been treated or has not received spray drift by day i, C_{ijk} = 0.
W = body weight of the bird or mammal (kg)

The food intake rate of food type k by a bird or mammal in field j on day i is given by:

$$FIR_{ijk} = \left(PF_{ij}\right)\left(TFIR_i\right)\left(PD_{ijk}\right)\left(FRD_{ik}\right)\left[1-\left(AV_{ijk}\right)\right] \quad \text{(Eq. 3.3-4)}$$

where,

PF_{ij} = proportion of total food or diet obtained from field j on day i (dimensionless)
$TFIR_i$ = total food ingestion rate = total food consumed on day i (kg dry weight/day)
PD_{ijk} = proportion of food or diet obtained from field j on day i that was derived from food type k
FDR_{ik} = fresh to dry weight ratio for food type k on day i (dimensionless)

AV_{ijk} = avoidance factor for food k in field j on day i = amount by which animal reduces consumption of food j in field k on day i when it is contaminated, as a fraction of what consumption would be if the food was not contaminated (dimensionless). The avoidance factor is a function of the contaminant level C_{ijk}.

Note that the representation of avoidance by AV_{ijk} in equation 3.3-4 is a simplistic representation of the combined effect of several types of possible avoidance behavior. Avoidance might occur by animals reducing the consumption of specific contaminated food items, by reducing their total food intake (e.g. if temporarily incapacitated, or suffering general loss of appetite), or by moving to feed in less-contaminated habitats. These three different types of avoidance behavior could be represented in more detail, by making PD_{ijk}, $TFIR_i$, and PF_{ij} all a function of C_{ijk}. In practice, it is unlikely to be possible to measure these different responses separately, so they are combined as AV_{ijk} . However, this is not entirely satisfactory as it does not specify whether animals compensate for avoidance of one food type by increasing the consumption of another. The estimation of AV_{ijk} is discussed further below and in Appendix C2.

Note that the fresh to dry weight ratio FDR is not needed in cases where residue concentrations are given in mg chemical/kg dry weight of food instead of the more usual units of mg chemical/kg fresh weight of food. The reason is that in such cases, the food consumed can also be kept on a dry weight basis. Conversion of food consumption to a fresh weight basis, to be consistent with concentration on a fresh weight basis, is then not necessary.

When possible, residue concentrations should be expressed on a dry weight instead of a fresh weight basis. When residue concentrations are expressed on a wet weight basis, changes in concentration often reflect changes in water content as well as dissipation and it is generally not possible to distinguish between the two different sources of the change. Also, as previously indicated, the FDR factor is not needed when residue concentrations are expressed on a dry weight basis.

Combining Equations 3.3-1 and 3.3-4 gives the full equation for the one-day dose in mg/kg BW*day:

$$\text{One Day Dose}_{\text{dietary (day i)}} = \sum_{i=1}^{i=N_i} \sum_{j=1}^{j=N_j} \left(PF_{ij}\right)\left(TFIR_i\right)\left(PD_{ijk}\right)\left(FDR_{ik}\right)\left[1-\left(AV_{ijk}\right)\right]C_{ijk} \; / \; W$$

(Eq. 3.3-5)

An analagous equation can be given for the Cumulative Dose by combining 3.3-4 with 3.3-2.

3.3.2 Simplified equations for dose through food

As already mentioned, Equation 3.3-5 implies a 'cell' model of habitat structure and animal movement. To use it as shown, in its detailed form, requires a very large amount of information. For example, estimates are required of pesticide concentrations on a range of food types in each field within the organism's foraging range, in each time unit (daily or even hourly). The movements of the animal between the fields, and its behavior in each, must also be modeled. If empirical data were used for all these parameters, the assessment would become prohibitively expensive. However, in most cases this level of complexity will not be required, as a much simpler version of the model will estimate exposure with sufficient certainty.

To simplify the equation, the overall habitat can be divided into only 2 categories: the area which is treated with pesticide, and that which is not. In this case a third category, a drift area, is not considered. If the untreated area contributes nothing to exposure, it can be disregarded in the model. The subscript j can then be dropped from the equation. Also, PF is replaced by the fraction of total food obtained in the treated area, which can be denoted as PT. Mathematically, PT and PF are related by the following equation:

$$PT_i = \frac{\sum_{j=treated-fields} PF_{ij}}{\left(\sum_{j=treated-fields} PF_{ij} + \sum_{j=untreated-fields} PF_{ij}\right)}$$

(Eq. 3.3-

6)

However, in practice it may more often be estimated or measured directly, as data on food intake for each individual field will rarely be available.

A further simplification is to assume AV is the same for all food types. This is a practical necessity as data on AV will usually be available for only one food type, i.e. standard test diet. (See below.)

With these simplifications, equation 3.3-5 becomes:

$$\text{One Day Dose}_{\text{dietary(day i)}} = \sum_{k=1}^{k=N_k} \left(PT_i\right)\left(TFIR_i\right)\left(PD_{ik}\right)\left(FDR_{ik}\right)\left[1-\left(AV_i\right)\right]C_{ik} \;/\; W$$

(Eq. 3.3-7)

PT, TFIR and AV now require only a single estimate for each day (although note that AV is still a function of C, as before). PD, FDR and C only require one estimate per food type (k). In effect, these six parameters are averaged over all fields in the treated area for Equation 3.6-6, whereas separate values are used for each field in equation 3.6-5. Where averages are used, care is required to ensure that they are properly representative of different parts of the treated area.

Equation 3.3-7 is equivalent to that given by Pastorok et al. (1996), except that the latter uses different parameter names (FIR for TFIR, and DWR for FDR) and does not include any term for avoidance (AV). Also, the Pastorok equation provides estimates for more than one species, by using an extra subscript to allow PT, FIR and PD to vary between species. Equation 3.3-7 is also similar to that of Sample et al. (1997).

The simplifications in Equation 3.3-7 imply some important assumptions. Perhaps most importantly, it is assumed that all treated areas are equivalent to one another. In reality, some of the untreated areas will receive spray drift – this can be accommodated easily in the full model (Eq. 3.3-5) but is ignored in 3.3-7. If equation 3.3-7 is used as the basis for a risk assessment,

consideration should be given to whether the result would be different using more realistic assumptions. If this appears possible, the assessment may need to be repeated with the full model.

Further simplifications can be made to Equation 3.3-7. For example, if it is assumed that the animal feeds exclusively within the treated area, and exclusively on one food type (for example, that with the highest concentration of pesticide), and there is no avoidance, then:

$$\text{One Day Dose}_{\text{dietary (day i)}} \text{ (in mg / kg body Wt)} = \left(TFIR_i\right)\left(FDR_i\right)C_i \,/\, W \quad \text{(Eq. 3.3-8)}$$

This is equivalent to the simple estimate of exposure which has been used in the past and is often regarded as conservative for screening purposes.

In a probabilistic assessment it may often be desirable to examine the effects of variation in PT, PD and AV. Equation 3.3-7 is therefore taken as the main basis for assessing exposure through food. Nevertheless, the preliminary screening assessment will often be equivalent to the simpler model 3.3-8, and it may sometimes be necessary to progress to the more complex model 3.3-5 in more refined assessments.

The following sections examine the types of data which are available for estimating the parameters in these simplified equations, and how the estimates can be refined when necessary. Estimating pesticide concentrations in food (C_{food}) is discussed in more detail in Section 3.10 and Appendix C4. Estimating PT and AV are also discussed in more detail in Appendices C1 and C2.

3.3.3 *PT* - Proportion of diet obtained in treated area

Animals which obtain all their food from within the treated area are likely to ingest a larger dose of pesticide than those which obtain a proportion of their diet elsewhere. This variation is represented by PT in Equation 3.3-7. Current approaches tend to assume PT = 1, at least in the screening stages of risk assessment. In fact, PT may be close to one in situations where there is little non-crop habitat and large areas are treated with the same pesticides at the same time.

Often, however, animals will obtain a significant proportion of their diet from non-crop areas, or from adjacent non-treated crops of the same or different types. In these cases, setting PT = 1 substantially overestimates exposure. Setting PT = 1 remains reasonable as a conservative assumption for the screening stages of the assessment. However, predicting the magnitude and frequency of exposure will require information on the distribution of PT for relevant species in relevant habitats.

The range of possible approaches to estimating PT is considered in detail in Appendix C1.

Ideally, one would estimate PT as the proportion by weight of the diet which is obtained from treated areas. This can be done in some circumstances using detailed field studies, but is generally too difficult to be a realistic option.

An alternative is to measure the proportions of time that the animal spends in treated and untreated areas. This is simpler but can only be used as a measure of PT if the amount of time spent in each area is proportional to the amount of food obtained there. This will not be true if some parts of the habitat are used primarily for foraging, and others primarily for other activities such as resting; or if feeding rate is higher in some parts of the habitat than others due to differences in food availability. The two main approaches to estimating PT for time are visual observations and telemetry (radio-tracking).

Counts of unmarked animals in treated and untreated areas are of little help in estimating PT, because it is not possible to determine (a) whether successive counts in the same area are the same animals or different ones, or (b) whether the individuals seen in one area are the same or different as those seen in adjacent areas.

A more reliable record of individual behaviour can be obtained if the animals are marked, for example with coloured bands. Even then, however, continuous observations are difficult to obtain, and foraging records are likely to be biased in favour of those habitats where animals are most easily observed (e.g. more open habitats).

In principle, these limitations can be overcome using radio-tracking techniques. These may be manual (where the radio-tagged animal is followed by observers on foot or in vehicles) or automatic (where fixed receiver stations automatically record signal information from which the animal's location can be calculated).

An example of manual tracking specifically designed to measure PT is provided by recent studies in UK apple orchards (Crocker et al., in prep.). The results showed that different species had different patterns of use of the orchard environment, and that the potential for exposure to pesticides varied widely between individuals. An example of the results is shown in Figure 3.3-1, for European blackbirds. Most individuals spent less than 10% of their time in the orchard center, but a few individuals spent up to 70% of their time there.

Distributions such as that shown in Figure 3.3-1 could be used for a probabilistic analysis of PT. (See Appendix C1.) However, the data may be affected by biases of several types. Careful interpretation is essential.

- Animals captured for tracking may be a biased sample of the local population,
- The populations which are studied may not be representative of other populations, and
- The proportion of time spent in the treated area may not be a good measure of the proportion of food obtained there.

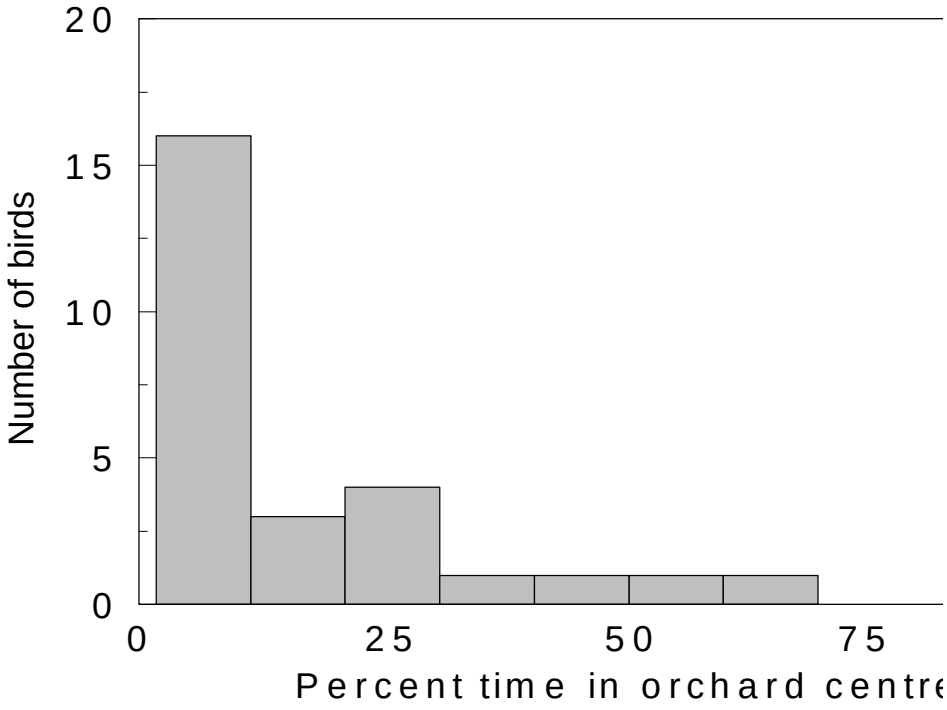


Figure 3.3-1. Distribution of time spent in the central (sprayed) areas of UK apple orchards by European blackbirds, obtained by radio-tracking.

A third approach to estimating PT might be to use existing information on home ranges. For example, if the average home range for a species was smaller than the area of a typical treated field, then at least some individuals may have their home range entirely contained within a single treated field. This at least would show that using a conservative assumption (PT = 1) is a reasonable upper limit for the species in question. However, it is more difficult to estimate the distribution of exposures by this approach. This would require data on the spatial and temporal distribution of pesticide applications, and a means of defining the central point of each home range. It is concluded that obtaining a reliable quantitative estimate of PT using home range is unlikely. However, if interpreted by suitable experts, data of this sort may be adequate to make semi-objective assessments of the upper limit to PT for a particular species and, perhaps, to guess at 'typical' values. This would not be reliable enough for a final assessment of exposure but might be helpful at intermediate levels of assessment, in deciding whether PT is sufficiently important to warrant measuring in the field.

So far, this section has implied that the world comprises just two types of habitat, treated and untreated, as assumed in Equation 3.3-7. In reality the situation is more complex. For example, some species might spend very little time in the treated crop itself, but obtain nearly all its food in the drift zone immediately around the crop. For example, in the study described earlier, most European blackbirds spent very little time in the orchard center, but about twice as much time (average about 35%) in hedgerows and scrub immediately adjacent to sprayed areas. To assess the contribution of these drift zone habitats to overall exposure would require estimates of PT for the drift zone as well as the treated area. It would also require estimates of pesticide residues in the drift zone, which will generally be much lower than in the treated area itself. These might be obtained by field measurements, or perhaps using models of spray drift to estimate the proportion of the application rate which is received by the drift zone. This approach could be accommodated in the full model (Equation 3.3-5), where PT is replaced by PF, by using the subscript j to distinguish the drift zone from the treated and untreated areas.

The full model could also be used to distinguish between different types of treated, drift, and untreated areas, if sufficiently detailed data on PF were available. For example, it might be desirable to distinguish fields with different crops, or fields treated with the same pesticide applied

at different times or different dose rates. In the real world, animals may encounter several different pesticides which may have additive or synergistic effects, but it is currently very rare to rake account of this in risk assessment and was not considered.

This section has referred to treated areas, untreated areas and drift zones without considering their spatial and temporal distribution. In reality, pesticide applications are clumped in time and space, not random, and the same is true of animals and their foraging activities. If pesticide applications and animal foraging were both randomly distributed in space, every individual would have the same chance of encountering a treated field. If pesticide applications and animal foraging were very strongly clumped, most individuals might never encounter a treated field, while a few might find their whole foraging range treated. Real exposure scenarios lie somewhere between these extremes, depending on the degree of clumping which is present. Ignoring clumping in situations where it is important will tend to under-estimate exposure for the most-exposed part of the population. The effects of clumping can be assessed using models of exposure which take account of spatial patterns.

Models of exposure can be made spatially explicit, for example by using the techniques of Geographic Information Systems (GIS). The components of such a system are illustrated in Figure 3.3-2. First, the model landscape would be defined. This could be a hypothetical landscape, or an actual one (e.g. based on maps or satellite imagery), but would need to be broadly representative of the type of landscapes relevant to the risk assessment. Residue distributions in the landscape could be simulated using information on spatial and temporal patterns of pesticide use within the landscape, and by modelling transfers between treated and untreated areas and degradation over time. The species present would be identified, for example from local surveys or information on national distributions. Animal movement patterns within the landscape would be defined using information on habitat preferences, home ranges and behavior, which could include visual observations or telemetry data of the types discussed

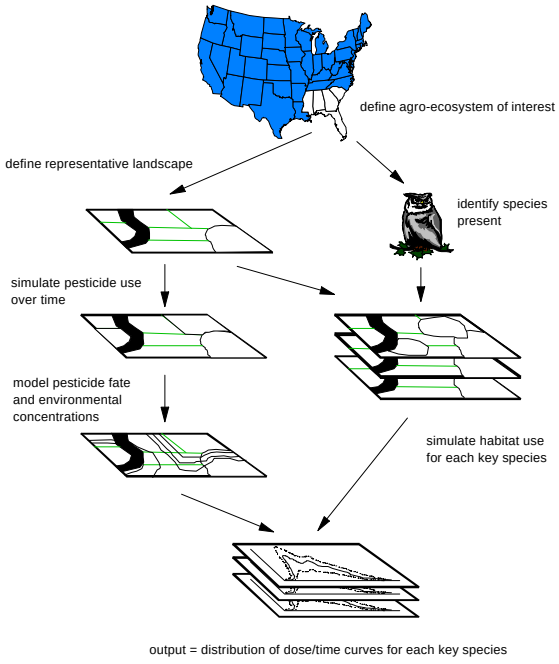


Figure 3.3-2. Illustration of a spatially explicit approach to modeling wildlife exposure to pesticides

earlier. This needs to be repeated for each of the species under consideration. Finally, exposure estimates could be obtained by simulating the movements of each individual and recording its intake of pesticide as it moves through the landscape. Using Monte Carlo techniques this could be repeated for many individuals (and perhaps landscapes), producing a set of dose/time curves to show the range of variation in the population.

Technology has advanced to a state where this type of approach is beginning to be feasible. An example of a model using standardized hypothetical landscapes, with simple rules for animal movements through the landscape, is provided by Freshman and Menzie (1996). Another example is the PARET model which has been developed as part of the Terrestrial Workgroup's efforts. (See Chapter 5.5 and Appendix A2). Examples of GIS approaches using data on real landscapes and behavior are provided by Henriques and Dixon (1996) and Banton et al. (1996). This type of approach is much more costly to develop, and is only likely to be considered in cases where spatial factors are thought to make a critical difference to the outcome of the risk assessment.

It is concluded that PT is likely to be an important and highly variable parameter influencing exposure, but is difficult and costly to measure reliably in many agricultural habitats. A sequential approach is therefore recommended, as outlined below, to ensure that effort is only expended on estimating or measuring PT in those cases where it is important to the outcome of the risk assessment.

If it appears that spatially-explicit approaches may be required often then there would be opportunity for sharing the cost of collecting much of the data, as they are not specific to individual pesticides.

For screening assessments, it will generally be appropriate to assume PT = 1. To refine the assessment, estimated lower and upper limits for PT could be developed using expert judgement and existing information on:

- Foraging ecology and behavior of key species, including time budgets, habitat use (including the drift zone) and home ranges;

- The spatial distribution of habitat types and crops; and
- The spatial and temporal distribution of pesticide applications.

If the data are good enough, they can be used to construct a hypothetical distribution for PT. If exposure in the drift zone is likely to be significant, the simple model (3.3-7) can be expanded to distinguish it from the treated and untreated areas. The proportion of food obtained in the drift zone can then be estimated as well as PT, and used to estimate the relative contributions of the drift zone and treated area to overall exposure.

If it appears (e.g. from sensitivity analysis) that PT has a critical influence on exposure, it may be worth attempting to measure it in field studies, or using a landscape model to examine spatial effects. Depending on the field scenario, visual observations or telemetry may be used to quantify distributions of PT in the field for appropriate species in a representative range of conditions relevant to the risk assessment. If it appears that the spatial distribution of treated areas may have a critical influence on the risk outcome, it can be accounted for in spatially-explicit models or GIS approaches.

3.3.4 *TFIR* – Total Food Intake Rate

Total food intake rate (TFIR) is an estimate of dietary consumption in units of kg or g food / time. TFIR is typically reported in units of dry matter.

The time step is critical in risk assessments and will often be standardized to match units of toxicology studies or time steps of toxicological concern. (See Chapter 2 for a discussion of time-scale.) For example, some animals may gorge-feed in short bouts, while others may graze steadily throughout a day or at a steady rate for weeks. Thus time steps of toxicological concern could be acute short-term feeding bouts (e.g., 5 min) or chronic multi-day exposure periods (e.g. 5 days or 20 weeks). These are referred to below as short-term and medium/long-term feeding scenarios, respectively.

In the wild, TFIR can be highly variable within and among individuals, age-classes, or species, and

over time, depending on factors such as metabolic demand, food availability, food type, weather, competition for food, and storage capacity of the animal. Birds and mammals may reasonably increase TFIR 2 to 3 fold after short bouts of starvation in poor weather. An upper limit to intake is thought to be about 5 fold normal daily consumption (Kirkwood 1983). Examples of gorge feeding are provided by data on pigeons feeding on treated seed. Captive feral pigeons can be trained to consume most of their daily requirement in less than 10 minutes (Pascual et al., in press). In the field, over 50% of Woodpigeons feeding on newly-sown cereals consumed less than 0.25 g/minute, but about 1% fed at over 2 g/minute (Hart et al., in press).

Methods for estimating daily food intake are presented by EPA (1993). TFIR can be estimated as:

$$TFIR = FMR / ME \qquad \text{(Eq. 3.3-9)}$$

where,

FMR = Field Metabolic Rate (kJ/day)

ME = Metabolizable Energy content of diet (kJ/g).

Field metabolic rate (FMR), is the daily sum of energy that a bird or mammal would use for maintenance, basal metabolism, thermoregulation and activity, but not reproduction, growth or fat storage. Field studies of FMR for birds and mammals that were conducted with similar methodology were examined by Nagy (1987). He derived regression equations to estimate FMR in units of kJ / day for birds and mammals. (See Table 3.3-1.) Different equations were calculated for different taxonomic and ecological groupings of birds and mammals. The equation takes the form of:

$$\log y = \log a + b \log x \qquad \text{(Eq. 3.3-10)}$$

Table 3.3-1. Summary of regression statistics for the relationship of body mass to field metabolic rates (kJ/d) and feeding (dry matter ingestion) rates (g/d), after Nagy (1987). Some equations for food intake by birds were recently updated by Nagy et al. (in prep) and have improved statistical relationships compared to the earlier equations: these are indicated by asterisks in the table.

Group	units of *y*	log *a* (SE)	95% CI of log *a*	b (SE)	95% CI of b	N	r^2	P
Mammals								
All eutherians	kJ/d	0.525 (0.057)	0.410 - 0.640	0.813 (0.023)	0.767 - 0.859	46	0.967	<0.001
	g/d	-0.629 (0.065)	-0.760 - 0.497	0.822 (0.026)	0.769 - 0.874	46	0.958	<0.001
Rodents	kJ/d	1.022 (0.141)	0.734 - 1.310	0.507 (0.087)	0.330 - 0.684	33	0.524	<0.001
	g/d	-0.207 (0.194)	-0.602 - 0.189	0.564 (0.119)	0.322 - 0.807	33	0.421	<0.001
Birds								
All birds	kJ/d	1.037 (0.064)	0.908 - 1.166	0.640 (0.030)	0.580 - 0.699	50	0.907	<0.001
	g/d	-0.188 (0.060)	0.310 - (-0.067)	0.651 (0.028)	0.595 - 0.707	50	0.919	<0.001
	g/d*	-0.310		0.720				
Passerines	kJ/d	0.949 (0.059)	0.809 - 1.088	0.749 (0.037)	0.663 - 0.835	26	0.899	<0.001
	g/d	-0.400 (0.075)	-0.554 - (-0.247)	0.850 (0.053)	0.741 - 0.960	26	0.915	<0.001
	g/d*	-0.409		0.822				
Non-passerines	kJ/d	0.681 (0.102)	0.442 - 0.920	0.749 (0.037)	0.663 - 0.835	24	0.899	<0.001
	g/d	-0.521 (0.132)	-794 - (-0.248)	0.751 (0.048)	0.652 - 0.850	24	0.919	<0.001
	g/d*	-0.373		0.740				

* improved estimates based on revised analysis (Nagy et al., in prep.).

where,

$\log y$ = $\log_{10}$ FMR (in units of kilojoules per day),
$\log a$ = intercept of the line,
a = untransformed value of FMR (kj/d) for a 1-g animal,
b = slope of the line,
x = body mass (g).

Metabolizable energy (ME) can be expressed as:

$$ME = (GE)(AE) \qquad \text{(Eq. 3.3-11)}$$

where,

GE = gross Energy content of diet (kJ/g)
AE = assimilation Efficiency (unitless), the fraction of ingested energy that is metabolizable.

Gross energy content (GE) varies between food types: average values for major categories of foods are presented by EPA (1993). Assimilation efficiency (AE) is more specifically defined for birds as a metabolizable energy coefficient (MEC) to account for nitrogen recycling (Karasov 1990). AE and MEC may be influenced by diet type (seed, invertebrate, meat), amount of food ingested (decreasing efficiency with increased intake), physiological conditions. Frequency distributions of MECs in birds reveal variability related to food type and are presented by Karasov (1990).

Combining Equations 3.3-9 and 3.6-11,

$$TFIR = FMR / (GE)(AE) \qquad \text{(Eq. 3.3-12)}$$

One option is therefore to substitute FMR/(GE x AE) for TFIR in the dose equations 3.3-5 and 3.3-7. This complicates the calculations but has several advantages, enabling the user to:

- Enter data for FMR, GE and AE which are specifically relevant to scenario under consideration,
- Incorporate uncertainties in the estimation of FMR, GE and AE into the overall assessment, and
- Take account of mixed diets, using the methods outlined by EPA (1993).

An alternative option is to use equations that predict dry food intake directly from body weight, provided by Nagy (1987). These were developed by combining the allometric equations for FMR (Equation 3.3-10) with generic assumptions on diet composition and standard values of ME for each food type. Some of the resulting equations are listed in Table 3.3-1. For example, for passerine birds Nagy (1987) gives the following equation:

$$\log\left(TFIR\right) = \log 0.4 + 0.85 \log W \qquad \text{(Eq. 3.3-13)}$$

where TFIR is total daily food intake in dry weight, and W is body weight (both in grams). Using this equation, a 30g passerine bird would be estimated to ingest 7.2g dry weight per day.

Using Nagy's (1987) equations for food intake has the advantage of simplicity, as they do not require the user to consider FMR, ME, GE and AE. However, they are based on generic assumptions about diet composition, GE and AE which may not be appropriate for particular exposure scenarios.

In screening assessments, TFIR could be estimated with existing information on actual intake, if available. Otherwise, Nagy's (1987) equations could be used to obtain a point estimate of TFIR for generic species. A case using a conservative assumption might be 2 to 3 times the daily TFIR. For short-term exposures, it would be assumed that this amount was ingested in a few minutes, equivalent to the timescale of exposure in the acute oral LD50 test. For medium/long-term exposures, TFIR would be assumed to distributed evenly over the whole feeding day.

In refined assessments, TFIR might be estimated from its separate components FMR, GE and AE, rather than from the Nagy (1987) equations. Also, information on the distribution of TFIR might be used. Suitable distributions from the literature would be used, if available. Otherwise, distributions could be estimated using the confidence intervals for Nagy's (1987) estimates of food intake, or for the separate components of TFIR, depending which method was being used. For short-term exposures, it would again be assumed that TFIR was ingested in a few minutes, as in the screening assessment. For medium/long-term exposures, diurnal variations in intake rate could be considered, if suitable effects data were available for comparison. In addition, the relative importance of the short- and medium/long-term exposure scenarios could be assessed by obtaining information on the relative frequency of gorging and non-gorging behavior in the wild.

If sensitivity analysis indicated that variation in TFIR was critical to the assessment outcome, then consideration would be given to obtaining improved estimates. In the first place it might be worth developing more refined distributions using existing data, for example by examining the original data on which the allometric equations are based. Alternatively, it might be decided to generate new data specific to the needs of the risk assessment, e.g. distributions of TFIR which are specific to the species, crops and regions being considered. These might be generated by field energetics studies of focal species to quantify distributions of FMR, and the assimilation efficiencies and energy contents of relevant food types. Alternatively it might be possible to measure TFIR directly in field studies, for example using radio-telemetry and/or video recording at feeding sites or nests, though this would be very difficult. If short-term exposures were critical, then it would likely be desirable to obtain specific field data on the frequency of gorge-feeding. TFIR for medium/long-term scenarios might take increasing account of diurnal and day-to-day variations, and how these differ between species and with environmental conditions (e.g. season). Other sources of variation such as age or sex could also be evaluated.

Further research is required to refine methods for estimating TFIR and its variability. Limitations exist in the use of currently available predictive equations for metabolizable energy demand and assimilation efficiencies of homeotherms for the following reasons:

- Only a limited range of species have been examined. The mammal database used by Nagy (1987) contains many marine mammals and breeding sea birds, but few nonrodent small mammals (e.g., no

shrews or voles) and few nonbreeding nonpasserines. Later work with mammals (Nagy 1994) expands the database to 61 species from 46 species, and includes additional small nonrodent mammals (e.g., bats), and

- There are limitations in sample size for certain body weights of animals, thus biasing regressions slightly.

Methods for combining the components of TFIR (FMR, metabolic efficiency and dietary energy content) need reviewing and refining, to take more account of the variability contributed by each component, and to take account of mixed diets. A literature review should be conducted to collate all existing data on TFIR in birds and mammals, such as the database being developed by the California EPA (Donohoe et al. 1997). TFIR distributions for focal species should be developed as a research effort. Finally, there is a need for better information on short-term exposure in the wild (e.g., meal size, gorging behavior) to match to effects testing with short intervals (e.g., LD50 studies with single bolus oral gavage dosing).

3.3.5 PD – Proportions of Different Food Types in the Diet

The proportion of diet from each food type k , PD_{ik}, is used in Equation 3.3-7 to denote that animals can consume a varied diet, such as a combination of insects, fruits, seeds and vegetation. The parameter PD_{ik} may vary from 0 to 1 with the sum of all PDs equal to 1. The purpose of including this parameter is to evaluate the potential impact of shifting diets on estimates of TFIR and exposure.

Dietary data may be found in the scientific literature in studies of animal food habits or foraging patterns, which are broadly available in journals of ecology, conservation and wildlife management or summary references such as Life Histories of Birds (Philadelphia Academy of Sciences, various authors). The USDA Biological Survey database on avian feeding habits contains >250,000 stomach sample records from >400 native North American bird species collected from 1885 to 1950. These data are summarized in USDA documents (e.g. Beal 1915) and by Martin et al. (1951). Diet or food habits may be reported as fresh or wet food, dry matter, or volumes, so attention to standardizing the units is important.

In screening assessments, point estimates may be used in the exposure assessment and may be based on existing information on animal diets. A conservative assumption might be to assume the diet consists

entirely of one realistic food type with the highest residue. For example, based on seasonal summaries of food habits in Martin et al. (1951), a breeding Canada goose would be assumed to consume 100% vegetation (with residues of 240 ppm per lb/acre applied), but no seeds or insects (with residues of 15 or 135 ppm per lb/acre applied). A breeding American robin would be modeled as consuming 100% small insects (135 ppm per lb/acre applied), but no fruits (15 ppm per lb/acre applied). The assumed concentrations are based upon the Fletcher et al. (1994) modifications to the Kenega nomogram..

In more refined assessments, hypothetical distributions of PD_i could be developed in the exposure assessment by selecting means and standard deviations from data from the literature. A sensitivity analysis could be performed at this level to examine possible extremes due to individual differences and temporal/spatial variation. For example, breeding American robins are characterized as consuming 2 diets in spring: approximately 79% animal matter and 21% plant matter, both with an approximate variation of 5% (Martin et al. 1951). A hypothetical distribution of proportion of animal matter in the diet can be generated based on several assumptions: normal distribution, mean of 0.79 and SD equal to the square root of 5% (0.22).

Empirical or fitted distributions of PD_i could be developed with data from individual birds or from species studies, if available. Access to original data would be needed. Wheelwright (1986) summarized the U.S. Biological Survey stomach samples for >1,900 American robins and found that diet was influenced by several factors: month, region, time of day, decade of collection, age, but not gender. Wheelwright (1986) reports that a wide range of plant and animal species were consumed, but identified no more than 6 distinct food types in robin stomachs. This database could be used to develop distributions of diet proportions for specific geographic or temporal scenarios (e.g., pesticide application timing in eastern fruit orchards).

To further refine the assessment, field research would be needed to quantify distributions of PD for particular species and conditions relevant to the scenario under consideration. Also, PD might be refined to take account of differences in the mix of food types available in different fields, and changes over time. Such variation occurs naturally. It can also occur as a result of pesticide application; for example an insecticide application may reduce the availability of insect prey but not that of seed or herbage. It is to allow for such differences that PD is allowed to vary between fields and over time in the full exposure

model (Equation 3.3-5). Estimating PD separately for each field or habitat type would provide a more precise risk assessment, but in practice such detailed information will be very difficult to obtain. It would therefore only be sought where it appeared critical to the assessment outcome.

It is important to note that the classification of food types needs to take account of their potential content of pesticide residues. For example, as small seeds typically contain higher levels of residues than large seeds (Fletcher et al.1994), separate estimates of PD are needed for small and large seeds. There may be a need to differentiate different sources of the same food type within the field. For example, in a dense growing crop, small insects from the crop canopy are likely to contain much higher residues than small insects from the soil surface. Also, dead invertebrates may contain more pesticide than live ones, and may be more (or less) likely to be eaten. These complications could be increasingly taken into account at in refined assessments.

Some predatory animals feed on vertebrate prey, which may themselves have been exposed and contain pesticide residues. Exposure of predators in this way is sometimes referred to as secondary exposure. Given the high intrinsic toxicity of many insecticides and rodenticides, it is feasible that there may be a secondary risk to predatory birds and mammals (Luttik et al. in press). There also may be a risk to scavengers feeding on dead rodents or other animals. Estimates of the proportional composition of specific prey items may be developed with the same approach as given above, with the initial assumption of feeding specialization (PD = 1) in screening assessments.

Finally, it is recommended that existing data on diets or food habits of focal species should be compiled in a single database, to facilitate future use of standard distributions by species and other significant sources of variation.

3.3.6 FDR – Fresh to dry weight ratio.

FDR is used to convert dry weight food intake (TFIR) to wet or ‘fresh’ weight. This is necessary to make the estimates of food intake consistent with estimates of their pesticide content (C, see below), which is

generally reported as mg pesticide per kg fresh food material (leaves, stems, fruits, vegetables, invertebrates, etc.). For example, the water content of fresh leafy and grassy vegetation is approximately 60% to 85%, such that dry matter would be 15% to 40% (Tiebout and Brugger, 1995). Thus 1 kg of fresh vegetation might have a dry content of 0.15 kg, in which case FDR would be 1:0.15, i.e. 6.7. A summary of typical FDRs is given in Table 3.3-2, on a per unit weight basis (per kg or per lb diet). Additional data on FDR for small insects is available from data of Fischer and Bowers (1997) and Brewer et al. (1997).

Table 3.3-2. Summary of fresh to dry weight ratios (FDRs) for common wildlife food items.

Food type	Dry matter (%)	Fresh to dry ratio	FDR
Leafy, grassy vegetation	15 – 40	1:0.15 -- 1:0.4	6.7 to 2.5
Small Seeds, grain	85	1:0.85	1.17
Small Fruits	8 – 46	1:0.08 – 1:0.46	12.5 – 2.2
Insects	15 – 25	1:0.15 – 1:0.25	6.7 – 4
Meat	20	1:0.2	5

In screening assessments, point estimates may be used in an exposure assessment and may be based on existing information in the literature for relevant food types. A conservative assumption would be assume the diet consists of one food type with the highest fresh to dry weight ratio. In the case of breeding American robins, a conservative assumption would be to focus on consumption of small fleshy fruits with an FDR of 12.5.

In refined assessments, one could develop hypothetical distributions based on means and standard deviations from the literature, with selection of distributions based on best judgement. A sensitivity analysis could be performed to identify and assess significant sources of variation. Alternatively, empirical or fitted distributions could be developed from data in the literature, if available. One might need access to original data to account for sources of significant variation (e.g. individual or seasonal).

To further refine the assessment, empirical distributions could be developed from field measurements taken under relevant conditions. These field studies could be conducted in such a way that the other major foraging parameters are also obtained (PT, TFIR, PD, and FDR).

3.3.7 AV - Avoidance

There are many examples of animals responding to the presence of noxious chemicals in their food by reducing consumption. Chemicals which induce this response include a wide range of plant secondary compounds which provide plants with a defense against herbivores (e.g. Buchsbaum et al. 1984). Similarly, some insects contain chemicals which are repellent to birds (e.g. Brower and Fink 1985). Many pesticides also induce reductions in consumption, as can be seen in the results of standard avian dietary toxicity tests (see data in Hill and Camardese 1986) as well as research studies (e.g. Grue 1982).

These avoidance responses clearly have the potential to reduce the exposure of birds and mammals to pesticides in their food. A key question is whether these responses are effective in the wild as well as in laboratory tests: this has been confirmed for two pesticides. First, a large number of field studies have demonstrated that, when used as an avian repellent, methiocarb can reduce the losses of fruit crops to predation by birds (Dolbeer et al. 1994), which implies that the ingestion of methiocarb by individual birds must be reduced to some extent. Second, surveys of fields sown with winter wheat in the UK have demonstrated significantly lower numbers of feeding woodpigeons on fields where the seed is treated with fonofos, compared to untreated fields (McKay *et al*., in press). Furthermore, it can be presumed that plants and insects would not have evolved defensive chemicals unless they were effective. It is concluded that avoidance can be important in reducing exposure, and hence should be given consideration in avian risk assessment (OECD 1996).

Methods for assessing avian avoidance have been developed over a long period, both for the purposes of pesticide risk assessment (BBA 1993, INRA 1990) and to assess the efficacy of avian repellents (Mason et al. 1989). Work to develop an OECD guideline for avoidance testing began at a SETAC/OECD workshop in December 1994 (OECD 1996), and has since been continued through a series of informal meetings at SETAC conferences. Industry associations have recently taken responsibility for producing a draft guideline.

The effect of avoidance is represented as AV in the model for dietary exposure (Equation 3.3-7). However, it is essential to remember that AV is a function of C, because the extent of the avoidance response generally increases with increasing concentration of pesticide in the food. AV takes values between 0 (no avoidance) and 1 (complete avoidance of contaminated food). It is reiterated that AV is a simplistic way of incorporating avoidance: a more sophisticated approach would be to make PD_{ijk}, $TFIR_I$ and PD_{ijk} all functions of C_{ijk}, as mentioned in Section 3.3.1.

The principal difficulty in assessing the effect of avoidance on exposure is that the avoidance response is highly variable, and is influenced by many factors (OECD, 1996). Quantifying this variation is a difficult task which is likely to be reserved for the later stages of risk assessment. In earlier stages of assessment, attention will focus on determining whether there is sufficient evidence of avoidance to be worth detailed investigation. A more detailed discussion of AV is included in Appendix C2.

In a basic screening assessment and in cases where no information on avoidance is available, it should be assumed that no avoidance occurs (conservative assumption). AV should therefore be set to 0.

A detailed assessment of avoidance requires non-standard data (Appendix C2), which may be costly to obtain. It is therefore desirable to have a simple method of screening pesticides, to determine whether they show sufficient signs of avoidance to make detailed assessment worthwhile.

For birds, the avian dietary test provides a convenient means of screening for avoidance. AV can be estimated for each test concentration by dividing the food consumption of the test group by that of the control group. Figure 3.3-3 illustrates this for fonofos using data from Hill and Camardese (1986). The concentrations used in the test are unlikely to correspond to those predicted in the wild. However, for the purposes of a screening assessment it will be sufficient to use simple linear interpolation to estimate AV for the relevant concentrations, provided it is remembered that the results are approximate. Note that in Figure 3.3-3 the calculation is made using consumption on the first day of exposure: this may be considered as representing the response of a bird on the first day it encounters a treated field. This is more conservative than taking data from later days, when the avoidance response is often stronger. In some studies consumption may only have been measured over longer periods, in which case the first such

period should be used. Caution is required to ensure that the consumption data are not biased by the effects of food spillage, which can be substantial (especially with mallards).

Some test protocols measure the consumption of animals given access to untreated food as well as the test diet (e.g. INRA 1990, Mason *et al.* 1989). If such studies are available they can be used to provide an alternative estimate of AV, dividing the consumption of treated food by total consumption on the first day of testing. This estimate is likely to represent a 'best case' situation (maximum avoidance), especially if the animals can readily detect which food is treated (e.g. if the foods differ in appearance

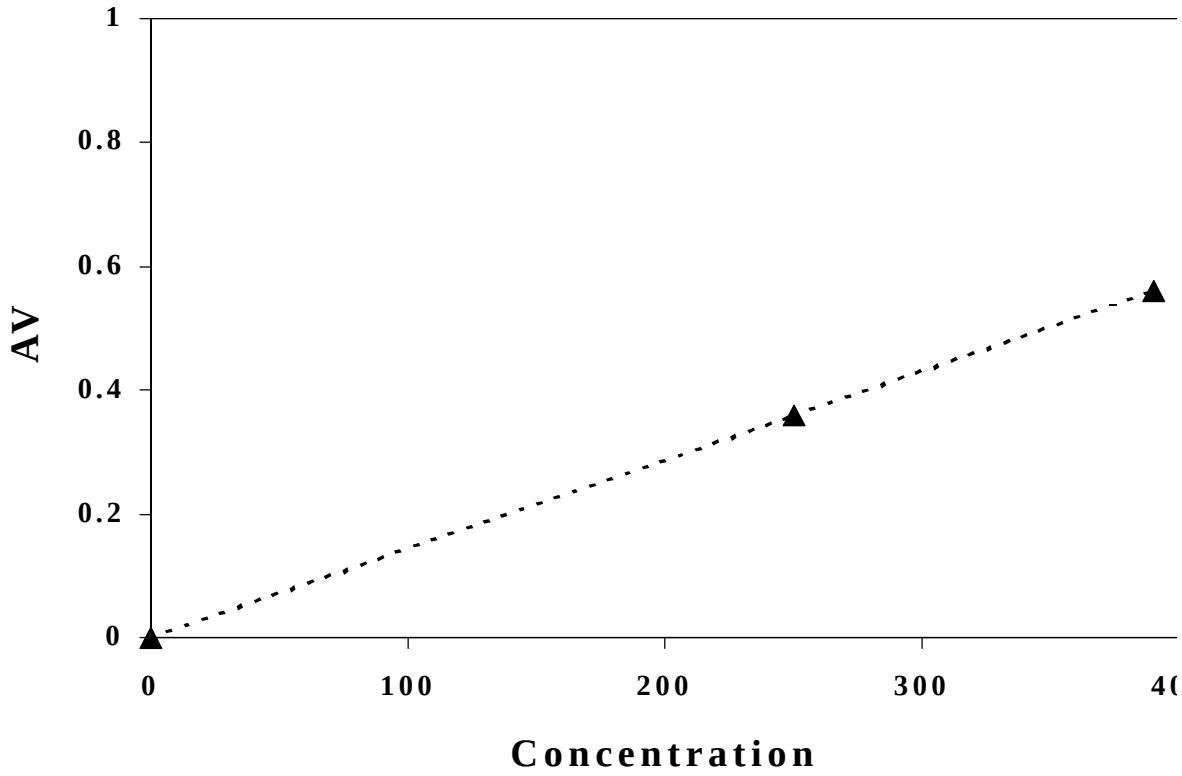


Figure 3.3-3. Preliminary estimation of AV for screening purposes, using data from the avian dietary toxicity test. AV is estimated as the *reduction* in consumption on the first day with treated diet, compared to consumption by control groups fed untreated diet. Data is for fonofos, from Hill and Camardese (1986). In this example, values of AV for intermediate concentrations are approximated by linear interpolation. C_i = concentration in test diet, ppm.

and/or presented in separate containers).

Estimates of AV obtained from tests with and without alternative food may therefore be used for screening purposes, to assess the *potential* contribution of avoidance to reducing risk. If they indicate that avoidance may be important in reducing risk below the level of concern, then further studies are likely to be needed to confirm whether the response will be effective in the wild. The types of studies which are appropriate differ for short-term and long-term exposures. For short-term exposures, no-choice feeding studies are appropriate and attention is centered on the rate at which animals feed. For longer term exposures, attention centers on the availability of alternative foods and the ease with which the animal can distinguish contaminated and uncontaminated foods, so feeding studies with an element of choice may be appropriate.

No standard test method yet exists to obtain refined estimates of AV, and the design of such studies is still the subject of research and discussion. In the meantime, studies will have to be designed case-by-case to meet the needs of the individual risk assessment. Factors which need to be considered are discussed in detail in OECD (1996), and possible approaches based on more recent research are discussed in Appendix C2.

An alternative to tests with captive birds might be to investigate the influence of avoidance on exposure and effects in the field. However, this is unlikely to be realistic for regulatory purposes. Bird foraging behavior is so variable that it is difficult to detect avoidance of treated areas, even when it is contributing significantly to reducing exposure (McKay et al. in press). Furthermore, the conditions under which avoidance breaks down and causes mortality may be relatively rare, and would be unlikely to appear in field studies unless they were repeated on a large number of sites. Thus field studies are unlikely to be effective either in demonstrating avoidance, or in determining how reliable it is.

In summary, the considerations above suggest the following approach:

- Basic screening assessments should assume no avoidance (set AV equal to 0).

- If the assessment indicates the potential for significant exposure, then data on food consumption

in dietary toxicity tests may be used to provide screening estimates of AV. These can be used for both short-term and longer-term exposures. However, they should be used solely to indicate whether there is potential for avoidance to reduce exposure, and should not be relied upon in a definitive assessment of risk.

- If the screening assessment indicates potential for avoidance to significantly reduce exposure, then a detailed assessment is required. (See Appendix C2 for further details.) Ideally this should aim to quantify the distribution of AV in the wild. For short-term exposures (minutes to hours), it may be possible to do this by combining data on the distribution of feeding rates in the wild with laboratory tests of the degree of avoidance at different feeding rates. For longer-term exposures, it may not be practical to obtain a distribution for AV as it depends on the ability of animals to discriminate between contaminated and uncontaminated foods. Instead, the best solution may be to obtain point estimates for AV under realistic conditions but tending towards the conservative side.

- Further research is required to refine and validate approaches to assessing avoidance.

3.3.8 C – Residues in Food

The pesticide concentration on/in foliage and insects will depend on numerous factors including the numbers and rates of application, the intervals between applications, spray drift, rates of foliar growth, foliar and insect surface area, and the rates of degradation, volatilization, depuration, uptake and washoff.

Currently, immediate post-application pesticide concentrations on/in foliage are generally estimated from the Fletcher et al. (1994) recommended modifications to the Kenaga nomograph. Further data for seeds have been produced experimentally by Edwards et al. (1999). In addition, the Kenaga/Fletcher data have been used to estimate residues on insects, by assuming that these will be similar to residues on seeds of similar size (on the expectation that residue load will be governed by surface area to volume ratio).

Immediate post-application concentrations as well as dissipation rates for various pesticides on insects can be obtained more accurately from the literature review of Fischer and Bower (1997), and from studies conducted by Brewer (1997). Dissipation rates for various pesticides on foliage can be obtained from the Willis and McDowell (1986) paper.

Estimates of initial foliar residue levels and foliar dissipation rates can be used as inputs to computer models to estimate foliar residue levels as a function of post-application time. (See Section 3.10 and Appendix C4.) Alternatively or for purposes of model validation and calibration, foliar residue levels at various times post-application can also sometimes be obtained from lab and/or field studies.

For vertebrates, models that estimate body burden as a consequence of uptake (dietary exposure) and depuration (from poultry or rat metabolism studies) will be needed.

Residues in foods ingested by animals may therefore be estimated at different levels of refinement, with increasing attention to reduce uncertainty. For screening assessments, estimates of initial residues and dissipation rates may be generated for categories of food types based on existing residue data, using the sources cited above. Usually, conservative estimates of residues (e.g. 'maximum' values) and dissipation (minimum) will be used as the first step. 'Typical' or average values could be used as a second step, to assess whether the influence of C on the risk assessment outcome is large enough for it to be worth assessing in more detail.

In refined assessments, distributions should be used in place of point estimates, if possible, for both initial values and dissipation. It may be possible to simulate these using confidence intervals from published sources or by obtaining access to the original data on which 'typical' and 'maximum' estimates were based. Alternatively, estimates of distributions may be available from new models of initial residues and dissipation over time. Examples of generating hypothetical PDFs for initial foliar residues, foliar and soil dissipation rate constants and soil/water partition coefficients are provided in Section 3.11. Examples of generating experimental CDFs for initial invertebrate residues are also provided in Section 3.11.

To further refine the assessment, field data could be used to validate and / or calibrate models and to obtain distributions of C at different points in time under conditions relevant to the scenario under consideration.

3.3.9 *W* - BODY WEIGHT

Body weights in mammals and birds may vary by time of day, seasonally, geographically, and by age or sex class (Clark 1979). Estimates of body masses for mammal and bird species, subspecies, and regional populations may be found in several sources. Two handbooks summarize global databases of body masses of mammals (Silva and Downing 1995) and birds (Dunning 1993) by species, sex and collection location. Sample size, arithmetic mean, range and standard deviation are provided when available. Taxonomic references, such as Walker's Mammals of the World (Nowak 1991) and Life Histories of Birds (individual species reports published by Philadelphia Academy of Sciences) provide complementary data. Species specific publications on topics such as physiology, nutrition or energetics may include arithmetic means and SDs of body mass. It is possible to contact authors to request primary data that can be used to develop distributions for use in probabilistic models.

Note that W is often used in estimating TFIR as well as being present in the denominator of the dose equation. This has two consequences. First, it will tend to cancel out to an extent (but not completely, due to its non-linear relationship with TFIR), so that W will have less influence on exposure than other variables. Second, in a Monte Carlo simulation, values of W should be sampled only once per iteration, and the same value should then used both for estimating TFIR and as the denominator of the dose equation.

In screening assessments, point estimates of arithmetic mean, range and standard deviation may be obtained from the major references. It can be assumed that body mass is distributed normally. If ranges are available, one could assume that the low and high values are the ends of the distribution, thus it is truncated. An example is given for American robins (*Turdus migratorius*). Dunning (1993) reports no sexual dimorphism in body mass. Mean body mass of 401 adult males and females from Pennsylvania is 77.3 g $\pm$ 0.36, ranging from 63.5 to 103.0 g.

In refined assessments, distributions may be derived from descriptive statistics and assumptions about distributions (truncated, normal). This could be expanded to include variability associated with geography, season, age or sex if these data are available and are considered significant sources of uncertainty in the models. For example, the distribution of body masses of American robins collected in February 1991 in Florida differed between age classes (Brugger, 1993). On average, third-year birds (n=15, mean = 83.9 g ± 8.9, range 64.5 – 95 g) were heavier than second-year birds (n=44, mean = 78.3 g ± 7.8, range 63.5 – 96 g), although the ranges of weights were similar. Where the raw data are available, empirical or fitted distributions can be used. To refine the assessment still further, site- or condition- specific distributions could be obtained in field studies.

3.4 DOSE RESULTING FROM INGESTION OF CONTAMINATED WATER

The Terrestrial Workgroup devoted only a small amount of time to development of probabilistic tools for estimating wildlife exposure via ingestion of water. This route of exposure is rarely considered in current pesticide risk assessments and is generally not considered a major route for most pesticides. The methodology proposed is an extension of that presented for food, in which Water Ingestion Rate (WIR) replaces Food Ingestion Rate (FIR) and the concentration in water replaces the concentration in food in the dose equations.

3.4.1 Dose Equations for Ingestion of Contaminated Water

The one day drinking water dose for any day i, the cumulative drinking water dose over N_i days and the average daily drinking water dose over N_i days a bird or mammal receives through ingestion of pesticide contaminated drinking water in one or more fields j per day are given respectively by:

$$\text{One Day Dose}_{\text{water}}(\text{day } i) \text{ in mg / kg BW * day} = \sum_{j=1}^{j=N_i} \sum_{p=1}^{p=N_p} WIR_{ijp} C_{ijp} / W$$

(Eq. 3.4-1)

$$\text{Cumulative Dose}_{\text{water}} (\text{over } N_i \text{ days}) \text{ in mg / kg BW} = \sum_{i=1}^{i=N_i} \sum_{j=1}^{j=N_j} \sum_{p=1}^{p=N_p} WIR_{ijp} C_{ijp} / W$$

(Eq. 3.4-2)

Average Daily Dose$_{water}$ in mg/kg BW*day = Cumulative Dose$_{water}$/N$_i$ (Eq. 3.4-3)

where,

p = index for different water sources (e.g., dew, puddles, pond)

N_p = maximum number of different water sources consumed by the bird or mammal (generally dew, puddles, pond = 3)

j = index for different foraging fields

N_j = maximum number of fields foraged by the bird or mammal over the foraging time interval of interest for which a dose is to be computed

i = index for different foraging days

N_i = number of days during the foraging interval of interest for which a dose is to be computed

WIR_{ijp} = water intake rate (L/day) of water source type p consumed by the bird or mammal in field j on day i (WIR_{ijp} = 0 if the bird or mammal is not in field j on day i or is = 0 for puddles and/or the pond if the field does not have puddles on day i and/or does not have a pond)

C_{ijp} = initial or average pesticide concentration in water source type p in field j on day i (mg pesticide/L of water). If the field j has not been treated or received spray drift by day i, C_{ijp} = 0.

W = body weight of the bird or mammal (kg)

By analogy to equation *** for the food intake rate, the water intake rate of water source type k by a bird or mammal in field j on day i is given:

$$WIR_{ijp} = f_{ip}(TWIR_i)(PW_{ijp})(WAV_{ijp}) \quad \text{(Eq. 3.4-4)}$$

where,

f_{ik} = fraction of total water obtained from field k on day i (dimensionless)

$TWIR_i$ = total water ingestion rate = total drinking water consumed on day i (L/day)

PW_{ijp} = proportion of water obtained from field j on day i that was derived from water source type p

WAV_{ijp} = avoidance factor for water source type j in field k on day i = fraction of water from source type p that would normally be consumed in field j on day i if the water was not contaminted at a contaminant level of C_{ijp} (dimensionless); The avoidance factor is a function of the contaminant level.

Methods for estimating TWIR, PW in water are discussed in the following sections. Methods for estimating f and WAV have not been developed, however, the analogous values for food presented in Section 3.3 are reasonable first tier estimates for these variables. Factors that influence pesticide concentrations in water are discussed here also, but see Section 3.10 and Appendix C4 for greater detail.

3.4.2 Estimation of Total Water Ingestion Rate

The EPA Wildlife Exposure Factors Handbook contains estimates of the water ingestion rates for representative species of birds and mammals. Drinking water is but one way animals meet their water requirements. Some water is produced as a product of metabolism. Water is also contained in food. Species differ in their need to take in additional water by drinking. In the absence of species-specific estimates of drinking water intake, the EPA Wildlife Exposures Handbook recommends the use of allometric equations derived by Calder and Braun (1983), as follows.

For birds,

$$\text{Total Water Ingestion Rate (L / day)} = 0.059 W^{0.67} \qquad \text{(Eq. 3.4-5)}$$

For mammals,

$$\text{Total Water Ingestion Rate (L / day)} = 0.099 W^{0.90} \qquad \text{(Eq.3.4-6)}$$

In the above equations W is body weight in kg. If necessary, values derived from the above equations may be normalized by dividing by body weight. The units of the resulting estimate become L water/kg BW*day, which is equivalent to g water/g BW*day.

3.4.3 Proportional Intake from Different Sources of Water (PW)

Three general categories of sources of water are dew, puddles and ponds. The Terrestrial Workgroup did not identify any studies that estimated proportional use of these sources of water by wildlife. The proportion of drinking water obtained from these sources is likely highly variable among species, individuals and field locations. It is likely that each of these routes predominates for at least some species under some field scenarios. One might conduct three independent assessments assuming in turn that all drinking water comes from dew, then puddles, then ponds, and determining the range of exposure values obtained and whether any of these values could contribute to a significant proportion of total oral exposure. If the range in variation or the contribution of water to the total dose received by the animal was small, further work to clarify PW would not be justified. However, if one source could potentially contribute a significant dose (e.g., drinking of dew drops on spayed vegetation) than the frequency of use of this source by the species of concern may warrant further investigation.

3.4.4 Pesticide Concentrations in Water

Pesticide concentrations in water will depend on numerous factors including application rates, spray drift and runoff/erosion loadings to the water, concentrations in soil and on foliage coupled with the magnitudes of soil/water and foliage/water partition coefficients, rates of water evaporation and infiltration, rates of degradation in water and volatilization rates from water (which depend in part upon the magnitude of Henry's Law constant).

Values of soil/water partition coefficients, Henry's Law constants, abiotic hydrolysis rates, direct photolysis rates, and sometimes combined abiotic/microbiologically mediated degradation rates in water can be obtained from fate studies commonly conducted by Registrants and submitted to OPP. Many such values are listed in the ARS/USDA and the OPP fate and chemical property databases.

More detailed discussions of methods to estimate pesticide concentrations in water are presented in Section 3.10 and Appendix C4.

3.5 DOSE RESULTING FROM INGESTION OF GRANULES

3.5.1 Overview of Granular Pesticide Exposure to Wildlife

In addition to direct ingestion of granules, wildlife may be exposed to granular pesticides through nearly all of the routes presented earlier in Figure 3.1-1. For example, oral exposure can occur via (1) ingestion of residues transported from intact granules to food, water or soil, (2) ingestion of residues on feathers or pellage during preening/grooming activity, (3) dermal contact with residues in/on soil, vegetation, water and the granules themselves, and (4) inhalation of volatilized molecules. Exposure to granular pesticides via these routes can be assessed using the same methods as discussed for flowable formulations. However, exposure levels via these routes will typically be much lower than for a flowable formulation because in the case of a granular formulation, the vast majority of the chemical that is applied remains adhered to the granules. The bioavailability of the chemical is therefore relatively low unless the granules themselves are ingested. Consequently, the direct ingestion of granules has been considered the primary route of exposure of wildlife to granular pesticides (U.S. EPA 1992, Best and Fischer 1992).

Granules may be ingested accidentally in the course of birds probing for or pecking at food in or on treated soil, or they may be ingested intentionally by animals that mistake them for grit or food. Of the commonly used granular carriers, only corncob granules seem likely to be mistakenly ingested as food (Best 1992, Best and Fischer 1992, Stafford and Best 1997). Exposure assessment for granular products formulated on corncob carrier should follow the methodology presented earlier for contaminated food (Section 3.3). In performing such an assessment, a key parameter that must be estimated is the proportion of the diet composed of corncob granules ($PD_{granule}$). This may be assumed to be some fraction of the total fraction of the diet composed of seeds. A method for estimating $PD_{granule}$ is discussed in Section 3.5.3.

For all other granular formulations (i.e., formulated on carriers such as clay, silica and gypsum), which includes the vast majority of granular pesticide products currently in use, the primary route of exposure is thought to be ingestion of granules accidentally or intentionally as grit. The workgroup devoted considerable time to the development of a probabilistic model of this exposure route. The steps taken in developing a working model are described in the following sections. The model focuses on birds because birds ingest more grit than mammals and are therefore more likely to ingest granules. Birds use more grit because they lack teeth and therefore must ingest grit to aid in the grinding of hard foods in their gizzard. A more detailed description of the new model, GEM (Granule Exposure Model), is in Appendix C3.

3.5.2 Review of Existing Assessment Methods

OPP currently uses a hazard index approach ($LD50s/ft^2$) to characterize risk of granular products. The exposure component (pesticide load available per square foot) is an estimate of residues present in the animal's environment. This residue load may be an index to wildlife exposure (i.e., as the index increases, so may exposure), but it is not an estimate of chemical intake *per se* and it cannot readily be used probabilistically.

Recently, attempts have been made to estimate ingestion rates of pesticide granules using individual-based probabilistic modeling. Abt Associates Inc. (1996) used such a model (Abt model). The Abt model assumed that (1) birds seek out and ingest on a daily basis a certain number of grit particles and that (2) granules present within the birds' foraging space have the same chance of being selected as natural grit particles if they are within the size range of the grit used by the species under consideration. The studies of Best and Gionfriddo (1991), Best (1992) and Gionfriddo and Best (1996) were used to determine the amount and size range of grit that species of birds ingest daily, and the overlap in the size of grit used versus that of applied pesticide granules. The availability of granules was estimated from the application rate and assumptions regarding soil incorporation by application machinery. The availability of natural grit particles of various size classes was estimated from soil texture data available from the USDA Soil Conservation Service. The Abt model also included a granule preference factor whereby the probability that a bird selects a granule vs. a natural grit particle could be increased or decreased if data were available regarding the relative attractiveness of the granule type in question. Because such data were lacking, this factor was set equal to 1 (meaning birds exhibited no preference or avoidance of granules). A Monte Carlo simulation approach was used to estimate the range of exposure levels for different individuals of the species under consideration. For each individual bird in the simulation, the model determined the number of granules ingested in one day. By taking into account the pesticide load of each granule (i.e., the % active ingredient multiplied by the average granule mass), the number of granules ingested was converted into an estimated pesticide dose (mg AI/ kg BW/ day). The Abt model assessed exposure levels over a single day immediately after application.

Dixon et al. (1997) recently developed an individual-based, probabilistic model (Dixon model) that also used a Monte Carlo approach to estimate pesticide exposure levels and resulting effects from the

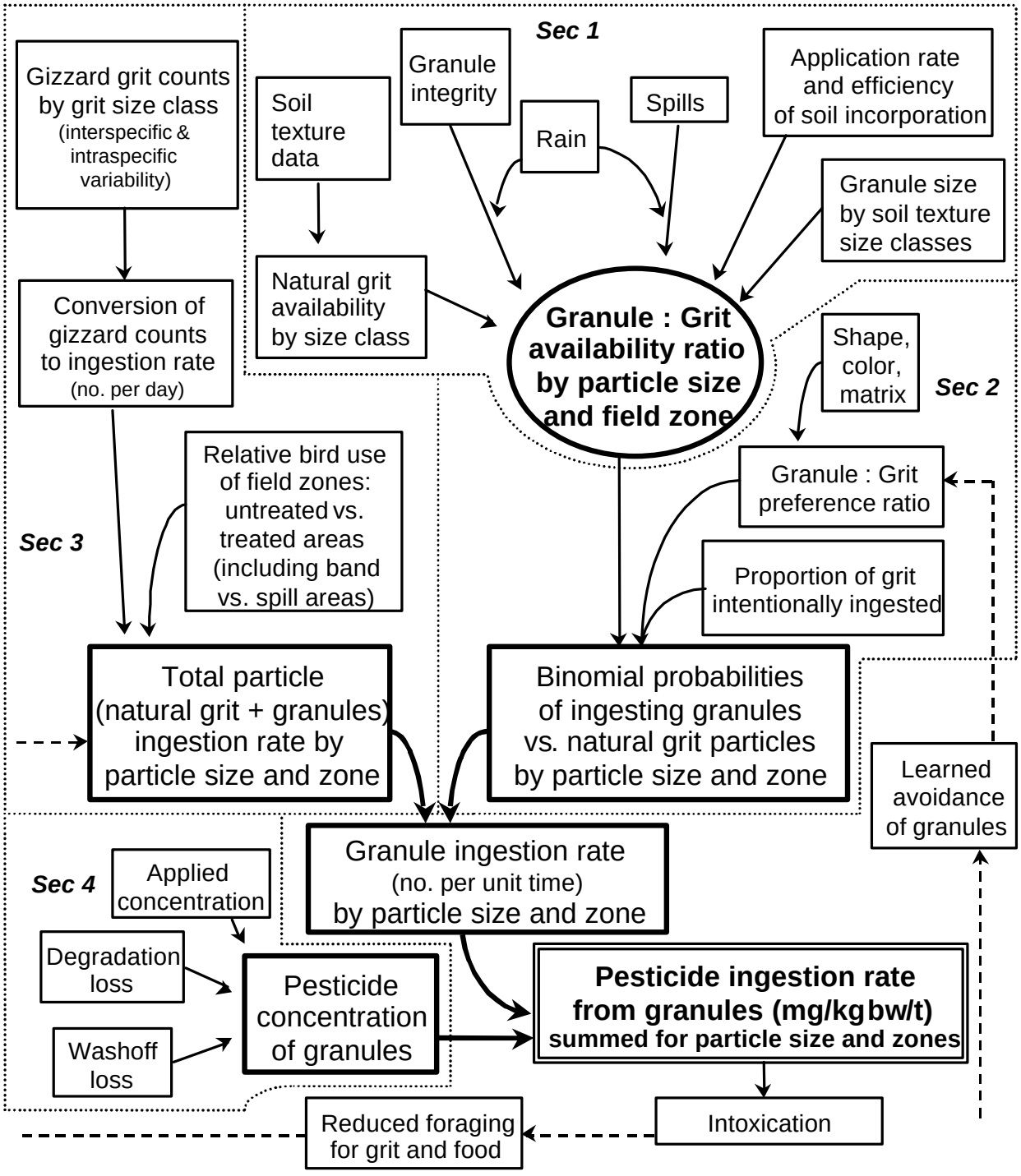
ingestion of granules as well as from other routes. Instead of modeling granule ingestion as a probabilistic function of availability of granules vs. other grit particles, granule ingestion rate was estimated by fitting a probability density function to actual field measurements of granule ingestion rates by birds (Fischer and Best 1995). A granule preference factor component allows for adjustment of the ingestion rate if there is evidence to show that the granule type being considered is selected by birds at a different rate than the granule type that was used in the field study. The model used a daily time step to assess exposure levels over multiple days and so included components that account for loss of pesticide from the granule with time, and pesticide metabolism and excretion after ingestion. The model calculated pesticide body burden through time and resulting fate (i.e., survival vs. mortality) for each individual of a theoretical population. The Dixon Model is discussed in greater detail in Appendix A3.

3.5.3 Conceptual Model for Granule Exposure Assessment

The Abt and Dixon models were developed independently and each contain useful features. To construct a more definitive modeling tool, a conceptual model of factors that potentially influence avian ingestion of pesticide granules was developed (Fig 3.5-1). The Abt model's approach of modeling granule consumption as probabilistic function of availability of granules vs. other grit particles was chosen over the Dixon model's approach of fitting a probabilistic density function to observations obtained in an actual field study in order to make the model applicable to a wider range of field conditions (e.g., soil types) than those evaluated in the Fischer and Best (1995) field study. If the conceptual approach to modeling granule ingestion behavior adequately represents this process as it occurs in the real world, it should be possible to model the field conditions studied by Fischer and Best (1995) and derive predictions of granule ingestion rates for birds that are reasonably close to those actually observed. Thus, the actual field study results can provide a "reality check" for modeling tools developed from this conceptual model.

The conceptual model may be subdivided into four sections. Section 1 includes factors that affect the relative availability of granules and natural grit particles in a bird's environment. From these factors, the availability ratio of granules to natural grit particles is estimated. In Section 2, the ratio of granule availability is considered with other factors (such as preference/avoidance of certain granule types) to estimate the expected probabilities that a particle selected by an individual bird will be a granule vs. a natural grit particle. In Section 3, the number of grit particles ingested per unit time is estimated. This

Fig 3.5-1. Conceptual Model of Bird Exposure via Ingestion of Granules



determines the number of times a bird selects a grit particle from its environment. From the outputs of Sections 2 and 3 the model derives an estimate of the granule ingestion rate. Section 4 includes factors that may modify the pesticide content of granules over time. Combining the output of Section 4 with the granule ingestion rate yields the pesticide ingestion rate, which is of course the desired output of the model. There are also feedback loops (dashed arrow lines) in which pesticide exposure produces sublethal intoxication which may lead to a reduction in grit use and/or a change in the probability for birds to ingest granules through a learned avoidance mechanism.

The underlying assumptions and theoretical basis for the model become more apparent as one considers the key parameters being estimated in more detail. Key parameters are discussed beginning with the "bottom line" output and working back through the various inputs.

Pesticide ingestion rate from granules (PIRG): This is the overall output of the model, expressed in mg pesticide ingested per kg body weight per unit time. PIRG is a function of the Granule Ingestion Rate (GIR) and the pesticide concentration in granules (AI) at the time period of interest. PIRG may then be added to exposure via other ingestion routes (e.g., via food or water) to calculate a total estimated ingestion exposure, which in turn may be integrated with toxicity information to predict risk.

Granule Ingestion Rate (GIR)**:** This is the number of granules a given individual bird ingests over the period of time of interest. GIR is estimated from the estimate of the number of particles the bird ingests as grit during the time period of interest that are in the same size range as granules, and the estimated probability that a particle in this size range that is being ingested will be a granule as opposed to a natural grit particle. Grit ingestion is modeled as a series of binomial trials. Each particle being ingested represents one trial. In each trial, the bird may ingest either a granule or a natural grit particle. The total number of granules ingested by an individual bird during a given time period becomes a function of the probability of ingesting a granule (p), the probability of ingesting a natural grit particle (q), and the number of trials occurring in that time period (N). The parameters p, q and N define a binomial distribution from which a random sample is drawn to estimate GIR for an individual bird (iteration), and the process may be repeated over many iterations to obtain a distribution for GIR.

Pesticide concentration of granules (AI): The pesticide concentration of granules will initially be the concentration formulated into the product, but may change over time as the result of degradation (e.g., photolysis, hydrolysis, biodegradation) or transport loss (e.g., volatilization, diffusion, washoff by rain). Equations for estimating pesticide concentrations in granules over time are discussed in Appendix C3 along with other components of the GEM Model.

Total particle ingestion rate (TPIR) and *N*: Total particle ingestion rate (TPIR) is simply the number of particles, including both naturally occurring grit and pesticide granules, ingested as grit per unit time. This may be estimated probabilistically for a number of avian species from the gizzard grit count data compiled by researchers at Iowa State University (Best and Gionfriddo, 1991, and Best unpublished) after applying a conversion factor to convert gizzard counts to a daily consumption estimate (see Fischer and Best, 1995). A randomly drawn observation from this data set may be used to establish the number of particles an individual bird is "programmed" to ingest in a given day. However, only some of the grit used by birds is of the same size range as pesticide granules. If one assumes that birds only may select a granule when they are seeking a particle within the size range of granules, then the number of occasions in a given day in which a bird could ingest a granule is TPIR multiplied by the fraction of particles in the same size range as granules. The resulting value is equivalent to *N*, the number of binomial trials in which a granule could be selected.

Many applications of granular pesticide are not uniformly made to the entire field, but rather are put down in narrow bands. In such cases, separate estimates of *N* are desirable for each zone of the field with a different probability of selecting a granule (*p*). For example, the probability of selecting a granule may be very high (99%) for a bird foraging in a spill area, small (1%) for a bird elsewhere within the "normal" pesticide band, and nill (0%) for a bird foraging between the bands. The number of particles a bird obtains from each of these zones may be assumed to be a function of their relative size and attractiveness as foraging habitat. (See Appendix C3 for example calculation.) The degree of attractiveness or preference of birds for specific field zones may in some cases be estimated from actual field data (e.g., Best et al., 1990). However, these estimates may have to be made in many cases on the bases of expert opinion.

Probability of ingesting granules (*p*) and alternative particles (*q*): These are binomial probabilities that are based on (1) the relative availability of granules and natural grit of similar size, (2) the preferences birds may have for granules or natural grit when they select particles, and (3) the proportion of all grit consumed that is intentionally selected as opposed to ingested accidentally/incidentally during feeding. The estimation of p and q is simplified if the assumption is made that birds have no preference for selecting granules vs. natural grit particles. In this case, p, and q are calculated directly from estimates of relative availability of these two particle types, as follows:

$$p = \frac{Availability\ of\ Granules}{Availability\ of\ Granules + Availability\ of\ Natural\ Grit} \quad \text{(Eq. 3.5-1)}$$

$$q = \frac{Availability\ of\ Natural\ Grit}{Availability\ of\ Granules + Availability\ of\ Natural\ Grit} = 1 - p \quad \text{(Eq. 3.5-2)}$$

where it is understood that *Availability of Natural Grit* refers here only to particles in the same size range as granules.

Several studies have demonstrated that birds may use some granule types as grit more readily than others (Best and Gionfriddo 1994, Best et al. 1996). This may have a large influence on exposure levels (Stafford et al. 1996, Stafford and Best 1997). Preference/avoidance of various granule types may be accounted for by introducing the Granule Grit Preference factor (GGP) into the following equation, relating the probability of ingesting a granule to the probability of ingesting a natural grit particle (Abt Associates 1996).

$$\frac{p}{1-p} = GGP \frac{Availability\ of\ Granules}{Availability\ of\ Natural\ Grit} \quad \text{(Eq. 3.5-3)}$$

GGP is a dimensionless number that relates the frequency that birds given equal access to granules and natural grit select granules. If a bird had no preference or aversion to pesticide granules compared to natural grit, GGP = 1, because 1 granule is ingested for every 1 natural grit particle ingested. If a bird preferred granules to natural grit, then GGP would be >1, and if a bird preferred natural grit to granules,

then GGP would be <1. For example, if birds were shown through empiracle tests to prefer natural grit over granules by a 3:1 margin, then GGP would be defined as 0.33. (0.33 granules selected for every 1 natural grit particle selected).

By solving for *p*, equation 3.5-3 may rewritten as:

$$p = \frac{GGP * Availability\ of\ Granules}{Availability\ of\ Grit + (GGP * Availability\ of\ Granules)} \qquad \text{(Eq. 3.5-4)}$$

The probability of selecting a natural grit particle (q) is then obtained by subtraction:

$$q = 1 - p \qquad \text{(Eq. 3.5-5)}$$

The above equations may be used to define the probabilities that bird will select a granule or natural grit particle. These probabilities vary depending upon where the bird is foraging, since availability of granules vs. grit changes in different zones of a field and between fields with different soil types. *P* and *q* also vary depending upon whether a particle is being ingested intentionally as opposed to accidentally. Note that for a particle ingested accidentally, by definition no preference/avoidance occurs, GGP therefore equals 1, and equation 3.5-4 reduces to equation 3.5-1.

A slight modification of Equation 3.5-4 may be used to estimate the probability that a bird will mistakenly ingest a corncob granule instead of a seed. As previously discussed, pesticides formulated on corncob granules may be consumed mistakenly as seeds and exposure via this route can be estimated using methodology presented in Section 3.3 for contaminated food if one can estimate the proportion of the bird's diet that corncob granules comprise ($PD_{granule}$). This will be a fraction of a larger fraction of the diet which is made up of seeds. The probability that a bird foraging on a field where granules have been applied will mistakenly ingest a corncob granule instead of a seed is:

$$p = \frac{GSP \bullet Availability\ of\ Granules}{Availability\ of\ Grit + \left(GSP \bullet Availability\ of\ \text{Granules}\right)} \qquad \text{(Eq. 3.5-6)}$$

where GSP (Granule:Seed Preference factor) is a preference factor relating the probability a bird will select a granule over a seed if access was equal. $PD_{granule}$, the corncob granule fraction of the diet may then be estimated as:

$$PD_{granule} = PD_{seeds} \bullet p \qquad \text{(Eq. 3.5-7)}$$

Once $PD_{granule}$ is estimated, assessment of dietary exposure to pesticides formulated on corncob granules may proceed using the methodology presented in Section 3.3.

Granule to Grit ratio (GGR): The availability of granules in relation to natural grit particles is assumed to be a key factor in determining granule ingestion rate. Factors that affect this ratio include the number of granules applied per unit area, the efficiency of the application equipment in incorporating granules beneath the soil surface, the spatial zone being considered (e.g., spill area vs. "normal" pesticide band area vs. outside the pesticide band), the integrity of the granule carrier under field conditions (some granular carriers disintegrate upon contacting moist soils), and the soil texture profile (i.e., amount of sand in the size classes used by birds as grit). Two additional factors that influence granule and grit availability are rainfall and crop residue cover. Rainfall has been shown to reduce availability of granule-sized particles on the soil surface (Fischer and Best 1995). The presence of crop residues obscures and limits birds' access to part of the soil surface of a field, and therefore may also in effect reduce grit availability. These two factors were left out of the model because we assume these factors affect the availability of both granules and natural grit equally, and thus do not influence GGR.

3.5.4 Implementation of the Conceptual Model: Development of GEM

A new modeling tool called GEM (Granule Exposure Model) was developed from the conceptual model presented above. GEM was developed using the Abt model as a starting point. However, significantly expanded and refined databases concerning grit use of birds and availability of natural grit particles in different soils have been collated and incorporated. GEM simulates grit consumption behavior of

replicate individual birds of a given species living in the vicinity of an agricultural field where a granular pesticide has been applied. The number of pesticide granules and resulting quantity of pesticide ingested each day over a 10-day period immediately post-application is calculated for each individual in the simulation. This is performed probabilistically through the use of Monte Carlo software programs Crystal Ball or @Risk which operate as add-ins to spreadsheet programs such as Microsoft Excel and Lotus 1-2-3. Assumed or actual distributions of data are used as inputs for the following model parameters: number of grit particles ingested by birds on a daily basis, field use factor by birds (analogous to PT in the dietary dose equation), soil texture type, fraction of soil particles at a field with a given soil type that are in the size range of granules, and fraction of granules remaining on the soil surface immediately after application. Separate analysis may be performed for 29 bird species and 10 different geographic regions of the U.S. The model output is a probabilistic distribution of peak-day pesticide exposure levels (dose from granules) expressed in mg pesticide per kg BW per day for birds of a particular species within a particular region. Such a probabilistic distribution of exposure could be integrated with dose-response information to predict the percentage of individuals of a theoretical population expected to be negatively impacted, or estimate the percentage of individuals receiving exposure above a benchmark level of concern. (See Chapter 5.)

A more detailed discussion of GEM, including an example simulation, are included in Appendix C3. Although a significant achievement by the Terrestrial Workgroup, this new tool should be considered at this point in time a prototype or "beta Model" subject to validation and further refinements. Appendix C3 also includes a compilation of data from the literature on the number of granules remaining on the soil surface on the day of application and at later times, and a kinetic model describing the release of pesticide from granules is also included.

3.5.5 Granule Ingestion Dose

The prototype model discussed above (GEM) evaluates a scenario in which a bird's home range contains two habitat categories: (1) an agricultural field that has been treated with a granular pesticide and (2) other untreated habitat. It does not address the situation in which a bird ranges among multiple agricultural fields which have been treated with a granular pesticide on the same or different days. For the latter, more general scenario, the one-day dose for any foraging day i, the cumulative dose over N_i

foraging days and the average daily granule dose over N_i foraging days a bird or mammal receives through ingestion of pesticide contaminated granules from foraging over one or more fields j per day are given respectively by:

One Day $Dose_{granule}$ (any day i) in mg/kg BW*day = $$\sum_{j=1}^{j=N_j} GIR_{ij} \bullet GnlWt \bullet AI_{ij} / W$$

(Eq. 3.5-8)

Cumulative $Dose_{granule}$(over N_i days) in mg/kg BW = $$\sum_{i=1}^{i=N_i} \sum_{j=1}^{j=N_j} GIR_{ij} \bullet GnlWt \bullet AI_{ij} / W$$

(Eq. 3.5-9)

Average Daily $Dose_{granule}$ in mg/kg BW*day = Cumulative $Dose_{granule}/N_i$ (Eq. 3.5-10)

where,

j = index for different foraging fields

$\boldsymbol{N_j}$ = maximum number of fields foraged by the bird or mammal over the foraging period of interest

i = index for different foraging days

$\boldsymbol{N_i}$ = number of days during the foraging period of interest for which a dose is to be computed

$\boldsymbol{GIR_{ij}}$ = granule intake rate (number granules ingested/day) by the bird in field j on day i (GIR_{ij} = 0 if the bird is not in field j on day i)

GnlWt = average weight of single granule (kg)

$\boldsymbol{AI_{ijk}}$ = initial or average pesticide concentration on/in granules in field j on day i (mg pesticide/kg granule). If the field j has not been treated by day i, AI_{ijk} = 0.

W = body weight of the bird or mammal (kg)

The dose calculations made within GEM are slightly more complicated than those presented above in that particle ingestion rates (including granules) and resulting dose are estimated separately for different size

categories for soil particles and then summed. For five pesticide products considered during development of the model, ≥96% of granules fell within two USDA soil particle size categories: medium sand and coarse sand. Medium sand particles are defined as having a diameter of 0.25 to 0.50 mm. Coarse sand particles have a diameter ranging from 0.50 to 1.0 mm. GEM estimates granule ingestion rate for medium and coarse particles (including granules) separately and uses separate estimates for average weight of medium and coarse granules in its calculation of the pesticide dose received.

3.6 DOSE RESULTING FROM INGESTION OF CONTAMINATED SOIL

The Terrestrial Workgroup devoted only a small amount of time to development of probabilistic tools for estimating exposure via ingestion of soil. This route of exposure is rarely considered in current pesticide risk assessments and is generally not considered a major route. The methodology proposed is an extension of that presented for food, in which Soil Ingestion Rate (SIR) replaces Food Ingestion Rate (FIR) and the concentration in soil (C) replaces the concentration in food in the dose equations.

3.6.1 Dose Equations for Ingestion of Contaminated Soil

The one day soil dose for any foraging day i, the soil dose over N_i foraging days and the average daily soil dose over N_i foraging days a bird or mammal receives through ingestion of pesticide contaminated soil from foraging over one or more fields j per day are given respectively by:

$$\text{One Day Dose}_{soil} \text{ on day } i \text{ in mg/kg BW*day} = \sum_{j=1}^{j=N_j} (SIR_{ij}) C_{ij} / W \qquad \text{(Eq. 3.6-1)}$$

$$\text{Cumulative Dose}_{soil} \text{ over } N_i \text{ days in mg/kg BW*day} = \sum_{i=1}^{i=N_i} \sum_{j=1}^{j=N_j} (SIR_{ij}) C_{ij} / W \qquad \text{(Eq. 3.6-2)}$$

$$\text{Average Daily Dose}_{soil} \text{ in mg/kg BW*day} = \text{Cumulative Dose}_{soil} / N_i \qquad \text{(Eq. 3.6-3)}$$

where,

j = index for different foraging fields

N_j = maximum number of fields foraged by the bird or mammal over the period of interest

i = index for different foraging days

N_i = number of days during the foraging period of interest for which a dose is to be computed

SIR_{ij} = soil ingestion rate (kg dry weight/day) by the bird in field j on day i (SIR_{ij} = 0 if the bird is not in field j on day i)

C_{ijk} = initial or average pesticide concentration on/in top soil in field j on day i (mg pesticide/kg dry weight). If the field j has not been treated or received spray drift by day i, C_{ijk} = 0.

W = body weight of the bird or mammal (kg)

Methods for estimating key parameters SIR and C are discussed briefly in the following sections, as well as in Appendix C3.

3.6.2 Estimation of Soil Ingestion Rate (SIR)

Soil ingestion rates of some wildlife species have been estimated from the acid-insoluble ash content of wildlife scats or digestive tract contents. Estimates of the fraction of the diet on a dry weight basis consisting of soil or sediment are listed in Table 4-4 of the EPA Wildlife Exposure Factors Handbook. SIR may be estimated straightforwardly by multiplying FIR by this fraction. This approach yields an estimate of the total amount of soil ingested per day. However, the above dose equations require an estimate of soil ingestion rate for individual agricultural fields. In the real world, birds and mammals may visit several different agricultural fields in a day and may spend a considerable amount of the day in other types of habitats. Therefore, SIR_{ij}, the amount of soil ingested at field j on day i, will be only a fraction of total SIR. To estimate SIR_{ij}, one must first estimate the proportion of the soil ingestion that occurs at each field j on day i (P_{ij}). The field and day specific soil ingestion rate (SIR_{ij}) may then be estimated as follows.

$$SIR_{ij} = SIR * P_{ij} \qquad \text{(Eq. 3.6-4)}$$

The problem of estimating P_{ij} is similar to that of the parameter PT in the food equation (Section 3.3.3), and the same estimation procedures can be used.

3.6.3 Pesticide Concentrations in Soil

Immediate post-application concentrations in soil can be estimated from application rates, foliar cover, and spray drift estimates. Values of soil/water partition coefficients, combined abiotic/microbiologically mediated degradation rates in soil, volatilization rates from soil and photodegradation rates in soil can be obtained from fate studies commonly conducted by Registrants and submitted to OPP. (See Appendix C7.) Many such values are listed in the ARS/USDA and OPP fate and chemical property databases. (See Appendix C8.)

Estimates of initial soil residue levels, soil dissipation rates and soil/water partition coefficients can be used as inputs to computer models to estimate bulk soil and pore water residue levels as a function of post-application time. Alternatively, or for purposes of model validation and calibration, bulk soil and/or pore water residue levels at various times post-application can also sometimes be obtained from lab and/or field studies.

3.7 OVERALL INGESTION DOSE

Doses due to ingestion of contaminated food, contaminated water, granules, and contaminated soil were discussed in Sections 3.3, 3.4. 3.5, and 3.6, respectively. In Section 3.3, it was shown that the overall dose due to the ingestion of contaminated food could be obtained by summing over the doses due to the ingestion of different food types (eg., long grass, short grass, pods/seeds, fruits, insects, earthworms, etc.). In Section 3.4, it was shown that the overall dose due to the ingestion of contaminated water could be obtained by summing over the doses due to the ingestion of water from different sources (eg. ponds, puddles, dew). By analogy, it can be seen that the overall ingestion dose can be obtained by summing over the overall food ingestion dose, the overall water ingestion dose, the granule ingestion dose, and the soil ingestion dose. However, as is discussed below, it is generally not possible to obtain a total dose by summing over the overall ingestion dose, the inhalation dose, and the overall dermal dose

3.7.1 Combining Ingestion Doses to Give an Overall Ingestion Dose

The overall ingestion dose a bird or mammal receives in field j on day i in mg/kg BW is given by:

$$Dose_{total\ ingestion(ij)} = Dose_{food\ ingestion(ij)} + Dose_{water\ ingestion(ij)} + Dose_{granule\ ingestion(ij)} + Dose_{soil\ \ ingestion(ij)}$$

(Eq. 3.7-1)

where,

$Dose_{food\ ingestion(ij)}$ = dose a bird or mammal receives in field j on day i from food ingestion
$Dose_{water\ ingestion(ij)}$ = dose a bird or mammal receives in field j on day i from water ingestion
$Dose_{soil\ ingestion(ij)}$ = dose a bird or mammal receives in field j on day i from soil ingestion
$Dose_{granule\ ingestion(ij)}$ = dose a bird or mammal receives in field j on day i from granule ingestion

The one day overall ingestion dose for any day i, the cumulative overall ingestion dose over N_i days and the average daily overall ingestion dose over N_i days a bird or mammal receives through ingestion of contaminated food, water, granules, and soil are given, respectively, by:

$$\text{One Day Dose}_{\text{overall ingestion}}\ (\text{in mg / kg body wt} \bullet \text{day}) = \sum_{j=1}^{j=N_j} Dose_{overall-ingestion(ij)}$$

(Eq. 3.7-2)

(Note that $Dose_{overall\ ingestion(ij)} = 0$ if the organism is not in field j on day i)

$$\text{Cumulative Dose}_{\text{overall ingestion}}\ (\text{in mg / kg body wt}) = \sum_{i=1}^{i=N_i} \sum_{j=1}^{j=N_j} Dose_{overall-ingestion(ij)}$$

(Eq. 3.7-3)

Average Daily $Dose_{overall\ ingestion}$ (in mg/kg body wt.*day) = Cumulative $Dose_{overall\ ingestion}/N_i$

(Eq. 3.7-4)

where,

j = index for different foraging fields

N_j = maximum number of fields foraged by the bird or mammal over the foraging time interval of interest for which a dose is to be computed

i = index for different foraging days

N_i = number of days during the foraging interval of interest for which a dose is to be computed

3.7.2 Problems With Combining Overall Ingestion, Inhalation, and Overall Dermal Doses

In Section 3.7.1, doses from ingesting different types of media (food, water, granules, soil) were combined to give an overall ingestion dose. In Section 3.9.2, dermal doses from different types of media (pond, puddle, foliage, air, soil/sediment) are combined to give an overall dermal dose. Therefore, a logical question would be can the overall ingestion dose, the inhalation dose, and the overall dermal dose be combined to give a total dose?

Inhalation and dermal doses cannot generally be combined with ingestion doses to give a total dose. A primary reason is that the fraction of the external dose that actually becomes available at a site or sites of toxic action within the organisms differs substantially between ingestion, inhalation and dermal exposure pathways. Another reason is that the site or sites of toxic action within the organism are often different for the different exposure pathways. The preceding two reasons combined indicate that the dose response curves generated with oral dosing would differ substantially from those generated with inhalation or dermal dosing. Therefore, even if ingestion, inhalation, and dermal doses were combined to give a total dose, it could not be compared to dose response data to generate a risk assessment.

3.8 DOSE RESULTING FROM INHALATION OF CONTAMINATED AIR

The Terrestrial Workgroup devoted only a small amount of time to development of probabilistic tools for estimating exposure via inhalation of contaminated air. This route of exposure is rarely considered in current pesticide risk assessments and is generally not thought to be a major route except within the canopy for several hours immediately post-application.

3.8.1 Dose Equations for Inhalation of Contaminated Air

Assuming the inhalation rate ***I*** is constant with respect to time, the inhalation dose (*ID*) a bird or mammal receives in field j on day i in mg/kg BW is given by:

$$\text{Inhalation dose in field j on day i} = ID_{ij} = \left(t_{ij2} - t_{ij1}\right) \bullet I \bullet C_{ij} / W \qquad \text{(Eq. 3.8-1)}$$

where,

I = inhalation (respiration) rate (L/hr or m^3/hr)

W= body weight (kg)

t_{ij1} = beginning of the exposure period in field j on day i (hr)

t_{ij2} = end of the exposure period in field j on day i (hr)(assigning ij subscripts to the beginning and end of exposure periods is necessary because a bird can be in more than one field on a given day and may revisit the same field on one or more additional days)

C_{ij} = initial or average pesticide concentration in air over the field j on day i (mg/L or mg/m^3)

Note that $ID_{ij} = 0$ if the organism is not in field *j* on day *i*.

The one day inhalation dose for any day i, the cumulative inhalation dose over N_i days and the average daily inhalation dose over N_i days a bird or mammal receives through inhalation of pesticide contaminated air are given respectively by:

$$\text{One Day Inhalation Dose } (ID_i) \text{ in mg/kg BW*day} = \sum_{j=1}^{j=N_i} ID_{ij} / (1\text{day}) \qquad \text{(Eq. 3.8-2)}$$

$$\text{Cumulative Inhalation Dose in mg/kg BW} = \sum_{i=1}^{i=N_i} \sum_{j=1}^{j=N_i} ID_{ij} \qquad \text{(Eq. 3.8-3)}$$

Average Daily Inhalation Dose (mg/kg BW*day) = Cumulative Inhalation Dose / N_i

(Eq. 3.8-4)

where,

j = index for different foraging fields

N_j = maximum number of fields foraged by the bird or mammal over the foraging time interval of interest for which a dose is to be computed

i = index for different foraging days

N_i = number of days during the foraging interval of interest for which a dose is to be computed

Key parameters in the above equations that must be estimated are inhalation rate (I) and concentration in air (C_{ij}).

3.8.2 Estimation of Inhalation Rate

The EPA Wildlife Exposure Factors Handbook contains estimates of the inhalation rates for representative species of birds and mammals. Inhalation rates vary with species, body size, body temperature, ambient conditions and activity levels.

Allometric equations for inhalation rates associated with standard metabolic rates (i.e., for an animal at rest) are available for non-passerine birds and mammals. For example, Lasiewki and Calder (1971) in the EPA Wildlife Exposure Factors recommended the following equations for for estimating the inhalation rates of non-passerine birds and mammals associated with standard metabolism rates:

$$\text{Non - Passerine } IR = 0.4089 \bullet WT^{0.77}$$

(Eqs 3.8-4 and 3.8-5)

$$\text{Mammal } IR = 0.5458 \bullet Wt^{0.80}$$

where,

IR = inhalation rate in m^3/day
Wt = body weight in kg

The above equations are applicable to post digestive, at rest metabolic rates. Inhalation rates for non-passerines and mammals during times when metabolic rates are higher may be several fold greater (EPA Exposure Factors Handbook). Also, inhalation rates in general are expected to be higher for passerines which have higher metabolic rates than for non-passerines.

3.8.3 Estimation of Pesticide Concentrations in Air

Pesticide concentrations in air will depend on numerous factors including degradation rates in air, air flow and mixing volume, deposition rates from the air, and volatilization rates from soil, foliage, and water. Volatilization rates depend in part upon the magnitudes of soil/water partition coefficients, water/foliar partition coefficients and Henry's Law constant.

Values of the various parameters listed in the previous paragraph are used as inputs to models such as PRZM to estimate pesticide concentrations in air within the canopy.

Values of soil/water partition coefficients, Henry's Law constants, abiotic hydrolysis rates, photodegradation in air rates, and sometimes volatilization flux rates can be obtained from fate studies conducted by Registrants and submitted to OPP. Some values are listed in the ARS/USDA and/or the OPP fate and chemical property databases. However, it is often difficult to separate volatilization rates from soil, foliage and water from overall dissipation rates in those media.

3.9 DOSE RESULTING FROM DERMAL CONTACT WITH CONTAMINATED ENVIRONMENTAL MEDIA

Dermal exposure and associated dose to birds and mammals has not been well characterized. Simple models for passive rates of chemical mass flux transfer across dermal membranes are based on Fick's law

of diffusion (Marzulli and Maibach (1991) - Dermato-toxicology. Hemisphere Publishing Company. 4th Edition P.17).

3.9.1 Dose Equations for Dermal Contact With Contaminated Environmental Media

Using Fick's law of diffusion, the passive rates of mass transfer are assumed to be proportional to the product of the contact time times the contact area times the diffusivity across the membrane times the pesticide concentration gradient across the dermal membrane and inversely proportional to the width of the membrane.

Assuming only passive transport across the membrane, the dermal doses from pond water, puddle water, foliage, air, and soil/sediment, a bird or mammal receives in field j on day i in mg/kg body weight could be approximately given respectively by:

$$Dose_{dermal(pond)ij} = \left(t_{ij2} - t_{ij1}\right)\left(f_{pond}\right)\left(D_m A_{cpond}\right)\left(C_{pond(ij)} - C_{blood(i)}\right) / zW \quad \text{(Eq. 3.9-1)}$$

$$Dose_{dermal(pudd)ij} = \left(t_{ij2} - t_{ij1}\right)\left(f_{pudd}\right)\left(D_m A_{cpudd}\right)\left(C_{pudd(ij)} - C_{blood(i)}\right) / zW \quad \text{(Eq. 3.9-2)}$$

$$Dose_{dermal(foliage)ij} = \left(t_{ij2} - t_{ij1}\right)\left(f_{foliage}\right)\left(D_m A_{cfoliage}\right)\left(C_{foliage(porewater)ij} - C_{blood(i)}\right) / zW$$

(Eq. 3.9-3)

$$Dose_{dermal(air)ij} = \left(t_{ij2} - t_{ij1}\right)\left(f_{pond}\right)\left(D_m\right)\left(A_c - A_{cpond}\right)\left(C_{air(ij)} - C_{blood(i)}\right) / zW +$$
$$\left(t_{ij2} - t_{ij1}\right)\left(f_{pudd}\right)\left(D_m\right)\left(A_c - A_{cpudd}\right)\left(C_{air(ij)} - C_{blood(i)}\right) / zW +$$
$$\left(t_{ij2} - t_{ij1}\right)\left(f_{foliage}\right)\left(A_c - A_{cfoliage}\right)\left(C_{air(ij)} - C_{blood(i)}\right) / zW +$$
$$\left(t_{ij2} - t_{ij1}\right)\left(1 - f_{pond} - f_{pudd} - f_{foliage}\right)\left(D_m A_c\right)\left(C_{air(ij)} - C_{blood(i)}\right) / zW \quad (3.9\text{-}4)$$

$$Dose_{dermal(soil/sed)ij} = \left(t_{ij2} - t_{ij1}\right)\left(D_m A_{feet}\right)\left(C_{soil/sed(pore-water(ij)} - C_{blood(ij)}\right) / zW \quad (3.9\text{-}5)$$

where,

D_m = diffusivity of the chemical across the membrane in cm^2/hr

z = width of the membrane in cm

W = body weight in kg

$C_{pond(ij)}$ = initial or average pesticide concentration in the pond in field j on day i (mg/L)

$C_{puddle(ij)}$ = initial or average pesticide concentration in the puddles in field j on day i (mg/L)

$C_{foliage(pore\ water)ij}$ = initial or average pesticide concentration in foliar pore water in field j on day i (mg/L)

$C_{air(ij)}$ = initial or average pesticide concentration in air over field j on day i (mg/L)

$C_{soil/sed\ pore\ water(ij)}$ = initial or average pesticide concentration in soil/sediment pore water in field j on day i (mg/L)

$C_{blood(i)}$ = initial or average pesticide concentration in the blood of the organism on day i (mg/L)

t_{ij1} = beginning of the exposure period in field j on day i (hr)

t_{ij2} = end of the exposure period in field j on day i (hr)(assigning ij subscripts to the beginning and end of exposure periods is necessary because a bird can be in more than one field on a given day and may revisit the same field on one or more additional days)

f_{pond} = fraction of the exposure period the organism is in the pond

A_c = total dermal area available for contact except for bottom of feet (cm^2)

A_{cpond} = dermal area in contact with pond water (cm^2)

f_{pudd} = fraction of the exposure period the organism is wading in puddles

A_{cpudd} = dermal area in contact with puddle water (cm^2)

$f_{foliage}$ = fraction of the exposure period the organism is in dermal contact with foliage

$A_{cfoliage}$ = dermal area in contact with foliage (cm^2)

A_{feet} = dermal area of the bottom of the feet

3.9.2 Combining Dermal Doses

The overall dermal dose a bird or mammal receives in field j on day i in mg/kg BW is given by summing over the dermal doses from dermal contact with different environmental media:

$$Dose_{dermal(overall)ij} = Dose_{dermal(pond)ij} + Dose_{dermal(puddle)ij} + Dose_{dermal(foliage)ij} + Dose_{dermal(air)ij} + Dose_{dermal(soil/sed)ij} \quad (3.9\text{-}6)$$

where,

$Dose_{dermal(pond)ij}$ = dermal dose a bird or mammal receives in field j on day i from pond water

$Dose_{dermal(puddle)ij}$ = dermal dose a bird or mammal receives in field j on day i from puddles

$Dose_{dermal(foliage)ij}$ = dermal dose a bird or mammal receives in field j on day i from foliage

$Dose_{dermal(air)ij}$ = dermal dose a bird or mammal receives in field j on day i from air

$Dose_{dermal(soil/sed)ij}$ = dermal dose a bird or mammal receives in field j on day i from soil/sediment

The one day overall dermal dose for any day i, the cumulative overall dermal dose over N_i days and the average daily overall dermal dose over N_i days a bird or mammal receives through contact with pesticide contaminated pond water, puddles, and air in one or more fields j per day i are given respectively by:

$$OneDayDose_{dermal(overall)}(\text{in mg / kg * day}) = \left[\sum_{j=1}^{j=N_j} Dose_{dermal(overall)ij}\right] / (1\ \text{day})$$

(Eq. 3.9-7)

(Note that $Dose_{dermal(overall)ij} = 0$ if the organism is not in field j on day i)

$$CumulativeDose_{dermal(overall)} \text{ (in mg / kg body wt.)} = \sum_{i=1}^{i=N} \sum_{j=1}^{j=N_j} Dose_{dermal(overall)ij} \quad (3.9\text{-}8)$$

Average Daily $Dose_{dermal(overall)}$ (in mg/kg body wt.*day) = Cumulative $Dose_{dermal(overall)}/N_i$ (3.9-9)

where,

j = index for different foraging fields
N_j = maximum number of fields foraged by the bird or mammal over the foraging time interval of interest for which a dose is to be computed
i = index for different foraging days
N_i = number of days during the foraging interval of interest for which a dose is to be computed

Estimating pesticide concentrations in the various environmental media with which birds and mammals have dermal contact is discussed in Section 3.10 and Appendix C4. Estimates of concentrations in the blood or specific tissues just below dermal membranes requires the use of multi-compartment pharmacokinetics models that are beyond the scope of this report.

3.9.3 Bird and Mammal Skin Surface Areas

The following equations are provided in the EPA Wildlfe Exposure Factors Handbook for estimating the skin surface area of birds and mammals:

$$\text{Bird } SA_{skin} = 10 \bullet Wt^{0.667}$$

(Eqs. 3.9-10 and 3.9-11)

$$\text{Mammal } SA_{skin} = 12.3 \bullet Wt^{0.65}$$

where,

SA_{skin} = surface area of the skin in cm^2

Wt = body weight in g

3.10 ESTIMATING PESTICIDE CONCENTRATIONS IN ENVIRONMENTAL MEDIA

The monitoring, experimental determination or model estimation of pesticide concentrations in various environmental media as a function of time and location is a necessary prerequisite to estimating the pesticide doses birds and other terrestrial wildlife receive. The pesticide doses they receive result from the ingestion of, inhalation of, and dermal exposure to various types of pesticide contaminated environmental media (plants, insects, water, air, soil). The magnitude of the ingested or inhaled dose received will be directly proportional to the product of the mass of media ingested or inhaled and the pesticide concentrations within the media. The magnitude of the dermal dose received should be approximately proportional to the product of the contact surface area times the duration of contact times the diffusivity across the membrane times the concentration gradient across the dermal membrane.

The relationship between pesticide concentrations in environmental media and the pesticide doses received by birds and mammals are demonstrated by the dose equations provided in Sections 3.3 - 3.9.

The concentrations of pesticides and their major degradates in various types of environmental media can be estimated with the use of computer models or experimentally determined or monitored in various field and monitoring studies. Inputs to computer models involve many types of parameters including meteorological, hydrological, pesticide application, agricultural practices, soil properties, plant properties, water properties, initial concentrations on foliage, and the environmental fate properties of the pesticide and its major degradates. Values for most of those types of parameters can be obtained from databases. Values of the environmental fate parameters for the pesticide and major degradates are determined primarily from laboratory (and occasionally field) environmental fate studies, and are often placed in databases.

In this section, brief overviews are provided of various topics related to the estimation and/or determination of the concentrations of pesticides and their major degradates in various types of environmental media. The overviews and topics correspond to ones discussed in greater detail in

Appendix C.

3.10.1 Pesticide Mass Balance Equations and Their Solutions

Computer models used to estimate pesticide concentrations in environmental media (plants, soil, water, air) are based in part upon analytical or numerical solutions to chemical mass balance ordinary or partial differential equations. The solutions to the mass balance equations give the pesticide concentration as a function of time (if they are ordinary differential equations) or as a function of both time and location (if they are partial differential equations). The solutions to the mass balance equations depend upon the initial conditions specified (if they are ordinary differential equations) or on both initial and boundary conditions specified (if they are partial differential equations).

Depending upon the complexity of a computer model, mass balance differential equations may be generated and solved for each environmental medium (e.g., plants, soil, water, air), each compartment within each medium (e.g., for plants: roots, stems, leaves, fruits/pods) and each phase within each medium or compartment (e.g., for soil: pore water, soil solids, pore air) simulated. If the model allows for reversible mass transfer between different environmental media, compartments, or phases, the mass balance differential equations must be solved simultaneously (see Appendix C4). If the model has hydrology components and is tied to weather, additional differential equations accounting for water balance and movement are also solved along with the chemical mass balance equations (see Appendix C4).

A simple example of a mass balance ordinary differential equation and its solution based upon a specified initial condition is as follows. The generic form of a mass balance equation for an environmental medium or a compartment within an environmental medium is:

Rate of mass change within the medium or compartment =
rate of mass input - rate of internal degradation - rate of mass output (Eq. 3.10-1)

For a daily time step, simple one compartment plant model, equation 3.10-1 becomes:

$$\frac{dm_{p(i)}}{dt} = \frac{d(B_{ag(i)}C_{p(i)})}{dt} = \sum_{j=1}^{j=j_{\max(trans)}} (TSCF)Q_{trans(ij)}C_{pw(ij)} - \left(k_{\deg r} + k_v\right)B_{ag(i)}C_{p(i)}$$

(Eq. 3.10-2)

where,

$dm_{p(i)}/dt$ = rate of change in pesticide mass in/on plant on day i

$B_{ag(i)}$ = above ground plant biomass as a function of time on day i (kg dry weight)

$C_{p(i)}$ = concentration of chemical in/on plants as a function of time on day i (mg chem/kg dry wt.)

TSCF = transpiration stream concentration factor

$Q_{trans(ij)}$ = transpiration flow on day I from soil compartment (layer) j (cm^3/day)

$C_{pw(ij)}$ = soil pore water concentration at the start of day i at $t=t_i$ in soil layer j (g/cm^3)

j = soil layer index

$j_{max(trans)}$ = the deepest soil layer from which transpiration is extracted

k_{degr} = degradation rate constant (1/day)

k_v = volatilization rate constant (1/day)

Equation 3.10-2 is based upon Carsel et al. 1997; Trapp and Matthies 1995; and Trapp 1995.

The three terms on the right side of equation 3.10-2 representing (in order) the rate of uptake by plants, degradation within/on the plants, and volatilization from the plants correspond to the “rate of mass input”, “rate of internal degradation”, and “rate of mass output”, respectively in generic equation 3.10-1. Note that in this example, the “rate of mass input” includes the rate of uptake by the plants from the soil, but does not include the application rate. That is because the time required for application is generally only a small fraction of the assumed daily time step upon which the differential equation is based. Consequently in this example, any application is considered to be more of an instantaneous event contributing to the initial concentration, rather than a continuous process that needs to be included as a term in the mass balance differential equation. As an alternative, we could have assumed that application was a continuous process extending throughout the day and included it as a term in the differential equation.. However, in addition to not representing reality as well as an assumption of instantaneous

application, a continuous application assumption would make using Fletcher time zero foliar values more difficult and much less direct (see below) .

The total transpiration on day i ($Q_{trans(i)}$) as well as well as the transpiration extracted from each soil layer j on day i ($Q_{trans(ij)}$) will increase with increasing biomass and leaf area index. However, in a daily time step model, increases in transpiration can be reflected at the beginning of each day while still assuming that the transpiration remains constant during any given day i. Likewise, changes in the soil pore water concentration can be reflected at the beginning of each day while still assuming that the soil pore water concentration remains constant during any given day i. Consequently, during any given day i, the uptake term in Equation 3.10-2 can be considered constant such that:

$$\frac{dm_{p(i)}}{dt} = \frac{d\left(B_{ag(i)}C_{p(i)}\right)}{dt} = k_{up} - k_p B_{ag(i)} C_{p(i)} \qquad \text{(Eq. 3.10-3)}$$

where,

$$k_{up} = \sum_{j=1}^{j=j_{\max(trans)}} (TSCF) Q_{trans(ij)} C_{pw(ij)} = \text{rate of pesticide uptake} \qquad \text{(Eq. 3.10-4)}$$

$$k_p = k_{\deg r} + k_v \qquad \text{(Eq. 3.10-5)}$$

Separating variables, integrating equation 3.10-3 from $m_{p(i)} = B_{ag(i)}C_{p(i)} = B_{ag}(t=t_i)C_p(t=t_i)$ to $B_{ag(i)}C_{p(i)} = B_{ag}(t=t_{i+1})C_p(t=t_{i+1})$ and from $t=t_i$ from $t=t_{i+1}$, allowing for a possible instantaneous addition at the beginning of day i+1 at $t=t_{i+1}$ due to direct application or spray drift, and rearranging generates the following daily time step algorithm. The algorithm gives the concentration of chemical on/in plants at the beginning of day i+1 at $t=t_{i+1}$ in terms of the concentration at the beginning of the previous day i at $t=t_i$:

$$C_p(t = t_{i+1}) = \frac{m_{p(add)}(t = t_{i+1})}{B_{ag}(t = t_{i+1})} + \left[\frac{k_{up}}{k_p B_{ag}(t = t_{i+1})}\right]\left[1 - \exp[-k_p(1\ \text{day})]\right] + \left[\frac{B_{ag}(t = t_i)}{B_{ag}(t = t_{i+1})}\right] C_p(t = t_i)\exp[-k_p(1\ \text{day})]$$

(Eq. 3.10-6)

where, the initial condition is

$$C_{p(i)} = C_p(\mathrm{t} = \mathrm{t}_\mathrm{i})\ \text{ at }\ t = t_i \qquad \text{(Eq. 3.10-7)}$$

The plant biomass at the beginning of each day can be calculated separately from one of several plant growth models including an exponential growth model and several more complex alternatives that generate characteristic sigmoidal shape plant growth curves (Jorgensen 1995).

For direct foliar application at $t=t_{i+1}$, $m_{p(add)}(t=t_{i+1})$ in equation 3.10-6 is given by:

$$m_{p(add)}(t = t_{i+1}) = \left[f_{\text{int}}(t = t_{i+1})\right]\left(1 - f_{sd}\right)\left[App(t = t_{i+1})\right] \qquad \text{(Eq. 3.10-8)}$$

where,

$f_{int}(t=t_{i+1})$ = fraction intercepted by plant when chemical is applied at $t=t_{i+1}$

f_{sd} = fraction loss by spray drift before hitting the targeted field

$App(t=t_{i+1})$ = nominal application rate at the beginning of day i+1 at $t = t_{i+1}$in mg chemical/m^2(convert from lb/acre or kg/ha)

As an alternative to computing the added mass of chemical on/in plants per unit field area $m_{p(add)}(t=t_{i+1})$ for direct application from equation 3.10-8 and then dividing by the biomass per unit field area $B_{ag}(t=t_{i+1})$, $m_{p(add)}(t=t_{i+1})/B_{ag}(t=t_{i+1})$ can be computed from the product of the Fletcher et al. (1994) time zero foliar

residues (normalized to an application rate of 1 lb ai/acre) times the application rate.

For spray drift to foliage at $t=t_{i+1}$, $m_{p(add)}(t=t_{i+1})$ in equation 3.10-6 is given by:

$$m_{p(add)}(t = t_{i+1}) = \left[f_{\text{int}}(t = t_{i+1}) \right] \left(SD_{avg} \right) \left[App(t = t_{i+1}) \right] \qquad \text{(Eq. 3.10-9)}$$

where,

SD_{avg} = average spray drift deposition

As an alternative to computing the added mass of chemical on/in plants per unit field area $m_{p(add)}(t=t_{i+1})$ for spray drift from equation 3.4-9 and then dividing by the biomass per unit field area $B_{ag}(t=t_{i+1})$, $m_{p(add)}(t=t_{i+1})/B_{ag}(t=t_{i+1})$ can be computed from the product of the Fletcher et al. (1994) time zero foliar residues (normalized to an application rate of 1 lb ai/acre) times the application rate times the average spray drift deposition fraction for the field receiving the spray drift.

Caution should be observed in using the Fletcher et al. (1994) time zero foliar values because of the large uncertainties associated with basing concentrations on a variable wet weight rather than a constant dry weight. Also, if residues on a wet weight basis are used to estimate ingestion dose, food intake must also be on a wet weight basis which may require the use of dry to wet factors (DWFs) to convert dry weight food ingestion to wet weight food ingestion.

3.10.2 Computer Models for Estimating Pesticide Concentrations in Environmental Media

Based upon the literature reviews by Golder Associates (1997) and Jorgensen (1995), there do not appear to be any residue computer models currently available that could be used to adequately generate distributions of pesticide concentrations in all relevant environmental media for use in probabilistic terrestrial exposure assessments. However, there are several existing residue models which could possibly serve together as a good foundation for such a model. These include the spray drift model AgDRIFT (Bird et al. 1995), the leaching/runoff model PRZM 3 (Carsel et al. 1997), the surface water model EXAMS (Burns 1990), the Uptake, Translocation, Accumulation, and Biodegradation (UTAB)

plant contamination model (Boersma et al. 1988, Lindstrom et al. 1991), the SNAPS/PLANTX plant contamination model (Matthies and Behrendt 1995; Trapp, McFarlane, and Matthies 1993; Trapp 1995), and the Soil-Plant-Air Fugacity plant contamination model (Paterson, Mackay, and McFarlane 1994; Paterson and Mackay 1995).. In addition, several correlations between the uptake of chemicals by plants and their physical chemical properties which may be useful in model development have been reported in the literature. All of these will be discussed in this section .

Other models which may also be helpful in developing a comprehensive terrestrial exposure model are ones that include animal behavior as well as residue algorithms to estimate dose such as the Terrestrial Exposure Assessment (TEEAM) model (Bird et al. 1991), the bird spray exposure model PARET (Appendix A2), the bird granule exposure model developed by Dixon et al. 1998(Appendix A3), the bird granule exposure model developed by Dow/Elanco, Fischer, and Best (GEM, Appendix C3), and the Terrestrial Risk Integrated Methodolgy (TRIM) model (U.S. EPA 1998).

The Paret Model is discussed in greater detail in Chapter 5 and in Appendix A2. The Dixon Model is discussed in greater detail in Section 3.6 and in Appendix A3. The GEM Model is discussed in greater detail in Section 3.6 and in Appendix C3.

OPP recently began using the spray drift model AgDRIFT to estimate spray drift pesticide loadings to ponds adjacent to treated fields as part of aquatic exposure assessments. Estimates of spray drift to off-site soil and water and to off-site vegetation are also important components of terrestrial exposure assessments. OPP plans to use AgDRIFT for terrestrial as well as aquatic exposure assessments. AgDRIFT was developed by modifying the USDA AGDISP model as part of a CRADA cooperative agreement between the SDTF and the U.S. EPA's Office of Research and Development (ORD).

OPP currently uses the leaching/runoff model PRZM 3 to estimate runoff pesticide loadings to ponds adjacent to treated fields as part of aquatic exposure assessments. Although not completely adequate for pesticide terrestrial exposure assessments, a number of outputs of PRZM3 are useful for interim terrestrial exposure assessments. As an option, PRZM3 can be run stochastically to give distributional outputs. However, the plant growth and plant fate algorithms of PRZM3 need to be strengthened for use in terrestrial exposure assessments and it lacks insect, granule, and puddle algorithms.

PRZM3 outputs of interest with respect to terrestrial exposure assessments include daily estimates of pesticide concentrations in soil pore water and of bulk soil concentrations for each of several hundred vertical computational compartments. PRZM3 uses its estimates of concentrations in soil to estimate runoff/erosion losses of pesticide which in turn are used as input to EXAMS to estimate pesticide concentrations in adjacent ponds (also important for terrestrial exposure assessments). Estimates of concentrations in soil can also be used by algorithms outside of PRZM3 to help estimate uptake by insects and other soil invertebrates.

For aquatic exposure assessments, estimates by PRZM3 of pesticide losses due to runoff water and soil erosion from a 10 ha treated field and by AgDRIFT of spray drift deposition are used as pesticide loading inputs to the surface water EXAMS. EXAMS than estimates dissolved and adsorbed concentrations in an adjacent 1 ha by 2 m deep pond. Comparable computations would also be useful in a terrestrial exposure assessments since birds and mammals utilize farm and/or natural ponds for drinking, food, and swimming.

EXAMS generates mass balance differential equations for each segment within a simulated water body and generates steady state solutions to the equations for each computational time step (Burns 1990). EXAMS outputs of interest with respect to terrestrial exposure assessments include daily estimates of dissolved and sediment bound concentrations of pesticide in each segment.

EXAMS cannot currently be run stochastically. Temporal and site distributions of estimated pesticide concentrations for aquatic exposure assessments are currently generated by running the model deterministically over multiple years and sites.

The original and subsequent versions of PRZM were developed as leaching/runoff models, not as terrestrial exposure models. PRZM3 does not estimate factors necessary for the conversion of pesticide mass/area of the field to pesticide mass/mass of plant such as the plant biomass. Furthermore, the linear and exponential canopy cover algorithms PRZM3 uses may be inadequate for estimating foliar interception. Other weaknesses of PRZM3 with respect to terrestrial exposure assessments are that it does not simulate the fate of granules, and does not estimate pesticide concentrations in the highly transient puddles formed on fields during rainfall events. Although PRZM includes a plant uptake term in

the mass balance equation for soil, it does not appear to include it in the mass balance equation for vegetation.

TEEAM was derived from PRZM in the late 1980s by the USEPA laboratory in Athens GA and its contractors for use in terrestrial exposure assessments (Bird, Cheplick, and Brown 1991). Although TEEAM was not supported beyond the testing phase, many of the algorithms developed for it could possibly be used or modified for use in a new model. TEEAM was a close derivative of the leaching/runoff model PRZM and used many of the same algorithms. However, it did contain improved plant growth algorithms, improved plant fate algorithms from EPIC (which included uptake), fate algorithms for granules, and algorithms for estimating pesticide concentrations in transient small puddles. In addition, algorithms for animal movement (based upon a Markov model), animal feeding, and animal uptake (including soil invertebrates as well as vertebrates) were included.

Most of the plant models described below are simple compartment models which divide the plant medium into compartments, assume first order mass transfer between compartments and assume first order degradation within each compartment. Mass balance ordinary differential equations and initial conditions are developed for each compartment and solved simultaneously to estimate pesticide concentrations as a function of time in each compartment. For this report, Moorhead (Appendix C4) has extended that concept to different media as well based on exposure pathway models. The matrix formulation of compartment and multimedia models is discussed in greater detail in Appendix C4.

The Uptake, Translocation, Accumulation, and Biodegradation (UTAB) plant contamination model divides the plant into one root, three stem, and three leaf compartments (Boersma et al. 1988; Lindstrom et al. 1991). Each compartment is further subdivided into xylem, phloem, and storage subcompartments. The compartments are represented as a series of continuous stirred flow reactors separated by membranes. Transport and accumulation within each compartment are represented by mass balance equations that account for diffusive transport into and out of each compartment, convective mass transport within each compartment and first order degradation and adsorption to solid matrices within each compartment. The series of differential equations are solved numerically to estimate chemical masses in each compartment.

SNAPS (Simulation Model Network Atmosphere-Plant-Soil) is actually a coupled series of 3 models used to simulate soil water content, and chemical transport and fate within the soil profile and in plants (Matthies and Behrendt 1995). The chemical transport and fate model for plants in SNAPS is called PLANTX (Trapp, McFarlane, and Matthies 1993; Trapp 1995).

The plant model consists of root, stem, leaf, and fruit compartments. The PLANTX model numerically solves simultaneously mass balance equations for the roots, stems, leaves, and fruits. The model simulates passive diffusive and transpiration uptake by roots from soil water and advective mass transport with transpiration and/or assimilation streams to and from the stems, leaves and fruits. It simulates first order degradation and partitioning between the aqueous phase and plant tissue in all of the compartments. PLANTX also simulates volatilization from leaves to the atmosphere.

The PLANT model is a simplified version of the PLANTX model in which the 4 compartments within the PLANTX model (roots, stems, leaves, and fruits) are replaced by a single overall aerial plant compartment (Trapp and Matthies 1995; Trapp 1995). Uptake is represented by the product of the transpiration flow times the Transpiration Stream Concentration Factor (TSCF) times the concentration in the soil pore water. For neutral organics, the TSCF can be estimated from the octanol/water partition coefficient as described below. The single mass balance equation for the plant compartment is solved analytically to give the bulk chemical concentration in the plant.

The TRIM Model is currently being developed by the USEPA Office of Air Quality Planning and Standards and its contractors. Like the other plant models previously discussed, the environmental fate module is a simple compartment model that allows for first order mass transfers between compartments and first order degradation within each compartment. A mass balance ordinary differential equation and initial condition is developed for each compartment. The system of ordinary differential equations are then numerically solved simultaneously to give the chemical mass in each compartment as a function of time.

A root-stem-foliage compartment model was developed to predict residue uptake from soil and fate and transport within plants (Paterson, Mackay, and McFarlane 1994; Paterson and Mackay 1995). The model involves solving simple mass balance equations for each compartment simultaneously. It is similar

in many aspects to the various other plant fate models discussed above, but it differs from most in using the concept of fugacity and the ratio of fugacity capacities of different phases to estimate equilibrium partition coefficients.

Plant uptake of pesticide residues can occur by uptake from the soil solution or by absorption of residue volatilized from the soil. Uptake of the residue from soil solution may be a passive process whereby the residue is transported by the transpiration stream to the foliage. Such a process would allow the prediction of foliage residue levels based upon such chemical properties as K_{ow}. Pesticide solubility and soil adsorption properties would also influence bioavailability of the chemical to the plant. Root growth and diffusion may also contribute to plant uptake.

Plant root uptake of six herbicides and a systemic fungicide was described by Shone and Wood (1974) using the Root Concentration Factor (RCF), where:

RCF = (Concentration in roots-wet weight)/(Concentration in external solution).

Translocation of the chemical from the roots to the shoots was described by the Transpiration Stream Concentration Factor (TSCF), where:

TSCF = (Conc. in transpiration stream or xylem sap)/(Conc. in external solution)

Using linear regression, Briggs et al. (1982) developed equations for estimating the RCF and TSCF for lipophillic compounds from the logarithm of their octanol/water partition coefficient.

Greater details on computer models for estimating pesticide concentrations in environmental media are provided in Appendix C4.

3.10.3 Computational Methods for Volatilization and Residues in Air

Pesticide doses to birds and mammals through direct inhalation of pesticide contaminated air is generally thought to be relatively small compared to pesticide doses from ingestion of food and water.

Nevertheless, air inhalation could occasionally be an important exposure pathway, particularly for inhalation of volatile chemicals by terrestrial birds and mammals who spend a considerable amount of time within a plant canopy.

Pesticide residues in air are determined directly in lab and field studies and can also be estimated with the use of computer models.

Computational methods for residues in air generally focus on volatilization fluxes from soil, water, and plants. The PRZM3/TEEAM models assume that pesticide concentrations in the air above bare soil, open water, and plant canopies are approximately equal to zero due to wind advection and turbulent dispersivity. However, the models use estimated volatilization fluxes to estimate pesticide concentrations in air within the plant canopy.

The PLANTX/PLANT models developed by Trapp and Matthies (1995, 1997) for estimating chemical residues in plant also contain an algorithm for estimating pesticide volatilization fluxes from leaves. Methods for estimating foliar volatilization rate constants are discussed by Riederer (1995).

Volatilization rates from water typically increase with increasing Henry's Law constant, water flow, wind speed, and temperature and with decreasing molecular weight and water depth [Schwarzenbach, Gschwend, and Imboden (1993) and Thomas (1990)]. The cited literature also contain discussions on how to estimate volatilization rates from water.

Greater details on estimating volatilization rates and pesticide concentrations in air are provided in Appendix C5.

3.10.4 Pesticide Dissipation Kinetics in Environmental Media

This overview of dissipation kinetics is applicable to various types of environmental media, but the concepts covered are most frequently used for soil. The concentrations referred to are generally experimental concentrations for a given bulk environmental medium, not individual phases. For example, soil concentration refers to the bulk soil, not to the individual pore water, soil solids and pore air

concentrations.

Dissipation kinetics data in environmental media are often fit to a single rate constant pseudo first order kinetics model. The reasons are because of the simplicity involved and because most computer models used to estimate pesticide concentrations in environmental media require as input, pseudo first order rate constants. Data can be fit to a single rate constant pseudo first order kinetics model using linear or non-linear regression.

If linear regression is used to fit data to a single rate constant pseudo first order kinetics model, the concentration data must first be ln transformed before it is regressed against time. In cases where the dissipation of a chemical fits a single rate constant pseudo first order kinetics model over the entire study duration, a plot of the natural logarithm of the concentration (ln C) versus time will be approximately linear.

Unfortunately, the dissipation of a chemical often does not fit a single rate constant pseudo first kinetics model very well over the entire duration of the study. In such cases, a plot of the natural logarithm of the concentration (ln C) versus time will not be linear. It will often appear temporally "biphasic" with the first phase having a substantially steeper slope than the second phase. The reasons for observed "biphasic" behavior may vary and have not been firmly established. Some reasons may include some of the chemical being gradually and irreversibly imbedded into the environmental media to a sufficient extent to inhibit dissipation processes, declines in microbiological activity over time, and the complexity of some dissipation processes such as volatilization.

Biphasic data can be fit to a number of different regression models. The most commonly used one is the biphasic linear regression model in which ln C is plotted against time. The plot is essentially divided by eye into an initial and subsequent phase representing different slopes. Linear regression of ln C versus time is then performed on both phases separately to estimate a rate constant and corresponding half-life for each phase.

The resulting estimates of pseudo first order rate constants for each phase can in some cases also be used as input to some computer models. However, the biphasic regression model itself is not very realistic

because it assumes the shift from one slope to another is essentially instantaneous whereas a more gradual shift in the slope is generally observed. Consequently, it is sometimes difficult and somewhat arbitrary to determine when the first phase ends and the second phase begins.

Whenever the data do not fit a single rate constant pseudo first order kinetics model very well over the entire duration of a study using linear regression on ln transformed data, there are a large number of alternate non-linear regression models which can also be fit to kinetics data. Fortunately, the widespread availability of relatively low cost spreadsheets and statistical software has made performing non-linear regression more routine than in the past.

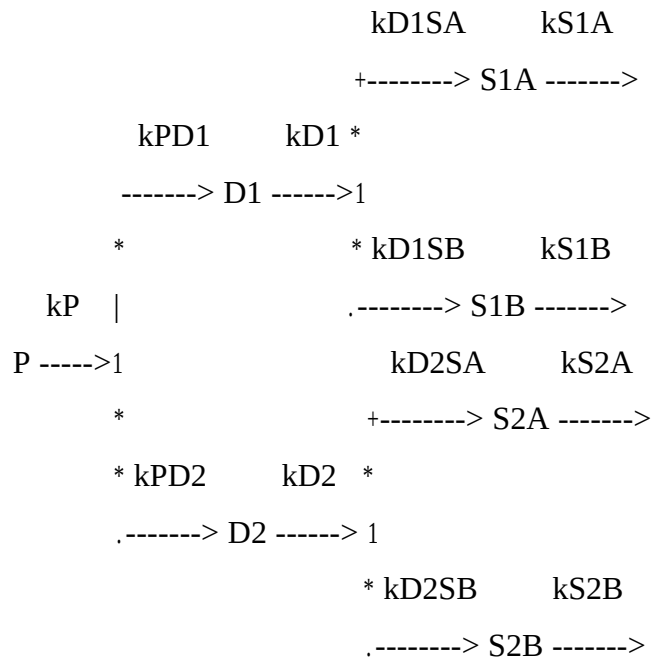
Non-linear regression models which can be used to fit observed chemical dissipation data include applying non-linear regression to the untransformed form of the single rate constant pseudo first order kinetics model, an empirical n order model, a reversible equilibrium 2 compartment model, a reversible non-equilibrium 2 compartment model, and a non-reversible non-equilibrium 2 compartment model. All of those models except the empirical n order model are also pseudo first order kinetics models. They are discussed in greater detail in Appendix C6.

Estimates of rate constants for the formation and decline of major degradates can be input into computer models to simulate the formation and decline of the degradates. Assuming pseudo first order kinetics, estimates of rate constants for the formation and decline of major degradates can sometimes be obtained by using nonlinear regression to fit time series data to the exponential solutions to the mass balance differential equation for each degradate.

To develop mass balance equations and their solutions for major degradates, it is first necessary to assume a degradation pathway such as the one provide below. This pathway represents a combination of series and parallel degradation pathways in which the parent chemical P simultaneously degrades to primary degradates D_1 and D_2 which in turn each simultaneously degrade to secondary degradates S_{1A} and S_{1B}, and S_{2A} and S_{2B}, respectively. Note that other pathways are also possible such as one primary degradate being formed from another primary degradate as well as the parent.

Note that concentrations should be in units of moles/volume rather than mass/volume to maintain the

correct stoichiometric relationship between the parent, primary degradates, and secondary degradates. If numerical methods of solution are used, equations for non-first order processes can also be developed.



Greater details on analyzing pesticide dissipation kinetics data in environmental media are provided in Appendix C6.

3.10.5 OPP-Required Pesticide Fate and/or Residue Studies

The Environmental Fate and Effects Division (EFED) and the Health Effects Division (HED) in OPP require pesticide registrants to submit numerous pesticide studies. The results of the studies help OPP evaluate the potential exposure and risks to non-target organisms and humans associated with pesticide use. Studies of interest with respect to terrestrial exposure assessments include laboratory fate studies, field fate and residue studies, and ecological residue/effects studies.

EFED required laboratory transformation studies (study requirements vary depending upon the pesticide's use and/or characteristics) include abiotic hydrolysis, direct photolysis in water, photodegradation on soil, photodegradation in air, aerobic soil metabolism, anaerobic soil metabolism, aerobic aquatic metabolism, and anaerobic aquatic metabolism. Laboratory transformation studies determine the transformation

pathways of the parent and major degradates, the decline rates of the parent and the formation and decline rates of major degradates. Parental decline rates are reported as half-lives and/or DT50s. A major degradate is defined as one accounting for $\geq$ 10% of applied or present at > 0.01mg/kg (whichever is lower) at any time during any laboratory study. The results are generally provided tabularly and graphically in concentration versus time series.

EFED required laboratory mobility studies (study requirements also vary depending upon the pesticide's use and/or characteristics) include adsorption/desorption batch equilibrium, soil column leaching, and volatilization from soil. The laboratory fish BCF study determines the accumulation and depuration of pesticides and their major degradates in whole fish, edible tissues, and non-edible tissues.

The results of the EFED laboratory fate studies are used for developing input to environmental fate and transport models. The results of laboratory fate studies are also used to develop protocols for conducting field studies.

EFED required field fate studies (study requirements vary depending upon the pesticide's use and/or characteristics) include terrestrial field dissipation, aquatic field dissipation, forestry dissipation

Field fate studies are conducted under actual use conditions using one or more formulated pesticide products. In all of the different fate field studies, the dissipation of the parent and formation and decline of major degradates are generally presented tabularly and graphically as concentration versus time series for any environmental compartments for which the number of detects is sufficient to do so. The dissipation of the parent in the various environmental compartments monitored is also characterized by computed half-lives and or DT50s.

The results of field fate studies are typically not used for inputs to models because they reflect the overall dissipation of the chemical from potentially multiple dissipation pathways whereas models generally require separate inputs for different dissipation pathways. However, the results of the EFED field studies are compared to modeling outputs and are used to assess the overall environmental fate of a pesticide and its major degradates resulting from multiple dissipation pathways.

Estimates of spray drift deposition as a function of distance downwind from the application site are necessary to predict residues on/in vegetation as well as on/in soil and in water. The Spray Drift Task Force (SDTF) is a consortium of approximately 40 registrants that was formed in 1990 to conduct research on droplet size distributions and spray drift depositions and to develop a computer model to estimate spray drift. The results of the SDTF research and the AGDRIFT model developed by the SDTF for estimating spray drift are currently being assessed by OPP and external peer review.

Over a number of years, EFED has required and/or received approximately 45 terrestrial ecological residue/effects studies covering 15 pesticides. The studies involve treating fields with maximum allowed numbers of applications and application rates. Various environmental media (including soil, water, vegetation, birds, mammals, and occasionally amphibians) were sampled at various sampling intervals. The samples were analyzed for the parent and occasionally for major degradates as well. Observed effects on non-target organisms were also reported.

Inhalation exposure studies are imposed by HED to determine the inhalation exposure of pesticide applicator workers (applicators and flaggers) during application and of farm workers post-application. The results of the studies can sometimes be used to estimate total pesticide concentrations in air reflecting pesticide adsorbed to particulate matter as well as pesticide in the vapor phase.

The HED requires foliar dislodgeable residue studies for foliarly applied pesticides of concern for potential risks to humans. Although of potential use in terrestrial exposure assessments, dislodgeable residues reflect only a part of the total foliar residues ingested by a bird or mammal ingesting contaminated foliage. Furthermore, the percentage of registered pesticides for which the foliar dislodgeable residue study has been required is relatively small.

The HED requires crop residue studies for pesticides foliarly applied to food crops. Crop residue studies involve the determination of total rather than dislodgeable residues and are required for a much higher percentage of registered pesticides than the foliar dislodgeable study. However, such studies rarely include more than two sampling times (immediately post-application and at the end of the proposed post-harvest interval). Indeed, many of the studies only include a sampling time at the end of the proposed post-harvest interval.

Greater details on OPP- required environmental fate and residue studies are provided in Appendix C7.

3.10.6 Environmental Databases

Types of environmental data/databases relevant to computer estimates of pesticide residues for terrestrial exposure assessments include fate, spray drift, pesticide use, crop distribution, land use, soil property, crop property and weather. Types of pesticide residue data/databases include foliar, insect, mixed media, and surface water.

3.10.6.1 Fate, Spray Drift, Pesticide Use, Crop, Soil, and Weather Databases

The ARS/NRCS/USDA maintains a chemical/fate pesticide properties database (which lists one or more values for up to 18 chemical/fate properties for 335 pesticides) at www.arsusda.gov/ppdb.html. OPP maintains a chemical/fate pesticide properties database that is comparable to that of the ARS/NRCS/USDA database. Properties for which data are listed include hydrolysis, direct photolysis in water, photodegradation on soil, aerobic soil, anaerobic soil, and terrestrial field dissipation half-lives and/or rate constants. Other properties of interest for which data are listed include soil/water partition coefficients (K_d values), air/water partition coefficients (Henry's Law Constant values), and the octanol/water partition coefficient.

Based upon studies conducted by the SDTF, the SDTF has developed a generic database containing data on the physical properties (dynamic surface tension, shear viscosity, extensional viscosity) of various spray tank mixtures, wind tunnel determined droplet size distributions for numerous combinations of experimental conditions, and spray drift deposition as a function of distance for aerial spray, orchard airblast, ground spray, and chemigation (Jones et al. 1997; Bird at al. 1995). Spray drift trials were conducted for numerous combinations of application equipment and conditions.

Non-proprietary estimated pesticide use data are maintained by the private company Resources for the Future. Other estimates are maintained by USDA's National Agricultural Statistical Service (NASS) at www.usda.gov/nass/pubs/pubs.htm. Estimated pesticide use on a county scale is available through the Census of Agriculture (conducted at 5 year intervals) at www.usda.gov/census/. To help interpret the

results of analyses for pesticides in water samples collected as part of the on-going National Water Quality Assessment Program (NAWQA), the USGS has used the 1992 Census of Agriculture data to generate nationwide pesticide use maps for numerous pesticides at the following internet address: http://water.wr.usgs.gov/pnsp/use92/.

Estimated crop distribution on a county scale is available through the Census of Agriculture which is conducted at 5 year intervals. Down loadable maps showing 1997 nationwide distributions of major row crops, and 1992 nationwide distributions of additional row crops as well as numerous vegetables, fruits and nuts can be obtained from www.usda.gov/census/.

Nationwide information distributed separately by state on numerous factors including land use, land cover, major crops, soil properties, geographic distribution of soils, wetlands, wildlife habitats, erosion, and conservation practices/needs is available in the National Resource Inventory (NRI) which is conducted by the NRCS every 5 years. Summary tables and graphs can be downloaded at the following USDA/NRCS address: www.nhq.nrcs.usda.gov/NRI/maps.html.

The NRCS has published thousands of soil surveys conducted throughout the United States. To house the soil survey data, the NRCS maintains a soil attribute database (MUIR) and several related soil geographic databases. MUIR lists for > 30,000 soil series phases within the U.S., various site descriptive characteristics and up to 28 physical and chemical properties for up to 6 vertical horizons (layers). The soil attribute database MUIR is linked to several different soil geographic databases that differ in scale (SSURGO, STATSGO, and NATSGO). The base map of the NATSGO soil geographic database is the USDA classified Major Land Resource Area (MLRA) which are described in SCS Agricultural Handbook 296 entitled "Land Resource Regions and Major Land Resource Areas of the United States." The National Resource Conservation Service (NCRS) internet addresses is www.nrcs.usda.gov/.

Historical daily weather data collected for many years from approximately 300 hundred of the NOAA first order weather stations are maintained by the National Climatic Data Center (NCDC) at www.ncdc.noaa.gov/ol/climate/climatedata.html. For use in the PRZM model, the USEPA's Center for Exposure Assessment Modeling (CEAM) maintains a weather database specifically designed for input into the PRZM model. Information on how to obtain the MRLA based weather database can be obtained

from www.epa.gov/epa_ceam/wwwhtml/ceamhome.htm.

3.10.6.2 Foliar Residue Databases

OPP has developed a method for estimating initial pesticide residues on various types of foliage that involves multiplying maximum or typical initial residue values normalized to an application rate of 1 lb ai/acre by the application rate. Maximum and typical normalized fresh weight values are: for short grass (240 and 125 ppm), for long grass (110 and 92 ppm), for leaves/forage (125 and 35 ppm), and for pods/fruit (12 and 3 ppm). The normalized values were derived from data compiled from the literature by Hoerger and Kenega (1972) and from recommendations from Fletcher et al. (1994) based on the far greater and more recent foliar residue data contained in the University of Oklahoma UTAB database. In evaluating the EPA methodology, Pfleeger et al. (1996) generated additional foliar residue data for 6 pesticides applied to 15 plant species.

OPP does not currently have access to the UTAB database or the raw data generated by Pfleeger et al. (1995), but is currently evaluating options for gaining access to it.

Willis and McDowell (1986) performed a literature review on the interception of pesticides by crops, and on the persistence of pesticides on foliage. In cases where a reviewed article did not contain an estimated half-life, Willis and McDowell calculated one based on tabular or graphical data and an assumption of pseudo first order kinetics. For purposes of tabular presentation and discussion, Willis and McDowell divided the pesticides for which data were reported into the following chemical family categories: organochlorines, organophosphates, carbamates, pyrethroids, and other (which consist of miscellaneous fungicides, insecticides, and herbicides).

The Beril foliar residue database is a compilation of mostly day 0-1 foliar residue data from over 500 international references primarily from the 1970s and 1980s. Data for numerous crops, pesticide active ingredients, and formulations are included. Data are generally expressed as mg/kg fresh weight, but are occasionally also expressed as ug/cm^2 leaf surface area.

As previously indicated, EFED has required and/or received approximately 45 terrestrial ecological

residue/effects studies covering 15 pesticides. The studies involve treating fields with maximum allowed numbers of applications and application rates. Various environmental media (including soil, water, vegetation, birds, mammals, and occasionally amphibians) were sampled at various sampling intervals. The samples were analyzed for the parent and occasionally for major degradates as well. Observed effects on non-target organisms were also reported. OPP is currently developing a database to house the data from the ecological field studies.

3.10.6.3 Insect and Other Terrestrial Invertebrate Residue Databases

A large number of bird and mammal species eat primarily terrestrial invertebrates (insects, spiders, earthworms, etc.) and consequently, estimation of residue levels on/in invertebrates is crucial to an assessment of dietary exposure of wildlife. Even among bird species in which the adults eat mainly plant material, young are usually fed mainly invertebrates in order to satisfy their high demands for protein (Gill 1989).

Terrestrial invertebrates may come into contact with pesticide residues in a variety of ways, including via ingestion of contaminated food and/or soil, walking on or crawling through contaminated vegetation or soil, and by being directly sprayed. Because routes of exposure are varied and chemical uptake rates are dependent upon life history and behavior factors that are either highly variable or poorly understood, it is difficult to model the processes that result in residues in/on invertebrates. The most straightforward approach to the problem is to obtain and use actual field measurements. However, measurement of residues in/on invertebrates is not part of the standard data development requirements for pesticides, and as a consequence, such data have traditionally not been available to risk assessors.

Because of the lack of direct measurements, current EPA assessments use residue data for plants as a surrogate for invertebrates. Kenaga (1973) suggested that residue levels deposited on invertebrates subjected to a direct spray application should be similar to that of plant parts with a similar surface area to volume ratio. On that basis, he further suggested that small insects should have residue levels immediately after application similar to forage crops (legumes) such as alfalfa, and large insects should have residue levels similar to fruits and seeds. Following this suggestion, EPA has established nomogram values (predicted residue per 1.0 lb/acre applied) of 135 ppm for small insects and 15 ppm for large insects,

based on the nomogram values recommended by Fletcher et al. (1994) for forage (legumes) and fruit, respectively.

Recently, a substantial data base of field measurements of residue levels in invertebrates has become available. Fischer and Bowers (1997) compiled measurements made in terrestrial field studies conducted by industry in the late 1980's and early 1990's. This data base included measurements made within 24 h of 175 foliar applications and 56 soil applications to actual field study sites. Descriptive statistics (mean, standard deviation, etc.) of these data sets are given in Table 3.10-1. Measurements at foliar sites were close to the Fletcher nomogram model estimates for fruits which EPA has assumed are a surrogate for large insects, but much less than the corresponding nomogram values for forage crops which EPA has assumed are a surrogate for small insects. For example, Fletcher et al. (1994) reported a mean and standard deviation residue level per 1 lb/acre applied in/on fruits of 5.4 and 9.8 ppm respectively. The comparative values measured by Fischer and Bowers for invertebrates were 5.7 and 9.2 ppm, respectively. Measured residues in invertebrates at sites where applications to the soil were made were much lower with the mean in these cases being <1 ppm. It is not surprising that these levels were lower since incorporation of the chemical into the soil mechanically, or via watering, “dilutes” the amount of residue that is likely to contact invertebrates crawling on or in the soil at these sites.

The invertebrates in these studies were mostly collected in pitfall traps set immediately after application and retrieved the next morning, or by sweep netting the top of the treated vegetation a few hours after application. These collection methods have potential biases that should be considered prior to using these data sets as a basis for setting probabilistic distributions of potential residue levels in invertebrates. For example, a net swept against the surface of treated vegetation is likely to remove dislodgeable residues and these residues may in turn adsorb to the surface of insects caught in the net. Thus, these insect samples might have artificially inflated pesticide concentrations. On the other hand, an opposite bias may be associated with pitfall trap samples. This is because although some individuals falling into the traps “rain down” from the vegetation upon death after an insecticide application, most probably fall in while walking across the ground. In the case of insecticide applications, which represent the vast majority of samples in Fischer and Bower’s data set, the most highly exposed individuals are expected to

Table 3.10-1. Pesticide residue levels measured in terrestrial invertebrates (mostly arthropods) sampled within 24 h of 231 field applications. (Derived from data sets of Fischer and Bowers, 1997).

Application Type	Distribution	N	Residue level (ppm) per 1.0 lb/acre applied				
			Mean	Stan Dev	Geometric Mean	Minimum	Maximum
Foliar	Lognormal	175	5.7	9.2	2.1	0.04	54.0
Soil-incorporated	Lognormal	56	0.60	3.4	0.04	0.00	25.2

Table 3.10-2. Pesticide residue levels measured in adult and larval insects confined to the spray swath during foliar applications to experimental field plots. (Derived from data sets of Brewer et al., 1997).

Insect Type	N	Residue level (ppm) per 1.0 lb/acre applied				
		Mean	Stan Dev	Geometric Mean	Minimum	Maximum
Adult crickets and beetles	5	3.7	2.1	2.7	0.38	5.4
Larval armyworms and beetles	5	2.3	2.8	1.4	0.33	7.2

become immobilized and therefore have a lower chance of encountering and falling into a pitfall trap. If this was true, the residue levels in pitfall trap samples might by biased on the low side.

An independent study has been conducted that controls for these sources of bias and allows one to judge their likely significance in the Fischer and Bowers data set. Brewer et al. (1997) conducted small plot residue trials with several compounds specifically to obtain measurements of residues in invertebrates (Table 3.10-2). In these trials, adult insects (crickets and/or beetles) and "wormy" larvae (beet armyworms and/or beetle larvae) were placed just prior to application on the ground or on vegetation within a spray swath and confined there until they were collected several hours later. Mobile individuals (i.e., adults) were confined to the spray path by pinning them to vegetation or placing them in enclosures. Residue levels in these samples fell well within the range of observations in the Fischer and Bowers data set. The average values for both adult insects (3.7 ppm) and larvae (2.3 ppm) were below the average of the Fischer and Bowers data set (5.7 ppm). This finding is inconsistent with the potential concern that Fischer and Bowers' data are biased on the low side due to the use of pitfall traps as a collection method. The Fischer and Bowers data set therefore appears to be suitable for use in defining probabilistic distributions of potential residue levels in invertebrates.

3.10.6.4 Water Residue Databases

The STORET database is maintained by the U.S. EPA/OW and contains a vast amount of general water quality and pollutant monitoring data (including for various pesticides) for many sampling sites for up to > 30 years. STORET information can be obtained at www.epa.gov/OWOW/STORET/.

The USGS National Water Quality Assessment Program (NAWQA) is an ongoing program to monitor the surface water and groundwater within 60 study units (representing 60 river basins and/or aquifers) widely spread throughout the U.S. Summaries and raw data for the first 3 years of sampling of the 20 study units in the first group are available on the internet at water.wr.usgs.gov/pnsp/. Although the NAWQA Program is providing a vast amount of data on pesticides in surface water, the utility of the data for terrestrial exposure assessments is somewhat limited by the data all being for flowing water instead of for ponds and lakes.

The ongoing USGS Toxic Substances Hydrology Program is also a substantial source of data on pesticides in the surface water of the Midwest, Mississippi Delta, and the Mid-Atlantic Coastal Plain. Data summaries and publication lists can be obtained at toxics.usgs.gov/toxics/regional/agchem-midwest.shtml and at toxics.usgs.gov/toxics/regional/cotton.shtml. Although the much of the pesticide data from the Toxic Substances Hydrology Program has also focused on flowing surface water, some data have also been collected on reservoirs and lakes.

Greater details on pesticide fate and residue databases are provided in Appendix C8.

3.10.7 Recommendations for Improving Estimates and Determinations of Pesticide Concentrations in Environmental Media

Listed below are a number of problems associated with estimating and/or determining pesticide concentrations in environmental media and recommendations for alleviating them.

3.10.7.1 Deficiencies in Existing Models

Based upon the literature reviews by Golder Associates (1997), Jorgensen (1995), and our analysis of existing models, there do not appear to be any terrestrial exposure computer models currently available that could be used to adequately generate distributions of pesticide residues in, and doses from, all relevant environmental media for use in probabilistic terrestrial exposure and risk assessments.

Long Term Recommendations - Deficiencies in Existing Models: A terrestrial exposure computer model needs to be developed that could be used to adequately generate distributions of pesticide residues in and doses from all relevant environmental media for use in probabilistic terrestrial exposure and risk assessments. The model should have the capability of estimating plant growth and distributions of pesticide residues in bulk soil, soil pore water, bulk plants, dew, puddles, ponds, air within the canopy, vertebrates, foliar and soil surface insects, worms, other soil invertebrates, and subterranean insects from both spray and granule applications. It should also have the capability of simulating bird and other terrestrial wildlife behavior/movement and of generating distributions of pesticide doses for those organisms from plant, insect, and invertebrate ingestion; dew, puddle, and pond water ingestion; air

inhalation, and dermal contact with various contaminate environmental media.

As previously discussed, there are several existing models which could possibly serve together as a good foundation for the residue component of such a model. Other existing models could possibly serve together as a good foundation for the dose and animal movement/behavior component of a terrestrial exposure model.

Interim Recommendations - Deficiencies in Existing Models: For interim spray residue estimates, PRZM 3, AgDRIFT, and EXAMS can probably be provided with adequate Monte Carlo simulation capabilities long before a new terrestrial exposure model can be developed. Although they cannot currently be coupled to Monte Carlo software such as @RISK or CRYSTAL BALL, the cost of developing software to do so is probably relatively low. The FIFRA Model Validation Task Force has funded the development of an interface between PRZM 3 and CRYSTAL BALL. If the existing models are provided with adequate Monte Carlo simulation capabilities, they can be used to generate interim level 1 single value estimates and level 2 distributional estimates of residues on/in soil, on/in plants, in water, and in air within the canopy until a new terrestrial exposure model is developed.

Until PRZM 3, AgDRIFT, and EXAMS are provided with adequate Monte Carlo simulation capabilities, at least two options should be considered for generating interim level 1 single value estimates and level 2 distributional estimates of residues on/in soil, on/in plants, in water, and in air within the canopy. One option is to use the current versions of PRZM 3, AgDRIFT, and EXAMS (despite their limited to no Monte Carlo simulation capabilities) to generate level 2 distributional estimates by running them deterministically over multiple years and sites. The distribution of outputs generated by running the models deterministically over multiple years and sites should adequately reflect natural year to year variations in weather at a given site and natural variability in average values across sites.. Furthermore, nonsensical combinations of inputs that are sometimes present in Monte Carlo simulations due to inadequate and/or inaccurate accounting for correlation can be avoided. However, unlike with Monte Carlo simulations, the distributional outputs will not reflect natural variability and/or measurement uncertainty in sensitive input variables within sites.

The other option is to use simpler mass balance based equations (discussed in Appendix C9) in

conjunction with deterministic outputs from AgDRIFT to generate interim level 1 single value estimates and level 2 distributional estimates of residues on/in soil, on/in plants, and in water, until PRZM 3, AgDRIFT, and EXAMS are provided with adequate Monte Carlo simulation capabilities. Such equations can be easily entered into spreadsheets and readily undergo Monte Carlo simulations with the use of Monte Carlo software such as @Risk, Crystal Ball, or DistGEN. The problems with such equations are that they are not coupled to weather, do not account for the effects of weather and hydrology on residue levels, and do not consider as many factors affecting residue levels as do PRZM 3 and EXAMS. Simple mass balance differential equations and their solutions for various environmental media are provided for possible interim Level 1 and Level 2 assessments in Appendix C9.

For interim granule residue and dose estimates, it may be possible to use the Dow/Elanco, Fischer, and Best model. For interim dose estimates, it may be possible to use the bird spray exposure model PARET and the bird granule exposure model developed by Dixon et al. (1998).

3.10.7.2 Fate and Residue Data Gaps for Vegetation, Insects and Soil Invertebrates

There is a general lack of data on uptake by plants, volatilization rates from vegetation, dissipation rates on/in vegetation, washoff from vegetation, and fate in insects and soil invertebrates. In addition, databases of time zero and time series pesticide residue data for vegetation and insects/soil invertebrates need to be expanded and based upon dry rather than wet weight. Such major foliar and invertebrate fate and residue data gaps make it difficult to accurately estimate pesticide concentrations on/in vegetation , insects and soil invertebrates using computer modeling.

Recommendations - Fate and Residue Data Gaps for Vegetation, Insects, and Soil Invertebrates:
Development of a laboratory or greenhouse terrestrial microcosm fate study that focuses on foliar and insect/invertebrate processes, expansion of the scope of terrestrial field dissipation studies to include a greater emphasis on foliar and insect/soil invertebrate processes and interim procedures for estimating foliar fate parameters from other data need to be considered.

(1) The Environmental Fate and Technology Team within the EFED should be asked to develop draft guidance on conducting laboratory, greenhouse, or small scale outside terrestrial microcosm fate studies

that focuses on foliar and insect/invertebrate as well as soil fate processes. Such studies should include the use of radiolabeled material and the generation of mass balance. EFED should then be asked to submit the draft guidance to OECD as a candidate for an OECD fate guideline.

(2) EFED is currently working with Canada on draft guidance for conducting terrestrial field dissipation studies that will include a greater focus on foliar processes. Expanding the scope to also include the sampling and analysis of insects and soil invertebrates is being considered. The draft guidance will be submitted to OECD as a candidate for an OECD guideline.

(3) In the interim, attempts should be made to correlate foliar fate parameters such as the overall foliar dissipation rate constant, the volatilization from foliage rate constant, and the washoff extraction coefficient with other fate properties. Fate parameters which should be considered for correlation with foliar fate parameters include dissipation rate constants in soil, photodegradation rate constants, hydrolysis rate constants, Henry's Law constant, and the octanol/water partition coefficients. Correlations with properties of the formulation and/or additives such as surfactants may also be necessary. Although developing a regression model for estimating foliar dissipation rates appears to be a difficult task, it is needed because the default assumption that the foliar dissipation rate is equal to the dissipation rate in soil appears to be overly conservative in most cases.

A number of correlations relating uptake by plants to fate parameters such as the octanol/water partition coefficient are already in the literature. (See Section 3.10.2 and Appendix C4).

3.10.7.3 Fate and Residue Data Gaps for Soil and Water

Fate and residue data gaps for soil and water include:

(1) Frequently inadequate fate data to extrapolate transformation rates in one soil or water/sediment system under a narrow range of experimental conditions (such as those for temperature and soil moisture) to other soils or water/sediment systems.

(2) A general lack of data on adsorption/desorption kinetics. The assumption by most models of chemical

equilibrium between soil and water may be a major source of error in some cases.

(3) The number of sampling intervals is generally too low to estimate rate constants for their formation and decline of degradates. (See Section 3.10.4 and Appendix C6.) In addition, separate metabolism studies on the degradates are seldom performed. Consequently, it is generally not possible to use modeling to estimate the concentrations of major degradates in the soil.

(4) Field data on concentrations of pesticides in soil are fairly extensive due to terrestrial field dissipation studies which are required by OPP for many terrestrial uses. However, due presumably to non-uniform applications and/or to inadequate numbers and size of samples and/or inadequate numbers and timing of sampling intervals, the data are frequently too variable or inadequate to adequately characterize the dissipation of the parent and the formation and decline of degradates.

(5) Most of the available data on pesticide residues in surface water are for flowing water. Data on pesticide residues in ponds, puddles, and dew on foliage are more appropriate for use in terrestrial exposure assessments.

Recommendations - Fate and Residue Data Gaps for Soil and Water: The recommendation numbers below correspond to the problem numbers above:

(1) The September 1997 draft OECD guideline for conducting laboratory transformation in soil studies does recommend conducting studies on 4 different soils which represents a vast improvement on current OPP guidance requiring only one soil. However, OPP is also recommending to OECD that at least as an option, studies also be conducted at various moistures and temperatures.

The July 1997 draft OECD guideline for conducting laboratory transformation in water/sediment studies does recommend conducting studies on 2 different water/sediment which represents an improvement on current OPP guidance requiring only one water/sediment system. However, OPP is also recommending to OECD that 2 additional water/sediment systems (to give a total of 4) also be included.

(2) OPP has recommended to OECD that the determination of adsorption/desorption rate constants be

included in the final OECD Guideline 106 for Adsorption/Desorption. PRZM3 and EXAMS do not currently simulate adsorption/desorption kinetics primarily because such data are rarely available. If adsorption/desorption data became routinely available, the models could be readily modified to simulate at least first order adsorption and desorption kinetics.

(3) OPP has recommended to OECD that the additional sampling intervals necessary to better quantify the formation and decline of major degradates be included in OECD guidance for conducting laboratory transformation in soil and water/sediment studies.

(4) EFED is currently working with Canada on draft guidance for conducting terrestrial field dissipation studies that will strengthen guidance on ensuring more uniform applications, adequate numbers and sizes of samples, and adequate numbers and timings of sampling intervals.

(5) Guidance for sampling ponds (when available), puddles and dew should be considered for inclusion in the guideline being currently developed for conducting terrestrial field dissipation studies.

3.10.7.4 Fate and Residue Data Gaps for Air

As previously mentioned, literature data on pesticide concentrations in air are somewhat limited and are generally on high use herbicides in the mid-west, in California, and around the Great Lakes (Majewski and Capel 1995). Data on pesticide concentrations in air derived from OPP- required studies are also limited. Volatility from Soil studies have only been infrequently required. Worker Inhalation Exposure studies are called for more frequently, but only for pesticides thought to be of potential risk to humans.

Data collected from worker inhalation studies may be of use in estimating average pesticide concentrations in air during application (though at a sampling height generally higher than the air inhaled by mammals and birds on the ground). However, such studies generally provide post-application data for only one or two days corresponding to proposed re-entry intervals. Consequently, such studies will generally be of little value for estimating post-application declines in pesticide concentrations in air. As previously mentioned, there is very little information on foliar volatilization rate constants and they are difficult to separate out from overall foliar dissipation rate constants.

Recommendations - Fate and Residue Data Gaps for Air: The guidance for conducting terrestrial microcosm and field dissipation studies should include conditional provisions for the collection of air samples at a number of sampling intervals and heights, and analysis of the samples for parent and major degradates. The emphasis on air sample collection should be on sampling within canopies. Based upon the data, fluxes and foliar volatilization rate constants should be estimated when possible.

3.10.7.5 Selection and Fitting of PDFs for Modeling Input and Residue Data

The generation of distributions of estimated pesticide concentration versus time series in environmental media from Monte Carlo computer simulations requires the selection and fitting of PDFs to sensitive input variables such as initial residue values, dissipation rate constants, and equilibrium partition coefficients. In many cases, the available data are inadequate to accurately select and fit PDFs to it.

Recommendations - Selection and Fitting of PDFs for Modeling Input and Residue Data: Existing databases containing time zero and time series or rate constant data on pesticide residues on/in environmental media such as vegetation and insects/soil invertebrates need to be analyzed and expanded. Databases containing information on modeling inputs also need to be analyzed and expanded. Existing data needs to be properly divided into categories such as the plant categories recommended by Hoerger and Kenega (1972) and chemical families as was done by Willis and McDowell (1986). Goodness of fit software that can be run iteratively need to be used to help select and fit (parameterize) PDFs to distributions of modeling input and to properly categorized distributions of initial pesticide residues in environmental media.

3.10.7.6 ***Establishing Correlations Between the Input Variables for Monte Carlo Simulations***

To avoid the random formation of nonsensical combinations of input values during Monte Carlo simulations, any correlations between sensitive input variables need to be accurately determined and preserved during the random sampling. The data and/or resources necessary to do so is often lacking.

Recommendations - Establishing Correlations Between the Input Variable for Monte Carlo Simulations: Sensitivity analysis need to be performed to focus resources and analysis on sensitive input variables. An

effort should be made to obtain the necessary data and resources to adequately characterize (and preserve during random sampling) correlations between sensitive input parameters.

3.11 OUTPUTS FROM AND INPUTS TO AN EXPOSURE ASSESSMENT

The primary output of a probabilistic exposure assessment for a given pesticide is a dose PDF for each pesticide use area and non-target species/population of concern. This section will describe how a dose PDF can be estimated with a Monte Carlo simulation using as input, distributions of animal characteristics affecting dose and distributions of parameters that affect pesticide concentration versus time series in environmental media.

3.11.1 Monte Carlo Based Generation of a Dose PDF

A dose PDF is generally obtained by performing a Monte Carlo simulation. In a Monte Carlo simulation, statistical distributions in the form of PDFs and/or empirical non-parametric distributions are assigned to one or more of the input variables affecting dose (the output variable). The computer algorithm used to estimate values of dose from a dose equation is then run numerous (generally thousands of) times. For each of the runs, the values of the input variables for which statistical distributions have been assigned are randomly selected from their distributions. The random selection of input values for each run gives different combinations of input values and therefore a different resulting dose estimate for each run. The thousands of runs results in a dose PDF.

As can be seen from the dose equations in Sections 3.4 - 3.9 as well as the pesticide concentration equations in Section 3.10 and Appendix C4, input variables for which a PDF or empirical non-parametric distribution can be assigned include:

- One or more animal characteristics affecting dose (such as food ingestion, water ingestion and body weight), and/or
- One or more parameters affecting pesticide concentration versus time series in environmental media (such as initial concentrations, plant biomass, dissipation rate constants and equilibrium partition coefficients).

To generate dose PDFs using Monte Carlo simulations, it is obviously necessary to use a fate model with the ability to run Monte Carlo simulations. In addition, any substantial correlations between input variables must be taken into account to avoid nonsensical input combinations.

3.11.2 Statistical Distributions of Pesticide Residue and Fate Data

In cases where the available pesticide residue and/or fate data are adequate to do so, the frequency predictions for various intervals by various PDFs and the same PDF with iterative changes in the initial estimates of distribution parameter values can be compared to actual frequency of data within the intervals to determine the PDF and the parameter values of the PDF that best fit the observed data. One of the most frequently used goodness of fit tests is the chi-square test. The chi-square statistic upon which the test is based is given by (Ott 1995):

$$X^2 = \sum_{j=1}^{j=m} (O_j - E_j)^2/E_j \qquad (3.11\text{-}1)$$

where,

X^2 = chi-square statistic
j = index for different intervals
O_j = observed cumulative fraction of data in interval j
E_j = PDF estimate cumulative fraction of data within interval j
m = number of intervals

The chi-square test is used to determine the probability that a PDF does not fit the data. Because the chi-square statistic increases with increasingly poor fit (Ott 1995), it can be also be used to rank PDFs as indicated by the magnitude of the chi-square statistic.

Software designed specifically for Monte Carlo simulations such as @RISK and CRYSTAL BALL

include as standard or as optional modulars, algorithms for fitting PDFs to observed data.

The lognormal distribution is the one most commonly used to describe environmental data (Ott 1995). However the normal, uniform, and triangular distributions are also frequently used. Although caution should be observed in selecting a distribution in cases where the available data are inadequate to adequately test it, there is some justification in selecting the lognormal and in some cases the normal distribution to describe limited sets of environmental data (Seiler and Alvarez 1995). However, Seiler and Alvarez (1995) are highly critical of the frequent use of the uniform and triangular distributions as default distributions to describe limited or no environmental data. That is due in part to discontinuities in those distributions.

For some input variables, the available data may be adequate enough to statistically fit it to a PDF for use in Monte Carlo simulations. For other input variables, the data may not be adequate enough to fit it to a PDF, but is adequate enough to accurately compute a mean and variance. In such cases it may sometimes be possible to assume a PDF type such as the lognormal distribution based upon any literature that indicates that the data for that variable generally fits well to a specific type of PDF. The mean and variance can then be transformed to estimate the values of the PDF parameters. For any input variables for which the data and literature are too limited to generate either a best fit or hypothetical PDF, an empirical non-parametric distribution or a single value will have to be used in the Monte Carlo simulation.

3.11.3 Hypothetical Lognormal PDFs for UTAB Time Zero Foliar Residues

Although the raw time zero foliar residue data in the UTAB database is not currently available to determine a best fit distribution for the data, Fletcher et al. (1995) did provide the arithmetic means and standard deviations of UTAB data for the Hoerger and Kenega 1972 crop categories (Table 3.11-1). For illustrative purposes, we have computed the ln transformed means and standard deviations from Equations 1.6-3 and 1.6-4 (Table 3.11-1) and used them to generate hypothetical lognormal distributions of time zero foliar residue data for each of the categories as shown in Figures 3.11-1 and 3.11-2.

As can be seen from Figure 3.11-1, the theoretical lognormal distributions for the long grass, leafy, and forage categories are somewhat comparable whereas the one for short grass is

Table 3.11-1) Arithmetic (m_x and s_x) and lognormal transformed (m_y and s_y) means and standard deviations for time zero foliar residues for the plant categories recommended by Hoerger and Kenega (1972). Arithmetic values are taken from Fletcher etal 1995. Transformed values are computed from equations 193 and 194. Values are for applications of 1 lb ai/acre and are in ppm (mg/kg) wet weight.

Category	m_x	s_x	m_y	s_y	Max	Min
Short Grass	84.8	60.3	4.24	0.640	194	15.3
Long Grass	36.0	40.6	3.17	0.906	197	0.12
Leaves	35.0	45.0	3.07	0.988	296	0.23
Forage	45.0	56.7	3.33	0.975	350	0.05
Pods /Seeds	5.4	5.9	0.809	1.07	24.0	0.05
Fruits	5.4	9.8	0.958	1.21	40.7	< DL

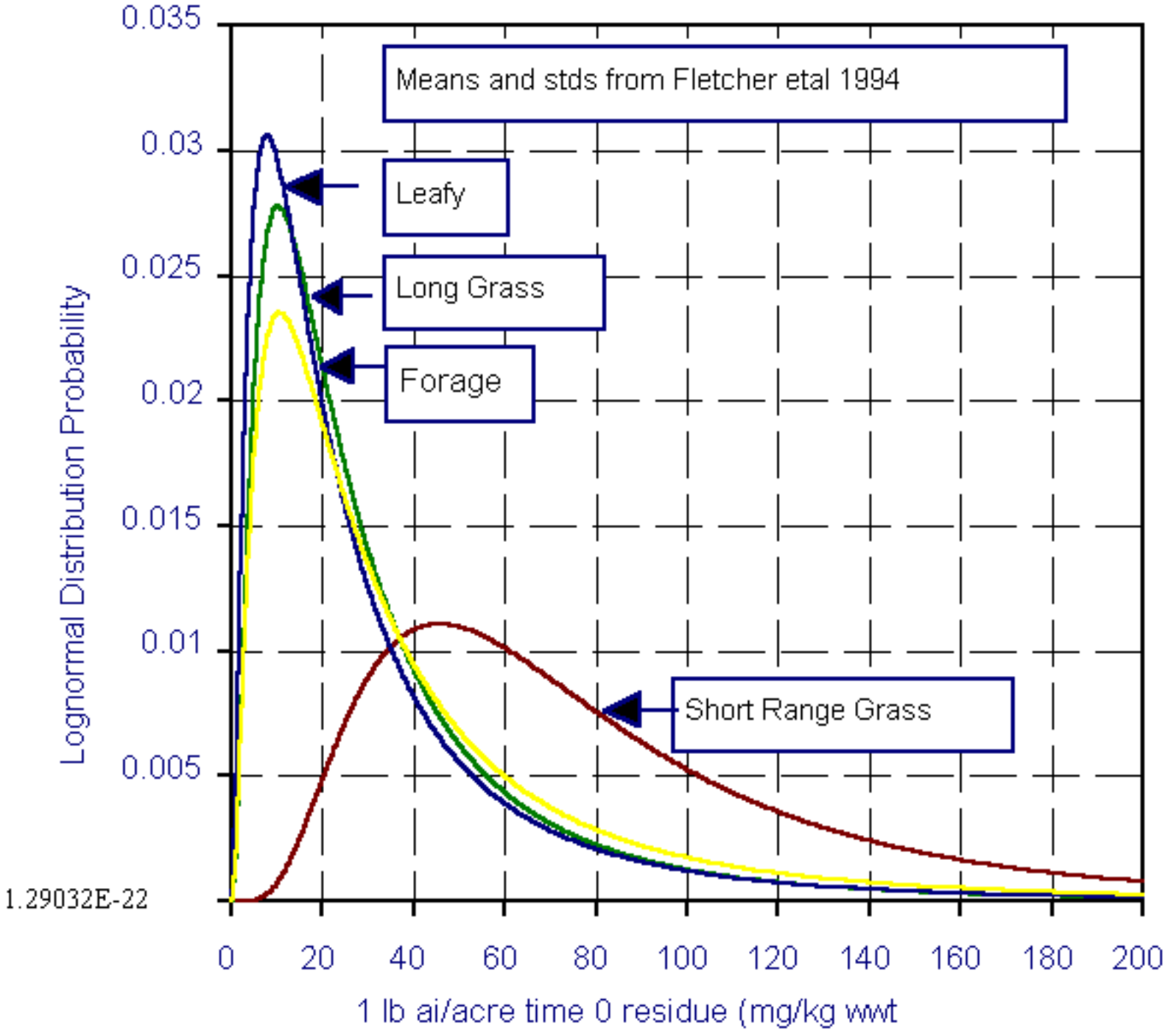


Figure 3.11-1: Time Zero Foliar residues.

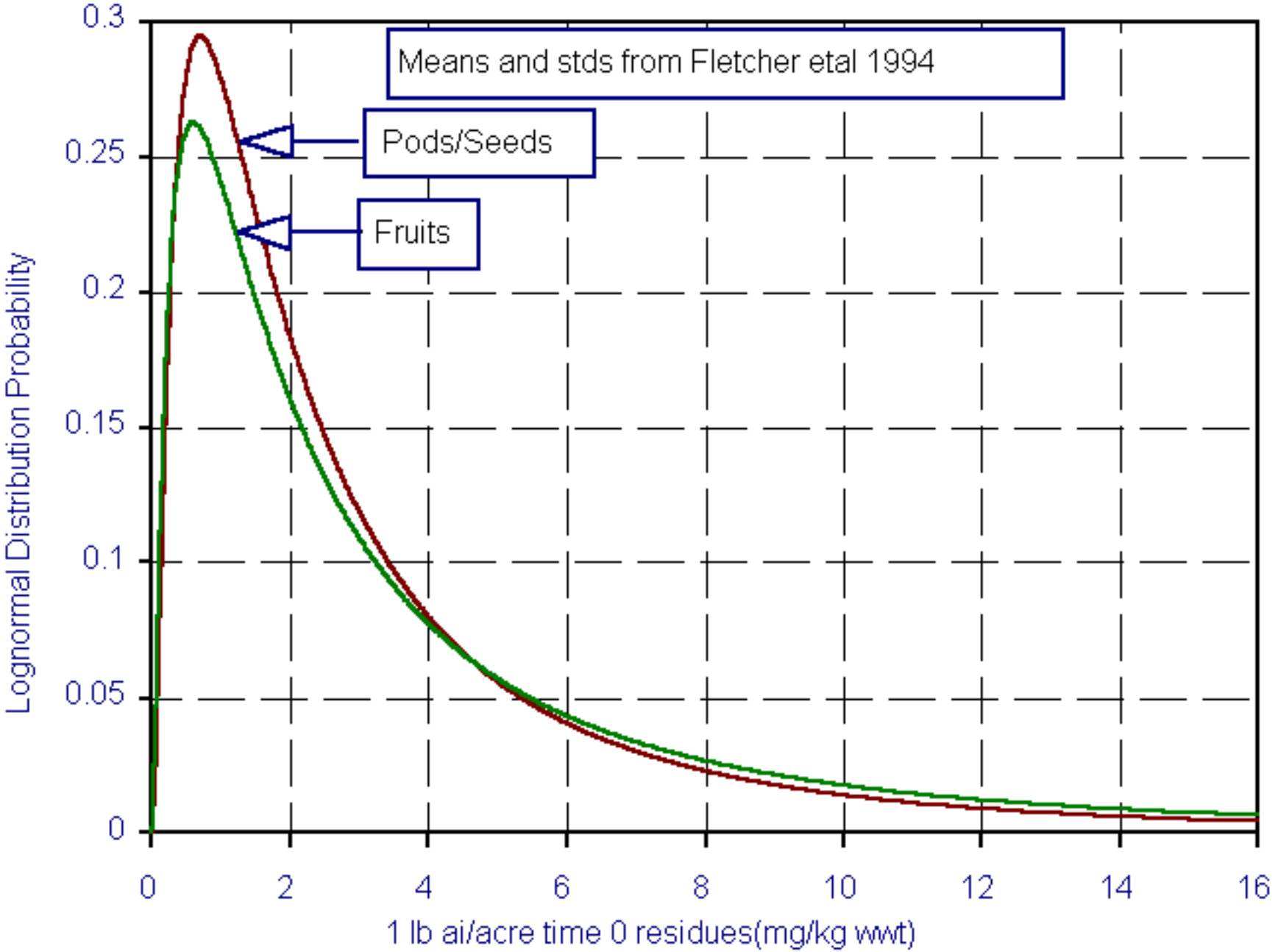


Figure 3.11-2. Time zero pod/seed or fruit residues

substantially different. It is substantially shifted to the right thereby indicating substantially higher time zero values for short grass than for the other categories. As can be seen from Figure 3.11-2, the theoretical lognormal distributions for fruit and for pods/seeds are also somewhat comparable with time zero residue values being much smaller than for the other plant categories.

Figures 3.11-1 and 3.11-2 support the Fletcher et al. (1995) recommendations that the forage and leaf categories be combined into a single broadleaf category and that fruits and pods/seeds be combined into a single category. However, the long grass distribution actually appears to be more comparable to the one for the leaf category than the one for the forage category that Fletcher et al. recommended be combined with the leafy category.

3.11.4 Hypothetical Lognormal PDFs for Foliar Dissipation Half-lives

Willis and McDowell (1986) reported arithmetic means and standard deviations of dislodgeable and total foliar dissipation half-lives for 4 different chemical families (Table 3.11-2). For illustrative purposes, we have computed the ln transformed means and standard deviations from equations 1.6-3 and 1.6-4 (Table 3.11-2) and used them to generate hypothetical lognormal distributions of dislodgeable and total foliar dissipation half-lives for 4 chemical classes as shown in Figures 3.11-3 and 3.11-4.

As can be seen from Figure 3.11-3, the theoretical lognormal distributions of dislodgeable foliar half-lives are similar for carbamates and organophosphates but are substantially different for organochlorines and for pyrethroids. As can be seen from the arithmetic means in Table 3.11-2 as well as by the shift in Figure 3.11-3, pyrethroids are the most persistent chemical family with respect to dislodgeable residues followed by the organochlorines.

As can be seen from Figure 3.11-4, the theoretical lognormal distributions of total residue foliar dissipation half-lives differ substantially for the 4 chemical classes. As can be seen from the arithmetic means in Table 3.11-2 as well as the shifts in Figure 3.11-4 compared to Figure 3.11-3, half-lives are somewhat longer for total residues than for dislodgeable residues. Also, the pyrethroids followed by the organochlorines again are generally more persistent than the

Table 3.11-2) Arithmetic (m_x and s_x) and lognormal transformed (m_y and s_y) means and standard deviations for dislodgeable and total foliar dissipation half-lives for the plant categories recommended by Hoerger and Kenega (1972). Arithmetic values are taken from Willis and McDowell 1986. Transformed values are computed from equations 193 and 194. Half-lives are in days.

	Carbamates	Organochlor	Organophos	Pyrethroid
Dislodge				
m_x	2.3	3.4	2.5	4.9
s_x	2.3	2.7	2.8	2.3
m_y	0.486	0.979	0.510	1.49
s_y	0.833	0.699	0.902	0.446
Total				
m_x	2.7	5.8	3.3	5.9
s_x	1.2	6.0	2.6	5.0
m_y	0.903	1.39	0.952	1.504
s_y	0.425	0.853	0.649	0.736

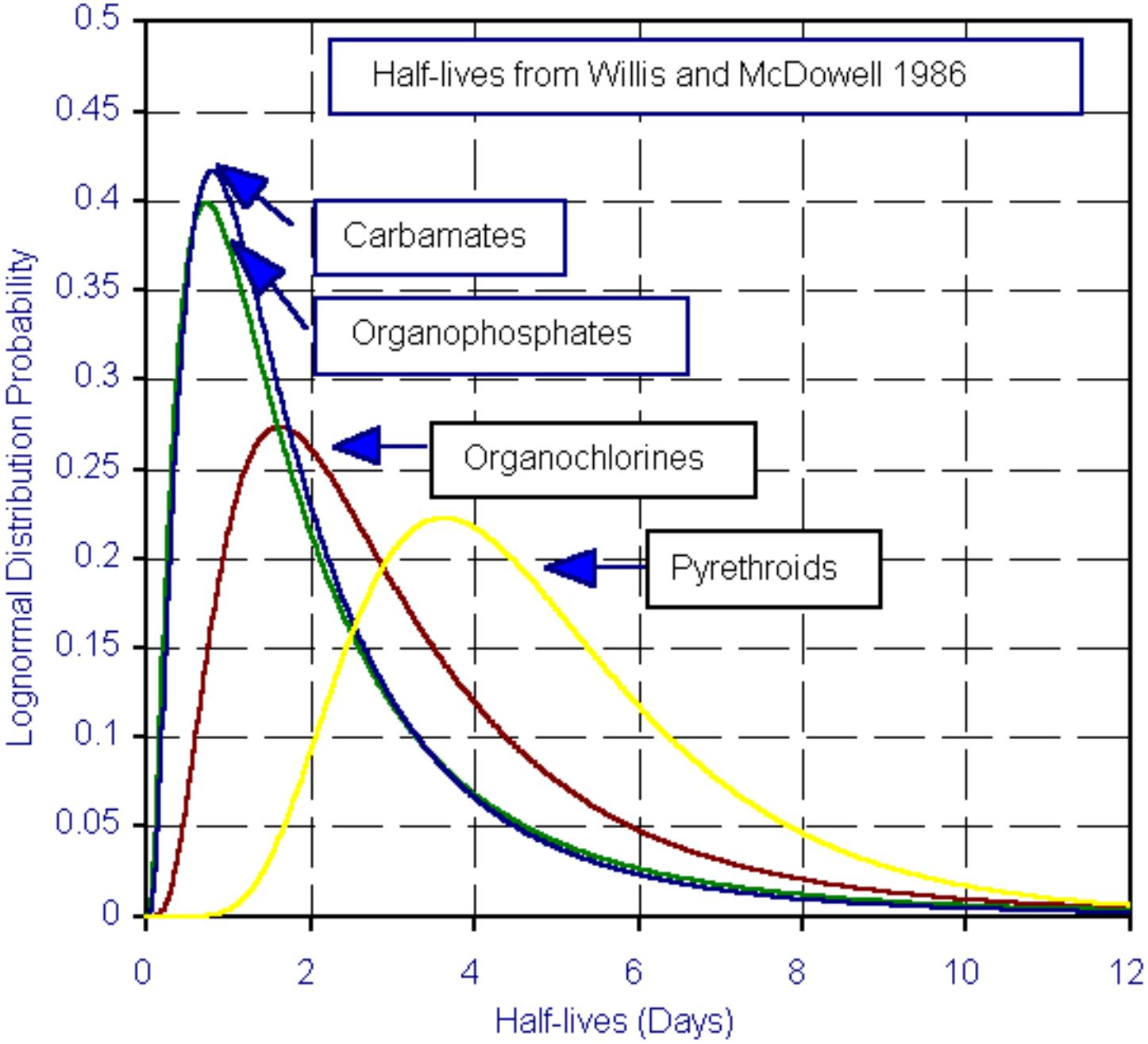


Figure 3.11-3: Dislodgeable residue half-lives.

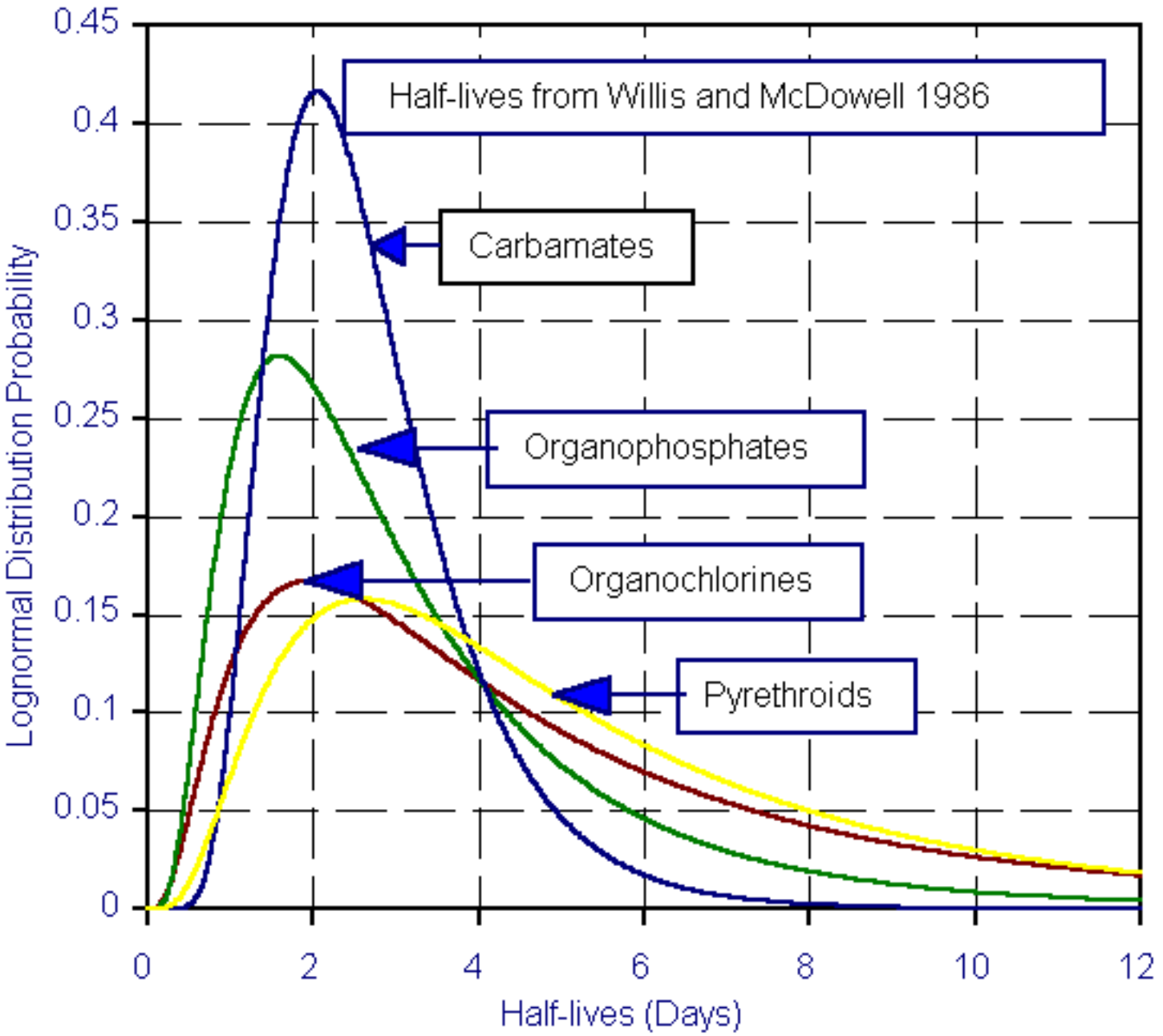


Figure 3.11-4: Total residue half-lives.

organophosphates and carbamates.

Variations of reported foliar half-lives for the same chemical are often comparable to variations within the same chemical families and sometimes even across chemical families. Also, most foliar half-lives are less than two weeks even for chemicals with much higher half-lives in soil and for chemicals with wide variations in other fate properties as well. That makes trying to develop regression equations to predict foliar dissipation half-lives from fate properties such as half-lives in soil, photodegradation half-lives, Henry's Law constant and the octanol water partition coefficient difficult. However, attempts will continue. In any event, assuming that the foliar half-life is identical to the soil half-life as is frequently done appears to be overly conservative in most cases.

3.11.5 Hypothetical Lognormal PDFs for Chlorpyrifos Half-lives in Soil and Soil/Water Partition Coefficients

Based upon chlorpyrifos data provided by Laskowski (1998), arithmetic means and standard deviations were computed as follows for chlorpyrifos:

- Half-lives in laboratory aerobic soil metabolism studies and terrestrial field dissipation studies,
- Soil/water partition coefficients (K_ds) in laboratory adsorption/desorption studies, and
- Organic carbon normalized soil/water partition coefficients (K_{oc}s) in laboratory adsorption/desorption studies (Table 3.11-3).

For illustrative purposes, we have computed the ln transformed means and standard deviations from equations 1.6-3 and 1.6-4 (Table 3.11-3) and used them to generate hypothetical lognormal distributions of those chlorpyrifos variables as shown in Figures 3.11-5 and 3.11-6. For the final report, we hope to have determined the actual distribution types that best fit the chlorpyrifos fate data and present them as examples instead of the hypothetical lognormal distributions (unless the lognormal distributions are the best fit distributions).

Table 3.11-3) Chlorpyrifos arithmetic (m_x and s_x) and lognormal transformed (m_y and s_y) means and standard deviations for laboratory aerobic soil metabolism half-lives, terrestrial field dissipation half-lives, soil/water partition coefficients (K_ds), and organic carbon normalized soil/water partition coefficients (K_{oc}s). Data are from Laskowski (1998). Transformed values are computed from equations 193 and 194. Half-lives are in days. K_d and K_{oc} values are in L/kg.

	m(x)	s(x)	m(y)	s(y)	Max	Min
Aer $t_{1/2}$	28.7	31.8	2.96	0.895	120	1.6
Terrt$_{1/2}$	27	24.2	3.00	0.768	91	4
K_d	106	87.4	4.40	0.720	400	13
0.01*K_{oc}	79.5	72.1	4.07	0.775	310	9.7

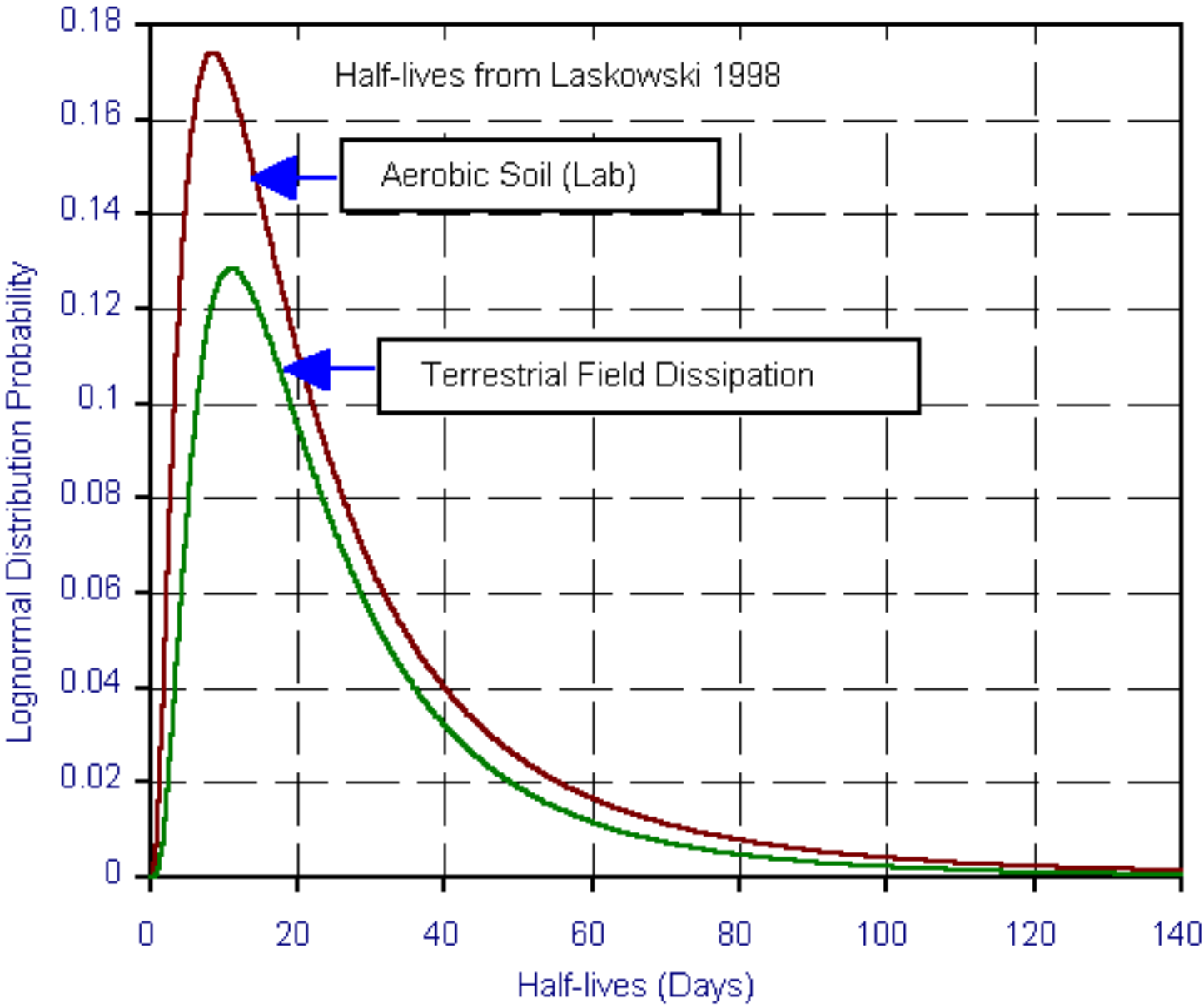


Figure 3.11-5: Chlorpyrifos half-lives.

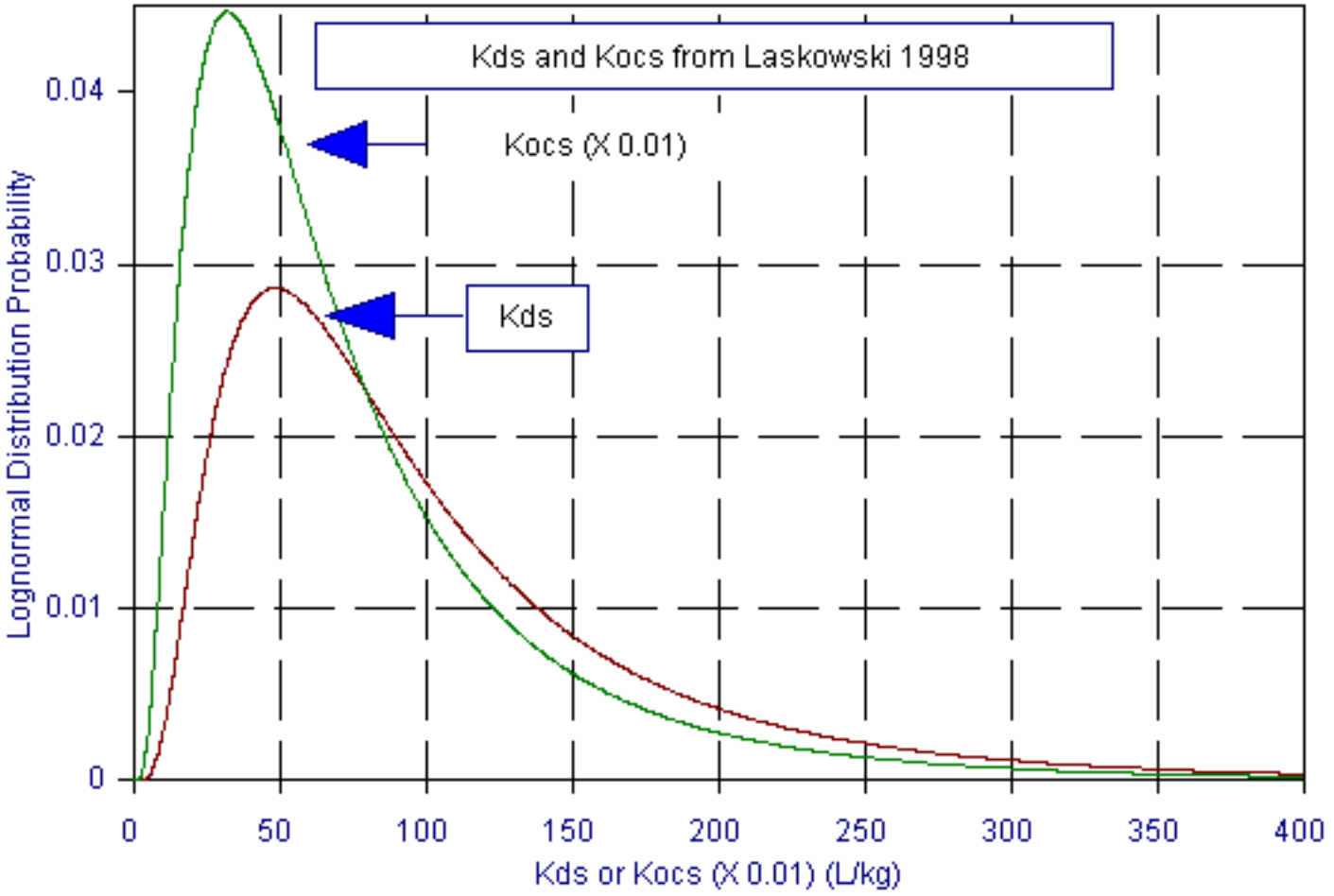


Figure 3.11-6: Chlorpyrifos Kds or Kocs (X 0.01) (L/kg)

3.11.6 Lognormal CDFs for Invertebrate Residue Data

Although it is customary to express the statistical distributions of input variables as PDFs, they can also be readily transformed to and expressed as their corresponding CDFs and readily transformed back to PDFs. Examples are as follows.

The measurements contained in the Fischer and Bowers data sets were provided by the authors to the Terrestrial Work Group. Following the approach taken by Hoerger and Kenaga (1972) and Fletcher et al. (1994), the authors normalized invertebrate residues to a 1.0 lb/A application rate. The combined data sets include measurements made within 24 h of 231 applications under a wide variety of environmental and agricultural conditions as part of 24 field studies of 10+ active ingredients. Observations were sorted from smallest to largest and cumulative exceedence probability curves (i.e., probability of equaling or exceeding a concentration) were plotted (Figs 3.11-7 and 3.11-8). The exceedence probability curves appeared to follow lognormal distributions ($r^2 = 0.99$ for foliar applications, $r^2 = 0.96$ for soil applications, $p < 0.01$ in both cases). Mean values were 5.7 ppm and 0.6 ppm for foliar and soil-incorporated applications respectively. However, because distributions were lognormal, the geometric mean is a better representation of the central tendency of these data. Geometric mean values were 2.1 and 0.04 ppm, respectively. For foliar applications, the residue level per 1.0 lb a.i./acre applied in/on invertebrates had approximately a 50% chance of exceeding 2 ppm, a 10% chance of exceeding 16 ppm, and a 5% chance of exceeding 23 ppm. For soil applications, the residue per 1.0 lb a.i./acre applied in/on invertebrates had approximately a 50% chance of exceeding 0.03 ppm, a 10% chance of exceeding 0.5 ppm, and a 5% chance of exceeding 1.3 ppm.

For screening assessments, a 5 or 10% exceedence value (i.e., a residue level expected no more than 5-10% of the time) may be selected from these distributions and used as a high-end estimate of residue levels in invertebrates. Such values would be analogous to the Fletcher nomogram values (Fletcher et al. 1994) currently used by EPA for plant matrices. For higher tier exposure assessments, lognormal distributions with means and standard deviations listed in Table 3.10-2 may be used as an input into a simulation model.

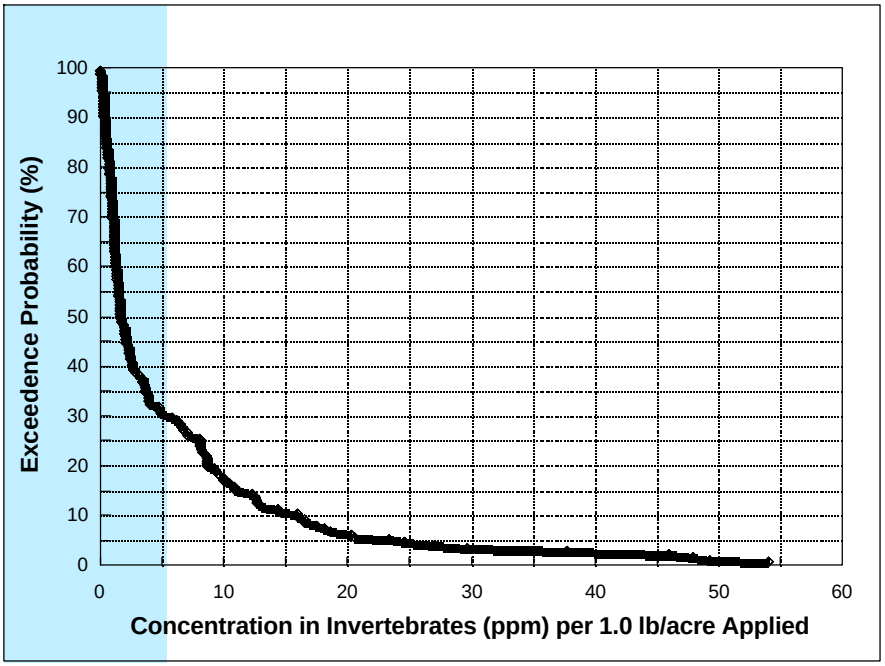


Fig.3.11-7. Exceedence Probability Curve for Residue Levels Measured in Invertebrates Collected within 24 h of Foliar Applications. Data (N=175) from Fischer and Bowers (1997). A log-linear regression demonstrated a highly significant relationship ($r^2 = 0.99$, $p < 0.01$).

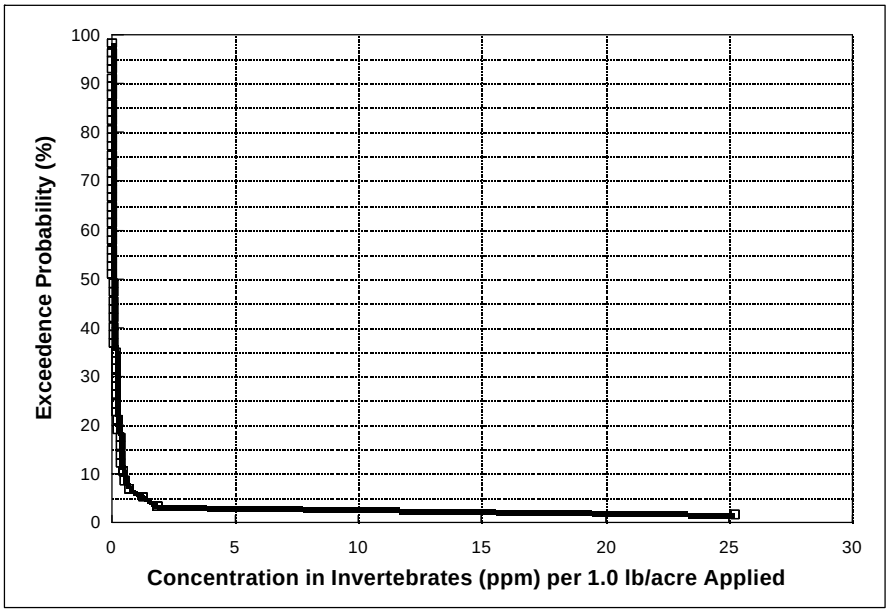


Fig. 3.11-8. Exceedence Probability Curve for Residue Levels Measured in Invertebrates Collected within 24 h of Soil Applications. Data (N=56) from Fischer and Bowers (1997). A log-linear regression demonstrated a highly significant relationship ($r^2 = 0.96$, $p < 0.01$).

3.11.7 Distributions of Biological Factors Affecting Dose

Information concerning distributions for biological factors affecting dose is limited. However, many of those factors such as food ingestion rates, water ingestion rates, inhalation rates, and skin surface areas can be estimated by substituting the body weight into equations provided in the EPA Wildlife Exposure Handbook and included in Sections 3.4 through 3.9. Therefore, in cases where distributions of the body weight can be estimated, distributions of the various biological factors depending on body weight can also be estimated.

3.12 LEVELS OF REFINEMENT FOR EXPOSURE ASSESSMENT

The preceding sections have shown how each input to the equations for exposure may be estimated in a number of ways. These range from simple, generic, deterministic estimates suitable for screening assessments, to very refined estimates using information specific to the scenario under consideration and taking more account of variation and uncertainty. These methods can therefore be organized into a series of 'Levels of Refinement', as illustrated in Table 3.12-1 for exposure through contaminated food. Methods for estimating exposure by other pathways can be organized in a similar way.

It is envisaged that organizing assessment methods into Levels of Refinement may help assessors to keep track of the status of the assessment and decide which parts of the exposure estimate to refine at different stages. The Terrestrial Workgroup intends that the Levels should be used in a flexible way, with different parameters being treated at different Levels according to the needs of the individual assessment. The process of refining the assessment is considered in more detail in Chapter 6.

Level 1 is intended as a simple Screening Level Assessment. The inputs are point estimates, though some represent conservative assumptions rather than average or typical estimates. The output at Level 1 comprises point estimates of dose for each time scale (short, medium and long-term as discussed in Chapter 2). The purpose of Level 1 is to assist the assessor in deciding which routes of exposure, if any, are significant enough to warrant more detailed analysis at higher levels of refinement.

Level 2 is intended to introduce simple distributions, either hypothetical (if data are not available

Table 3.12-1. Summary of levels of refinement for the estimation of exposure via contaminated food. Exposure by other pathways may be treated in similar ways.

Parameter	Level 1	Level 2	Level 3	Level 4
PT – proportion of food from treated area	• Conservative assumption- PT=1 (100% of food obtained from treated area)	• Allow PT < 1, i.e. take account of untreated area. • Use existing information and expert judgment to estimate distribution of PT	• If appropriate, take account of time spent in drift zone and residue levels there	• Field data on actual PT in relevant conditions • Landscape models using GIS to overlay animal movements on residue distributions
TFIR – total food intake rate (dry weight)	• Use existing estimates of intake, e.g. Nagy's equations • Adjust to conservative assumption (e.g. 3 x average daily intake) • For medium/long-term exposure, assume feeding rate constant over time	• Estimate distribution based on confidence intervals for Nagy's equations • Allow food intake to vary over time	• Estimate distributions of TFIR from original data on FMR, GE and AE (Eq. 3.6-11) • Take account of mixed diets • Assess relative frequency of short-term scenario (e.g. gorging behavior)	• Field data on actual FIR in relevant conditions
PD – proportion of diet from each food type	• Conservative assumption – diet consists entirely of the food type with the highest residues	• Hypothetical distributions based on published data • Consider seasonal variations	• Obtain raw data underlying published values and use to estimate distributions for relevant scenarios	• Field data on actual PD in relevant conditions
FDR – Fresh to dry weight ratio.	• Use average estimates for relevant food types, from the literature	• Use confidence limits for these estimates to define hypothetical distributions	• Obtain raw data underlying published values and use to estimate distributions	• Field data on actual FDR in relevant conditions • Consider dessication of food items (e.g. dead insects)

AV - avoidance	• Conservative assumption- AV = 0 (animal does not avoid contaminated food)	• Estimate AV from food consumption in dietary toxicity tests to decide whether avoidance may be important in short- and long-term exposures.		• Conduct special studies with captive animals to quantify the distribution of AV under the range of relevant conditions. Separate studies required for short- and long-term scenarios
C, residues in food.	• Estimate initial residues from application rate using empirical relationship (e.g. Fletcher et al.) • Estimate dissipation over time using data from Willis & McDowell, or soil degradation • For vertebrate prey, model intake and depuration to estimate body burden	• Models (under development) • Use hypothetical distributions for initial residues and dissipation based on confidence limits from literature, if available	• Models (under development) • Obtain raw data underlying published values and use to estimate distributions	• Field studies to validate and/or calibrate models, or measure distributions of C in relevant conditions
W, body weight	• Use average estimates for relevant species, from the literature	• Use confidence limits for these estimates to define hypothetical distributions	• Allow for age/sex differences • Obtain raw data underlying published values and use to estimate distributions	• Field data on actual W in relevant conditions
OUTPUT OF EXPOSURE ASSESSMENT	• Dose estimates are conservatively high due to conservative assumptions for PT, TFIR, PD, AV and C • Point estimate of dose for short-term exposure • Time series of point estimates of dose for medium and long-term exposures	• More realistic estimates based on approximate distributions for some parameters • Distribution of doses for short-term exposure • Distribution of doses for each time point in medium and long-term exposures	• As for Level 2, but taking account of additional factors (e.g. drift zone, mixed diets) and using better information for input distributions • Estimate frequency as well as magnitude of short-term exposures	• Distributions of doses over time based on field data for specific scenarios. • If landscape models used, output could include maps of spatial distributions of exposure at different points in time.

to develop distributions) or based on summary statistics from the literature, such as means and standard deviations. The input distributions are generic, i.e. applicable to a wide range of pesticides and scenarios, and not specific to the assessment in hand. For medium and long term exposures, the output at Level 2 and above is a distribution of doses at each point in time (e.g. daily). The purpose is to help the assessor to begin taking account of variability and uncertainty, and to identify (with the aid of sensitivity analysis) which parameters are most important so that they can be targeted in further refinement if necessary.

Level 3 provides for further refinements in parameter estimation and the quantification of uncertainty. Distributions are still generic and based on existing data, but are based on the original data rather than summary statistics. The data may be used directly to provide an empirical distribution or standard distributions may be selected (e.g. normal, lognormal etc), based on statistical tests of goodness of fit. Again, sensitivity analysis may help to decide which parameters to refine further, if any.

Level 4 is intended to focus on site- and species-specific conditions relevant to particular risk assessment scenarios. It may often require the generation of new data, including field studies focussed on providing the specific information which is required. However, it is expected that only a small proportion of assessments will proceed to Level 4. Even when this is necessary, only a few critical parameters will require estimation at Level 4, with the others continuing to be treated at lower Levels. If an explicit spatial model (e.g. GIS) is used, the outputs could include maps of the spatial distribution of exposure at different points in time (e.g. daily).

4.0 EFFECTS ASSESSMENT

4.1 OBJECTIVE AND SCOPE OF EFFECTS ASSESSMENT

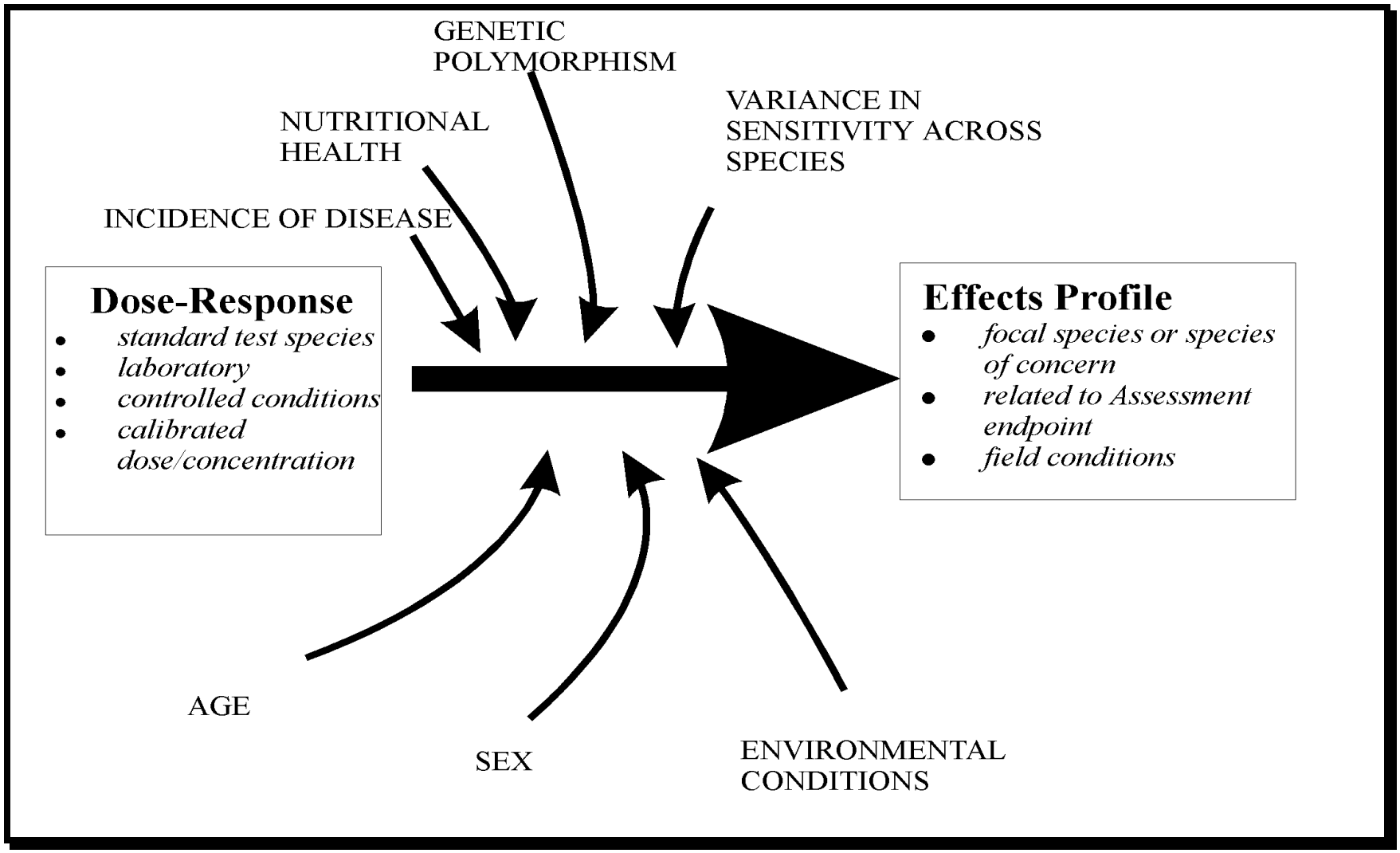
4.1.1 Introduction

An effects assessment quantifies the relationship between the dose administered (e.g. dermal, oral) or the concentration of a pesticide in media (e.g. air, food) and the effects endpoint. The objective is to evaluate and present measures of effects in a way that they can, in conjunction with the exposure assessment, be related to assessment endpoints and ultimately to management goals. This requires the use of dose-response studies conducted under controlled laboratory conditions using standard laboratory animals. The results are then "extrapolated" to a focal species in a field situation, thus defining the effects profile. (See Figure 4.1-1.) This transition from a laboratory-derived dose-response to an effects profile has traditionally assumed a one to one relationship with little accounting for the variables which will affect the toxicological response.

The purpose of this chapter is to (1) identify and quantify the sources of uncertainty and variability involved in defining the effects profile and (2) to identify and propose the data requirements, the methods, and the algorithms which provide measures of the nature and magnitude of the effects.

The output of the effects assessment is an effects profile that estimates the probability and magnitude of a specified effect to a species or taxonomic group at a given level of exposure along with the uncertainty of that estimate. The effects profile quantifies the relationship between exposure to the pesticide and the assessment endpoint. If the focus of the assessment endpoint (i.e. the species of concern) is the same as the species tested in a toxicity study, the effects profile may be the same as the dose-response relationship derived from the study. More often, however, the assessment is focused on species that are not likely to be tested; therefore the effects profile needs to account for the various

Figure 4.1-1. Transition from laboratory-derived dose-response to an effects profile.



sources of uncertainty known to exist in estimating toxicity (Figure 4.1-1). Consequently, the nature of the effects profile varies with the amount of data available, the desired level of certainty for the analysis, and the nature of the assessment endpoints.

Although some sources of uncertainty can be incorporated into the effects profile, other sources remain that are not quantified and difficult or impossible to address. One of the greatest unknowns is the relationship between laboratory results and effects in the field. This is a major problem, not only for probabilistic assessments, but also with the current use of the quotient method. Although it is possible to apply a known quantity of pesticide and document resulting effects, the exposure to individual animals at a field site varies greatly and is not directly quantifiable. Consequently, the relationship between laboratory tests and field responses can only be defined crudely. Other unquantified sources of uncertainty include the differences in inherent sensitivity between laboratory and field populations, the representativeness of the exposure scenario simulated in the laboratory, and the variable influence of stress of captivity on toxic responses among species.

4.1.2 Overview

4.1.2.1 Route of Exposure

Although the Terrestrial Workgroup focused on the oral route of exposure for purposes of developing probabilistic models, it was recognized that dermal or inhalation exposure may be important in the field in some cases. The role of the route of exposure is discussed in Section 4.1.3.1.

4.1.2.2 Data Needs

The robustness of the effects assessment is determined by the quantity and quality of the data. For many new pesticides only a single toxicity value may be available, or there could be a much more extensive data set in the case of many existing pesticides. Ultimately the data base has a controlling influence on the assumptions necessary to generalize from test species to focal species,

and the resulting uncertainty associated with such extrapolations. Further, the assessment is dependent on the level of uncertainty considered acceptable (i.e precision of the estimate of effects) and the specificity of the assessment endpoint(s). Laboratory toxicity tests provide the most common effects data available. Current test requirements, their design, and suitability for probabilistic assessments are examined in Section 4.2.

4.1.2.3 The Dose-Response Relationship

The basic element of an effects assessment for direct short-term direct toxicological effects is the dose-response relationship derived from acute oral or dietary tests with laboratory test species. The dose-response relationship describes dependence of measures of effects, usually mortality, on exposure to a pesticide over time. Each test provides a quantitative description of this relationship for one species under the conditions of the test. For any given dose, the dose-response for an acute study gives the probability that an individual will be killed at that dose, so that the dose-response is inherently probabilistic. In addition, the parameters of the dose-response (e.g., LC50, LD50, or slope) will be subject to various uncertainties. Sources of uncertainty include the statistical error associated with an individual study (conventionally represented by standard errors and confidence intervals) and various extrapolations (e.g., laboratory to field or across species). This variability and uncertainty can be expressed in the form of distributions that can be used in probabilistic assessments in place of the point estimates such as an LC50 or LD50.

4.1.2.4 Factors That Influence the Dose-Response Relationship

Several factors limit the ability of laboratory-derived dose-response models to predict the magnitude and extent of effects on natural populations. The relationship between laboratory tests and field responses can only be defined crudely because of the inability to clearly define the relationship between laboratory results (the dose-response relationship) and effects in the field. Field investigations can quantify effects on non-target species following the application of a known quantity of pesticide. However, exposure of individual animals at a field site is not quantifiable. Therefore a dose-response relationship can not be directly determined.

Other sources of uncertainty in laboratory to field extrapolations include the differences in inherent sensitivity between laboratory and field populations, the adequacy of the exposure scenario simulated in the laboratory, and the influence of the stress of captivity on the toxic response of test species. Furthermore, factors such as differences in age sensitivity, nutritional or breeding status all can affect the vulnerability of individuals to a stressor. The most important of these factors are examined in Section 4.4 for their effect on the variability in sensitivity within populations. Unfortunately too little is known to currently propose ways to quantify the uncertainty associated with each one.

As noted previously, assessments are most often required for focal species for which toxicity data are not available. Interspecific variability is a factor that introduces uncertainty in the dose-response relationship. Variation among species in sensitivity to pesticides has been demonstrated to be substantial and may be the greatest source of uncertainty in providing effects estimates of untested species. To interject a level of predictability in the effects assessment, the uncertainty associated with extrapolating effects on test species to the focal species must be considered. Methods for including this uncertainty in probabilistic assessments are discussed in detail in Section 4.5.

4.1.2.5 Higher-tier Dose Response Methods

Currently, the dose-response relationship is usually quantified using the probit model, where that model can be fitted to the data. Sometimes only a LC50 or LD50 is available. As well as discussing how to use probit results in a probabilistic analysis (or results of some other empirical model such as the logistic model), this chapter discusses at some level a variety of more refined options that may be considered for higher-tier assessments. In particular, incorporation of pharmacokinetic information may be desirable at higher tiers (Section 4.1.3.3).

4.1.2.6 Sublethal and Indirect Effects

A full accounting of sublethal effects resulting from sublethal exposure is generally lacking. These effects may result from intoxication related to the mechanism of action of the pesticide, side effects unrelated to the toxic mechanism (e.g. egg shell thinning resulting from DDT exposure), or second generation effects. If information is available, it may not be quantifiable and thus may have to be dealt with qualitatively. A discussion of the scope of sub-lethal effects and their impact is discussed in Section 4.3.

In this same section the indirect effects of pesticides are also discussed. These occur when the direct toxic effects of pesticides on individuals of a species have consequences unrelated to the toxic effect of the compound on other individuals of the same species or other species. While these effects are well beyond the capacity of existing probabilistic risk assessment methods, they should be acknowledged.

4.1.2.7 Completing the Effects Assessment

The estimated dose-response relationship for a species of concern conceptually may be derived as follows:

$$DRR_j = DRR_{tested} * Intra_F * InterF_j * SublF$$

where,

DRR_j = dose-response relationship for species j;

DRR_{tested} = dose-response relationship for one or more tested species;

IntraF = intraspecific factor is a unitless index reflecting the range of variation among studies, among age groups, etc. (default = 1);

$InterF_j$ = interspecific factor is a unitless index to account for variation among species; the index may be specific for species j based on body size (Baril and Mineau 1996) or known relationship to tested species (index = 1 if species j is the tested species);

SublF = sublethal factor is a unitless index to account for observations of sublethal

effects in laboratory toxicity tests that may have ecological implications in the field, (default = 1).

In addition to serving as a conceptualization of sources of uncertainty and variability, this scheme has been implemented partially in a quantitative manner. Multiplicative, stochastic factors can be generated corresponding to a subset of the components indicated. Levels of complexity may be added to this formula as the assessment process moves through succeeding levels of refinement. Section 4.6 discusses the process of moving through progressively more complex levels of effects assessment, where the type and amount of data used changes and the uncertainty accounted increases and/or is reduced.

4.1.3 Scope of Effects Assessment

From the time pesticides are applied and the residues settle on the landscape to the time when a toxic response is induced in wildlife, a complicated chain of events takes place. This sequence, illustrated in Figure 4.1-2, involves

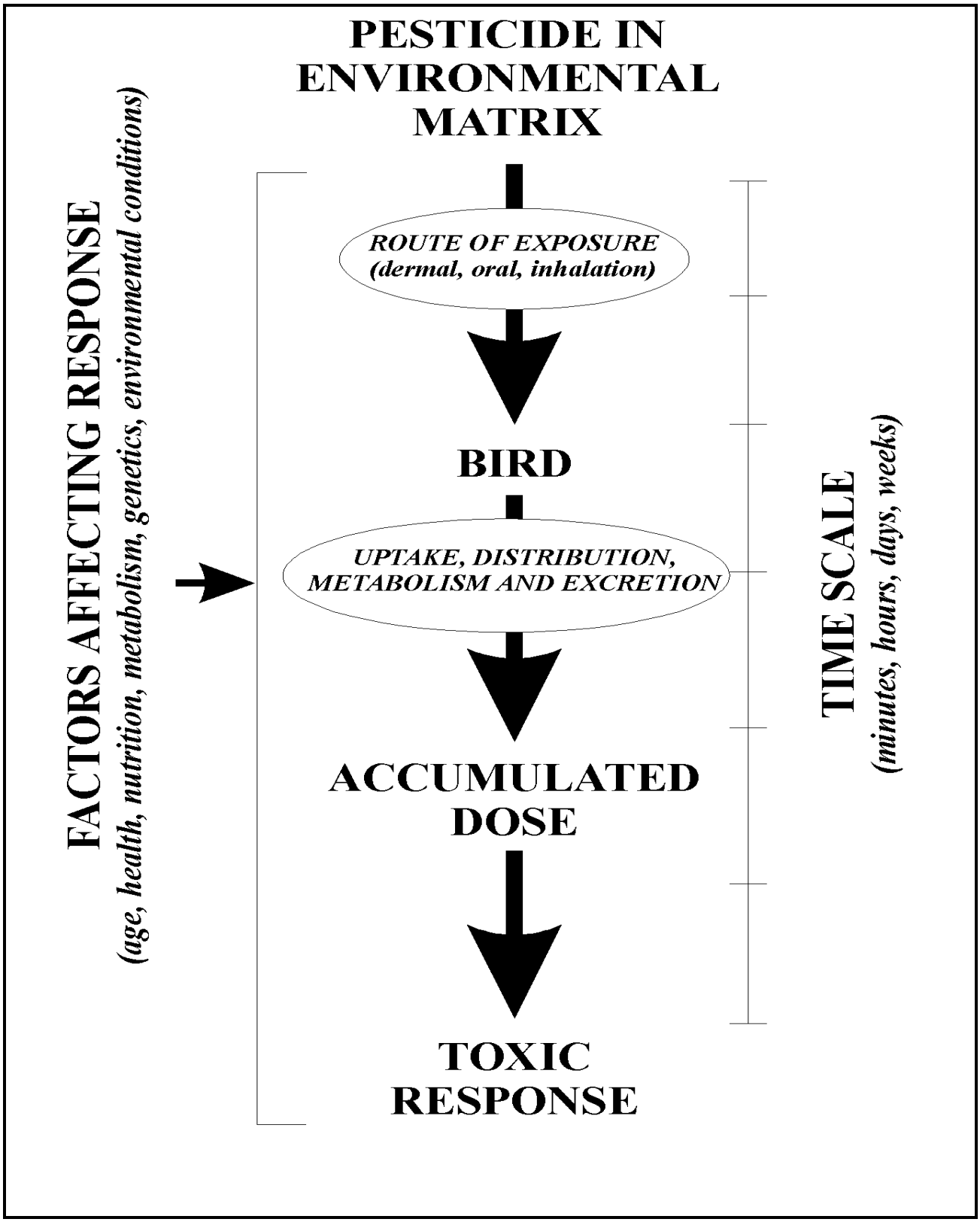
- A route of exposure (oral, dermal, inhalation), which determines how and when the individuals are exposed and the rate and amount of uptake occurring;

- The pharmacokinetic properties of the chemical within the test organism, which determines the rate of accumulation and elimination of the internal dose; and

- The interaction of accumulated dose with the target site, which causes the toxic response.

This sequence of events has a time scale, ranging from minutes to weeks, and is strongly affected by numerous factors, some inherent to the biological characteristics of the species, and others which originate from the environmental conditions in the field. As can be deduced from Figure 4.1-2, there are innumerable combinations of time scale, pharmacokinetic properties and routes

Figure 4.1-2 Sequence of events leading to a toxic response in exposed birds



of exposure not to mention the other variables. When products are tested for their toxicological effects only three sequences of the numerous possible scenarios are examined:

Test	Route	Time scale	Toxic endpoint
Acute oral LD50	Oral	minutes (or less)	Mortality
Acute dietary LC50	Oral	days (5)	Mortality
Avian reproduction	Oral	weeks (20)	Reproductive endpoints

Furthermore, the variables that may affect the results are controlled under laboratory conditions. Thus, extrapolating study results on test species to the focal species in the field includes not only the consideration of the numerous variables not dealt with in the studies, but also the route of exposure, time scale of exposure, and uptake as these factors relate to the dose calculations in the laboratory and in the field. The routes of exposure, the units of dose used in the effects assessment and how they relate to time scale, and alternate methods to arrive at the dose are discussed in the next section.

4.1.3.1 Routes of Exposure

The current testing with birds is conducted through oral dosing. However, the dermal route of exposure can be the dominant route for certain compounds and/or particular use circumstances. (Driver 1991.) Yet, standard risk assessment practices have not taken into account the other potential routes such as dermal and inhalation, and testing of compounds via other routes is presently not considered. One can argue that situations where testing through dermal or inhalation is likely to be more relevant to the particular assessment have not been identified. Furthermore, it could be argued that interpretation of the results would be more difficult because of the added difficulty of quantifying the exposure end of the assessment. Finally, more may be gained from the modeling efforts described in Section 4.1.1.3 , where dose is calculated as a body burden. At this point, the exact route of exposure of the study becomes of less important and determinations of accumulated dose become more important.

Much could also be learned from examining the results of mammalian studies. The Terrestrial Workgroup decided to focus mainly on the oral route since the studies currently available involve oral routes of exposure. The Workgroup also believed that the findings regarding this form of exposure should be applicable to other routes for the purpose of demonstrating the feasibility of conducting probabilistic assessments.

4.1.3.2 Time Scale and Dose Calculations

The importance of time scale and the options available to consider time scale for assessment purposes are discussed earlier in Chapter 2. Three time scales, which correspond to realistic exposure scenarios, are proposed in that section. This is very relevant to the calculation of dose from studies with the test species and the determinations of the matching exposure regime expected with the focal species. The difficulty comes from the studies themselves since, except for the acute oral study, the exposure is through the food and the amount of residue consumed by test individuals cannot be reliably determined. (See section 4.2.) This means that only the LD_{50} study provides information relevant to one of the proposed time scales and the associated exposure calculations. The single "bolus" exposure of the study is relevant to birds gorging on food, for diurnal feeding peaks, baits, granules, seed treatments and scenarios of secondary poisoning. For the other exposure scenarios, medium and long term, difficulties arise when trying to match dosing regime from the appropriate studies to the exposure predictions. The latter are calculated on the basis of mg of chemical per kg body weight per day. For medium and long term scenarios, the best way to express exposure is to determine the cumulative dose consumed over a period of time t. For medium term scenarios, it then remains to match the cumulative dose calculated for t=5 days with the equivalent cumulative dose from the LC_{50} study. For long term scenarios, the cumulative dose calculated for t=20 weeks is matched with the equivalent cumulative dose from the reproduction study. Unfortunately these options are currently limited by the inability to determine dose ingested over time for these two latter studies. Given this limitation three options are proposed to deal with this issue:

- Modify existing studies to accommodate individual-based determinations of daily food consumption,

- Use group mean estimates of food consumption from existing studies to obtain approximate estimate of dose consumed over time and assume 100% assimilation and 0% depuration, and

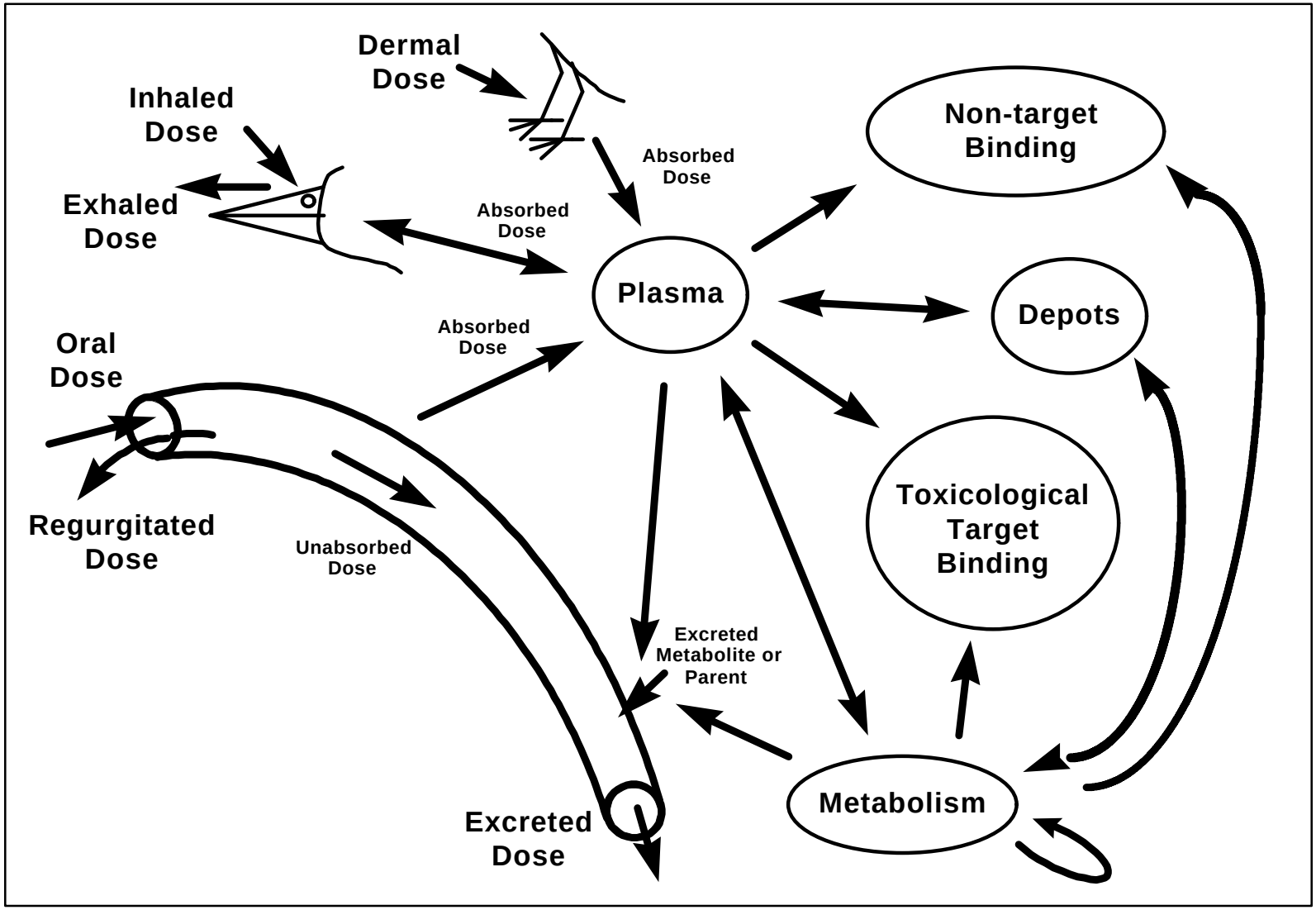
- Adopt a modeling approach, as described in the next section, with the accompanying required research and studies.

4.1.3.3 Distribution and Elimination Rates

Health effects in wildlife exposed to pesticides occur when the chemicals interact with critical molecular receptors. The amount of pesticide reaching those receptors is a function of the level of intake, balanced by elimination processes. Exposures occurring from oral, dermal or inhalation sources are the focus of most models. Elimination processes are generally based on established elimination constants that are developed using radioactivity depuration rates from animals dosed with radiolabeled pesticide. (The EPA requirement for metabolism studies of pesticides that might occur in livestock feed, OPPTS 860.1300, results in the development of chicken excretion data for many pesticides, though these studies are rarely published in the open literature). Several issues should be considered when using elimination rates and developing models that are reflective of actual elimination processes.

Once inside the body, the fate of a pesticide, and its eventual absorption and elimination, varies as a function of the pesticide's chemical characteristics, the particular species' physiology, and the health status of the exposed individual. Modeling can effectively predict pesticide levels to which an organism is exposed. Modeling of absorption and elimination processes is more complex and requires an understanding of the chemical's distribution, storage, metabolism, binding to critical and non-critical sites, and elimination (Figure 4.1-3). The importance of, and necessity for, determining these model inputs is dependent on the degree of accuracy that is desired to quantify the availability of the absorbed body burden to critical molecular receptors.

Figure 4.1-3 Absorption and elimination processes to consider for assessments using body



The maximum possible dose accessible to these receptors is that represented by total chemical dose entering the body through exposure pathways. Radiolabeled pesticide studies that document fecal excretion of labeled parent and breakdown products provide excretion rates sufficient for balancing exposure rates in screening level assessments. Should the chemical body burden reach levels of concern using this screening approach, more detailed analyses of the chemical's status in the body may be required. The following factors reflect the more intricate series of events that occurs following pesticide exposure.

Of the dose ingested, inhaled or placed on the skin, only a portion will be absorbed into the systemic circulation. The unabsorbed chemical can be regurgitated, excreted in the feces, exhaled or washed from the skin. Absorbed chemical is moved into the plasma via capillaries at the site of contact. Once in the plasma, a chemical is distributed to any of a variety of peripheral sites where it can be stored in tissue depots, metabolized, excreted or where it may react with non-target or target binding sites. The amount of chemical that actually arrives at critical receptors where it causes a toxicological response is generally much less than that applied at the site of exposure. With cessation of exposure, the presence of available chemical at the target site will generally decrease over time, whether the chemical actually is eliminated, degraded or stored in a tissue depot. The field of physiologically-based pharmacokinetic (PBPK) modeling uses detailed analyses of the absorption, distribution, metabolism and excretion processes in a variety of tissues and "compartments" in the body to predict the levels of pesticides that will actually be present at critical receptors (Medinsky and Klaassen 1996, Krishnan and Andersen 1994). Though the use of a "chemical in / chemical out" approach may be sufficient in a preliminary screening assessment of pesticide effects, assessment levels above the screening approach may require PBPK tools to better assess the kinetics of pesticide exposure to toxicological targets.

The nature of the interactions that occur at the target site must also be considered in a dynamic fashion, giving consideration to whether the interaction is reversible or irreversible. Reversible inhibitors, such as organochlorines and pyrethrins, act by inhibiting or altering the action of receptors (ion channels, signaling systems, enzyme systems) as a function of their concentration in

the vicinity of the receptor. As pesticide excretion from the organism will decrease the effective body burden of the compound, and therefore the concentration at the receptor,an elimination constant in the model will adequately reflect the reduced toxicity that occurs with time. The frequency and level of exposure will therefore determine the amount of toxicant at the target site.

Irreversible inhibitors, though they will also diffuse away from target sites with decreased body burden, have a residual effect that leads to additive effects with successive doses. The regeneration time of the target must be considered, in addition to dose level and frequency, when evaluating effects over time. Organophosphate inhibition of acetylcholinesterase (AChE) is a good example of an irreversible interaction with a target receptor. Carbamate inhibition of AChE, though generally considered an irreversible inhibition at acutely toxic doses, can be considered reversible if the interval between exposures is sufficient to allow AChE reactivation, which can often occur in a matter of hours.

A final consideration in the assessment of the reversibility of target site interaction is the potential for residual effects that might occur due to the target site-pesticide interaction. Though the mechanism of action of pesticides is generally assumed to be interaction with a particular molecular target, data show that the recovery from that interaction may not account for all of the potential effects that the interaction may induce. In particular, work with organophosphate insecticides indicates that recovery of AChE inhibition precedes recovery from many of the neuropsychological manifestations occurring from the exposure. (See Section 4.3.)

4.1.4 Mechanistic and Empirical Models

Current practice is to represent the results of an acute toxicity test using a median effective dose (LC50 or LD50). Where the data permit, a complete dose-response curve is obtained by fitting a curve. In practice usually a probit curve is fitted, determined by two parameters (the slope and the median effective dose). Other functions such as the logistic are proposed on occasion.

The resulting curve can be termed an “empirical model” because the parameters are not measured directly. The values are assigned using a statistical procedure that optimizes the agreement between observed and predicted response fractions. A more “mechanistic” approach may involve a PBPK model, with parameters that are measurable physiological or chemical variables such as fluxes and partition coefficients.

For higher tier assessments, consideration may be given to the use of a PBPK model to estimate the body burden or to estimate the concentration at a site of action. Then the probit model (or logistic model, etc.) can be fitted using the “internal” dose generated by the PBPK model in place of the “external” dose that would otherwise be used.

Possible advantages of such an approach could be an enhanced ability to extrapolate to field exposure scenarios, enhanced extrapolation across species, or better prediction of individual variability. However, such advantages may depend on availability of a database of physiological measurements beyond that required to implement a PBPK model for a single test species. For example, a PBPK may result in improved extrapolation from a test species to a focal species, if we have physiological measurements for both species. Similarly, a database of measurements for a crucial physiological parameter may help in predicting individual variation in sensitivity.

Other aspects of mechanistic modelling, which the Workgroup did not explore but recognizes as of possible interest for ecotoxicology, are

- The movement in pharmacology towards *population pharmacokinetics*, an attempt to quantify the variation in pharmacokinetic parameters in the human population in order to address variation in the effects of a given drug , and

- A less data-hungry approach than PBPK model, which would involve statistical fitting of a simplified model, e.g., a 2-compartment model. This type of approach is common in pharmacology.

While it is recognized that a reliable pharmacokinetic model would be a very useful tool in higher tier assessments, the remainder of this section focuses primarily on use of results from standard toxicity calculations such as the median effective dose and slope, which will be available even in first-tier assessments.

4.2 SUITABILITY OF CURRENT TOXICITY TESTS

Three standardized avian toxicity tests (i.e., acute LD_{50}, dietary LC_{50}, and reproduction tests) outlined in Subdivision E of Pesticide Assessment Guidelines (US EPA 1982) provide the core data for vertebrate species in an ecological risk assessment. A wild mammal toxicity test (Series 71-3) in Subdivision E is used only for specific assessments where additional mammal data are required beyond the lab rat and mouse tests from the Health Effects Division in OPP. The utility of these tests in a probabilistic assessment were evaluated for the (1) the suitably of the experimental designs to provide data required in a probabilistic assessment, and (2) adequacy of current toxicity tests as models for effects potentially experienced by wildlife.

The utility of the tests for use in PRA is dependent, in part, on how exposure is characterized. The Workgroup has proposed models to characterize exposure as the dose received through various routes of exposure (i.e., mg/kg or mg/kg/day) rather than as a measure of concentrations available in the environment (e.g., ppm in food items). As a result, the suitability of the toxicity tests must be evaluated for their potential to provide information on the toxicity of the chemical relative to dose, either in mg/kg or mg/kg/day.

4.2.1 Acute Oral Toxicity Test

The avian acute oral test provides a measure of acute toxicity to 50% of the test population (i.e., LD_{50}) in units of dose (mg/g body weight). This is pertinent to situations where active ingredients are ingested rapidly (i.e., simulating a single oral ingestion, such as with granules and baits, or

when gorging on certain food types). To calculate the dose-response curve, the test requires an adequate number of dose levels producing death in a portion of the test animals. Although the test is designed to define the dose-response relationship with emphasis on estimating the dose lethal to 50% of the test population, the risk assessment objective may be to understand the level of exposure, which will result in any mortality (i.e. the threshold dose). However, uncertainty (such as expressed by the 95% confidence interval) is much greater for estimates of the LD_5 or LD_{10} compared to the LD_{50}. To reduce the uncertainty of estimates of a threshold dose, the acute oral test would have to be designed to concentrate doses in the vicinity of the threshold, which may require a large increase in the number of animals.

Additional consideration should be given to non-lethal endpoints. Sublethal effects such as behavioral modification or lack of fright response can affect nest attentiveness, which is relevant to successful rearing of young and survival. An improved acute oral toxicity test should incorporate relevant sublethal observations, which are quantifiable and amenable to analysis. Such endpoints could include paralysis or response to stimuli.

To address questions related to the range of sensitivities among species, the Workgroup determined that the " up-down" tests (also referred to as Approximate Lethal Dose or ALD) on additional species maybe adequate to supplement data from one or more definitive acute oral tests. This up down test procedure allows additional species to be tested with a minimum of animals, because one or two animals are dosed at a time, focusing on the dose producing partial mortality.

An important consideration in conducting the ALD test is the ability to determine a slope for the dose-response relationship. The current ALD design does not determine a dose-response, and therefore the slope cannot be established. It is not clear whether the current ALD test can be modified to determine the full dose-response and the slope without reverting to the existing design of the full LD_{50} test. The Terrestrial Workgroup recommends that this issue of changes to the design of the ALD test be investigated.

One approach to creating slope estimates for these smaller data sets is based on distributions of natural variability and parameter uncertainty from existing data. This approach can be particularly useful if the test compound belongs to a class of chemicals with existing data and the species is one for which data exist for comparison. Testing of this method for concurrence with existing data sets will be necessary, but the approach offers a means by which the small data toxicity tests might provide useful data for inclusion in toxicity distributions.

4.2.2 Acute Dietary Test

The avian dietary test (i.e., LC_{50}) provides an estimate of the dietary concentration (ppm) that is toxic to birds during a 5-day exposure followed by at least a 3-day post-treatment period. The mammalian toxicity test also is a short-term dietary test, but the guidelines are less standardized.

There are several aspects of the avian dietary tests that limit their utility for probabilistic risk assessment. First, the endpoint is reported as the concentration mixed with food that produces a response rather than as the dose ingested (i.e., mg/kg/day). Although food consumption is measured, calculation of the mg/kg/day is confounded by undocumented spillage of feed (especially by mallards). Also, the group housing of birds only allows for a measure of the average consumption per day for a group. This measure is also confounded if animals die within the treatment group.

Second, the exposure period is fixed at five days, and thus the test is limited to providing a measure of effect during this arbitrary exposure period, without allowing for the differences in the temporal pattern of effects that may result from different modes of action. The interpretation of this test is also confounded because the response of birds is not only a function of the intrinsic toxicity of the pesticide, but also the willingness of the birds to consume treated food. Therefore the LC_{50} is a measure of vulnerability to the pesticide rather than a measure of inherent toxicity. Because, the LC_{50} value is partially an artifact of the study design, its adequacy as a model of

dietary toxicity in the field has been questioned (Mineau and Baril 1994). As Hill (1995) stated, "The LC_{50}, per se, has little value as a quantitative descriptor of toxicity because far too many factors affect chemical fate and availability to be accommodated by any standard laboratory test".

Third, dietary concentrations are held constant throughout the study. Consequently, the effects will be more representative for chemicals that degrade slowly or that are bioaccumulative, while effects for chemicals that degrade rapidly may be greatly overestimated.

In the short-term, the current avian dietary test can be used to provide an estimate of the dose-response relationship during a five-day exposure period. This will require an estimate of dose in mg/kg per bird per day from estimates of food consumption. Clearly several other modifications in the study design will be required to improve its utility in predicting pesticide effects. The test must be designed to account for the daily dose that produces an effect over time (e.g. a dose-time response relationship). This will provide not only information on a species tolerance to a pesticide through a dietary route of exposure, but insights into the temporal development of effects. The length of the study must be modified to accommodate the temporal pattern of potential exposure to the pesticide rather than basing the effects endpoint on a fixed exposure duration. New and innovative analytical techniques (such as time to event or dose to event analyses) will be required to expand the understanding of the dose-response relationship beyond the LC_{50} determination.

The temporal pattern of effects could also be evaluated, as proposed through OECD, by calculating an incipient LC_{50}, defined by the point in the study when the LC_{50} does not decrease by more than 10% over two days, based on a test of at least 5 days but not more than 21 days. As discussed in Section 4.2.1, the dietary toxicity test should incorporate relevant sublethal observations that are quantifiable and amenable to analysis. Such endpoints could include paralysis or response to stimuli or challenges. Lastly, the experimental design should mandate individual housing of test animals to allow for measures of individual food consumption to better facilitate a calculation of the dose-response relationship. This will require using older birds and de-emphasizing mortality as the only endpoint, since the response of birds may vary greatly

depending on the mode of action, and sublethal effects may more accurately define the hazard of the test material. The proposed guideline for a dietary toxicity test being developed by OECD addresses many of these issues and provides an appropriate basis for designing a test that is more suited for a probabilistic risk assessment. The proposed revisions are intended to address the deficiencies of the current test, primarily the failure of the current design to provide hazard information that is relevant to free-ranging birds.

4.2.3 Avian Reproduction Test

The avian reproduction test provides an estimate of the dietary concentration (ppm) at which statistically significant effects are detected on a suite of parental and reproductive parameters after an exposure period of approximately 20 weeks-approximately 10 weeks prior to egg laying and 10 weeks during laying. There are several aspects of this test that limit its utility for probabilistic risk assessment. The endpoints are reported as the concentration in food rather than as the dose ingested (i.e., mg/kg/day). Like the LC_{50} test food consumption is measured; but, the calculation of the mg/kg/day is confounded by undocumented spillage of feed (especially by mallards) and significant increases in food consumption once the photoperiod is extended to induce egg laying. The reproduction test is not designed to determine a dose-response relationship. The study endpoints are the no-observable-effect concentration (NOEC) and lowest-observable-effect concentration (LOEC), which are a function of the selection of the dietary concentrations to test and the power of the test. The effectiveness of identifying an effects threshold is highly variable among tests. The NOEC could be well below the true effects threshold or represent a concentration that produces an effect that is not detectable given the power of the test. Recently, the concept of the NOEC has been criticized by ecotoxicologists for these reasons. Additionally, the test usually does not provide information to predict the magnitude of effect at a specified concentration or dose above the effects threshold. An exposure assessment can calculate the probability of exposure exceeding the NOEC, but with current information the effects assessment the probability of a specific magnitude of effect cannot be calculated. Also like the LC_{50}, the avian reproduction study uses constant dietary concentrations throughout the treatment period

while the concentration of a pesticide in the field usually is reduced over time. Consequently, the observed effects will be more representative for chemicals that degrade slowly or that are applied repeatedly, while effects of chemicals that degrade rapidly will be overestimated. The reproduction study as it was initially designed was intended for bioaccumulative chemicals and recommended that exposure begin well before the onset of egg production. As such, the results provide little insight into the temporal development of effects, such as whether the onset of effects occurs rapidly after exposure or is delayed after a long period of accumulation. Mineau et al. (1994) in a review of reproduction studies concluded that the study, as it is designed currently, be recognized only as a rough screening tool.

The proposed OECD guideline for avian reproduction addresses one of the points above. By starting pesticide treatment with birds already in egg production, the temporal onset of effects to egg and juvenile production can be determined. It also is designed to have increased statistical power over the current design. However, the OECD guideline also remains focused on determination of the NOEC (expressed as a dietary concentration) rather than the dose-response relationship and uses constant dietary concentrations.

The Terrestrial Workgroup discussed study design changes which would permit a determination of a dose-response relationship by increasing the number of dietary concentrations in the range of partial effects and using regression analysis to define the dose-response relationships. These changes are technically feasible but require additional discussion on the specific questions to address, endpoints of primary interest, and statistical procedures appropriate to analyze temporal patterns of effects. However, the committee ultimately concluded that uncertainties inherent in extrapolating from a laboratory reproduction study to reproductive effects of free-ranging birds with vastly different life history strategies are too great at this point to justify a major redesign of the current avian reproduction study to generate a dose-response relationship. For some higher tier assessments it should be possible to specifically design a dose-response reproduction test that is predictive of reproductive effects for a specific pesticide use scenario. For example, in situations where guideline reproduction studies fail to consider specific characteristics of the

pesticide, such as rapid degradation rate or alternative routes of exposure, an alternative avian reproduction study could be designed to simulate the predicted exposure profile of a pesticide for a specific species. The study could be designed to develop a dose-response relationship by using starting concentrations that are representative of the distribution of exposure concentrations. Modifications to the avian reproduction test for probabilistic assessments should be coordinated with harmonization efforts through OECD.

4.2.4 Summary

The acute oral study as currently designed is suitable for use in probabilistic risk assessments, but is most relevant for acutely toxic chemicals that can be consumed rapidly, such granular products or formulations applied to food types consumed rapidly (e.g., gorge feeding). The dietary test has several aspects that limit its use in an effects assessment where exposure is expressed as a dose rather than as a dietary concentration. Both the dietary LC50 and avian reproduction studies could be modified to calculate dose ingested. However, additional design changes would be required to improve their usefulness in PRA. The proposed OECD guidelines address several of these design changes, but other issues remain to be addressed in the further development of probabilistic risk assessments.

4.3 INDIRECT AND SUB-LETHAL EFFECTS

These items are discussed briefly here because research results have implicated these effects in documented impacts on individuals or populations. It is necessary to identify these issues which currently lack adequate study, models and test data necessary to develop probabilistic assessment methods.

4.3.1 Indirect Effects

Indirect effects of pesticide applications occur when one group of individuals, not necessarily exposed to a pesticide, is affected by changes resulting from direct toxicity to another, different group exposed and affected individuals. For instance, if the individuals directly affected by the pesticide are adults caring for eggs or young, their death, lack of attention or abandonment will result in the death of the offspring, who may have never received any exposure to the toxic compounds. This type of effect has been demonstrated under simulated and actual field conditions with organophosphate insecticides (Meyers and Gile 1986, Brewer et al. 1988). Alternatively when the individuals affected by the pesticide are another species that represents food, cover, competition or a predation threat to the first species, others may suffer from the loss of these individuals.

All pesticides are intended to kill certain organisms, and those target organisms have ecological connections to other non-target organisms (e.g., insects used as food by birds, weed plants used as cover by mammals). The best documented example of indirect effects of pesticides is the decline of the grey partridge in Sussex, England. A series of studies over a 30-year period documented the reduction in invertebrates along the border of crop fields due herbicides and broad-spectrum insecticides and the subsequent effects on partridge chick survival due reduced insect food availability. In a recent review of 40 species of farmland birds in the United Kingdom (Campbell et al. 1997) the authors concluded that 50% of these were in decline. There was evidence of short and long term declines in the abundance of many of the types of invertebrates and plants on which these birds feed, and that these declines were, in part, attributable to the effects of pesticides.

Indirect effects may be more important than direct toxicity in many pesticide use scenarios, but they are considerably more complex to understand and to quantify experimentally. This is because the ultimate extent of indirect effects is often larger in scope than can be clearly determined by short-term localized field studies. They also may result through a combination of

actions, including cultivation, irrigation, and the suite of agricultural chemical practices, rather than simply the application of a single pesticide. As a result, the pesticide registration process historically has not adequately addressed indirect effects, and as currently constituted, may be incapable of addressing them.

4.3.2 Sub-lethal Effects

In the development of an ecological risk assessment for a specific chemical, sublethal effects on non-target organisms pose an unpredictable scenario. Current FIFRA registration data provide information on mortality and some reproductive effects, but very little data on adverse effects of sublethal exposures.

Sublethal effects can be grouped into several categories:

1) Direct effects related to the intended toxic mechanism of action,
2) Those which are side effects unrelated to the toxic mechanism, and
3) Unanticipated effects in progeny of exposed breeding adults.

Examples of the first category are mechanism specific, with, for example, neurotoxin effects such as morbidity, depression, and appetite loss in adults exposed to organophosphates or carbamates, or hematocrit loss and internal bleeding of birds exposed to anticoagulants. The list of anticipated sublethal effects is as long as the list of mechanisms of action. The consequences of direct toxic sublethal effects may be temporary or permanent, and result in reduced fitness of exposed individuals with likely consequences of decreased food consumption, reduced growth, decreased resistance to disease, and/or increased susceptibility to predation. This group of sublethal effects could be included in any risk assessment model, by incorporating a term for the anticipated loss of some individuals through decreased fitness.

Side-effects unrelated to the intended toxic action include such consequences as eggshell thinning

by DDT or dicofol, an effect not related to the neurotoxic effects of these sodium channel disrupters. Estrogenic effects of o,p'-DDT, methoxychlor, and lindane are also actions not related to the intended toxic mechanism. Such side effects are not predictable, and can only be detected by empirical observation, but screening for all unanticipated consequences in adults is unrealistic. FIFRA incorporated eggshell thickness screening only because of historical data linking DDT to effects on wildlife, and this test was included because of the importance to non-target birds. Similarly, some other endocrine disruptive effects will be evaluated under the Food Quality Protection Act, but no universal screening for other side effects is planned. The incorporation of sublethal side-effects into risk assessment models is complicated, because a specific element must be incorporated into the model for each identified side-effect. It is very important to include such effects in the risk assessment model, however, because side effects unrelated to the direct toxic mechanism lead to a second universe of risk to the exposed population. The eggshell thinning effects, for example, were more important than the direct toxic effects of DDT as a hazard to birds in the environment.

Behavioral effects of organophosphates, including suppression of incubation and nest defense, and alterations in migratory orientation of juvenile birds are additional examples of unanticipated direct side-effects. Each of these must be included in the risk assessment separately, for a complete risk assessment to be constructed.

The third major category includes pesticides and other chemicals which have adverse effects on the progeny of exposed breeding birds. These effects are usually mediated by incorporation of chemical into the egg, with consequential alteration of embryonic development. Testicular feminization and/or suppression of copulatory behavior in male progeny by estrogenic compounds, liver P450 induction by incorporation of PAH-like compounds into yolk, and alterations in avoidance behavior through exposure of eggs to organophosphates are examples of this class of effect. These effects can be either organizational effects, which will permanently alter the differentiation of an organ, or they can be temporary, activational effects, with the physiological state of the embryo or hatchling returning to normal following metabolism or

excretion of the compound. The universe of second generation side-effects is not well characterized, and poses a difficult problem for risk assessment. Current FIFRA registration tests do not screen for side effects in birds in a rigorous manner, and completely ignore second generation effects. The choice of test species in current testing is quite limited, with only precocial birds being examined, because of the necessity to artificially incubate eggs and rear young birds independently from the exposed adults within the current test framework. Many known sublethal effects are missed by not evaluating the behavior of adult breeding birds, and most sublethal effects of endocrine disrupters are missed by not evaluating the anatomy or physiology of the progeny. Development of testing procedures with passerine birds using natural incubation and parental care of chicks would greatly increase the breadth of detection of possible side-effects.

There is currently a move to better quantify some of the sublethal endpoints that threaten wildlife species, particularly in the area of subtle and second-generation reproductive effects. Modification of LC_{50} and reproductive test guidelines, as part of the harmonization process with OECD, proceeds with inclusion of endpoints including quantification of food consumption, observance of behavioral response and expansion into less traditional species (OECD Reference). The Endocrine Disrupter Screening and Testing Advisory Committee (EDSTAC) was formed to recommend specific tests for sublethal effects of endocrine disrupting and modulating chemicals. The recommendations from their final report include screens for effects in hormone and hormone receptor levels, tissue response to modulators and, at higher tiers of assessment, avian reproduction testing modified to include substantial sublethal assessments in the parental, f1 and f2 generations (US EPA 1998).

Though these testing procedures will test for specific and developmental side effects, it should be noted that individual specific tests will not address the general problem of screening for other unanticipated effects of a test compound. It will remain a challenge to develop a protocol that would be universal in its ability to screen for a wide variety of unanticipated side effects. In the absence of such an all encompassing protocol, there is much to be gained by increasing the

information gathered in conventional testing protocols and using the harmonized and supplemented EDSTAC protocols to better assess sublethal effects of test compounds. Further, with the development of new pesticide chemistries posing unknown risks, an understanding of the mechanism of action of the new compounds in their toxicity to wildlife can provide additional insights necessary to anticipate some of the more subtle sublethal effects that can occur.

Risk assessment models for birds should include elements for assessing sublethal effects. Direct toxic sublethal effects could be included by incorporating an additional term in the set of equations assessing mortality effects. Side-effects not related to the direct toxic mechanism of action will be more difficult to incorporate, but should be included when identified. The example of eggshell thinning should be used as a model for inclusion into the risk assessment, and other side-effects, when identified, should be included in a similar manner. Since side effects may be of greater hazard to birds in environmental conditions, it is highly important for any ecological risk assessment that they be included.

The charge to the committee was to develop tools and processes that account "for direct and indirect effects that pesticides may cause," but went on to focus attention on direct acute and chronic effects on terrestrial avian vertebrates due to the limitations of time and resources for the committee. As a result, the Workgroup focused attentions on improving the process for the assessment of direct toxicity, with the acknowledgment that indirect and sublethal effects also need to addressed if the pesticide risk assessment process is to understand the full ramifications of the use of pesticides. It is recognized that the proposed models and approaches emanating from the Terrestrial Workgroup do not and cannot address indirect and sublethal effects, and that additional work is required before the ecological effects of pesticide use can be realistically assessed.

4.4 UNCERTAINTIES ASSOCIATED WITH INTRA-SPECIES VARIABILITY

The dose-response relationship based on a laboratory study represents the effects information for a single species, under the specific conditions of the study. For an acute toxicity study,

evaluation of the results leads to an expression for the probability of response as a function of dose, which is inherently a probabilistic result (relating to variation in response within a species).

Use of laboratory dose-response information in a risk assessment is subject to diverse uncertainties including statistical error associated with estimates (as represented by standard errors or confidence bounds), and an array of extrapolative uncertainties. A number of factors, intrinsic to the species, the test population and conditions, and the toxicity measurement process, can contribute variability around toxicity estimates. An understanding of the sources of this variability makes possible selection and development of better data for probabilistic assessments and facilitates the extrapolation processes necessary for under-represented species. This section documents sources of this variability and methods to account for it in probabilistic risk assessments.

4.4.1 The Probit Model and Other Dose-Response Models

A full discussion of alternatives to current use of the probit model is beyond the scope of ECOFRAM. Because of the general familiarity of toxicologists with that model, it is used here for most of the illustrations of probabilistic calculations.

The concept of a distribution of tolerances. Even under carefully controlled laboratory conditions, some animals will be killed at a given dose while other survive; variability under field conditions is likely to be substantially greater. It is conventional to describe the probit model by assuming a distribution of tolerances among individuals. The animal's tolerance is the highest dose of a pesticide it can ingest without dying. For the probit model specifically, it was assumed that the tolerances have a lognormal distribution.

For concreteness, assume a dietary study is available, so that the parameters are the LC50 and the slope. Expressing the probit results in terms of a tolerance distribution, the distribution of logs of tolerances is normal with parameters:

mean=log(LC50),

standard deviation=1/slope.

(Base-10 logs are conventional in probit calculations.) Output of SAS Proc Probit includes the mean and standard deviation calculated in this way. (SAS is a trademark of SAS Inst. Inc.)

For the sake of probabilistic analysis, it is sometimes helpful to note that the dose response function is equivalent to the cumulative distribution function (CDF) for the distribution of tolerances. For any distribution, the CDF [conventionally denoted F(x)] gives the probability that a value drawn at random from the distribution will fall below x. If F(d) denotes the probability that a random tolerance will fall below dose d, then

$$P(\text{mortality at dose } d) = P(\text{ tolerance} < d\ ) = F(d).$$

The Slope Parameter for the Probit Model and Other Models. It seems important that a large database of ecotoxicity results is available based on the probit model. To use results based on the probit model in some alternative model (such as the logistic) would not necessarily be straightforward -- to use an alternative model may require fitting the preferred model to the raw data.

This applies in particular to the slope parameter. For the probit model, the slope expresses the change in response (in probit units) per unit change in dose (expressed as logarithms). For some other choices of a dose-response function (and for the logistic model in particular) it is possible to define a slope parameter analogous to the probit slope. However, the slope would not be interchangelable with the probit slope because different “probability units” would be involved (e.g., logits instead of probit units). In addition, the specific version of the logistic model suggested in Appendix A3 does not involve logarithmic transformation of the dose, unlike with standard application of the probit model.

4.4.2 Sources Of Intra-Species Variability And Their Relative Magnitudes

4.4.2.1 An Evaluation Of Sources Of Variability For Laboratory Toxicity Measurements

Current acute toxicity testing protocols are designed so that the slope of the dose-response can be estimated and reported along with a measure of the statistical confidence of the estimate. The question thus arises, when reporting the uncertainty associated with the slope in probabilistic risk assessments, on whether the error reported on the estimate of the slope accounts for all the sources of uncertainty expected from laboratory-derived data. Also, the problem of the relevance of a slope determined on one species to all other species remains. The variability in the response of the test population has many sources:

- The source of the animals (genetic stock, wild-caught vs. captive-bred vs. domesticated),
- The condition of the animals (nutritional status, incidence of disease),
- Environmental conditions in captivity,
- Method of dosing and other aspects of the experimental protocol, and
- Inherent toxicodynamic and toxicokinetic characteristics of the compound.

Along with the differences among species in morphology and biochemical and physiological processes, the last variable is at the source of inter-species differences in the slope of the dose-response curve. (See discussion on this in Section 4.6.) More subtle variations in these characteristics are also the cause of variation between individuals within a single species. To decide whether the error reported with the slope within a study is sufficient to account for all the uncertainty expected, four sources of variability were examined using a variety of data. The results are presented in Table 4.4-1. The four sources of variability examined were:

Table 4.4-1 Various sources of variability associated with the slope of the dose-response curve.

Sources of variability	Source of data	Number and nature of data points	Measure of variability	Recorded variability
Within test	LD_{50} historical database, multiple laboratories, all replicates, multiple species	39 estimates of slope and the standard error	Standard error as % of slope	22-65% (median=27%)
	LC_{50} data, dieldrin positive controls (Hill and Camardese 1986), same species	45 estimates of slope and the standard error	Standard error as % of slope	11-44% (median=20%)
	LC_{50} data, dicrotophos positive controls (Hill and Camardese 1986), same species	28 estimates of slope and the standard error	Standard error as % of slope	12-31% (median=20%)
Within laboratory	LC_{50} data, dieldrin positive controls (Hill and Camardese 1986), same species	45 replicate tests	Standard deviation as % of mean slope	24%
	LC_{50} data, dicrotophos positive controls (Hill and Camardese 1986), same species	28 replicate tests	Standard deviation as % of mean slope	26%
Among tests	LD_{50} historical database, multiple laboratories, same species (includes some replicates within the same laboratory)	4 chemicals with at least three replicates	Standard deviation as % of mean slope	17-52% (median= 36%)
Among species	LD_{50} historical database	5 chemicals chemicals with at least three species	Standard deviation as % of mean slope	26-122% (median=53%)

1. Within-test variability. This is the error associated with the estimate of the slope; for every slope reported with a standard error, the ratio of the two was determined. The range and median of the ratios are reported. For the three sets of data, the medians are approximately 20%.

2. Within-laboratory variability. Replicate tests on the Japanese Quail, reported by Hill and Camardese (1986) as positive controls in acute lethal dietary tests (LC_{50}) were examined. While the variability in the response is expected to be larger for the LC_{50} test than for the LD_{50} test, it was the degree of replicability of the slope estimate that is examined here. It is assumed that this should be the same for the two toxicity tests. The ratio of the standard deviation of all the slope values over the mean of the same yields values of 24 and 26% for dieldrin and dicrotophos respectively.

3. Among-test variability. The historical database of LD_{50} values was examined for products where replicate tests were conducted on the same species, including those from the same laboratory and those from multiple laboratories. The ratio of standard deviation to the mean of the reported slopes ranged from 17 to 52% with a median of 36%.

4. Among-species variability. The historical database of LD_{50} values was examined for products where the slope was determined for at least three species. The ratio of the standard deviation over the mean of the estimates for 5 chemicals ranged from 26 to 122% with a median of 53%.

If the variability from differences among species is ignored, the variability within a test is not outside the range of the values reported among laboratories and among tests. This would seem to indicate that use of the reported error on the estimate from any given test would account for most of the variability expected across tests. This is not, however, a formal statistical approach to this question which merits greater attention then what is given here. At the very least, the standard error should be used as the measure of uncertainty surrounding the estimate of the slope, until further work is carried out.

This analysis provides an idea of the relative magnitudes of different sources of variation and uncertainty. For additional analysis application of variance-components models may be desirable. Variance components models are a statistical tool adapted to quantifying the relative contributions of variance from different sources. However, further analysis is significantly limited by the available data, so it may not be possible to pursue the analysis of sources of variability significantly beyond what is presented. The ideal database for this type of analysis would result from systematically repeating a study, in the same and different laboratories for one chemical.

4.4.2.2 Factors Influencing Intra-Species Variability

The factors discussed above concerned characteristics of the dose-response of the test population itself. Of equal importance are those factors which influence this response either in the laboratory or in the field and which can play a significant role in determining the shape of the effects profile for the key species. The influence of these factors, some intrinsic to and some outside the population, is what has been traditionally accounted for by a "laboratory to field" correction factor. In the following section the effects of the age of the birds on their sensitivity is discussed as this is a crucial element from the point of view of assessing population impacts. The last section will briefly touch on other factors thought to influence the variability in the response of birds to pesticides.

Life Stage Sensitivity. Within the test species, life stage can play an important role in the level of chemical sensitivity. Younger birds and mammals can be more sensitive to pesticides than their adult counterparts. Other considerations, such as breeding or migration status, can also affect toxicity. Documentation of these occurrences and understanding of their mechanisms are important to allow for adjustments in toxicity distributions and accounting for most-sensitive life stages. Similarly, extrapolation from tested to non-tested species must proceed carefully, giving consideration to the life stage of the laboratory-generated data and that of the species to which it is being extrapolated.

Due to their greater nutritional needs during development, young animals, overall, consume greater amounts of food as a function of their body weight, per day. They are thus exposed to higher relative doses of chemicals compared to their parents. In addition to their increased exposure levels, both mammalian and avian species have demonstrated age-dependence in their sensitivity to organochlorine and organophosphate pesticides. Whether toxicity increases or decreases with age depends on the chemical class and species.

Studies with avian species have shown mixed sensitivities to pesticides at the youngest ages of exposure. Many organochlorine and a few organophosphate compounds are less toxic at the earliest exposure ages (1.5 days post hatch) in precocial mallards. Most organophosphate pesticides, however, are more toxic to younger ducklings and become less toxic as the birds mature (Hudson et al. 1972). Acute oral toxicity studies with altricial passerine species, focusing on European starlings and red-winged blackbirds, consistently show increasing nestling sensitivity to organophosphates with decreasing age (Grue and Shipley 1984, Meyers et al. 1992, Wolfe and Kendall 1998). The European starling appears to be the most extreme case, with nearly a 100-fold increase in sensitivity to diazinon in nestlings compared to adults (Wolfe and Kendall 1998). In this case, increasing amounts of the enzyme, butyrylcholinesterase, protect the older starlings and its selective removal can experimentally decrease adult LD_{50} values down toward those of the nestlings (Leopold 1996, Parker 1998). Little more is known about the occurrence or mechanisms of nestling sensitivity to the many other pesticides in use today.

Data on the sensitivity or resistance to pesticides in older wildlife age groups is lacking. The cost of maintaining test animals into their latter years of life and the consideration that long-lived animals have had adequate time to effectively reproduce prior to their exposure have likely minimized the effort made to collect these data. As the concern for wildlife does not simply imply that they are disposable once they have successfully bred, further study is needed to assess wildlife at later stages in their life.

There are currently insufficient data on age-dependent toxicity of pesticides to allow their incorporation into probabilistic risk assessments. What little data are available indicate that

estimates of toxicity made for adult wildlife can underestimate the toxicity potential that exists for their young by a factor up to 100-fold. A mechanism for development of these data and their inclusion into the risk assessment process is needed. Until that time, assessments of pesticides applied during the breeding season should consider the potential for nestling sensitivity at exposure levels lower than for adults.

Additional Factors Influencing Intra-specific Variability. Intra-specific variability in toxicity test responsiveness can occur due to a variety of factors in addition to age. These include test animal health, nutritional status, metabolic status and the occurrence of genetic polymorphisms. Deviation from standard test protocols leading to changes in test conditions can also affect the responsiveness of test animals and thus the comparability of generated data with those collected under standard conditions.

The overall health of the test animals can affect their sensitivity to toxicants. Animals in poor health may have less capacity to withstand insecticide exposure. Nutritional status can also influence toxicity, whether considering the long-term pre-dosing period, or the 24 hours prior to initiation of exposure. The pre-exposure extremes of starvation and ad libitum feeding can strongly affect the toxicity of an insecticide compared to animals maintained on a diet that keeps them healthy yet lean. Dietary components, such as phyto-estrogens in feed, can affect animals in reproductive toxicity tests, altering background data or interacting with test chemicals (Donaldson 1994).

Other factors that increase intra-specific variability are those that create or account for differences in the physiology of test animals. In particular, those factors that can cause changes in metabolic rates can influence both the profile and quantities of pesticide metabolites as well as the duration they are resident in the exposed animal. Factors that can affect metabolism include age, gender, hormonal status, pregnancy, disease and diurnal and seasonal cycles (Ronis and Cunny 1994).

Genetic polymorphisms within a species can lead to distinct sub-populations of test animals having specific sensitivities or tolerances to test chemicals. These differences can have their basis

in subtle differences in chemical disposition or receptor sensitivity. The development of pesticide resistant insect populations provided early evidence of this effect, however wild rodent populations that have evolved a resistance to endrin and a number of rodenticides have demonstrated that vertebrates contain, in their genomes, similar capabilities (Walker 1994). These polymorphic genes that impart resistance to one portion of a population also leave a portion of the population with a selective sensitivity to the same chemical. Variability of polymorphism prevalence and expression in test populations can increase variability in test response. Limited studies show that some wildlife test species have low occurrence of cross strain variability in test endpoints (Hill et al. 1984) but little work exists to allow extrapolation of these findings to wildlife species in general.

Though the potential for increased variability exists due to the above factors, the control of test animal health and husbandry, and test conditions can provide stability to the test system that minimizes much of the potential interference. When combined with controls on other potentially interfering test factors, such as ambient temperature, light/dark periods, chemical formulation and administration techniques, intra-species variability can be minimized to the greatest extent. Yet these same factors are present in wild populations and are likely influence the outcome of exposure to pesticides. Currently, little is sufficiently know about the influence of these factors to consider incorporating this uncertainty in probabilistic risk assessments. Nevertheless one should be aware that under certain circumstances their influence may be substantial and highly relevant to the assessment endpoint.

4.4.3 Use Of Dose-Response Information In Risk Assessment

In the context of probabilistic calculations, probit results of particular interest include: (1) The point estimates of the probit parameters (slope, median and effective dose). These two parameters define the complete dose-response. The dose response gives the probability that an animal will be killed at a given dose, and thus may be viewed as inherently a probabilistic result. (2) Confidence intervals represent the precision of the estimates of the probit parameters, taking into account the spacing of doses, the number of test animals used per dose, and the variability in

the response variable. This chapter discusses ways of using this information in risk assessment (See Chapter 5.) Analogous results are available for alternative dose-response models, such as the logistic model; the probit model is used for illustrations of probabilistic techniques.

4.4.3.1 Extrapolation of LD_5's or Other Low-response Dose Level

Earlier approaches to protecting sensitive individuals involved choosing a fixed fraction of the median lethal dose (e.g., $LD_{50}/10$) for comparison with expected environmental concentrations of a chemical. This method did not incorporate chemical specific information on the slope of the toxicity dose-response curve, so that adverse effects at low exposures may be underestimated when the dose-response curve is shallow. As an alternative, an estimate of another response level (e.g., LD_5, LC_1or $LD_{0.01}$) can be calculated based on the calculated LD_{50} (or LC_{50}) value and the slope of the probit-line (Finney 1971, Hill and Camardese 1986). Estimates of lower-end response levels, based on the median lethal dose and its associated slope, provide greater confidence (Baker et al. 1994). Therefore some probabilistic effect assessments have focused on LD_5 or LD_{10} values as more conservative estimates in toxicity distributions.

Concern over the reliability of such extrapolations arises because of variability in slope estimates between and within laboratories for any given chemical, and because of the relatively wide confidence intervals for low-toxicity dose levels. Determinations of acute toxicity are generally made with measurement techniques biased toward highest statistical precision in the midrange value, the LD_{50} or LC_{50}. The statistical error of the estimates, quantified by the 95% confidence interval, increases as one moves away from the median measure. Regulatory levels of concern set at 5% or 10% response values, for example, have substantially lower confidence in their estimates than do estimates set around the 50% range.

In choosing a level of response, the need for using low levels of effect to protect wildlife should be balanced with lower precision for the response measure. This variability stems from the parameter error associated with the determination of the slope and LD_{50}. This aspect of

paramater uncertainty is examined in Section 4.4.3.3 and a method is proposed for incorporating this uncertainty into probabilistic assessments.

4.4.3.2 Generating Random Mortality Decisions

A complete account of variability will address variability in exposure, and also address variability in the responses of individuals to a given exposure level. This section is concerned with the second source of variability (variability of response, given exposure). Algorithms are presented for generating "random mortality decisions" for individual animals. Let d denote the exposure for a single animal in a Monte Carlo risk assessment algorithm. Then the outcome of the random mortality decision is either that the animal is scored as "killed" or "survives." The probabilities for these two events are P(d) and 1- P(d) respectively, where P(d) can be calculated using the dose-response function. (See Chapter 5.)

Alternatively, in some situations where the number of individuals is large, the need for random mortality decisions can be avoided and the value of P(d) used directly. Details of the Monte Carlo simulation scheme may depend very much on the problem formulation, particularly with regard to issues of spatial scale.

Note that this section treats the parameters of the dose-response model (e.g., slope, LC50) as if they are known. (Random mortality decisions are based on a given slope and LC50, but those parameters are not varied in the Monte Carlo algorithms.) In actuality, these parameters are subject to a range of uncertainties.

Regarding the form of P(d), the probability of response at exposure d, the range of possibilities is not reviewed here thoroughly. However, two possibilities have actually been suggested in parts of this document. First, for the probit model without background mortality,

$$P(d) = \Phi(\text{slope} * [\log d - \log LD_{50}])$$

There $\Phi(x)$ denotes the CDF of the N(0,1) distribution. (In other words, $\Phi(x)$ is the tail area of a N(0,1) distribution corresponding to values below x.) The function $\Phi(x)$ is an integral that cannot be solved analytically; however programs for numerical evaluation of the function are widely available, including "@functions" in some widely used spreadsheet programs.

Second, f or a form of logistic model suggested in Appendix A3,

$$P(d) = P_1 / \{ 1 + \exp[(2.2 / (LD_{10}-LD_{50})) * (LD_{50} - d)] \}.$$

Here P_1 (≤ 1) denotes the maximum response percentage: as dose increases the it is assumed that the response percentage approaches P_1, which may be less than 100%. Appendix A3 may be consulted for additional details on use of this expression.

Access to random number generators is assumed for : (1) a uniform distribution on the range 0 to 1, and (2) a standard normal distribution (a normal distribution with mean 0 and variance 1). If a software package has random number generators for two or more distributions, these two distributions will ordinarily be included. Adopting conventional notation, these two distributions are here denoted U(0,1) and N(0,1).

Algorithm 1. Having generated d, calculate P(d) using the preferred dose-response model (e.g., the probit or logit model), a random probability decision can be generated as indicated in Appendix A3:

Step 1: Select a random number from the U(0,1) distribution; and

Step 2: If the value generated in Step 1 falls below P(d) then the animal is scored as a mortality; otherwise as a survivor.

Algorithm 2. In some situations (particularly for the probit model), an alternative algorithm emphasizes the notion of a tolerance distribution:

Step 1: A random tolerance is generated from an appropriate distribution. Based on the probit model, the following formula may be used:

$$\text{random tolerance} = LD_{50} * 10^{(z / slope)}$$

where z has the N(0,1) distribution. The derivation of this formula is outlined in Technical Note 1 in Appendix D1.

Step 2: The random tolerance generated in Step 1 is compared to the exposure d. The individual is scored as a mortality if its exposure exceeds its tolerance; otherwise it is scored as a survivor.

This approach may have heuristic appeal because it relates directly to the idea of a distribution of tolerances. Also, the need for numerical evaluation of $\Phi(x)$ is avoided in the case of the probit model. The approach has been implemented in the PARET model (Appendix A2).

Technically, this approach can be applied with dose-response functions other than probit, by drawing tolerances from a distribution other than the lognormal distribution. However, it appears that this approach would be equivalent to Algorithm 1 in terms of the resulting distributions, but numerically inferior. (See Technical Note 2 in Appendix D1)

4.4.3.3 Statistical Confidence in the Dose-response

The methods described to this point treat the dose response function as if the parameters (e.g., slope and median effective dose) are known. In actuality they are subject to a range of uncertainties. This section is concerned with how statistical precision (as quantified by confidence intervals in probit analysis) can be addressed in probabilistic analyses. Because acute toxicity studies are optimized for estimating a median effective dose, the uncertainties considered will be particularly important in extrapolating effects at low exposure levels. This section proposes specific algorithms, as well as discussing some conceptual issues.

The early chapters of the text by Hahn and Meeker (1991) are helpful for placing the information provided by confidence intervals in perspective.

Cases involving extremely wide bounds for the LD_{50}. It has been observed that for some data, the confidence bounds for the LD_{50} may equal zero or infinity. Such outcomes may be prevented by the constraints encoded in the ToxAnal program regarding the data that will be accepted. However, the following hypothetical data displayed below meets the constraints but produces an extreme bound for the LD_{50}, relative to the point estimate.

For the following hypothetical data, the chi-square test indicates a good fit of the probit model:

	1	2	4	8	16
dose:					
#on test:	10 (all)				
#killed:	3	5	7	7	7
Slope (CI)	0.88 (0.02 - 1.7)				
LD_{50}	2.3 (10^{-11} - 7)				

Problem cases are likely to involve little change in the response fraction over the range of doses tested. Technically, the LD_{50} is related to the ratio of the probit intercept to the probit slope, and if the intercept and slope are both close to zero precise inferences regarding the ratio are difficult (Cox and Hinkley, 1974, Example 7.13).

In this type of situation use of the point estimate of the LD_{50} would seem risky, but this does not mean that the data are useless for any purpose (Cox and Hinkley 1974). The hypothetical data just given suggests that mortality is substantial at least for the upper range of doses tested, possibly useful information. The Workgroup suggests that the Monte Carlo approach described in the section can make use of whatever information is available from a given study. The

uncertainty associated with reliance on less-than-perfect data can sometimes be placed in proper perspective by adopting a probabilistic approach.

Natural Variability, Uncertainty, and Parameter Uncertainty. An important distinction from the risk assessment literature is the difference between uncertainty and natural variability (e.g., Burmaster and Wilson 1996, Brattin et al. 1996). A rule of thumb sometimes used to understand this distinction is that uncertainties can be reduced by collection of more information; we seek to characterize natural variability. According to this rule, confidence intervals can be viewed as representing a component of uncertainty (Brattin et al. 1996). To some extent the widths of the intervals can be reduced (indicating greater confidence) by using more animals. Using more animals is not necessarily expected to result in higher or lower values of the slope. Specifically, confidence intervals can be described as quantifying a form of parameter uncertainty. Note that the category of uncertainty is diverse – the Workgroup makes no claim that confidence intervals will capture all or most of the uncertainties that apply in a given situation.

Hierarchical Monte Carlo. The parameters of the probit model can be viewed as parameters of a probability distribution. (In the $\log_{10}$ scale, the mean tolerance is the log of the median effective dose (LC50 etc.); the standard deviation equals the inverse of the slope.) However, these parameters are themselves subject to uncertainty. For this type of situation, the risk assessment literature suggests hierarchical Monte Carlo simulation (e.g., Burmaster and Wilson 1996, Brattin et al., 1996). This type of approach, sometimes described as using a "distribution of distributions", involves nested Monte Carlo simulations. In an outer loop, values of a parameter are drawn from distributions chosen to represent parameter uncertainty. For each sample of parameter values, an inner loop involves a Monte Carlo simulation to represent variability.

Can parameter distributions be based on confidence intervals? In Monte Carlo simulations, it is common to select distributions based on confidence intervals, e.g., by fixing the 2.5th and 97.5th percentiles of the distribution at the bounds of a 95% 2-sided confidence interval. Actually the standard interpretation of a confidence interval (e.g., Sokal and Rohlf 1995) treats the interval as random and the parameter as fixed (not having a distribution). The intervals are viewed as

random because they are calculated from variable data. According to this formulation, the confidence coefficient (e.g., 95%) is the probability that a randomly-generated interval will enclose the true parameter value. Therefore some authors have objected to basing Monte Carlo input distributions on confidence intervals (e.g., Warren-Hicks and Butcher 1996). Cox and Hinkley (1974) advise against manipulating confidence coefficients as probabilities, in particular to treat the joint uncertainty for multiple parameters.

A response sometimes given invokes Bayesian theory, which does assign distributions to parameters (the prior distribution and the posterior distribution). In many situations there are standard uninformative prior distributions for which the resulting Bayesian intervals (termed credible intervals) are equivalent to familiar confidence intervals. There is no general principle that such a Bayesian interpretation can be given to a confidence interval calculated by any method. However, there are some grounds for a Bayesian interpretation of the standard intervals from probit analysis (Box and Tiao 1973, Seber and Wild 1989, Gelman et al., 1995).

While this is a type of Bayesian approach it is not equivalent to Bayesian analysis, Bayesian results depend on the choice of prior distribution. In particular, one is relying on a very flat prior, as appropriate in situations where much prior information is not available or the results could be strongly influenced by prior information. Some “Bayesians” would argue that prior information is usually available and should be incorporated into the prior distribution.

Alternatively these issues may be approached from a classical viewpoint, by undertaking Monte Carlo “coverage” experiments. Such experiments involve generating simulated data sets based on fixed parameter values, and calculating the probability that an interval calculated from a simulated data set will enclose (cover) the true parameter values. If the 95% probability intervals from the proposed Monte Carlo method have approximately 95% coverage, then the approach should be acceptable from a classical viewpoint.

From a practical standpoint, if the confidence intervals quantify some kind of uncertainty, an approach is needed to capture that uncertainty in probabilistic assessments. When a particular

approach is roughly appropriate from either a Bayesian or classical perspective, the distinction may seem like splitting hairs.

Distributions for the probit parameters. Chapter 5 provides an illustration of a hierarchical Monte Carlo simulation and includes a simulation which involved the following assumptions for the distributions of the probit parameters:

- The slope was assumed to be normal,
- The median effective dose was assumed to be lognormal, and
- The slope and median effective dose were assumed to be statistically independent.

For the slope, the mean and variance were obtained by fixing percentiles equal to standard confidence bounds as output by a probit program. Similarly, percentiles were equated to confidence bounds to obtain a lognormal distribution for the median effective dose.

This section describes a more refined joint distribution for the two probit parameters, for the situation not involving control mortality. The distributions suggested are the asymptotic distributions suggested in Finney (1971). For the slope, the result will be identical to the distribution just described. However the marginal distribution of the median effective dose will differ. Also, the two parameters are not assumed to be independent. The approach has been implemented in a spreadsheet program.

Outline of the asymptotic distributions from Finney (1971). Following Finney (Expression 4.30), it is convenient to "reparameterize" the probit model. Instead of the parameters being the slope and the LD50, the parameters chosen are the slope (denoted b) and a quantity. Finney denotes $\bar{y}$, evidently analogous to a grand mean in the context of ordinary linear regression. The re-parameterized probit line can be expressed as:

$$\text{probit response} = \bar{y} + b\,(x - \bar{x}).$$

Here x is the dose (ordinarily in the log base 10 scale) and $\bar{x}$ is a weighted average dose.

The purpose of expressing the probit model in this form is that b and $\bar{y}$, unlike b and the LD50, can be treated as having normal distributions and as statistically independent. Formulae for the variances of b and $\bar{y}$ are found in Finney (Ch. 4) and are not repeated here. (The variance formulae make use of intermediate calculations in Finney's iterative fitting scheme. The formulae are available in a spreadsheet.)

The independence and normality of b and $\bar{y}$ are convenient in deriving the standard ("fiducial") confidence intervals; these features are convenient here for Monte Carlo simulation. In Monte Carlo simulation values for $\bar{y}$ and b can be generated from independent normal distributions, as described in the scheme below. Having generated random values of $\bar{y}$ and b, the value of the LD50 can be calculated using the formula:

$$\log(\text{LD50}) = \bar{x} + (5 - \bar{y}) / b.$$

The weighted average dose $\bar{x}$ is not treated as uncertain in standard probit analysis. As in regression, no distribution is assumed for an independent variable. Technically, $\bar{x}$ does have a statistical error because it is calculated using weights that depend on the independent variable.

As an approximation, it is customary to ignore this error in weighted nonlinear regression calculations.

<u>Application in Monte Carlo Simulation.</u> These results justify the following Monte Carlo scheme, given here in outline, applicable in cases that do not involve control mortality:

Step 1. Calculate $\bar{x}$, $\bar{y}$, and the slope (b) from raw acute data using standard probit calculations.

Step 2. Calculate the variance of $\bar{y}$ and the variance of b (standard probit calculations)

Step 3. Repeat Steps 3a-c a large number of times, generating a distribution of parameter values:

Step 3a. Generate a random value for $\bar{y}$. The random value has a normal distribution. The mean of the distribution is the value calculated in Step 1; the variance is calculated in Step 2.

Step 3b. Generate a random value for b. The random value has a normal distribution. (The mean is from Step 1; the variance is from Step 2.)

Step 3c. Calculate the random LD50 from the random $\bar{y}$ and the random b.

The Marginal Distribution of the LD50. If these expressions are used, then the marginal distribution of the slope is a normal distribution; for the distribution of the LD50, no distribution is assigned directly: distributions are assigned directly to b and $\bar{y}$; a random values of the LD50 may be calculated from random values of b and $\bar{y}$.

The resulting distribution of the LD50 will often be approximately lognormal; however, in the historical development of the probit method, the possibility of assuming a lognormal distribution was considered and rejected as "unsatisfactory as a general technique" (Finney 1971, Bliss 1945). However, a lognormal approximation will be accurate when the standard errors of parameter estimates are small. (This seems to follow from asymptotic normality of maximum likelihood parameter estimates.)

Correlation of the Slope and LD50. When multiple parameters are estimated from the same data, they cannot be assumed to be independent. SAS Proc Probit routinely prints the covariance of the slope with the log of the LD50. For probit analysis, the correlation may be positive or negative, depending on whether the LC50 is in the upper range of doses tested or in the lower range. (See Technical Note 3 in Appendix D1).

Should the probit parameters be treated as independent in Monte Carlo simulations? Note that the result above applies to the correlation of statistical errors for estimates of the two probit parameters, when they are estimated using the results of a single study. However, the distributions used in a Monte Carlo simulation may represent variation among studies. The statistical correlation just discussed may have mininal affect on the correlation of actual slope and LC50 values across studies.

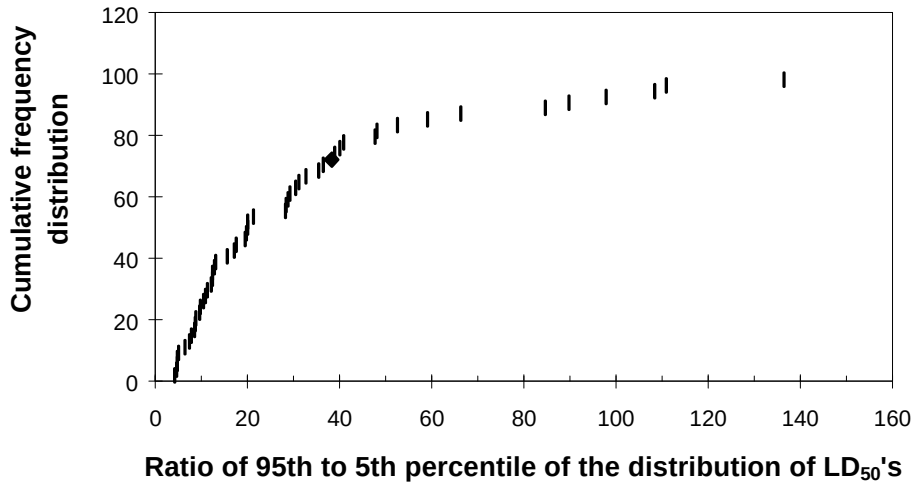
The Workgroup suggests that if the Monte Carlo input distributions represent primarily variation among studies (particularly among species), the correlation of the parameters across studies should be evaluated graphically, using scatterplots. If there is no indication of correlation across studies, the parameters can be treated as independent in Monte Carlo simulations.

4.5 INTERSPECIFIC METHODS AND VARIABILITY

4.5.1 Introduction

One of the largest sources of uncertainty associated with field predictions of the impacts of pesticides on terrestrial animals comes from the large variability in the sensitivity of species to toxic chemicals. It is well recognized that for plants and animals alike, both in terrestrial and aquatic environments, the range of sensitivities can extend up to three orders of magnitude. This is illustrated for birds in Figure 4.5-1. For 53 carbamate and organophosphate insecticides the LD_{50}'s among species of birds range from 5 to over one hundred (ratio of 95^{th} to 5^{th} percentiles of the lognormal distribution). For 70% of the products this range extends between 10 and 100. Thus, not only can the range be wide but the variance changes dramatically among compounds.

Figure 4.5-1. Range in species sensitivities for 53 insecticides tested with at least six species of birds



For technical and financial reasons only a few species of birds can ever be tested for their susceptibility to pesticides. Only rarely are test species the same as those likely to be exposed under field conditions. This implies that test results from one or a few standard test species need to be extrapolated to all field species. Given the large amounts of variability among species it is expected that interspecific differences in sensitivity will yield large amounts of uncertainty in the risk assessment process. This uncertainty can be accounted for in the process of developing probabilistic risk assessment methods.

This section will argue for the use of historical test data to develop standardized factors for extrapolating across species and to account for the expected variance among species. Taxonomic relationships among species sensitivity data are examined and the implications for the development of extrapolation methods are discussed. Two approaches are proposed, each fitting into one or more of the risk assessment methods discussed in chapter 5. The first approach consists of methods to extrapolate, from test species data, to a fixed level of protection; in this case, a level which encompasses 95% of the predicted species sensitivity distribution. The second approach generates a predicted distribution of species sensitivity again from one or more test species studies.

The data generated from acute oral toxicity studies (i.e. the LD50 study) conducted on birds for the past two decades form the basis to the development of the methods discussed here. The reasons for this are that (1) the acute oral toxicity study better reflects the "inherent" toxicity of a compound than any of the other existing acute tests, (2) a large number of tests were conducted on many species for numerous compounds, and (3) the methods used to conduct the LD50 studies conform to well established protocols which have changed little over time.

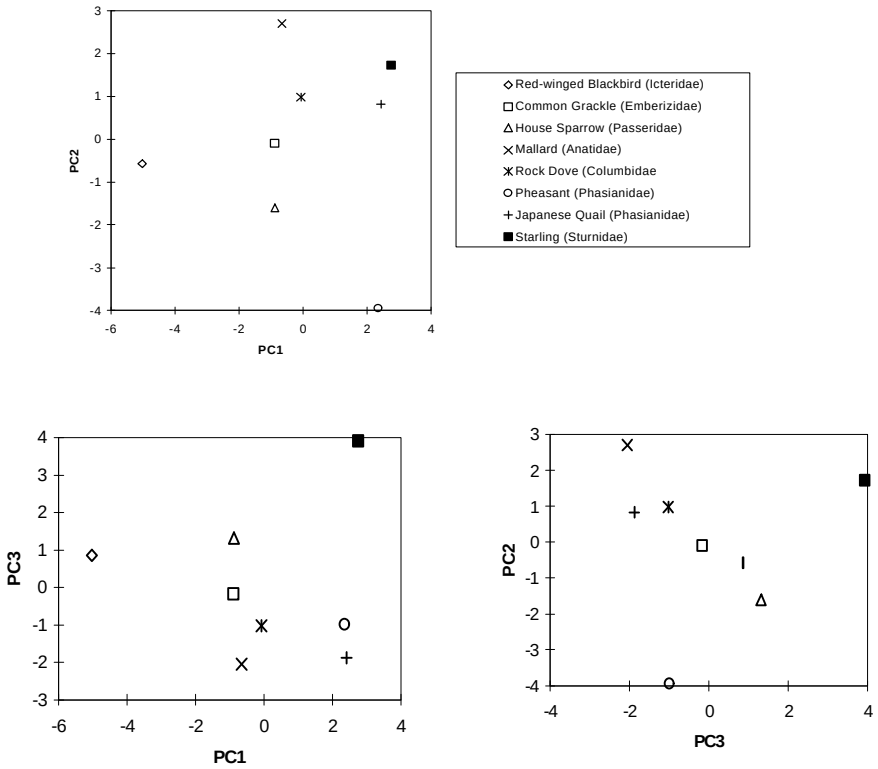
4.5.2 Analysis of Phylogenetic Relationships among Species Sensitivity Data

In order to investigate interspecies differences, it is critical to determine whether data from any group of species can be considered independent estimates of the toxicity of a given product to birds at large or whether phylogenetic aspects have to be taken into consideration.

Baril et al. (1994) conducted two separate statistical analyses to detect patterns in the sensitivity relationships among species and to determine whether these patterns are due to phylogenetic relationships. First, a principal component analysis (SAS, 1988) was conducted on a subset of a database of avian LD_{50} values. This subset of 176 LD_{50} values for 8 species and 22 cholinesterase-inhibiting chemicals was selected to avoid missing data. Principle component analysis is an ordination technique that allows for the visual inspection of multivariate data. Any existing trends in species sensitivities to chemicals should emerge by collapsing the data into a number of principal components. A three-way analysis of variance was also conducted on the main database with the exclusion of chemicals or species with only one observation and of phylogenetic groups with only one species. This dataset consisted of 489 observations for 74 chemicals, 25 species and 6 phylogenetic categories. The latter were obtained by grouping the 25 species into five families and one sub-family: Anatidae (4 species), Columbidae (3), Emberizidae (2), Phasianidae (9), Icteridae (5) and Passeridae (2).

The results of the principal component analysis run with eight species and 22 chemicals are illustrated in Figure 4.5-2. The analysis by species shows that the ranking of species sensitivities tends to persist across chemicals. Red-winged Blackbirds are by far the most sensitive followed,

Figure 4.5-2 . Illustration of the principal component analysis run on 8 species and 22 chemicals.



as a group, by the Common Grackle, the House Sparrow, the Mallard and the Rock Dove. A second group of species, the Pheasant, Japanese Quail and the Starling, trails off as the least sensitive. This pattern is illustrated on the first principal component in Figure 4.5-2. The loadings of the chemicals on this component (30% of the variation explained) are consistently high indicating that these three groupings are ranked consistently across insecticides. The second and third principal components separate out the Pheasant and Starling respectively. These observations are most likely due to deviations from the pattern noted above, where for some compounds, these two species are either extremely sensitive or insensitive. These "outliers" may reflect real differences in sensitivity or problems with the studies. From a phylogenetic point of view the only obvious separation seemed to be between the two Icteridae and the two Phasianidae.

The results of the three-way analysis of variance showed that each of the three variables, species ($F=4.2$, $P<0.0001$), chemicals ($F=21.3$, $P<0.0001$) and phylogeny ($F=7.9$, $P<0.0001$), explained a statistically significant proportion of the variability. A multiple comparison procedure (Ryan-Einot-Gabriel-Welsch Multiple Range Test) again allowed for the statistical separation of only two taxonomic groupings: the Icteridae and the Phasianidae.

A number of other authors have examined the phylogenetic patterns in the sensitivity of avian species to pesticides (Joermann 1991, Schafer and Brunton 1979, Tucker and Haegele 1971). These have demonstrated, as discussed above, that across many pesticides, patterns of sensitivity exist between some families of birds. Yet, each species shows a wide range of sensitivities among the same pesticides. For instance, while some are generally less sensitive than others, they can occasionally be ranked as the most sensitive. In conclusion, there are probably enough exceptions to prevent the development of a predictive approach based on phylogenetic relationships. Nevertheless, taxonomy has to be considered when making inter-species extrapolations. Based on our analysis, at least two groupings of species, based on taxonomic relationships, can be separated according to their sensitivity across cholinesterase-inhibiting chemicals.

4.5.3 Derivation of Extrapolation Factors to Predict a Pre-detemined Protection Level

4.5.3.1 An Introduction to Distribution-based Approaches to Interspecific Variability

The concept of using distributions to represent the possible universe of species sensitivities to toxic chemicals is not new. In essence, this approach assumes that "…sensitivity of species is a stochastic variable that can be characterized by fitting a probability density function to test endpoints (e.g. LC_{50}s) for several species…" (Suter 1993). This concept was used in deriving water quality criteria for the protection of aquatic life by the U.S. EPA (Stephan et al. 1985). The Netherlands also uses this approach to establish protection standards for both soil (Van Straalen and Denneman 1989) and aquatic (Kooijman 1987) organisms. A number of probability distribution functions were proposed such as the log-triangular, log-logistic and log-normal. These differ in their shapes, in particular, at the tail-ends of the distributions. This is significant, especially for triangular distributions, which implies that a threshold dose or concentration exists below which there are no sensitive species. This implies in theory that protection thresholds can be defined which protect 100% of all species. The issue of threshold values for toxic chemicals is still the subject of debate. Work done with experimental toxicity data on aquatic invertebrates does indicate that there is a good fit to the log-logistic model.

For obvious reasons the whole universe of wild species cannot be tested for their sensitivity to pesticides and therefore the true parameters of the distribution cannot be determined. Thus, estimates of distribution parameters based on small sample sizes have some uncertainty associated with them. Dutch investigators have incorporated this uncertainty in the determination of confidence limits for thresholds protective of a fixed percentage of species (Van Straalen and Denneman 1989, Aldenberg and Slob 1993). The implication is that, for any given chemical, as the sample of species tested increases the protection threshold also increases.

A number of criticisms have been raised regarding distribution-based extrapolation models. Forbes and Forbes (1993) provide a criticism of such models. The authors question the validity of the assumptions inherent to these models, including that (1) "the distribution of species sensitivities in natural ecosystems closely approximates the postulated theoretical distribution", (2)

"the sensitivity of species used in laboratory tests provide an unbiased measure of the variance and mean of the sensitivity distribution of species in natural communities", (3) " by protecting species composition, community function is also protected", and that (4) "interactions among species in communities/ecosystems can be ignored". While these questions raise important issues, little can be done at this time, with current knowledge, to address them. Some of the issues surrounding the validity of current lab to field extrapolations can be examined in the context of intraspecific variability as discussed in section 4.3. In spite of these criticism it should be noted that the adoption of a distribution approach to dealing with species differences in sensitivity is an improvement to the assessment of risks to wildlife and essential to probabilistic assessments.

As mentioned previously distribution-based approaches to species sensitivity are used to set specific protection criteria for various media in different jurisdictions. These distributions, in conjunction with distributions of exposure can also be used to calculate proportions of species affected under specific exposure models or scenarios. For products with acute oral tests (LD_{50}) on four species or more the values can be fitted to a log-normal or log-logistic distribution directly. The parameters of the distribution are thus determined for the product undergoing assessment with some error associated with parameter determination that is a function of the sample size. The mean and standard deviations are determined directly from the data and used as inputs into the methods described in chapter 5 to characterize risk. With birds, the minimum number of species required to apply this direct approach to tackle interspecific variability was established by Luttik and Aldenberg (1995) at four. These authors explained that when n (the number of species) is small, the likelihood of underestimating the variance is very high. Therefore, when predicting the 5th percentile (or any percentile) of the distribution with small n, the estimate will tend to be closer to the mean than where the real value (for the population) lies.

Aldenberg and Slob (1993) derived a series of extrapolation constants, each of which is tailored to a specific n, so as to compensate for this bias. When Luttik and Aldenberg tried to use these same factors to obtain the 5th percentile with their data they found that when n<=4 the extrapolation constant are so big that the predicted 5th percentile would be exceedingly low. This is somewhat arbitrary and the optimum number, in terms of minimizing uncertainty while keeping

the amount of testing within reasonable bounds is yet to be established and will require some work. (See recommendations in Chapter 7.) For the moment, the Terrestrial Workgroup does support the use of this threshold of four species to establish the shape of the distribution. Furthermore, the relationship between body weight and toxicity needs to be considered. (See discussion following.)

Under current testing requirements for avian risk assessment, only one or two species are usually tested. This precludes the use of the distribution approach discussed above for the assessment of new products. The uncertainty associated with extrapolating from studies conducted on usually no more than two species to the universe of possible wild species is large. Two similar methods to quantifying the uncertainty as a function of the number of test species were proposed independently (Baril, Jobin, Mineau and Collins 1994, Baril and Mineau, 1996, Luttik and Aldenberg 1995) and are summarized below. Both of these approaches are based on (1) a retrospective analysis of historical data on the acute oral tests (LD_{50}) with numerous pesticides and bird species, and (2) the assumption that the distribution of species sensitivities, or LD_{50}s, approximates a log-logistic distribution. The objective of both methods is to derive extrapolation factors that, when applied to a small sample of LD_{50}s yields an estimate of the 5th percentile of the predicted distribution of the species sensitivities for that product. They differ in some of the assumptions and variables considered: Baril and co-authors take into account the scaling of toxicity on body weight and the taxonomic trends in sensitivity discussed in the previous section. While the extrapolation factors developed by Luttik and Aldenberg are the same regardless of the test species, those of Baril and co-authors are specific to the test species or the combination of test species available.

While these methods do not predict the full range of the distribution they may be useful for initial screening purposes of new compounds or for comparative work among many products where indices of effects are developed. Depending on the questions asked they may represent flags or benchmarks of effects in the risk characterization phase, especially where methods 1 and 2 are used. (See Chapter 5)

4.5.3.2 Method developed by Luttik and Aldenberg (1995)

Using a database of historical data that includes insecticides of varying modes of action, the authors propose an algebraic approach based on the following points:

- The standard deviation of the logarithm of the LD_{50}s is independent of the respective means across pesticides. A "pooled" standard deviation is thus calculated from the historical data and used when nothing is known about the variation in species sensitivity (i.e. when the number of test species data are less than 4), and

- No assumption is made about which species are to be used as test species from which extrapolations are made. That is, it assumes that species sensitivities are randomly distributed without any trends or patterns associated with phylogeny. Thus it also assumes that no prior knowledge about the nature of the test species is necessary.

The following steps were used in deriving extrapolation factors:

Step 1: The "pooled" standard deviation is calculated from all the LD_{50} data across all pesticides in the database.

Step 2: An algebraic solution is derived for the calculation of the extrapolation factor based on the "pooled" standard deviation and the number of LD_{50}s available. The extrapolation factors, when applied to the test species data predict the 5th percentile of the log-logistic distribution (sensitivity across species) and the one-sided 95% left confidence limit of the normal distribution.

The resulting calculations arrive at a constant extrapolation factor for the median estimate, the 5th percentile of the distribution and a series of extrapolation factors, decreasing with the number of LD_{50} values available, for the one-sided 95% confidence limit of the estimate of the 5th percentile of the distribution (Table 4.5-1).

Table 4.5-1 Extrapolation factors developed by Luttik and Aldenberg (1995) which aim to predict the 5th percentile of the species sensitivity distribution from one or more test species LD_{50}s.

Number of test species	Median estimate	95% one-sided left confidence limit
1	5.7	32.9
2	5.7	19.6
3	5.7	15.6

4.5.3.3 Method Developed by Baril and Mineau (1996)

This approach recognizes the following points:

- Phylogenetic patterns in species sensitivities do exist, although there are enough exceptions to prevent the development of a predictive approach based on phylogeny alone. (See section 4.5.2.) Nevertheless, the derivation of extrapolation factors from historical databases needs to recognize that standard test species are used for testing products. Therefore extrapolation factors, specific to commonly tested species, are derived for use with LD_{50}s.
- As demonstrated by Mineau, Collins and Baril (1996), the median lethal dose frequently scales with weight, usually to a power greater than zero. The use of toxicity measurements expressed in mg/kg body weight to extrapolate across species can lead to serious under-protection of small-bodied birds. This effect is illustrated in Figure 4.5-3, where the cumulative frequency distribution of the logarithm of the LD_{50}s is plotted for the insecticide methiocarb. Once the values are adjusted to scale for body weight (see explanation below) and projected to a body weight of concern, such as that of the focal species, the curve is shifted up or down depending on the body weight. Thus small-bodied birds are predicted to have an increased sensitivity when compared to the original distribution whereas the opposite is true for the larger birds. The parameters of the distributions illustrated in Figure 4.5-3 are shown in Table 4.5-2. Taking

the body weight scaling into account shifts the mean of the distributions.

Figure 4.5-3 Effect of scaling for body weight on the distribution of species LD_{50}s for the insecticide methiocarb

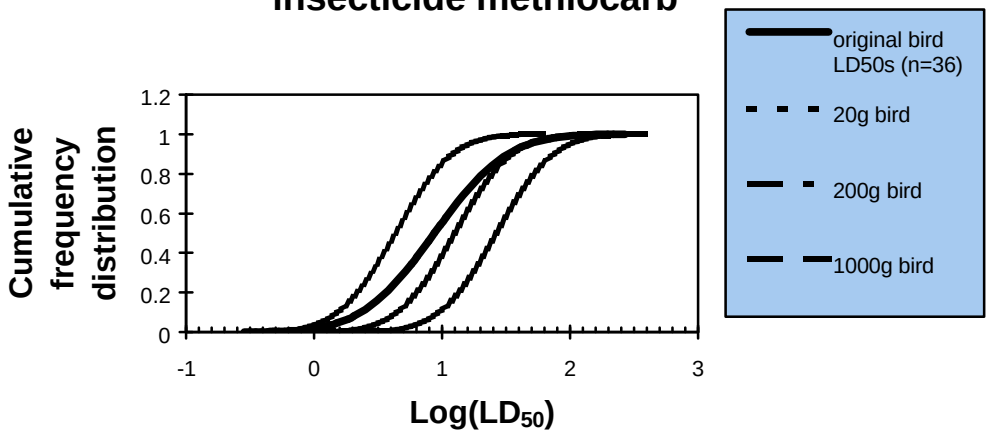


Table 4.5-2. Effect of scaling for body weight on parameters of the distribution of species LD_{50}s.

	Original data	Extrapolation to		
		20g bird	200g bird	1000g bird
Mean	8.7	4.3	13	27
5th percentile	1.6	1.1	3.3	7.0
95th percentile	48	16	48	101
Ratio of 5th to 95th perct.	30	14	14	14

but, also, removes a substantial amount of variance in the data. The ratio of the 95th to the 5th percentiles of the distribution decreases from 30 to 14. While it was argued that this relationship simply reflects the greater sensitivity of small passerines (Fischer and Hancock, 1997), it does account for a significant portion of the variance in the data. Whatever the correct explanation for the pattern, by taking this factor (body weight) into account, some of the inherent uncertainty can be reduced.

The following steps were used in deriving extrapolation factors based on a historical data base on cholinesterase inhibiting insecticides tested on at least six species (Figure 4.5-4):

Step 1: LD_{50}s were corrected with the appropriate scaling factor b for each insecticide ($LD_{50}'=LD_{50}/W^{b}$)

Step 2: The median estimate of the 5th percentile of the log-logistic distribution of the corrected LD_{50}'s is calculated for each insecticide (as per Aldenberg and Slob, 1993).

Step 3: The ratio of the LD_{50} of a designated surrogate test species (Mallard, Bobwhite Quail, Japanese Quail, House Sparrow or Rock Dove, or the geometric mean of a combination thereof) to the 5th percentile, calculated in step 2, is determined for each compound.

Step 4: A weight dependent extrapolation factor is thus derived for each testing scenario (i.e. specific combination of test species LD_{50} values) by calculating the geometric mean of the ratio across all insecticides, for each of the scenarios (Table 4.5-3). For single test values the extrapolation factor is simply applied to it. With more than one test species LD_{50} the appropriate extrapolation factor is applied to the geometric mean of the data.

Since the extrapolation factors are averages, they will overestimate the real 5^{th} percentile in about 50 % of the cases and underestimate it the rest of the time. This uncertainty can be determined by calculating the standard deviation of the ratios that went into the derivation of the factor in the first place. Table 4.5-3 illustrates that as the number of test species increases the standard deviation of the ratios decreases substantially. Thus there is a benefit in increasing the number of species tested in that the uncertainty surrounding our predictions of the 5^{th} percentile decrease substantially.

Figure 4.5-4. Derivation of extrapolation factors to account for differences in species sensitivities.

For each product:

- From the historical database correct the LD_{50} values to account for scaling with body weight such that:

$LD_{50}' = LD_{50}/W^b$

where b is the slope of the regression of $Log(LD_{50})$ against log(body weight).

- Fit the logarithm of the LD_{50}' to a logistic distribution, calculating the mean and standard deviation; calculate the 5th percentile' of the distribution using the extrapolation constants of Aldenberg and Slob (1993) to adjust for the sample size. The correction for body weight carried out earlier implies that the predicted 5th percentile becomes itself a function of body weight. In fact, the whole distribution will take a slightly different shape depending on the weight of the focal species to which we wish to extrapolate (i.e. 20g bird vs. 200 g bird). Therefore the 5th percentile is re-adjusted for the body weight of interest:

$5^{th}\ perct. = 5^{th}\ perct.` * W^b$

where W is the weight of the focal species.

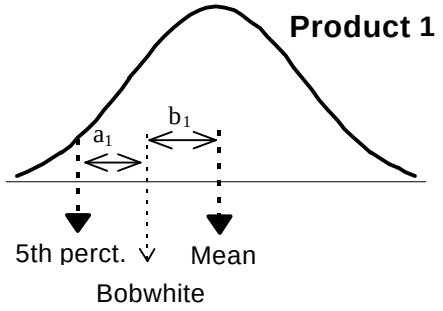
- Calculate the ratio a_i of the 5th percentile of the distribution to the LD_{50} of the Bobwhite Quail.

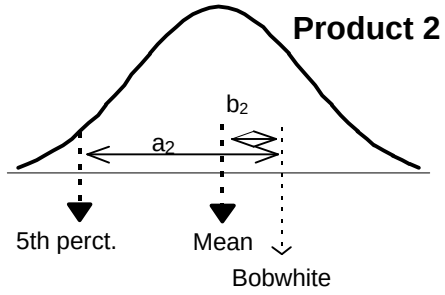
- Calculate the ratio b of the mean of the distribution to the LD_{50} of the Bobwhite Quail.

Final extrapolation factors:

- Extrapolation factors are simply the average of all the ratios previously calculated for each product; thus the factor which allows to extrapolate from the Bobwhite Quail LD_{50} to the 5th percentile, EF_5, is simply the average of all a_i; similarly the factor which allows to extrapolate from the Bobwhite Quail LD_{50} to the mean, EF_{50}, is simply the average of all b_i.

$$EF_5 = \frac{\sum_{i=1}^{m} a_i}{m} \qquad EF_{50} = \frac{\sum_{i=1}^{m} b_i}{m}$$





Product 3

Product 4

“

“

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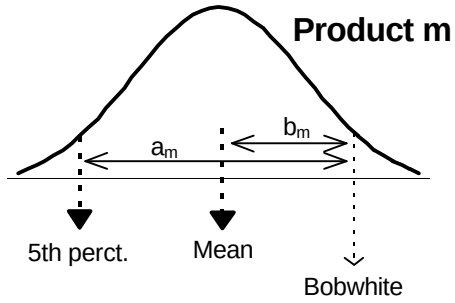


Table 4.5-3. Extrapolation factors developed by Baril and Mineau (1996) which aim to predict the 5th percentile of the species sensitivity distribution from one or more test species LD_{50}s. The effect of scaling for body weight was taken into account when calculating these extrapolation factors and those given here are predictions for 200g birds.

Species	Extrapolation factor[a]	N	Mean ratio	Standard deviation of ratios (on which factors are based)[b]
One species:				
Bobwhite Quail	4.6	29	0.66	0.51
Japanese Quail	5.5	43	0.74	0.36
Mallard	4.9	46	0.69	0.46
Two species:				
Bobwhite Quail and Japanese Quail	4.2	25	0.62	0.33
Bobwhite Quail and Mallard	4.9	26	0.69	0.36
Japanese Quail and Mallard	4.9	40	0.69	0.33
Three species:				
Bobwhite Quail, Japanese Quail and House Sparrow	4.4	21	0.64	0.28
Bobwhite Quail, Mallard and House Sparrow	4.1	21	0.61	0.30
Japanese Quail, Mallard and House Sparrow	4.3	33	0.63	0.26
Four species:				
Japanese Quail, Mallard, House Sparrow and Rock Dove	3.9	33	0.59	0.20

a: to be applied to the un-transformed test species LD_{50}s; where more than one test species LD_{50} is available the factor is applied to the geometric mean of the values.

b: Ratios and standard deviation were calculated from the logarithms of the LD_{50}s

This second method for deriving factors which allows for the extrapolation of test species data to fixed levels of protection is dependent on extrapolation "constants" which are used in the calculation of the 5th percentile of a distribution (Aldenberg and Slob 1993). These constants were developed to compensate for the tendency of small sample sizes to under-estimate the variance and thus over-estimate the 5th percentile of distributions. In order to incorporate the body weight scaling variable another series of constants will need to be established so as to account for the error associated with the estimate of slope of the toxicity-body weight relationship. (See Chapter 7.)

4.5.4 Derivation of Extrapolation Factors to Predict Distribution Parameters

The preceding section discussed methods to develop extrapolation factors which, when applied to the geometric mean of the LD_{50}s for one or more test species, will predict the dose which corresponds to the 5th percentile of the species sensitivity distribution. Using the same method based on historical data, the average distance between the logarithm of test species LD_{50}s and the mean of the distribution can be calculated (Figure 4.5-4). This average distance becomes an extrapolation factor which is applied to test species LD_{50}s to predict a mean for the distribution.

Table 4.5-4 illustrates some extrapolation factors calculated from a database of LD_{50} values for 56 cholinesterase-inhibiting insecticides. These calculations did not involve an adjustment for body weight scaling which would be required when establishing "definitive" extrapolation factors. The factors shown in Table 4.5-4 illustrate the taxonomic patterns associated with species sensitivity data discussed previously. On average the Mallard, Japanese Quail and Bobwhite Quail tend to be somewhat less sensitive with respect to the mean; whereas the Red-winged Blackbird and the Starling lie at opposite tails of the distribution. From the point of view of reducing uncertainty, it is not the exact value of the factor, but the error associated with its use that is of interest. This can be estimated by looking at the standard deviation (S.D.) of the ratios from which the factors are derived. For instance, Table 4.5-4 shows a lower S.D. for the Japanese Quail than for the Mallard, indicating that the Quail is more predictable in its sensitivity than the duck and would thus lead to fewer errors in predicting the mean. More relevant, however, is the

Table 4.5-4. Some extrapolation factors for use with specific test species values to predict the mean of the distribution.[a]

Species	Extrapolation factor[b]	N	Mean ratio	Standard deviation of ratios (on which factors are based)[c]
One species:				
Bobwhite Quail	0.96	30	-0.018	0.38
Mallard	0.90	49	-0.046	0.40
Japanese Quail	0.76	44	-0.119	0.30
Rock Dove	1.09	43	0.037	0.26
Red-winged Blackbird	2.27	45	0.356	0.35
House Sparrow	1.30	41	0.114	0.30
Starling	0.61	40	-0.215	0.53
Ring-necked Pheasant	0.84	47	-0.076	0.38
Two species:				
Mallard and Bobwhite Quail	0.92	29	-0.036	0.23
Japanese Quail and Rock Dove	0.89	38	-0.051	0.18
Bobwhite Quail and Red-winged Blackbird	1.38	25	0.140	0.19
Three species:				
Bobwhite Quail, Mallard and House Sparrow	1.01	21	0.004	0.16
Japanese Quail, Rock Dove, House Sparrow	1.03	34	0.013	0.16

a: The effect of scaling for body weight was not taken into account when calculating these extrapolation factors.
b: to be applied to the un-transformed test species LD_{50}s; where more than one test species LD_{50} is available the factor is applied to the geometric mean of the values.
c: Ratios and standard deviation were calculated from the logarithms of the LD_{50}s

finding that as the number of test species increases, the S.D. decreases significantly. The greater the number of species tested, the greater the confidence in the predictions of the mean of the distribution.

Whereas ways are found to use historical data to predict the mean of the distribution the same method cannot be used to determine the variance associated with the distribution. Luttik and Aldenberg (1995) have argued that since the standard deviation cannot be estimated from sample sizes of less than four a "generic" or pooled standard deviation s_p is calculated using the datasets of log(LD_{50})s for all pesticides using the following equation:

$$s_p = \sqrt{\frac{\sum\left(x_i - \bar{x}\right)^2 + \sum\left(y_i - \bar{y}\right)^2 + \ldots + \sum\left(w_i - \bar{w}\right)^2}{n_1 + n_2 + \ldots + n_m - m}}$$

where x, y, …, w are the respective datasets for m pesticides. The single condition the authors set to the use of this generic standard deviation was that the standard deviations for the historical data be independent of the mean of the logarithm of the LD_{50}s. The value calculated by Luttik and Aldenberg was 1.071 for the ln(LD_{50}) from a database of 55 pesticides encompassing many different modes of action. If the same calculations are conducted on a database of avian toxicity values for 56 cholinesterase-inhibiting insecticides, the generic standard deviation for the log10(LD_{50})s is 0.428. These two numbers, when back-transformed to the antilog, are essentially identical. This suggests that the variance to be found among compounds in the width of the distributions may not be introduced by differences among compounds in their mode of action.

4.5.5 Points of Caution about These Methods

The following important points about the distribution-based methods described above need to be made:

- There is some bias in the historical database used to derive the extrapolation factors. Cholinesterase-inhibiting insecticides, compared to other modes of action, are the dominant

group within the database. These products were tested on many species because of their toxicity to birds. This bias would have to be evaluated by calculating factors based on organophosphate and carbamate insecticides alone and comparing these to similar factors determined for all other products combined (see recommendations in chapter 7). If the variance associated with the factors is similar for both groups of products than factors based on the pooled data could be used.

- Another bias stems from the use of LD_{50} values determined with the Approximate Lethal Dose method. This method which provides an "approximate" estimate of the median lethal dose lacks precision and any confidence bounds. A large part of the data consists of determination made with this method. Further work needs to be carried out to determine the influence of these data on the methods proposed here (see recommendations in Chapter 7).

- It is important to stress the point that distributions do not replace knowledge about the patterns of toxicity observed across species. In fact trends in toxicity as a function of body weight, as described previously, have exceptions to them. While in the majority of cases the larger birds tend to be less sensitive, the raptors are an exception to this. For cholinesterase-inhibiting insecticides, in 8 out of 10 chemical-species comparisons, the bird of prey was more sensitive, sometimes by a wide margin, than predicted from the distribution and weight of the bird (Mineau et al. 1999). Furthermore, some chemicals exhibit very different patterns in toxicity to various taxa than what is usually found. For instance insecticide fipronil is more toxic to most of the Phasianidae than would be predicted from the historical distributions.

- Should we make assumptions about which species are going to be tested in the future? If this is still open to debate then the method proposed by Luttik and Aldenberg would appear to be the best at the present time if it is modified to deal with body weight scaling. If, however, the Mallard, Bobwhite Quail and the Japanese Quail remain as the preferred test species, perhaps a method to derive extrapolation factors should be closer to the one proposed by Baril et al.

4.5.6 Example of the Use of Extrapolation Factors to Predict the 5th Percentile of the Species Sensitivity Distribution

As a summary of the previous sections, Figure 4.5-5 illustrates the methods proposed to predict the 5th percentile of the species sensitivity distribution from small datasets. Progression from one method to another is dependent on the number of species (N) for which an LD_{50} value is determined. When N is less than four, three methods are proposed which rely on the use of extrapolation factors (EF). These factors, as explained above, were established from historical data. The EF appropriate to the species tested are used to determine the median estimate of the 5th percentile (output no. 3). When used in combination with the standard deviation (S_{EF}) associated with the estimate of the EF the 5th percentile can be predicted with a specific level of confidence that it is not overestimated (output no. 2). Alternately a distribution of predicted values of the 5th percentile can be generated using a distribution of factors with EF as the mean and S_{EF} the standard deviation (output no. 3). When N is equal to four or more species the parameters of the distribution are determined directly without the use of extrapolation factors. The technique used is that of Aldenberg and Slob (1993). Two outputs are thus obtained: the median estimate of the 5th percentile (output no. 4) and the one-sided 95% left confidence limit of the 5th percentile (output no.5).

An example of these methods is presented in Table 4.5-5 for a hypothetical insecticide. The input data required to apply the methods and the output from each are presented. The “real” value of the 5th percentile was established at 6.5 mg/kg based on data for 18 species. The predicted values are compared to this “real” value. It is apparent that for this compound methods 2, 4, 5 provided ample protection in that they underestimated the value of the 5th percentile. Method 5, however, tends to provide an exceedingly high safety margin. Methods 1 and 4 predicted values closest to the real value, usually within a factor of two. This is not a justification for the use of one method over the others but only to demonstration their use. Such an examination is warranted, however, to establish the preferred option. This could be carried out using the historical database itself, not as a validation, but as a verification of the precision of the predictions.

Figure 4.5-5. Illustration of the methods used to predict the 5th percentile of the distribution of species sensitivities from small datasets. The different methods lead to separate outcomes which are are numbered 1 to 5.

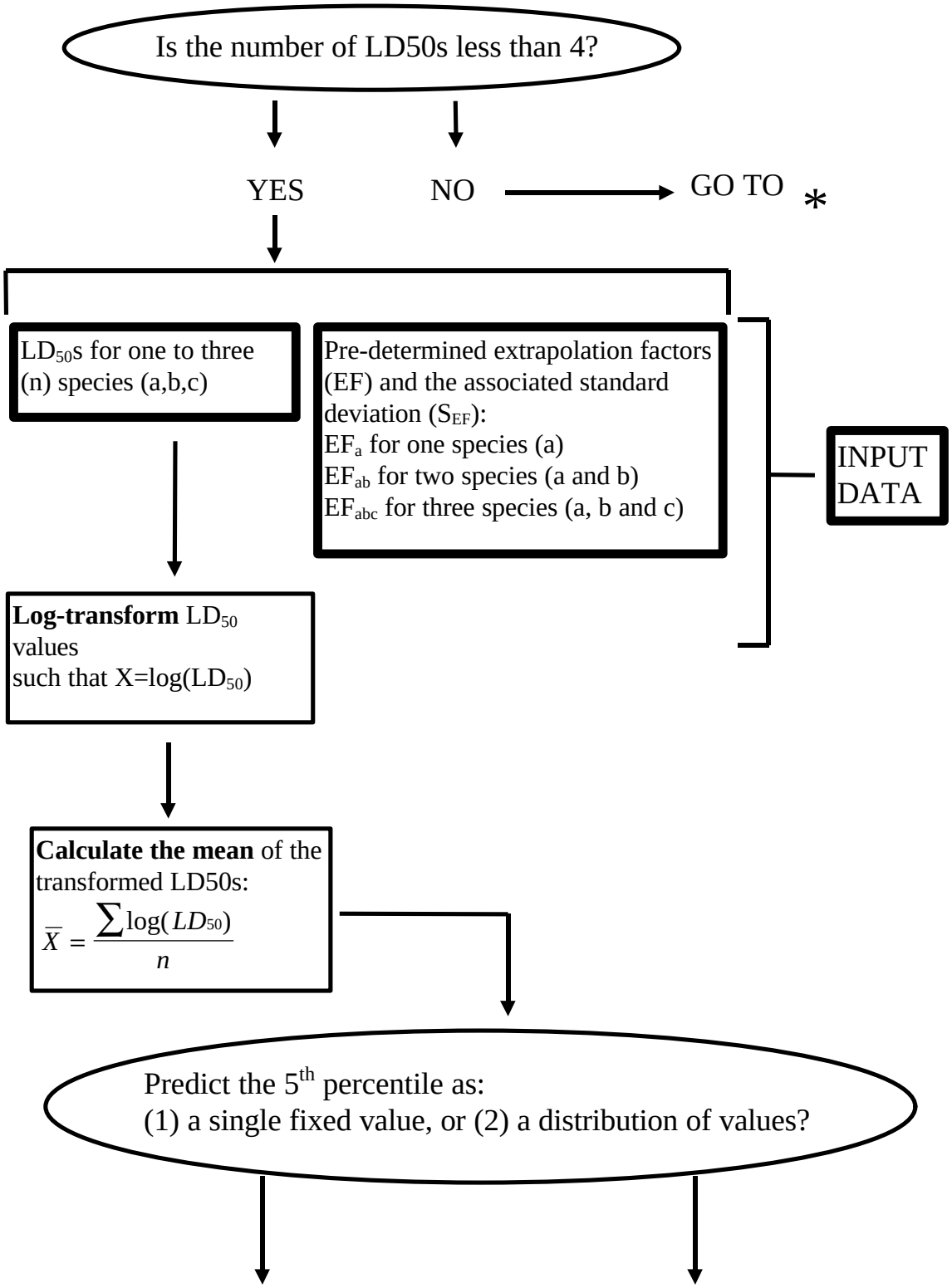


Figure 4.5-5. Cont'd.

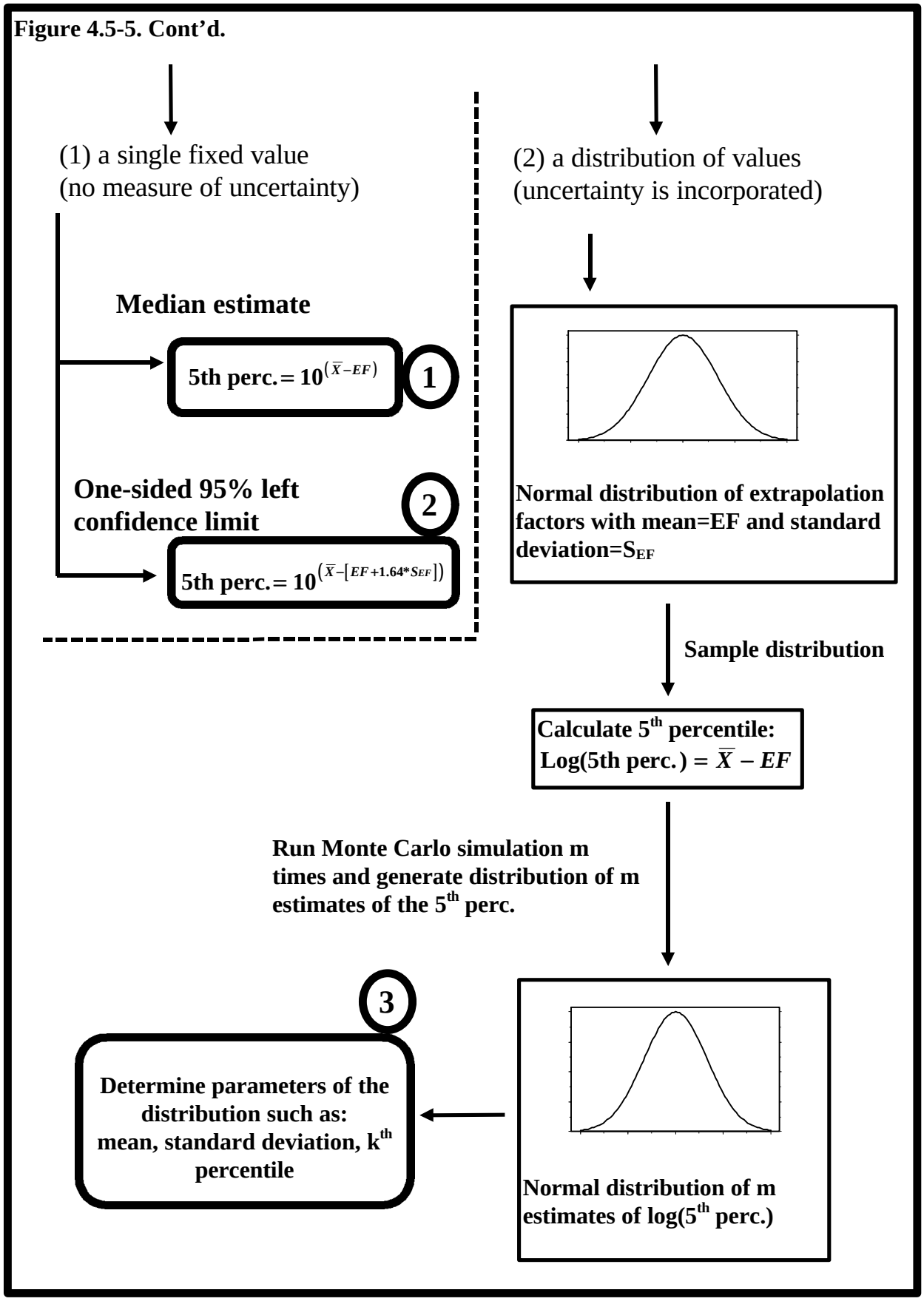


Figure 4.5-5. Cont'd.

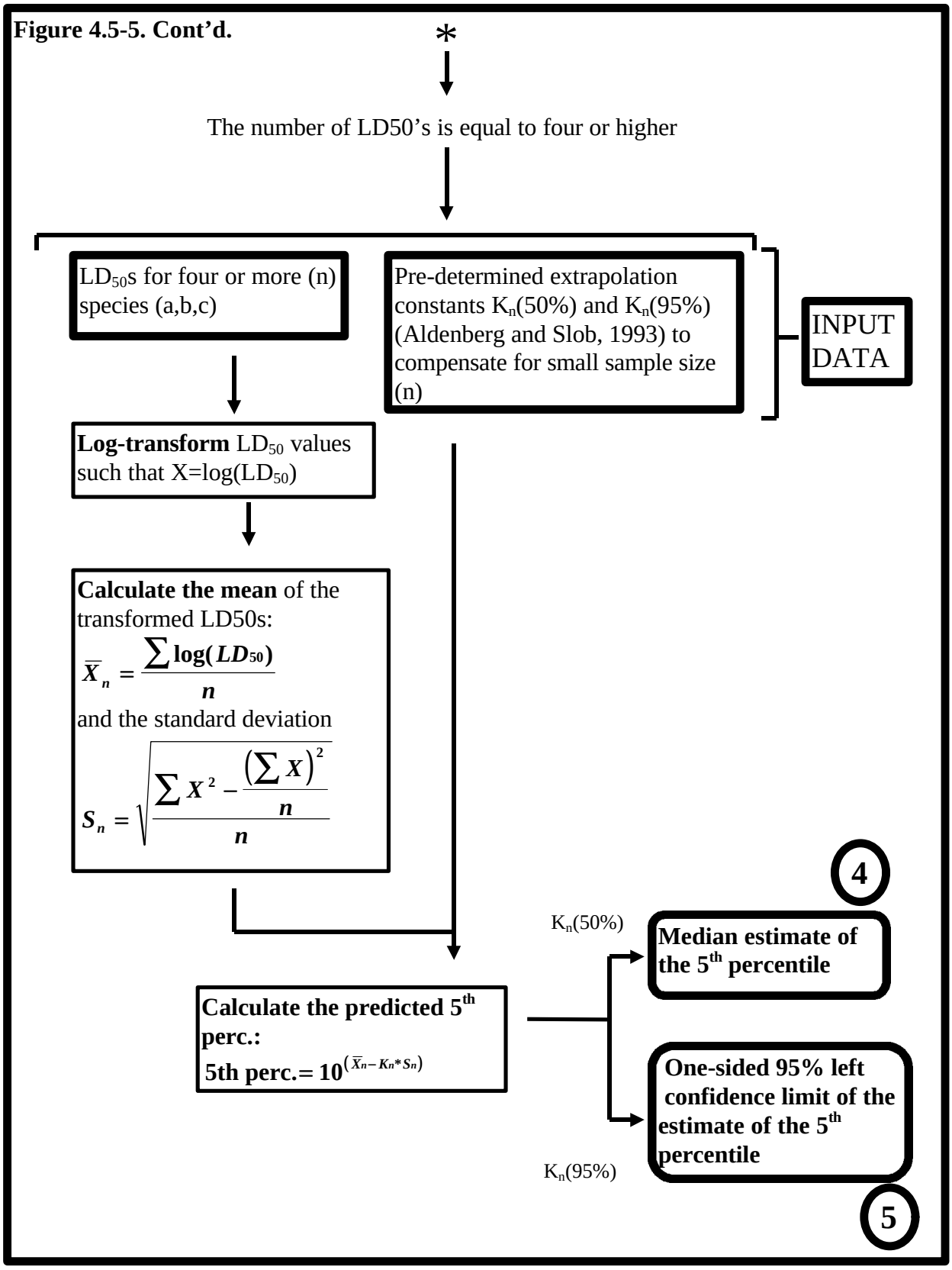


Table 4.5-5. Example of the use of methods to predict the 5th percentile of the species sensitivity distribution from small datasets. The outputs from the five methods are labelled 1 to 5. Acronyms for the species names: Bob=Bobwhite Quail, Mall=Mallard duck, Hsp=House Sparrow, Japa=Japanese Quail, Rock=Rock Dove, Rbq=Red-billed Quelea.

INPUT DATA

	mean log(LD50)	Stdev (log LD50)	N	EF	stdev (EF)
Bob	1.51		1	0.65	0.51
Mall, Bob	1.83	0.47	2	0.69	0.36
Mall, Bob, Hsp	1.61	0.51	3	0.6	0.30
				Kn(50%)	**Kn(95%)**
Mall, Bob, Hsp, Japa	1.51	0.47	4	1.92	5.49
Mall, Bob, Hsp, Japa, Rock	1.45	0.42	5	1.85	4.47
Mall, Bob, Hsp, Japa, Rock, Rbq	1.41	0.39	6	1.81	3.93

OUTPUT

			Predicted 5th percentile					
			Fixed		**Distribution parameters**			
	mean LD_{50}	**N**	**median estimate**	**estimate with 95% confidence**	**frequency of overestimate[a]**	**5th perc.**	**95th perc.**	**Range**
Bob	32	1	7.2 (1)	1.0 (2)	53% (3)	1.0	49.0	47
Mall, Bob	68	2	13.9	3.9	82%	3.5	53.7	15
Mall, Bob, Hsp	41	3	10.2	2.9	74%	3.2	31.6	12
Mall, Bob, Hsp, Japa	32	4	4.1 (4)	0.1 (5)				
Mall, Bob, Hsp, Japa, Rock	28	5	4.6	0.4				
Mall, Bob, Hsp, Japa, Rock, Rbq	26	6	5.0	0.7				
			5th percentile determined with 18 species					
all species	29	18	**6.5**					

a: establishes the frequency with which the values in the distribution overestimate the real value of the 5th percentile.

4.5.7 Slope of the Dose-response Curve

The slope of the dose-response curve is thought to differ among species due to the differences in morphology, and biochemical and physiological processes which interact with the inherent pharmacokinetic characteristics of the compound. The variability in the variance of the slope originating from differences among species needs to be distinguished from that originating from other sources. In essence, the question becomes the following: if we cannot make predictions about the slope based on taxonomic relationships, which at this point in time is not possible due to the lack of appropriate data, is the variability introduced by species differences any greater than the existing variability originating from other sources? In section 4.4, Table 4.4-1, the sources of variability in the estimate of the slope were examined. This brief analysis showed that variance, as determined by the standard error of the estimate or the standard deviation of the mean of the replicates, originating from within-test and from replicate test variability rarely exceeded 30%. Conducting tests in different laboratories did not result in variability (S.D./mean) exceeding 50%. When test results including different species were added to the analysis the variability ranged between 26 and 122% with a median of 53%. The analysis of the sources of variability cannot be pursued beyond what is presented here. Much of the toxicity data is obtained using the up-and-down method which does not provide an estimate of slope. Thus few species, other than the standard test species used for regulatory purposes, are tested in such a way that slopes can be determined. This prevents a more thorough examination of the species differences in slopes. Nevertheless, the level of variability noted in Table 4.4-1 tend to suggest that inter-species differences do not contribute much more than what is already present.

The following options can be considered for use when extrapolating from test species data to the focal species in a probabilistic risk assessment.

<u>Option 1:</u> When there is only one dose-response:

A. Use the slope as the mean of a distribution of slopes and a coefficient of variation of 53% (median in Table 4.4-1 for the “global” variance); this is for use in Monte Carlo simulations.

B. Use as in "A" to determine the 5th percentile of this distribution to set a lower "conservative" bound; a small slope value is considered conservative since it predicts mortality at lower doses than a higher value for the slope.

C. Do the same as in "A" or "B", but using the standard error of the estimate from the study itself, as a measure of variance.

Option 2: When there is more than one dose-response (n >1):

A. Do as in Option 2, "A" or "B" above, but substitute the mean of n slopes for the mean of the distribution.

B. Use a uniform distribution with the minimum and maximum values defining the range.

4.5.8 Choice of Test Species

As noted earlier it is quite clear that much uncertainty regarding the sensitivity of species to chemicals can be reduced significantly by testing for toxicity with more species than is currently done. It has been argued that testing additional species with the up-and-down method would be sufficient to obtain this additional information (OECD, 1996). What needs further clarification, however, is the types of species chosen for further testing. It is assumed for the purpose of this discussion that the existing test species most often used, the Bobwhite Quail, Mallard and the Japanese Quail, will continue to be used for determining the acute toxicity of pesticides.

In section 4.5.2 the taxonomic patterns in species sensitivities were discussed. It was acknowledged that the information collected so far indicates that broad patterns exist. The Phasianidae are less sensitive than the ducks, and passerines, in general, especially the Icteridae, are more sensitive. This evidence suggests that any further testing of species should move away from testing more Phasianidae. Edwards and Schafer (1998) discuss some of the criteria set out to select species for testing. They considered the following factors as important:

Phylogeny: Passerines make up more than 50% of all species; other major classes of agricultural birds include Anseriformes, Galliformes, Columbiformes, Psittaciformes and Falconiformes.

Tolerance to laboratory conditions: There should be a preference for captive breeders over wild caught birds which must be acclimatized to laboratory conditions quickly; low stress and uncomplicated laboratory requirements are highlighted.

Availability: Captive bred birds available commercially (other than the standard test species) include Parrots and fringillids. Falconiformes such as the American Kestrel are difficult to breed in captivity. Wild caught birds include abundant species such as the feral Pigeon and various Passeridae, Icteridae, Corvidae, Fringillidae or Emberizidae.

Regurgitation: Regurgitation may be unavoidable although smaller dose volumes and capsules may reduce it.

Sensitivity: A rough ranking of average sensitivity across species is available (see section 4.5.2), however, it is not applicable across all compounds.

Effect of size on sensitivity: Whatever the reason for the size effect seen by Mineau et al. (1996) "…it would seem prudent to include at least two passerine species in any shortlist of species…" for testing "…because of their significance in agriculture and sensitivity due to their size or phylogeny."

Edwards and Schafer conclude with the following short list of species: Quail (Bobwhite or Japanese), Mallard, Zebra finch, Icteridae or Turdidae, feral Pigeon, and the Bugerigar.

4.5.9 Extrapolation Across Species for Other Tests

The methods developed for inter-species extrapolation with the avian acute oral LD_{50} test owe their strength to the availability of extensive collections of LD_{50} data from numerous species for

each of a number of agricultural chemicals. For each of the multi-species distributions of compound specific LD_{50} values, the relative positioning of key test species within the distribution provided the predictive power to approximate anticipated distributions based on limited data sets made up of those key species. Inter-species extrapolations are thus made by predicting toxicity distributions (based on demonstrated acute toxicity distributions) using data from those key test species, the Mallard Duck, Japanese Quail and the Northern Bobwhite.

Inter-species extrapolations of the other principle toxicity tests, the avian dietary LC_{50} and avian reproduction test, as well as any other new test protocols, could be approached using a similar method. Toxicity data from key test species are compared to other species within data groupings for key agricultural chemicals for which large databases exist. This, unfortunately, is where our ability to perform similar inter-species extrapolations ends. Avian LC_{50} and reproduction tests generated for agrochemical registration purposes for the past 30 years have relied, almost exclusively, on the Mallard Duck, Japanese Quail and the Northern Bobwhite. Unlike the LD_{50} test that has been applied to wide varieties of test species in many test compounds, there are few distributions of multi-species data available for the standard LC_{50} or reproduction tests. In order to develop inter-species extrapolation capability for these tests, more must be known about the comparative responsiveness of a variety of avian species in order to predict sensitivity of wild birds in the environment from results with key test species.

There are several examples of chemicals that have been examined for specific reproductive endpoints that might offer insight into the nature of distributions. The principle example is the large data base on the occurrence of eggshell thinning with DDT and its metabolites (Lloyd Kiff, The Peregrine Fund, pers. comm.). A wide variety of species has been tested for eggshell thinning and a review of that literature may provide insight into the nature of distributions of sensitivity. Another similar database may be constructed from work investigating effects of dioxin-like compounds and their teratogenic effects on avian embryos. Aside from these compounds, there is little data available in sufficient breadth for use in distribution development.

To effectively develop inter-species extrapolation capability similar to that used for LD_{50}s, there are two data collection needs. First, to appropriately interpret LC_{50} and reproduction test data, findings with the three key test species must be put into perspective with data from other relevant wild species. Until there are sufficient data to create distributions of comparative sensitivity, the relevance of standard test species data cannot be effectively assessed. Second, in order to make optimal use of this approach, key representative chemicals and avian species, chosen for their abundance of data in the LD_{50} database, should be chosen for further focused assessment. This approach will yield benefits at two levels. It will provide the data necessary to develop "horizontal" distributional analysis and creation of inter-species extrapolation techniques necessary for the LC_{50} and reproduction tests. Perhaps as important is that the choice of test compounds and species similar to those with rich LD_{50} data will allow "vertical" integration between toxicity tests. A better understanding of the comparative distributions of toxicity data within each test, and how those distributions change in between-test comparisons may allow for extrapolation not only between species, but between tests. Taken to its extreme, it may be possible, given sufficient background data on a variety of chemicals, to predict LC_{50} or reproduction distributions based on minimal key species tests or even from an LD_{50} distribution. The ability to perform these types of comparisons will require, however, an effort to better characterize distributions of toxicity beyond the mallard duck, Japanese quail and northern bobwhite for the avian LC_{50} and reproduction toxicity tests (see recommendations in chapter 7).

It is proposed that, until further work is done with the LC_{50} test, that the factors developed with the LD_{50} be applied to the results of LC_{50} tests. It could be argued that the "real" interspecies variability associated with the LC_{50} is just as likely to be lower than greater than observed with the LD_{50} test. It is important to remember that the LC_{50} test deals with issues beyond the sensitivity of birds to toxicants such as the onset of illness, food avoidance and body burden, all related to the temporal components of dose consumption, absorption, metabolism and excretion. Extrapolations from one species to another cannot be made except with a compound that has been well-studied for its pharmacokinetic properties. At the moment, given how little is know, it must be assumed that the inter-species variability seen with the LD_{50} test is applicable to the LC_{50}. At the very least,

it is the best measure of the sensibility of species to toxicants and that is definitely an element involved in the variability associated with the LC_{50} test.

For the reproduction study, however, the factors from the LD_{50} work should not be used. The toxic mechanisms are most often different from the ones involved in acute toxicity. Predictions are difficult to make. In a review of reproduction studies done with the Mallard and Bobwhite Quail (Mineau, Boersma and Collins 1994) showed that for developmental effects results differed significantly between the two species. There was greater similarity between the rat and bird results than between those obtained in the two bird species. This suggested there are doubts about the ability to extend the results of an avian reproduction study to any potentially affected bird species. The authors concluded that the current reproduction study be recognized only as a rough screening tool. Therefore it is proposed that if any significant effect is detected in either of the two species that further work be done on more species, but that the study be tailored to the focal species and to understand the origin of the observed effect. This implies that, for the purpose of a probabilistic risk assessment, the reproduction endpoint would always consist of one point. The probabilistic element would have to come only from the exposure side of the modeling efforts.

4.6 OUTPUT OF EFFECTS ASSESSMENT

The basic output of the effects assessment is an estimated dose-response profile, that estimates the probability or magnitude of a specified effect to the focal species at a given level of exposure, along with the uncertainty of the estimate. This effects profile quantifies the relationship between exposure to the pesticide and the assessment endpoint. In the event that the focus species representing the species of concern for the risk assessment is the same as the species tested in the toxicity study, the effects profile would be the same as the dose-response relationship derived from the study. Typically, the test species will not be the same as the focal species and the effects profile must account for the uncertainty associated with extrapolating among species. Uncertainty from interspecies variability is one major source of uncertainty that must be considered. Other sources include uncertainty from intraspecific variability and sublethal effects. Another large unknown is the relationship between laboratory results and effects in the field which will be affected by the quality of the simulated exposure, differences in inherent toxicity between

laboratory and field populations, and the variable influence of stress of captivity on toxic responses among species.

The nature of the effects profile varies with the amount of data available, the desired level of certainty for the analysis, and the nature of the assessment endpoints. Depending on the desired level of certainty and the assessment endpoints, additional testing and chemical and/or biological data may be required. Uncertainty analysis has not been explicit in the current regulatory assessments and has been managed by introducing conservatism into the risk assessment. The proposed effects characterization will identify and incorporate various sources of uncertainty into the effects profile and aim to characterize and reduce these at increasing levels of refinement. The objective of this section is to summarize options for refined effects testing, effects analysis, and consideration of uncertainty into Levels of Refinement that focus efforts on the most sensitive parameters in the analysis, and enable the risk assessment to be refined. Ideally, the effects characterization should consider measurements of acute (mortality), reproductive and other sublethal) effects across short-, medium- and long-term periods of exposure. However to date, chronic effects have focused on reproduction and have been associated with only long-term exposure (Table 4.6-1). Consequently, considerable research is required to develop new toxicity tests. As a result, the Levels of Refinement for effects analyses will reveal that only acute assessments of mortality following short-term exposure can be determined reasonably well using existing tools, and that other areas require considerable research associated with developing suitable toxicity tests and associated methods for effects characterization.

Table 4.6-1. The relationship between current toxicity tests and assessment endpoints associated with various periods of exposure. Ideally, each endpoint should be assessed at short-, medium- and long-term periods of exposure.

	Short-term Exposure	Medium-term Exposure	Long-term Exposure
Acute endpoints	*Oral LD_{50} test*	*Dietary LC_{50} test*	*No assessment*
Reproduction endpoints	*No assessment*	*No assessment*	*Reproduction Test*
Other Sublethal endpoints	*No assessment*	*No assessment*	*No assessment*

In order for a valid risk assessment to be conducted, the periods of exposure used in toxicity

studies and considered in the effects analysis must approximate those used in the exposure analysis. Four distinct Levels of Refinement for the characterization of effects have been identified (Tables 4.6-2, 4.6-3, 4.6-4) for each period of exposure (short-, medium- and long-term) and the three toxicity tests most often carried out on birds (acute, dietary, and reproduction). The progression from low to higher levels is not rigid and aims to reduce or at least quantify various uncertainties associated with the effects characterization. Depending on the situation, any element recommended at higher levels could be put into place earlier in the risk assessment process.

Similarly, the effects characterization may remain unchanged and yet the resulting risk assessment could be refined due to a refinement of the exposure assessment. The need to move to higher Levels of Refinement for the effects characterization is generally dependent on the acceptability of risk from the risk assessments and uncertainty. Results from a sensitivity analysis may indicate a need for refinement in exposure or effects, or both. The characteristics of further studies and tests especially at higher Levels of Refinement will be driven by the results of a sensitivity analysis. Effects analysis at various Levels of Refinement are very much limited by available test species for toxicity testing and suitable study designs. It is often very difficult to obtain permission from U.S. Fish and Wildlife Service to test wild avian species to provide additional data to that from common test species (i.e., mallard duck, bobwhite quail, Japanese Quail). Consequently, the methods for effects analysis are tailored to make the most of available data while giving due consideration to uncertainty with an emphasis on an outstanding need to redesign dietary tests. Tables for Levels of Refinement illustrate the types of responses obtained, the analysis providing the profile of the effect, the sources of variability accounted for, the modifications to current tests, additional tests recommended and the sources of variability not accounted for. The effectiveness of these Levels of Refinement in refining the risk assessment and reducing uncertainty will be determined as part of future “Proof-of-Concept” research involving case studies.

Table 4.6-2 Levels of refinement for avian toxicity testing and effects analysis associated with short-term periods of exposure by direct ingestion of the pesticide within minutes or hours.

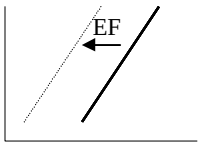
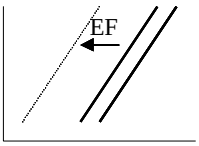
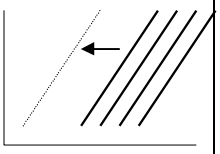
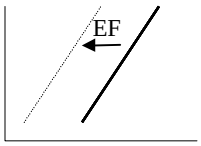
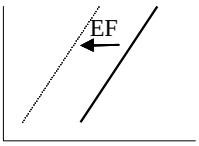
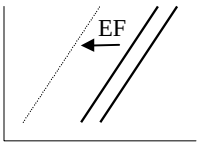
Short-term	Level I	Level II	Level III	Level IV
Test Species **Focal Species** **Dose-response (DR) for mortality**				Focused study dependent on: -Sensitivity analysis -Uncertainty -Exposure
Toxicity Test	-Full LD_{50} DR for 1 test sp. (N<4)	-Full LD_{50} DR for 1 test sp. -LD_{50} for 1 or 2 test spp by ALD or full DR (N<4) -Granular formulation test	-Full LD_{50} DR for 1 test sp. -LD_{50} for 3 test spp by ALD or full DR (N≥4)	-Field data on focal or surrogate spp -Pen-type study
Effects Analysis for Focal Species	-EF based on historical data -Extrapolate to "fixed" LD_{50} (5^{th} %tile) or -Extrapolate to distribution		-Probability distribution defined for focal species - Calculate 5^{th}%tile	-Mortality estimates based on field exposure -Inputs for modeling effects on population dynamics
Interspecific Variability	Application of EF to LD_{50}	Application of EF to geometric mean of LD_{50}'s	Distribution is defined	Extrapolations to focal species as necessary
Intraspecific Variability	*Accounts for:* -Variability in sensitivity (slope of DR) among individuals - Variance in estimate of mortality from dose ingested			Variability within study population measured
Uncertainty not accounted for	-Variability in response from age -Variability in slope of DR among species -Variability from environmental conditions -Effects of short-term exposure on sublethal endpoints			Regions, crops, uses and species of concern that differ from field study
Modifications (research)	-Determining effects on sublethal endpoints from short-term exposure -Further evaluation of use of EF approach -Appropriateness of ALD or alternative test -Requirement for toxicity testing non-granule formulations - Test method under development for avoidance behavior associated with seeds and baits and avoidance for granule and spray formulations needs to be developed.			

Table 4.6-3 Levels of refinement for avian toxicity testing and effects analysis associated with medium-term periods of exposure to the pesticide in the diet over a period of days.

Medium-term	Level I	Level II	Level III	Level IV
Test Species **Focal Species** **Concentration-response (CR) for mortality**	 As for short-term			Focused study dependent on: -Sensitivity analysis -Uncertainty -Exposure
Toxicity Test	-Full short-term exposure LD_{50} DR for 1 test sp.[1]	-Full LD_{50} from CR for 1 test sp. (new test)	-Full LD_{50} from CR for > 1 test sp. (new test)	-Field data on focal or surrogate spp -Pen-type study
Effects Analysis for Focal Species	As for short-term	-EF based on historical LD_{50}'s [2] -Extrapolate to "fixed" LD_{50} (5^{th} %tile) or -Extrapolate to distribution		-Mortality estimates based on field exposure -Inputs for modeling effects on population dynamics
Interspecific Variability	As for short-term	Application of EF to LD_{50}	Application of EF to geometric mean of LD_{50}'s	Extrapolations to focal species as necessary
Intraspecific Variability	As listed for short-term	*Accounts for:* -Variability in sensitivity (slope of CR) among individuals -Variance in estimate of mortality from dose or conentration ingested		Variability within study population measured
Uncertainty not accounted for	- As listed for short-term -Test from short and not medium-term exposure	-Variability in response from age -Variability in slope of DR among species -Variability from environmental conditions - Medium-term exposure resulting in sublethal effects		Regions, crops, uses and species of concern that differ from field study
Research [3]	-Development of appropriate trigger for movement to Level II [1]	-New test (quantifiable observations of sublethal effects[4], individual caging, frequent measures of food consumption, food avoidance assessment, dynamic exposure regime) -Appropriate EF (number of test spp.)	-New test (quantifiable observations of sublethal effects[4], individual caging, frequent measures of food intake, food avoidance assessed, dynamic exposure regime) -Refined exposure in toxicity test -Food avoidance test (separate) -Determine number of spp. to be tested -Determine when EF unnecessary	-Aviary or pen testing

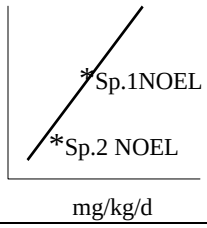
[1] The full short-term LD_{50} test is used to assess Level I medium-term effects. Level II (medium-term effects) will be triggered based on an unknown or new chemistry, mechanistic (e.g., where delayed action), potential to bioaccumulate, or persistence.

[2] Currently, historical data available only for acute oral LD_{50}. Future objective to base EF for effects from medium-term exposure on a new medium-term dietary toxicity test.

[3] Research is necessary because 1) there is no confidence in the existing dietary LC_{50} test 2) there is no historical data appropriate for determining EF's for medium-term effects

[4] May result in trigger for assessment of sublethal effects in chronic tests

Table 4.6-4 Levels of refinement for avian toxicity testing and effects analysis associated with long-term periods of exposure to the pesticide in the diet over a period of weeks.

Long-term	Level I	Level II	Level III	Level IV
Point estimate NOEL from most sensitive species assumed to equal NOEL for focal species		-Possibly an aviary or small pen study -Dependent on outcome of further research	-Risk assessment refined only on basis of exposure assessment not toxicity	Focused study dependent on: -Sensitivity analysis -Uncertainty source -Exposure
Toxicity Test	-Reproduction toxicity test for 2 test species[1]	-Refined exposure regime -Focus on sensitive/critical endpoints -Refinement of NOEL (or development on concentration-response for new test)	No additional toxicity studies	-Field data on focal or surrogate spp -Field assessment of reproductive effects on marked populations of birds or sentinel populations (e.g. nest box studies)
Effects Analysis for Focal Species	-Lowest NOEL value selected to represent sensitivity of focal species	-Dependent on outcome of further research		-Reproductive effects based on field exposure -Inputs for modeling effects on population dynamics
Interspecific Variability	Data available for only 2 test spp.			Extrapolations to focal sp. as necessary
Intraspecific Variability	Test not designed to deal with this aspect			Variability within study population measured
Uncertainty not accounted for	-No DR (cannot predict magnitude of effect as a function of exposure) -Variability within and among spp. -Variability from environmental conditions -Effects of short-term exposure on sublethal endpts			Regions, crops, uses and species of concern that differ from field study
Research	-New test (dynamic exposure regime, proven egg-layers using pre-treatment laying as covariate) -Determine appropriate EF for extrapolation to focal species	-Large aviary test -Include emphasis on parental care (egg incubation) -Focus on critical endpoints - Dose-response testing		

[1] The current reproduction test with modifications to the exposure regime will be used until replaced by a new reproduction test

There are four Levels of Refinement for avian toxicity testing and effects analysis associated with short-term periods of exposure (minutes or hours) following direct ingestion of the pesticide (Table 4.6-2). The basic element of the effects profile from short-term exposure is the dose-response relationship generated from the existing acute oral toxicity test. At Level I, a single dose-response test that quantifies mortality is required. Assuming the response takes a typical sigmoidal shape relative to the dose, the Probit model can be fitted to the data to get the slope and LD50 estimates From the resulting regression equation, one can estimate the proportion of the test population affected at a given exposure dose. For each test there is uncertainty associated with the estimate of the LD50 and the slope. Consequently, for each exposure dose there is a distribution of possible values of the effect which can be used in a probabilistic assessment in place of a single point estimate. A specific dose may be determined to represent the LD50 in a test, but based on the uncertainty in the dose-response relationship, the possible effect at that dose, for example, may have ranged from 30% to 70%. In addition, most risk assessments are faced with estimating the risk of a pesticide to species that have not been directly tested in the laboratory or field. Variation among species in sensitivity to pesticides has been demonstrated to be substantial and may be the greatest source of variation for integrating effects estimates of untested species into the probabilistic assessment (see Section 4.5). Where no data exist on the toxicity of the focal species, the distribution of potential toxicity values is estimated by applying an Extrapolation Factor (EF) to LD50 data for test species (Section 4.5).

To refine this extrapolated mortality estimate at Level II (Table 4.6-2), it is necessary to conduct a toxicity test on the focal species or, if this is not possible, another acceptable test species. In the case of the acute toxicity test, an ALD (up-down) test for one or two additional species may be adequate to estimate the LD50 with the slope of the relationship assumed from the definitive test conducted on another species. Further research is required to assess the benefits of using ALD tests over full dose-response tests for obtaining data on additional test species at Levels II and III. This would entail an assessment of the confidence in assuming similarity in slope (intraspecific variability) among species. At Level II an EF is applied to the geometric mean value of the LD50's for each test species to extrapolate to an estimated LD50 for the focal species that

is based on the 5th percentile. Where the chemical of interest is a formulated as a granule, a separate acute oral dose-response test would be conducted with the granular formulation. Additional research is necessary to determine the necessity for testing with other types of formulation and to determine how these results would be considered in the effects characterization. In addition, research is required to develop tests for assessing avoidance behavior associated with short-term exposure. Some work has been conducted on avoidance associated with seeds and baits however techniques for measuring avoidance associated with granule and spray formulations still needs to be developed.

At Level III, additional toxicity testing (ALD or full dose-response test) is conducted so that LD50 values are available for at least four test species. With greater than or equal to four test species, it is appropriate to calculate the parameters of the estimated dose-response distribution for the focal species (section 4.5). The uncertainty in slope and LD50 parameter values is represented by the standard error of the mean of the LD50 values (see section 4.5). It is recommended that additional research include further statistical review of the EF methods including the appropriate number of test species for calculating parameters of a distribution, and use of slope estimates in extrapolations. The proposed approach also assumes that the variance in species sensitivity for toxic pesticides is similar to that for less toxic chemicals. Additional consideration of this assumption could potentially provide a means of explicitly accounting for differences in sensitivity from different modes of action. A further problem is that in practice, acute oral toxicity tests often result in an absence of mortality at a limit dose. Further research is required to determine an appropriate approach for characterizing effects for use in risk assessment when this situation occurs.

The methods outlined in Levels I through III account for variability among species, variability in the sensitivity among individuals within a species as estimated from the slope. In addition, the methods account for variance in the predicted mortality of the focal species as estimated from the dose ingested. The methods do not explicitly account for uncertainty resulting from variance in the age of animals or environmental conditions affecting sensitivity to the pesticide nor variability

in the slope of the dose-response among species. A limitation is that only mortality and not sublethal endpoints from short-term exposure are considered in the effects characterization. Important sublethal effects associated with some compounds are neglected with current toxicity testing. For instance, transient paralysis in a laboratory situation, under controlled conditions, while insignificant in this setting, become critical to the survival of the individual in the natural world. Also effects of short-term exposure on parental behavior could affect their success in rearing off-spring. While observations are made of such sublethal effects they are not quantified in a manner amenable to statistical treatment or input into a dose-response model. Numerous methods, developed by animal behaviorists, could be adopted to better integrate this neglected aspect of acute toxicity testing. Further research is necessary to determine how to quantify these effects and to incorporate such measurements in the effects characterization.

Effects characterizations associated with short-, medium- and long-term exposures at Level IV involve focused pen-type studies or field studies (Tables 4.6-2, 4.6-3 and 4.6-4). The guiding principles for these studies is that they are case specific and driven by a need to further assess key parameters identified in a sensitivity analysis associated with the risk assessment. Consequently, the studies may focus on refining exposure assessments rather than effects or on reducing uncertainty associated with parameters such as Food Intake Rate (FIR) and Avoidance (AV). Field studies may also provide estimates of mortality based on more realistic exposure regimes. They may also provide input values for modeling longer-term effects on population dynamics. Level IV studies will be site and scenario specific and therefore will not account for uncertainty associated with differences among regions, crops and species of concern that differ from the study scenario but are relevant to the risk characterization.

Levels of refinement for toxicity testing and effects analysis associated with medium-term exposure in the diet over a period of days are shown in Table 4.6-3. Toxicity testing involving medium-term exposure does not occur synchronously with short-term exposure assessments. Level I short- and medium-term effects assessments are the same. However, specific criteria for triggering the requirement for Level II medium-term assessment have been identified. The

principles of these criteria include

- The test chemical is from a relatively unknown or new chemistry ,
- An evaluation of the mechanism of toxicity indicates that a medium-term effect could occur e.g., a delayed action,
- The test chemical has the potential to bioaccumulate ,
- The test chemical is likely to be very persistent on avian food stuffs in the environment.

At Level II, a full concentration-response dietary study for 1 test species that follows a new testing design is required and at Level III, tests on additional species would be required. The existing dietary test has many problems rendering it inappropriate for risk assessment. The study does not provide a reasonable estimate of toxicity because measurements of dose ingested per individual are not possible and apparent toxic effects are confounded by starvation. The proposed changes to the study for Level II and III assessments will replace the existing dietary study and will be based on the 21 day exposure OECD proposed test design (section 4.2) and will include quantitative measurements of sublethal effects, individual caging and measures of food consumption, and an assessment of food avoidance. Unlike the proposed OECD dietary test design, this new study would include an option for using a dynamic exposure regime that could be aligned with dissipation rates of the chemical on avian food items in the environment. Individual assessments of food consumption will be used to estimate the daily dose consumed and related to mortality (mg/kg food to mg/kg body weight per day). In addition, the concentration-response will include non-lethal endpoints. At higher levels, where the exposure regime is refined, better estimates of daily “dose” consumed can be obtained and the concentration-response will better reflect the predicted exposure pattern. To further refine effects assessments at Level III, a stand alone avoidance test would be an option where avoidance was considered to be an important factor based on Level II assessments.

The preferred method for analysis of effects from medium-term exposure would be to use the EF approach described for short-term assessments (Table 4.6-2) but to base the EF on historical data from dietary studies. However, a major limitation is that a historical data base on which to derive appropriate EF's for dietary tests does not exist. In addition, unlike the acute oral toxicity study, there is minimal confidence in results from the existing dietary test. Until such a time that a historical data base for medium-term dietary toxicity studies can be developed, and associated EF's derived, the medium-term effects characterization will use the EF's proposed for Levels I and II short-term assessments.

Levels of Refinement for toxicity testing and effects analysis for chronic effects following long-term exposure are shown in Table 4.6-4. In summary, the current avian reproduction test has severe limitations concerning its use in ecological risk assessments and needs to be redesigned. For Level I, avian reproduction tests will be conducted on two test species and the current test will be used until it can be replaced. The NOEC and LOEC can be compared to the exposure profile to determine the degree of exceedence (Chapter 5) and for both Levels I and II the NOEL from the most sensitive species will be used in this assessment. However, in order to estimate the magnitude of reproductive effects, the study needs to be redesigned to determine a dose-response relationship with an acceptable level of statistical power and to address issues of compatibility with the exposure profile. Following the development of a dose-response type study, appropriate EF's will have to be determined to apply to appropriate effect-concentration thresholds to account for various sources of uncertainty. This dose-response test would be required at Level II. The new avian reproduction test will be based on the proposed OECD test method and will include an option for refining the exposure regime to simulate the use pattern and behavior of the test chemical on avian food stuffs in the environment for both Level I and II. Recommended research also includes modifications to the design at Level II to assess effects on parental care and criteria for necessitating measurements for sublethal effects based on those measured in the medium-term dietary study. At this stage, Level III long-term assessments would involve only a refinement of the exposure analysis and not further refinement of effects beyond that identified in Level I.

In conclusion, the certainty in generating a reasonable analysis of effects for risk assessment is greatest for the short-term assessment that utilizes the existing acute oral toxicity study. Certainty decreases for medium-term assessments where the existing dietary study needs to be redesigned, and an absence of historical data prevents the development of specific EF's. Certainty is least for long-term effects assessments where the existing reproduction study is inappropriate for probabilistic risk assessment. Important modifications to medium and long-term toxicity studies include

- Flexible exposure regimes,
- Assessments indicative of quality of parental care,
- Individual data thus improving options for effects analysis models, and
- Avoidance.

The Levels of Refinement are presented in such a way that risk assessments can be improved with existing tools while new ones studies and analyses methods being developed. The proposed Levels of Refinement will require modification depending on the outcome of further research, and the hypothesis that new tests are significant improvements to existing studies must be tested. The outcome of further method development will have implications for management of uncertainty associated with intraspecies and interspecies variability, methods of effects analysis and risk assessment.

5.0 RISK ASSESSMENT METHODOLOGY

5.1 OBJECTIVE OF RISK ASSESSMENT

Risk characterization is a final stage of ecological risk assessment where results of exposure and effects analyses are integrated to evaluate the likelihood of adverse ecological effects occurring following exposure to a stressor. The risk assessment is different from the effects profile characterization (Chapter 4.0), in that the risk assessment integrates the effects profile with the exposure profile for the pesticide, and the probability and magnitude of effects on non-target organisms in the environment can be determined. In the risk characterization, the ecological significance of the adverse effects should be discussed, including consideration of the types and magnitudes of the effects, their spatial and temporal patterns, and the likelihood of recovery (USEPA, 1992). This section discusses methods for risk assessment. Risk assessment is the analysis component of the risk characterization that integrates exposure and effects and evaluates uncertainties (USEPA, 1998). In addition to an evaluation of uncertainty, the risk characterization should provide a discussion of the ecological significance of effects with particular emphasis on the magnitude and spatial-temporal extent of effects. The risk characterization should link back to risk associated with the assessment endpoints that were defined in the Problem Formulation stage. The assessment endpoints determined by ECOFRAM in the Problem Formulation stage (Chapter 2.0) were i. effects on the survival and reproduction of individual birds and mammals ii. effects on population size and persistence of birds and mammals. Risk associated with assessment endpoints needs to be interpreted in the risk characterization to provide concise information that can be used for risk management. If the information is insufficient to support decision-making by risk managers, or the risk assessment needs to be further refined, it may be necessary to proceed to a further iteration of the risk assessment or to a higher level of refinement in the risk assessment process (Chapter 6.0).

A suite of potential methods for ecological risk assessment are described that include deterministic quotients, comparisons of exposure to effects distributions (or point estimate), integrated exposure and effects distributions (using Monte Carlo simulations) and mechanistic models. The basic objective of each different method is to demonstrate how the exposure and

effects analyses may be combined to provide an estimate of risk. The risk output can be displayed in many different formats and should be modified according to the questions being asked by risk managers. In general, the risk assessment is portrayed using a cumulative probability distribution to illustrate the probability of a certain size of effect affecting a certain % of a population. Examples are provided to demonstrate the risk assessment methods, including "spreadsheet model" methods that integrate exposure and effects distributions by using stochastic modeling to simulate many individuals in a population. This particular method will help to determine effects at a population level however, the risk assessment provided is still inadequate in its capability to truly provide assessments for determining effects on actual population size and persistence. Options for risk assessment methods for terrestrial vertebrates are affected by major limitations in available data to characterize exposure and effects. Consequently, the methods will need to further evolve as these research needs are addressed and also improve in their capability of characterizing the risk associated with assessment endpoints of interest.

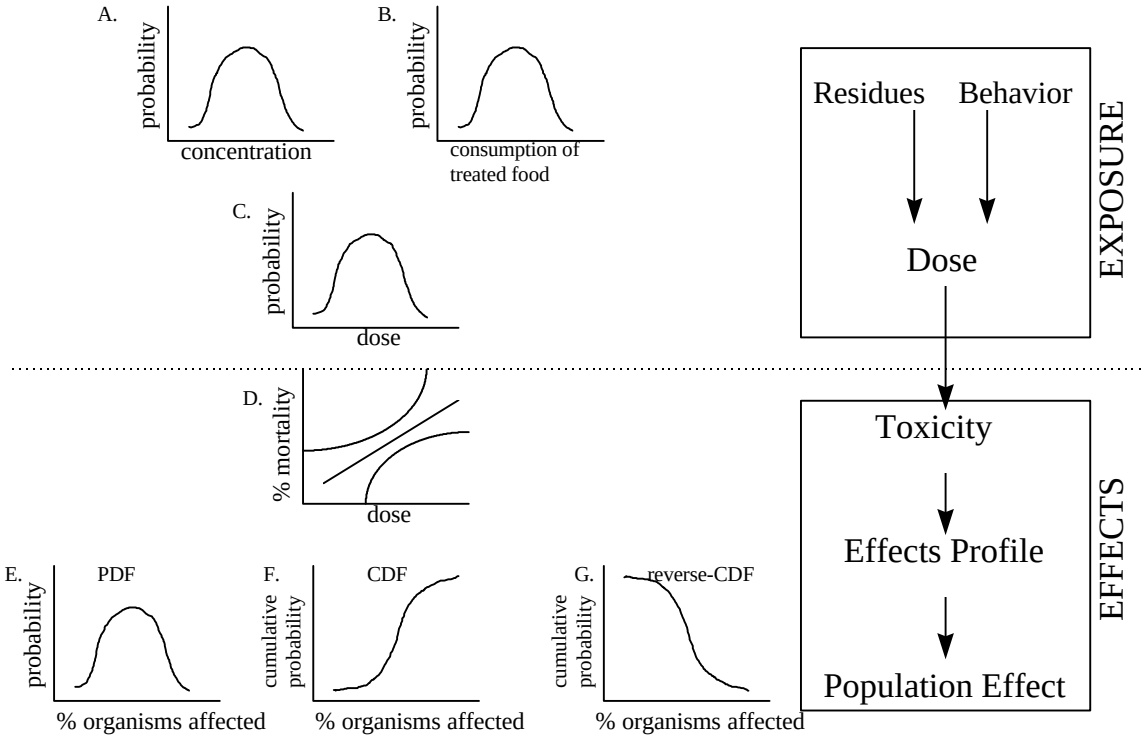
The following are general criteria for selecting tools for risk assessment that will provide probabilistic estimates of risk:

- For effective decision making, risk managers need to be provided descriptive information on risk that describes the probability and magnitude of adverse effects.
- A suite of methods may be the most effective way of providing the flexibility necessary to manage a diversity of pesticide scenarios where a refined risk assessment is necessary.
- Methods within the suite are grouped according to the level of sophistication, effort required, data required, and extent of risk refinement. This forms the basis of the risk characterization process (Chapter 6.0)
- Risk assessment methods must be aligned appropriately with methods used for exposure and effects analysis with due consideration to the unit of time used in the analysis and the different uncertainties.

5.2 OVERVIEW OF RISK ASSESSMENT METHODS

All of the risk assessment methods considered integrate outputs from the exposure analysis (Fig. 5.2.1, graphs A., B., and C.) with the effects profile (Fig. 5.2.1, graph D.) in order to determine the probability of an adverse effect on non-target organisms. How risk is expressed will vary depending on the risk assessment method used and the questions that need to be addressed with the risk assessment (Fig. 5.2.1, graphs E., F., and G.). For example, the probability distribution function (PDF) is useful for illustrating the discrete probability of various input parameters whereas the cumulative distribution function (CDF) can more clearly show the probability that a value on the x-axis will not be exceeded (graph F.) or the probability of exceeding a value on the x-axis (graph G.)

Fig. 5.2.1 A conceptual model of the distributions associated with an ecological risk assessment. The exposure analysis is composed of a residue and a biological component resulting in an estimate of dose. The exposure dose is integrated with the effect analysis resulting in an estimate of risk which can be expressed in a number of different ways



Various options for risk assessment have been considered in order of increasing complexity and potential realism (see Fig. 5.2.2). Less realistic risk assessment methods will tend to be more conservative and with increasing realism, conservative assumptions including values in the risk assessments can be replaced as further information is obtained. These risk assessment methods can generally be divided into three categories:

i. **Deterministic quotients** that are simply a ratio of single values of exposure divided by toxicity (Fig. 5.2.2; Method 1). A major limitation of this method is that the result is not expressed probabilistically.

ii. **Assessment methods that involve a comparison of the exposure distribution or fixed value for exposure to a fixed value for effects or distribution.** These provide a probability

of exposure levels (from a cumulative frequency distribution) exceeding a fixed effect level (ratio-based) or vice-versa (Fig. 5.2.2; Methods 2 and 3). A limitation of these methods is that an estimate of the probability of magnitude of effect occurring, based on the complete exposure and effects distribution is not given. In other words, risk is expressed as the "probability of exceeding a fixed value". This method has been proposed by the aquatic ECOFRAM workgroup for aquatic risk assessments.

iii. **Methods that incorporate functions to integrate exposure and effects distributions** (Fig. 5.2.2; Methods 4, 5 and 6). These methods use stochastic modeling (Monte Carlo techniques) to simulate variability associated with parameters and individuals. In Method 4, distributions of quotients are generated using Monte Carlo simulations to randomly sample values from exposure and effects distributions. Here, the probability of exceedance is based on a ratio of exposure to effects rather than fixed values of exposure or toxicity. Method 5, integrates exposure and effects distributions by simulating the resultant fate (e.g., dead or alive) of large numbers of individuals (using Monte Carlo) based on a dose-response distribution or survivorship model. Risk is expressed as a probability of a magnitude of effect occurring based on randomly sampling the complete distributions of exposure and effects. Method 6 refers to more complex and data-intensive individual-based and population-level models. Unlike the previous methods described, these models should not only integrate exposure and effects distributions using algorithms that represent various ecological or physiological processes but also provide a spatial-temporal analysis of the non-target organism and/or information that describes cause and effect. These models may also incorporate risk assessment modules based on Methods 1 through 5.

Fig. 5.2.2 Overview of Risk Assessment Methods

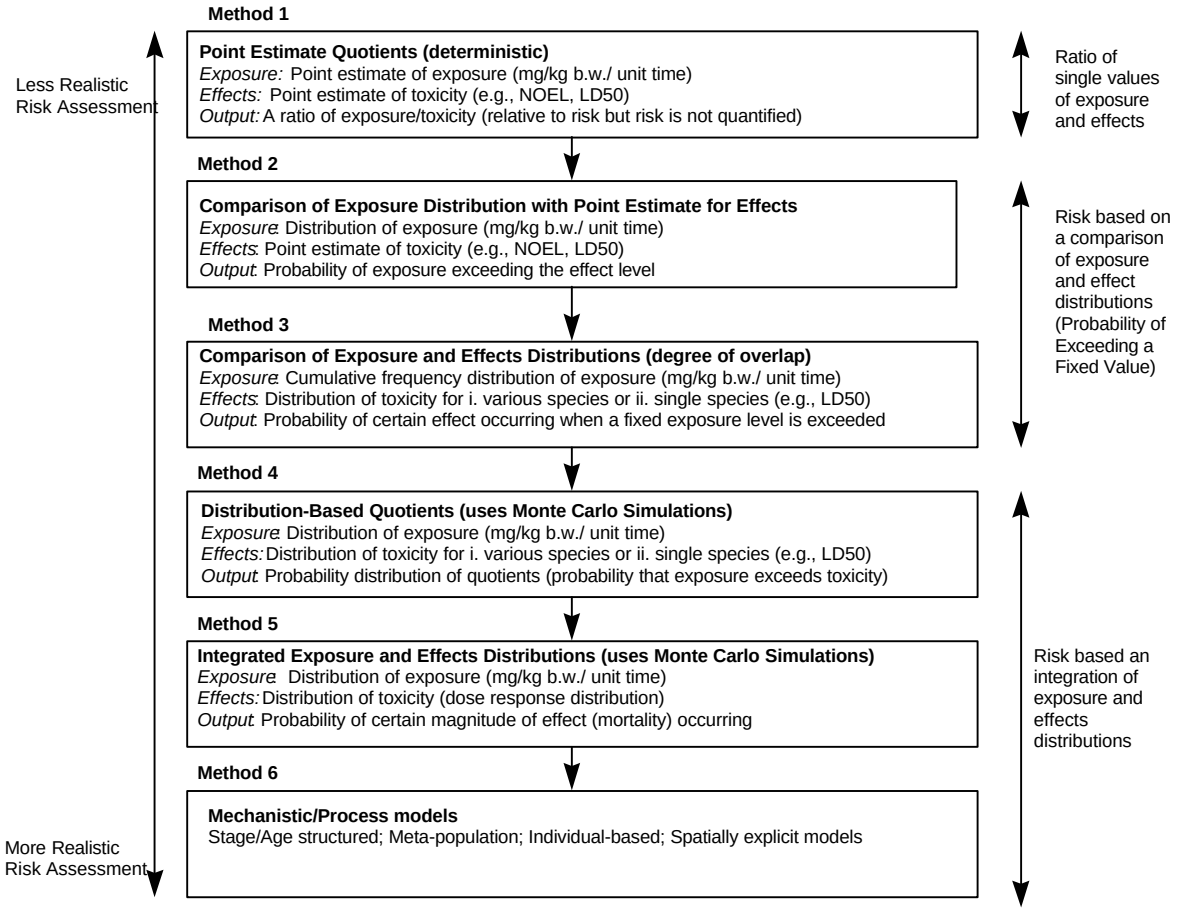


Table 5.2.1 summarizes the advantages and limitations of Methods 2 through 5. All of these methods have their value and are equally applicable to risk assessments for birds and mammals. Future development of risk assessment models together with communication with risk managers will be necessary to determine which of these risk assessment methods are most useful in a regulatory framework. The simplest methods may serve as tools for screening in order to scope the risk assessment (Method 1) or they may be the only applicable method due to limitations in available data. For example, current avian reproduction test endpoints are limited to a NOEL and therefore are dependent on Methods 1 and 2 because it is not possible to apply risk assessment methods that depend on a knowledge of the dose-response distribution (e.g., Method 5). In all methods, deterministic estimates or distributions of exposure and effects are expressed in mg/kg body weight per unit time. The unit time will be dependent on whether the assessment is for short-, medium- or long-term periods of exposure.

TABLE 5.2.1 STRENGTHS AND WEAKNESSES OF DISTRIBUTION-BASED PROBABILISTIC RISK ASSESSMENT METHODS (METHODS 2 THROUGH 5)

Method	Type	Description	Strengths	Weaknesses
2	Comparison of Exposure Distribution with toxicity Point estimate	-Risk is the probability that a fixed effect level lies within the exposure distribution	-spatial-temporal analysis of exposure possible -can be used where no dose-response available	-under utilization of toxicity data -no cause-effect information -no spatial-temporal analysis of effects -no probability of magnitude of effect
3	Comparison of Distributions of exposure and effects	-Analysis of degree of overlap of distributions -Risk is probability of exceeding a fixed value -Effects distribution may represent several species or single species	-spatial-temporal analysis of exposure possible -use of point estimate (e.g., 10th%tile) from distribution could be modified to use entire distribution	-no spatial-temporal analysis of effects -no cause-effect information -risk based a sample population -no probability of magnitude of effect
4	Distribution-based Quotients: (distribution of quotients (exposure/ toxicity)	-Calculate distributions of quotients by sampling from distributions of exposure and toxicity -Risk is based on the probability of quotients (of exposure and effects) exceeding fixed levels	-more information than single quotient -can utilize all available toxicity data - can consider varying exposures -can be used where no dose-response available	-no probability of magnitude of effect -no cause-effect information -no spatial-temporal analysis of effects
5	Integrated Exposure and Effects Distributions	-Simulations (e.g., Monte Carlo) of large numbers of individuals - uses mortality response function to integrate distributions -Quantal response used	-probability of magnitude of effects based on exposure and effects distributions -spatial-temporal analysis of exposure possible	- no cause-effect information -no spatial-temporal analysis of effects (survivorship model provides a temporal analysis)

Examples based on hypothetical data sets were developed to illustrate ecological risk assessment Methods 1 through 5. These examples are not case studies and do not provide a proof-of-concept but do allow a conceptual comparison of the risk assessment methods and their outputs. The examples use distributions of exposure values (Table 5.2.2) and distributions of effects (Table 5.2.3 and 5.2.4). For purposes of simply illustrating the risk assessment method, the exposure values are entered to the risk assessments models as a fixed distribution (i.e., it is assumed that the exposure analysis has been run separately). The risk assessment methods as presented do not illustrate spatial and temporal elements. For the purpose of these examples, it is assumed the time period of exposure in the field is equivalent to that used to derive the LD_{50} in the laboratory (see section 2.8). Effect distributions 1a and 1b are from median lethal dose values for several different test species and can either represent the universe of sensitivity for the focal species, where the actual median lethal dose is unknown, or the sensitivity of several species for a multi-species risk assessment model. Effects distribution 2 equates to the effects analysis output described in Chapter 4.0 and represents the estimated or actual dose-response for the focal species (i.e., a single species model). The estimated LD_{50} for the focal species may be assumed to equal that of the test species, or may be modified using an extrapolation factor that varies according to the number of species tested. The single-species risk assessment is more appropriate for population level assessments where the magnitude of effects and recovery are the important aspects of the assessment. It assumes that the toxicity to the focal species is known or that a specific level of protection is sought.

Table 5.2.2 Exposure distributions used in risk assessment examples. Risk assessment methods 2 and 3 used the probability distributions. The parameters of the distribution were used for methods 1,4 and 5.

Exposure Distribution				
Exposure mg/kg/d	**% Discrete Probability**	**% Cumulative Probability**		
30	10	10		
33	10	20	**Distribution Type =**	Lognormal
45	10	30	**Mean =**	77.61
60	10	40	**Standard Deviation =**	40.05
81	10	50	**95 percentile =**	153.37
88	10	60	**90 percentile =**	128.56
89	10	70		
95	10	80		
120	10	90		
126	10	100		

Table 5.2.3 Effects distribution 1a expressed as a probability distribution was used in risk assessment examples for method 3. The parameters of effects distribution 1a were used in examples for methods 1 and 4. Effects distribution 1b was used in risk assessment examples for method 3. Effect distributions 1a and 1b are from median lethal dose values for several different test species and can either represent the universe of sensitivity for the focal species, where the actual median lethal dose is unknown, or the sensitivity of several species for a multi-species risk assessment.

Effects Distributions 1a					**Effects Distribution 1b**	
LD_{50} mg/kg/d	**% Probability Discrete**	**Cum.**			**LD_{50} mg/kg/d**	**% Prob. Cum.**
90	25	25	**Distribution Type =**	Lognormal	150	20
120	25	50	**Mean =**	203.51	155	40
250	25	75	**Standard Deviation=**	119.92	195	60
350	25	100	**5 percentile =**	71.43	210	80
			10 percentile =	87.1	350	100

Table 5.2.4 Effects distribution 2 was used in risk assessment examples for methods 2,3,4 and 5. Effects distribution 2 represents the estimated or actual dose-response for the focal species. The estimated LD_{50} for the focal species may be assumed to equal that of the test species, or may be modified using an extrapolation factor that varies according to the number of species tested.

Effects Distribution 2			
NOEL mg/kg/d	**LD_{50} mg/kg/d**	**95%tile mg/kg/d**	**5%tile mg/kg/d**
120	220	260	180

For avian risk assessments there will typically be a separate assessment (and exposure distribution) representing each type of focal species. In some instances, it may be only the exposure distribution that changes according to the focal species with a more generic effects analysis based on available test species. However, the effects analysis may also change where estimates of the median lethal dose or dose-response are available for the focal species or in a situation where toxicity data is available for the focal species. It is important to note that the characteristics of the distributions for exposure and effects including what these distributions (or point estimates) actually represent will affect the interpretation of the risk assessment output. The selection of a risk assessment model and the expression of risk should be modified according to the question being asked by risk managers. For each example, details of the output information from the risk assessment is provided to illustrate how the output could be interpreted. Probabilistic risk assessment examples involving stochastic modeling were generated using Monte Carlo analysis within Crystal Ball (an MSExcel add-in for conducting model simulations). Using this software (or similar software e.g, @Risk) it is very easy to view data and

to fit distributions to data. Distributions can be used instead of a fixed value to represent the uncertainty associated with the fixed value. Where actual data are available, these data should be preferentially used and the appropriate statistical distribution carefully fitted to data. Selection of distributions based on minimal data, or data that poorly fit the distribution, should be used with caution. Where data are adequate, the empirical distribution based on the data should be used.

Each risk assessment method will include assumptions and associated uncertainties. As methods increase in sophistication, and their ability to provide a refined risk characterization for assessment endpoints improves, in general, uncertainty should become better defined. An essential element of the risk characterization stage will be to analyze and summarize the major sources of uncertainty. Types of uncertainty include uncertainty associated with natural variability (stochasticity), measurement or parameter error, and incomplete knowledge including model error. The uncertainty in the ecological risk assessment will include the uncertainties within the exposure and effects analysis and uncertainties associated with the risk assessment method. Consequently, the risk assessment will include a hierarchy of levels of uncertainty that will vary according to the scenario being simulated. Uncertainties within the exposure and effects analysis are typically associated with natural variability and parameter error whereas additional uncertainty ensuing from the risk assessment method may include incomplete knowledge. Depending on the method of analysis used in the risk assessment, a sensitivity analysis can be performed to identify the parameter most affecting the output such that a further iteration of the risk assessment can be refined. Risk assessment refinements should focus on these sensitive variables particularly those with the greatest uncertainties.

5.3 POINT ESTIMATE QUOTIENTS (METHOD 1)

In the FIFRA regulatory process to date, the quotient method has been used in risk assessment for pesticides. Results from this method are not probabilistic. The quotient is a ratio that represents the simplest approach for comparing estimates of exposure and effects. A quotient of single values for exposure and effects are calculated (exposure value/toxicity value) and if the quotient exceeds a trigger value (equal to or less than 1), an adverse effect is considered likely to occur. The quotient values do not quantify risk but provide results that are relative to risk.

Limitations of this approach include:

- There is no quantification of the magnitude and probability of adverse effects occurring.
- Output cannot be compared to assessment endpoints.
- Output cannot be compared to probabilistic estimates.
- There is an increased dependence on expert judgment as the quotient approaches 1.
- Only single points that usually represent the more sensitive or conservative data are used in the estimate, other available data are usually ignored.
- Because the estimate is conservatively biased, the safety margin may be large. However, the actual size of the safety margin will remain unknown.
- The method does not account for space or time.
- Species tested in the laboratory are assumed equal to those in the field.
- An evaluation of the effect of risk mitigation measures is difficult.

Advantages of this approach include:

- Provides a crude index of magnitude of effects and therefore could be used for comparisons amongst alternative compounds (where comparable data are available).
- May identify certain groups of non-target organisms where risk is low and further assessment unnecessary.
- Identifies pesticides that are likely to be very safe in the environment when used in conjunction with conservative safety margins.
- Simple and low-effort method
- Risk managers are familiar with the quotient method.

The quotient approach may have utility as a first step (e.g., Level 1 and/or during Problem Formulation) when it matches the needs defined in the conceptual model. The rationale for this, is that if a chemical does not trigger a level of concern then resource for further risk assessment effort could be saved. A single quotient (Method 1) is generated by selecting point estimates from the exposure or effects distribution (Table 5.3.1) for example the 95^{th} percentile value for exposure and the 5^{th} percentile for toxicity.

Table 5.3.1 An example assessment using the point estimate quotients (Method 1)

Inputs for Exposure and Effects (Effects Distribution 1a)	Exposure mg/kg/d	LD_{50} mg/kg/d	Quotient Value (exposure/toxicity)
Based on 95 and 5 %tile	153	71.4	2.1
Based on 90 and 10%tile	128.6	87.1	1.5
Based on worst case data points	126	90	1.4

The example shows that the exposure values exceed the LD_{50} values resulting in quotient values greater than 1. This assessment does not indicate that an effect is unlikely. It does indicate that a refined assessment is necessary to determine the risk. The assessment provides no information on either the probability of an effect occurring or the size of the effect.

5.4 COMPARISON OF EXPOSURE DISTRIBUTION AND POINT ESTIMATE FOR EFFECTS (METHOD 2)

In some circumstances, data supporting exposure assessments may be more available than toxicity data and therefore resulting distributions for exposure more easily obtainable than distributions of the effects profile. In this method, a single distribution of exposure is generated and a point estimate of toxicity is selected. Risk is estimated based on the probability of the effect level occurring within the distribution of exposure. This method is applicable where a dose-response is not available and toxicity is represented by a NOEL. This method is also applicable to situations where a point estimate of exposure is available and a distribution of effects.

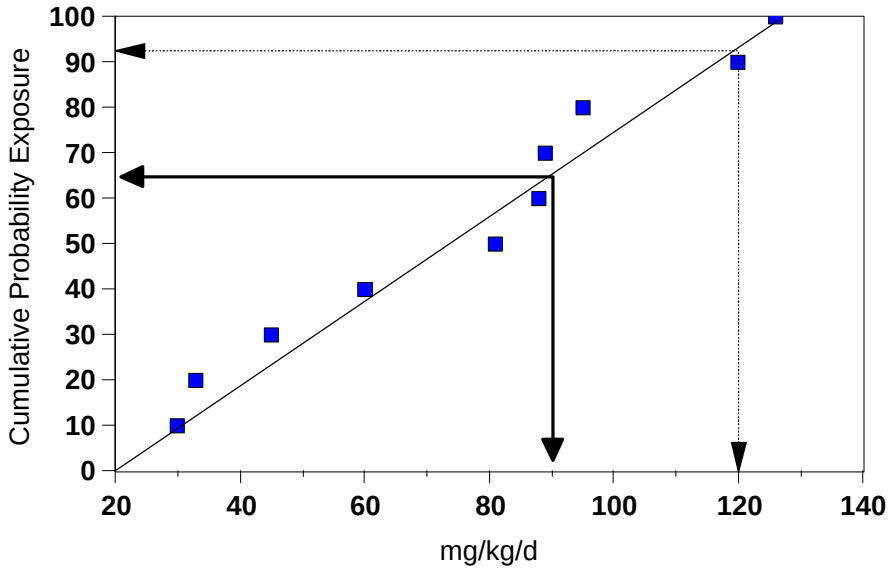
Exposure: A probabilistic distribution of exposure may be generated from two basic models i. Dietary model ii. Granule model.

Effects: Several options are available and include: i. The point estimate represents a toxicity endpoint (e.g., $LD_{50,}$ NOEL) from the most sensitive species where dose-response data were unavailable (e.g., avian reproduction test). ii. The toxicity estimate for the species could be obtained from a generic species sensitivity distribution where there is no information on the toxicity to the focal species. iii. The toxicity to the focal species has been estimated on the basis of data from test species modified by an extrapolation factor. iv. The toxicity data for the focal species is available.

Risk: Risk is expressed from a cumulative probability distribution of exposure to provide a % exceedance of a fixed effect level. For example, there is a 20% probability that exposure values will exceed the effect point estimate (e.g., a NOEL).

An example: Method 2 (Fig. 5.4.1) uses the distribution for exposure and point estimates for toxicity. The arrows on the solid line illustrate where the point estimate for toxicity of 90 mg/kg/d (equal to the lowest LD_{50} value from Effects distribution 1a) intercepts with the exposure distribution. This shows that 65% of the calculated exposure values will not exceed the effect threshold of 90 mg/kg/d which corresponds to 50% mortality of exposed birds, and that 35% of exposure values would exceed the effect threshold and lead to more than 50% mortality of exposed birds. The arrows on the dashed line illustrate where the toxicity threshold of 120 mg/kg/d (equal to the NOEL value from Effects distribution 2) intercepts with the exposure distribution. This shows that over 90% of the calculated exposure values will not exceed the effect threshold of 120 mg/kg/d which corresponds to a no effect level. In other words, < 10% of exposure values would exceed this no effect threshold.

Fig. 5.4.1 Example of Method 2 (Comparison of Exposure Distribution with Point Estimate for Effects). The arrows on the solid line illustrate where the point estimate for toxicity of 90 mg/kg/d intercept the exposure distribution. The arrows on the dashed line illustrate where the toxicity threshold of 120 mg/kg/d intercept the exposure distribution.



5.5 COMPARISON OF EXPOSURE AND EFFECTS DISTRIBUTIONS (METHOD 3)

Where sufficient data exist to provide meaningful distributions of both exposure and effects, joint distributions can be compared to determine the extent of overlap. Risk can be expressed as a probability of exceedance of a fixed exposure level. In contrast to method 2, the probability of exceeding different effect levels can be determined because the dose-response profile is known.

Exposure: A probabilistic distribution of exposure may be generated from two basic models i. Dietary model ii. Granule model. This is expressed as a cumulative probability distribution or a discrete probability distribution.

Effects: i. The distribution is based on several toxicity values (LD_{50}'s) each representing a different species or the distribution represents possible sensitivities for the untested focal species (Effects Distributions 1a and b). Or, ii. The toxicity distribution represents a dose-response distribution for the focal species. Variability associated with the dose-response (i.e., the LD_{50} and slope) can be introduced into the assessment using Monte Carlo techniques (see Method 4 below) or using statistical confidence limits.

Risk: Risk is expressed from a distribution of mortality probabilities. The probability of occurrence of an effect level of a specific magnitude (e.g.,10, 25 or 50% mortality) when a fixed level of exposure is exceeded can be determined.

Examples of Method 3 use the distribution for exposure and Effects Distributions 1a, 1b and 2. A risk assessment based on Effects Distribution 1a where multiple LD_{50} values are represented is shown in Fig. 5.5.1. Here there is a fairly extensive overlap between the distributions for exposure and effects (species sensitivities represented by LD_{50} 's). At 129 mg/kg/d, the 90^{th} percentile for exposure values, LD_{50} toxicity thresholds for 40% of species would be exceeded. However, where the effects distribution represents uncertainty in sensitivity for the focal species rather than sensitivities for multiple species, then for 90% of calculated exposure values there is a 40% probability that the median lethal dose (LD_{50}) for the key species will be exceeded. A Margin of Safety (quotient) can be calculated (Fig. 5.5.1) by dividing the 10^{th} percentile for the sensitivity distribution by the 90^{th} percentile for the exposure distribution (Solomon *et al*, 1996). This gives a value of 0.68 (87.1 / 128.56) which is considerably less than 1.0 indicating a potential for unacceptable risk. Depending on the question asked, the same data used in Fig. 5.5.1 can be used to show the % Probability of Exceedance (reverse cumulative probability distribution) for different species sensitivities as shown in Fig. 5.5.2. For example, there is a 10% probability of exceeding the median lethal dose for 40% of species where the distribution represents multiple species. Alternatively, there is a 10% probability of exceeding the 40^{th} percentile median lethal dose (LD_{50}) for the focal species (Fig. 5.5.2). Where, the effects distribution represents a dose-response for the focal species (e.g., Effects distribution 2), this type of plot can be used to show the probability of exceedance for % mortality (x-axis). This is the method proposed by the aquatic ECOFRAM group for aquatic risk assessments.

A risk assessment based on Effects distribution 1b (Fig. 5.5.3) shows that at 129 mg/kg/d, which represents 90% of exposure calculations, median lethal doses for approximately 20% of species would be exceeded. This approach, based on representing multiple species, may be useful where there is a need to interpret effects on a community of species (e.g., aquatic risk assessments). In this type of assessment, there may be more than one relevant exposure distribution because exposure for each species within the community may not be equal. The risk assessment could be

based on the most conservative distribution or some other appropriate representation of exposure to the community. However, typically in terrestrial risk assessment, the distribution of species sensitivities will represent the uncertainty associated with predicting the sensitivity of the focal species. Thus in Fig. 5.5.3 it could be concluded that for 90% of exposure values, there is a 20% probability that median lethal dose for the focal species will be exceeded. In other words, for 10% of the time, there is a 20% probability that the dose lethal to 50% of the focal species population is exceeded. Fig. 5.5.4 illustrates a risk assessment for a focal species where the effects distribution is based on a single dose-response distribution (Effects Distribution 2). At the 90th %tile for exposure, negligible mortality would be expected.

Fig. 5.5.1 Example of Method 3 (Comparison of Exposure and Effects Distributions) using Effects Distribution 1a. The y_1 axis represents the % cumulative probability distribution for exposure and the y_2 axis represents the % species sensitivity (cumulative distribution of median lethal doses). The shading shows the area of overlap of the 90thpercentile exposure with the species sensitivity distribution (intercepts at 129 mg/kg/d).

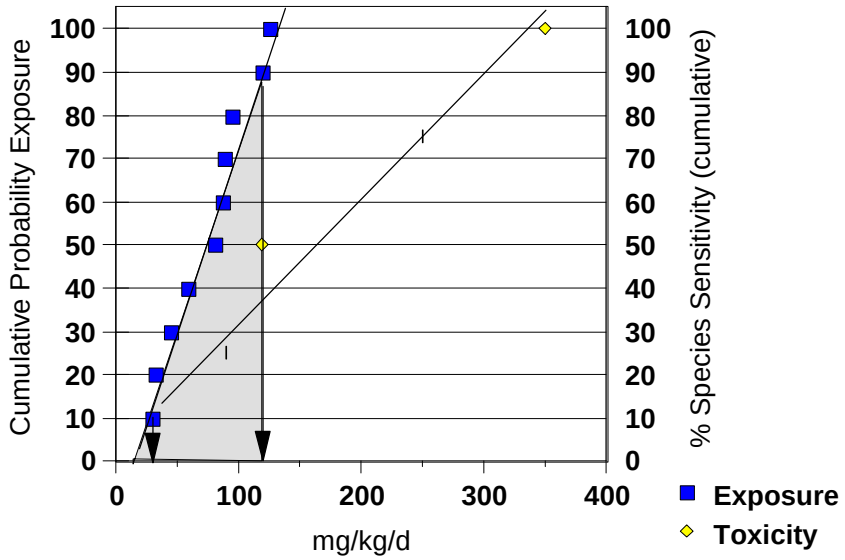


Fig. 5.5.2 Example of Method 3 (Comparison of Exposure and Effects Distributions) based on Effects Distribution 1a. This shows the probability that exposure values will exceed a specified portion of the species sensitivity distribution using a reverse cumulative distribution.

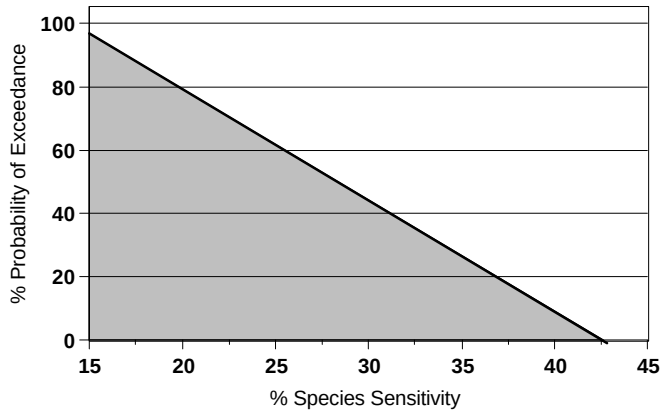


Fig. 5.5.3 Example of Method 3 (Comparison of Exposure and Effects Distributions) using Effects Distribution 1b. The shading shows the area of overlap of the 90thpercentile exposure with the species sensitivity distribution.

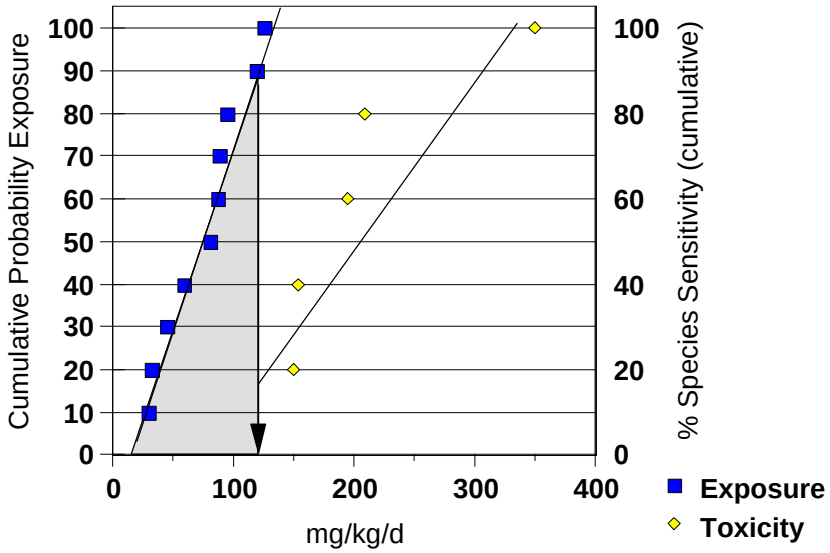
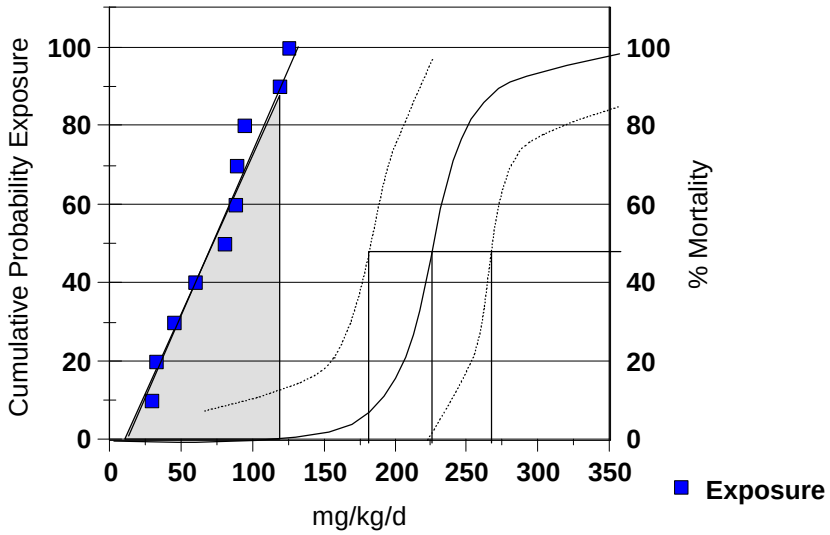


Fig. 5.5.4 Example of Method 3 (Comparison of Exposure and Effects Distributions) using Effects Distribution 2. Error bounds (95% confidence intervals) around the dose-response are shown by dashed lines.



5.6 DISTRIBUTION-BASED QUOTIENTS (METHOD 4)

In the Distribution-Based Quotient Method, each individual quotient represents a ratio of exposure to toxicity. The exposure and effects distributions are integrated using Monte Carlo simulations to randomly sample values from distributions of exposure and toxicity to generate a probabilistic distribution of quotients. Distributions of exposure and toxicity may be derived from various sources. In the simplest form, uncertainty associated with point estimate values can be incorporated by assigning distributions to the exposure and effects variables. In some instances, adequate empirical data may be available to develop actual distributions for exposure and effects. The output shows the probability of exposure exceeding effect thresholds. However, the probability of a certain magnitude of effect occurring is unknown. Risk is expressed from a probability distribution of quotient values, and the probability of the quotient exceeding 1 or any other quotient value. For example, there is a 20% probability that exposure levels exceed effect levels (based on a quotient of 1).

Two different examples of the Distribution-based Quotient methods were developed to reflect a toxicity profile with multiple LD_{50} values (Effects distribution 1a) and another composed of a single dose-response with uncertainty around the LD_{50} value (Effects distribution 2). The exposure and toxicity data were each fitted to a log normal distribution (Fig. 5.6.1). Monte Carlo methods were used to randomly sample from the distribution (10,000 simulations). The assumptions used to generate probabilistic quotients are shown in Fig. 5.6.1. The resultant probabilistic distribution from the simulation shows that there is a 90% probability that the quotient will not exceed 1.0 (Figures 5.6.2 and 5.6.3), i.e. a 90% probability that exposure levels will not exceed effect levels. Fig. 5.6.2 shows the results as a probability distribution whereas Fig. 5.6.3 illustrates the results as a cumulative probability distribution. The risk statement must be modified depending on what the distributions represent. Where the species sensitivity distribution represents possible LD_{50} values for the focal species, and the lack of knowledge concerning the sensitivity for the focal species, the output can be expressed as a 90% chance that the sensitivity of the key species (as expressed by the median lethal dose) will be less than estimated exposure levels (Figures 5.6.2 and 5.6.3).

The output from the second example shows that there is 90% probability that the quotient value will not exceed 0.65 (Figures 5.6.4 and 5.6.5). In this example, there is a 99% probability that the quotient will not exceed 1.0. Specifically, where the distribution of LD_{50}'s represent the error around the LD_{50} for the focal species, the model output can be expressed as a 99% probability that exposure will be below levels that result in 50 % mortality of the population of focal species.

Fig. 5.6.1 The individual distributions for exposure (graph 1) and toxicity (graphs 2 (Effects Distribution 1)) and 3 (Effects Distribution 2)) used to generate Distribution-based Quotients (Method 4). Plot 2 represents potential LD_{50} values for the focal species and therefore the uncertainty (lack of knowledge) associated with estimating an LD_{50} value for the focal species. Plot 3 represents the uncertainty (model and measurement error) associated with the actual estimated LD_{50} value for the focal species.

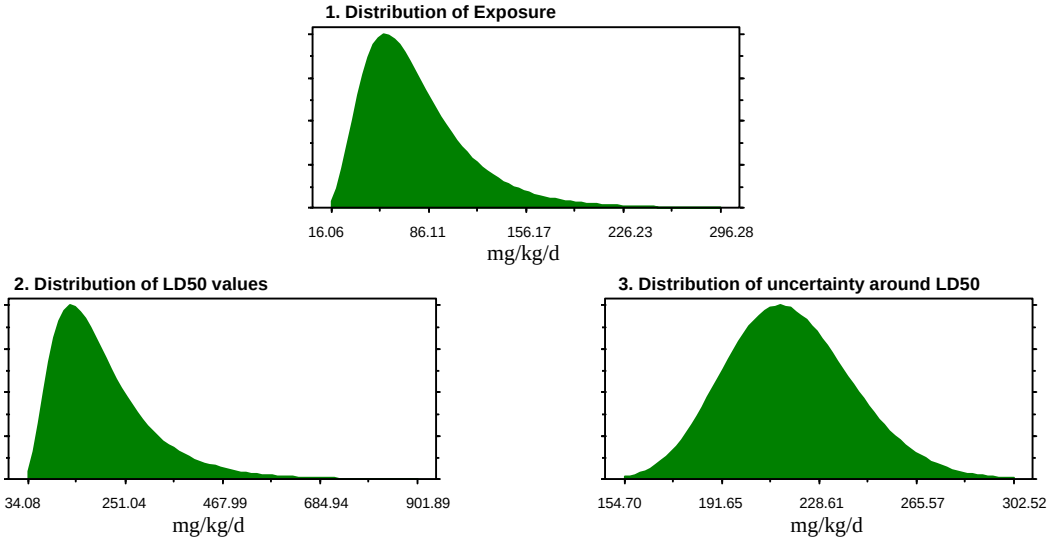


Fig. 5.6.2 An example of Distribution-based Quotients (Method 4) based on Effects Distribution 1 which contains multiple LD_{50} values illustrated as a Discrete Probability plot. The right arrow shows a quotient value of 1.0 (equal to the 90th% tile).

0

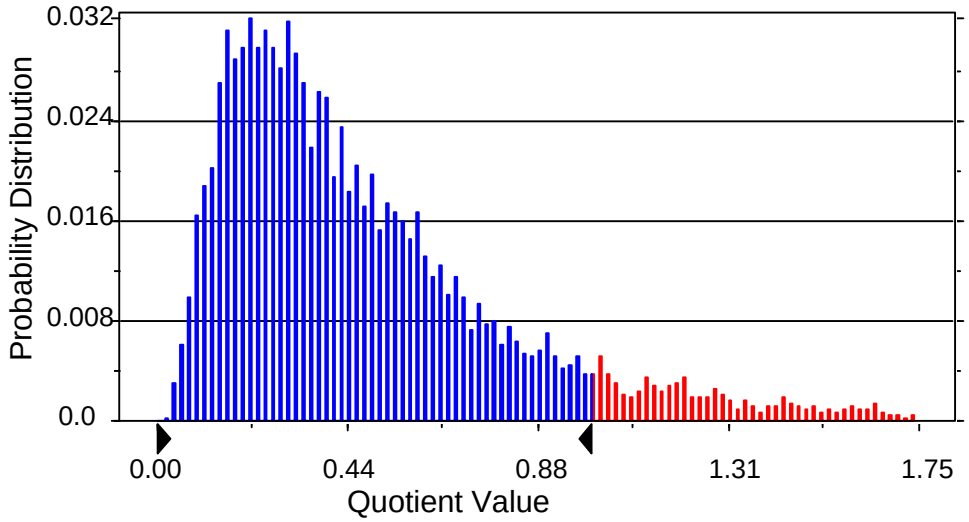


Fig. 5.6.3 Distribution-based Quotients (Method 4) based on Effects Distribution 1 illustrated as a reverse cumulative probability plot or exceedance plot. The arrow on the x-axis shows a quotient value of 1.0. There is a 10% probability of exceeding a quotient of 1.0.

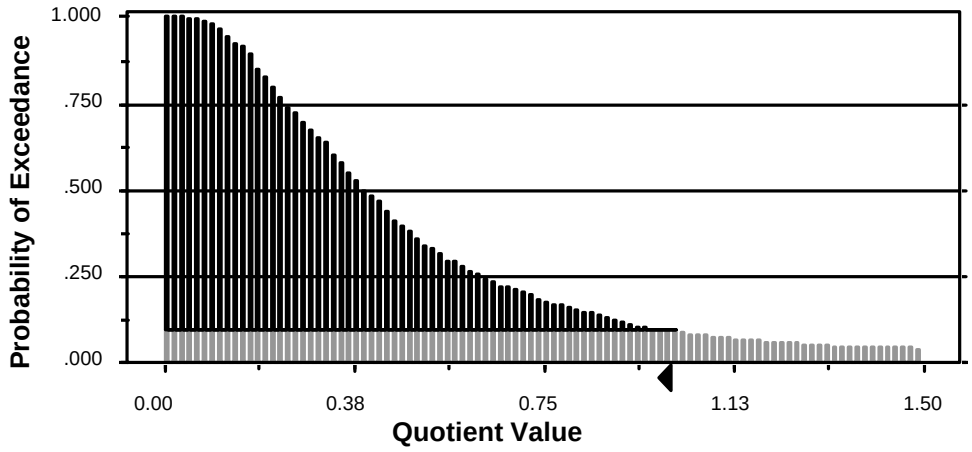


Fig. 5.6.4 Distribution-based Quotients (Method 4) represented as a Discrete Probability plot. This is based on Effects Distribution 3 which represents the distribution around the LD_{50} from a single dose-response distribution. The right arrow shows the 90% probability level which is equal to quotient value of approximately 0.65.

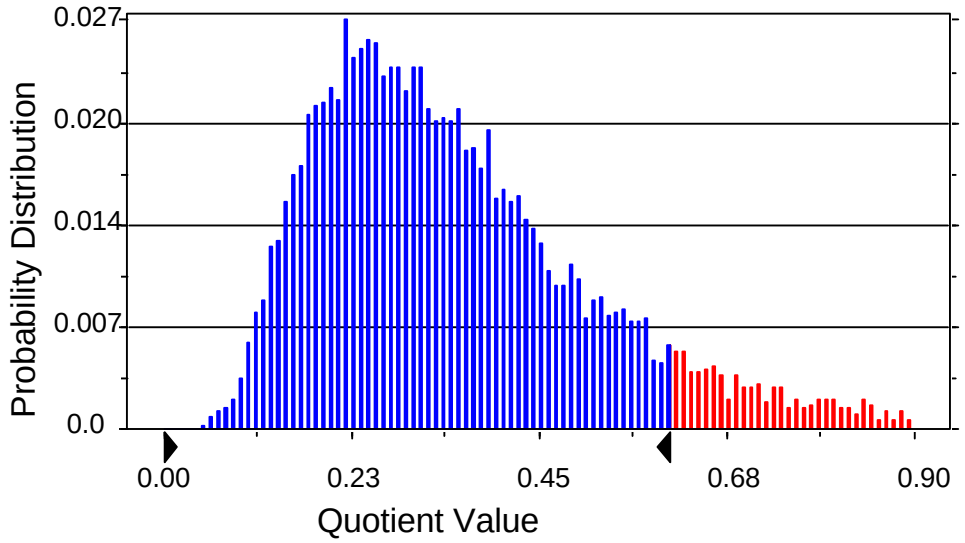
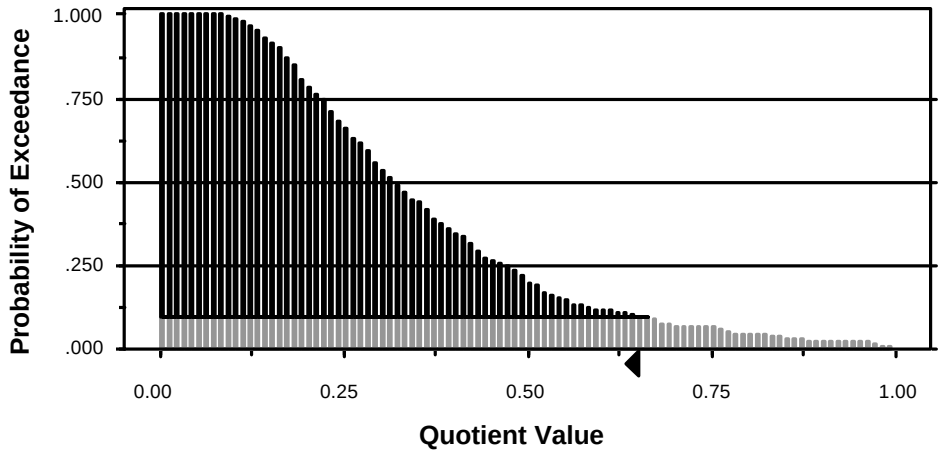


Fig. 5.6.5 Distribution-based Quotients (Method 4) based on Effects Distribution 2 illustrated as a reverse cumulative probability plot or exceedance plot. The arrow on the x-axis shows a quotient value of 0.65. There is a 10% probability of exceeding a quotient of 0.65.



5.7 INTEGRATED EXPOSURE AND EFFECTS DISTRIBUTIONS (METHOD 5)

This risk assessment method uses a probabilistic distribution of exposure that may be generated from the two basic exposure models i. Dietary model ii. Granule model. Generally, the resulting risk may be expressed such that there is a probability that a certain magnitude of effect will occur e.g., a 20% probability that 40% mortality will occur within a population. The integrated exposure and effects method is applicable to risk assessments where data is available to characterize the dose-response relationship for the focal species or the functional relationship based on survivorship is described. Method 5 is similar to Distribution-Based Quotients (Method 4) in that the exposure and effects distributions are integrated using Monte Carlo simulations to sample from both distributions to provide an assessment of risk. However, in Method 5 the quotient (in Method 4) is replaced with a mortality response function, therefore the results of the risk assessment can be expressed as a probability of a certain magnitude of mortality (or some other effect). Also, unlike risk assessment Methods 2 and 3, where risk is based on a probability of exceeding a fixed effect level, the output is a probability associated with a certain size of effect derived by "sampling" from the complete distributions for exposure and effects. The probability that an effect occurs (e.g., mortality) is estimated by observing the frequency of occurrence of the event in a large population of similar individuals. Consequently, Method 5 simulates both individual variability and parameter uncertainty whereas previously

described risk assessment methods describe only parameter uncertainty. The dose-response curve is essentially the cumulative distribution function (CDF) for the distribution of tolerances of individuals to a pesticide. The CDF describes the variability in susceptibility of individuals within a population, where *F(t)* is the proportion of individuals in the population with tolerance less than or equal to *t*. For the individual drawn at random, the probability of mortality is related to the CDF by:

$$P(\text{mortality to exposure dose d}) = P(\text{tolerance} \leq d) = F(d)$$

The response of an individual is dependent on the parameters of the CDF or dose-response (e.g., normal, probit, lognormal or logistic response curves) and these describe the probability of an effect for an individual in relation to a dose. For the probit model, tolerances follow a lognormal distribution and the proportion reacting will be related to the logarithm of the exposure dose by the normal CDF. The logistic curve can also be used to describe the probability of an effect. It has a similar shape to the normal CDF and may be preferred because it is simpler to interpret. In all these models, each individual in the population has a tolerance to a dose and if the susceptibility of the individual is less than the received dose then the individual will react. For example, for a given dose and tolerance, an animal may die or survive (quantal response).

Two different approaches for simulating variability in response by individuals are described to illustrate the Integrated Exposure and Effects Distributions risk assessment method: i. A dose-response approach based on a distribution of tolerances ii. A survivorship approach.
A more detailed explanation of the derivation of the dose-response approach is described in Chapter 4.0. Examples of the dose-response using the same exposure and effects distributions as earlier risk assessment examples are used to demonstrate how different types of uncertainty associated with the effects analysis can be considered within the risk assessment. In addition, other risk assessment examples provided show how the different mortality response functions described for Method 5 can be integrated with the various exposure analysis models developed for dietary and granular ingestion and previously discussed in Chapter 3. Finally, an approach that is based on survivorship or time-to-event is described where temporal consideration is given to effects as data on individuals transitions over time. Mortality (or other effects) probability distributions are based on specific times, ages or stages.

5.7.1 Dose-Response Approach

The mortality response function in these examples is based on a dose-response approach where the sensitivity of each individual is represented by a distribution of random tolerances. Three different models with varying degrees of representation of uncertainty were developed (Table 5.7.1). Each is based on the example distribution for exposure (Table 5.2.2) and the single dose-response (Effects Distribution 2, Table 5.2.4) where an extrapolation factor may have been used to estimate the median lethal dose for the focal species. Model 1 uses fixed values for the LD_{50} and slope of the dose-response. Models 2 and 3 use distributions to represent the LD_{50} and slope where uncertainty associated with interspecies and intraspecies variability can be represented. In addition, model 3 incorporates a distribution to represent uncertainty associated with extrapolation from the laboratory derived LD_{50} to the LD_{50} for the species of concern in the field. This would account for uncertainty associated with the realism of the exposure simulated in the laboratory for example, differences in inherent toxicity between field and laboratory populations and variability resulting from increased stress in the laboratory affecting sensitivity.

Table 5.7.1 The assumptions in the three examples for a dose-response approach based on random tolerances for risk assessment Method 5 (Integrated Exposure and Effects Distributions).

Parameter	Model 1	Model 2	Model 3
Dose (exposure) (D)	Lognormal Distribution	Lognormal Distribution	Lognormal Distribution
LD_{50}	Fixed Value	Normal Distribution	Normal Distribution
Slope	Fixed Value	Normal Distribution	Normal Distribution
Lab to Field Extrapolation Uncertainty Factor (UF)	none	none	UF= 75% Probability that the Field LD_{50} is within 2X Lab LD_{50}
Number of Individuals	20	20	20
Number of simulations	500	500	500
Tolerance of each Individual (T)	T= LD_{50}*10^(z/slope) z=standard normal distribution (mean=0, F =1)	T= LD_{50}*10^(z/slope) z=standard normal distribution (mean=0, F =1)	T= (LD_{50}*UF)*10^(z/slope) z=standard normal distribution (mean=0, F =1)
Fate of Each Individual	if D>T then mortality if D<T then survival	if D>T then mortality if D<T then survival	if D>T then mortality if D<T then survival

In models 2 and 3, the error in the LD_{50} and slope estimates are represented by normal distributions (Fig. 5.7.1). In this example, these distributions are not correlated, however, if LD_{50} and slope is correlated, this modification could be made. In model 3, the uncertainty factor for extrapolation to the species of concern in the field was estimated by assuming the ratio of the laboratory and field LD_{50}s have a lognormal distribution with median 1, implying that underestimation and overestimation are equally probable. For illustrative purposes, the variance of the distribution was calculated by assuming a 75% probability that field LD_{50} values would be within a factor of 2 of the laboratory LD_{50}. The examples are based on the probit model (other dose-response models could also be used) where tolerances are assumed to have a lognormal distribution and the logarithms of the tolerances have a mean of $\log(LD_{50})$ and standard deviation of 1/slope. This can be simplified using the equation:

$$\text{Random Tolerance} = LD_{50}*10^{(z/\text{slope})}$$

where z is a random number from a standard normal distribution (mean=0, variance=1).

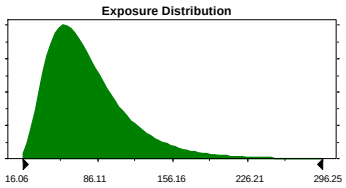
The sample population in these examples has 20 individuals and 500 simulations were conducted for each (Table 5.7.1). The mortality probability function is a quantal response, and for a given dose and sensitivity, an individual either dies (where the tolerance of the individual is less than the dose received) or survives.

The results of model 1, 2 and 3 assessments are expressed as a probability of a certain mortality occurring in the sample population (Figs. 5.7.2, 5.7.3 and 5.7.4) and are illustrated as both cumulative probability distributions and discrete probability distribution. For model 1 where fixed values for the dose-response parameters were used, there is a 100% certainty that mortality will not exceed 40% of the population. There is a 12.4% probability that no mortality will occur in the population and a certainty of 87.6% that 5 to 35% mortality will occur in the population (Fig. 5.7.2). For Model 2 where dose-response parameters were variable, there is a 100% certainty that mortality will not exceed 30% of the population. This model predicts no mortality with a 9.6% certainty and a 90.4% probability that 5 to 30% mortality will occur in the population (Fig. 5.7.3). For Model 3 where dose-response parameters were variable and an uncertainty factor for lab to field uncertainty was applied, there is a 100% certainty that mortality will not exceed 60% of the population. In only 1% of cases is no mortality predicted and there is a 99% probability that 5 to 60% mortality will occur in the population (Fig. 5.7.4). The probability of mortality increases (distributions shift to the right) as uncertainty associated with lab to field extrapolations is considered in the model (Model 3 compared to Model 1 and 2). This results from uncertainty not explicit in Models 1 and 2 being quantified in Model 3. The contribution of each source of uncertainty can be explored further in a sensitivity analysis.

Fig. 5.7.1 Assumptions for parameters characterizing the exposure distribution and dose-response used in Models 2 and 3.

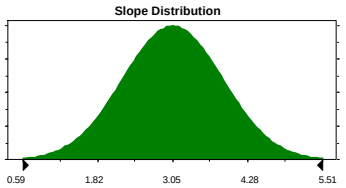
Lognormal distribution with parameters:

5% - tile	31.02
95% - tile	153.37



Normal distribution with parameters:

5% - tile	1.70
95% - tile	4.40



Normal distribution with parameters:

5% - tile	180.00
95% - tile	260.00

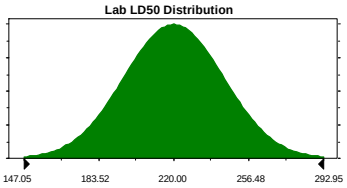
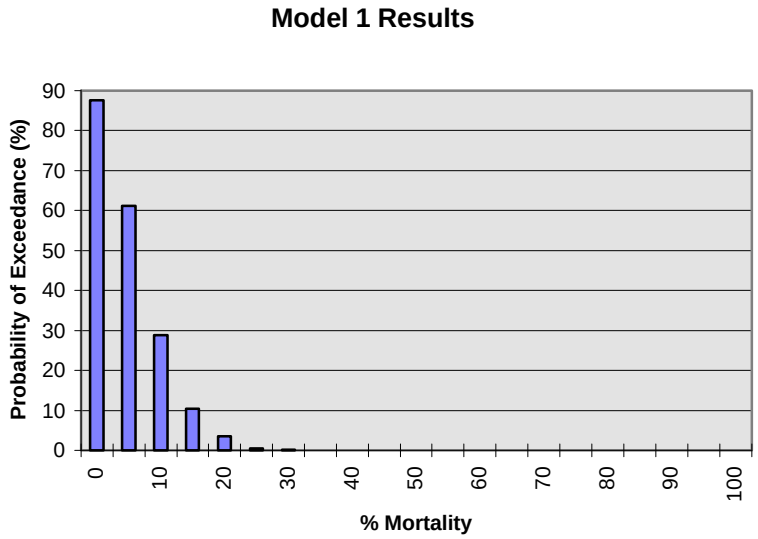
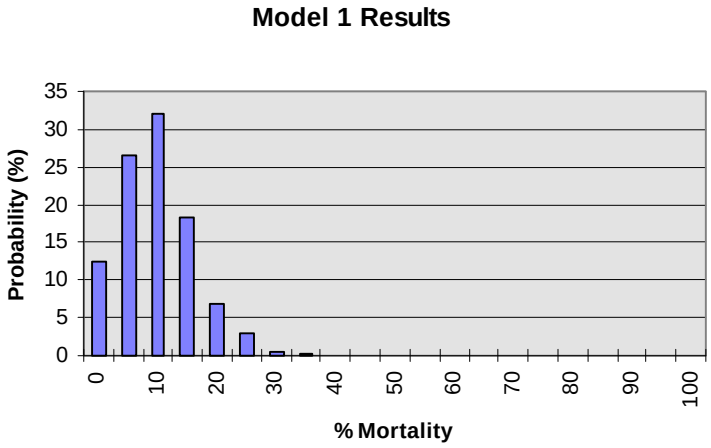


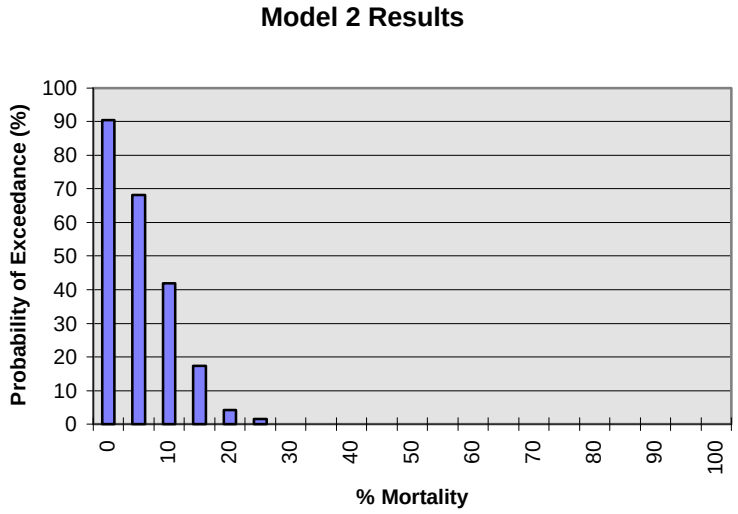
Fig. 5.7.2 Example outputs for Integrated Exposure and Effects (Method 5) based on a dose-response approach with random tolerances and fixed values for dose-response parameters (Model 1). The graphs show reverse-CDF, CDF and discrete PDF respectively.

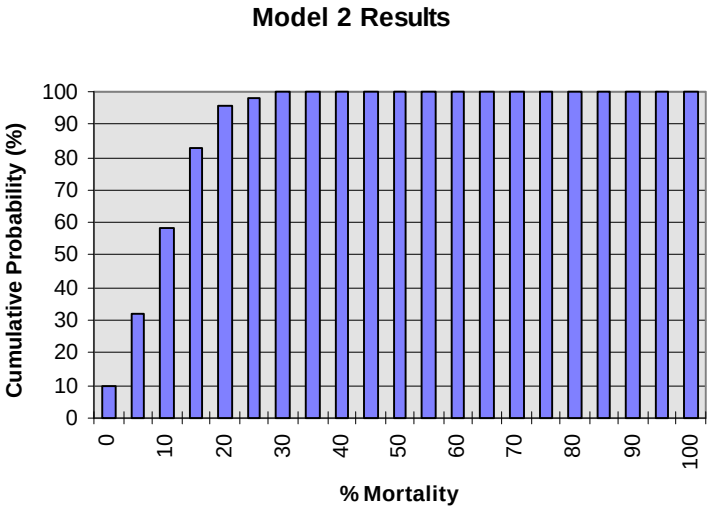


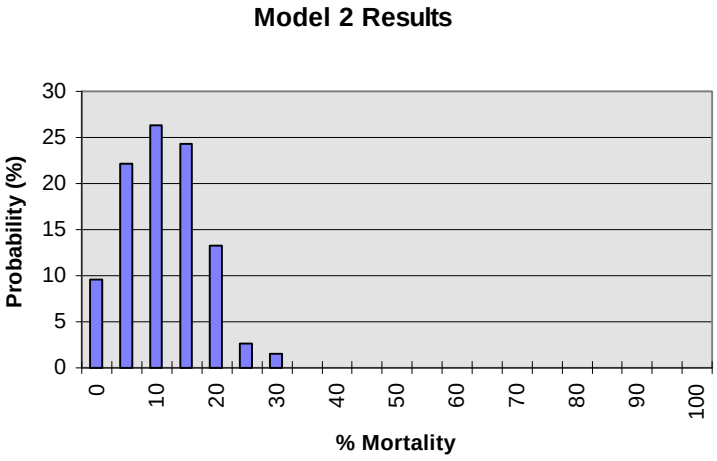

Model 1 Results
Probability (%)
35
30
25
20
15
10
5
0
0
10
20
30
40
50
60
70
80
90
100
% Mortality

1

Fig. 5.7.3 Example outputs for Integrated Exposure and Effects (Method 5) based on a dose-response approach with random tolerances and distributions for dose-response parameters (Model 2). The graphs show reverse-CDF, CDF and discrete PDF respectively.



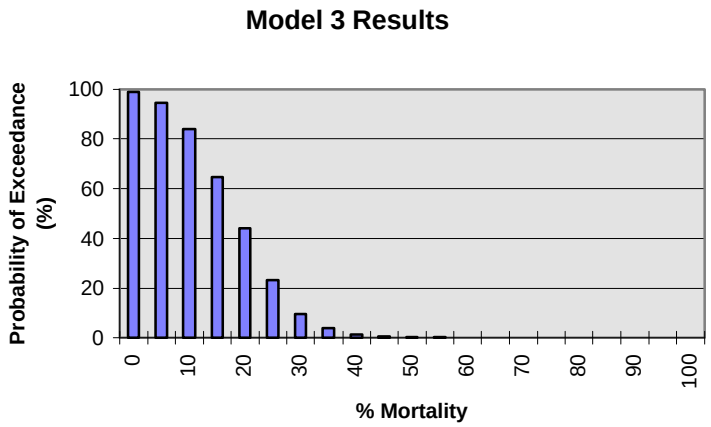


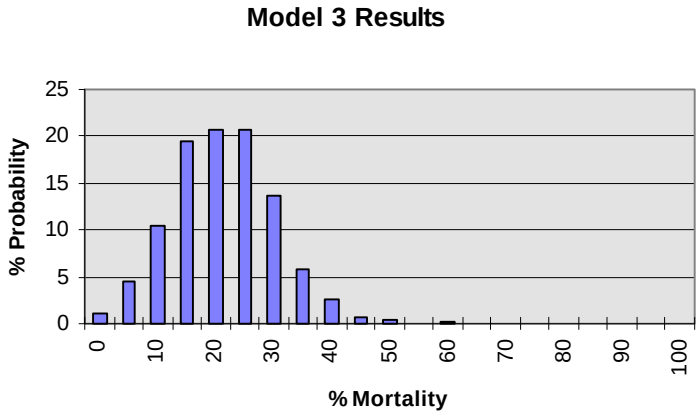

Model 2 Results
Probability (%)
30
25
20
15
10
5
0
0
10
20
30
40
50
60
70
80
90
100
% Mortality

1

2

Fig. 5.7.4 Example outputs for Integrated Exposure and Effects (Method 5) based on a dose-response approach with random tolerances, distributions for dose-response parameters and an uncertainty factor for lab to field extrapolation (Model 3). The graphs show reverse-CDF, CDF and discrete PDF respectively.





The simulations provided in the examples above require that a certain number of individuals (n) be specified. It should be noted that when the number of individuals is increased beyond a certain threshold that sampling variability may be essentially eliminated as a source of variation among simulated populations. In this case, mortality can be generated directly from the dose-response without the use of the random mortality component (see Appendix D1).

The Pesticide Agro-eco Risk Evaluation Tool (PARET) is a risk assessment model under development that uses the dose-response approach based on a random distribution of tolerances (Appendix A2). PARET assesses the risk posed by the use of a pesticide using a simple comparison of exposure and effect on an individual basis. Development of PARET to date has been based on the dietary exposure model including pesticide intake through drinking water (Chapter 3). Random number generators are used to select application dates within an application window. Distributions are used to describe exposure in a spatially and temporally variable agro-ecosystem with temporal variability built into the model in a daily time-step. A grid-based approach is used to represent treated and treated fields on which an animal may move at random (not behavior specific). The number of fields on which an individual feeds is a function of the median size of field in the local area relative to the local range of that species. Effects are assessed using the parameters of the dose-response and by assuming a random distribution of tolerances. The model does not account for depuration of body burden. For each individual the exposure is compared to the effect level and depending on whether exposure levels exceed effect levels, the individual is counted as dead, reproductively impaired or alive.

A further variation of the dose-response approach is described below. As for the previous example, for a given dose and tolerance, an animal may die or survive. The functional relationship is described by the CDF of a standard normal distribution, however, the tolerances do not follow a hypothetical random distribution as in the previous examples. For the probit model, the CDF for the probability of mortality at exposure dose *d* can be described as follows:

$$F(d) = \Phi(slope*\log_{10}(d / LD_{50}))$$

The logistic curve can also be used to describe the probability of an effect and an example of this approach is the individual-based risk assessment model described in Appendix A3. In this model, pesticide ingestion and mortality in avian species is used to link pesticide exposure concentrations to predict mortality on populations of avian species with different feeding habits associated with agricultural fields. The model consists of two parts i. a calculation of the body concentration, or dose, for each individual in the population, and ii. a calculation of the probability of mortality of many individuals of a given species in a population. Each component of the model is stochastic. Random variables include the ingestion rate of granules, pesticide residues in other diet components, and the probability of mortality. The proportion of consumed food items with pesticide residues will depend on the relative time spent in treated areas compared to untreated areas. Each individual accumulates pesticide over time and primary mechanisms for reducing body burdens are excretion and metabolism of absorbed pesticide. The probability of mortality occurring in an individual is determined by a dose-response function in which mortality probability is a logistic function of dose or body concentration. The quantal response is determined using a random number generator. This model uses the following form of the logistic function:

$$F(d)= P_1 / (1 + e\text{^}[(2.2/P_3)(P_2-d)])$$

where F(d)=probability of mortality at dose d; P_1=maximum probability of mortality; P_2=LD_{50}; P_3=difference between LD_{10} and LD_{50}; d= dose or body concentration.

A further variation of this dose-response approach based on non-random tolerances provides an approximation of the cumulative standard normal distribution. An example of a risk assessment

based on this mortality response function provides an assessment of the effects of the insecticide chlorpyrifos on blue tits in orchards in the U.K. (Appendix C10).

5.7.2 Survivorship (or time-to-event) Models

Survivorship models have potential application to ecological risk assessment for example the "Hazard Analysis" method described by Caswell and John (1992). Unlike the majority of integrated risk assessment examples as presented above, survivorship or time-to-event- models give temporal consideration to effects. Survivorship models yield estimates of population level transition rates, estimated from event history data on individuals and could be useful in estimating the probability of mortality under a number of exposure or risk scenarios. They therefore provide an opportunity to improve utilization of information on times or ages of death of individuals, or generation of predictions with a time dimension (e.g., as in life tables). For example, Hazard analysis uses individual-based modeling to estimate rates or probabilities of parameters such as survival, reproduction, or mortality where the data consist of individual transitions over time (e.g., the dependent variable may be monthly rate of mortality). Hazard Analysis is essentially a regression model where the dependent variable is the rate at which the transition (the hazard) occurs. The method can incorporate censored data (i.e., data in which the fate of some individuals is not observed), such as the probability f(t) of an event happening at time t and the cumulative probability F(t) of the event happening before time t to derive the hazard function f(t)/[1-F(t)], which gives the risk of an event occurring at time t, given that it has not yet occurred.

In simple situations such as construction of life tables, the methods may involve obvious calculations involving age- or time-specific mortality rates. For example IBMOD (see Appendix E1) , an individual-based growth model, uses probabilities for fecundity and survival on each individual in separate age classes (similar to a Leslie-matrix type population model). The fecundity probabilities form a cumulative probability distribution used to create a specific number of off-spring per individual. IBMOD tracks off-spring numbers and survival by sex and age class and will simulate growth of a population over time.

5.8 MECHANISTIC (PROCESS) MODELS FOR POPULATION EFFECTS (METHOD 6)

Part of the charge to ECOFRAM was to develop methods for ecological risk assessment that are based on risks to populations where both spatial and temporal scales are considered. There are several types of models that are applicable to estimating the risk of pesticides to populations of non-target organisms (Barnthouse, 1996) that may fulfill this remit. These include models that are individual-based, stage/age structured, meta populations or spatially explicit landscape models. A summary of the advantages and disadvantages of these approaches for probabilistic risk assessment is shown in Table 5.8.1. Like risk assessment Method 5 above, these models integrate exposure and effects distributions to provide a risk estimation. However, unlike the distribution-based methods discussed above, these models are more sophisticated and include mathematical expressions that represent the various mechanisms in the system under evaluation. Mechanistic models can be used to characterize the abundance and/or persistence of populations and can characterize the spatial and temporal characteristics of effects. Each model may be more specific to certain species and/or scenario in comparison to the more generalized distribution approaches. Consequently, reference data sets for representative species associated with certain agricultural ecosystems where pesticides are used may be necessary. The extent of use of the pesticide and persistence, and how this affects the rate of recovery of exposed populations may also be considered. These models, due to their increased realism, may imply a higher level of certainty in comparison to earlier methods, however, to surmise this may not always be appropriate, and careful consideration should be given to underlying assumptions in the model.

Population level effects are traditionally modeled by treating all individuals as genetically, morphologically, and physiologically equal. Different age groups, sexes, body size classes, and even individuals can react differently to exposure to a toxicant. The development of probabilistic risk assessment approaches will explore several approaches for the modeling of population level effects. There are several excellent summaries of the approaches discussed below (DeAngelis and Gross, 1992; Emlen, 1984; Engen, 1978; Freedman, 1980; Gutierrez, 1996).

Population models are available and many could potentially be modified for use in ecological risk assessment. However it should be noted that a major limitation in the use and development of these models is an absence of adequate data. Given this, it was concluded by ECOFRAM that the use of these models should be a longer-term objective.

5.8.1 Age Class Structured

Grouping individuals by age and sex can provide much better estimates of population growth; combining this approach with estimates of differential toxicity will greatly improve risk projections. Models are available that allow for either discrete generations (e.g. the Leslie Matrix) or continuous reproduction (e.g. McKendrick-VonFoerster or distribution delay models). The major advantages of age-class structured models are their relative simplicity, especially in discrete models, and the ability to segregate exposure or risk by age. Research has shown that post-exposure mortality is often age dependent. The disadvantages of this approach relate to the difficulty of obtaining reliable field derived vital rates as inputs to the modeling process. In addition, vital rates are species specific and vary intra-specifically across habitats, and even with the range of a species in a single habitat. Finally, age is not always easy to determine in the field adding to inaccuracy in the population projections derived by the models. Major challenges will include collecting vital rates for age and sex classes for the wide array of species under risk.

5.8.2 Stage And Size Structured

Individuals of different body sizes can be differentially susceptible to exposure to environmental contaminants. Several matrix-based procedures, such as Lefkovitch stage-classified models, allow exposure and risk to be partitioned among life-stage or body size classes (e.g., Caswell, 1989; Slade, 1994). These matrix models have the advantage that they are relatively simple and do not require ages of organisms. It is only necessary to be able to define the life-cycle stages or sizes of the organisms. The disadvantages are similar to age-class structured models; life-cycle or size specific vital rates are difficult to obtain under field situations and these rates will vary in space and time. Even accurately obtained, expected values lack estimates of variability in the wild. The incorporation of estimates of levels of environmental stochasticity also is a major challenge.

5.8.3 Composite Age And Size Structured

There are several models that combine age and size structured data in developing population projections. They include discrete (Slobodkins model) and continuous (Sinko-Streifer equation) forms. Advantages include the capability to consider size differences within ages and relative

simplicity of the models. The disadvantages are a composite of those of age and stage structured matrix approaches. Vital rates must now be obtained or estimated for ages and sizes within ages. Again, these rates will vary in space and time, and age must be determined under field conditions with precision.

All of the above matrix-based models can be modified to include density dependence, stochastic variation, and contaminant-induced impacts. Sensitivity analyses can be run on any of the parameters in the model. However, all are aggregate models to some degree and assume that all individuals in a particular class are behaviorally, morphologically, and physiologically identical. In many cases, this assumption is violated, however, there is a class of models that allows for the incorporation of individual differences.

5.8.4 Individual-based

Individual-based models simulate large numbers of individual organisms at various life stages with explicit consideration of foraging and predation, physiology, behavior, and/or pharmacodynamics. Individual-based models may also be called physiologically-based models, where they focus on physiological differences among individuals in exposure and response. Historically, these models have been applied almost exclusively to aquatic systems. Individual-based models hold great heuristic promise, however, they often require extensive data on individuals in order to characterize the dynamics of a population of individuals with consideration of physiology, behavior and pharmacodynamics at various life stages. Individual-based models possess the following advantages:

- They recognize the reality of individual variation in morphology, behavior and physiology.
- There is, in principle, no loss of biologically important information.
- The responses of interest can be determined under controlled laboratory or field conditions (to a degree).
- These models can be modified to include spatial dependence.

Disadvantages of individual-based models include:

- A dependence upon biological data on individual organisms.
- The fact that these models are computationally intense.
- A history of application primarily in aquatic toxicology.

The great attraction of individual-based modeling approaches is the ability to incorporate physiological, behavioral, competitive, and habitat differences, all of which are known to influence exposure and risk under field situations.

5.8.5 Spatially Structured Populations

In the Problem Formulation stage of the risk assessment the population structure and spatial scale of the risk assessment should be determined. Examples of risk assessment methods described in earlier sections assume that a single population is being exposed to a particular distribution of exposure. As methods become further developed it may be necessary to link several different exposure scenarios to spatially separate subpopulations. The exposure may vary within and/or among subpopulations. This concept is described in detail in Appendix C1. In reality populations are exposed to environmental contaminants distributed unequally across the landscape. Agricultural fields will contain more pesticides, for example, than surrounding woodland. It will be important to include information on the density and reproductive output of species in different habitats as well as the different levels of exposure in these habitats. This information should be included in a variation of source-sink modeling. A specific expression of source-sink models is that of the meta-population (Pulliam, 1994). A meta-population represents a group of geographically separated subpopulations of a species where each patch is separated from others by unsuitable habitat. Some of the subpopulations can be sources and others sinks. The degree of migration among subpopulations can be modeled. The meta-population modeling approach can incorporate information on which patches are likely to be exposed to contaminants and which are distant from agricultural areas.

Spatially explicit risk models can be developed either in matrix-based aggregate models or individual-based approaches. Data inputs can be life-history data specific to each habitat and images of the habitat mosaic derived from some remote sensing approach (aerial photos, satellite imagery). Many spatial database software packages can develop a number of estimates of risk based upon these inputs. The advantages are that the results are site and species specific, locally relevant, and not data-input intensive. The major disadvantages include the lack of generality of

the results, except in a theoretical sense. This approach becomes essentially a case-by-case analysis.

Table 5.8.1 Strengths and Weaknesses of Mechanistic Models for Probabilistic Risk Assessment (Method 6)

Section	Type	Description	Strengths	Weaknesses
5.8.1, 5.8.2, 5.8.3	- Stage/age-structured	- demographic - behavior of population - effects at different ages or life-stages related to overall population effects	- causal mechanisms given - direct link to lifecycle toxicity data (if available) - existing models for resource management could be modified - modification for probabilistic expression of risk - include predicted or observed effects on populations - could use reference data sets for species of interest and their habitats - long-term exposure and effects	- define population (statistical vs ecologically relevant) -difficult to obtain vital rate input information - multiple species - spatially homogeneous - unable to link to spatial & temporal variation in exposure - steady state -data intensive -increasing complexity resulting in increasing propagation of error
5.8.4	Individual-based	-Model large numbers of individual organisms at various life stages with consideration of foraging and predation, physiology, behavior, pharmacodynamics	-to warrant the effort consider use where special review, specific concern for organism at a high trophic level, large body size and longevity -dynamic -focus on benchmark popln. -easy to extend individual based information to population level study -input data most readily accessible or easily obtainable	-focus on single species -considerable effort to provide detailed individual data
5.8.5	- Meta-population	-set of subpopulations -linked by immigration and emigration following local extinction of	-may be useful to evaluate specific problem -habitat considerations could be linked to pesticide use areas (ag	-data intensive -increasing complexity resulting in increasing propagation of error -determining size of Astudy@ area

		species within subpopulation	ecosystems) -able to incorporate important spatial information giving high realism	-in part site specific
5.8.6	- Landscape/ spatially explicit	-simulation of interactions between organisms and landscapes	-improved link to exposure mitigation -spatial & temporal description of risk -GIS software accessible and inexpensive -high realism	-too specific to be generally applicable -spatial representation of stressor and receptor -data intensive -increasing complexity resulting in increasing propagation of error -determining size of Astudy@ area

5.9 FURTHER TESTING AND SELECTION OF METHODS

Several methods for risk characterization were identified by ECOFRAM. Some of these methods may be very similar in function and possibly redundant. The final process implemented for terrestrial ecological risk assessment should focus only on those methods that are most useful in a regulatory risk assessment framework. To achieve this, further evaluation of these methods using case studies is necessary to ascertain redundancy in the proposed methods (see Chapter 7.0). This evaluation is necessary to refine the process for risk assessment. Risk assessment methods must be suitable to use in a regulatory context and therefore must be adequately calibrated and validated. An evaluation of methods proposed by ECOFRAM in case studies should consider several criteria:

- Estimated costs and benefits
- Description of the probabilistic components and expression of risk
- Development of case scenario examples that rigorously test the methods
- Directly address assessment endpoints of regulatory significance
- Easy link to probabilistic distributions of exposure and easy incorporation of appropriate toxicity data
- Consideration of utility within a tiered regulatory process
- Timing of exposure for pesticides needs to be accurately reflected (particularly where a minimal number of applications and minimal persistence will result in a greater probability of not coinciding with a critical biological event).
- Need to understand significance of effects of a perturbation compared to stochastic variability
- Expect to make predictions based on incomplete information and therefore need to be able to assess the uncertainty
- Model error may be a major contributor to overall uncertainty and difficult to measure
- Ease of use in a regulatory context where consistency in requirements for refining assessments may be essential

.

- In models that use populations of individual organisms, the risk characterization needs to consider differences between the collective statistical population used in the model as oppose to the actual population being risk assessed

6.0 LEVELS OF REFINEMENT FOR THE ASSESSMENT PROCESS

6.1 Objective

Terrestrial ECOFRAM has identified a wide variety of possible tools and processes for exposure and effects analysis, and risk characterization. Alternative methods are necessary to provide the flexibility to manage a diversity of pesticide risk assessment scenarios, where different degrees of refinement may be required in order to achieve an adequate understanding of risk. However, in order to be useful within a regulatory framework, these methods need to be organized within an overall, streamlined process that allows efficiency and transparency in conducting regulatory terrestrial risk assessments. As stated in the charge to ECOFRAM, procedures for risk assessment need to be standardized and specific enough to allow different assessors supplied with the same information to produce similar estimates of risk (which is essential for the credibility of the assessment). In fact, the tools and processes discussed in this report are in their infancy, so it would be premature to attempt to standardize them at this stage. Therefore, the objectives of this chapter are to:

- Consider how the principle of Levels of Refinement (developed in earlier chapters) can be applied to the risk assessment as a whole.
- Consider the relative advantages of rigid and flexible assessment procedures.
- Explore ways of deciding how far to refine assessments and how they might work in practice.
- Consider what steps can be taken towards developing more standardized procedures.

6.2 Levels of refinement for the assessment components

At the end of each preceding chapter, the various tools and processes developed by ECOFRAM have been organized into four different levels of refinement. Table 6.2-1 summarises the methods at each level of refinement, and attempts to illustrate the

integration of exposure analysis, effects analysis and risk characterization to form the basis of a risk assessment process.

Table 6.2-1 Overview of Levels of Refinement for ecological risk assessment

	Level I	Level II	Level III	Level IV
Spatial	Treated Field PT=1	Treated Field & Non-target areas PT<1	Treated Field, Non-target areas & Drift Zone PT<1	Landscape -clumping -explicit sizes - pesticide market
Unit Time	• short-term= minutes, hours • medium-term= hours, days • long-term = weeks		Effects assessment adjusted to pattern of exposure over time	
Species of Concern	• generic	• generic/focal	• focal	
Use Pattern	• label maximum	• label maximum	• label maximum • typical/distribution	
Crop	• generic	• linked to focal species • generic		• linked to focal species • individual crop • individual region
Exposure Output	• short-term: conservative single bout exposure • medium-long term: peak daily dose & time-weighted average (TWA, mg/kg/d)	• short-term: distributions for size of single-bout dose, plus frequency of single-bout exposures • medium-long term: distributions of daily dose, & distribution of TWA	• improved distributions (more data) • consideration of drift zones • distributions replacing fixed defaults for parameters • consider additional mechanisms, e.g. avoidance	• improved distributions (more data) • field data on focal species • consideration of landscape factors in spatially explicit models
Effects Output	Short: 1 LD_{50} dose-response * EF Medium: as for short-term Long:2 NOELS for Reproduction	Short: 2-3 LD_{50} * EF Medium: 1 LD_{50} concentration-response * EF Long: refinement of NOEL	Short: 4+ LD_{50} * EF Medium:>1 LD_{50} concentration-response * EF Long: refinement of NOEL	Field options but only in combination with exposure assessments
Risk Characteriz-ation Method	Deterministic Quotients or Method 2	Short: methods 2-5 as appropriate Medium: methods 2-5 as appropriate Long: method 2		
Risk Characteriz-ation Output	Quotient or Method 2	Probability distribution specific to method selected		

This logical progression of methods provides the basis for a process for refining exposure and effects analysis, and risk characterization. Early levels within the process have greater simplicity and conservative assumptions moving towards more realistic estimates of risk at later stages. However, the Levels of Refinement are intended to be used in a flexible manner, so that at any stage of the assessment different elements may be assessed at different Levels of Refinement (see later for elaboration of this important issue). The four levels of refinement may be characterized as follows:

Level 1 is designed to provide a protective screening assessment, and is therefore not predictive of actual risk. Consequently, conservative assumptions are made at this Level for many parameters. For example, animals are assumed to feed only in the treated field, following application of a pesticide at maximum label rates. The assessment is typically based on a conservative scenario (i.e. tending towards the worst case), in which crops and species are represented generically. Toxicity data may be limited at this level and a conservative uncertainty factor is applied to compensate for this uncertainty. Level 1 is a deterministic analysis that culminates in the calculation of a quotient. The objectives of the Level 1 assessment are to:

- Identify products that have minimal ecological concern even under a conservative exposure and effects scenario.
- Identify sensitive taxa (birds or mammals, types of birds or mammals) for further risk assessment refinements.
- Determine whether acute and/or chronic effects are of concern.
- Identify use patterns, crop scenarios, or formulations of products of environmental significance that require further risk assessment refinements.

The objectives of ECOFRAM are to move away from deterministic quotients because they do not provide information on the probability and magnitude of effects. At this stage, deterministic quotients have not yet been dismissed and feature as the risk assessment method in Level 1, for the following reasons:

- Quotients may serve as an interim measure that provides a bridge for risk assessors and risk managers between current and new probabilistic risk assessment methods.

- Quotients remain a primary method within the aquatic ECOFRAM proposal and may continue to be used by EPA risk managers.
- Terrestrial ECOFRAM has not yet conducted case studies to further evaluate proposed risk characterization methods therefore it is premature to eliminate deterministic quotients. Quotients may also play a role in future evaluations by providing a benchmark to which new methods could be compared.
- Further evaluation of risk characterization methods and further development of a Levels of Refinement process may demonstrate that quotients serve a useful purpose in scoping the risk assessment and identification of scenarios of concern (e.g., during the Problem Formulation stage). On the other hand, it may be demonstrated that quotients are redundant.

However, simple probabilistic methods of risk characterization (e.g. Method 2) are also feasible in Level 1 and may allow decisions about the need for refined assessment to be made in a manner consistent with higher levels of the process (see later).

Level 2 is designed to be protective but also introduces greater realism into the assessment by substituting some conservative estimates with more realistic values, and deterministic values with distributions. For instance, the exposure assessment may explore more realistic estimates of the portion of time that a non-target animal resides in the treated field. The Level 2 assessment could be based on either generic species or the focal species associated with the target use of the product. The uncertainty in the effects assessment is decreased by using additional toxicity data and more accurate estimates of dose. The resulting risk assessment is based on probabilistic distributions generated from Methods 2 through 5. The risk assessment for reproductive effects is limited to Method 2 due to the constraints of the current test design (a comparison of the exposure distribution with a point estimate for effects).

Level 3 is similar to Level 2 but incorporates greater biological realism resulting from improved distributions (e.g. empirical or statistically-fitted distributions) and considering additional parameters in the exposure assessment. The effects estimate is refined by testing additional species, and specialised tests may be used (here or at Level 4) to quantify avoidance behavior. Flexibility is introduced for customizing the exposure

regime in toxicity tests. The resulting risk assessment is based on probabilistic distributions as described for Level 2.

Level 4 is the highest level of refinement and considers landscape factors in spatially explicit exposure models and consequently the risk assessment may be crop and regionally specific. Improvements to distributions for exposure and effects may involve focused field studies that provide more accurate measurements of key parameters. The resulting risk assessment is based on probabilistic distributions as described for Levels 2 and 3.

6.3..... LEVELS OF REFINEMENT FOR THE OVERALL ASSESSMENT

A consequence of the flexible approach advocated by the Workgroup is that most completed assessments will include elements at more than one Level of Refinement. However, users are likely to want to describe the overall level of their assessments without having to refer to the Levels of all the component parts. It is possible to categorise the overall assessment in broad terms so, to avoid confusion, the following descriptions are offered:

Level 1 Assessment	Entirely deterministic assessment. All inputs and outputs are point estimates, although some inputs may be 'worst case' values drawn from a distribution (e.g. 95 percentiles).
Level 2 Assessment	At least one input and the output are in the form of distributions, but the input distributions are all hypothetical or generic (i.e. not specific to the pesticide and scenario in question), and may be based on relatively limited information (e.g. means and standard deviations available from the scientific literature).
Level 3 Assessment	At least one input and the output are in the form of distributions. Input distributions are generally not specific to the pesticide and scenario in question, but are likely to include statistically-fitted distributions and/or empirical distributions. Likely to use more distributions than at Level 2 and consider additional parameters.
Level 4 Assessment	At least one input and the output are in the form of distributions, with at least one input distribution being specific to the pesticide and scenario in question (e.g. derived from field studies or non-standard effects studies). May use a spatially-explicit model.

For the overall assessment, the Level of Refinement refers to the extent that biological realism, risk and uncertainty are incorporated in the risk characterization and how well actual risk is described. Level 1 is

suitable for screening purposes, and information is not provided on the probability of a certain magnitude of effect occurring. The purpose of higher levels is to address additional data needs, reduce uncertainty in the risk characterization, and reduce the need for the use of conservative assumptions. Consequently, more explicit information on risk, and improvements in the prediction of actual risk will occur at increasingly higher levels. In general the progression from lower to higher levels of refinement is based on:

- Point estimates for parameters in the exposure assessment are replaced with distributions.
- Additional parameters in the exposure model are considered.
- Increased spatial realism. Both treated and untreated habitat are considered.
- An improved estimate of mg/kg/b.w. per unit time for test animals.
- Number of species tested is increased.
- Pattern of exposure in toxicity test is refined.
- Increased realism in the risk assessment.
- More uncertainty is explicitly considered in the analysis.
- Decreased uncertainty in the estimate of actual risk.
- Increased understanding of risk, and increased credibility of the assessment.

Each refinement of the assessment should be preceded by a review of the Problem Formulation. The measurement endpoints employed may change as the risk assessment progresses through higher levels. Assessment endpoints, however, remain unchanged as the assessment is refined, although some assessment endpoints may be adequately addressed at lower Levels and not require as much refinement as others.

As experience is accumulated it may be possible to define more standardized sets of parameters, distributions and models to use at each Level, for particular types of pesticide (e.g. granulars vs. foliar sprays vs. seed treatments). Cooperative case studies would be a good way to start identifying these (see later).

6.4 Levels versus tiers

Traditional approaches to pesticide eco-risk assessment have tended to be organised in hierarchical frameworks, in order to focus assessment resources on the pesticides and impacts of most concern. The levels in these frameworks have often been called Tiers. Tiers have been used simultaneously to classify the tools for risk assessment (particular types of study are done in specific Tiers) and define the process for risk assessment (a step-wise progression from lower to higher Tiers, triggered by levels of concern). They have also tended to be rather rigid, although this is not always the case (the Aquatic ECOFRAM has defined a Tiered process but emphasizes that the Tiers are flexible). An extreme example might proceed as follows:

1. conduct all studies in Tier 1
2. conduct risk characterization
3. if risk unacceptable, proceed to Tier 2
4. conduct all studies in Tier 2
5. repeat risk characterization… and so on.

This has the advantage of transparency but is very unlikely to be *efficient*. Usually, only some of the studies within a Tier will be really necessary for the risk manager's decision

to be made. So if the Tiers are applied rigidly to every pesticide, many studies may be conducted and evaluated unnecessarily.

It has been stated many times in this report that the Terrestrial Workgroup regards the Levels of Refinement as flexible. Specifically,

- in a completed assessment, some components may have been refined to a higher Level than others
- there is no requirement to refine every component to one Level before proceeding to the next.

Furthermore, the Workgroup does not regard the assignment of methods to Levels in this report as definitive: further development and experience might suggest modifications (see later). It is partly to avoid the traditional expectation of rigidity, that the term 'Levels of Refinement' is preferred to 'Tiers'.

The issue of flexibility versus rigidity is not a trivial one. As the charge to ECOFRAM implied, consistency between risk assessors is important, and different assessors are more likely to produce the same estimate of risk if procedures are standardized. This is particularly true when they are faced with new approaches, and with the wide variety of possible tools and processes identified in this report.

This diversity of options raises two key questions:

- how far to refine the assessment?
- which parameters to refine?

These questions are important. Without answers, it will not be known which parts of the risk assessment to refine, nor when to stop. This would lead to unnecessarily complex risk assessments, and inefficient use of resources for both regulator and registrant. Rigid Tiers and triggers are designed to help the risk assessor answer these questions. Rigid Tiers and triggers also provide transparency for the registrants, making it easier for them to anticipate what studies will be required and plan product development. It is therefore important to consider whether more flexible procedures can also provide efficient answers to these questions.

6.5 How far to refine the assessment ?

The purpose of risk assessment is to enable EPA risk managers to decide if the risk from a particular pesticide use is acceptable or requires mitigation. The assessment therefore needs to be refined to the point where the actual risk is known with sufficient certainty for risk managers to decide which side of the threshold of acceptability it lies.

The closer the actual risk is to the threshold of acceptability, the more precision is required in the risk assessment to enable a decision to be made. To put it another way, the closer the actual risk is to the threshold of acceptability, the more refined the assessment needs to be to provide sufficient understanding and credibility for the risk manager to make a decision. Consequently, *the degree of refinement required depends on how close the actual risk is to the threshold of acceptability.* This concept is illustrated in Figure 6.5-1.

The Workgroup recognizes that the concept of a threshold of acceptability is a sensitive issue. However, the fact that risk management decisions are made implies that thresholds exist, even if they are never explicit.

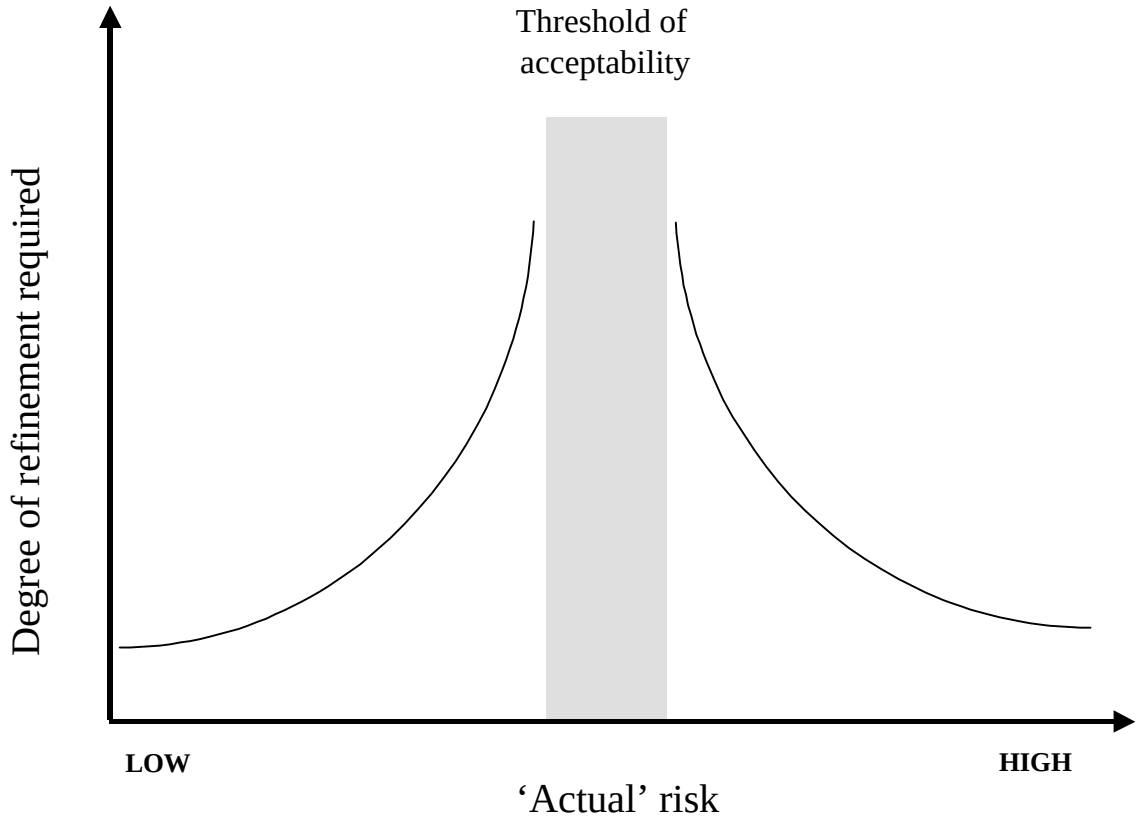
Figure 6.5-1 shows that, if the threshold of acceptability is not defined, it is very difficult to decide how far to refine the assessment. Even if the position of the threshold is known, it may vary from case to case depending on the balance between risk and benefit. Nevertheless, if the actual risk is much higher than the acceptable level, or much lower, this may be apparent from a very simple initial assessment. A risk prediction with a high level of uncertainty may be sufficiently far from the threshold that a decision can be made with adequate certainty.

6.6 Which parts of the assessment to refine ?

Comparison with the acceptability threshold provides the key to deciding how far to refine the assessment. For example,

- If the initial prediction of risk is far enough *below* the threshold, further refinement may be unnecessary.
- If the initial prediction of risk is *close to* the threshold, further refinement is likely to be essential.
- If the initial prediction of risk is far enough *above* the threshold, then it may be more cost-effective to look for mitigation methods than to invest in refining the assessment.

Figure 6.5-1. The closer the actual risk is to the threshold of acceptability, the more the assessment has to be refined for the risk manager's decision to be taken with adequate certainty. The threshold is shown as a broad band rather than a line, because its position can vary from case to case and may never be defined precisely.



If it is decided to progress beyond the initial assessment, the next question is which of the assessment parameters to refine. An efficient approach would identify those refinements which will achieve adequate certainty in a given assessment with the minimum cost in time and money. At any point in the assessment, all the parameters will have been addressed at some Level of Refinement. To decide which parameter(s) to refine:

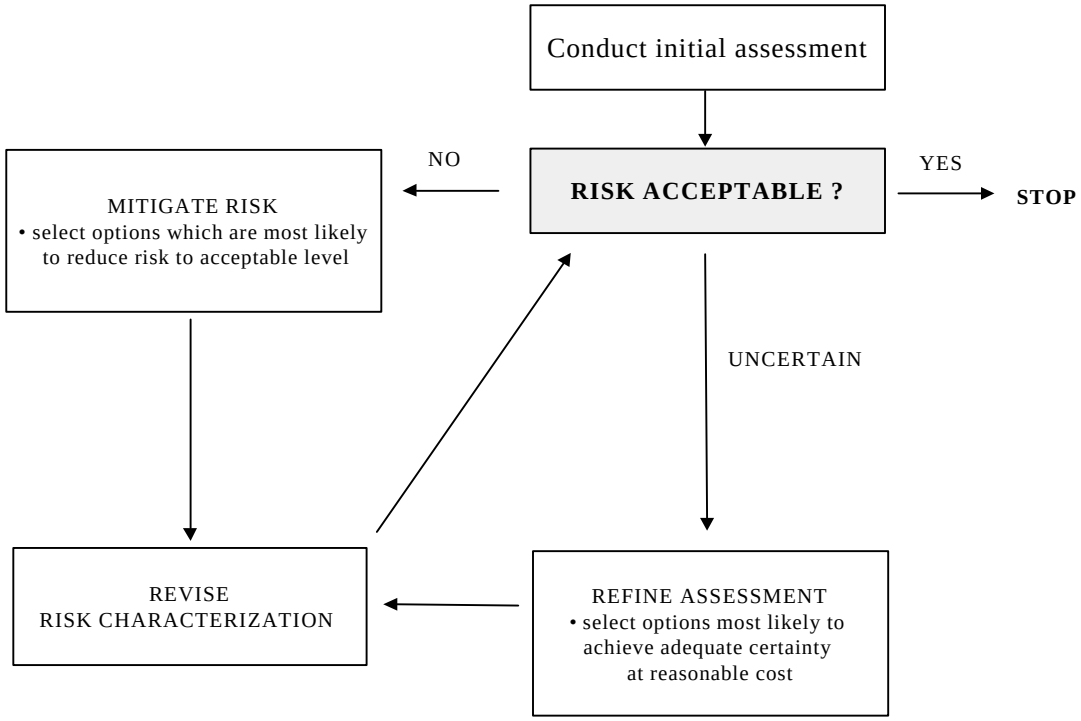
1. assess how much uncertainty will be reduced by refining each parameter
2. assess how much each will cost in time, money etc.
3. choose the most cost-effective option or set of options.

The selected options would then be implemented in the next phase of assessment, producing a refined estimate of risk. If it was concluded that there was still too much uncertainty, then the cycle could be repeated to identify options for a further phase of refinement. Thus the overall process would be *an iterative refinement of the assessment which would stop when the result was sufficiently certain for the risk manager's decision to be made* (Figure 6.6-1).

Note that risk mitigation options could also be considered at any stage in the process, if the earlier results suggested that the result of refining the risk was likely to be unacceptable. This is also illustrated in Figure 6.6-1.

Note also that this process can be applied equally to the registration of new pesticides and re-registration of existing pesticides. For new pesticides, one will probably start with the lowest level of refinement for every parameter. For older pesticides, the process may start at higher levels, if the necessary data already exist.

Figure 6.6-1. Possible iterative approach to refining the risk assessment, so as to provide the information required for the risk manager's decision with the minimum cost and effort. The shaded box represents the decision to be taken by the risk manager. Other boxes represent actions by the risk assessor.



6.7 MAGNITUDE AND PROBABILITY OF EFFECTS

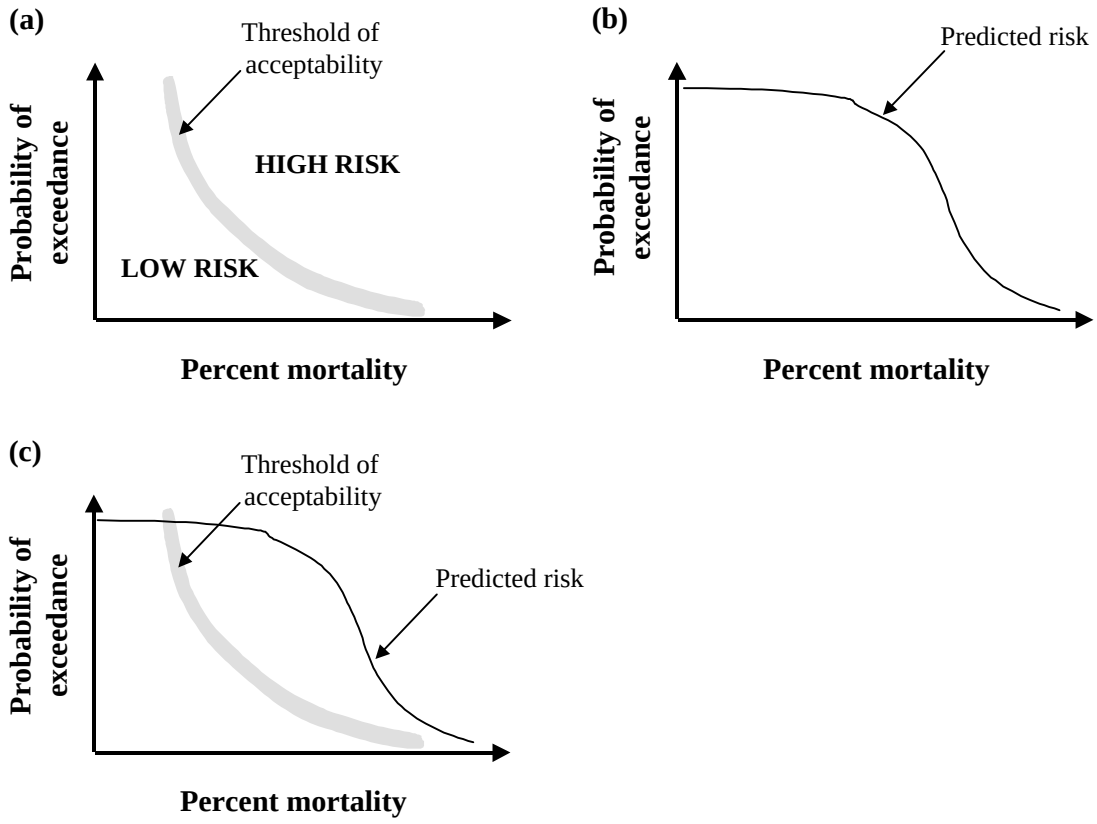
Figures 6.5-1 and 6.6-1 imply that the flexible assessment process will involve a series of comparisons between a distribution of predicted risk and a threshold of acceptability. For convenience, the discussion so far has referred to risk and the threshold in simple terms. In practice, as indicated by the charge to ECOFRAM, the assessment should predict both the *magnitude* and *probability* of effects. The threshold of acceptability therefore needs to be defined in terms of magnitude and probability as well.

For example, if the assessment endpoint is mortality, the threshold of acceptability might be, say, a 5% chance of 5% mortality for the focal species. At community level, a 5% chance of more than 5% of species suffering more than 5% mortality might be unacceptable. It is emphasized that the percentages chosen for these and the following examples are purely illustrative: in practice they would be determined by the risk manager, taking account of many factors. In the past thresholds have not been expressed in this way, perhaps because adequate tools to quantify risk in these terms were lacking.

The thresholds of acceptability for the probability and magnitude of effects will generally be interdependent. For example, if a 5% chance of 5% mortality was acceptable, 10% mortality might be acceptable at a lower level of probability. If the probability and magnitude of effects are plotted on a graph, then a line could be drawn to join the points marking the threshold of acceptable risk (a similar representation has been used by the Aquatic ECOFRAM). In practice, it is unlikely to be realistic to define the threshold precisely, so it may be more appropriately represented by a broad band than a line (Figure 6.7-1a).

Predicted risk can also be characterized in terms of magnitude and probability, using Methods 2-5 in Chapter 5. These can be plotted as an exceedance curve (Figure 6.7-1b). Plotting this on the same graph as the acceptability threshold enables a direct comparison (Figure 6.7-1c).

Figure 6.7-1. (a) Graphical representation of the risk manager's threshold of acceptability in terms of the probability and magnitude of effects. The threshold is shown as a broad band rather than a line, because its position can vary from case to case and may never be defined precisely. (b) Graphical representation of risk assessor's prediction as an exceedance curve, showing the probability that the magnitude of the effect exceeds each point on the horizontal axis. (c) Comparison of predicted risk with acceptability threshold. Areas where the prediction exceeds the threshold indicate potentially unacceptable risk.

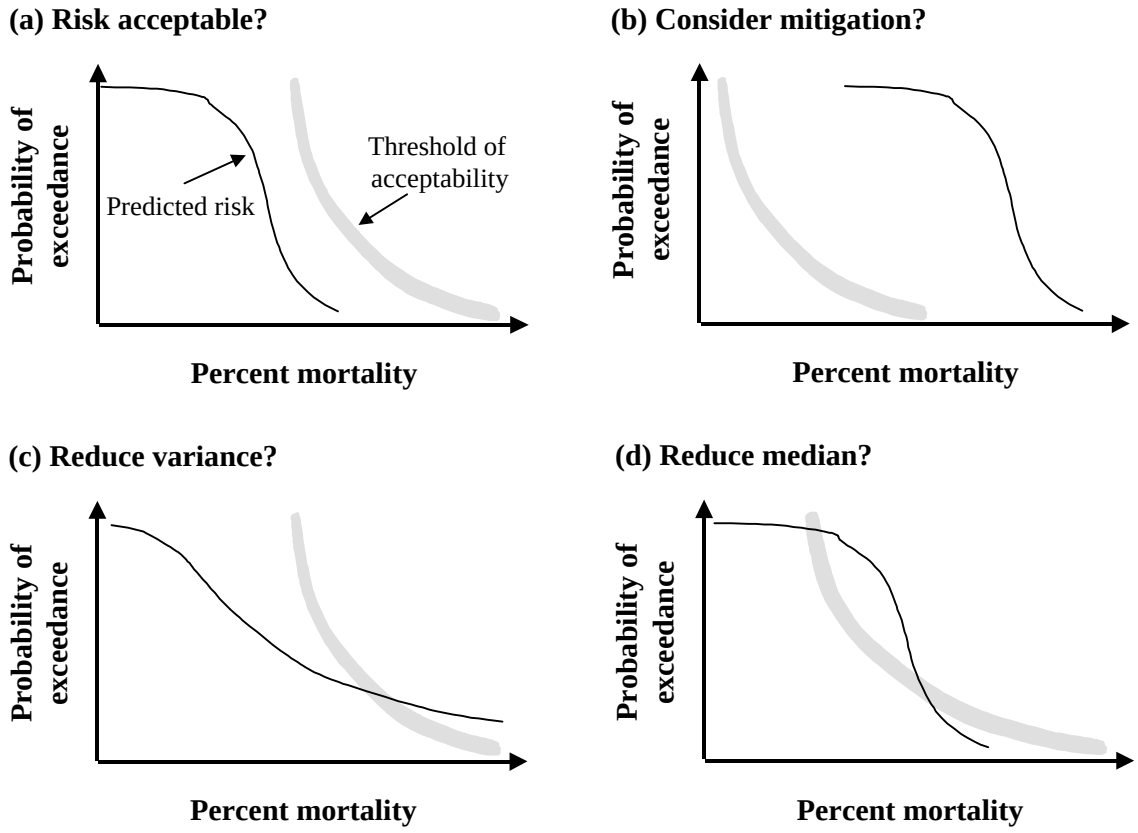


At any point in the risk assessment, this comparison between predicted risk and acceptability threshold can help decide how to proceed. For example:

- If the whole of the exceedance curve is well below the threshold, the risk is likely to be acceptable and further refinement may not be required (Figure 6.7-2a).
- If the whole of the exceedance curve is well above the threshold, the risk is likely to be unacceptable and no further refinement is required (Figure 6.7-2b).
- If only the bottom tail of the curve exceeds the threshold (Figure 6.7-2c), refinements which reduce the variance of the predicted risk may be sufficient to achieve an acceptable outcome. For example, reducing measurement error in exposure parameters, or conducting effects tests with additional species to decrease the variance of the mean LD50.
- If the median of the curve exceeds the threshold, refinements which move the median to the left (lower risk) will be necessary (Figure 6.7-2d). Replacing ‘worst-case’ assumptions with real distributions is the most effective way of doing this, even though it will increase the variance of predicted risk. For example, replacing ‘maximum’ residues with a measured distribution, or using a distribution for PT instead of setting it to 1. Alternatively, the median can be moved to the left by risk mitigation measures.

In the last 2 categories, it may not be obvious which variable it is best to refine. Perhaps the most practical way to decide is to use expert judgement to guess the effects of each possible refinement, and then use sensitivity analysis to compare their effects on the assessment outcome. For example, before deciding to quantify PT (the proportion of time spent in the treated area) by radio-tracking, one might define a hypothetical best-case distribution for PT. If including this in the assessment was not enough to reduce the risk below threshold, one would hesitate to proceed with radio-tracking. This combination of expert judgement and sensitivity analysis should be a powerful way to optimize the refinement of the assessment.

Figure 6.7-2. Comparison of the distribution of predicted risk with a threshold of acceptability could help decide how to proceed with the assessment. Here percent mortality is used as an example of an assessment endpoint, and the curve shows the uncertainty in the predicted mortality: (a) low probability of exceeding threshold – risk acceptable? (b) low probability of being below threshold – consider mitigation? (c) variation too great for adequate certainty whether risk exceeds threshold – reducing measurement error may be sufficient; (d) curves overlap but median risk exceeds threshold – may need to replace worst-case assumptions with distributions or consider risk mitigation.

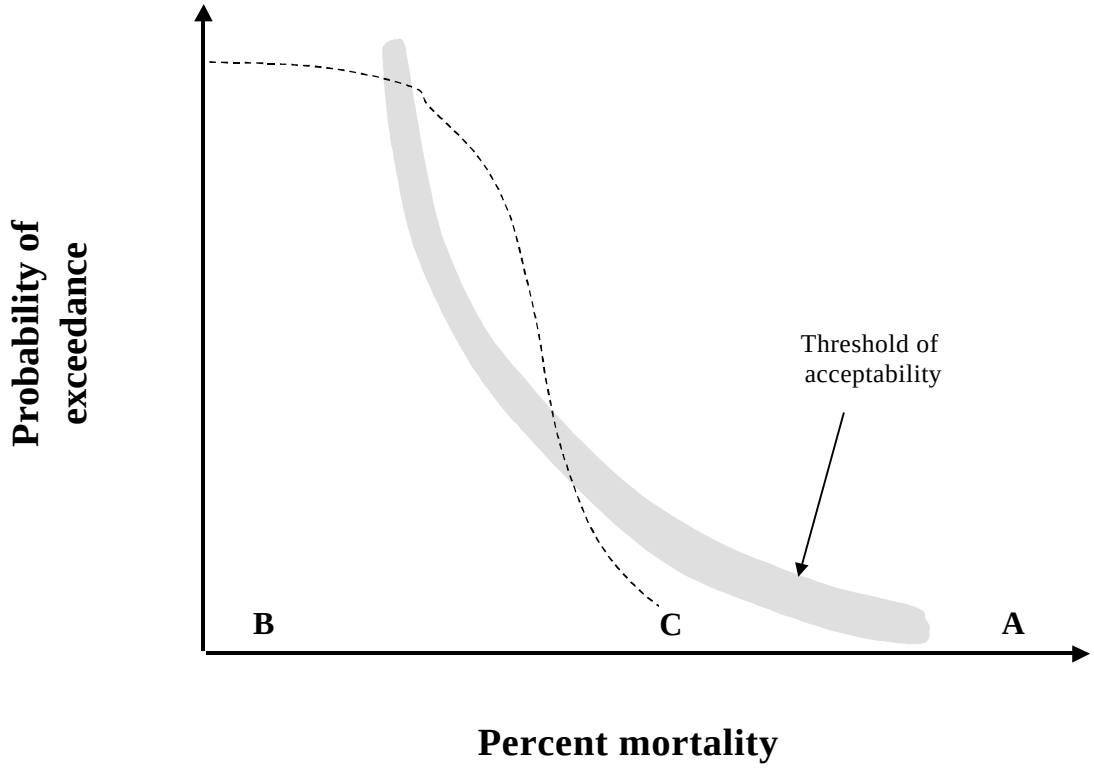


This approach can also be used for a preliminary, ‘screening’ assessment. The magnitude of the effect for a specified level of exposure can be estimated from a single dose-response curve. The probability is unlikely to be quantified but will be very low, because the exposure assessment will incorporate ‘worst-case’ assumptions and a conservative extrapolation factor may have been applied to the effects data. The predicted magnitude of effects can therefore be plotted as having a probability close to zero. The position of this point relative to the threshold indicates whether refinement of the assessment is required (Figure 6.7-3). The use of this approach is illustrated in Appendix C10.

As well as being efficient, this approach has a number of other advantages:

- Although defining the threshold may be sensitive and difficult, it need not be precise, and should help risk managers to be explicit about what they are trying to protect. This should be an improvement over the ‘triggers’ and ‘bright lines’ of the past, which have perhaps suffered from arbitrary over-precision and less-than-explicit justification.
- Uncertainty is dealt with explicitly in the risk assessment and assigned to the parameters it affects, rather than being accommodated by implicit safety factors built into a ‘level of concern’. This avoids confusion as to whether particular types of uncertainty have been allowed for, and to what extent.
- The whole assessment process becomes focussed on quantifying the magnitude and probability of effects in a manner compatible with the threshold of acceptability. It should therefore deliver precisely the information the risk manager needs to make a decision.

Figure 6.7-3. Comparison of screening-level assessment (Level 1). The magnitude of effects is estimated using a conservative extrapolation factor, for a conservatively high level of exposure. The predicted effect therefore has a probability close to zero and is plotted close to the horizontal axis. For example, point A indicates that the predicted risk may exceed the threshold, so further refinement of the assessment is required. Point B indicates that the risk is well below the threshold. Point C may require further assessment, as the full curve could cross the threshold if its slope was very steep (illustrated by dotted line).



6.8 Practical implications

Currently, there are no generally-accepted definitions of assessment endpoints and thresholds. It is unlikely there will ever be a standard list of definitions, if only because the threshold of acceptability varies from case to case depending on the balance of risk and benefit, as already mentioned. Therefore, risk assessors may need to consult risk managers to agree definitions case-by-case at the start of each assessment. Initially setting thresholds will be difficult, but it should become easier over time as precedents are established.

The flexible approach envisaged here should be more efficient than rigid Tiers, but it does imply that completed risk assessments will vary in the types and amounts of data they contain. Therefore, when risk assessments are presented, the endpoints and thresholds which were used and the choices made in refining the assessment, should all be clearly explained.

Note that the flexible approach is not inconsistent with the division of responsibility between risk assessors and managers in EPA. For example, in Figures 6.6-1 and 6.7-1, the risk assessor quantifies the distribution of predicted risk, but the risk manager determines the position of the threshold and makes the decision. However, to realize the efficiency gains of the flexible approach requires close interaction between risk assessor and risk manager: if this occurs only at the end of the process, the assessment may often be refined unnecessarily far, or not far enough.

Throughout this chapter, risk assessment and risk management have been described as functions conducted by USEPA, whose formal responsibilities they are. In practice, risk assessment and management are also carried out informally by most registrants, as part of their approach to product development and stewardship. The iterative process envisaged in Figure 6.6-1 should be well suited to this, as it would help registrants to identify for themselves which products may raise environmental concerns, which studies may be required for risk assessment, and whether mitigation is likely to be required. This could also benefit the Agency, by increasing the chance that the data submitted for registration

are appropriate, and avoiding unnecessarily large or complex submissions which require additional resources to evaluate. These benefits will be increased for both sides if there is good communication between registrants and Agency about the principles of assessment, including the definition of acceptability thresholds. Again, this is something which should become easier over time as precedents are established.

6.9 Development of standardised procedures

As stated in the charge to ECOFRAM, procedures for risk assessment need to be standardized and specific enough to allow different assessors supplied with the same information to produce similar estimates of risk.

The flexible approach described in this chapter is not necessarily inconsistent with these objectives:

- The principles and tools could be standardized, even if the process is not.
- Assessment endpoints could be standardized.
- Thresholds of acceptability could be standardized as broad zones, perhaps with standard variations for specified types of situation.
- Perhaps even the paths through the assessment process could be standardized to an extent, without too much loss of efficiency. As experience with probabilistic methods accumulates, it is anticipated that the most efficient routes will follow a limited number of paths through the options for refinement, with particular paths being more suitable for particular types of pesticide (e.g. granulars vs. foliar sprays vs. seed treatments). These paths could then form the basis for defining a standard set of assessment sequences, which might be represented either as tiered processes or decision-trees.

Even if it were desired to impose a rigid structure, all of the tools for probabilistic assessment are in their infancy so it is too early to say where they should fit in the structure (e.g. which studies go in which Tier). It would be necessary, therefore, to adopt a flexible approach initially until sufficient experience accumulated to define a more structured process.

Whether the eventual process is to be flexible or rigid, cooperative case studies would provide a means of testing the feasibility of ECOFRAM's proposals by applying them to data on existing pesticides whose environmental effects are already well understood. These case studies could be used to explore alternative assessment sequences, compare rigid and flexible approaches and if possible identify a limited number of standard sequences. They could also be used to explore issues relating to the definition of assessment endpoints and acceptability thresholds. Given the crucial role of the risk managers it would be important for them to participate fully in the case studies, in cooperation with risk managers and registrants.

Finally, given the potential complexities of probabilistic analyses, it may be useful to establish standard approaches to presenting them so that they can be readily understood.

7.0 RECOMMENDATIONS

7.1 OVERVIEW

The following recommendations result from hours of discussion over many months by the ECOFRAM Terrestrial Workgroup. So that the reader can understand the rationale for, and the significance of, the recommendations, it is necessary to briefly review the process and the progress made to date.

7.1.1 The ECOFRAM Process -- Charge, Scope, and Limitations

EPA presented its Risk Quotient methodology to the FIFRA Scientific Advisory Panel (SAP) in May of 1996. As a result of the SAP recommendations, ECOFRAM was formed and given the charge to help EPA move past its current deterministic procedures. Specifically, ECOFRAM was to expand the pesticide risk assessment process to include probabilistic risk assessment tools and methods for non-target organisms. It was not a certainty that the Workgroup would conclude that this charge was feasible, given the current database and the challenges involved.

To fulfill the charge, ECOFRAM began by evaluating the primary goal of ecological risk assessment for pesticides. The resources the assessment is designed to protect were identified. Conceptual models and assessment endpoints that would provide a broad estimation of the ecological consequences of pesticide applications were identified. All relevant guideline environmental fate and effects studies and models were reviewed in detail. The potential utility of these studies and models in probabilistic assessments was critically evaluated. Also, the strengths and limitations of current EPA risk assessment methodology were discussed. These reviews and discussions formed the basis for developing approaches to increase the usefulness and validity of risk assessment outputs.

Early in the review and discussion process, the Workgroup was forced to acknowledge the enormity and complexity of the charge. It became clear that the charge, as given,

simply could not be achieved in the time allotted with the databases available. Therefore, the Workgroup chose to limit the scope of its efforts. It would place most emphasis on birds, on oral exposure, and on direct effects. The Workgroup wants to emphasize that this decision was based solely on resource limitations. Other taxa, other routes of exposure, and other types of effects are also important and need to be considered. However, these other areas will have to be covered in future efforts. Despite the limited scope of effort, the Workgroup thinks that the concepts and approach developed will be applicable to other taxa, routes of exposure, and types of effects. Thus, the present recommendations of ECOFRAM can serve as a model for future improvements in the ecological risk assessment process for pesticides. Specifically, recommendations identify dermal and inhalation routes of exposure as requiring additional work. Indirect and sublethal effects merit consideration. Other vertebrate taxa, such as small mammals and amphibians, will need to be considered. The Workgroup reluctantly agreed that current mechanistic models were not generally applicable to probabilistic assessments for pesticides. These models should be modified to allow their use in probabilistic assessments and efforts should be made to gather the datasets necessary to run them. Also, the Workgroup acknowledged that spatial scale and the relationship of croplands to non-croplands might be crucial in assessing the risk of a pesticide use. However, these factors could not be considered in detail. The reader should note that ECOFRAM recommendations include the orderly timing of efforts to advance ecological risk assessment in the areas just mentioned above.

7.1.2 The Value of Probabilistic Ecological Risk Assessment – Key Concepts from ECOFRAM

Despite the somewhat limited scope of the ECOFRAM effort, the Workgroup recognizes and endorses the tremendous value of probabilistic approaches. The current procedures used by EPA provide deterministic, screening level, hazard assessments. These methods can only give indirect estimates of the likelihood and magnitude of effects. The approach advocated by ECOFRAM illustrates why probabilistic assessment is better than the way things are being done now. Specifically, ECOFRAM has reached consensus agreement on several key concepts that will form the basis for continued advancements in

terrestrial risk assessment. These concepts are, in and of themselves, recommendations. The key concepts agreed upon by ECOFRAM, and being recommended by ECOFRAM as foundations for terrestrial risk assessment in general, include:

- Exposure should be expressed as the dose (mg/kg/day) a bird might receive. Exposure should no longer be estimated as parts per million of a pesticide in the environment. The new exposure analysis should draw on the equations of EPA (1993), Pastorok (1996), Sample et al. (1997) and Nagy (1986). It will allow inclusion of bird behavior that governs risk. For example, factors such as avoidance of food items with pesticide residues and the proportion of its diet that a bird gathers from treated fields can be included in the analysis. Also, mechanistic models expressing avian exposure to granular and foliar insecticides as mg/kg/day were developed.
- Existing databases on pesticide residues in food items (e.g., Hoerger and Kenaga (1972), Fletcher et. al. (1994)) should be obtained and analyzed. The Workgroup thinks that there is enough information in these databases to derive distributions of residues to support probabilistic assessments.
- The agro-ecosystem should be used as a unit for analysis and the identification of key or focal species. Current EPA procedures do not fully take into account the bird species that may actually be using the treated crop. In the ECOFRAM proposal, screening level analysis would be done with generic species that represent different feeding guilds. Higher levels of analysis would use focal species, the species actually exposed to the pesticide, or species of special concern, such as endangered species.
- Three feeding scenarios should be considered for a dietary assessment -- short term, medium term, and long term exposures. The Workgroup recommends that all three feeding scenarios be addressed for each compound, unless a compelling argument can be made about the relevance of medium or long term exposures. Short term exposure scenarios would be evaluated to determine dose distributions for birds exhibiting gorge feeding behavior and for birds feeding on granular pesticides. Longer periodic exposure scenarios would represent more normal diurnal feeding patterns and would be indicative of doses eliciting longer term acute and subchronic

toxicity. The long term exposure scenario would also be used to assess effects. All three scenarios should be evaluated in all risk assessments even at the screening level unless there is specific evidence one is not relevant.

- Existing acute avian toxicity tests should be modified or replaced to reflect the above exposure scenarios. Exposure assessments under all three scenarios should present the toxicity in terms of a distribution of doses based on the hourly or daily dose (mg/kg/hr or mg/kg/day). Thus, effects tests would provide a dose that relates directly to the detailed exposure analysis.
- Extrapolation factors should be used to address inter-species variability issues. The present report already includes techniques that can be used, with caution, to address inter-species variability. Historical databases should be analyzed to refine and standardize extrapolation factors for inter-specific variability.
- Higher tier refinement of exposure and effects should be based on sensitivity of the models used. Early stage screening evaluations are intended to be conservative. Higher levels of refinement would systematically define the uncertainties inherent in screening level assessments. The higher levels of refinement are driven by the sensitivity of the models to changes in their input variables. The likely results of reducing uncertainties in effects (susceptibility) or exposure will be evaluated. These sensitivity analyses would enable risk assessors to efficiently move through the higher levels of refinement.
- A suite of techniques for combining information on exposure and effects to characterize risk should be used and evaluated. These techniques are keyed to the different levels of refinement and would help risk assessors and managers visualize the results of an assessment. Many of these techniques can be used immediately and they represent a major step past the current Risk Quotient approach. These techniques would allow some inferences to be made about effects at the population level by simulating effects on individuals. However, additional work is still needed on population models.

The Workgroup acknowledges that some of the above concepts do not relate solely to probabilistic risk assessments. Nonetheless, we think that these concepts will form the basis for the development of sound probabilistic assessments.

7.1.3 The Need for Further Development and Validation

The Workgroup also acknowledges that many of the methods and procedures we are proposing, although plausible, have not been validated. In the context of this report, validation is defined as a thorough characterization of the behavior and predictions of the proposed methods and procedures, and comparison with the predictions from current methods, as well as comparison with effects observed in the field. The Workgroup urges the Agency to support analysis of several realistic case studies, such as the ones discussed at the June 1997 meeting. The case studies should be developed into complete ecological risk assessments. The assessments should build on the conceptual models and assessment endpoints being proposed. They should use the methods and processes of refinement for exposure, effects, and risk that are being proposed. The Workgroup wants to emphasize that this development and validation exercise, which could be termed a "proof of concept", should be completed before EPA can develop a full process for probabilistic ecological risk assessment.

The proof of concept exercise would be invaluable in exploring issues related to assessment endpoints, evaluating assessment sequences, and providing a reality check for the process. Predictions from the various levels of refinement can be compared to the predictions using current procedures. The proof of concept exercise should be the basis for an ongoing dialogue between risk assessors and risk managers within the EPA and elsewhere. This dialogue should be the foundation and justification for agreement on what additional efforts, detailed below, will be most useful to risk managers. In the near term (1-2 years) to medium term (3-4 years), these efforts may be additional research projects, analyses of existing data, or new tests. In the long term (5 years and beyond), these efforts could include a follow-up ECOFRAM that focuses on other taxa.

The above overview should be kept in mind as the reader considers the following recommendations. The recommendations will be organized into 3 areas: exposure assessment and characterization; effects assessment and characterization, and; risk assessment. For each area, near term and medium term activities will be proposed. At

this time, the Workgroup does not think it useful to make detailed recommendations for long term activities. The necessary long term activities will depend on the outcomes of the near and medium term activities. Nonetheless, the Workgroup wishes to point out that long term activities will be needed to fully implement probabilistic assessments.

7.2 EXPOSURE ASSESSMENT AND CHARACTERIZATION

7.2.1 Near Term Activities

7.2.1.1 Improved Test Designs or New Tests

There are two significant gaps in the current data requirements. These gaps are information on foliar dissipation and information on fate in invertebrates. ECOFRAM is recommending that EPA develop guidance for a radio-labeled study, which evaluates the degradation rate on a variety of plant types. It would include volatilization and washoff rates on vegetation, dissipation rates on vegetation, and the fate of compounds in invertebrates. Also in the near term, other data gaps, highlighted in Section 3.10, which are critical to the prediction of the environmental fate of a compound and potential concentrations in wildlife food items, should be reviewed and prioritized. The most critical needs should then be included in medium term activities.

7.2.1.2 Model Development, Validation, or New Models

In keeping with the basic concept of using the sensitivity of models to drive the refinement process, models should be subjected to sensitivity analyses. These exercises are important for data development activities because they will focus time and resources. They will also form the basis for efficiently moving through the levels of refinement.

The EPA currently estimates pesticide concentrations in wildlife food items using databases developed by Hoerger and Kenaga (1972) and Fletcher et. al. (1994). Residue estimates used from these papers are point estimates immediately following application of the pesticide. ECOFRAM recommends that EPA move away from point estimates of

environmental residue concentrations, particularly in wildlife food items, and begin the process of developing models specifically designed to predict concentrations in the terrestrial environment. The Hoerger and Kenaga, 1972 and Fletcher et. al., 1994 databases can be used probabilistically. By gaining access to the full databases, it will be possible to develop distributions of residue concentrations. This activity should start immediately.

Although there are aquatic exposure models that could be adapted to predict some terrestrial residue concentrations, there does not appear to be any exposure model designed specifically for terrestrial environmental concentrations. A short term solution to the current deficiency could be utilization of the simple mass balance equations presented in Chapter 3 and Appendix C4 –C9, or reworking existing aquatic models (i.e., PRZM, EXAMS, AgDrift) to incorporate Monte Carlo simulations.

An analysis of the components of the nutritional (ecological energetics) equations should be performed to produce distributions for various species. These distributions could then be used rigorously in probabilistic assessments. Efforts for this activity should initially aim to develop distributions for the focal species. The Workgroup is aware that research is underway in the UK to break down one ecological energetics equation into various elements, based on the extensive existing database.

Also, there should be development of models such as TEAAM, PARET, and the granular models. In the interim, various spreadsheet models, using available risk analysis software, will be important tools for the proof of concept exercise. At some time in the future, based on the results of the proof of concept exercise, there will be a need to standardize the various models.

7.2.1.3 Analyses of Existing Data or New Research Projects

The prediction of pesticide residue concentrations in terrestrial media is the basis for all pesticide risk assessments. Environmental fate data currently required by the EPA are generally adequate in providing data to run deterministic residue estimation models.

However, only one study of each type is generally required, eliminating the possibility of further developing the distributions needed for probabilistic assessments. Based on the results of the above sensitivity analyses, there should be an exploration of ways to develop the distributions needed for probabilistic assessments. Options could include using empirical distributions, performing additional tests, or reviewing the literature and agreeing on standard distributions. Simulations that employ, for example, empirical (where adequate data available), uniform, log-normal, and triangular distributions can evaluate the consequences of using empirical or assumed distributions.

There are several data sets that should be developed to reduce uncertainty and improve the accuracy of exposure assessments. Registrants should pool their habitat use information and develop a database characterizing wildlife species in and around agricultural crops. If possible, information should be included on the home ranges of these species. A similar type of database project should be undertaken for dietary habits, and residues in the diets, of wildlife associated with agricultural systems. If such information is not available from the registrants, the EPA should make the development of these databases a priority. Information of this type would greatly increase our confidence in performing risk assessments.

Based on the above results, EPA and the regulated Industry should agree on sets of focal species for major crops.

Field studies can play an important role to 1) refine field residue and fate data, 2) provide relevant life history and behavior information on focal species, 3) test estimates of exposure to focal species, and 4) test hypotheses on exposure pathways. However, there are many uncontrollable factors, which can confound the results and make interpretation difficult. Consequently, field studies should be considered if they are designed to answer specific questions that will help to clarify issues raised by the risk assessment. These studies should be designed on a case-by-case basis from the results of the near term effort and, if desirable, implemented in the medium and long term activities.

Field studies should also be considered for the purpose of characterizing proposed risk assessment models prior to full scale implementation of those models. ECOFRAM recommends that EPA and Industry work together to design such studies.

7.2.2 Medium Term Activities

7.2.2.1 Improved Test Designs or New Tests

Develop guidance for the proposed test for foliar wash-off from plants and fate in invertebrates. Do this as a ring test and evaluate the utility of the data for probabilistic assessments. If the test is useful, it could then be required. HED and EFED could explore coordinating changes in crop residue studies to increase the number of sampling intervals, or other ways to make the tests more useful for estimating exposure of wildlife.

7.2.2.2 Model Development, Validation, or New Models

Validate exposure models, such as TEAAM, PARET, and granular models, developed in the near term effort.

Critically review and evaluate the evidence of the significance of the inhalation and dermal routes of exposure. If appropriate, develop models or criteria for deciding when inhalation or dermal exposure, or non-dietary exposure, such as via puddles, may be important and needs to be included in an assessment.

Other taxa, such as small mammals, amphibians, and insects, although part of the charge, were not fully addressed. Look into models for exposure of other these other taxa.

7.2.2.3 Analyses of Existing Data or New Research Projects

Parameterize the standard scenarios for the various major crops developed and agreed upon in the near term effort.

7.2.3 Long Term Activities

As mentioned above, long term activities will depend on results from the near and medium term efforts. Some examples of possible activities follow.

7.2.3.1 Improved Test Designs or New Tests

Develop guidelines, if appropriate, for tests needed to estimate exposure of small mammals, amphibians, and non-target insects.

7.2.3.2 Model Development, Validation, or New Models

Develop models that will accommodate spatial considerations in assessments.

7.2.3.3 Analyses of Existing Data or New Research Projects

Use existing public databases to incorporate spatial characteristics of crops. Evaluate the cost and feasibility of developing geographical information systems for major and minor crops. This would likely be done on a case-by-case basis.

7.3 EFFECTS ASSESSMENT AND CHARACTERIZATION

7.3.1 Near Term Activities

7.3.1.1 Improved Test Designs or New Tests

"Up and Down" or "Approximate Lethal Dose" test. The feasibility and utility of the various mammalian and avian test designs should be evaluated. If a feasible and useful test design can be agreed upon, draft guidance for it and perform ring tests. Correlate the results of this activity with interspecies extrapolation factor analyses. Also, look into and assess the benefits of using the ALD test compared to the full dose-response test for obtaining data on additional test species. This is especially important with regard to the robustness of assuming a slope from the full dose-response test for ALD test results.

The current avian acute dietary study is inadequate for incorporating into probabilistic assessments. To be more suitable, the test should be designed to provide an estimate of the daily dosage, which produces toxicity (i.e., mg/kg/day). It must provide a better estimate of food consumption per individual. Draft guidance that considers ring testing. Until this test is redesigned a crude estimate of dose could be extracted from the current study or perhaps from the reproduction test. However, it must be realized there is great uncertainty in the estimate and the output must be used with a clear description of how the uncertainty could affect the outcome of the risk assessment.

It should be noted that the OECD is currently addressing many of the problems identified by the workgroup in the standard toxicity tests. ECOFRAM recommends the EPA work with the OECD in developing test methodology for the ALD, acute dietary and reproduction test. The final design of all standardized toxicity tests should anticipate the need to develop quantitative measures of behavioral, and possibly physiological, effects.

7.3.1.2 Analyses of Existing Data or New Research Projects

Given the wide range of variability in species sensitivities to pesticides, it is expected that interspecific differences in sensitivity will result in large uncertainties in the risk assessment. Practicalities associated with sample sizes, availability of test species, and costs, need to be considered when designing a test program. To circumvent this problem and still provide estimates of expected sensitivities, ECOFRAM has evaluated interspecific relationships relying heavily on historical data. Section 4.2.3 discusses various methods, which could be used to extrapolate sensitivity between species. All of the methods presented utilize extrapolation factors based upon historical data until the number of species tested is greater than or equal to four. ECOFRAM recommends that studies be done to determine the amount of uncertainty extrapolations between compounds introduce into the assessment. This should first be done for the short term exposure scenario, and ultimately for the medium term exposure scenario.

7.3.2 Medium Term Activities

7.3.2.1 Improved Test Designs or New Tests

The avian acute oral test is well designed for producing an LD50. The output from this test can be easily included in a probabilistic assessment. However, it may be important, in some circumstances, to develop better estimates of low levels of mortality, e.g., the LD5 or LD10. Modifications of the test would be required to reduce the uncertainty around these low levels of mortality. The need to re-design the test will depend in part on the results of the proof of concept exercise.

Look in to adding relevant sublethal observations to the acute oral LD50 study. Such observations must be quantifiable and amenable to analysis and could include paralysis or changes in response to stimuli or challenges. Also, look into including a dynamic exposure regime for the revised LC50 study. Develop this based on experience with the re-designed LC50 study and the new exposure data that will be available.

Avoidance behavior of a bird to a pesticide is a parameter overlooked in current assessments. However, as research has shown (Section 3.3.4.1.3), it can play a significant role in the exposure equation. Screening assessments should assume no avoidance, however, if the screen indicates significant exposure to a compound, then an estimate of avoidance can be extracted from food consumption data obtained in the acute dietary test. Ideally, if it is thought avoidance significantly lowers the exposure potential, at higher tiers of the assessment an avoidance test could be conducted. OECD is currently drafting avoidance testing guidelines. Bearing in mind that research to date has avoidance of treated seeds, work on avoidance of granules and foliar sprays would be desirable.

Re-design the standard avian reproduction test. This test presents the greatest challenge for probabilistic assessments and in its current form is not suitable for probability based assessments. The current reproduction test is not designed to produce dose response relationships. The standard output is the NOEL, a point estimate with no indication of the variability around that estimate. Beyond the design of the test lays an even larger problem of being able to detect chronic effects observed in the laboratory in field situations. Section 4.2 discusses in great detail what the workgroup thinks are the many limitations of the test and suggestions for its improvement.

Another issue relative to avian reproduction is how to incorporate modifications to address changes in behavior, such as parental care. Possible study designs for this higher tier test should be explored and evaluated.

As probabilistic risk assessments improve, estimates of depuration and metabolism may become critical in providing accurate predictions of risk. Thus, a study that evaluates kinetics, including rates of depuration and metabolism, may be warranted on a case-by-case basis. In the interim, depuration and metabolism can be ignored with the understanding it is a factor hidden in the acute dietary toxicity test. Before a test is required EPA could evaluate the variation of pesticide metabolism between species. If

significant relationships were found it may be possible to use the rat data generated for the human health assessment.

Human health assessments require a metabolism study to evaluate the distribution of the compound within various tissues and its depuration rate. These data are not required for terrestrial ecological risk assessments but are also of great importance when evaluating the effects on a pesticide when exposures are longer than that represented by an acute oral toxicity study. The metabolism of a compound becomes important when secondary toxicity is a concern. The importance of metabolism and depuration and how they affect the risk assessment is discussed in Sections 3.3.7. Guidance should be developed for this study.

Based on the conclusions from the analysis of the significance of dermal and inhalation routes, guidelines should be developed for these routes of exposure, along with "when required" criteria.

7.3.2.2 Model Development, Validation, or New Models

Building on the results of the species sensitivity analyses, look into developing standard models for estimating sensitivities of species of concern.

7.3.2.3 Analyses of Existing Data or New Research Projects

One of biggest problems facing effects characterization is extrapolating laboratory toxicity test results to effects under field conditions. This source of uncertainty in the risk assessment may never be fully understood. However, as recommended throughout this document, work must be done to validate any model put forth for ecological risk assessments. Well designed field studies targeted to answer specific questions could provide valuable insight into the accuracy of laboratory to field extrapolations.

7.3.3 Long Term Activities

As mentioned above, long term activities will depend on the outcome of the near and medium term activities. One possible effort would be, once avian reproduction study is re-designed and validated, to look at incorporating dynamic exposure regimes.

7.4 RISK ASSESSMENT

7.4.1 Near Term Activities

A suite of methods for ecological risk assessment has been investigated. The most critical activity in the near term is further development of these methods in the proof of concept exercise. This exercise should employ realistic case studies. Comparisons should be made among risk assessment outputs from the various methods to help determine the most useful and valid outputs. The exercise will require input and feedback from risk managers. The first level of refinement may be deterministic. At higher levels of refinement, various options from the suite of methods may be used depending on the outcomes of the proof of concept exercise. It is critical to evaluate the new scheme and to refine it in actual assessments.

7.4.2 Medium Term Activities

- Modify population models for probabilistic assessments. Look into adding other routes of exposure and types of effects into the Levels of Refinement.

7.5 PROCESS FOR CARRYING OUT THE RECOMMENDATIONS

It is suggested that this process be essentially the same for near and medium term activities. Results from the near and medium term activities will determine what long term activities should be pursued and the most efficient process for pursuing the long

term activities. For near and medium term activities, EPA and Registrants should be discouraged from attempting to develop the information above as part of evaluating new chemicals, that is, on a case-by-case basis. This piecemeal approach does not permit sufficient standardization of individual activities, or coordination of overall programs. There must be a partnering of Industry, EFED, ORD, and other interested groups as needed. Past experience has shown that developing a Cooperative Research and Development Agreement (CRADA) will be very time consuming. However, this type of agreement allows for efficient use of public and private resources, and should be pursued as soon as possible.

Due to the likely time involved in finalizing a CRADA, other mechanisms should also be pursued. Another avenue for accomplishing the goal would be the formation of an informal research steering committee. Current members of ECOFRAM, EFED's Implementation Team, ACPA, and other interested parties could meet to set the research agenda, review projects for consistency, divide up projects and costs, and carry out the needed research. This activity could also include provision for contracting work to independent labs or universities. The research steering committee would also have the accountability of integrating the results of other ongoing projects, such as OECD guideline development and the SETAC protocol effort. At different phases of the activities, representatives from different interested groups could be added to, or step down from, the research steering committee. This approach would allow the implementation process to move forward as the CRADA is being finalized.

7.6 CONCLUSIONS

7.6.1 Summary of Recommendations

The key ECOFRAM recommendations are summarized in Table 7.6.1.

Table 7.6.1 Summary of ECOFRAM Recommendations.

Timeframe	Exposure Assessment and Characterization	Effects Assessment and Characterization	Risk Assessment	Implementation Process
Near Term	-Develop protocol for study on washoff, fate in invertebrates - Perform sensitivity analyses of models - Analyze residue databases, make probabilistic - Analyze nutritional equations, make probabilistic - Develop exposure models, e.g., TEAAM, PARET - Identify focal species, home ranges, residue levels by agro-ecosystem	- Evaluate the utility and feasibility of the ALD test - Re-design and ring test the LC50 test - Evaluate the amount of uncertainty interspecies extrapolations introduce into the assessment	-Proof of Concept Exercise	-Develop CRADA -Form *ad hoc* Steering Committee -Form EPA Implementation Teams

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Timeframe	Exposure Assessment and Characterization	Effects Assessment and Characterization	Risk Assessment	Implementation Process
Medium Term	- Perform ring test for study on washoff, fate in invertebrates - Explore changes in crop residue studies to enhance usefulness for wildlife assessments - Validate exposure models, e.g., TEAAM, PARET -Evaluate the significance of dermal and inhalation exposure, develop techniques to include these if appropriate - Include other taxa, e.g, small mammals, amphibians - Parameterize models for standard scenarios	- If needed, look into re-designing the LD50 test to get better estimates of the LD5 or LD10 - Add sublethal obseravtions or a dynamic exposure regime to the LC50 study - Include evaluations of avoidance behavior for granules and foliar sprays - Re-design the standard avian reproduction test - Evaluate test designs to study effects on parental behavior in reproduction - Develop guidance for a kinetics study of metabolism and depuration - Include inhalation and dermal exposure, if needed - Develop standard models for estimating sensitivities of species of concern - Look into extrapolations from laboratory to field	- Modify population models so they are better suited for probabilistic assessments - Include other routes of exposure	-As above, ideally under a CRADA

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7.6.2 Evaluation of How the Workgroup Fulfilled the Charge

Given the above caveats, a key question that needs to be considered is "To what extent did the Terrestrial Workgroup fulfill its charge?" The various elements of the charge, in bold italics, and how these were addressed, follow. This evaluation is useful for establishing additional follow-up efforts in probabilistic ecological risk assessment.

- ***Develop and validate risk assessment tools and processes that address increasing levels of biological organization (e.g., individuals, populations, communities, ecosystems) accounting for direct and indirect effects pesticides may cause.*** This goal, as expected, was not achieved in the available time.
- ***First address acute and chronic effects of pesticides on individuals and populations of high risk species. Consider terrestrial vertebrates and aquatic vertebrates and invertebrate first.*** The Terrestrial Workgroup made good progress towards developing tools and processes for individual birds, and to some extent, bird populations. Validation work remains to be done.
- ***The process and tools should predict magnitude and probability of adverse effects. Methods developed should consist of standardized procedures that integrate estimates of pesticide exposure with knowledge about potential adverse effects. Methods should account for sources of uncertainty and should be developed in the context of FIFRA and EPA's Framework.*** The process and tools will predict magnitude and probability of adverse effects. Exposure and adverse effects information are integrated, but procedures have not been standardized. Some important uncertainties have been identified and accounted for, while work remains for others. The process and tools are entirely congruent with FIFRA and the EPA's Framework.
- ***The tools developed need to have reasonable scientific certainty and be capable of being validated in a reasonable time frame. Probabilistic techniques should use existing fate and effects data where possible. However, it may be necessary to modify or discontinue current tests or develop new ones.*** The tools developed are expected to have reasonable certainty and validation is the next step in the process.

The Workgroup carefully reviewed the utility of all current fate and effects tests and recommended how these could be used. Similarly, recommendations were made for how to modify current tests so that they will be more useful for probabilistic assessments.

- ***Methods developed for risk estimates should reflect a solid foundation in environmental toxicology and should account for species sensitivity, environmental fate, and other variables. The type of pesticide formulation, application techniques, habitat types, and species associated with these habitats need to be considered. The translation of residue estimates into exposure estimates and routes of exposure should be incorporated into the methodology.*** The several key concepts (see 7.1.2) provide a solid foundation in for future development of probabilistic assessments. The Workgroup proposed methods to account for species sensitivity, environmental fate, habitat types, and species associated with the agro-ecosystem. Methods were also proposed for translating residue estimates into exposure estimates, another key concept. Work on other dermal and inhalation routes of exposure needs to be done.
- ***Methods should be specific enough to allow different risk assessors supplied with the same information to estimate similar values of risk. The rationale for the choice of scenarios needs to be clearly stated. Assumptions and extrapolations need to be specified and explained so the significance of the ecological risk estimates is easily understood.*** The Workgroup stated the rationale for choices of exposure and agro-ecosystem scenarios. Many unstated assumptions and extrapolations inherent in the screening level assessments were explicated. It remains to be seen if the methods are specific enough to allow different risk assessors supplied with the same information to estimate similar values of risk.
- ***The Workgroups are asked to define any additional developmental or validation efforts that are needed for the probabilistic methods developed.*** These efforts are detailed in sections 7.2 through 7.5.

The science of probabilistic risk assessment for pesticides is still in its infancy with years of development before it. This document should not be misconstrued as the final word on future direction for probabilistic risk assessments of pesticides. The methods proposed here represent what the Workgroup thought would be the best directions to take. These

directions were limited by the data currently available and what we foresaw as the best data we could obtain in the future. Undoubtedly these methods will undergo modification as the EPA and outside parties apply probabilistic risk assessment procedure to everyday problems.

The efforts of the Workgroup should begin the process of providing probabilistic risk assessments to the risk manager. The result will be predictions of the probability and magnitude of the ecological effects resulting from pesticide application. However, the evolution of probabilistic risk assessment cannot occur in the absence of input from the risk manager. It is now critical that risk managers provide the risk assessors direction in developing methodology to supply the most useful information for making risk management decisions. ECOFRAM strongly recommends that EPA establish a formal method for risk assessors and managers to jointly review of risk assessment inputs and outputs for their usefulness to risk management decisions. To start the development of this formal method, risk managers should be full participants in the proof of concept exercises.

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APPENDIX A1

Sixteen Guiding Principles for Probabilistic Risk Assessments

The following 16 guiding principles has been developed by the Environmental Protection Agency to help ensure good scientific practices in the development of probabilistic risk assessment (USEPA 1997). While the focus of the general framework and broad set of principles is on Monte Carlo Analysis the principles apply equally to the various techniques for conducting probabilistic risk assessment.

Selecting Input Data and Distributions for Use in Monte Carlo Analysis

1. Conduct preliminary sensitivity analyses or numerical experiments to identify model structures, exposure pathways, and model input assumptions and parameters that make important contributions to the assessment endpoint and its overall variability and/or uncertainty.

The capabilities of current desktop computers allow for a number of "what if" scenarios to be examined to provide insight into the effects on the analysis of selecting a particular model, including or excluding specific exposure pathways, and making certain assumptions with respect to model input parameters. The output of an analysis may be sensitive to the structure of the exposure model. Alternative plausible models should be examined to determine if structural differences have important effects on the output distribution (in both the region of central tendency and in the tails).

Numerical experiments or sensitivity analysis also should be used to identify exposure pathways that contribute significantly to or even dominate total exposure. Resources might be saved by excluding unimportant exposure pathways (e.g., those that do not

contribute appreciably to the total exposure) from full probabilistic analyses or from further analyses altogether. For important pathways, the model input parameters that contribute the most to overall variability and uncertainty should be identified. Again, unimportant parameters may be excluded from full probabilistic treatment. For important parameters, empirical distributions or parametric distributions may be used. Once again, numerical experiments should be conducted to determine the sensitivity of the output to different assumptions with respect to the distributional forms of the input parameters. Identifying important pathways and parameters where assumptions about distributional form contribute significantly to overall uncertainty may aid in focusing data gathering efforts.

Dependencies or correlations between model parameters also may have a significant influence on the outcome of the analysis. The sensitivity of the analysis to various assumptions about known or suspected dependencies should be examined. Those dependencies or correlations identified as having a significant effect must be accounted for in later analyses.

Conducting a systematic sensitivity study may not be a trivial undertaking, involving significant effort on the part of the risk assessor. Risk assessors should exercise great care not to prematurely or unjustifiably eliminate pathways or parameters from full probabilistic treatment. Any parameter or pathway eliminated from full probabilistic treatment should be identified and the reasons for its elimination thoroughly discussed.

2. Restrict the use of probabilistic assessment to significant pathways and parameters.

Although specifying distributions for all or most variables in a Monte Carlo analysis is useful for exploring and characterizing the full range of variability and uncertainty, it is often unnecessary and not cost effective. If a systematic preliminary sensitivity analysis (that includes examining the effects of various assumptions about distributions) was undertaken and documented, and exposure pathways and parameters that contribute little to the assessment endpoint and its overall uncertainty and variability were identified, the risk assessor may simplify the Monte Carlo analysis by focusing on those pathways and parameters identified as significant. From a computational standpoint, a Monte Carlo analysis can include a mix of point estimates and distributions for the input parameters to the exposure model. However, the risk assessor and risk manager should continually review the basis for "fixing" certain parameters as point values to avoid the perception that these are indeed constants that are not subject to change.

3. Use data to inform the choice of input distributions for model parameters.

The choice of input distribution should always be based on all information (both qualitative and quantitative) available for a parameter. In selecting a distributional form, the risk assessor should consider the quality of the information in the database and ask a series of questions including (but not limited to):

- *Is there any mechanistic basis for choosing a distributional family?*

- *Is the shape of the distribution likely to be dictated by physical or biological properties or other mechanisms?*

- *Is the variable discrete or continuous?*

- *What are the bounds of the variable?*
- *Is the distribution skewed or symmetric?*
- *If the distribution is thought to be skewed, in which direction?*
- *What other aspects of the shape of the distribution are known*?

When data for an important parameter are limited, it may be useful to define plausible alternative scenarios to incorporate some information on the impact of that variable in the overall assessment (as done in the sensitivity analysis). In doing this, the risk assessor should select the widest distributional family consistent with the state of knowledge and should, for important parameters, test the sensitivity of the findings and conclusions to changes in distributional shape.

4. Surrogate data can be used to develop distributions when they can be appropriately justified.

The risk assessor should always seek representative data of the highest quality available. However, the question of how representative the available data are is often a serious issue. Many times, the available data do not represent conditions (e.g., temporal and spatial scales) in the population being assessed. The assessor should identify and evaluate the factors that introduce uncertainty into the assessment. In particular, attention should be given to potential biases that may exist in surrogate data and their implications for the representativeness of the fitted distributions.

When alternative surrogate data sets are available, care must be taken when selecting or combining sets. The risk assessor should use accepted statistical practices and

techniques when combining data, consulting with the appropriate experts as needed.

Whenever possible, collect site or case specific data (even in limited quantities) to help justify the use of the distribution based on surrogate data. The use of surrogate data to develop distributions can be made more defensible when case-specific data are obtained to check the reasonableness of the distribution.

5. When obtaining empirical data to develop input distributions for exposure model parameters, the basic tenets of environmental sampling should be followed. Further, particular attention should be given to the quality of information at the tails of the distribution.

As a general rule, the development of data for use in distributions should be carried out using the basic principles employed for exposure assessments. For example,

- *Receptor-based sampling in which data are obtained on the receptor or on the exposure fields relative to the receptor;*

- *Sampling at appropriate spatial or temporal scales using an appropriate stratified random sampling methodology;*

- *Using two-stage sampling to determine and evaluate the degree of error, statistical power, and subsequent sampling needs; and*

- *Establishing data quality objectives.*

In addition, the quality of information at the tails of input distributions often is not as good as the central values. The assessor should pay particular attention to this issue when devising data collection strategies.

6. Depending on the objectives of the assessment, expert[1] judgment can be included either within the computational analysis by developing distributions using various methods or by using judgments to select and separately analyze alternate, but plausible, scenarios. When expert judgment is employed, the analyst should be very explicit about its use.

Expert judgment is used, to some extent, throughout all exposure assessments. However, debatable issues arise when applying expert opinions to input distributions for Monte Carlo analyses. Using expert judgment to derive a distribution for an input parameter can reflect bounds on the state of knowledge and provide insights into the overall uncertainty. This may be particularly useful during the sensitivity analysis to help identify important variables for which additional data may be needed. However, distributions based exclusively or primarily on expert judgment reflect the opinion of individuals or groups and, therefore, may be subject to considerable bias. Further, without explicit documentation of the use of expert opinions, the distributions based on these judgments might be erroneously viewed as equivalent to those based on hard data. When distributions based on expert judgement have an appreciable effect on the outcome of an analysis, it is critical to highlight this in the uncertainty characterization.

Evaluating Variability and Uncertainty

7. The concepts of variability and uncertainty are distinct. They can be tracked and evaluated separately during an analysis, or they can be analyzed within the same computational framework. Separating variability and uncertainty is necessary to provide greater accountability and transparency. The decision about how to track them separately must be made on a case-by-case basis for

[1] According to NCRP (1996), an expert has (1) training and experience in the subject area resulting in superior knowledge in the field, (2) access to relevant information, (3) an ability to process and effectively use the information, and (4) is recognized by his or her peers or those conducting the study as qualified to provide judgments about assumptions, models, and model parameters at the level of detail required.

each variable.

Variability represents the true heterogeneity or diversity inherent in a well-characterized population. As such, it is not reducible through further study. Uncertainty represents a lack of knowledge about the population. It is sometimes reducible through further study. Therefore, separating variability and uncertainty during the analysis is necessary to identify parameters for which additional data are needed. There can be uncertainty about the variability within a population. For example, if only a subset of the population is measured or if the population is otherwise under-sampled, the resulting measure of variability may differ from the true population variability. This situation may also indicate the need for additional data collection.

8. There are methodological differences regarding how variability and uncertainty are addressed in a Monte Carlo analysis.

There are formal approaches for distinguishing between and evaluating variability and uncertainty. When deciding on methods for evaluating variability and uncertainty, the assessor should consider the following issues.

- *Variability depends on the averaging time, averaging space, or other dimensions in which the data are aggregated.*

- *Standard data analysis tends to understate uncertainty by focusing solely on random error within a data set. Conversely, standard data analysis tends to overstate variability by implicitly including measurement errors.*

- *Various types of model errors can represent important sources of uncertainty. Alternative conceptual or mathematical models are a potentially important source of uncertainty. A major threat to the accuracy of a variability analysis is a lack of*

representativeness of the data.

9. Methods should investigate the numerical stability of the moments and the tails of the distributions.

For the purposes of these principles, numerical stability refers to observed numerical changes in the characteristics (i.e., mean, variance, percentiles) of the Monte Carlo simulation output distribution as the number of simulations increases. Depending on the algebraic structure of the model and the exact distributional forms used to characterize the input parameters, some outputs will stabilize quickly, that is, the output mean and variance tend to reach more or less constant values after relatively few sampling iterations and exhibit only relatively minor fluctuations as the number of simulations increases. On the other hand, some model outputs may take longer to stabilize. The risk assessor should take care to be aware of these behaviors. Risk assessors should always use more simulations than they think necessary. Ideally, Monte Carlo simulations should be repeated using several non-overlapping subsequences to check for stability and repeatability. Random number seeds should always be recorded. In cases where the tails of the output distribution do not stabilize, the assessor should consider the quality of information in the tails of the input distributions. Typically, the analyst has the least information about the input tails. This suggests two points.

- *Data gathering efforts should be structured to provide adequate coverage at the tails of the input distributions.*

- *The assessment should include a narrative and qualitative discussion of the quality of information at the tails of the input distributions.*

10. There are limits to the assessor's ability to account for and characterize all sources of uncertainty. The analyst should identify areas of uncertainty and

include them in the analysis, either quantitatively or qualitatively.

Accounting for the important sources of uncertainty should be a key objective in Monte Carlo analysis. However, it is not possible to characterize all the uncertainties associated with the models and data. The analyst should attempt to identify the full range of types of uncertainty impinging on an analysis and clearly disclose what set of uncertainties the analysis attempts to represent and what it does not. Qualitative evaluations of uncertainty including relative ranking of the sources of uncertainty may be an acceptable approach to uncertainty evaluation, especially when objective quantitative measures are not available. Bayesian methods may sometimes be useful for incorporating subjective information into variability and uncertainty analyses in a manner that is consistent with distinguishing variability from uncertainty.

Presenting the Results of a Monte Carlo Analysis

11. Provide a complete and thorough description of the exposure model and its equations (including a discussion of the limitations of the methods and the results).

Consistent with the Exposure Assessment Guidelines, Model Selection Guidance, and other relevant Agency guidance, provide a detailed discussion of the exposure model(s) and pathways selected to address specific assessment endpoints. Show all the formulas used. Define all terms. Provide complete references. If external modeling was necessary (e.g., fate and transport modeling used to provide estimates of the distribution of environmental concentrations), identify the model (including version) and its input parameters. Qualitatively describe the major advantages and limitations of the models used.

The objectives are transparency and reproducibility - to provide a complete enough

description so that the assessment might be independently duplicated and verified.

12. Provide detailed information on the input distributions selected. This information should identify whether the input represents largely variability, largely uncertainty, or some combination of both. Further, information on goodness-of-fit statistics should be discussed.

It is important to document thoroughly and convey critical data and methods that provide an important context for understanding and interpreting the results of the assessment. This detailed information should distinguish between variability and uncertainty and should include graphs and charts to visually convey written information. The probability density function (PDF) and cumulative distribution function (CDF) graphs provide different, but equally important insights. A plot of a PDF shows possible values of a random variable on the horizontal axis and their respective probabilities (technically, their densities) on the vertical axis. This plot is useful for displaying:

- *the relative probability of values;*
- *the most likely values (e.g., modes);*
- *the shape of the distribution (e.g., skewness, kurtosis); and*
- *small changes in probability density.*

A plot of the cumulative distribution function shows the probability that the value of a random variable is less than a specific value. These plots are good for displaying:

- *fractiles, including the median;*

- *probability intervals, including confidence intervals;*
- *stochastic dominance; and*
- *mixed, continuous, and discrete distributions.*

Goodness-of-fit tests are formal statistical tests of the hypothesis that a specific set of sampled observations are an independent sample from the assumed distribution. Common tests include the chi-square test, the Kolmogorov-Smirnov test, and the Anderson-Darling test. Goodness-of-fit tests for normality and lognormality include Lilliefors' test, the Shapiro-Wilks' test, and D'Agostino's test.

Risk assessors should never depend solely on the results of goodness-of-fit tests to select the analytic form for a distribution. Goodness-of-fit tests have low discriminatory power and are generally best for rejecting poor distribution fits rather than for identifying good fits. For small to medium sample sizes, goodness-of-fit tests are not very sensitive to small differences between the observed and fitted distributions. On the other hand, for large data sets, even small and unimportant differences between the observed and fitted distributions may lead to rejection of the null hypothesis. For small to medium sample sizes, goodness-of-fit tests should best be viewed as a systematic approach to detecting gross differences. The risk assessor should never let differences in goodness-of-fit test results be the sole factor for determining the analytic form of a distribution.

Graphical methods for assessing fit provide visual comparisons between the experimental data and the fitted distribution. Despite the fact that they are non-quantitative, graphical methods often can be most persuasive in supporting the selection of a particular distribution or in rejecting the fit of a distribution. This persuasive power derives from the inherent weaknesses in numerical goodness-of-fit tests. Such graphical methods as probability-probability (P-P) and quantile-quantile (Q-Q) plots can provide

clear and intuitive indications of goodness-of-fit.

Having selected and justified the selection of specific distributions, the assessor should provide plots of both the PDF and CDF, with one above the other on the same page and using identical horizontal scales. The location of the mean should be clearly indicated on both curves [See Figure 1]. These graphs should be accompanied by a summary table of the relevant data.

13. Provide detailed information and graphs for each output distribution.

In a fashion similar to that for the input distributions, the risk assessor should provide plots of both the PDF and CDF for each output distribution, with one above the other on the same page, using identical horizontal scales. The location of the mean should clearly be indicated on both curves. Graphs should be accompanied by a summary table of the relevant data.

14. Discuss the presence or absence of dependencies and correlations.

Covariance among the input variables can significantly affect the analysis output. It is important to consider covariance among the model's most sensitive variables. It is particularly important to consider covariance when the focus of the analysis is on the high end (i.e., upper end) of the distribution.

When covariance among specific parameters is suspected but cannot be determined due to lack of data, the sensitivity of the findings to a range of different assumed dependencies should be evaluated and reported.

15. Calculate and present point estimates.

Traditional deterministic (point) estimates should be calculated using established

protocols. Clearly identify the mathematical model used as well as the values used for each input parameter in this calculation. Indicate in the discussion (and graphically) where the point estimate falls on the distribution generated by the Monte Carlo analysis. Discuss the model and parameter assumptions that have the most influence on the point estimate's position in the distribution. The most important issue in comparing point estimates and Monte Carlo results is whether the data and exposure methods employed in the two are comparable. Usually, when a major difference between point estimates and Monte Carlo results is observed, there has been a fundamental change in data or methods. Comparisons need to call attention to such differences and determine their impact.

In some cases, additional point estimates could be calculated to address specific risk management questions or to meet the information needs of the audience for the assessment. Point estimates can often assist in communicating assessment results to certain groups by providing a scenario-based perspective. For example, if point estimates are prepared for scenarios with which the audience can identify, the significance of presented distributions may become clearer. This may also be a way to help the audience identify important risks.

16. A tiered presentation style, in which briefing materials are assembled at various levels of detail, may be helpful. Presentations should be tailored to address the questions and information needs of the audience.

Entirely different types of reports are needed for scientific and nonscientific audiences. Scientists generally will want more detail than non-scientists. Risk managers may need more detail than the public. Reports for the scientific community are usually very detailed. Descriptive, less detailed summary presentations and key statistics with their uncertainty intervals (e.g., box and whisker plots) are generally more appropriate for non-scientists. To handle the different levels of sophistication and detail needed for different audiences, it may be useful to design a presentation in a tiered format where the level of detail increases

with each successive tier. For example, the first tier could be a one-page summary that might include a graph or other numerical presentation as well as a couple of paragraphs outlining what was done. This tier alone might be sufficient for some audiences. The next tier could be an executive summary, and the third tier could be a full detailed report. For further information consult Bloom et al., 1993.

Graphical techniques can play an indispensable role in communicating the findings from a Monte Carlo analysis. It is important that the risk assessor select a clear and uncluttered graphical style in an easily understood format. Equally important is deciding which information to display. Displaying too much data or inappropriate data will weaken the effectiveness of the effort. Having decided which information to display, the risk assessor should carefully tailor a graphical presentation to the informational needs and sophistication of specific audiences. The performance of a graphical display of quantitative information depends on the information the risk assessor is trying to convey to the audience and on how well the graph is constructed (Cleveland, 1994). The following are some recommendations that may prove useful for effective graphic presentation:

- Avoid excessively complicated graphs. Keep graphs intended for a glance (e.g., overhead or slide presentations) relatively simple and uncluttered. Graphs intended for publication can include more complexity.

- Avoid pie charts, perspective charts (3-dimensional bar and pie charts, ribbon charts), pseudo-perspective charts (2-dimensional bar or line charts).

- Color and shading can create visual biases and are very difficult to use effectively. Use color or shading only when necessary and then, only very carefully. Consult references on the use of color and shading in graphics.

- When possible in publications and reports, graphs should be accompanied by a table of the relevant data.

- If probability density or cumulative probability plots are presented, present both, with one above the other on the same page, with identical horizontal scales and with the location of the mean clearly indicated on both curves with a solid point.

- Do not depend on the audience to correctly interpret any visual display of data. Always provide a narrative in the report interpreting the important aspects of the graph.

- Descriptive statistics and box plots generally serve the less technically-oriented audience well. Probability density and cumulative probability plots are generally more meaningful to risk assessors and uncertainty analysts.

APPENDIX A2

Description of Pesticide Agro-eco Risk Evaluation Tool (PARET)

A demonstration computer model written in Fortran was completed as a first phase in implementation of the ideas developed in the ECOFRAM terrestrial exposure and terrestrial effects work groups. The model was written as an interim step between the concept development stage and full development of the official model to be used by EPA and the pesticide registration community in assessment of the risk of pesticide application to birds and mammals. It was designed to be as consistent as possible with the other portions of this report. The model has a number of Monte Carlo components and a number of parameters of the model are generated randomly from selected distributions.

There are two possibilities for development of the final official terrestrial model. The less complex option is to develop a model such as PARET in which hydrologic parameters and events would be represented by typical or average values. This would mean assuming default values for parameters such as rainfall amount and frequency, runoff volume, soil moisture, temperature, plant growth rates, infiltration rates, etc. The more complex option is to base the terrestrial risk assessment model around a hydrologic computer model in which hydrologic events are simulated one at a time and runoff, infiltration, plant growth and soil moisture are updated based upon these events. In this case, the model could be based around an existing hydrologic model such as the USEPA PRZM3 model or the USDA AnnAGNPS model. The later model is new and not yet well known but has the advantage of using a grid to represent hydrologic processes and might be well suited to a variable spatial representation of exposure.

In the PARET model, the exposure and effects portions of the model are integrated on an individual-by-individual basis within the program. The model user first chooses the agro-ecosystem scenario, (eg. Iowa corn, Louisiana cotton, Washington apples) which he/she

wishes to simulate. He/she then chooses one or more bird or mammalian species within that scenario on which to assess the potential pesticide impact. Data (e.g. size of home range, typical diet, typical weight etc.) for number of avian and mammalian species are available within the model for each scenario.

A. Modeling of Pesticide Effects

Pesticide effects are modeled for each individual bird or mammal by randomly generating a lethal dose amount based upon laboratory toxicity data. The model user is given a choice between entering the raw LD_{50} test result data and having the program calculate the LD_{50} and the slope of the dose response curve or entering the LD_{50} and dose/response slope values directly. The model also calculates a sub-lethal reproductive dose which is also based upon laboratory data entered by the user.

The lethal dose for each successive individual bird or mammal is calculated by the following formula:

$$LD_i = LD_{50} * 10.0^{(Z/m)}$$

where:

LD_i = Dose Lethal to the i^{th} individual feeding in the agro-ecosystem,

LD_{50} = Dose lethal to 50% of the individuals in the laboratory test,

Z = Unit normal random variate (mean of 0.0, standard deviation of 1.0), and

m = Slope of the dose/response curve from the laboratory LD_{50} test.

This is the method used to represent intra-species variability in pesticide effect. This generated lethal effect value is compared to an exposure value which is calculated later in the program (as described later in this section) to determine whether the individual is killed, survives in a reproductively impaired state or is unaffected. Overall sums for these three groups are tallied to determine the impact of the pesticide in this agro-ecosystem under the conditions tested.

B. Modeling of Pesticide Exposure

Pesticide exposure for each individual of each species in the selected agro-ecosystem is also estimated by the model. The exposure portion of the model is more complex in structure than the effects portion described in section A above. In the exposure sections of the model, each individual bird or mammal is exposed to variable and dissipating pesticide residues as it feeds over a period of days to weeks in a spatially variable landscape. The pesticide which has been ingested is, at the same time, being metabolized or otherwise depurated from the body of the bird or animal. As soon as the accumulated body burden in the bird or mammal exceeds the generated effects value, it is assumed to die. If it survives, it continues to feed on items which have continually dissipating pesticide residues. If the average body burden during this longer, user-specified period exceeds the reproductive effects level, it is considered to be reproductively impaired.

i. Spatial variability

Spatial variability of the pesticide within the agro-ecosystem and of feeding is represented by assuming that the agro-ecosystem is a grid of fields. Some of the fields are planted into the defining crop, some into other crops and some are non-crop land. In addition, not all of the land planted into the defining crop may receive the pesticide application. There are therefore four categories of land:

(1) Land in the defining crop which has been treated,
(2) Land in the defining crop which has not been treated,
(3) Land in another crop which has not been treated, but which may or may not receive spray drift, and
(4) Land which is not cropped and which may or may not receive spray drift from adjacent treated land.

The model user designs the agro-ecosystem by selecting the percent of land in each of these four land use categories. This selection is made based upon time budget, behavioral studies for each species being modeled. This is generally derived from telemetry or observational study data.

The model develops a ten-by-ten grid of fields which contains land in one or more of the above categories. The number of fields in the program grid in which the individual feeds is a function of the median size of field in the local area relative to the local range of that species. Each individual will have feeding access only to the number of fields located within its home range and each will have access to different fields. The program allows the user to determine the daily allocation of time between land planted to the defining crop, land planted to any other crop, and any other non-crop land to which the bird or mammal has access. The model then sums the pesticide residue on a daily basis across each field to which the individual has access based on the time allocated to each land use.

ii. Temporal Variability

Temporal variability is built into the model through the daily time step. This time step is used within the model in several ways. First it is used in terms of the variable application window in which the chemical is applied to those of the fields which are treated. The model user specifies the time period over which the first annual application is made. The actual application date within the selected window is generated randomly by the program. Secondly,

it is used to calculate the pesticide residue remaining on avian or mammalian food items as the chemical dissipates (as a function of the assumption of a first order degradation process.) Thirdly, it functions through depuration, by which chemical is eliminated from the body of the bird or mammal as the summation of several natural first order processes acting simultaneously.

iii. Timing of Pesticide Application

The program user selects the length of the window over which the first applications are made. The actual application dates are selected randomly within that window. Each date within the selected window is equally likely. The bird or mammal feeding the grid of fields may therefore feed the first day in a group of fields which includes a cropped, treated field on the day of application, a cropped, untreated field which has received spray drift, an unplanted field with no pesticide residue and a field to which pesticide will be applied on a subsequent day. The following day he will feed on the same group of fields, but residues will have degraded on those fields which had residues on the previous day and the field which was untreated may have been treated by then.

iv. Application rate and interval

The mean application rate, the number of applications, and the interval in days between successive applications is taken from the pesticide label. This rate may be used without variation on each field to which the chemical is applied or the rate can be varied by the user. To simulate a variable application rate, the user may choose between bounded uniform, normal and log-normal distributions of rates. **Note**: Each field is consider to have a uniform rate across it. The generated variability is among fields.

v. Spray drift

Drift onto adjacent, down-wind fields is simulated through inclusion of a subroutine developed by the Spray Drift Task Force (SDTF) and represents upper 90th percentile spray drift percentage for aerial, ground and orchard air blast applications. Birds or mammals feeding on fields immediately down-wind from application fields are assumed to ingest pesticide at a level proportional to the percent of spray drift on that field. The user chooses between aerial, ground and airblast application methods and between varying droplet size distributions and specialized applications within each of these three methods.

vi. Routes of Exposure

The model considers five routes of exposure. These are through the ingestion of the bird's or mammal's normal food items contaminated with pesticide spray, ingestion of whole pesticide granules incidently or as grit, ingestion of pesticide in contaminated drinking water, direct inhalation of pesticide spray and dermally through direct body contact with a contaminated item. The basic exposure equation is as follows:

$$DTD = (DDD + DDDg + DWD + DCD + DID),$$

where:

DTD = Daily Total Dose (mg/kg/day),

DDD = Daily Dietary Dose from ingestion of contaminated food (mg/kg/day),

DDDg = Daily Dietary Dose from ingestion of granules (mg/kg/day),

DWD = Daily drinking Water Dose (mg/kg/day),

DCD = Daily dermal Contact Dose (mg/kg/day),

DID = Daily Inhalation Dose (mg/kg/day), and

$PTD = \Sigma^{t} (DDD + DDDg + DWD + DCD + DID) * (1 - e^{-kt})$,

where:

PTD = Period Total Dose (mg/kg/day),

Σ^{t} = Cumulative Dose Over a Period of 't' Days, and

k = first order depuration rate constant.

a. Dietary intake - DDD

Dietary exposure is simulated through the Pastorok Equation as follows:

$DDD = \Sigma FIR * PD * PT * C * FDR / WT$, where

DDD = daily dietary dose (mg/kg/day) summed across each food type,
FIR = food ingestion rate (kg dry weight/day),
PD = proportion of each food type in the diet,
PT = proportion of food type eaten in the contaminated area,
C = concentration of pesticide in each food type (mg pest/kg food),
FDR = fresh weight to dry weight ratio for each food type (dimensionless),
WT = body weight of the bird or mammal (kilograms).

1. FIR. The program assumes that the mean daily quantity of food

consumed by each bird (FIR in the Pastorok equation) can be calculated using the following formula (Nagy, 1998):

FIR = 0.490 * WT exp(0.720),

and for each herbivorous mammal by (Nagy, 1987)

FIR = 0.576 * WT exp(0.727), where

FIR = food ingestion rate (kg dry weight/day),
WT = body weight of the bird or mammal (kg), and
EXP signifies an exponent.

2. PD. To input the proportion of each food type in the diet, the model user can select a default diet of measured values or select his/her own percentages based on specific local knowledge. The model user is supplied with default literature values which can be used or local values may be chosen if available and more appropriate. The model user chooses percentages among short grass, long grass, fruits, insects, broadleaf plants, seeds and worms.

3. PT. The proportion of the food type eaten in the contaminated area is assumed to be the same as the proportion of time spent in the contaminated area and is an input value. It is the same as the percent of the area planted to the defining crop which is treated with the pesticide. See section on spatial variability.

4. C. The concentration of the pesticide residue contained in each food type is expressed in milligrams of pesticide per kilogram of the food type consumed. It is calculated as the product of the actual label application rate (or generated variant) times the mean of ten randomly generated, day-zero concentration values drawn from a distribution of food type specific, concentration values. Distributions of concentration values are provided either from

Kenaga/Fletcher data or from other measured data sources. In notation, for the first field, this is as follows:

$C_1 = R_p * \Sigma^1_{10} C_{i\,/}10$, where:

C_1 = average residue concentration on ten food items in field one, and

R_p = rate of pesticide application (pounds/acre) on field one and

$\Sigma^1_{10} C_{i\,/}10$ = average of ten concentration values generated from Kenega/Fletcher or other distributions.

5. FDR. The dimensionless fresh weight to dry weight ratio for each food type is taken from published literature values. Values used in the program are:

Grasses =
Broadleaf plants =
Fruits =
Insects = 3.85 (@ 74% water)
Seeds = 6.67 (@ 85% water) to 1.18 (@ 15% water)
Worms =

6. WT. The mean body weights of the bird or mammal modeled are taken from published literature values. Default values are provided within the program or the model user can selected his/her own values based upon specific local conditions.

b. Granular intake - DDDg

The program includes a very simplistic granular model. Other granular models which

have been presented to ECOFRAM are more rigorous and account for more processes. The granular model calculates pesticide intake through the following equation:

$$DDDg = \Sigma \; MSg_i * C_i * PT / WTsp, \text{ where}$$

DDDg = daily dietary dose of pesticide in granules (mg/kg/day),
Σ = summation across all 'n' granules ingested,
MSg_i = mass of the i^{th} granule (mg),
C_i = conc of pesticide in the i^{th} granule (mg pest/mg granule),
PT = proportion of the granules consumed in the treated area, and
WT_{sp} = body weight of the bird or mammal species (kg)

The number of granules, n, is calculated by the Dixon formula:

$$n = INT (-1.0 * GR_{\mu} * \log (Z)), \text{ where}$$

INT represents an integer value or whole number

GR_{μ} = mean number of granules per day consumed on a species basis from the following table (Dixon):

Omnivores:	Mean Granules Per Day
Ring-necked Pheasant	19.92
Horned Lark	1.45
Indigo Bunting	4.62
Vesper Sparrow	1.58
Red-winged Blackbird	2.24

Insectivores:

Killdeer 1.06

Vermivores

American Robin 1.58

Granivores

Mourning Dove 1.31, and

Z = Unit normal random variate (mean of 0.0, standard deviation of 1.0).

c. Pesticide Intake Through Drinking Water - DWD

The program assumes that all drinking water comes from one or more of three sources: from perennial ponds and streams, from continuous puddles remaining from rainstorms and from morning dew remaining on leaf surfaces. The assumption is also made that all three sources are always available and that the choice is up to the bird or animal as represented by the model user. The following paragraphs describe the methods by which PARET models the pesticide concentration in these drinking water sources.

Pesticide concentrations in ponds and streams in the PARET model are simulated using the same method that the Office of Pesticide Programs (OPP) uses to simulate surface water for aquatic risk assessment. The program assumes a one hectare static 'standard' pond which receives pesticide in storm runoff water and from spray drift from an adjacent, ten-hectare, treated field. The resulting initial dissolved concentration in the pond ranges from one percent to ten percent of the applied chemical as a function of partitioning estimated by the organic carbon partition coefficient (K_{oc}) of the chemical. The concentration values on days subsequent to the first are calculated assuming first order degradation with a combined half-life that includes metabolic, hydrolytic and photolytic processes.

Puddles are modeled assuming either direct application or direct spray drift to standing puddles. The dissolved concentration is calculated based upon K_{oc} partitioning in the puddle. It is assumed that the puddle has a continuous depth of 10.0 centimeters. As with the pond, the concentration in the puddle on subsequent days is calculated assuming first order degradation with a combined half-life that includes metabolic, hydrolytic and photolytic processes.

The pesticide concentration in dew drops on leafy surfaces is modeled based upon a one milliliter fixed droplet volume on a leaf and partitioning from the leaf surface into the water droplet as a function of the K_{oc} value. It is assumed that all droplets are either consumed or evaporate each day. The concentration in dew drops is however lower each day due to degradation on the leaf surface from which the pesticide partitions. Degradation is assumed to take place at the first order rate at which is degrades on the leaf surface.

d. Dermal Exposure - DCD

Pesticide exposure due to dermal contact is not yet implemented in the program.

e. Inhalation - DID

Pesticide exposure due direct inhalation of pesticide after a spray event or of volatilized pesticide is not yet implemented in the program.

C. Modeling of Pesticide Risk

PARET addresses the risk posed by use of a pesticide within an agro-eco system in two ways. First, a simple comparison of exposure and effect is made on an individual-by-individual basis. If the lethal exposure value is higher than the lethal effect value, the individual is considered to be dead. If the reproductive exposure value is higher than the sublethal or reproductive effect value, the individual is considered to be reproductively

impaired. If neither of these happens then there is no impact. In this case, a simple summing is carried out for each of the three categories: those that are dead and those that are reproductively impaired those that are not impacted. Simple percentages are calculated for each.

The second method of assessment which is carried out concurrently with the first is to calculate a simple risk quotient for each of the individuals in the agro-ecosystem and to develope a mean and standard deviation for these risk quotients.

D. Tiering vs. Smoothly Varying Levels of Complexity

PARET is written in such a way as to enable many levels of complexity in an assessment using the same model. At the simplest level, conservative, single valued inputs can be used to complete a classic, pre-ECOFRAM, deterministic risk assessment. To estimate a lethal effect value, an LD_{50} value can be entered without considering the variability implied by the slope of the dose/response curve to provide a single effects estimate for all individuals. To estimate exposure at this level, the user assumes 100% of the area is cropped, 100% of the crop is treated, all of the crop is treated on the same day and 100% of the birds eat short grass having a residue level of 240 ppm. The result is the current risk quotient.

At the other end of the spectrum, the user may generate varying effects values for each individual from the intra-species variability data and select values from available distributions to fully describe exposure in a spatially and temporally variable agro-ecosystem. The result is a fully temporal and spatial assessment to the extent that the availability of distributional input data for the model allows.

The model may be run at any level of complexity to take full advantage of the quantity, quality and distributions of the available input data. Tiers can be chosen that allow use of the model at any desired level. Cost and complexity of developing input values can then

be the criteria that are used to select the levels at which the tiers are set. At lower tiers, more processes may be represented by single valued inputs with distributions used for a few simple parameters. At successively higher levels, more and more processes are represented by values selected randomly from distributions when it is felt that the expense to collect additional input values is worth the added cost.

APPENDIX A3

AN INDIVIDUAL-BASED MODEL OF PESTICIDE INGESTION AND MORTALITY IN AVIAN SPECIES

(Dixon Model)

Introduction

Mathematical models and computer simulation can be used to link pesticide exposure concentrations with effects such as mortality. We developed an individual-based mathematical model to predict the effects of pesticide ingestion on the populations of avian species with different feeding habits in and around agricultural fields.

Conceptual Model

The model consists of two parts: (1) a calculation of the body concentration, or dose, for each individual in the population, and (2) a calculation of the probability of mortality for the current dose. Population survival is estimated by determining the mortality of many individuals of a given species in a population. Each part of the model is stochastic in that it contains random variables. The random variables in the first part (dose calculation) are the ingestion rate of granules and the residues in other diet components. The random variable in the second part (mortality estimation) is the probability of mortality. These random variables provide the capability to conduct stochastic simulations.

Structure

The change in body concentration of a pesticide in an individual bird between time *t* and time *t+1* can be described by the difference equation:

$$Q_{t+1} = Q_t + \sum_{i=1}^{n} I_{i,t}\ \alpha_{i,t} - \lambda\ Q_t \qquad \textbf{(1)}$$

where

Q_t = pesticide body burden at time *t*, mg·kg $^{-1}$

Q_{t+1} = pesticide body burden at time *t+1*, mg·kg $^{-1}$

$I_{i,t}$ = ingestion rate of pesticide in granules or food item *I* at time *t*, mg·kg $^{-1}$·day $^{-1}$

$\alpha_{i,t}$ = proportion of total diet contributed by item *I* at time *t*

λ = elimination rate constant, day $^{-1}$

Ingestion

The weight-specific mass ingestion rate of pesticide, $I_{i,t}$, (mg·kg $^{-1}$·day $^{-1}$) may be written as

$$I_{i,t} = \frac{p_i C_i v_i}{Wt} \qquad \textbf{(2)}$$

where

p_i = proportion of food item, *I*, consumed that is contaminated

C_i = consumption rate of granules or food item *I* , g·day $^{-1}$

v_i = pesticide concentration in granules or food item *I* , mg·kg $^{-1}$

Wt = consumer body weight, g

Food consumption rates. The amount of food consumed in grams (dry matter) per day, C_I, was estimated using the power functions (Nagy 1987, USEPA 1993) that describe consumption as a function of body weight:

$$C_i = \begin{cases} 0.398\, Wt^{0.850} & passerines \\ 0.301\, Wt^{0.751} & non-passerines \end{cases} \qquad \textbf{(3)}$$

Body weights were obtained from Dunning (1993).

Consumption of pesticide granules. Consumption of pesticide granules was assumed to be a random variable. The number of granules actually consumed in a given day of the simulation was randomly selected from an exponential probability distribution. The distribution was based on a frequency histogram of granule counts in gizzards. Data from both the study on Iowa cornfields by Fischer and Best (1995) and the study of mostly Midwestern states by Gionfriddo and Best (1996) were used. Estimates of the mean of the exponential density function were calculated by two different methods. The first method used the mean gizzard grit count from Gionfriddo and Best (1996) and adjusted it by the conversion factor of 4.2 granules consumed per day per each granule detected in the gizzards, and then adjusted for the difference between ingestion of clay and silica granules. The consumption rate of silica granules was greater than that of clay granules by a factor of 6. The second method was based on the study of ingestion of clay granules in house sparrows by Best and Gionfriddo (1994). The estimate for each of the focus species was calculated by taking the mean value for house sparrows and multiplying it by the ratio of gizzard grit count in the focus species to that of the house sparrow. The greater of the estimates from the two methods then was used in the simulations. A probability density function was obtained by fitting an exponential function to the data using the nonlinear regression procedure in PRISM (GraphPad 1994-1995):

$$f(x) = \begin{cases} \frac{1}{\beta} e^{-\frac{x}{\beta}} & if\ x \geq 0 \\ 0 & otherwise \end{cases} \qquad \textbf{(4)}$$

where β is the mean of the distribution. The actual number of pesticide granules consumed is treated as a random variate that is generated from the distribution function for equation (4):

$$F(x) = \begin{cases} 1 - e^{-\frac{x}{\beta}} & if\ x \geq 0 \\ 0 & otherwise \end{cases} \qquad \textbf{(5)}$$

The inverse-transform method was used to obtain the random variate for granule consumption, X (Law and Kelton 1991). To find F^{-1}, we set $u = F(x)$ and solve for x to obtain

$$F^{-1}(u) = -\beta \ln(1 - u) \qquad \textbf{(6)}$$

To generate the random variate X we first generate a random variate U from a uniform distribution U(0,1). The second step is to return $X = -\beta \ln (1 - U)$.

Pesticide granule degradation. The integrated material balance equations for the degradation of pesticide from the granules, developed by Cryer and Laskowski (1994), were incorporated into the model. The amount of pesticide in the granule at time t, C_A, is dissipated by diffusion into the soil and volatilization into the atmosphere:

$$C_A = C_{A\,o}\, e^{-(k1+k3)t} \qquad \textbf{(7)}$$

where $k1$ = the rate constant for release of pesticide into the soil, and
$k3$ = the rate constant for volatilization.

Proportion of components in diet. The two focus species can be characterized, in terms of their feeding habits as omnivores . The percentage of the diet that is plant food is reported in Martin, et al. (1951). The percentage in the summer diet was used because that is most representative of the exposure period from spray applications. These percentages were used to provide the proportion of plant material, α_i, in the diets of the two species (Table A3-1). The balance of the diet consists of animal components. In the case of bobwhites and red-winged blackbirds, data on grasshoppers were used.

Time spent in treated areas

The proportion of consumed food items that are contaminated with pesticide, p_i , will depend upon the relative time spent in treated areas compared to untreated areas. The untreated areas include both untreated areas surrounding treated agricultural fields and, in the case of banded applications, the

areas between bands. The proportion of food items contaminated, p_i, then is the product of the proportion of time feeding in a treated field, p_f, and the proportion of time feeding in treated areas within the field given that the bird is feeding in the field, p_w.

Edge vs. field. The time spent feeding within a field and adjacent to the field can be estimated from observations of the number of birds feeding in each area. Assuming that the location of feeding over a period of time is a random process, the proportion of time spent feeding in a field will be equal to the proportion of the total number of birds observed in the field. Data from Iowa and Illinois cornfield studies (Best, et al 1990) were used to obtain estimates of p_f. The highest reported field-use percentage was used.

Band vs. non-band. Pesticide granules are applied in bands approximately 18.0 cm wide and 76.2 cm apart. On an area basis, the proportion of time spent in a treated area is 0.19. For the estimates of granule consumption based on data from Fischer and Best (1995) in which birds were observed

Table A3-1. Parameters used in the model for two avian focus species.

	Species	
Parameter	Northern Bobwhite	Red-winged Blackbird
Proportion of plant food in diet, α_i Source: Martin, et al. 1951	.73	.50
Body weight, *Wt*, in grams Source: Dunning 1993	178	53
Proportion of food items that are contaminated, p_f Source: Best, et al. 1990	.01	0.16

over an entire field, a value of p_w of 1.0 was used for granule consumption. For the estimates of granule consumption based on data from Gionfriddo and Best (1996), a value of p_w of 0.19 was used. Although spray treatments sometimes are applied in bands, a continuous coverage was assumed; therefore, p_w also was 1.0 for other food items.

Residues in diet components

Dietary components. The concentration of pesticide in the plant component (parameter, v_i) was taken from data on seed residues. For the insect component of the diet, residue data were obtained on invertebrates collected from corn fields. Each residue value was treated as a normally distributed random variable. The random variates N(0,1) were generated using the method of Box and Muller (1958) (See Law and Kelton 1991:491).

Dissipation from diet components following application. Pesticides dissipate from plant surfaces following spraying. Assuming an exponential decay function, the estimated rate constant can be estimated from the equation:

$$C_t = C_0 e^{-kt} \qquad \textbf{(8)}$$

Dry Weight to Wet Weight Conversion Factor. Because fonofos residues are based on mg of fonofos per kg (wet weight) of tissue and food consumption is based on dry weight, a factor to convert dry weight to wet weight is needed. The conversion factor, f_i, is a function of water content:

$$f_i = \frac{1}{1 - p_{H_2O}} \qquad \textbf{(8)}$$

where p_{H2O} is the proportion of water in the food item. The water content of the three food items used in the model were 0.10, 0.50, and 0.90 for seeds, insects, and earthworms respectively.

Avian Loss Rates

The primary mechanisms of pesticide removal from avian species are excretion and metabolism of absorbed pesticide and voiding of the pesticide granules. A single compartment elimination model was used to obtain elimination rate constants, λ, in equation (1):

$$\lambda = \frac{-\log(a(1 - p))}{t} \qquad \textbf{(10)}$$

where a is the fraction of excreta that is pesticide (≤ 0.5), p is the fraction of dose excreted, and t is time between dosing and final sampling of excreta. Elimination of pesticide granules from gizzards (Fischer and Best 1995) also showed a negative exponential decrease to a plateau in both house sparrows and red-winged blackbirds.

Mortality

Mortality response function. The probability of mortality occurring in an individual is determined by a dose-response function in which mortality probability is a logistic function of dose or body concentration, Q (Brown 1978, Finney 1964). The following form of the logistic function was used:

$$F(Q) = \frac{P_1}{1 + e^{(2.2/P_3)(P_2 - Q)}} \qquad \textbf{(11)}$$

where

$F(Q)$ = probability of mortality at dose Q

P_1 = maximum probability of mortality

P_2 = LD_{50}

P_3 = difference between LD_{10} and LD_{50}

Q = dose or body concentration

The parameter P_2 is exactly the LD_{50} value. There is a one-to-one relationship between the slope and the parameter P_3. As the slope increases, toxicity increases and the range between LD_{50} and LD_{10} decreases. The parameter P_3 has to be less than P_2 and should define the dose response curve at the point (0,0). In other words, there has to be zero mortality probability at a zero dose. As P_2 decreases, the value of P_3 also decreases. The P_3 value then was adjusted until the estimated mortality probability was 0.001 at zero dose.

Mortality probability function. To determine the quantal response (i.e., whether or not mortality occurs), a random number generator was used to obtain a sample from a uniform distribution, U(0,1). If the value of the random variable is less than or equal to P(Q), mortality is assigned to the individual. A population response is obtained by simulating many individuals.

Examples with fonofos

Granular Applications

Simulations were run for each of the focus species in Table A3-1, with dose (body burden) and survival as state variables. In other words, both dose and survival were followed over time.

Although the model captures the essence of what is known about avian feeding behavior in and around cornfields, several conservative assumptions were made that assured that these simulations produced estimates of population mortality which were not likely to be exceeded in field situations:

1) Where data were missing for a given species, a conservative estimate based on values for other avian species was used,
2) The process contributing to the greatest rate of fonofos degradation on the granule, advection during rainfall events, was not used in the model,
3) The elimination rate from birds was based on the lowest reported value of percentage reduction in body burden,
4) The possible behavior of avoiding fonofos granules was not included in the model.

The exposure scenario for all simulations was that the start time of the simulation was the application date of fonofos granules at plant. Model parameters for each species are presented in Table A3-2.

Species

Simulations were run for two focus species: the northern bobwhite, and red-winged blackbird.

Predicted dose

For each focus species, Monte Carlo simulations of 100 individuals were run to obtain a population mean and 95 percent confidence interval of dose (Figure 1a-b).

Northern bobwhite

The predicted dose was relatively low, with a peak of about 0.015 mg/kg, primarily a result of the low percentage of time spent in the field (0.01%). The peak occurred about six days following application as fonofos accumulated in the body. Elimination was fairly rapid, declining to less than ten percent of the maximum dose within fifty days post application.

Table A3-2. Parameters used for simulation of fonofos granular applications.

	Species	
Parameter	Northern Bobwhite	Red-winged Blackbird
Mean number of granules consumed per day Source: (See text)	3.31	2.24
Excretion rate constant, λ Source: Bauriedel 1986	0.5116	0.5116
LD_{50}, p_2, in mg/kg, Source: (See footnotes)	12.0[a]	10.0[b]
LD_{50}-LD_{10}, p_3, in mg/kg Source: (See text)	4.0	3.3

[a] Source: Hill and Camardese 1984.

[b] Source: Schafer and Brunton 1979.

Red-winged blackbird

The pattern of the predicted dose was similar to that of the bobwhite, although the maximum dose is significantly higher. This resulted from a lower body weight and greater amount of time spent in the field (16%). The peak dose of 0.54 mg/kg again was about six days following application. The elimination to ten percent of the maximum also took about fifty days.

Predicted mortality

Each simulation also predicted mortality for each dose trace. Mortality was subtracted from the population of 100 individuals to estimate probability of survival. The model predicted zero mortality for all species even with the conservative assumptions included in the model. Comparing the peak doses in Figure A3-1, a-b**,** with the LD_{50} values in Table A3-2 suggests that the dose is not great enough to cause mortality in these focus species.

Sprayable Applications

Simulations were run for each of the focus species in Table 1, with dose (body burden) and survival as state variables as with the granular application simulations. Although the model captures the essence of what is known about avian feeding behavior in and around cornfields, several conservative assumptions were made that assured that these simulations produced estimates of population mortality which were not likely to be exceeded in field situations:

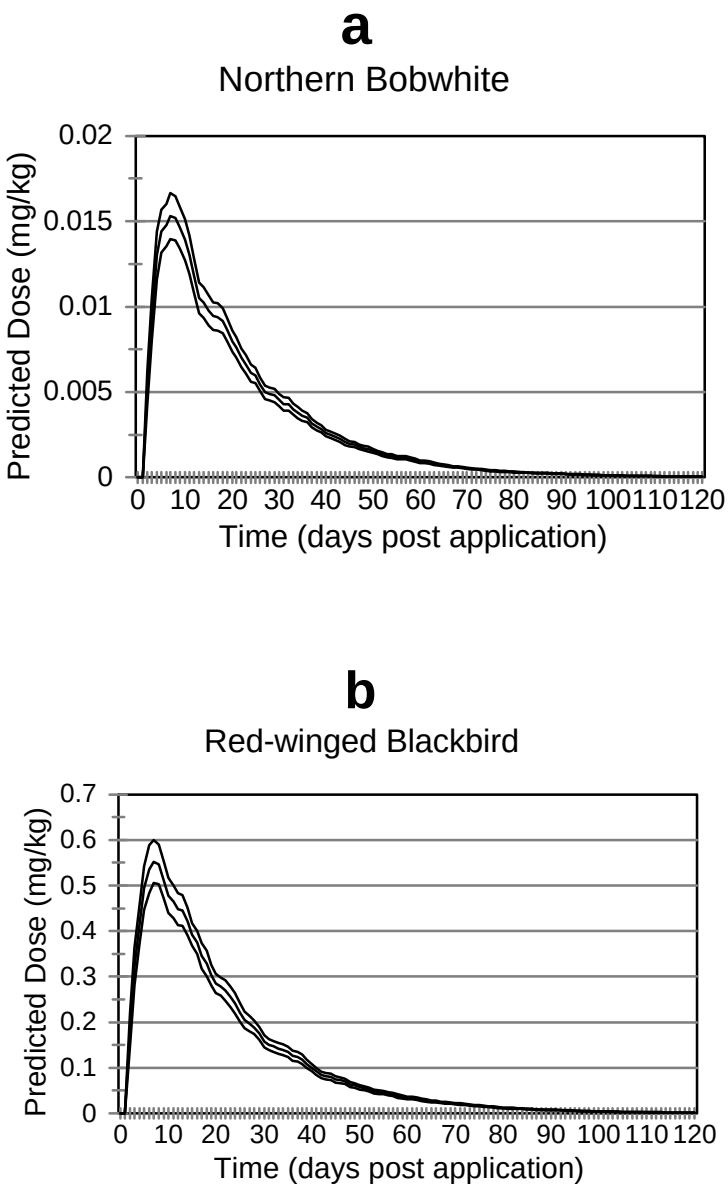
1) Where data were missing for a given species, a conservative estimate based on values for other avian species was used,
2) The maximum mean values of fonofos residues were used for the parameter v_i,
3) The elimination rate from birds was based on the lowest reported value of percentage reduction in body burden.

The exposure scenario for all simulations was that the start time of the simulation was the application date of fonofos. Model parameters for each species are presented in Table A3- 3. Other model parameters are as in Tables A3-1 and A3-2.

Table A3-3. Values used in the model for residues in the diets of the two avian focus species.

Parameter	Mean	Standard Deviation
Residues on plant food in diet	33.3	3.33
Residues on insect food in diet	15.0	1.50

1



2 **Figure A3-1.** Predicted dose in mg/kg for two avian species (a) northern bobwhite and (b) red-
3 winged blackbird from granular application of fonofos.

Species

Simulations were run for two focus species: the northern bobwhite, and red-winged blackbird.

Predicted dose

For each focus species, Monte Carlo simulations of 100 individuals were run to obtain a population mean and 95 percent confidence interval of dose (Figure A3-2,a-b).

Northern bobwhite

The predicted dose was relatively higher compared to the granular dose, with a peak of about 0.08 mg/kg, primarily a result of the higher fonofos ingestion from diet residues. The peak occurred about four days following application as fonofos accumulated in the body. Elimination was fairly rapid, declining to less than ten percent of the maximum dose within 25 days post application.

Red-winged blackbird

The pattern of the predicted dose was similar to that of the bobwhite, although the maximum dose is significantly higher. This resulted from a lower body weight and greater amount of time spent in the field (16%). The peak dose of 1.48 mg/kg again was about four days following application. The elimination to ten percent of the maximum took about 34 days.

Predicted mortality

Each simulation also predicted mortality for each dose trace. Mortality was subtracted from the population of 100 individuals to estimate probability of survival. The model predicted zero mortality for both species even with the conservative assumptions included in the model. Comparing the peak doses in Figure A3-2a-b with the LD_{50} values in Table A3-2 suggests that the dose is not great enough to cause mortality in these focus species.

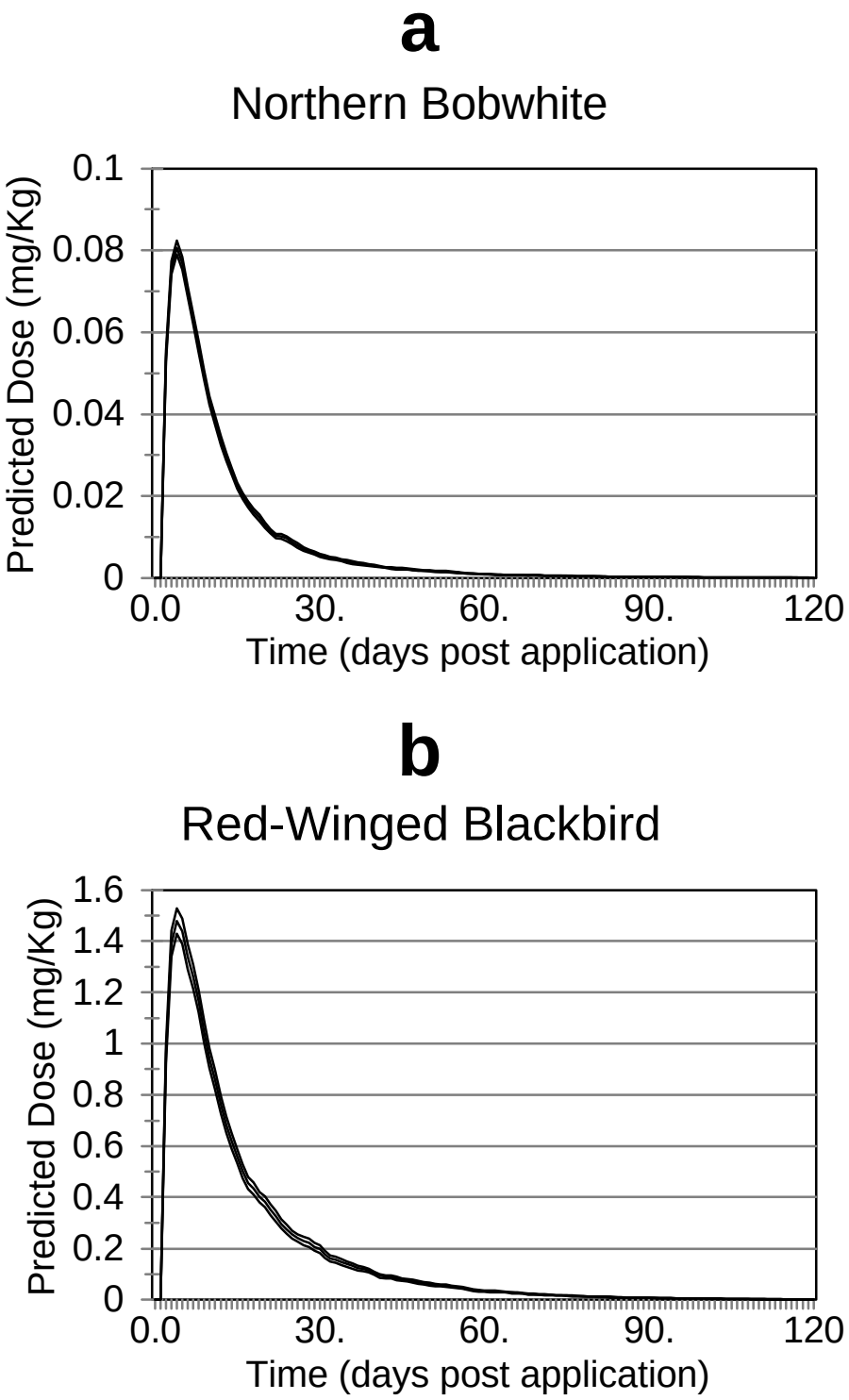


Figure A3-2. Predicted dose in mg/kg for two avian species (a) northern bobwhite and (b) red-winged blackbird from a spray application of fonofos.

Interpretation of Results

There is much uncertainty associated with the model parameters. An analysis of model sensitivity showed that parameters P_2 and P_3 had the greatest effect on the model predictions. It is necessary to have both LD_{50} and slope values on the same species. This lends support for the reporting of both values in the publication of research. Given sufficient data, the model can provide improved estimates of dose and survival in avian species exposed to applications of insecticides in agricultural crops. The model predicts that the dose from sprayable applications is greater than that from granular applications. This results from the fonofos concentrations of the residues in diet components (Table 3). Lower residue concentrations could reduce the predicted dose to that of granular applications. The model simulations and post-simulation analysis predict no mortality will occur in the two focus species from either granular or sprayable applications. Given the conservative assumptions used in the model, it is unlikely that significant and widespread mortality in avian populations in Midwestern corn agroecosystems will occur from normal fonofos use.

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APPENDIX B1

PROBLEM FORMULATION

There are three major phases to the ecological risk assessment process as set forth by the *Framework for Ecological Risk Assessment* (1992). These phases are Problem Formulation, Analysis, and Risk Characterization. The first phase, Problem Formulation, includes preliminary characterization of exposure and effects, examination of scientific data and data needs, policy and regulatory issues, and site-specific factors to define the feasibility, scope, and objectives of the risk assessment (EPA 1992). Successful completion of this phase will result in: assessment endpoints that adequately reflect management goals and the ecosystem they represent; conceptual models that describe key relationships between a stressor and assessment endpoint; and an analysis plan (EPA 1996).

The problem formulation phase appears to have received relatively little explicit attention in the pesticide registration process. This circumstance has likely occurred for at least two reasons. First, it has only been recently that formalization of the ecological risk assessment process and subsequent guidance have been in place (EPA 1992, 1996). Second, historically, the typical screening assessment for pesticides has been primarily a hazard assessment. Moving past the current initial hazard assessment to a risk assessment is part of the ECOFRAM process. Hence, an important outcome from the ECOFRAM process should be recommendation for inclusion of an explicit Problem Formulation phase in ecological risk assessments under FIFRA. There should also be provisions that Problem Formulation may be carried out for the various levels of refinement outlined in Chapter 6.

OBJECTIVE

The general objectives of the initial Problem Formulation phase, i.e., a preliminary characterization of exposure and effects, examination of scientific data and data needs, identifying policy and regulatory issues, and definition of the feasibility, scope, and objectives of the risk assessment apply to all registration or reregistration actions under FIFRA. For some registration or reregistration

actions, the resulting assessment endpoints, conceptual models, and analysis plan will be adequate to allow a regulatory decision. For other registration or reregistration actions, there will be unacceptable uncertainties and a regulatory decision will not be possible. Higher levels of refinement of the assessment will be needed to support a regulatory decision.

Ecological risk assessment was, from the outset, contemplated to be an iterative process (see EPA 1992). Therefore, the more refine probabilistic assessments should include a refined Problem Formulation phase. It is hoped that there will be few, if any, changes in the assessment endpoints to be addressed by the refined assessment. Assuming this to be the case, therefore, efforts in Problem Formulations will center on refined characterizations of exposure, effects, or both, gathering and evaluation of new data, refined conceptual models, and new analysis plans. The relative emphasis on each of these activities will take place on a case-by-case basis and depend greatly on the crop protection product and use in question.

It should be evident from the above discussion that the Problem Formulation phase will remain an essential component of the refined ecological risk assessment. With the refinements based on previous assessments and additional data and analyses, the identified uncertainties from the lower assessments should be reduced. As ECOFRAM procedures are introduced and implemented, it will be essential for regulators and registrants to agree on the major sources of uncertainty and the most efficient ways to reduce them to acceptable levels. Again, the most efficient course for reducing uncertainties will depend to a great extent on the crop protection product and use in question.

To provide some more concrete information on what might be included in a refined Problem Formulation table B1-1 is provided.

Table B1-1. Examples of Components of the Problem Formulation Phase

Stressor Characteristics	Summary of Physical and Chemical Characteristics General Information on Use Pattern Physical and Chemical Properties and Fate in the Environment Mode of Action Overview of Toxicity to Vertebrates Metabolism in and Excretion from Biological Systems: Potential for Biomagnification and Bioaccumulation
Ecosystem Potentially at Risk	The Crop Agroenvironment Cultural Practices in the Crop Agroenvironment Field Borders
Assessment Endpoints for Avian Risk	Individual Birds, Local Bird Populations, Regional Bird Populations
Measurements Endpoints for Avian Risk	Individual Birds, Local Bird Populations, Regional Bird Populations
Ecological Effects Conceptual Model	Potential Pathways and Routes of Avian Exposure General Partitioning into Air, Soil, Plants and Other Possible Food Items, and Water Physical and Chemical Properties Spatial and Temporal Aspects of Exposure
Analysis Plan for This Risk Assessment	

ASSESSMENT AND MEASUREMENT ENDPOINTS

The scope of the ECOFRAM's assignment includes designing probabilistic risk assessment guidelines for all current and future pesticides, including all application methods, crops, in all environments throughout the United States. Clearly this task is too broad to define specific assessment endpoints for each agroecosystem. The ecological entity of concern in Florida avocado fields treated with foliar

insecticides will be different from that in a California strawberry field treated with a soil fumigant and the risk assessment must be tailored for each unique situation. However, generalized assessment endpoints and measures of effects (measurement endpoint) can be drawn which are applicable to all pesticide risk assessments.

ASSESSMENT ENDPOINTS FOR RISK TO TERRESTRIAL VERTEBRATES

According to the EPA *Framework*, assessment endpoints are explicit expressions of the actual environmental value that is to be protected which are directly related to a characteristic of an ecological component that may be affected by exposure to a stressor (EPA 1992 -- Framework). There are several criteria for selecting assessment endpoints. These criteria include ecological relevance, susceptibility to the stressor, and the relationship of the assessment endpoints to management goals and societal value.

Each assessment endpoint must contain two elements: the valued ecological entity and the characteristic of that entity which is potentially at risk and which is important to protect (EPA 1996). It is suggested that the valued ecological entity is the terrestrial vertebrate species associated with the crop agro-ecosystem defined above. Endpoints are established for three levels of biological organization of the valued ecological entity: the individual, the population and the community/ecosystem (Chapter 2). The population level of organization can be further subdivided into the local population (i.e., terrestrial vertebrates associated with a single crop agro-ecosystem – and the regional population (i.e., terrestrial vertebrates in a county or larger unit). It is clear that this use of the term “population” could be debated. The 2 or 3 pairs of, for example, songbirds inhabiting the border around a crop field are not a population in the strictest sense. Such a small number of pairs of birds would be highly subject to the vagaries of weather and predators, and might easily become “extinct”. Nonetheless, because the field is the basic management unit, as well as the likely experimental unit, some term needs to be used to describe the birds associated with individual units of the agro-ecosystem.

At the individual level, reductions in survival and reproduction due to direct effects of are suggested

as primary assessment endpoints. However, it is recognized, growth, development and morbidity of the valued ecological entity are also important considerations in assessing the impact of pesticides, however, their empirical relationship to the survival of an individual is more difficult to assess. At the local and regional population level, change in population size due to changes in survival or reproduction and the persistence of the population are suggested as assessment endpoints. It is recognized that the demographics of a population provide invaluable information on the health of a population, but assessing a population in such detail might only occur at the highest and most refined probabilistic risk assessment. At the community/ecosystem level, patterns of taxonomic and functional diversity are suggested as endpoints while recognizing the importance of nutrient cycling and energetics. The assessment endpoints selected are for direct effects, not secondary or "cascading" effects (EPA 1996). Indirect effects and sublethal effects will have to be dealt with based on refinements in current testing procedures.

The assessment endpoints selected clearly have ecological relevance, and are potentially susceptible ta stressor. Furthermore, both the valued ecological entity and the characteristic to be protected are identified. The major shortcoming of the assessment endpoints selected is that they are not measured directly under the current FIFRA Pesticide Assessment Guideline requirements for testing. Therefore, it will be necessary to use measurement endpoints that are different from the assessment endpoints. Some uncertainty may be introduced into the assessment because of this difference. However, these assessment endpoints can be represented by variables that are possible to measure, monitor, or model with reasonable confidence.

The relationship between assessment endpoints and measures of effect (measurement endpoint) must be well defined and directed so that the collected information provides the ability to draw clear conclusions on the assessment endpoints. It would be ideal if assessment endpoints could be measured directly and thereby serve also as measurement endpoints (EPA 1998 -- Guidelines). Such a direct relationship would reduce the uncertainty in the assessment.

MEASURES OF EFFECT (MEASUREMENT ENDPOINTS) FOR TERRESTRIAL VERTEBRATE RISK

As defined in 1992 *Framework* document, measurement endpoints are measurable responses to a stressor that are related to the valued characteristics identified by the assessment endpoints (EPA 1992). There are several considerations for selecting measurement endpoints. These considerations include: relevance to the assessment endpoint; consideration of indirect effects; sensitivity and response time; signal-to-noise ratio; consistency with assessment endpoint exposure scenarios; diagnostic ability, and practicality (EPA 1992).

Since the 1992 *Framework* document, the EPA has issued a guidance document for ecological risk assessment (1998). In this guidance document, the term "measurement endpoint" was replaced with the term "measure of effect" and subsequently supplemented by two other categories of measures, "measures of exposure" and "measures of ecosystem and receptor characteristics." Measures of effect are measures used to evaluate the response of the assessment endpoint or a surrogate when exposed to the stressor. Measures of exposure are measures of how exposure may be occurring, including how a stressor moves through the environment and how it may co-occur with an assessment endpoint. Measures of ecosystem and receptor characteristics include ecosystem characteristics that influence the behavior and location of ecological entities of the assessment endpoints, the distribution of a stressor, and life history characteristics of the assessment endpoint that may affect exposure or response to a stressor. In fact, all of these measures are inter-related to some extent.

Some general observations about the approach taken in deciding upon the measures used in this assessment are in order. The assessment endpoints selected are not measured in the standard testing battery required by the current Pesticide Assessment Guidelines. Therefore, it may be necessary to employ a suite of measures and a weight-of-the-evidence approach rather than relying on a single index or measure. An advantage of endpoints at different levels of biological organization is that the likelihood of effects at one level can be inferred from the likelihood of effects at lower levels. The use of a suite of measures at different levels of biological organization can build greater confidence

in the conclusions of the assessment (EPA 1992). While this approach may not make regulatory decision making easy, because it does not necessarily provide point estimates that indicate risk or lack of risk, it does provide the risk manager with a wealth of information with which to evaluate relative risks and to recommend effective risk mitigation measures.

As noted above, the various measures – effects, exposure, ecosystem and receptor characteristics – are, by their nature, inter-related. The same statement holds true for all levels of biological organization. It is somewhat artificial to draw a sharp distinction between survival and reproduction of individual terrestrial vertebrates versus survival and reproduction of local or regional populations of terrestrial vertebrates. Nonetheless, it is also clear that risk managers have questions about potential effects of a stressor at the different levels of biological organization. In an attempt to address these questions, the various parts of a stressor's data base will have to be relied on differentially for the different levels of biological organization. Again, this is a somewhat artificial distinction, because in a sense the entire data base relates to all levels of biological organization.

Although the distinctions being drawn are somewhat artificial, they provide a major advantage in a refined assessment compared to a traditional assessment. In a traditional assessment, which relies primarily on risk quotients derived from published residue levels, it is difficult to integrate information on other measures, such as measures of ecosystem and receptor characteristics.

Individual Terrestrial Vertebrates

Protection of individual terrestrial vertebrates is a valid risk management objective, especially for threatened or endangered species. The current risk assessment methodology provides the risk manager with a certain degree of comfort knowing the degree of safety built into this method. However, simply combining toxicity information obtained from the standard laboratory toxicity tests under Subdivision E and the "Hoerger and Kenaga" (1972), estimates of residues on certain terrestrial vertebrate food items may not be adequate when a more complete picture of risk is required. Toxicity information in and of itself may be an indicator of effects only when a terrestrial vertebrate receives a dose. Current risk assessment methodology does not take into consideration the vagaries of

terrestrial vertebrate feeding behavior (see Section on Test Suitability) which greatly affects the dose an animal may receive.

The measure of effect used for individual terrestrial vertebrates is suggested to be the general toxicity profile for the stressor. These measures include information currently collected such as lethal dose estimates and should include dose estimates sufficient to elicit subtle yet significant responses (see Section on Test Suitability). The measure of exposure used will be the general partitioning and degradation of the stressor in the environment. Measures of ecosystem and receptor characteristics could include: state lists of terrestrial vertebrates in crop agro-ecosystem regions, along with information on their habitat preferences, seasonal occurrence, and feeding and breeding habits; data from terrestrial vertebrate censuses in and around crop agro-ecosystems across the area a crop is grown; terrestrial vertebrate field study information, and estimates of the food base for terrestrial vertebrates in crop agro-ecosystems and associated non-crop habitats. This latter estimate can be made from the entomological literature and the scouting guides published by state Extension Services.

Local Terrestrial Vertebrate Populations

In the context of this discussion, local terrestrial vertebrate populations are defined as those populations inhabiting individual crop agro-ecosystems. It should be clear that the information used to assess risk to individual terrestrial vertebrates is also applicable at this higher level of biological organization. The information for individual terrestrial vertebrates helps to focus the assessment on the terrestrial vertebrates most likely to be exposed and identifies species at risk. Also, the conclusions for risk to individual terrestrial vertebrates will be important in evaluating risk to local terrestrial vertebrates populations.

The measures of effect used for local populations will be the numerical results of the standard laboratory toxicity tests under Subdivision E, i.e., LD50, LC50, 28-day feeding, and avian reproduction study results, and similar non-guideline toxicity studies. The measures of exposure used could be the results of field studies that provide residue levels, and their decline over time, in relevant food items. The measures of ecosystem and receptor characteristics could be incorporated by

selecting terrestrial vertebrate species that are likely to be exposed to the stressor due to their feeding habits and the times they use the crop agroecosystem.

Regional Terrestrial Vertebrate Populations

In the context of this discussion, regional terrestrial vertebrate populations are defined as those populations inhabiting the crop agroecosystems in convenient politically-based units such as counties and states, or biologically-based ecoregions. It should be clear that the information used to assess risk to individual terrestrial vertebrates and local population is also applicable to this level of biological organization. Also, the conclusions for risk to local terrestrial vertebrates populations will be important in evaluating risk to regional terrestrial vertebrate populations.

At the regional population level of organization, the measure of effect could again be the general toxicity profile for the stressor. The measure of exposure will be the general partitioning and degradation of the stressor in the environment. Measures of ecosystem and receptor characteristics could include information on the borders of the crop agro-ecosystem, information on the extensiveness of applications of the stressor, and information on the extensiveness of crop production.

The suites of measures selected and the different levels of biological organization assume applicable exposure scenarios, are likely to be susceptible to the stressor on the same time scale as the assessment endpoints, and are practical to measure. It is assumed that they have acceptable signal-to-noise ratios. The measures do not relate particularly well to indirect or sublethal effects, as explained above. However, minor changes to current test methodology and interpretation could allow these effects to be considered in risk assessments.

Table B1-2. Analysis Plan Outline – Data to be Considered and How they will be Used

Level of Biological Organization/ Assessment End-points	Measure of Effect	Measure of Exposure	Measure of Ecosystem and Receptor Characteristics	Type of Risk Estimate
Individuals and Threatened and Endangered Species				
Survival of valued ecological entity *	LD_{50} /LC_{50} /NOEC with 95% CL (slope of dose response curve; time to death); EC_{25} or EC_{50} with 95% CL (visual phytotoxicity: % germination; emergence) Progeny Survival/average longevity; Embryonic viability/death; Number of dead organisms in the 'field'	General partitioning and degradation in the environment	Terrestrial vertebrates in the crop's range. Terrestrial vertebrates actually using the crop (censuses). Timing of applications. Suitability of the crop as terrestrial vertebrate habitat (e.g., insect biomass in the crop and environs). Field study results	Qualitative Deterministic

Table B1-2. Analysis Plan Outline – Data to be Considered and How they will be Used

	Level of Biological Organization/ Assessment End-points	Measure of Effect	Measure of Exposure	Measure of Ecosystem and Receptor Characteristics	Type of Risk Esti-mate
1	Reproduction of	Clutch Size; Clutch Characteristics (No.			
2	valued ecological	eggs cracked, egg shell thickness or			
3	entity *	strength); Progeny Characteristics (Nor-mal offspring, weight at time 'X'); Embryonic viability/death; No. Females showing signs of abortion/Pregnant fe-males; Length of gestation period; No. Corpus lutea/Live fetus/dead fetus/ time to death in utero; No. Normal fetuses and litters with normal fetuses; No. Still pups born/Progeny survival; Male fertility; Pa-rental behavior			

Table B1-2. Analysis Plan Outline – Data to be Considered and How they will be Used

	Level of Biological Organization/ Assessment End-points	Measure of Effect	Measure of Exposure	Measure of Ecosystem and Receptor Characteristics	Type of Risk Esti-mate
1	Growth and devel-	Food consumption; Growth rate/Body			
2	opment of ecologi-	weight			
3	cal entity	Age at first breeding; Fluctuating Asym-metry; Fledgling or weanling weight/Post fledgling/weaning survival; Plant height/dry weight/root dry weight, length, mass			
4	Morbidity of val-	Incidence of abnormality in physiological			
5	ued ecological en-	response/internal morphology/behavior;			
6	tity	Body load/Parasite load/incidence of dis-ease; Immuno-suppression; Biomarkers; Genetic damage			

Table B1-2. Analysis Plan Outline – Data to be Considered and How they will be Used

Level of Biological Organization/ Assessment End-points	Measure of Effect	Measure of Exposure	Measure of Ecosystem and Receptor Characteristics	Type of Risk Esti-mate
Population-Level Assessment Endpoints- Local Populations				
Population size and persistence of valued ecological entity *	Numerical results of the standard laboratory toxicity tests under Subdivision E, i.e., LD50, LC50, 28-day feeding, and avian reproduction study results, and similar non-guideline toxicity studies	Measured levels of residues of the stressor and their decline in relevant food items	Terrestrial vertebrate species likely to be exposed to the stressor	Quantitative (RQs) Deterministic or probabilistic
Demographics of valued ecological entity	Sex ratio; Age structure; Longevity; Proportion of reproductive females; Fecundity, fertility; Recruitment; Sustained yield; Immigration/Emigration; Age specific survivorship			
Population-Level Assessment Endpoints- Regional Populations				
Population size and persistence of valued ecological entity *	Numerical results of the standard laboratory toxicity tests under Subdivision E, i.e., LD50, LC50, 28-day feeding, and avian reproduction study results, and similar non-guideline toxicity studies	General partitioning and degradation in the environment	Crop agro-ecosystem borders, extent of area treated, extent of area in the crop	

Table B1-2. Analysis Plan Outline – Data to be Considered and How they will be Used

	Level of Biological Organization/ Assessment Endpoints	Measure of Effect	Measure of Exposure	Measure of Ecosystem and Receptor Characteristics	Type of Risk Estimate
1	Demographics of valued ecological entity	Sex ratio; Age structure; Longevity; Proportion of reproductive females; Fecundity, fertility; Recruitment; Sustained yield; Immigration/Emigration; Age specific survivorship			Semi-quantitative Deterministic or probabilistic
4	**Community and System Assessment Endpoints**				
5	Patterns of taxonomic and functional diversity	Species richness/diversity	General partitioning and degradation in the environment		Semi-quantitative Deterministic or probabilistic
8	Nutrient cycling	Soil carbon metabolism and nitrogen fixation			
9	Changes in compositional integrity				
12	Energetics				

13 * Primary assessment endpoints considered by ECOFRAM

APPENDIX B2

EXAMPLES OF AGRO-ECOLOGICAL SCENARIOS

Iowa Corn

Delineating the agro-ecological scenario as corn crops in Iowa will establish a regional range of vegetative types, wildlife species, rainfall, temperatures, soils, etc.. This is probably adequately definitive to establish the boundaries of the risk assessment. These defining ranges of characteristics may be relaxed by expanding the agro-ecological scenario to encompass all corn in the Midwestern corn belt states, or it may be made more restrictive by concentrating on a smaller, more homogeneous geographic region such as corn in south-central Iowa. Since south-central Iowa is characterized by rolling terrain with a relatively high amount of non-crop habitat distributed among the corn crops, and supports greater wildlife density and diversity than most other parts of the state, the region may maximize the potential for wildlife and pesticide interaction and, therefore, may be an ideal agro-ecological scenario for wildlife risk assessment for corn. On the other hand, in areas where little non-crop habitat exists, those species found utilizing corn crops may be more dependent on the corn and spend more time foraging or nesting in the crop. Corn is usually not grown under irrigation in Iowa nor in most of the Midwestern corn belt. However, it is grown under irrigation in many of the western and southwestern states. A risk assessment conducted for an Iowa or Midwestern corn scenario may not be representative of corn grown in irrigated semi-arid conditions since the wildlife species and crop-use behavior may be quite different between the two conditions. Therefore, they may need to be defined as separate agro-ecological scenarios. Assessments of wildlife numbers and species using these two corn growing situations can provide insight into whether the two are substantially different and whether or not they should be considered separate agro-ecological scenarios.

Apple Orchards in Pennsylvania and Washington

Apple orchards in Pennsylvania and Washington are examples of agro-ecological scenarios that are distinctly separate because of geographic and meteorological variables. Both areas are major apple producing regions of the U.S., but the similarities essentially end with that distinction. Apple trees are common throughout the northeastern U.S. where they are one species of deciduous tree among many species in a region characterized by mixed deciduous forests. When cultured as an agricultural crop, they are typically planted in monocultured blocks which are often bordered by mixed deciduous forest and they are typically not grown under irrigation. Thus, they are a block of deciduous trees in a deciduous tree environment. Therefore, the species that inhabit the orchards usually also inhabit other non-apple deciduous forest. Such species would be present in the region in the absence of apple orchards, even though orchards may be more attractive as habitat to some species than to others.

In Washington, the vast majority of apple orchards are grown on the eastern foothills of the Cascade Range. This is a semi-arid, high desert environment characterized by coniferous trees and desert shrubs such as sagebrush and bitterbrush. Deciduous trees are uncommon in this environment. Apples are grown here under intense irrigation, without which they would not persist. Many of the bird species that inhabit these orchards inhabit this region only because of the large blocks of irrigated apple trees present. If the orchards were removed, many of these species would disappear from the region. Thus, not only are the apples tenuously maintained by an artificial moisture regime, but many of the avian populations inhabiting the orchards are also tenuously maintained by the same system. At the same time, there are native species that live in natural habitats adjacent to the orchards and which, in some cases, have incorporated the orchards into their habitat use patterns. These species may be enhanced by the irrigation and other aspects of orchard culture, but they also become susceptible to pesticide exposure as a result of being attracted to the placement of the apple irrigated orchards into an otherwise semi-arid region. A major difference in toxicological risk assessments between these regions may be the selection of

assessment endpoints what values (species) are most important to protect in an essentially native environment, versus an artificially maintained environment?

Cotton Crops in Southern and Western U.S.

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Cotton, although a crop grown in many states, can be evaluated on the basis of two general agro-ecological scenarios: cotton grown in the Southeastern U.S. and cotton grown in the western U.S. The southeastern cotton region extends from the eastern high planes of Texas, through Louisiana, Mississippi, Alabama, Georgia, Tennessee, Arkansas, South Carolina, and North Carolina. The western cotton region includes the remainder of Texas, Arizona and California. The southeastern cotton is grown under similar agricultural practices and among similar non-cotton habitats that maintain similar avian fauna. This region receives enough rainfall such that cotton crops are usually not irrigated until mid-way through the growing season. Then it is used on an as needed basis. Risk assessment conducted in any area within this region would probably provide information germane to the entire region. Soil differences might produce different result for soil run-off, ground water and surface water assessment. However, these variables could likely be evaluated using existing models.

The western cotton region is generally semi-arid and cotton is usually grown exclusively under irrigation. Similar to the non-irrigated apple orchard scenario, the southeastern cotton scenario is characterized by an avifauna that would be present in the region regardless of the presence of the cotton crops. On the other hand, the avifauna representative of the western cotton region may be the result of the presence of irrigation, in the absence of which many of the species would not be present or there would be fewer individuals. The constant summer water source associated with irrigation often attracts and concentrates wildlife in and around the cotton crops. Irrigation practices also influence run off, leaching and the hydraulic distribution of pesticides.

Golf Course Turf

Golf courses have been established in practically every habitat type that exists in the U.S. from ocean front sand dunes in South Carolina to the rain forests of the Olympic Peninsula in Washington and from southern deserts to Alaska. Golf courses, regardless of their setting, usually have two factors in common: 1)They have intensely managed turf habitat and 2) they are maintained under a consistent irrigation regime. The intense management practices include heavy use of pesticides and maintenance of waterways and non-fairway areas (roughs) that, along with the turf, provide habitats that are highly attractive to a diverse array of wildlife species. Golf courses often provide increased edge habitat, waterways and a variety of vegetation types, often introduced ornamentals, and structures. Golf courses in arid regions usually attract and maintain abnormally high wildlife density and diversity. Even with all the different ecological settings, the turf habitats of golf courses can be remarkably similar. It provides excellent foraging habitat for ground-feeding birds and is usually the area on a golf course that receives the greatest chemical inputs. Wildlife populations may vary tremendously among golf courses depending on their location and ecological setting. Within this variation, however, there are often species represented that have similar feeding habits and other life history characteristics (e.g. shrub nesting, ground feeder that primarily gleans turf for crawling or flying insects) that would be found on golf courses in other geographic areas. In this case the geographic area that would be included in one risk assessment could be maximized if appropriate key species were selected (see nest section) on which to focus the assessment. Such an approach is useful in many agro-ecological scenarios.

APPENDIX B3

KEY SPECIES SELECTION

RECOMMENDED CRITERIA FOR THE SCREENING-LEVEL, HYPOTHETICAL BIRD AND MAMMALS.

Birds

1) Passerine granivore -

a. Weight: 20 g

b. Forage technique: ground gleaning

c. Food preference: 100 percent seeds

d. Proportion of diet from treated field: 100 percent

e. Proportion of time spent on treated field: 100 percent

f. Sensitivity to pesticide: use oral acute and dietary laboratory toxicity tests for quail or mallard or representative passerine if available.

2) Passerine insectivore

a. Weight: 20 g

b. Forage technique: ground and crop foliage gleaning

c. Food preference: 100 percent insects

d. Proportion of diet from treated fields: 100 percent

e. Proportion of time spent on treated fields: 100 percent

f. Sensitivity to pesticide: use oral acute and dietary laboratory toxicity tests for quail or mallard or representative passerine if available.

3) Raptor

a. Weight: 110g

b. Forage technique: hawking

c. Food preference: 50 percent small birds, 50 percent small mammals

d. Proportion of diet from treated fields: 100 percent

e. Proportion of time spent on treated fields: 100 percent

f. Sensitivity to pesticide: use oral acute and dietary laboratory toxicity tests for quail or mallard or representative passerine if available.

Mammals

1) Small herbivore/granivore

a. Weight: 25g

b. Forage technique: opportunistic vegetarian

c. Food preference: 100 percent seeds or herbaceous plant material

d. Proportion of diet from treated field: 100 percent

e. Proportion of time spent on treated fields: 100 percent

f. Sensitivity to pesticide: use acute and chronic toxicity test results for lab mice.

2) Insectivore

a)Weight 25 g

b) Forage technique: opportunistic predation of invertebrates.

c) Food preference: 100 percent insects

d) Proportion of diet from treated fields: 100 percent

e) Proportion of time spent on treated fields: 100 percent

f. Sensitivity to pesticide: use acute and chronic toxicity test results for lab mice.

EXAMPLES FOR SELECTING KEY SPECIES

To provide examples of key species selection and an example of grouping of species for risk assessment, we used three field studies, one in canola agro-ecological scenario in Saskatchewan, Canada (Tank *et al.* 1997) and two in an apple orchard scenarios in Washington an Pennsylvania (Brewer et al, 1999). The canola study provided an example of grouping species censused on the study areas by three variables: 1) taxonomic organization, 2) foraging technique and 3) body size. Table B3-1 provides the basic groupings used in evaluating risk. The last group in Table B3-1, Sparrows/Towhees/etc., demonstrates a large grouping with the primary emphasis being on

foraging technique and body size. While this example emphasizes foraging technique within the taxonomic scheme, it would certainly be feasible, and at times preferable, to base the grouping on feeding guilds. A useful reference on bird feeding guilds is Foraging Guilds of North American Birds by R.M. DeGraaf, N.G. Tilghman, and S.H. Anderson, 1985 in *Environmental Management 9:493-536,*

The apple orchard studies provided the following types of data: 1) bird species present in and near apple orchards, 2) relative frequency and abundance by species, 3) number of bird nests in and near the orchards by species, and 4) the percentage of live-trapped birds, by species, that demonstrated exposure to the test chemical as determined from blood plasma cholinesterase analysis and from the presence of alkyl phosphate leaving groups in fecal-urate samples. From these data we developed a table to rank those species most likely to be present in the orchards or most likely to be at risk of exposure to a pesticide application or both (Tables B3-2 and B3-3). Pesticide incident reports indicated grazing geese and ducks (e.g. Canada geese and American widgeon) are susceptible to exposure pesticides and sensitive to the effects of the test chemical. Additionally, several grazing Canada geese died from exposure to diazinon during the conduct of the study on one orchard in Washington. Therefore, we added Canada geese to the list of key species even though little other information was available relative to apple orchards. One objective was to have the list of key species represent as many different groups as practicable, and have just one representative of each group. Tables B3-2 and B3-3 list the species selected based on this multivariate selection process. These are not the only acceptable selection criteria. The approach may vary with different scenarios depending on how much empirical data is available in each case.

In most avian risk assessments, it is practical and effective to utilize this key species approach. The basis on which the key species are selected should always be fully detailed and if an obvious species is not selected its elimination from consideration should be explained. Threatened and endangered species associated with the scenario under evaluation should be given strong consideration for inclusion in the key species list.

Table B3-1. Example of Taxonomically Based Bird Grouping Which Emphasizes Foraging Technique, Body Size and Primary Food Items, for Those Birds Actually Censused in a Canola Agro-Ecosystem Scenario

GROUP	FORAGING TECHNIQUE	FOOD(S)
GEESE/PUDDLE DUCKS		
Mallard	dabble	greens; seeds; aquatic inverts; insects
Canada Geese	graze and dabble	Aquatic and non-aquatic vegetation, turf grass, herbs, seeds (grain crops).
LONG-LEGGED WADING BIRDS		
Great egret	stalk and strike	fish; sm. vertebrates; aquatic invertebrates; also insects, lower vertebrates, sm birds
FOWL-LIKE BIRDS		
California quail	ground glean	seeds, leaves; plant shoots, some fruit; few insects
Northern bobwhite	ground glean	greens; seeds; insects
NON-PASSERINE LAND BIRDS		
PIGEONS/DOVES		
White-winged dove	ground glean; foliage glean	seeds; fruit; (shrubs, herbaceous) waste grain, cactus fruit, berries, acorns
Mourning dove	ground glean; foliage glean	seeds; grain (herbaceous)
CUCKOOS AND ALLIES		
Yellow-billed cuckoo	foliage glean; hover & glean; hawks	insects, esp. caterpillars; few eggs, lizards, frogs; berries, fruit
HUMMINGBIRDS		
Ruby-throated	hover; foliage glean (herbaceous, shrubs)	nectar; also spiders.
SWIFTS		
Chimney swift	aerial forage	flying insects
WOODPECKERS		

Table B3-1. Example of Taxonomically Based Bird Grouping Which Emphasizes Foraging Technique, Body Size and Primary Food Items, for Those Birds Actually Censused in a Canola Agro-Ecosystem Scenario

	GROUP	FORAGING TECHNIQUE	FOOD(S)
1	Red-bellied	foliage glean	insects; nuts; fruits; seeds
2	woodpecker	(trees); hawks	
3	Downy woodpecker	bark glean	insects; some fruit, seeds, sap
4	**PASSERINES**		
5	FLYCATCHERS		
6	Scissor-tailed	foliage glean	insects; few berries
7	flycatcher	(trees, shrubs); hawks; ground glean	
8	Eastern kingbird	hawks; hover and glean	insects
9	LARKS		
10	Horned lark	ground glean	seeds; insects; also spider, snails
11	SWALLOWS		
12	Barn swallow	aerial foraging	insects
13	Cliff swallow	aerial foraging	insects; occasional berries
14	Purple martin	aerial foraging	insects
15	CROWS/RAVENS/JAYS		
16	Blue jay	ground glean; hawk	omnivore
17	American crow	ground glean	omnivore
18	TITMICE, CHICKADEES, VERDINS		
19	Carolina chickadee	foliage glean; (tree, shrub) bark glean	insects; conifer seeds; fruit
20	Verdin	foliage	insects; fruit; seeds
21		glean;(tree, shrub)bark glean	
22	WRENS		

Table B3-1. Example of Taxonomically Based Bird Grouping Which Emphasizes Foraging Technique, Body Size and Primary Food Items, for Those Birds Actually Censused in a Canola Agro-Ecosystem Scenario

	GROUP	FORAGING TECHNIQUE	FOOD(S)
1	Carolina wren	ground glean;	insects; invertebrates; sm. vertebrates; few
2		bark glean;	seeds
		foliage glean	
		(Tree, shrub)	
3	GNATCATCHERS, KINGLETS		
4	Blue-gray gnatcatcher	foliage glean;	insects
		(tree,	
		shrub)hawks	
		hover and glean	
5	MIMIC THRUSHES		
6	Brown thrasher	ground glean;	insects; fruit
		foliage glean	
		(shrubs)	
7	Northern mockingbird	ground glean	insects; fruit; also crayfish, sow bugs, snails
8	**EMBERIZIDS**		
9	WOOD WARBLERS		
10	Common yellowthroat	foliage glean;	insects, including spiders
		(tree, shrub)	
		bark glean;	
		hawk; hover	
		and glean	
11	BLACKBIRDS/ORIOLE		
12	Brown-headed	ground glean	insects; seeds
13	cowbird		
14	Red-winged blackbird	ground glean;	insects; seeds
		hawk; foliage	
		glean (shrub,	
		herbaceous)	
15	Common grackle	ground glean;	omnivore
		hawk	

Table B3-1. Example of Taxonomically Based Bird Grouping Which Emphasizes Foraging Technique, Body Size and Primary Food Items, for Those Birds Actually Censused in a Canola Agro-Ecosystem Scenario

	GROUP	FORAGING TECHNIQUE	FOOD(S)
1	SPARROWS/TOWHEES/JUNCOS/GROSBEAKS/BUNTINGS		
2	Lark sparrow	ground glean	seeds; insects
3	Abert's towhee	ground glean	seeds; insects
4	Rufous-sided towhee	ground glean	insects; seeds; fruit
5	(Spotted towhee)		
6	Northern cardinal	ground glean	insects; seeds; fruit
7	Blue grosbeak	ground glean;	insects; seeds; foliage glean, also snails; occ. fruit
8	Indigo bunting	foliage glean;	insects; seeds; ground glean; fruits
9	Painted bunting	ground glean; foliage glean	seeds; insects

10 Note: All North American species are not accounted for in this example.

11 Source: Tank *et al.* 1997.

Table B3-2. Key Species Ranking and Selection Criteria for Pennsylvania Apple Orchards

Species	Group	percent Relative Abundance	percent Relative Frequency	Number of Nests	Percent Exposed
American Robin	Thrushes	21	24	94	33
Mourning Dove	Columbiforme	15	14	23	26
Common Grackle	Blackbirds & Orioles	18	9	9	22
Chipping Sparrow	Sparrow/towhees/	11	12	30	No Data
Gold Finches	Finches	5	6	0	No Data
House wren[1]	Wrens	No Data	No Data	24	No Data

[1] Wren was selected because of the number of nests found in the apple orchards. They were censused but frequency and abundance data was provided for only those 10 species censused most frequently.

Source: Brewer *et al.* 1990.

Table B3-3 Key Species Ranking and Selection Criteria for Eastern Washington Apple Orchards

Species	Group	percent Relative Abundance	percent Relative Frequency	Number of Nests	Percent Exposed
American Robin	Thrushes	16	18	84	28
Gold Finch	Finches	11	14	15	No Data
Mourning Doves	Columbiformes	6	6	64	4
Califonia Quail	Galiformes	6	5	21	14
Canada Goose[1]	Waterfowl (grazer)	No Data	No Data	No Data	100

[1] Canada goose chosen because of mortality incident on one orchard and mortality incidence records elsewhere relative to Diazinon applications.

Source: Brewer *et al.* 1990.

RECOMMENDATIONS

1) For initial assessments, use generic birds and mammals as provided above.

2) For refined assessments, identify key species which represent those most at risk for selected agro-ecological scenarios. Identify they selection criteria, using specific data for exposure coupled with standard toxicity test results scaled to the species of interest.

3) For refined risk assessments use the criteria provided above or other well defined criteria for selection of key species. In all cases clearly define the criteria used.

APPENDIX C1

PT - PROPORTION OF DIET OBTAINED IN TREATED AREA

Animals which obtain all their food from within the treated area are likely to ingest a larger dose of pesticide than those which obtain a proportion of their diet elsewhere. This is represented by PT in the model for dietary exposure (Equation 3.6-6). Current approaches tend to assume PT = 1, at least in the screening stages of risk assessment.

Actual values of PT may be close to one in situations where there is little non-crop habitat and large areas are treated with the same pesticides at the same time. This may apply, for example to horned larks in corn; robins, goldfinches and wrens in large orchards; and starlings and localised populations of Canada geese on golf course turf.

Often, however, animals will obtain a significant proportion of their diet from non-crop areas, or from adjacent non-treated crops of the same or different types. In these cases, setting PT = 1 substantially overestimates exposure. Setting PT = 1 remains reasonable as a conservative, worst - case assumption for the screening stages of the assessment. However, predicting the magnitude and frequency of exposure will require information on the distribution of PT for relevant species in relevant habitats. Note that PT may vary widely between species (see examples cited below).

This Appendix, therefore, considers possible approaches to estimating PT. First, we consider ways of estimating PT as the proportion of the diet overall which is obtained in the treated area. Then we consider ways of estimating PT as the proportion of time animals spend in the treated area, or from information on home range sizes. We also consider the estimation of PT at larger spatial scales, to take account of landscape structure. Finally, we consider how these approaches might be used at different levels of refinement, in a sequential or tiered approach to exposure assessment. The examples which are given refer to birds, but the same principles apply to mammals.

ESTIMATING *PT* BY MONITORING THE DIET

Ideally, one would measure the proportion by weight of the diet which is obtained from treated areas. This is very difficult to measure directly.

It may sometimes be possible to make visual observations of individual animals foraging in treated and untreated areas, identify the food items collected, and estimate their weights. However, this will be possible only in open habitat where visual contact can be maintained over long periods from cover without disturbing the animal's behavior.

Another possibility is to sample the diet, for example by examining stomach contents or fecal material, or by using techniques such as emetics or esophageal constriction (Mellott and Woods, 1993) or by filming parent birds entering the nest with food in their bills. The difficulty in these cases is with identifying the source of the food items, which is necessary to estimate PT. If the study is conducted in conjunction with an actual pesticide application and the food items can be retrieved (e.g. using esophageal constriction) it would be possible to analyse them for the presence of pesticide residues. However, this would be difficult to interpret due to the diluting factor of food from untreated areas

ESTIMATING *PT* FROM TIME BUDGETS

An alternative to measuring PT as proportions of the diet may be to measure the proportions of time that the animal spends in treated and untreated areas. This is simpler but can only be used as a measure of PT if the amount of time spent in each area is proportional to the amount of food obtained there. This will not be true if some parts of the habitat are used primarily for foraging, and others primarily for other activities such as resting; or if feeding rate is higher in some parts of the habitat than others due to differences in food availability. The two main approaches to estimating PT for time are visual observations and telemetry (radio-tracking).

The suitability of visual observations for estimating PT depends on the extent to which individual animals are identifiable. Counts of unmarked animals in treated and untreated areas provide a measure of the overall level of use of each area by the species. However, in most situations they are of little help in estimating PT because it is not possible to determine (a) whether successive counts in the same area are the same animals or different ones, (b) whether the individuals seen in one area are the same or different as those seen in adjacent areas. Strongly territorial animals (e.g. some birds in the breeding season) may be identified from their location and behaviour. Even so, records of their use of treated and untreated parts of their territories are likely to be biased in favour of those habitats where they are most easily observed (e.g. more open habitats).

These difficulties may be overcome if the same individual can be observed continuously as it moves between treated and untreated habitats. However, this is only possible for animals in very open habitats. More often, only part of the animal's foraging activity can be observed. For example, Brewer et al. (1992) watched unmarked birds during the breeding season on 37 urban lawns which were separated by enough distance to limit the chance of observing any bird on more than one site. When a bird left the study site, observations continued with the next bird, changing species if possible to reduce double counting on any given day and site. The results provided a detailed time budget of activities on the lawns which were observed, but it is not known what the birds were doing elsewhere. These data are therefore insufficient for estimating the proportion of their overall diet which birds obtained from the observed lawns, or from lawns in general.

In some situations individuals can be identified by association with their territory or nest. An example of this is provided by a study of tree sparrows in the UK (Hart, 1990), although in this case the male and female members of each pair were not distinguished. The birds were rearing young in nest boxes in hedgerows with a wheat field on one side and other habitats (pasture or woodland) on the other. Observers watched birds leaving the nest and recorded whether they flew into the wheat field. However, it was only possible to identify the initial destination of each trip because birds were lost to view on entering the crop. Also, the destination of birds not entering the field under observation was usually unknown, and could have included other

(potentially treated) crops in nearby fields. Such limitations make it difficult to obtain a reliable estimate of PT from observations of this type.

A more reliable record of individual behaviour can be obtained if the individuals are marked, for example with coloured tags or dyes, or if they can be identified by their natural markings. Even then, however, continuous observations are difficult to obtain, and foraging records are likely to be biased in favour of those habitats where animals are most easily observed (e.g. more open habitats).

In principle, these limitations can be overcome using radio-tracking techniques. Manual tracking (where the radio-tagged animal is followed by observers on foot or in vehicles) and automatic tracking (where fixed receiver stations automatically record signal information from which the animal's location can be calculated) are compared in Table 1. For birds in the breeding season, either manual or automatic tracking could be combined with automatic filming of parents returning to the nest, in order to determine which types of food are obtained in different areas. It is important to note that high resolution will be particularly important when animals are foraging near the field edge, as the potential for exposure will change sharply between the crop and the unsprayed margin.

Table C1-1. Comparison of manual and automatic methods of radio-tracking.

Manual tracking	**Automatic tracking**
Low equipment cost	High equipment cost
High manpower cost	Low manpower cost
Track one/few animals per observer	Can track many animals at once
Risk of observer disturbing subjects	No disturbance
Can obtain visual observations of feeding etc.	No visual record of behavior
Resolution high when subject visible	Resolution depends on sophistication of system
Resolution poor when subject not visible	Virtually continuous record of locations

An example of manual tracking specifically designed to measure PT is provided by recent studies in UK apple orchards (Crocker et al., in prep.). Tracking schedules were organised to obtain

about one day's data for each individual, spread evenly over the daylight hours. Observers recorded location, whether the bird was active or inactive, and (when visible) behavior. The results showed that different species had different patterns of use of the orchard environment, and that the potential for exposure to pesticides varied widely between individuals. Blackbirds and robins tended to spend a greater proportion of time in orchards, but mostly along the perimeter hedgerows which are not directly sprayed with pesticides. Chaffinches spend less time in the orchard but tend to visit the orchard center, where spray deposition is highest. An example of the results is shown in Figure C1-1, for blackbirds. Most individuals spent less than 10% of their time in the orchard center, but a few individuals spent up to 70% of their time there. None of the individuals tracked spent 100% of their time in the center.

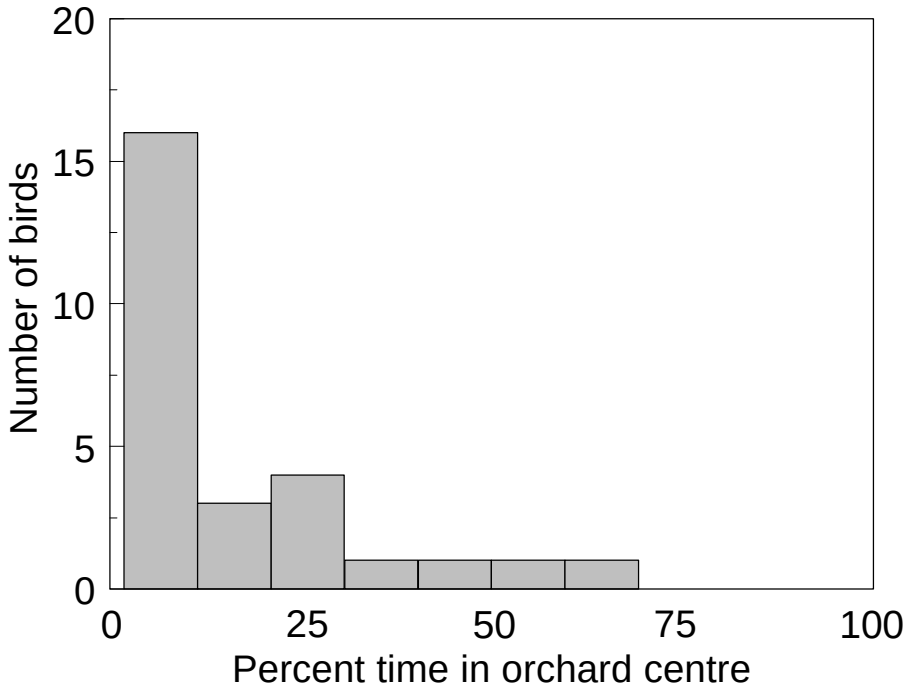

Figure C1-1. Distribution of time spent in the central (sprayed) areas of UK apple orchards by European blackbirds, obtained by radio-tracking. See text for details.

Distributions such as that shown in Figure C1-1 could be used for a probabilistic analysis of PT. (See APPENDIX C10) However, careful interpretation is essential. First, the subjects were clearly a biased sample of the local population, as they were caught by mist-netting inside the orchards. Those individuals which use the orchards most may be more likely to be caught and

tagged. It might be possible to correct for this by weighting the observations by the inverse of the time spent in the orchard. The effect of this on Figure C1-1 would be to skew the distribution still more strongly towards the left. Second, the proportion of time spent in the orchard may not be a good measure of the proportion of food obtained there. In this case, blackbirds were significantly more likely to be recorded as 'active' when they were in the central part of the orchard than when they were in hedges or outside the orchard. In this case it would be prudent to use only 'active' time in estimating PT, to avoid under-estimating exposure. Third, it is important to consider whether the data are representative of orchards in general. In this case, the study included a large number of orchards, selected to include a representative range (differing tree ages and management practices, differing adjacent habitats). This study thus illustrates both the potential and the complications of using telemetry to estimate PT.

ESTIMATING *PT* USING INFORMATION ON HOME RANGE

A third approach to estimating PT might be to use existing information on home ranges. For example, if the average home range for a species was smaller than the area of a typical treated field, then at least some individuals may have their home range entirely contained within a single treated field. This at least would show that the worst-case situation (PT = 1) is a reasonable upper limit for the species in question. However, it is more difficult to estimate the distribution of exposures by this approach. This would require data on the spatial and temporal distribution of pesticide applications, and a means of defining the central point of each home range (e.g. for tree-nesting birds in the breeding season this would probably be in the hedgerows or adjacent woodlands, and not in the treated crop). Many other complications are possible: for example home range may vary within species according to habitat, season and region; and the area of the home range which is treated may be a poor guide to the proportion of the diet obtained there (i.e. foraging may be concentrated in only part of the home range).

These factors suggest that obtaining a reliable quantitative estimate of PT using home range is unlikely. However, if interpreted by suitable experts, data of this sort may be adequate to make semi-objective assessments of the upper limit to PT for a particular species and, perhaps, to guess

at ‘typical’ values. This would not be reliable enough for a final assessment of exposure but might be helpful at intermediate levels of assessment, in deciding whether PT is sufficiently important to warrant measuring in the field.

TAKING ACCOUNT OF THE DRIFT ZONE AND ADDITIONAL TREATED FIELDS

So far, this section has implied that the world comprises just two types of habitat, treated and untreated, as assumed in Equation 3.6-6. In reality the situation is more complex. For example, some species might spend very little time in the treated crop itself, but obtain nearly all its food in the drift zone immediately around the crop. For example, in the study described earlier, most European blackbirds spent very little time in the orchard center, but about twice as much time (average about 35%) in hedgerows and scrub immediately adjacent to sprayed areas. To assess the contribution of these drift zone habitats to overall exposure would require estimates of PT for the drift zone as well as the treated area. It would also require estimates of pesticide residues in the drift zone, which will generally be much lower than in the treated area itself. These might be obtained by field measurements, or perhaps using models of spray drift to estimate the proportion of the application rate which is received by the drift zone. This approach could be accommodated in the full model (Equation 3.6-5), where PT is replaced by PF, by using the subscript j to distinguish the drift zone from the treated and untreated areas.

The full model could also be used to distinguish between different types of treated areas, if sufficiently detailed data on PF were available. For example, it might be desirable to distinguish fields with different crops, or fields treated with the same pesticide applied at different times or different dose rates. In the real world, animals may encounter several different pesticides which may have additive or synergistic effects, but it is currently very rare to rake account of this in risk assessment and it has not been considered by ECOFRAM.

TAKING ACCOUNT OF LANDSCAPE STRUCTURE

The sections above refer to treated areas, untreated areas and drift zones without considering their spatial and temporal distribution. In reality, pesticide applications are clumped in time and space, not random, and the same is true of animals and their foraging activities. If pesticide applications and animal foraging were both randomly distributed in space, every individual would have the same chance of encountering a treated field. If pesticide applications and animal foraging were very strongly clumped, most individuals might never encounter a treated field, while a few might find their whole foraging range treated. Real exposure scenarios lie somewhere between these extremes, depending on the degree of clumping which is present. Ignoring clumping in situations where it is important will tend to under-estimate exposure for the most-exposed part of the population. The effects of clumping can be assessed using models of exposure which take account of spatial patterns.

For example, consider a species of birds which nest in hedgerows between agricultural fields. For any individual bird, the two fields may be of the same crop, or different crops. One, both or neither of the fields may be treated with a given pesticide. If both are treated, the two applications may be done on the same day or a number of days apart. If only one is treated, the other may receive some pesticide input due to drift, but the extent of this will depend on wind direction and other factors. Consequently, the spatial and temporal distribution of treated crops and drift zones combine with animal movements to generate a different pattern of exposure over time for each individual.

This has important implications for the use of visual or telemetry data to estimate PT. For example, if PT is measured in a field study in which only one or a few fields are treated, then the data may under-estimate the exposures which would occur if adjacent fields were also treated. A conservative solution is to measure the proportion of time spent in all fields of a particular crop type (as in the orchard study described above). Using this as the estimate of PT would in effect assume that all fields of that crop type were treated, and would therefore often over-estimate exposure. A third possibility is to multiply the latter estimate of PT with an estimate of the

proportion of fields which are treated (e.g. from USDA pesticide use surveys or infestation statistics). However, this assumes that the proportion of fields treated is the same for every individual, so it would not reveal the upper and lower ends of the range of actual exposures. This again emphasises the importance of examining the underlying assumptions when using field data to estimate PT.

An alternative approach is make models of exposure which are spatially explicit, for example by using the techniques of Geographic Information Systems (GIS). The components of such a system are illustrated in FigureC1-2. First, the model landscape would be defined. This could be a hypothetical landscape, or an actual one (e.g. based on maps or satellite imagery), but would need to be broadly representative of the type of landscapes relevant to the risk assessment. Residue distributions in the landscape could be simulated using information on spatial and temporal patterns of pesticide use within the landscape, and by modelling transfers between treated and untreated areas and degradation over time. The species present would be identified, for example from local surveys or information on national distributions. Animal movement patterns within the landscape would be defined using information on habitat preferences, home ranges and behavior, which could include visual observations or telemetry data of the types discussed earlier. This needs to be repeated for each of the species under consideration. Finally, exposure estimates could be obtained by simulating the movements of each individual and recording its intake of pesticide as it moves through the landscape. Using Monte Carlo techniques this could be repeated for many individuals (and perhaps landscapes), producing a set of dose/time curves to show the range of variation in the population.

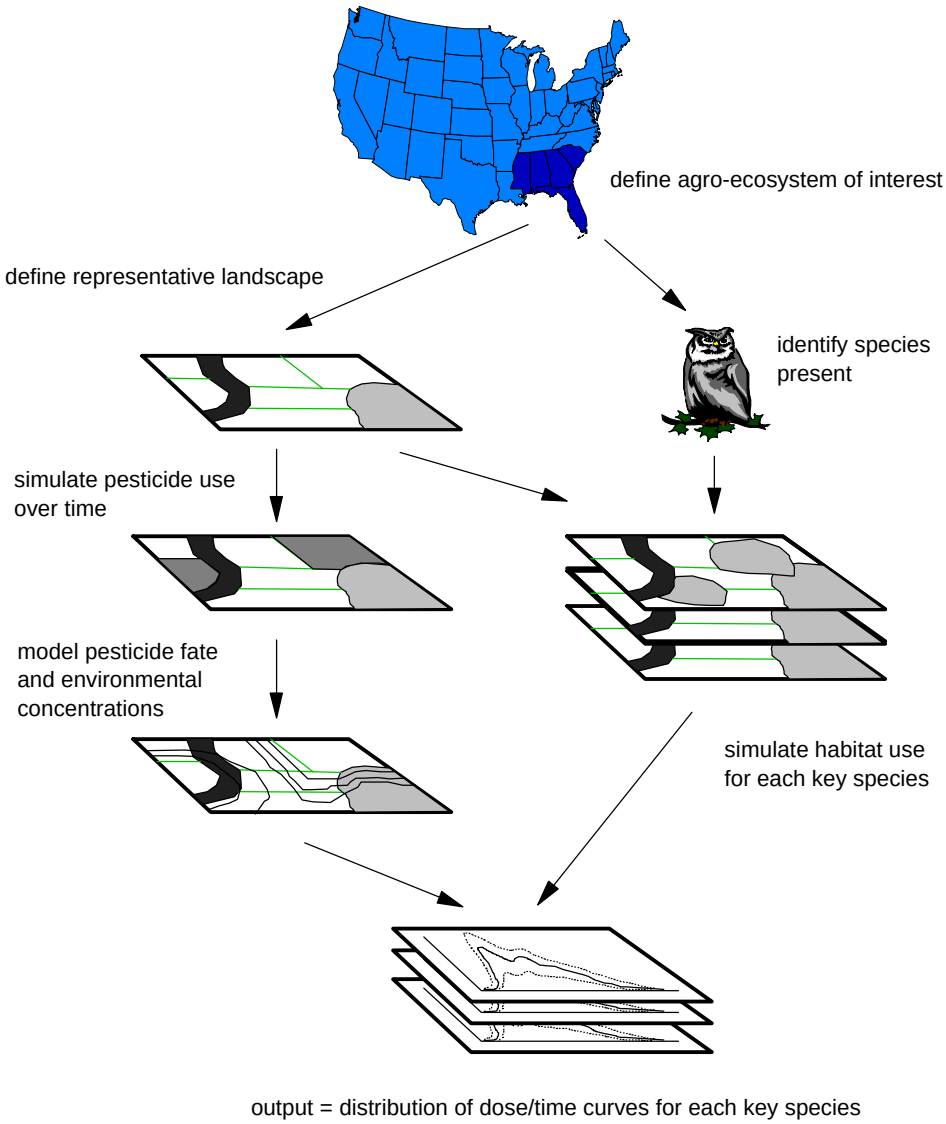

Figure C1-2. Illustration of a spatially explicit approach to modelling wildlife exposure to pesticides. See text for explanation.

Technology has advanced to a state where this type of approach is beginning to be feasible. An example of a model using standardised hypothetical landscapes, with simple rules for animal movements through the landscape, is provided by Freshman and Menzie (1996). Another example is the PARET model which has been developed as part of the ECOFRAM project (see Sections 2 and 5.5, and Appendix A2). Examples of GIS approaches using data on real landscapes and behavior are provided by Henriques and Dixon (1996) and Banton et al. (1996). This type of approach is much more costly to develop, and is only likely to be considered in cases where spatial factors are thought to make a critical difference to the outcome of the risk assessment.

CONCLUSIONS

It is concluded that PT is likely to be an important and highly variable parameter influencing exposure, but is difficult and costly to measure reliably in many agricultural habitats. A sequential approach is therefore recommended, as outlined below, to ensure that effort is only expended on estimating or measuring PT in those cases where it is important to the outcome of the risk assessment.

It is recommended that these approaches be evaluated by means of case studies, using scenarios for which relevant data are already available. If it appears that assessment at Level 3 may be required often then there would be opportunity for sharing the cost of collecting much of the data, as they are not specific to individual pesticides.

For screening assessments, it will generally be appropriate to assume PT = 1. To refine the assessment, estimated lower and upper limits for PT could be developed using expert judgement and existing information on:

- foraging ecology and behavior of key species, including time budgets, habitat use (including the drift zone) and home ranges;
- the spatial distribution of habitat types and crops;
- the spatial and temporal distribution of pesticide applications.

If the data are good enough, they can be used to construct a hypothetical distribution for PT. If exposure in the drift zone is likely to be significant, the simple model (3.6-6) can be expanded to distinguish it from the treated and untreated areas. The proportion of food obtained in the drift zone can then be estimated as well as PT, and used to estimate the relative contributions of the drift zone and treated area to overall exposure.

If it appears (e.g. from sensitivity analysis) that PT has a critical influence on exposure, it may be worth attempting to measure it in field studies, or using a landscape model to examine spatial effects. Depending on the field scenario, visual observations or telemetry may be used to quantify distributions of PT in the field, for appropriate species in a representative range of conditions relevant to the risk assessment. If it appears that the spatial distribution of treated areas may have a critical influence on the risk outcome, it can be accounted for in spatially-explicit models or GIS approaches.

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APPENDIX C2

AV - AVOIDANCE

There are many examples of animals responding to the presence of noxious chemicals in their food by reducing consumption. Chemicals which induce this response include a wide range of plant secondary compounds which provide plants with a defense against herbivores (e.g. Buchsbaum et al. 1984). Similarly, some insects contain chemicals which are repellent to birds (e.g. Brower and Fink 1985). Many pesticides also induce reductions in consumption, as can be seen in the results of standard avian dietary toxicity tests (see data in Hill and Camardese 1986) as well as research studies (e.g. Grue 1982).

These responses clearly have the potential to reduce the exposure of birds and mammals to pesticides in their food. A key question is whether these responses are effective in the wild as well as in laboratory tests: this has been confirmed for two pesticides. First, a large number of field studies have demonstrated that, when used as an avian repellent, methiocarb can reduce the losses of fruit crops to predation by birds (Dolbeer et al. 1994), which implies that the ingestion of methiocarb by individual birds must be reduced to some extent. Second, surveys of fields sown with winter wheat in the UK have demonstrated significantly lower numbers of feeding woodpigeons on fields where the seed is treated with fonofos, compared to untreated fields (McKay *et al*., in press). Furthermore, it can be presumed that plants and insects would not have evolved defensive chemicals unless they were effective. It is concluded that avoidance can be important in reducing exposure, and hence should be given consideration in avian risk assessment (OECD 1996).

There are a number of contrasting mechanisms by which avoidance can operate:

- primary repellency - due to inherently aversive properties of the chemical which are detected immediately upon ingestion, e.g. repellent taste or texture.
- secondary repellency - where animals reduce consumption due to intrinsic reactions which develop after ingestion, e.g. post-ingestional illness leading to reductions in feeding in general

(sometimes referred to as pesticide-induced anorexia, Grue 1982) or reductions in activity in general (lethargy, ataxia, e.g. Hudson et al. 1984).

- learned avoidance - where animals learn to associate particular foods with the aversive experiences due to primary or secondary repellency, and consequently show stronger or more rapid avoidance on successive exposures.

It would be difficult to determine, for any particular chemical, the extent to which each mechanism contributes to the overall avoidance response. However, for the purpose of characterizing exposure it is not necessary to do this: it is sufficient to quantify the extent to which the combined mechanisms reduce exposure. Therefore no attempt is made to distinguish them here, and they are referred to collectively as 'avoidance'. It is true that, while all these mechanisms are beneficial to the extent that they reduce exposure, some of them may also have adverse consequences for the animal: for example lethargy may increase the risk of predation or impair care for young, while anorexia may increase the risk of starvation or hypothermia. These issues need to be addressed as part of the characterization of effects: here we are concerned with the potential for avoidance to reduce exposure.

Methods for assessing avian avoidance have been developed over a long period, both for the purposes of pesticide risk assessment (BBA 1993, INRA 1990) and to assess the efficacy of avian repellents (Mason et al. 1989). Work to develop an OECD guideline for avoidance testing began at a SETAC/OECD workshop in December 1994 (OECD 1996), and has since been continued through a series of informal meetings at SETAC conferences. The approaches described below are based on those discussions.

The principal difficulty in assessing the effect of avoidance on exposure is that the avoidance response is highly variable, and is influenced by many factors (OECD, 1996). Furthermore, avoidance may break down under some conditions (see below). The mechanisms involved are sufficiently complex that it is unlikely to be possible to model them reliably. Instead, assessment must be aimed at quantifying the variation in avoidance which is expected in the wild. This is a difficult task which is likely to be reserved for the later stages of risk assessment. In earlier stages

of assessment, attention will focus on determining whether there is sufficient evidence of avoidance to be worth detailed investigation.

REPRESENTATION OF AVOIDANCE IN THE DIETARY DOSE EQUATION

The effect of avoidance is represented as AV in the model for dietary exposure (Equation 3.6-6). However, it is essential to remember that AV is a function of C, because the extent of the avoidance response generally increases with increasing concentration of pesticide in the food. AV takes values between 0 (no avoidance) and 1 (complete avoidance of contaminated food).

By representing avoidance simply as AV, no presumption is made as to the form the response will take in the wild. Possible responses include selecting less contaminated food within the treated area, leaving the treated area to feed elsewhere, switching to different food types, or simply eating less food. These could be represented by making PT_{ij}, PD_{ijk} and $TFIR_i$ functions of C_{ijk}, as mentioned in Section 3.6.1. In detailed assessments of avoidance, it may be necessary to distinguish these responses and consider the availability of alternative feeding areas (see below).

INITIAL ASSESSMENT

In the initial assessment of risk, and in cases where no information on avoidance is available, it should be assumed that no avoidance occurs (conservative worst case). AV should therefore be set to 0.

SCREENING FOR AVOIDANCE

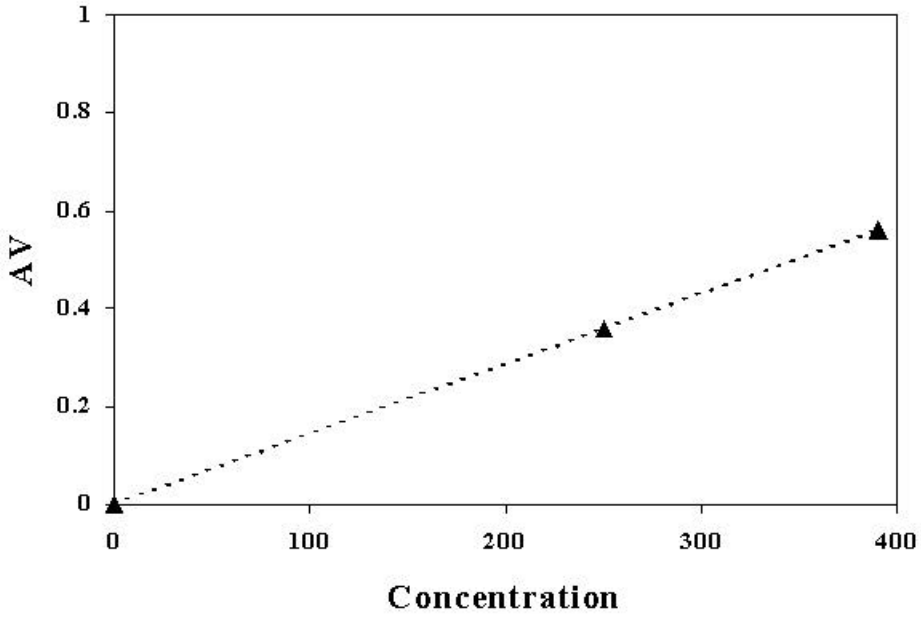
A detailed assessment of avoidance requires non-standard data (see below), which may be costly to obtain. It is therefore desirable to have a simple method of screening pesticides, to determine whether they show sufficient signs of avoidance to make detailed assessment worthwhile.

For birds, the avian dietary test provides a convenient means of screening for avoidance. AV can be estimated for each test concentration by dividing the food consumption of the test group by that of the control group. Figure C2-1 illustrates this for fonofos using data from Hill and Camardese (1986). The concentrations used in the test are unlikely to correspond to those predicted in the wild. In Figure C2-1 AV is obtained for intermedate concentrations by linear interpolation. This implies assuming the dose-response relationship for avoidance is linear, which is unlikely. If consumption data are available for a sufficient number of different concentrations, it may be possible to fit a non-linear relationship such as the threshold concentration model assumed by Luttik (1998).

Note that in Figure C2-1 the calculation is made using consumption on the first day of exposure: this may be considered as representing the response of a bird on the first day it encounters a treated field. This is more conservative than taking data from later days, when the avoidance response is often stronger. In some studies consumption may only have been measured over longer periods, in which case the first such period should be used. Caution is required to ensure that the consumption data are not biased by the effects of food spillage, which can be substantial (especially with mallards).

Estimates of AV obtained from the avian dietary test are likely to represent something approaching a worst case (i.e. minimum avoidance), due to the lack of untreated food. It might be thought that avoidance should always be stronger than this in the field, where at least some untreated food is likely to be available. However, this depends on the timescale of exposure. It may be true when food consumption and exposure are considered over periods of a day or more,

Figure C2-1. Preliminary estimation of AV for screening purposes, using data from the avian dietary toxicity test. AV is estimated as the *reduction* in consumption on the first day with treated diet, compared to consumption by control groups fed untreated diet. Data is for fonofos, from Hill and Camardese (1986). In this example, values of AV for intermediate concentrations are approximated by linear interpolation. C_i = concentration in test diet, ppm.



as this will usually (though perhaps not always) give animals time to find alternative foods. However, the standard avian dietary test may be unconservative for short-term exposures over minutes or hours, for situations where animals are gorging on an easily-available food. This appears to be the explanation for the examples of diazinon (Mineau et al, 1994) and fonofos (Hart et al., in press). Both pesticides are strongly avoided in the avian dietary test, yet have caused poisoning of birds in the wild. Mineau et al. suggested that these mortalities were due to wild birds feeding faster than birds in the dietary test, and therefore consuming a lethal dose before the avoidance response set in. This mechanism has since been confirmed experimentally for pigeons feeding on fonofos-treated wheat (Hart et al., in press). Consequently, values of AV estimated from the avian dietary test should not be regarded as worst case for short-term exposures.

AV may be estimated for mammals in the same way as for birds, if suitable dietary studies are available.

Note that if a dietary toxicity study is used to estimate AV and is also used to characterize toxicity, it is important to ensure the avoidance effect is not double-counted. To avoid this consumption data should be used to express toxicity in terms of actual dose ingested per unit time (as proposed by ECOFRAM) and not in terms of dietary concentration. This is preferred to the alternative solution of omitting AV and using dietary toxicity unadjusted for consumption as that would conceal the avoidance effect, making it more difficult to assess how it might vary in the wild.

Some test protocols measure the consumption of animals given access to untreated food as well as the test diet (e.g. INRA 1990, Mason *et al.* 1989). If such studies are available they can be used to provide an alternative estimate of AV_{Ci}, dividing the consumption of treated food by total consumption on the first day of testing. This estimate is likely to represent a 'best case' situation (maximum avoidance), especially if the animals can readily detect which food is treated (e.g. if the foods differ in appearance and/or are presented in separate containers).

Estimates of AV_{Ci} obtained from tests with and without alternative food may therefore be used for screening purposes, to assess the *potential* contribution of avoidance to reducing risk. If they indicate that avoidance may be important in reducing risk below level of concern, then further studies are likely to be needed to confirm whether the response will be effective in the wild. The types of studies which are appropriate differ for short-term and long-term exposures. For short-term exposures, no-choice feeding studies are appropriate and attention is centered on the rate at which animals feed. For longer term exposures, attention centers on the availability of alternative foods and the ease with which the animal can distinguish contaminated and uncontaminated foods, so feeding studies with an element of choice may be appropriate. These issues are discussed in more detail below.

DETAILED ASSESSMENT FOR SHORT-TERM EXPOSURES (MINUTES TO HOURS)

Poisonings of pigeons by fonofos-treated wheat in the UK have been shown to be caused by very short-term exposures in which birds feed very rapidly, taking the majority of their daily requirement in a few minutes (Hart *et al.*, in press). In this situation, they ingest a lethal dose before the avoidance response intervenes. As already stated, a similar mechanism has been suggested for some poisonings of waterfowl by diazinon (Mineau *et al.* 1994). If risk assessment is to be successful in predicting such mortalities it must give separate consideration to short-term exposures and take account of the dependence of AV on feeding rate.

In the case of fonofos-treated wheat, a direct relationship was found between feeding rate of captive feral pigeons, the amount of pesticide ingested before feeding stopped, and mortality. Data was also available on the distribution of feeding rates for Woodpigeons feeding on wheat seed in the wild. By combining these two types of data (and assuming similar responses between species of pigeon) it was possible to predict how often wild pigeons feed fast enough to cause mortality. The results showed that Woodpigeons do feed fast enough to cause mortality, but only in less than 1% of observations. This conclusion agrees very well with the very low frequency of fonofos poisoning for Woodpigeons in the UK (Hart *et al.* in press).

The approach developed for fonofos-treated seed should in principle be applicable to other treated seeds and other formulations where the pesticide is concentrated on an attractive food item (e.g. baits). Two things are required: data on the distribution of feeding rates of relevant species in the wild (from field studies); and quantification of the relationship between feeding rate and AV (from lab studies in which birds are trained to feed at different rates and then exposed to treated food for up to one day, without access to untreated food). Combining these data provides a distribution of AV for the concentrations tested. Further research is underway to develop a draft guideline for an avian avoidance test based on this approach, and to test whether results for one species can be extrapolated to others. To extend the approach to other formulations (sprays and granulars) and to mammals would require additional research.

The approach described above is the only one which has been developed specifically to address avoidance in short-term exposures, taking account of the influence of feeding rate. It also has the advantage of providing a distribution for AV, rather than a point estimate. Other existing test designs do not examine the influence of feeding rate, and generally include a choice of treated and untreated foods; they are therefore more relevant to longer-term exposures (see below).

DETAILED ASSESSMENT OF LONGER-TERM EXPOSURES (HOURS TO DAYS)

In the very short-term exposures considered above, attention centered on how much the animal would ingest of a contaminated food source before the avoidance response set in. In longer-term exposures, it is necessary to consider what the animal does after the avoidance response sets in. This depends on whether alternative foods are available.

If there is no alternative food source whatsoever, the animal may continue eating the contaminated food at a reduced rate. Whether it survives will depend on whether it can eat enough of the contaminated food to avoid starvation, without accumulating a lethal body burden of the pesticide (this depends on whether the rate at which the pesticide is ingested exceeds the rate at which it is metabolized and excreted). This situation is addressed by the avian dietary test, in which birds are exposed to treated food for 5 days without access to untreated food.

If uncontaminated food sources are present, or if the degree of contamination varies between food items, the extent to which the animal can avoid the pesticide will depend on how well it can distinguish between foods containing different levels of pesticide residues. This in turn depends on whether the animal can detect the presence of the pesticide itself (e.g. by taste, colour or smell), and whether there are any other cues to the presence of the pesticide (e.g. if some types of food are contaminated but not others). The relative attractiveness and availability of the various food types may also influence the degree of avoidance. All of these factors are complex and vary widely in the wild. It seems unlikely that there is any single underlying variable which determines their influence on AV and can be measured in both lab and field, as is the case for feeding rate in short-term exposures. If this is true, then the only option for assessing avoidance in this situation (long-term exposure with access to uncontaminated foods) is to conduct tests in conditions which simulate the choice of contaminated and uncontaminated foods in the wild. The problem is that conditions in the wild vary widely, in ways that will affect the ease of discriminating contaminated and uncontaminated foods. This potential variation is recognised in the German protocol (BBA 1993) which provides two test designs referred to as the 'A' and 'B' tests. Both provide animals with a choice of treated material and untreated standard diet, mixed together and spread on a sandy surface. In the 'A' test, representing 'rigorous' conditions, the ratio of treated to untreated food is 75:25, whereas in the 'B' test representing 'normal' conditions it is 10:90. In the wild, of course, a distribution of other ratios occurs. Furthermore, in the wild the most important alternative foods may be located at a distance from the contaminated foods: e.g. in an adjacent field or non-crop habitat. This situation can also be simulated with captive birds, as in the flight pen experiments of Avery et al. (1994). Measurements of consumption in tests like these can be used to obtain point estimates of AV for particular sets of conditions. However, it is impractical to test all possible conditions, and difficult to extrapolate from conditions which are tested to those which are not tested. It will therefore be difficult to arrive at a distribution for AV. Instead, the most practical solution may be to obtain point estimates for AV under conditions which are realistic for the assessment scenario but tending towards the worst case. The range of issues to be considered in test design are discussed in more detail in OECD (1996).

Another approach might be to investigate the influence of avoidance on exposure and effects in the field. However, this is unlikely to be realistic for regulatory studies. Field studies of pigeons and fonofos (referred to earlier) shows that bird foraging behavior is so variable that it is difficult to detect avoidance of treated areas, even when it is contributing significantly to reducing exposure (McKay *et al.* in press). Furthermore, the conditions under which avoidance breaks down and causes mortality may be relatively rare, and would be unlikely to appear in field studies unless they were repeated on a large number of sites. Thus field studies are unlikely to be effective either in demonstrating avoidance, or in determining how reliable it is.

CONCLUSIONS

1. Initial assessments should assume no avoidance (set AV_{Ci} equal to 0).

2. If the initial assessment indicates the potential for significant exposure, then data on food consumption in dietary toxicity tests may be used to provide screening estimates of AV. These can be used for both short-term and longer-term exposures. However, they should be used solely to indicate whether there is potential for avoidance to reduce exposure, and should not be relied upon in a definitive assessment of risk.

3. If the screening assessment indicates potential for avoidance to significantly reduce exposure, then a detailed assessment is required. Ideally this should aim to quantify the distribution of AV in the wild. For short-term exposures (minutes to hours), it may be possible to do this by combining data on the distribution of feeding rates in the wild with laboratory tests of the degree of avoidance at different feeding rates. For longer-term exposures, it may not be practical to obtain a distribution for AV as it depends on the ability of animals to discriminate between contaminated and uncontaminated foods. Instead the best solution may be to obtain point estimates for AV under realistic conditions but tending towards the worst case.

4. Further research is required to refine and validate approaches to assessing avoidance.

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APPENDIX C3

GRANULE EXPOSURE MODEL (GEM) FOR BIRDS

C.1 OVERVIEW

A Monte Carlo model called GEM (Granule Exposure Model) was developed from the conceptual model of exposure of birds to granular pesticides that was presented in section 3.5 (Fig. 3.5-1). GEM has been developed as a computer spreadsheet program that uses the Monte Carlo add-in programs Crystal Ball (Decisioneering, Inc., Denver, Colorado) or @RISK (Palisade Corp., Newfield, New York) to perform probabilistic analysis. The goal of GEM is to estimate the probability distribution of the dose of pesticide ingested as a result of the consumption of granules for birds living in association with agricultural fields receiving applications of a granular pesticide. For example, we wish to be able to make a statement about exposure such as "In a simulation of 1000 horned larks associated with cornfields treated with Product X in the Central Plains, 50% received no pesticide exposure, while 20% and 5% received peak day exposures $\geq$ 1 and 10 mg/kg BW, respectively." The output exposure distribution might then be integrated with effects distributions (dose-response information) to develop probabilistic estimates of risk of mortality or other adverse effects.

GEM simulates the grit ingestion behavior of individual birds and determines how many granules they ingest each day during a 10-day period. Each of these birds is assumed to be living in the vicinity of and potentially foraging at an agricultural field where a granular pesticide has been applied. The scheme GEM follows to model granule ingestion behavior is depicted in Fig. C-1.

Each bird is randomly assigned a daily grit "appetite" from a large database of grit use measurements for the species being considered. This defines the number of medium- and coarse-sized particles (i.e., particles in the same size range as pesticide granules) that the individual will ingest each day of the simulation.

Fig 3.5-1. Conceptual Model of Bird Exposure via Ingestion of Granules

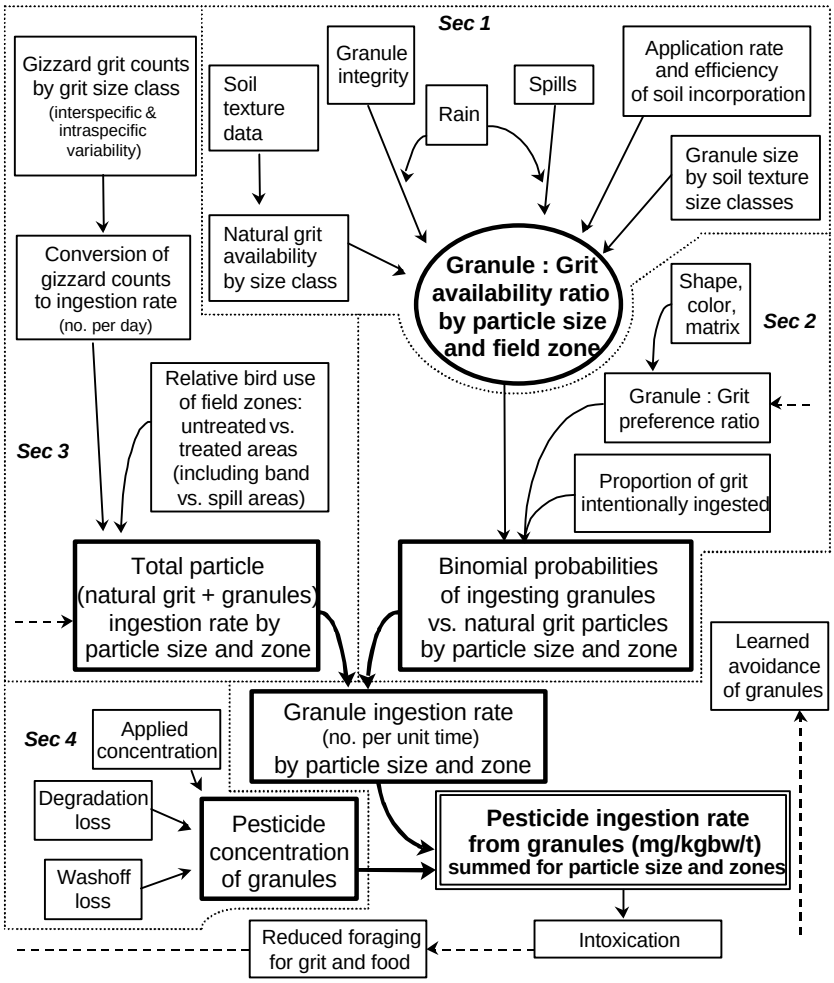


Figure 3.5-1 is reproduced here for ease of reference. See also discussion in section 3.5

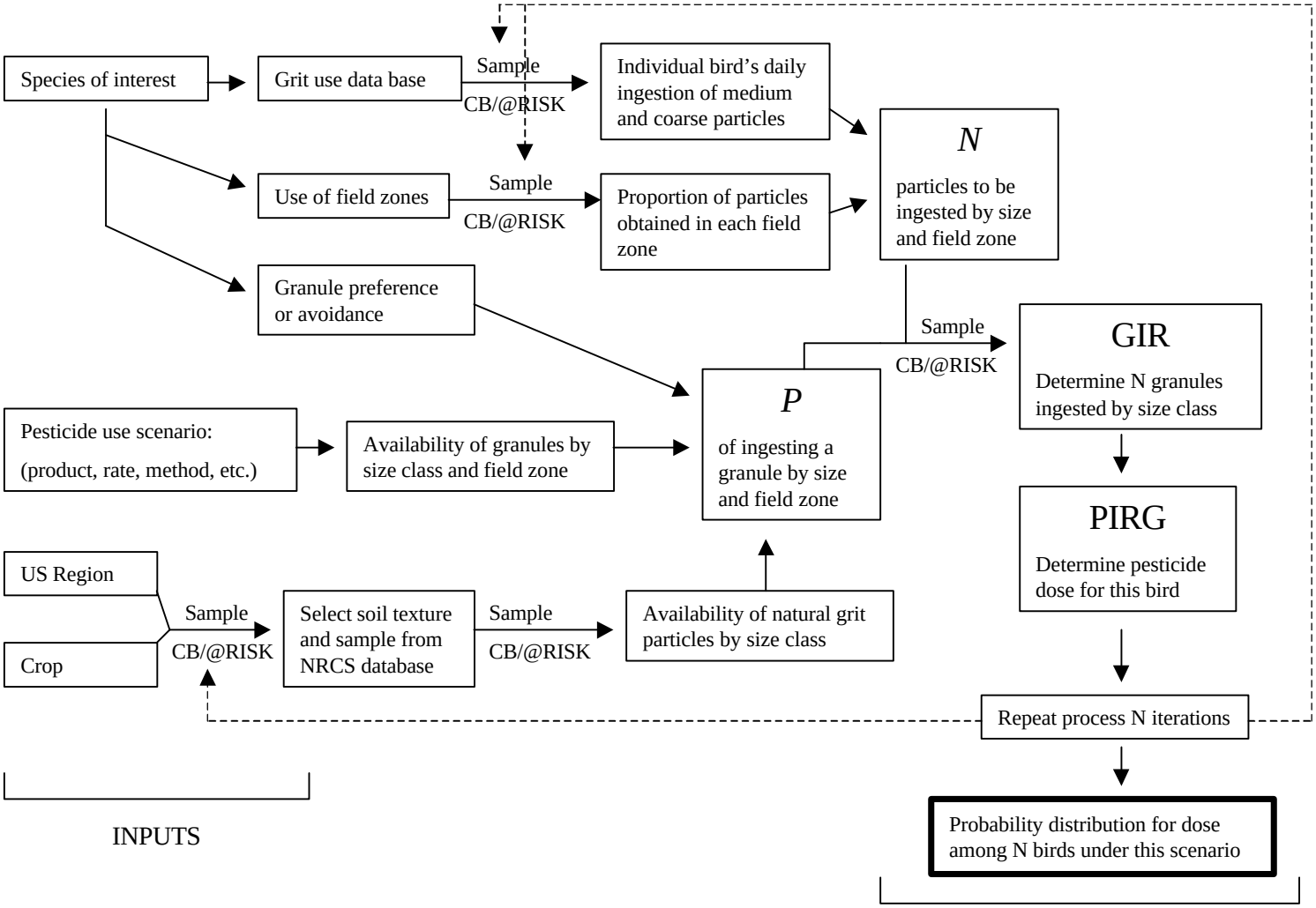


Figure C-1. Implementation scheme of the granular exposure model (GEM).

Each granular application site is randomly assigned a soil texture (e.g., Silt-Loam) with a likelihood equal to that texture's fraction of the total specific crop-capable acreage within a region of interest. The data base currently built into the model is set up for corn (which is grown in a variety of soils), but it could be modified for any crop type of interest. The user also has the option of focusing the assessment on a single surface soil texture. This allows one to compare results from simulations with different textures and determine how exposure levels change. Once the soil texture category is assigned, the application site is then randomly assigned a specific soil particle size profile (% of soil mass represented by various particle size categories) from a large soils data base of actual measurements. This defines the levels of medium- and coarse-sized sand particles available as grit.

The user defines the application scenario (pesticide product, method of application, rate of application, etc.) bird species, region of interest and the number of iterations (individual birds and sites) included in the simulation. The choice of product defines the relative numbers of medium- and coarse-sized granules applied. The application scenario determines the spatial placement of these granules and the number that is assumed to be available as a source of grit to birds. The choice of species influences the amount of grit ingested and assumptions built into the model regarding use of the application site.

Each time a bird using the application site ingests a grit particle, the particle may be either a granule or a piece of natural grit. The default assumption of the model is that birds forage for grit within a given size range randomly, and therefore the probability p of selecting a granule is equal to the relative availability of granules in comparison to natural particles of the same size. However birds may select grit particles non-randomly and show preference for some types of particles over others (Best and Gionfriddo 1994, Best et al., 1996). The user has the option to input the relative preference birds have for selecting granules in comparison to natural grit. If this factor is inputted, GEM modifies the estimate of p (probability of ingesting a granule) accordingly. Once p is defined, the number of granules ingested on a given day is determined by randomly sampling from a binomial distribution defined by N (number of particles ingested that

could be either ganules or natural sand) and *p*. This calculation is made separately for medium- and coarse-sized granules, and for spatial zones of the field which differ from one another in either the relative availability of granules or relative use by birds. The number of particles the bird obtains from a given zone (*N*) is estimated from the zone's relative size and use by birds.

If the model indicates a bird has ingested a granule, then the pesticide loading on the granule on that day is added to the dose the bird receives. The dissipation of the active ingredient from the granule is accounted for by a first-order decline function. Once the dose has been calculated for an individual for each of the 10 days of the simulation, a new bird is carried through the same process, with new values selected by Crystal Ball or @RISK for daily grit use, soil texture, mass fractions of sand sizes, use of field zones and preferences for granules vs. grit. This can continue for a sampling of a thousand or more birds to build a probabilistic distribution of dose obtained through the ingestion of granules.

Underlying methodology for this approach was developed by Abt Associates Inc. under contract to EPA (Abt, 1996). Implementation here differs from that in the original Abt effort since this implementation uses larger databases and provides greater detail and more supporting information. It also includes a working model developed in a linked set of Microsoft Excel workbooks, employing Crystal Ball and /or @RISK probabilistic functionality.

Sections following this overview present the methodology and data needed for implementation. Information is presented for each input so by the end the reader can assemble all of the data needed to perform a probabilistic state-of-the-art assessment of exposure to birds by pesticides formulated as granules.

C.2 ESTIMATION OF GRANULE:GRIT RATIO (GGR)

The Granule:Grit Ratio (GGR) determines the likelihood a bird will choose either a granule or a piece of grit with each peck a bird makes in search of grit if it selects particles at random. Data and methodology for estimation of GGR are presented in the following sections; each subheading provides guidance on how to arrive at the various data components that influence GGR, as outlined in Section 1 of Figure 3.5-1.

C.2.1 Available Granules (AvlGnl)

Granules available on the soil surface (AvlGnl) are calculated from the application rate (App) of formulated product, the fraction of granules remaining on the surface on day 0 (Sur), the fraction of granules remaining on the surface at later times (SurTime), the weight of an individual granule (GnlWt), and the section the field where the bird feeds (see section C.2.5, below). For this implementation granules are categorized into coarse (1.0-0.5 mm) and medium-sized (0.5-0.25 mm) granules to correspond with the natural grit ranges for coarse sand and medium sand, which are discussed later. For estimation of numbers of each, one must characterize the formulation in terms of the fraction that each size category occupies, as well as a single granule's weight within a size category and the availability of granules for the particular section of the field. If data are available the information could be treated as a distribution, but for sake of computational efficiency this implementation uses average values for fraction and particle weight.

$$AvlGnl = \frac{App \times Sur \times SurTime \times 10^6}{(fM \times MGnlWt) + (fC \times CGnlWt)} \qquad \text{[eq. C-1]}$$

where:

AvlGnl	=	Granules available on soil surface per unit area in a particular part of the field
App	=	Rate of formulation application (kg ai/ha)
Sur	=	Fraction of granules applied remaining on soil surface at day 0
SurTime	=	Fraction of "Sur" granules remaining on surface at time "t" (default = 1.0)
fM	=	Average fractional number of medium-sized granules in the formulation (0.5-0.25 mm)
MGnlWt	=	Average weight (mg) of medium-sized granule in formulation
fC	=	Average fractional number of coarse-sized granules in the formulation (1.0-0.5 mm)
CGnlWt	=	Average weight (mg) of coarse-sized granule in formulation
10^6	=	Conversion from kg to mg

The number of medium and coarse-sized granules can then be calculated in the following manner:

$$MGnl = fM \times AvlGnl \qquad \text{[eq. C-2]}$$

$$CGnl = fC \times AvlGnl \qquad \text{[eq. C-3]}$$

where:

MGnl	=	Number of available medium-sized granules per unit area (hectare)
CGnl	=	Number of available coarse-sized granules per unit area (hectare)

Information on incorporation efficiency and loss of granules from the soil surface with time after application are presented in the next two sections.

C.2.2 Application Incorporation Efficiency (Sur)

Several researchers studied granule incorporation efficiency during the application of granular insecticide formulations to corn (Erbach and Tollefson, 1983; Hummel et al., 1992; Idema et al., 1993; Fischer and Best, 1995; Tollner and Cryer, 1997). Collectively, they characterized granule placement with a variety of corn planters using band, T-band, and in-furrow application methods with/without further incorporation. Their work is summarized in Table C-1.

The work by Hummel et al. (1992) involved application of Furadan 10G granules to synthetic soil (10 parts fireclay:1 part mineral oil) similar to a damp, coarse, silt soil and which was contained in a large soil bin. Three planter configurations were used: the John Deere Max-Emerge, the J. D. Max-Emerge with spring-tooth incorporation tines, and the J.D. Model 71 Flexi-planter. Each configuration was mounted interchangeably on a drive carriage assembly used to drive the planter in the synthetic soil bin. Granules coated with dye were applied at 30-60 times normal rates, and numbers of granules remaining on the surface were determined by photography of the soil surface in ultraviolet light after completion of a run. Granule numbers were determined by counting them in the photographs and comparing the counts to total number applied as calculated from application rate and weight of a known quantity of granules. Results (Table C-1) showed variable amounts of incorporation depending on the planter and incorporation method. It was also noted that more granules remained on the surface at the higher ground speeds when no spring-tooth incorporation tines were used.

Tollner and Cryer (1997) carried out their experiments in the field with Lorsban 15G applied at normal rates to natural soil by a John Deere Max-Emerge planter. The 15G granules were coated with lead powder prior to application so they could be detected by x-ray Computed Tomography scanning of soil cores extracted from within a planter row. Variables evaluated in the study were tillage effects (conventional-till, minimum-till, no-till), effects of slope, and dry vs wet soil

conditions. Percentages of the applied number of granules remaining on the surface are given in Table C-1. None of the variables had statistically significant (5 % level) impact on the number granules remaining on the surface after application.

Erbach and Tollefson (1983) also performed experiments in the field at normal application rates of Furadan 10G and Lorsban 15G. They used International Harvester Model 400 and John Deere Model 7000 planters to evaluate T-banding and banding with and without additional incorporation (includes application before or after the press wheel, with or without spring tines or drag chain). Quantitation of granules remaining on the surface was by the same dye/U.V. photographic methodology used by Hummel and coworkers described above. Results from these tests as reported in Erbach and Tollefson (1983) are included in Table C-1.

Table C-1. Percentage of granules remaining on soil surface after application of granular rootworm insecticide to corn by a variety of planters and application methods.

Formulation	Type of Planter[1,3]	Placement[2]	Method of Incorporation	Tillage[3]	% of Applied on Surface	Reference
Furadan 10G	JD M-E	T-Band	Press Wheel	CT	31.0	Hummel et al., 1992
Furadan 10G	JD M-E	T-Band	Press Wheel	CT	23.8	Hummel et al., 1992
Furadan 10G	JD M-E	T-Band	Press Wheel	CT	18.1	Hummel et al., 1992
Fur 10G/Lors 15G	JD M71/JD M7000	T-Band	Press Wheel	CT	14.7	Erbach & Tollefson, 1983
Aztec 2G	?	T-Band	Press Wheel	CT	11.3	Idema et al., 1993
Silica Granule	?	Band/T-Band	Press Wheel	CT	10.2	Fischer & Best, 1995
Silica Granule	?	Band/T-Band	Press Wheel	CT	8.8	Fischer & Best, 1995
Silica Granule	?	Band/T-Band	Press Wheel	CT	7.4	Fischer & Best, 1995
Silica Granule	?	Band/T-Band	Press Wheel	CT	7.1	Fischer & Best, 1995
Silica Granule	?	Band/T-Band	Press Wheel	CT	6.2	Fischer & Best, 1995
Lorsban 15G	JD M-E	T-Band	Press Wheel	CT	6	Tollner & Cryer, 1997
Aztec 2G	?	T-Band	Press Wheel		5.4	Idema et al., 1993
Silica Granule	?	Band/T-Band	Press Wheel	CT	4.6	Fischer & Best, 1995
Aztec 2G	?	T-Band	Press Wheel		4.3	Idema et al., 1993
Silica Granule	?	Band/T-Band	Press Wheel	CT	4.2	Fischer & Best, 1995
Lorsban 15G	JD M-E	T-Band	Press Wheel	CT	4	Tollner & Cryer, 1997
Lorsban 15G	JD M-E	T-Band	Press Wheel	NT	4	Tollner & Cryer, 1997
Aztec 2G	?	T-Band	Press Wheel		3.8	Idema et al., 1993
Silica Granule	?	Band/T-Band	Press Wheel	CT	3.3	Fischer & Best, 1995
Lorsban 15G	JD M-E	T-Band	Press Wheel	?	3	Tollner & Cryer, 1997
Lorsban 15G	JD M-E	T-Band	Press Wheel	MT	2	Tollner & Cryer, 1997
Lorsban 15G	JD M-E	T-Band	Press Wheel	?	2	Tollner & Cryer, 1997
Lorsban 15G	JD M-E	T-Band	Press Wheel	?	1.7	Tollner & Cryer, 1997
Lorsban 15G	JD M-E	T-Band	Press Wheel	?	1.6	Tollner & Cryer, 1997
Lorsban 15G	JD M-E	T-Band	Press Wheel	NT	1	Tollner & Cryer, 1997
Lorsban 15G	JD M-E	T-Band	Press Wheel	MT	0	Tollner & Cryer, 1997
				Mean	**7.3**	
				Median	**4.5**	
Fur 10G/Lors 15G	JD M71/JD M7000	T-Band	Drag Chain	CT	7.9	Erbach & Tollefson, 1983
Furadan 10G	JD M-E	T-Band	Tines	CT	6.8	Hummel et al., 1992
Fur 10G/Lors 15G	JD M71/JD M7000	T-Band	Tines	CT	5.8	Erbach & Tollefson, 1983
Furadan 10G	JD M-E	T-Band	Tines	CT	4.9	Hummel et al., 1992
Furadan 10G	JD M-E	T-Band	Tines	CT	3.7	Hummel et al., 1992
				Mean	**5.8**	
Fur 10G/Lors 15G	JD M71/JD M7000	BandR	Drag Chain	CT	16.0	Erbach & Tollefson, 1983
Fur 10G/Lors 15G	JD M71/JD M7000	BandR	Tines	CT	7.4	Erbach & Tollefson, 1983
				Mean	**11.7**	
Fur 10G/Lors 15G	JD M71/JD M7000	BandR	Press Wheel	**CT**	**40.2**	Erbach & Tollefson, 1983
Furadan 10G	JD M71-F	In-Furrow	Press Wheel	CT	0.8	Hummel et al., 1992
Furadan 10G	JD M71-F	In-Furrow	Press Wheel	CT	0.4	Hummel et al., 1992
Furadan 10G	JD M71-F	In-Furrow	Press Wheel	CT	0.5	Hummel et al., 1992
				Mean	**0.57**	

[1] **JD M-E** = John Deere Max-Emerge; **JD M71, M71-F** = John Deere Model 71 Flexi-planter; **JD M7000** = John Deere Model 7000

[2] For purposes of this table the following definitions are used. **T-Band** = granules applied with a bander centered over the open seed furrow and producing a band of granules about 6 inches wide in front of a press wheel that followed. **In-furrow** = granules applied into open seed furrow in front of a press wheel, with no bander in place. **Band** = band application in front of press wheel. **BandR** = band application behind press wheel.

[3] **CT** = Conventional Tillage; **MT** = Minimum Tillage; **NT** = No Tillage; **?** = Not stated

The final sets of experiments were conducted by Fischer and Best (1995) and Idema et al. (1993). They, too, conducted studies in a series of fields under normal agricultural practices by having corn growers apply blank silica granules the size of natural grit or Aztec 2G granules by means of the growers' own corn-planting equipment. Percentages of the total numbers of applied silica or Aztec granules remaining on the soil surface immediately after application were determined by direct counting of the numbers of visible granules in a square foot of surface area centered over the corn row. Measurements were replicated five to six times at midfield points; fields were separated from each other by 400 m to >2 km. Table C-1 presents the data from each of the twelve fields.

Table C-2 summarizes the data from Table C-1 according to method of application and the presence or absence of an incorporation device included as part of the corn planter. Table C-1 can be used directly as model input if the intent is to express incorporation efficiency as a distribution of values, or Table C-2 can be used as a source of single point estimates of incorporation efficiency.

Table C-2. Percentage of corn rootworm formulation granules remaining on the soil surface after application by a variety of methods. Data are summarized from Table C-1.

Method of Application	% of Applied on Surface		Number of Values
	Mean[1]	Median	
Band/T-Band + press wheel	7.3±7.3	4.4	26
T-Band + press wheel + tines/chains	5.8±1.6	--	5
In-furrow + press wheel	0.57±0.2	--	3
Band behind press wheel	40.2	--	1
Band behind press wheel + tines/chains	11.7±6.1	--	2

[1]Plus/minus values are the standard deviation of the mean.

C.2.3 Effect of Time on Granule Availability (SurTime)

Granules can be lost from a soil's surface through their disintegration or by being covered with soil during rainfall or erosion of soil by wind. This is a part of the calculation of Granule:Grit Ratio (GGR) as shown in Figure 3.5-1, and the input variable SurTime adjusts the GGR to reflect this change in granule availability at the soil's surface with time. SurTime is implemented as an lumped first-order decline process.

Fischer and Best (1995) evaluated the disappearance of granules from the soil's surface by performing a recount eleven days after application of granules to each of their eight fields described in the previous section. The data are summarized in Table C-3 for both midfield and endrow sampling locations, and show that by day 11 the numbers of granules still visible on the soil surface at midfield had decreased to 0.9 - 12.0 % of their original numbers (mean of 5.4 %). Endrow spills had 0.6 to 1.9 % (mean of 1.2 %) of their original numbers still visible.

Table C-3. Numbers of granules on the soil surface at 0 and 11 days after application (Fischer and Best, 1995).

Midfield Counts, granules/sq ft			Endrow Counts, granules/sq ft			
Day 0	**Day 11**	**%[1]**	**Day 0**	**Day 11**	**%[1]**	**Endrow:Midfield[2]**
40.0	4.8	12.0	1033.6	19.6	1.9	25.8
44.4	3.8	8.6	1723.8	10.6	0.6	38.8
30.8	2.6	8.4	669.8	7.6	1.1	21.8
104.4	4.6	4.4	458.2	4.6	1.0	4.4
142.2	6.0	4.2	2512.6	45.4	1.8	17.7
53.4	1.6	3.0	356.0	3.0	0.8	6.7
65.4	1.2	1.8	487.0	4.8	1.0	7.5
64.8	0.6	0.9	68.2	1.0	1.5	1.1
	Mean	**5.4±3.9[3]**			**1.2±0.47[3]**	**15.5±12.9[3]**

[1] The percentage of granules counted at day 11 in comparison to granules at day zero.
[2]Endrow:midfield ratio of granules at day zero.
[3]Plus/minus values are standard deviation of the mean.

The authors attributed loss of granules from the soil surface mainly to a series of rainfall events that occurred between the 0 and 11-day measurements. Counts were not conducted after each rain event, and so it is not possible to correlate quantitatively the change in granule availability with the rain events. Therefore, without further study of the relationship between rainfall and loss of granules from the soil surface, granule availability cannot be adjusted quantitatively by the decrease that does occur after application of granules.

If granules are stable entities and do not disintegrate readily when wet, exposure assessors are advised to assign a value of 1.0 to this modification factor until additional experimentation provides a more quantitative understanding of granule disappearance from the soil surface over time. Assignment of 1.0 may err on the side of conservatism in the exposure assessment since it is assumed that granule availability remains constant during the assessment of exposure to birds. However, the model also assumes that availability of natural grit remains constant, yet it seems reasonable to expect that natural grit particles may be physically incorporated into the soil by rainfall events in the same way that the granules studied by Fischer and Best were. Unless it can be shown that the availability of granules decreases at a greater rate than the availability of natural grit, a SurTime value of 1.0 is recommended.

C.2.4 Available Granules Endrow and Endrow Spill Preference (EAvlGnl, HsIF)

Corn endrows tend to have greater numbers of granules exposed on the soil surface due to spills and the turning of equipment. Endrow granule counts from Fischer and Best (1995) are included in Table C-3. These counts were taken within a 1 square foot area centered on the largest visible spill at the end of randomly selected rows. Comparison to midfield counts indicate endrow spill areas provide approximately 15 (mean = 15.5±12.9) times the number of granules at midfield. Thus, available granules per unit area at endrows (EAvlGnl) can be estimated by multiplication of granules at midfield (AvlGnl) by the average value of of 15x or, alternatively, calculated from

each ratio in Table C-3 in a Monte Carlo fashion. Besides being more numerous, the concentrated granules at the endrows may be more attractive as a grit source for some species, which is accounted for by the HsIF (Hot Spot Ingestion Factor) factor in the model. Data to define this factor are scarce, however, a study performed by researchers at Iowa State University found that house sparrows ingested 2-5 times more granules when identical numbers of granules were presented in an aviary setting as spills rather than as six-inch wide bands (Fischer, D. L., Best, L. B. and J. P. Gionfriddo, 1993, platform presentation to SETAC 14th Annual Meeting, Houston, TX). Based on these results, the model has a default assumption of 5x greater use of spill zones in comparison to the "regular" application band.

C.2.5 Preferential Feeding Patterns (PT, FMuF)

Although a great many species of birds have been observed to utilize agricultural fields for habitat, they will not spend all of their grit-foraging time within a field. The relative time spent foraging a accounted for by a the simple fractional multiplier PT. Even when the bird is on the field, it will not feed randomly across the entire field; for example, a great number of species are likely to preferentially use the edges of the fields (Best et al., 1990), perhaps to reduce their vulnerability to predators. The behavior is accounted for by a simple ratio expressed as a Field Margin Utilization Factor (FMuF).

C.2.6 Relative Field Areas

In the banded application scenarios most commonly employed for granular, at-plant insecticides, the granules are not spread evenly throughout the field, an assumption often made in simpler exposure models. Indeed, the purpose of banded application rigs is to direct a more concentrated application of granules to the planted rows themselves. In addition, as alluded to in section C.2.4, the rows do not extend all the way to the ends of the field. These factors can be accounted for by the size/geometry of the field and the application bands to define specific field zones (e.g., within

the pesticide band, between pesticide bands, within a spill area) and calculate the fraction of the total field area of composed of each zone, along with their corresponding granule availabilities.

C.2.7 Available Grit (AvlGrt)

Available natural grit in a corn field is a function of soil texture, correlating directly to sand content; the more sandy the soil, the greater the numbers of natural grit particles available to birds. Best (1992) indicated that the size range of granules for the five insecticide formulations most frequently used in cornfields was 0.2 to1.6 mm in diameter. Therefore, it is the number of available grit particles in this size range that impacts whether a bird will select a granule or natural grit particle. The granular exposure model estimates the number of natural grit particles in this size range that are present in soils of different texture and sand content. To make these estimations, distributions of surface soil textures within areas of the continental United States are developed first, and this is followed by estimations of numbers of grit particles within the 0.2 to 1.6 mm size range for soils of different textures.

Texture distributions for soils capable of growing corn were developed from the publicly available NRCS State Soil Geographic Data Base (STATSGO; NRCS, 1994). STATSGO contains soils information at the generalized soil phase level. It can be implemented as a database of 15 relational tables for each state in any relational database management system (RDBMS); the implementation used here was in the Oracle7 RDBMS. This database is queried by geographic area to determine the area-weighted distribution of soil textures within an area of interest. The area of interest can be delineated by political boundary (by state, for example) or by visual delineation within a GIS system. Refinement of the soils in the area of interest was performed using a Structured Query Language (SQL) query in the Oracle7 RDBMS. Table C-4 shows the soil texture distribution for corn-capable soils in the Central Plain region, defined by Abt (Abt, 1996) as the states of Kansas and Nebraska. Other regions delineated by Abt and used in this model are listed in Table C-5. Information on the distribution of soil textures for each region is

stored in the model as the worksheet "texture distribution.xls", and it is available in the form of a lookup table that allows selection of any of the regions for analysis of exposure.

Table C-4. Distribution of soil texture for corn-capable soils of the Central Plains Region defined as the states of Kansas and Nebraska.

Texture	Acres	Percent of Area
SIL	33,755,916	52.9606%
SICL	11,128,261	17.4594%
LFS	4,119,460	6.4631%
L	3,913,144	6.1394%
FSL	3,791,989	5.9494%
CL	1,899,530	2.9802%
FS	1,279,564	2.0075%
SIC	1,157,672	1.8163%
SL	599,386	0.9404%
LS	597,473	0.9374%
VFSL	563,189	0.8836%
C	533,387	0.8368%
LVFS	376,685	0.5910%
S	21,548	0.0338%
LCOS	646	0.0010%
(Total Acres)	63,737,851	

Table C-5. Geographic regions of the continental U.S. as defined by Abt (Abt, 1996).

Region	States
Appalachian	KY, TN, WV, VA, NC
Central Plains	KS, NE
Corn Belt	MO, IA, IL, IN, OH
Lake	MN, WI, MI
Mountain	CO, WY, MT, ID, UT, NV
Northeast	New England, NY, PA, NJ, DE, MD
Northern Plains	ND, SD
Pacific Northwest	CA, OR, WA
Southeastern	AR, LA, MS, AL, GA, FL, SC
Southern Plains	OK, TX, NM, AZ

Estimation of grit particles for a specific soil texture is achieved in the following manner. Natural particles used by birds are mineral components of soil that fall into the size classification for sands. According to the USDA soil classification scheme, these size ranges are:

	Diameter range (mm)	Average diameter (mm)
Very coarse sand	2.0-1.0	1.5
Coarse sand	1.0-0.5	0.75
Medium sand	0.5-0.25	0.375
Fine sand	0.25-0.10	0.175
Very fine sand	0.10-0.05	0.075

This delineation of sizes is not contained within the STATSGO database; STATSGO particle size characterizations were determined for engineering purposes, according to the American Association of State Highway and Transportation Official (AASHTO) scheme. In the AASHTO system, the soil mineral fraction is fractionated at the AASHTO fine sand (0.074-0.4 mm) and coarse sand (0.4-2.0 mm) size classes.

However, the NRCS also publishes (on CD-ROM) the National Soils Characterization database (often called the 'pedon' database) in relational form, which does contains USDA particle size distributions for representative pedons of a large number of soils. The current product (Sept, 1997) contains complete sand distribution information for 12,097 soil pedons. The information contained on the CD-ROM was transferred into a Microsoft Access95 database and then moved into the Microsoft Excel workbook 'pedons.xls.' Using this information, data (expressed as weight percentages of the soil mineral fraction) were grouped by sand size classification and soil texture to yield medium- and coarse-sized weight percentage distributions for each soil texture. The resultant distribution of weight percentages for the medium-sized sand in Silt Loam soils is shown in Figure C-2.

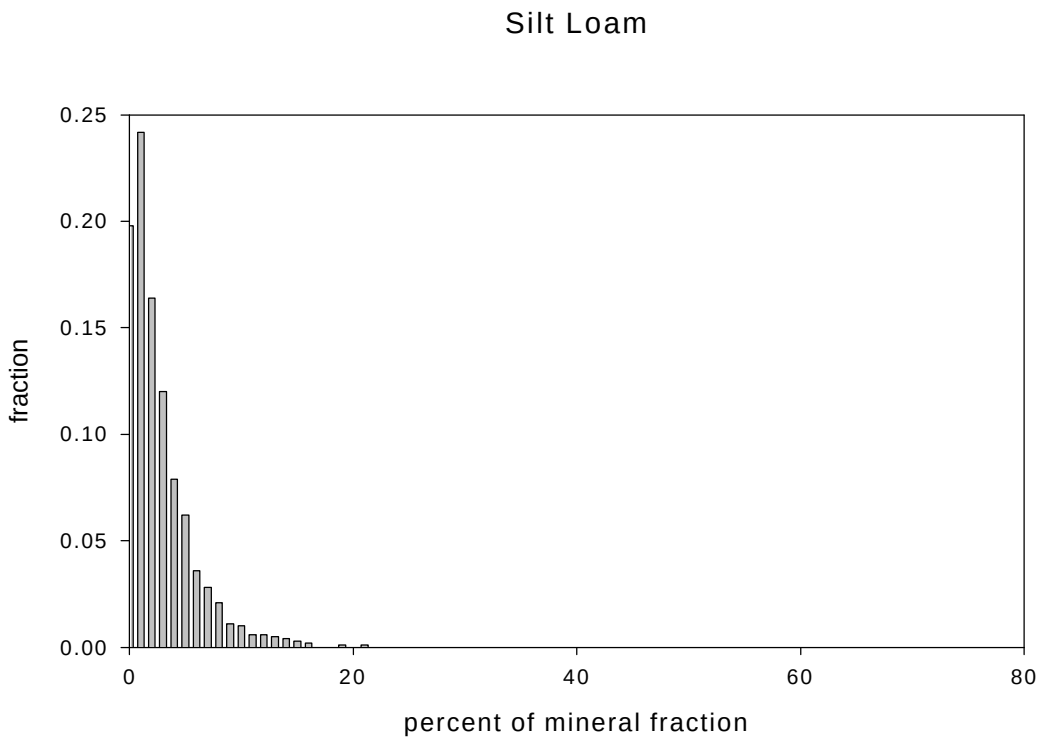
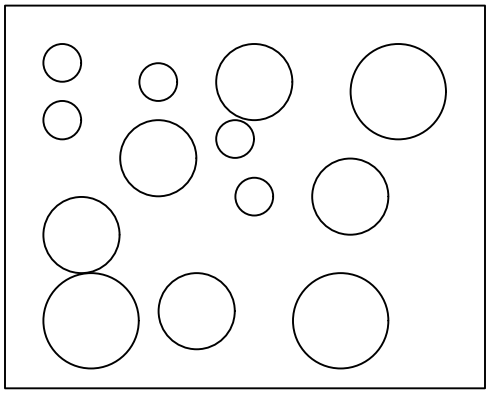


Figure C-2. Frequency distribution of the mass fractions of medium-sized sand in silt loam soils from the NRCS soil pedon database

In order to convert this information into a number of natural grit particles available for ingestion per unit area, conversion from the mass fraction to a number of particles is required. Since the sand particles in soil are primarily composed of silica, the mass fraction of the various sand sizes was assumed to be equivalent to their volume fractions (i.e., the sand particles all have the same density). Therefore, the mass fraction is related to the volume fraction by a factor of the cube of the grit particle radius. The resulting volume fraction can be reduced to a number of particles per unit area by conceptualizing the unit area as follows:



where the circles are sand particles (of three average sizes). This approach assumes the depth of the surface layer is not important; i.e., the unit area of field is viewed from above in two dimensions and there is a monolayer of particles available for feeding on the surface (assume layer of one mm to work in units of volume). With this assumption, the number of particles is calculated in the following manner:

$$MVol = \frac{4}{3} \times p \times Mr^3 \qquad \text{[eq. C-4]}$$

$$CVol = \frac{4}{3} \times p \times Cr^3 \qquad \text{[eq. C-5]}$$

where:

MVol = Average volume of single medium-sized sand particle in mm^3

Mr = Average radius of single medium-sized sand particle in mm.

CVol = Average volume of single coarse-sized sand particle in mm^3

Cr = Average radius of single coarse-sized sand particle in mm

then:

$$MAvlGrt = \frac{\frac{MMassfrac}{100}}{MVol} \times 10^{10} \qquad \text{[eq. C-6]}$$

$$CAvlGrt = \frac{\frac{CMassfrac}{100}}{CVol} \times 10^{10} \qquad \text{[eq. C-7]}$$

where:

MAvlGrt = number of medium-sized sand particles per hectare

MMassfrac = mass percentage of mineral fraction occupied by medium-sized sand for a given soil pedon

MVol = as above

CAvlGrt = number of coarse-sized sand particles per hectare

CMassfrac = mass percentage of mineral fraction occupied by coarse-sized sand for a given soil pedon

CVol = as above

10^{10} = conversion from mm^3 to hectare

The result of these calculations is an estimate of the number of particles of natural grit similar in size to medium- and coarse-sized formulation granules according to actual measurements of sand fractions in a soil pedon from the pedon database. To include variation in mass fraction of the sand sizes within a texture classification, Crystal Ball or @RISK is used to sample the Excel soil pedon spreadsheet uniformly so that the entire range in mass fraction is included in natural grit calculation according to the distribution of values within the pedon database.

C.3 MODIFICATION OF GGR BY BIRD PREFERENCE

C.3.1 Grit Size Preference (GSP)

The size of grit found in bird gizzards is related to the birds' body sizes; the mean grit size increases with bird body mass (Best and Gionfriddo 1991, Gionfriddo and Best 1996). The grit-size distribution profiles of most species have definite peaks, with the grit found in gizzards declining abruptly on either side of the modal grit size. Although the mean grit sizes found in gizzards of some larger bird species exceed the upper size range of pesticide granules, almost all species typically have some grit in their gizzards that overlaps with the particle sizes used for granular pesticides (Best and Gionfriddo 1991; Gionfriddo and Best, unpubl. data). Thus, on the basis of grit size, there is the potential for virtually all common farmland birds to consume granules for grit. The probability that granules will be consumed, however, likely depends on the overlap in size between the grit naturally consumed and the pesticide granules (Best 1992)--the greater the overlap, the more probable the consumption.

If the size distribution of the granules of a particular pesticide formulation is known, that distribution can be compared with the grit size distributions of bird species likely to be exposed to the pesticide. Such overlap can be expressed as a percentage, and that percentage can then be used in determining the probability of ingesting granules versus natural grit particles. The best source of data on grit size use by North American birds is that reported in Gionfriddo and Best (1996), wherein they present information for 35 bird species. Although the published account reports only a mean grit size for each bird species, information on the grit size distributions within

gizzards of individual birds of each species also is obtainable from the original database (Gionfriddo and Best, unpubl. data).

For purposes of implementation in this model, data from the original database are used to provide grit size preference and grit daily ingestion rates for 29 of the 35 species. (Species with less than 5 gizzard samples were excluded from consideration.) This information is contained in the Excel workbook "Grit Data by Species.xls", which was constructed by re-grouping the original 0.2-mm size fractions of the database into fractions fitting more closely with the USDA groupings, and then by recalculation of grit percentage size distributions according to the numbers of grit in each new fraction. Although the fractions in the spreadsheet do not agree completely with the USDA classification, they are very close: fine sand = 0.1-0.2 mm, medium sand = 0.2-0.6 mm, coarse sand = 0.6-1.0 mm, and very coarse sand = 1.0-2.0 mm.

Crystal Ball or @RISK is utilized to sample uniformly the grit percentages for medium- and coarse-sized particles from the spreadsheet for a given bird species. All individual sets of values within a species dataset are assumed to be equally probable, and the data do not consider gender differences.

C.3.2 Granule:Grit Preference (GGP)

When given a choice between naturally occurring grit and particles of a granular pesticide, birds may preferentially select one over the other. Such preferential consumption should be considered when estimating granule consumption rates. Granule:Grit Preference factor (GGP) is a dimensionless number that relates the frequency that birds given equal access to granules and natural grit particles select granules. If a bird had no preference or aversion to pesticide granules compared to natural grit, GGP = 1, because 1 granule is ingested for every 1 natural grit particle ingested. If a bird preferred granules to natural grit, then GGP would be >1, and if a bird preferred natural grit to granules, then GGP would be <1. For example, if birds were shown through empiracle tests to prefer natural grit over granules by a 3:1 margin, then GGP would be defined as 0.33. (0.33 granules selected for every 1 natural grit particle selected).

The best documentation for bird preferences for grit versus pesticide granules comes from an aviary experiment conducted by Best and Gionfriddo (1994). House sparrows were given pairwise choices between silica granules and five other carrier types. The silica granules were composed of a material (quartz) that birds normally consume for grit and could be considered a reasonable surrogate for natural grit. The five carrier types included heat-treated montmorillonite clay, a bentonite form of montmorillonite clay, gypsum, corncob, and cellulose complex. Preference was documented in several ways, which included the number trips birds made to trays containing each of the granules types being compared, the number of pecks at particles within the trays, and the number of pecks per trip. In all cases the sparrows preferentially consumed silica granules over the alternative granule choices, although the degree of preference differed among the carrier types. The mean number of trips per bird to the trays containing silica granules ranged from 2.3 to 21.0 times greater than that to trays containing alternative carrier types, and the mean number of pecks per trip was from 5.7 to 36.6 times greater. The percentage of pecks made to ingest silica granules as opposed to the alternatives ranged from 92.8 to 99.9% of all pecks.

Results from preference tests, similar to that of Best and Gionfriddo (1994), could be used to estimate GGP. For example, based on the overall number of pecks made to ingest grit, GGP values of 0.001 (1 granule per 999 natural grit particles) to 0.077 (7.2 granules per 92.8 natural grit particles) could be derived for the five other carrier types. Bird preferences for granule types probably are not constant and may vary under different environmental conditions (e.g., Stafford et al., 1996; Stafford and Best, 1997). Caution should be exercised in relying too heavily on the results from a single study or protocol. Furthermore, granule preference tests have been limited to only a few granule types, thus other yet untested granule types still need to be evaluated relative to their attractiveness to birds. However, it is clear from the Best and Gionfriddo study that GGP may be an important factor in reducing exposure to at least some types of granular pesticides.

Because of the uncertainty in actual patterns of granule:grit preference at this point in time, this factor is assigned a default value of 1.0 so that it has no impact on granule selection. However, the user has the option to input a different value.

C.4 PARTICLE INGESTION RATE (PIR)

Counts of grit in bird gizzards have been documented for several avian species. The most extensive database is that of Gionfriddo and Best (1996), where they present gizzard grit count information for 35 North American bird species. The sample sizes vary among the species, but all are represented by at least five gizzards. The data reported include the mean (standard deviation) and median grit counts per gizzard, as well as the frequency of occurrence of grit in gizzards. Of the two measures of central tendency, median counts probably reflect overall grit use most accurately because mean values can be greatly influenced by a few individual birds with unusually high grit counts.

The original database for the studies cited above was used to develop particle ingestion rate distributions for 29 of the original 35 species (Gionfriddo and Best, unpublished data); this is presented along with the size preference distributions in the Excel workbook 'Grit Data by Species.xls' described earlier. The workbook provides data on total number of birds sampled within a species; the number that contained no grit particles in their gizzards; the number of birds that had grit, plus the total number of grit particles in a bird's gizzard.

These counts of gizzard contents represent static (i.e., point sample) measures of grit use, and as such are not a direct assessment of grit consumption rate. Unfortunately, there is little information on the particle ingestion rate (PIR) for birds. Fischer and Best (1995) conducted an experiment with blank silica granules in an attempt to evaluate the relationship between gizzard contents and granule consumption rate in house sparrows. On the basis of their results, gizzard granule counts were estimated to represent 24% of the total number of granules consumed per day. The 24% conversion factor, however, should be used with caution for several reasons. (1) The 24% value is based on only one experimental design using only one species. (2) In the Fisher and Best study the granules were intermixed with dog food and thus the birds consumed them "unintentionally"--that is, they did not pick up individual grit particles as is normally the case. The degree to which this might have influenced the grit retention process is unknown. (3) There was a great deal of "scatter" in the data depicting the relationship between granule consumption rates and gizzard granule counts (Fischer and Best, unpubl. data), suggesting high variability in the

responses of individual birds. The scatter is great enough to prevent the establishment of a strong relationship between grit particles fed and particles retained within the birds' gizzards. Despite these limitations, the 24% conversion factor is a place to begin, particularly given that no other information on the relationship between grit/granule consumption rates and gizzard contents is available. Additional research is needed to validate the general applicability of using a conversion factor and to determine the degree to which such a factor might vary among species and under different environmental conditions. In the implementation of this model, PIR (the Particle Ingestion Rate) is calculated according to the following:

$$PIR = \frac{GrtObsv}{GrtTrnovr} \qquad \text{[eq. C-8]}$$

where:

PIR = grit ingestion rate (particles per day)

GrtObsv = grit count in bird gizzard

GrtTrnovr = correction factor for grit turnover in gizzard (default = 0.24)

The grit turnover correction factor (GrtTrnovr) in this implementation of the model is defaulted to 0.24 but can be changed if new information becomes available. Gizzard count data from the 'Grit Data by Species' Excel workbook are divided by GrtTrnovr to correct for the continuous clearance of grit particles from a bird's gizzard.

C.5 GRANULE INGESTION RATE (GIR)

Granule ingestion rate (GIR) is determined by assuming there is a probability ***p*** of a bird choosing a granule over a grit particle according to the availability of medium- and coarse-sized granules and natural grit particles. This probability is caculated in the following manner:

$$p_{medium} = \frac{GGP * MGnl}{(GGP * MGnl) + MAvlGrt} \qquad \text{[eq. C-9]}$$

$$p_{coarse} = \frac{GGP * CGnl}{(GGP * CGnl) + CAvlGrt} \quad \text{[eq. C-10]}$$

where:

p_{medium} = probability a particle ingested is a medium-sized granule

p_{coarse} = probability a particle ingested is a coarse-sized granule

Other = as defined earlier.

Once $\boldsymbol{N}$, the number of particles that will be ingested and $\boldsymbol{p}$, the probability of a given particle ingested will be a granule, have been estimated, The number of granules ingested is determined by randomly sampling from a binomial distribution. This is done for each field zone, and each particle size class, as follows.

$$X_{sijk} = Binomial(N_{sijk}, p_{sj}) \quad \text{[eq. C-11]}$$

where:

$\boldsymbol{X}_{sijk}$ = number of granules of size s ingested by bird i at field zone j on day k

$\boldsymbol{N}_{sijk}$ = number of particles of size s ingested by bird i at field zone j on day k

$\boldsymbol{p}_{sj}$ = probability that a particle of size s being ingested in zone j is a granule

The total number granules ingested by bird i on day k is then determined by summing across field zones for medium and coarse granules separately, or

$$MGIR_{ik} = \sum_{j=1}^{N_j} mediumX_{ijk} \quad \text{[eq. C-12]}$$

$$CGIR_{ik} = \sum_{j=1}^{N_j} coarseX_{ijk} \quad \text{[eq. C-13]}$$

where:

$MGIR_{ik}$ = number of medium-sized granules ingested by bird i on day k

$CGIR_{ik}$ = number of coarse-sized granules ingested by bird i on day k

$medium X_{ijk}$ = number of medium-sized granules ingested by bird i in field zone j on day k

$coarse X_{ijk}$ = number of coarse-sized granules ingested by bird i in field zone j on day k

Once the number of granules consumed by a bird has been estimated, the one remaining factor needed to calculate the amount of pesticide ingested is the pesticide loading of a single granule as a function of time after application of the granule. This is discussed in the next section.

C.6 GRANULE LOADINGS OVER TIME (AI)

Release devices such as granules are designed to maintain some efficacious concentration in surrounding soil over a finite time interval. The chemical mass within a granule is at a maximum when first placed into the field and decreases over time as the pesticide is released from the granule and into the surrounding environment. Therefore, the dose a bird may receive from ingesting granules is a function of time and is dependent upon the release characteristics of the granule, environmental conditions, and the physicochemical properties of the pesticide.

Release rates can be described as either reservoir systems where the release rate is governed by diffusion across a membrane (diffusion equation) or by a monolithic system where the pesticide is dispersed or dissolved within the granule and the release rate is given by the rate of change in surface area of the granule (Lewis and Cowsar, 1977). Diffusion mechanisms are well understood with respect to the resulting linear differential governing equation, and van Genuchten and Alves (1981) provide solution summaries for various differential and partial differential equations describing this process. More complicated problems with diverse boundary conditions can be found in the book by Carslow and Yeager (1959).

Two approaches can be employed to account for sorption and degradation effects on granular release rates. The first is to solve the full conservation of mass equation directly. This approach can give insight into the physical phenomena of rate of release and diffusive transport into the soil matrix. Additional information gleaned from such an approach includes the time dependent spatial distribution of the pesticide. This could be useful for predicting efficacy as a function of the coupled sorption, half-life, and release rate variables.

Often, pesticide parameters such as the diffusion coefficient in soil, degradation rate constant dependency on soil moisture and temperature, etc. are not known or readily accessible. It would be useful to deploy a simplistic model which can capture the field behavior of a granule with respect to release characteristics. Coefficients for such a model should be easily obtainable from existing field and/or laboratory experiments. An empirical kinetic approximation or "lumped sum" approach meets these constraints, is simple, and can provide reasonable comparisons with experimental observations. This approach assumes the physical phenomena of mass transfer from a granule particle and subsequent degradation/partitioning in the soil environment can be modeled by a simple kinetic expression(s). A major advantage other than simplicity for this approach is that it automatically conserves mass.

Leonard and Knisel (1989) described how the GLEAMS model can be used to simulate controlled-release pesticides such as those on pesticide granules through the use of the model's pesticide metabolite and degradation routines. Analytical solutions for these mechanisms can be easily found and thus a numerical model such as GLEAMS does not need to be used. In the most simplistic form, a granule can be described by the reaction pathway given by Figure C-3.

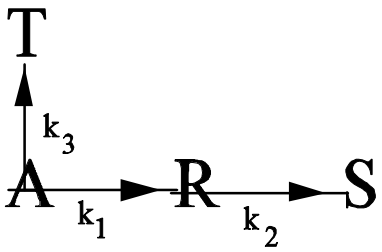


Figure C-3. Proposed "reaction" pathway for pesticide mass contained within a granule. A = mass of pesticide in granule, T = pesticide mass volatilized, R = mass of pesticide released from the granule into surrounding medie, and S = mass of degradation products as the pesticide degrades outside the granule.

Here "A" represents the mass of pesticide contained within the granule, "R" is the pesticide mass released from the granule and into the surrounding media, "S" is the mass of degradation products as the pesticide breaks down within the environment, and "T" is used to represent pesticide mass lost to the atmosphere via volatilization. If it is assumed that the rate of release and degradation is proportional to the mass initially present, then the resulting material balance equations and initial conditions can be represented by equations 14-16. The constants governing the relative rate of "reaction" are the k_i's.

$$\frac{dM_A}{dt} = -k_1 M_A - k_3 M_A = -(k_1+k_3) M_A \qquad \text{[eq. C-14]}$$

$$\frac{dM_R}{dt} = -k_2 M_R + k_1 M_A \qquad \text{[eq. C-15]}$$

$$\frac{dM_T}{dt} = k_3 M_A \qquad \text{[eq. C-16]}$$

$$M_A{}^o = M_A + M_R + M_S + M_T \qquad \text{[eq. C-17]}$$

with initial conditions

$$M_T = M_R = M_S = 0.0 \text{ and } M_A = M_A{}^o \quad \text{at } t=0 \qquad \text{[eq. C-18]}$$

M_i's are concentrations and $M_A{}^o$ is the initial concentration of pesticide on the application date.

Equations 14-16 subject to Eq's 17-18 can be easily solved by first solving eq. (14) for M_A. Substituting the expression for M_A into Eq. (15) yields a separable ordinary differential equation which can be integrated analytically through an appropriate choice of an integrating factor. M_T can be obtained by substituting the results for M_A into Eq. (16), separating variables and integrating. M_S can be obtained from Eq. (17) once M_A, M_R, and M_T are known. The results are:

$$\frac{M_A}{M_A{}^o} = e^{-(k1+k3)\,t} \qquad \text{[eq. C-19]}$$

$$\frac{M_R}{M_A{}^o} = \frac{k_1}{k_2 - (k_1 + k_3)} \left(e^{-(k1 + k3)\,t} - e^{-k2\,t} \right) \qquad \text{[eq. C-20]}$$

$$\frac{M_T}{M_A{}^o} = \{1 - e^{-(k1+k3)\,t}\} \qquad \text{[eq. C-21]}$$

$$\frac{M_S}{M_{A^o}} = \{ 1 - e^{-(k1+k3)\,t} - () [e^{-(k1+k3)\,t} - e^{-k2\,t}] - () [1 - e^{-(k1+k3)\,t} \}.$$

[eq. C-22]

The constants in Eq's 19-22 require laboratory and/or field data for evaluation. The rate constants are adjusted until model predictions fit experimental observations. Software packages such as SimuSolv or ASCL Optimize (MGA Software, Concord, MA) provide optimization routines with their ordinary differential equation solvers to aid in the rate constant selection process. Pesticide mass should be given in moles to avoid stoichiometry mistakes involved with chemical reactions or degradation pathways.

Errors are often made in interpreting field studies to estimate a degradation half-life when a granulated material is used. What's measured by extracting pesticides from soil samples taken at various times may actually be the combination of release rate plus degradation and volatilization. Typical mistakes in interpreting dissipation data for granule materials resides in developing a "lumped sum" rate constant parameter which describes the observed dissipation of the pesticide, that is, $A \xrightarrow{k_{lump}} S$. This lumped sum ($k_{lump}$) rate constant contains both the release rate mechanism, plus any other dissipation pathway and as such can be a poor measure for the intrinsic release rate kinetics.

A simple experiment of placing granules on petri dishes and analyzing for pesticide mass at various time intervals can be used to estimate the rate of volatilization (the coefficient k_3 in Figure C-3) using first order kinetics. Similarly, two soil dissipation experiments run concurrently under identical conditions can properly distinguish between release kinetics (k_1) and the compounds soil degradation rate (k_2). The first experiment should use the active ingredient only, while the second experiment uses the granule formulation. Thus, the first experiment can be used to calculate k_2. With k_2 known, k_1 can be determined using observations from the second experiment and Eq. 20. Thus, the release kinetics are now quantified via Eq. 20 with k_1 known.

Rate constants are typically functions of soil temperature and moisture conditions (Walker and Barnes, 1981). Temperature dependence can usually be represented by an Arrhenius type expression. Temperatures in field studies can fluctuate both diurnally and regionally. Thus, if available, field/lab data obtained at various temperatures/soil moisture conditions, etc. should be used to refine the predictions for the rate constants. An example of accounting for rate constant dependence on soil moisture and temperature is given by Walker and Barnes (1981).

If multiple experiments are performed under different climatic and soil conditions, than empirical regression relationships can be established between k_1 and k_2. In this manner, probability density functions can be generated for the release coefficient (k_1) given distributions for the pesticide soil degradation rate constant (k_2) which may be correlated with other physical parameters such as soil type, moisture, etc.

Although rate constants are strictly empirical (based upon experimental observations), the kinetic approach has the benefit of conserving mass and incorporating a functional dependence of the pesticide half-life in soil (k_2) with the release rate into the soil environment (k_1). Rate constant dependence on soil moisture and temperature can be incorporated if field and lab data are available at different soil moisture and temperatures. The kinetic model approach should prove useful for probabilistic modeling which is a method utilized for incorporating variability (Laskowski et al., 1990). Thus, the amount of active mass within a granule can be estimated using Eq. 19 which is the solution to a simple first order ordinary differential mass balance equation.

Water flowing past a granule can be extremely effective in releasing pesticide mass for certain granule types. Water induced convection can occur during precipitation or irrigation events when water is infiltrating into the soil surface and past granule surfaces. Davis et al. (1996) have explored water release rates for fenamiphos, atrazine, and alachlor and have documented the coupling between water release rates and environmental fate for these materials. Water induced release rates scale as the square root of time for small times based upon theoretical arguments surrounding the diffusion equation (Collins et al., 1973; Collins, 1974). The released mass of pesticide from a granular carrier can scale with the square root of the water infiltration magnitude

and duration. Thus, the amount of pesticide mass within a granule with respect to time may be much less than what would be predicted by Eq. 14 if water-induced convection release rates are important. Uncertainty techniques such as monte carlo, coupled with numerical simulation, must be employed to account for the impact on granule release rates due the highly variable nature of weather patterns and thus the flow of water past granules. This is beyond the scope of the methodology presented here but water-induced release rates should be accounted for (when appropriate) on the time scale when precipitation occurs. Equation 14 can be used on all other days (i.e., days when infiltration events do not occur) and the resulting methodology can be used to develop probability density functions for regionally specific release characteristics.

In the current implementation of the model, a lumped first-order half-life is used to simulate the dissipation of active ingredient from the granule. The concentration of active ingredient in the granules is thus reduced by this first-order rate process over the ten day simulation period performed for each individual. Because of the probabilistic nature of the grit ingestion behavior simulated (via a bionomial distribution), it is possible for an individual bird to receive higher exposure to pesticide later in the simulation period (i.e., by ingesting more granules). Therefore, the exposure value of interest is the maximum an individual bird receives over the ten-day period.

C.7 ESTIMATION OF PESTICIDE INGESTION RATE (PIRG)

Pesticide ingestion rate from granules (PIRG) is the measure of dose to a bird in mg/kg/day. It is calculated according to the following:

$$MAi = \frac{Ai}{100} \times MGnlWt \qquad \text{[eq. C-23]}$$

$$CAi = \frac{Ai}{100} \times CGnlWt \qquad \text{[eq. C-24]}$$

$$MDose = MAi \times MGIR \qquad \text{[eq. C-25]}$$

$$CDose = CAi \times CGIR \quad \text{[eq. C-26]}$$

where:

MAi = amount of pesticide on single medium-sized granule (mg/granule)

Ai = percentage mass loading of pesticide on formulation at time t

MGnlWt = average weight of single medium-sized granule (mg)

CAi = amount of pesticide on single coarse-sized granule (mg/granule)

CGnlWt = average weight of single coarse-sized granule (mg)

MDose = pesticide dose due to medium-sized granules (mg/day)

CDose = pesticide dose due to coarse-sized granules (mg/day)

Total pesticide daily dose from ingestion of granules is the sum of pesticide from ingestion of medium and coarse-sized granules.

$$PIRG = \frac{MDose + CDose}{BW} \quad \text{[26]}$$

where:

PIRG = pesticide ingested by single bird as a result of granule ingestion (mg/kg/day)

BW = body weight of individual bird in kg

PIRG provides the estimate of dose and completes the implementation of the conceptual granular model outlined in Figure 3.5-1. With information supplied in this section, the reader can estimate a pesticide dose an individual bird can receive. The next section deals with propagation of uncertainty and variability in the analysis so that it is possible to estimate dose stochastically through the process of Monte Carlo modeling.

C.8 MONTE CARLO ANALYSIS

So that estimation of exposure to birds reflects the probability of achieving various exposure levels, the uncertainty and variability of input parameters used to calculate dose is propagated by means of Monte Carlo spreadsheet add-in tools Crystal Ball (Crystal Ball, 1998) and/or @RISK (@RISK, 1997). The approach utilizes the equations cited above to calculate dose for an individual bird, and it does this for a thousand or more birds by using the Monte Carlo add-ins to sample input parameter ranges according to the distributions displayed by the databases for those parameters. This, then develops a probability pattern for estimates of exposure and allows the assignment of probability to a given exposure level.

Input parameters that are varied in the model are the following:

Bird parameters:

- Total numbers of grit particles ingested per day
- Fraction of grit particles falling into medium and coarse size classes
- Field utilization (PT) - - - user-defined distribution over a range (default is a uniform distribution.

Soil and application parameters:

- Soil texture distributions by region, according to distribution of acreage for soils suitable for growth of corn or random sampling of pedons with a user-defined surface texture.
- Medium- and coarse-sized sand mass fractions according to distributions observed for soils of different texture in the pedon database
- User-selectable pesticide application scenario (band spacings and band width, for example).

An exposure assessment begins with the selection of one of 10 corn-growing regions (or soil texture), followed by the selection of a bird species known to inhabit cornfields. Formulation

characteristics such as application rate, size distribution, and pesticide loading are entered into the spreadsheet, along with the entry of values for factors that influence availability of granules on the soil's surface or express bird preferences for granules vs natural grit. The number of iterations (individual birds and application sites) for simulation of exposure is set in Crystal Ball or @RISK; the program is begun; and it then selects values from ranges of soil texture distributions, sand size distributions, total numbers of grit, size preferences, and field utilization habits of birds from data tables contained in Excel workbooks. The output is a probabilistic listing of exposure estimates for birds exposed to pesticide through ingestion of pesticide granules.

C.9 GRANULE EXPOSURE MODEL (GEM) EXAMPLE

To demonstrate the use of the probabilistic avian granule ingestion model, the following example is presented. Each source of input data is described and referenced to show the reader how such an assessment should be performed and documented.

The scenario examined is the exposure of the vesper sparrow, a common bird associated with midwest cornfields, to the soil-applied insecticide fonofos. Fonofos, formulated as granular Dyfonate II 10G™ (Zeneca Agricultural Products), is no longer registered in the United States but in previous years was used widely as an at-planting treatment to control corn root worm. A large body of data is available for the product, which makes it ideal candidate for an example.

C.9.1 Inputs

C.9.1.1 Region

As fonofos was a widely-used corn insecticide, the region defined in the Abt Corn Cluster report (Abt Associates, 1996) as the "Corn Belt" was chosen as the region for simulation. This region includes the states of Missouri, Iowa, Illinois, Indiana, and Ohio. In 1991, these states accounted for 65% of the total pounds of fonofos applied to corn (USDA/NASS data). The corn-capable

soils in the region are, by areal extent, 57% Silt Loams, 21% Silty Clay Loams, 12% Loams, and small percentages of other types.

C.9.1.2 Formulation & management information

About 80% of the Dyfonate 10G sold was used as an at-plant, banded application to corn (1991 USDA/NASS data) . The material, a clay granule formulation, was most commonly used at a rate of 12 ounces of formulation per 1000 linear feet of row. In keeping with the manufacturer's label application instructions, a 7-inch band was used, with incorporation by a press wheel, drag chains, or spring tines, leading to 15% of the granules remaining on the surface in the bands (the EPA default value). A 30-inch band spacing was assumed. For consistency with the data of Fischer and Best (1995) an endrow spill concentration factor of 15 was assumed (i.e., 15 times more granules per unit area in an endrow spill than present in the rest of the band) within an endrow spill area of one square foot. This was assumed to occur at the end of every row.

By employing the data presented in Best (1992), Dyfonate II 10G was determined to be made of 81% medium granules and 18 % coarse granules by weight (as defined for the model). It was 10% active ingredient by weight (fonofos). Medium granules were determined to have an average weight of 0.037g, while coarse granules had a weight of 0.27 g. The overall dissipation half-life of fonofos in/on the exposed granules was assumed to be five days.

C.9.1.3 Avian species information

The indicator species of interest was the vesper sparrow, a common cornfield-dwelling bird. The body of information for this species is relatively robust, with gizzard grit counts from 125 individuals available (Gionfriddo and Best, unpublished data). In addition, behavioral information on this species' use of corn fields has been collected (Best, et al., 1990 and Frey, et al., 1994). These studies indicate that vesper sparrows which live in corn production areas are present in corn fields in a range of 13 to 54% of the time. Field utilization (PT) was implemented in the model as a triangular distribution over this range, with the mean value of 34% as the most

probable value. The Best, et al. (1990) study showed that this species tended to be present in the margins of corn fields roughly 3.4 times more frequently than in field centers. Therefore, the field margin utilization factor (FMuF) was set at 3.4. The width of the field margin was assumed to be 30 feet. Granules in endrow spills were assumed to be 5 times more attractive to the birds than granules in the bands (L. Best, personal communication). Grit turnover was assumed to be 24% per day (Fischer and Best, 1995) and an average body weight of 30.7 g was used (Dunning, 1993). Avoidance behavior is not implemented in this example. Fonofos granules were assumed to be equally attractive to birds as natural grit particles.

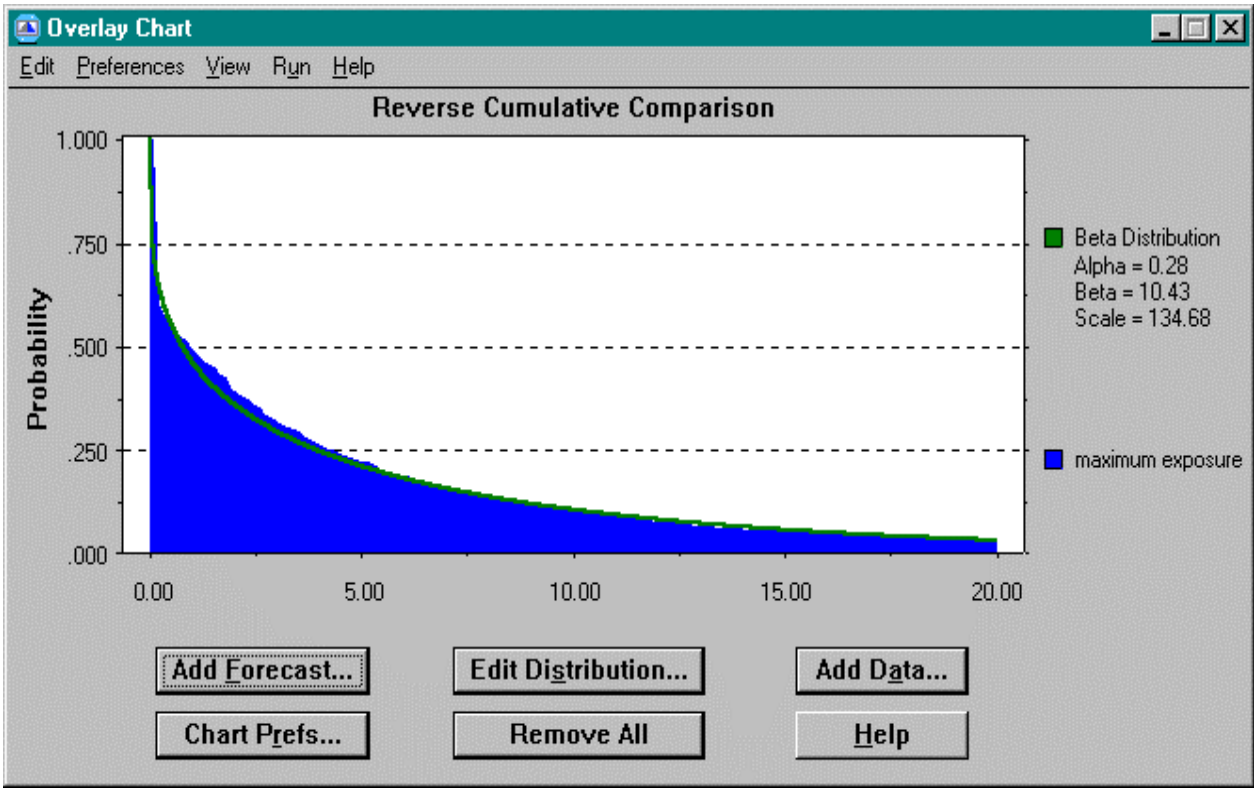
C.9.2 Results

Employing simulation of 10,000 individuals, the following percentiles for maximum daily exposure (in mg of fonofos per kilogram of body weight) were obtained:

Percentile	mg /kg bw
0%	0.00
5%	0.00
10%	0.00
15%	0.00
20%	0.00
25%	0.00
30%	0.00
35%	0.00
40%	0.16
45%	0.42
50%	0.88
55%	1.44
60%	1.85
65%	2.60
70%	3.33
75%	4.24
80%	5.46
85%	7.51
90%	10.04
95%	15.28
100%	66.67

Examination of these percentiles shows the distribution to be weighted toward zero exposure, with > 35% of the trials resulting in no exposure.

This output distribution is well-fitted by a beta distribution:

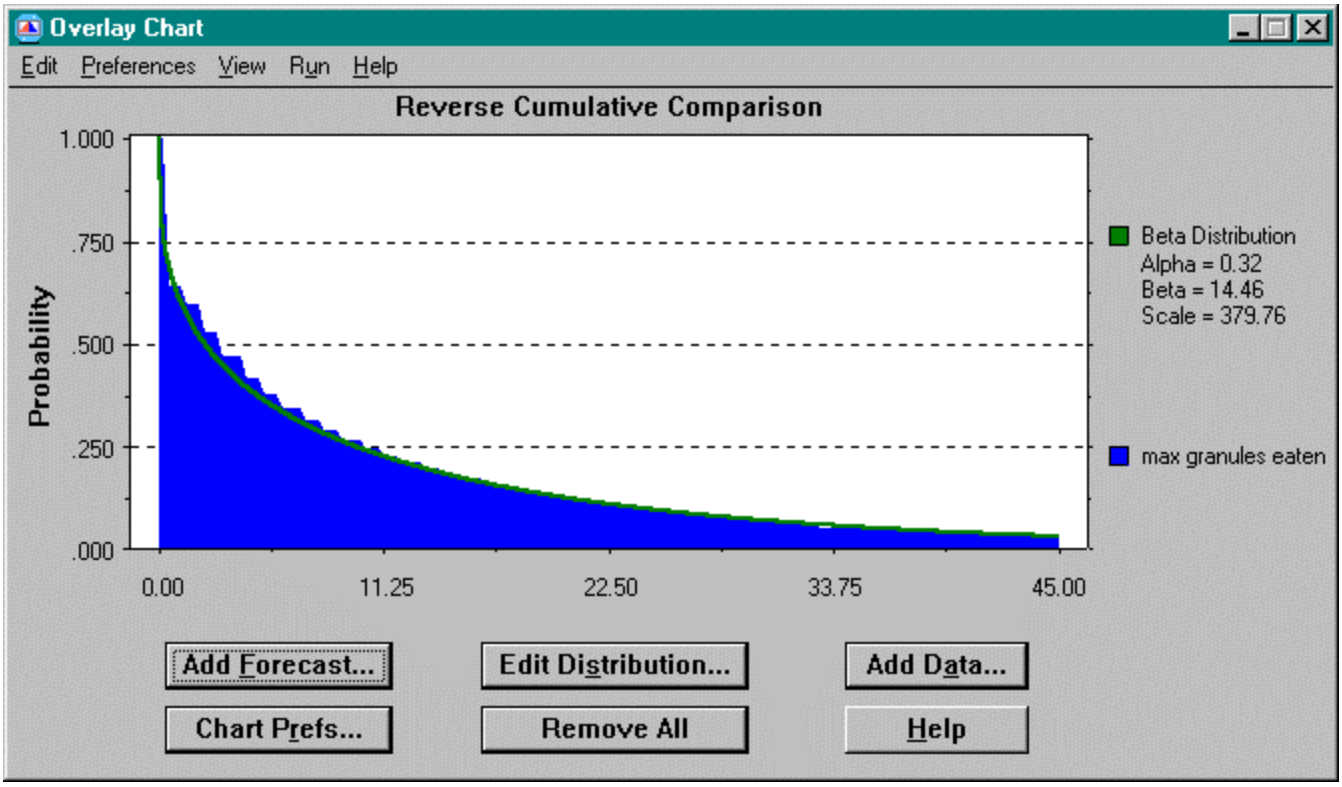


As would be expected, most (nearly 70%) of the high doses were received on the day of application (before granule dissipation took place).

The maximum daily number of total insecticide granules eaten during the 10-day period exhibited the following percentiles:

Percentile	Value
0%	0.00
5%	0.00
10%	0.00
15%	0.00
20%	0.00
25%	0.00
30%	0.00
35%	0.00
40%	1.00
45%	2.00
50%	3.00
55%	4.00
60%	5.00
65%	6.00
70%	8.00
75%	10.00
80%	13.00
85%	17.00
90%	23.00
95%	35.00
100%	188.00

This output also appears to be well represented by a beta distribution:


Overlay Chart
Edit Preferences View Run Help
Reverse Cumulative Comparison
1.000
.750
.500
.250
.000
Probability
0.00
11.25
22.50
33.75
45.00
Beta Distribution
Alpha = 0.32
Beta = 14.46
Scale = 379.76
max granules eaten
Add Forecast...
Edit Distribution...
Add Data...
Chart Prefs...
Remove All
Help

1

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APPENDIX C4

COMPUTER MODELS FOR ESTIMATING PESTICIDE CONCENTRATIONS IN ENVIRONMENTAL MEDIA

Based upon the literature reviews by Golder Associates (1997) and Jorgensen (1995), there do not appear to be any residue computer models currently available that could be used to adequately generate distributions of pesticide residues in all relevant environmental media for use in probabilistic terrestrial exposure assessments. However, there are several existing models which could possibly serve together as a good foundation for such a model. These include the spray drift model AgDRIFT, the leaching/runoff model PRZM 3, the surface water model EXAMS, the Terrestrial Exposure Assessment (TEEAM) model, the Uptake, Translocation, Accumulation, and Biodegradation (UTAB) plant contamination model, the SNAPS/PLANTX plant contamination model, the Soil-Plant-Air Fugacity plant contamination model, and the Terrestrial Risk Integrated Methodology (TRIM) model. In addition, several correlations between the uptake of chemicals by plants and their physical chemical properties which may be useful in model development have been reported in the literature. All of these will be discussed in this section.

Other models which include animal behavior algoritms as well as residue algorothms may also be helpful in developing a comprehensive terrestrial exposure model are the bird spray exposure model PARET, the bird granule exposure model developed by Dixon et.al 1998, and the bird granule exposure model developed by Dow/Elanco, Fischer and Best. These models are discussed in other sections of this report.

C4.1 AgDRIFT Spray Drift Model

The USEPA/OPP recently began using the spray drift model AgDRIFT to estimate spray drift pesticide loadings to ponds adjacent to treated fields as part of aquatic exposure assessments. Estimates of spray drift to off-site soil and water and to off-site vegetation are also important components of terrestrial exposure assessments. The U.S EPA/OPP plans to use AgDRIFT for terrestrial as well as aquatic exposure assessments. AgDRIFT was developed by modifying the USDA AGDISP model as part of a CRADA cooperative agreement between the SDTF and the U.S. EPA's Office of Research and Development (ORD).

The description of AgDRIFT below is based primarily upon A Jones, Clem, and Thurman (1997) and on Bird, Ray, Teske, Esterly, Perry, and Gustafson (1995).

AgDRIFT was developed by modifying an existing USDA spray drift model (AGDISP) based upon:

(1) The results of the tank mixture physical property, droplet size distribution, and spray drift deposition studies conducted by the SDTF.

(2) The needs of U.S. EPA/OPP for a spray drift model that could be used to predict spray drift depositions on off-site ponds, fields, and vegetation up to at least 1000 feet downwind.

The AgDRIFT model can be run in a "Tier I, Tier II, or Tier III" mode. The Tier I mode is used for screening purposes.

In the Tier I mode, a number of input parameters are assigned default values (described as "reasonable but conservative" including the wind speed (10 mph), wind direction (perpendicular to the flight path), the atmospheric stability (neutral), and the application height (10 feet). Droplet size spectrum input is restricted to one of 5 droplet size spectra,

each representing a different droplet size category (very fine, fine, medium, coarse, and very coarse as defined by the British Crop Protection Council).

Droplet size spectra are not specified on labels, but generally correlate somewhat to spray volume ranging from very fine or fine for low volume applications to coarse or very coarse for high volume applications. If the spray volume is specified a droplet size spectrum is selected based upon the magnitude of the spray volume. If a spray volume magnitude is not specified, a fine/medium droplet size spectrum is used as the default.

Model outputs for Tier I runs are graphically presented as spray drift deposition versus distance downwind curves for the upper boundaries of each of the droplet size categories (Figure 3 which is a photocopy of Figure 2 in Bird etal 1995). Tier I estimates of spray drift deposition at any distance downwind up to 1000 feet are obtained from the graphs by graphical interpolation.

The Tier II and Tier III modes require progressively more input, but are designed to provide progressively more accurate estimates of spray drift for use in higher tier exposure assessments. The upper tier modes allow the user several options for generating a droplet size distribution input. The user can define a distribution, select one from the "library" of droplet size spectra generated by the SDTF or generate one. Droplet size distributions are generated by AgDRIFT using regression equations developed by the SDTF that relate droplet size distribution characteristics to nozzle characteristics, application characteristics and the physical properties of the tank mixture.

Although AgDRIFT is currently a deterministic model, it is being modified to allow for the input of distributions for wind speed and directions rather than a single wind direction. Although the model will still be primarily deterministic except for the wind speed and direction, some other variables could also be made stochastic with additional modifications.

C4.2 PRZM3

The U.S. EPA/OPP currently uses the leaching/runoff model PRZM 3 to estimate runoff pesticide loadings to ponds adjacent to treated fields as part of aquatic exposure assessments. Although not completely adequate for pesticide terrestrial exposure assessments, a number of outputs of PRZM3 are useful for interim terrestrial exposure assessments. As an option, PRZM3 can be run stochastically to give distributional outputs. However, the plant growth and plant fate algorithms of PRZM3 need to be strengthened for use in terrestrial exposure assessments and it lacks insect, granule, and puddle algorithms.

Assuming chemical equilibrium, PRZM3 combines separate pesticide mass balance equations for the soil pore water, soil solids, and soil pore air into a single mass balance equation for soil in terms of the pesticide concentration in the pore water (Carsel et. al 1997 - PRZM 3 Manual):

$$\frac{\partial \left(q_w C_w\right)}{\partial t} + \frac{\partial \left(K_d r_s C_w\right)}{\partial t} + \frac{\partial \left(f_g K_H C_w\right)}{\partial t} = D_w \frac{\partial^2 \left(q_w C_w\right)}{\partial z^2} + D_g \frac{\partial^2 \left(f_g K_H C_w\right)}{\partial z^2} - \frac{\partial \left(V q_w C_w\right)}{\partial z} - k_{ws} q_w C_w - k_{ws} K_d r_s C_w - k_g f_g K_H C_w - f q_w e \; C_w - \left(Q / A_w \Delta z\right) C_w - \left(b X_e r_{om} K_d / A_w \Delta z\right) C_w + \left(J_{app} / A_s \Delta z\right) + \left(E P_r m_p / A_s \Delta z\right)$$

(Equation C4-1)

where

C_w = pesticide concentration in soil pore water (g/cm^3)

Θ_w = fractional volumetric soil water content (volume/volume)

K_d = soil/water equilibrium partition coeff.(cm^3/g)

ϱ_s = bulk density of soil (g/cm^3)

Φ_g = fractional volumetric soil air content (cm^3/cm^3)

K_H = dimensionless Henry's Law constant (cm^3/cm^3)

t = time (day)

D_w = molecular diffusivity of pesticide in pore water (cm^2/day)

D_g = molecular diffusivity of pesticide in pore air (cm^2/time)

z = depth (cm)

Δz = thickness of soil layer (cm)

v = water velocity (cm/day)

k_{ws} = pseudo first order degradation rate constant (1/day) for pesticide in the pore water or adsorbed to soil solids (assumed to be equal in PRZM)

k_g = pseudo first order rate constant for the pesticide in air (default value = 0 in PRZM)

f = fraction of total water used per transpiration per day (1/day)

ϵ = uptake efficiency factor (dimensionless)

Q = daily runoff volume (volume/day)

A_w = watershed area (cm^2)

b = conversion factor (g/ton)

X_e = sediment erosion per day (metric tons/day)

r_{om} = enrichment ratio for organic matter (g/g)

J_{app} = pesticide application rate (g/day)

A_s = pesticide treated area (cm^2)

E = foliar extraction coefficient (1/cm)

P_r = daily rainfall (cm)

m_p = pesticide mass on/in plants (g)

Equation C4-1 is the mass balance equation for the top soil layer(s). Mass balance equations for the lower soil layers are comparable except terms only applicable to the upper layer(s) such as runoff loss, and washoff addition to the soil are equal to zero for soil layers beneath the surface soil.

The three terms on the left side of equation C4-1 represent contributions to the overall change in pesticide mass with time within the soil layer due to changes in mass with time of pesticide in the pore water, adsorbed to soil solids, and in the pore air, respectively. The first three terms on the right side of the equation represent pesticide mass transport in the soil due to molecular diffusion in the pore water, molecular diffusion in the pore air, and advection associated with downward percolation of water through the soil layers, respectively. The next 3 terms on the right side of the equation represent degradation of the pesticide in the pore water, adsorbed to soil solids and in the pore air, respectively. The next 3 negative terms represent losses from the soil layer due to uptake by plants, dissolution in runoff water, and adsorption to eroding soil. The last 2 terms (which are positive) represent pesticide additions to the soil layer due to application and washoff, respectively.

PRZM3 uses a finite difference numerical method for solving equation B4-1 to give the pore water concentration C_{pw} at the beginning of each daily time step and for each of several hundred user specified vertical computational steps (referred to as compartments in PRZM3). Concentrations in the soil solids C_s and in the pore air C_a are computed from those in the pore water by assuming chemical equilibrium such that:

$$C_s = K_d C_w$$

(Eq. C4-2)

and

$$C_a = K_H C_w$$

(Eq. C4-3)

where

K_d = soil/water equilibrium partition coeff.(cm^3/g)

K_H = dimensionless Henry's Law constant (cm^3/cm^3)

Losses due to runoff water and soil erosion depend upon the pore water concentration C_{pw}, the soil solids concentration C_s, the runoff volume Q and the sediment Yield X_e. Previous versions of PRZM allowed pesticide extraction for runoff down to 1 cm with an uniform extraction equivalent to the pore water concentration. PRZM3 allows pesticide extraction for runoff down to 2 cm, but assumes exponentially decreasing extraction with depth down to 2 cm.

PRZM3 uses the SCS curve number method to estimate runoff volume. Predicted runoff volume increases with increasing SCS curve numbers which in turn depend upon the soil moisture prior to the rainfall event, the inherent infiltration potential of the soil (as indicated by the hydrologic group to which it belongs), land use, and tillage/plant residue practices. In general soils with relatively low inherent infiltration potential such as hydrologic Group C and D soils produce more runoff than soils with relatively high inherent infiltration potential such as hydrologic Group A and B soils.

To estimate sediment yield, PRZM3 lets the user select among three similar equations: the Modified Universal Soil Loss Equation (MUSLE), the MUSS equation or the MUST equation. In all three equations, the estimated sediment yield depends upon the product of the (total runoff volume X the peak runoff to a fractional power) X the soil erodibility factor X the length/slope factor X the soil cover factor X the conservation practice factor. The erodibility factor depends upon the soil texture and increases with decreasing organic

content. The soil cover and conservation practice factors depend upon factors such as the crop, crop rotation, tillage type and plant residue management.

PRZM3 outputs of interest with respect to terrestrial exposure assessments include daily estimates of pesticide concentrations in soil pore water and of bulk soil concentrations for each of several hundred vertical computational compartments. PRZM3 uses its estimates of concentrations in soil to estimate runoff/erosion losses of pesticide which in turn are used as input to EXAMS to estimate pesticide concentrations in adjacent ponds (also important for terrestrial exposure assessments). Estimates of concentrations in soil can also be used by algorithms outside of PRZM3 to help estimate uptake by insects and other soil invertebrates.

PRZM3 uses its estimates of concentrations in pore water to estimate pesticide uptake by plants. Slightly modifying the uptake equation in PRZM to reflect uptake on a specific day i from a specific soil compartment (layer) j within the root zone gives:

$$\left(\frac{dm}{dt}\right)_{up(ij)} = e\, Q_{trans(ij)} C_{w(j)}(t = t_i) \qquad \text{(Eq. C4-4)}$$

where

ϵ = uptake efficiency factor often referred to as a reflectance coefficient (dimensionless)

$C_{w(j)}(t=t_i)$ = pore water concentration at the start of day i at $t=t_i$ in soil compartment (layer) j (g/cm^3)

$Q_{trans(ij)}$ = transpiration flow on day i from soil layer j to the roots (cm^3/day)

and where the transpiration flow on day i from soil compartment (layer) j is given by:

$$Q_{trans(ij)} = f_{ij} \bullet q_{w(j)}(t = t_i) \bullet A_s \Delta z_j \quad \text{(Eq. C4-5)}$$

where

f_{ij} = fraction of total water in soil compartment (layer) j used for transpiration on day i (1/day)

$\Theta_{pw(j)}(t=t_i)$ = volumetric water fraction at the beginning of day i at $t=t_i$ in soil compartment (layer j) (cm^3/cm^3)

A_s = area of the field (cm^2)

Δz_j = width of soil compartment (layer) j (cm)

In PRZM3, the total evapotranspiration demand for any given day i is generally estimated from pan evaporation data. According to the PRZM3 manual, the total evapotranspiration demand is met sequentially in PRZM3 by canopy storage, ponded water (irrigation), and then from each soil compartment (layer) down until the demand is met or until the wilting point of each layer is reached. On any given day i, the evapotranspiration from soil layer j is given by:

$$ET_{ij} = MIN\left[[SW_j(t = t_i) - WP] f_{d(ij)},\ ET_{p(i)} - \sum_{j=1}^{j=j-1} ET_{ij} \right] \quad \text{(Eq. C4-6)}$$

where

MIN {a, b} = minimum of a or b

ET_{ij} = evapotranspiration on day i from soil layer j (cm)

$SW_j(t=t_i)$ = soil water at the beginning of day i at $t=t_i$ in soil layer j (cm)(derived from water balance equations)

WP_j = wilting point of soil layer j (cm)

$ET_{p(i)}$ = remaining evapotranspiration demand on day i not satisfied by canopy storage or ponded water (cm)

ΣET_{ij} = total evapotranspiration on day i from all of the soil layers 1 to j-1 above soil layer j

$f_{d(ij)}$ = depth factor on day i for layer j (dimensionless) which depends upon the root mass within layer j (PRZM3 assumes an inverted triangular distribution for root density which decreases with root depth)

The PRZM Manual indicates that equation C4-6 means that all of the available water for evapotranspiration, $[SW_j(t=t_i) - WP_j)f_{d(ij)}$, will not be used for evapotranspiration unless the remaining demand, $ET_p - \Sigma ET_{ij}$, is greater than the available water.

The PRZM3 manual does not provide an equation for the evaporation from the soil (E_{ij}) but indicates that E_{ij} is extracted to meet evapotranspiration demand (ET_{ij}) before transpiration from the soil (T_{ij}) such that presumably

$$T_{ij} = ET_{ij} - E_{ij} \quad \text{(Eq. C4-7)}$$

The leaf area index (LAI) is the ratio of leaf area to field area. In two leaching models that estimate the leaf area index LAI (PESTALA and MACRO), potential evapotranspiration is divided into potential evaporation and potential transpiration as follows (Rasmussen 1995):

$$E_{pot} = ET_{pot} \exp(-0.6 \bullet LAI)$$ (Eq. C4-8)

$$T_{pot} = ET_{pot} \left[1 - \exp(-0.6 \bullet LAI)\right]$$ (Eq. C4-9)

Assuming the uptake on day i from soil layer j is given by equation C4-4, the total uptake from all of the soil layers from which transpiration is extracted should be given by:

$$\left(\frac{dm}{dt}\right)_{totup(i)} = \sum_{j=1}^{j=j_{\max(trans)}} e \; Q_{\text{trans(ij)}} C_{pw(ij)}$$ (Eq. C4-10)

where

$(dm/dt)_{totup(i)}$ = total uptake rate on day i

$j_{max(trans)}$ = the deepest soil layer from which transpiration is extracted

The PRZM3 manual recommends as one option, setting the reflectance coefficient ϵ = TSCF = transpiration stream concentration factor. The TSCF is defined as the steady state ratio of the concentration in the above ground biomass transpiration stream to the concentration in the soil pore water:

$$TSCF = C_{trans} / C_{pw}$$

(Eq. C4-11)

As will be discussed later, TSCF can be estimated from the octanol/water partition coefficient of a chemical.

The mass balance equation for vegetation in the PRZM3 manual appears to be only for pesticide residues on the foliage:

$$\frac{dm_{p(i)}}{dt} = App_{pl(i)} - \left(k_p + EP_{r(i)}\right)m_{p(i)} \quad \text{(Eq. C4-12)}$$

where

$m_{p(i)}$ = $m_p(t_{i+1}<t<t_i)$ = pesticide mass on plants/area of the field as a function of time over day i from $t=t_i$ to $t=t_{i+1}$ (g/cm^2)

k_p = overall foliar dissipation rate constant accounting for both degradation and volatilization (1/day)

E = foliar washoff extraction coefficient (1/cm)(depends upon the chemical and the plant - PRZM default value is 0.1)

$P_{r(i)}$ = rainfall per day on day i (cm/day)

$App_{(pl)i}$ = application rate to the plant on day i (g/cm^2*day)

Because the vegetation mass balance equation in PRZM3 does not consider pesticide residues in the foliage, it does not include a term for plant uptake even though plant uptake is included in the mass balance equation for soil. Any modification to PRZM 3 to improve its use for terrestrial exposure assessments would presumably include adding a

term for uptake by plants to generate a mass balance equation for pesticide residues in as well as on vegetation:

$$\frac{dm_{p(i)}}{dt} = App_{pl(i)} + \left[\sum_{j=1}^{j=j_{\max(trans)}} e\, f_{ij} \bullet q_{pw(j)}(t = t_i) \bullet \Delta z \bullet C_{pw(j)}(t = t_i) \right] - \left(k_p + EP_{r(i)} \right) m_{p(i)}$$

(Equation C4-13)

Note that in the PRZM3 vegetation mass balance equation (equation C4-12) and in the above modification to the PRZM3 equation (equation C4-13) to include an uptake term, the application to the plant $App_{pl(i)}$ is included as a term in the mass balance equation, not as an instantaneous event modifying the initial conditions. The associated implication is that application is more a continuous event dragged out over the entire day than an instantaneous event. In reality, application is somewhere in between the two extremes.

Note that the application rate to the plants $App_{pl(i)}$ is less than the nominal application rate to the field $App_{nom(i)}$ due to spray drift and partial penetration of the canopy to soil.

To be useful for terrestrial exposure assessments, estimates of pesticide mass on plants/area of the field (m_p) at any given time need to be converted to pesticide mass/mass of plant (C_p) at the same time. The bulk concentration of a chemical on/in plants at any given time t' is related to in mass on/in plants at the same time by:

$$C_p(t = t') = m_p(t = t') / B_{ag}(t = t')$$ (Equation C4-14)

where

$C_p(t=t')$ = pesticide mass on/in vegetation/plant mass at time t=t' (g chemical/kg plant)

$m_p(t=t')$ = mass of chemical on foliage per unit area of the field at time t=t' (g chemical/m^2 of field)

$B_{ag}(t=t')$ = above ground plant biomass per unit area of the field at time t=t' (kg dry weight/m^2 of field)

C4.5 EXAMS

For aquatic exposure assessments, estimates by PRZM3 of pesticide losses due to runoff water and soil erosion from a 10 ha treated field and by AgDRIFT of spray drift deposition are used as pesticide loading inputs to the surface water EXAMS. EXAMS than estimates dissolved and adsorbed concentrations in an adjacent 1 ha by 2 m deep pond. Comparable computations would also be useful in a terrestrial exposure assessments since birds and mammals utilize farm and/or natural ponds for drinking, food, and swimming.

EXAMS generates mass balance differential equations for each segment within a simulated water body and generates steady state solutions to the equations for each computational time step (Burn 1990). EXAMS outputs of interest with respect to terrestrial exposure assessments include daily estimates of dissolved and sediment bound concentrations of pesticide in each segment.

Although the hydrology and sediment algorithms in EXAMS are somewhat more simplistic than in WASP (whose fate algorithms were based primarily upon those in EXAMS), they are probably adequate for estimating pesticide concentrations in ponds for use in terrestrial exposure assessments. Furthermore, the input requirements for EXAMS are reasonable. Also, EXAMS does a good job of simulating chemical transformation processes such as hydrolysis, direct photolysis in water, and biodegradation. EXAMS does not directly simulate adsorption/desorption kinetics, but the time required to reach

equilibrium does decrease with increasing magnitude of the sediment/water partition coefficient.

EXAMS cannot currently be run stochastically. Temporal and site distributions of estimated pesticide concentrations for aquatic exposure assessments are currently generated by running the model deterministically over multiple years and sites.

C4.6 TEEAM

The original and subsequent versions of PRZM were developed as leaching/runoff models, not as terrestrial exposure models. PRZM3 does not estimate factors necessary for the conversion of pesticide mass/area of the field to pesticide mass/mass of plant such as the plant biomass. Furthermore, the linear and exponential canopy cover algorithms PRZM3 uses are inadequate for estimating foliar interception. Other weaknesses of PRZM3 with respect to terrestrial exposure assessments are that it does not simulate the fate of granules, and does not estimate pesticide concentrations in the highly transient puddles formed on fields during rainfall events. Although PRZM includes a plant uptake term in the mass balance equation for soil, it does not include it in the mass balance equation for vegetation.

TEEAM was derived from PRZM in the late 1980s by the USEPA laboratory in Athens GA and its contractors for use in terrestrial exposure assessments (Bird, Cheplick, and Brown 1991). Although TEEAM was not supported beyond the testing phase, many of the algorithms developed for it could possibly be used or modified for use in a new model. TEEAM was a close derivative of the leaching/runoff model PRZM and used many of the same algorithms. However, it did contain improved plant growth algorithms, improved plant fate algorithms (which included uptake), fate algorithms for granules, and algorithms for estimating pesticide concentrations in transient small puddles. In addition, algorithms for animal movement (based upon a Markov model), animal feeding, and animal uptake (including soil invertebrates as well as vertebrates) were included.

The plant growth algorithms employed by TEEAM were based primarily upon ones in EPIC which was designed in part to simulate plant growth. The total biomass B in kg/m^2 is computed on a daily time step as a function of solar irradiation (modified by the leaf area index) and a measure of temperature stress dependent upon the difference between the optimal growth temperature and the average daily temperature on day i. The leaf area index LAI is the ratio of leaf area to the area of the field.

The root biomass (RWT) is computed on a daily time as a function of the total biomass and the ratio of the number of heat units accumulated as of day i (ΣHU_i) to the total number of heat units required for maturation (PHU). A heat unit for a given day i is given by:

$$HU_i = T_i - T_b \qquad \text{(Eq. C4-15)}$$

where

T_i = average daily temperature in ^0C

T_b = user specified base temperature in ^0C

The root depth is computed on a daily basis as a function of the maximum root depth, HU_i, and PHU. The canopy height is computed on a daily basis as a function temperature stress, HU_i, and PHU.

The leaf area index LAI is computed on a daily basis as a sigmoidal function of the above ground biomass (total biomass - root biomass) with the function approaching the maximum leaf area index LAI_{max} as the above ground biomass approaches its maximum. Likewise, the canopy cover is computed on a daily basis as a sigmoidal function of the LAI with the function approaching the maximum canopy cover COVMAX as the leaf area index LAI approaches its maximum.

TEEAM uses the Green-Amp equation to estimate decreases in puddle depth due to infiltration through the soil beneath the puddles. Due to the transient nature of puddle depths, TEEAM uses an hourly rather than daily time step in its puddle algorithms. Unfortunately, most available weather data that are needed to estimate puddle depths are on a daily rather than hourly basis.

C4.7 Compartment Models

Simple compartment models generally assume first order mass transfer between compartments and assume first order degradation within each compartment. Mass balance ordinary differential equations and initial conditions are developed for each compartment and solved simultaneously to estimate pesticide concentrations as a function of time in each compartment.

An example of a compartment model is one proposed by Moorhead for this report. The compartments considered by Morehead (based on a consideration of exposure pathways) were (1) air, (2) plants, (3) soil solution, (4) soil solids, (5) free-standing water such as puddles, (6) invertebrates, and (7) vertebrates. Morehead allows for any significant abiotic and/or biotic mass transfer between compartments (which he represents as the cells of a 7 X 7 matrix - Figure ?) as well as external inputs and internal losses.

As is the case with other compartment models, the Morehead model involves generating a set of mass balance ordinary differential equations consisting of one equation for each compartment. Based upon a set of initial conditions (one for each compartment), the equations would then be solved simultaneously with numerical methods to estimate pesticide concentrations as a function of time in each compartment.

Morehead represents the set of differential equations by:

$$\frac{d\mathbf{X}}{dt} = a\mathbf{X} + b\mathbf{X} + \mathbf{Y} + \mathbf{Z}$$ (Eq. C4-16)

where

X = vector representing the pesticide concentration in each compartment

a = matrix of coefficients representing mass transfers between compartments due to abiotic processes.

b = matrix of coefficients representing mass transfers between compartments due to biological processes

Y = vector of external inputs to compartments such as pesticide application

Z = vector of internal losses from compartments such as chemical degradation

The Morehead equation C4-16 differentiates between abiotic and biological transfer processes and considers internal decay within compartments separately. Such specificity is sometimes quite useful. However, for illustrative purposes, we will add the abiotic and biotic matrices together. Futhermore, like the abiotic and biotic mass transfers, the internal decay Z in the Morehead equation can also be represented as a first order process = $k_{decay}X$. Therefore, the Morehead equation can be further simplified to give:

$$\frac{d\mathbf{X}}{dt} = h\mathbf{X} + \mathbf{Y}$$ (Eq. C4-17)

where

h = matrix representing the sum of matrices a, b, and k_{decay}

Note that for the purpose of adding the matrices a, b, and k_{decay} together, the decay matrix (k_{decay}) can be represented as a matrix with the same order (7 x 7) as the abiotic mass transfer matrix "a" and biological mass transfer matrix "b". However, the only elements in the k_{decay} matrix that are not equal to zero are the diagonal elements where i=j because internal decay does not involve mass transfer from one compartment to another.

It should be noted that equation C4-17 is a shorthand matrix representation of a series of coupled differential equations of the form:

$$\frac{d\mathbf{X_1}}{\mathrm{dt}} = k_{11}\mathbf{X_{11}} + k_{12}\mathbf{X_2} + k_{13}\mathbf{X_3} + k_{14}\mathbf{X_4} + k_{15}\mathbf{X_5} + k_{16}\mathbf{X_6} + k_{17}\mathbf{X_7} + \mathbf{Y_1} \quad \text{(eq. C4-18)}$$

$$\frac{d\mathbf{X_2}}{dt} = k_{21}\mathbf{X_1} + k_{22}\mathbf{X_2} + k_{23}\mathbf{X_3} + k_{24}\mathbf{X_4} + k_{25}\mathbf{X_5} + k_{26}\mathbf{X_6} + k_{27}\mathbf{X_7} + \mathbf{Y_2} \quad \text{(eq. C4-19)}$$

$$\frac{d\mathbf{X_3}}{dt} = k_{31}\mathbf{X_1} + k_{32}\mathbf{X_2} + k_{33}\mathbf{X_3} + k_{34}\mathbf{X_4} + k_{35}\mathbf{X_5} + k_{36}\mathbf{X_6} + k_{37}\mathbf{X_7} + \mathbf{Y_3} \quad \text{(eq. C4-20)}$$

$$\frac{d\mathbf{X_4}}{dt} = k_{41}\mathbf{X_1} + k_{42}\mathbf{X_2} + k_{43}\mathbf{X_3} + k_{44}\mathbf{X_4} + k_{45}\mathbf{X_5} + k_{46}\mathbf{X_6} + k_{47}\mathbf{X_7} + \mathbf{Y}_4 \quad \text{(eq. C4-21)}$$

$$\frac{d\mathbf{X_5}}{dt} = k_{51}\mathbf{X_1} + k_{52}\mathbf{X_2} + k_{53}\mathbf{X_3} + k_{54}\mathbf{X}_4 + k_{55}\mathbf{X_5} + k_{56}\mathbf{X_6} + k_{57}\mathbf{X_7} + \mathbf{Y}_5 \quad \text{(eq. C4-22)}$$

$$\frac{d\mathbf{X_6}}{dt} = k_{61}\mathbf{X_1} + k_{62}\mathbf{X_2} + k_{63}\mathbf{X_3} + k_{64}\mathbf{X_4} + k_{65}\mathbf{X}_5 + k_{66}\mathbf{X_6} + k_{67}\mathbf{X_7} + \mathbf{Y}_6 \quad \text{(eq. C4-23)}$$

$$\frac{d\mathbf{X_7}}{dt} = k_{71}\mathbf{X_1} + k_{72}\mathbf{X_2} + k_{73}\mathbf{X_3} + k_{74}\mathbf{X_4} + k_{75}\mathbf{X_5} + k_{76}\mathbf{X_6} + k_{77}\mathbf{X_7} + \mathbf{Y_7} \quad \text{(eq. C4-24)}$$

where

k_{ij}(i not = j) = first order coefficient for overall (abiotic and/or biological) mass transfer from compartment j to compartment i = a_{ij} + b_{ij} in the Morehead representation

Y_i = external mass addition to compartment i

$$k_{11} = -\left(k_{decay1} + k_{21} + k_{31} + k_{41} + k_{51} + k_{61} + k_{71}\right) \quad \text{(Eq. C4-25)}$$

$$k_{22} = -\left(k_{decay2} + k_{12} + k_{32} + k_{42} + k_{52} + k_{62} + k_{72}\right) \quad \text{(Eq. C4-26)}$$

$$k_{33} = -\left(k_{decay3} + k_{13} + k_{23} + k_{43} + k_{53} + k_{63} + k_{73}\right) \quad \text{(Eq. C4-27)}$$

$$k_{44} = -\left(k_{decay4} + k_{14} + k_{24} + k_{34} + k_{54} + k_{64} + k_{74}\right) \quad \text{(Eq. C4-28)}$$

$$k_{55} = -\left(k_{decay5} + k_{15} + k_{25} + k_{35} + k_{45} + k_{65} + k_{75}\right) \quad \text{(Eq. C4-29)}$$

$$k_{66} = -\left(k_{decay6} + k_{16} + k_{26} + k_{36} + k_{46} + k_{56} + k_{76}\right) \quad \text{(Eq. C4-30)}$$

$$k_{77} = -\left(k_{decay7} + k_{17} + k_{27} + k_{37} + k_{47} + k_{57} + k_{67}\right) \quad \text{(Eq. C4-31)}$$

where

$k_{decay(i)}$ = first order decay constant in compartment i

The full matrix representation of differential equations C4-18 through C4-24 (as opposed to the shorthand representation given by equation C4-17) is:

$$\frac{d}{dt}\begin{bmatrix}\mathbf{X_1}\\ \mathbf{X_2}\\ \mathbf{X_3}\\ \mathbf{X_4}\\ \mathbf{X_5}\\ \mathbf{X_6}\\ \mathbf{X_7}\end{bmatrix} = \begin{bmatrix} k_{11} & k_{12} & k_{13} & k_{14} & k_{15} & k_{16} & k_{17}\\ k_{21} & k_{22} & k_{23} & k_{24} & k_{25} & k_{26} & k_{27}\\ k_{31} & k_{32} & k_{33} & k_{34} & k_{35} & k_{36} & k_{37}\\ k_{41} & k_{42} & k_{43} & k_{44} & k_{45} & k_{46} & k_{47}\\ k_{51} & k_{52} & k_{53} & k_{54} & k_{55} & k_{56} & k_{57}\\ k_{61} & k_{62} & k_{63} & k_{64} & k_{65} & k_{66} & k_{67}\\ k_{71} & k_{72} & k_{73} & k_{74} & k_{75} & k_{76} & k_{77}\end{bmatrix} \bullet \begin{bmatrix}\mathbf{X_1}\\ \mathbf{X_2}\\ \mathbf{X_3}\\ \mathbf{X_4}\\ \mathbf{X_5}\\ \mathbf{X_6}\\ \mathbf{X_7}\end{bmatrix} + \begin{bmatrix}\mathbf{Y_1}\\ \mathbf{Y_2}\\ \mathbf{Y_3}\\ \mathbf{Y_4}\\ \mathbf{Y_5}\\ \mathbf{Y_6}\\ \mathbf{Y_7}\end{bmatrix} \quad \text{(Eq. C4-32)}$$

To estimate the residue level in each compartment i as a function of time, $X_i(t)$, differential equations C4-18 through C4-24 must be solved simultaneously because they are coupled by the reversible mass transfers between the compartments. To solve the equations, an initial condition at t=0, $X_i(t=0)$, must be specified for each compartment.

Solving a series of coupled mass balance differential equations simultaneously using numerical methods is a common element of simple compartment models involving first order mass transfers between compartments and first order decay within each compartment. Examples of terrestrial residue models that approximately follow such an approach are UTAB, PLANTX, the Soil-Plant-Air Fugacity Model and the environmental fate module of TRIM. Those models will be discussed in greater detail below.

C4.8 UTAB

The Uptake, Translocation, Accumulation, and Biodegradation (UTAB) plant contamination model divides the plant into one root, three stem, and three leaf compartments (Boersma et. al 1988, Lindstrom etal 1991). Each compartment is further subdivided into xylem, phloem, and storage subcompartments. The compartments are represented as a series of continuous stirred flow reactors separated by membranes.

The transport of chemical between compartments is simulated as passive diffusive transport across membranes separating the compartments. Partition coefficients and reflection coefficients are used to reflect the ease by which a chemical penetrates and crosses the membranes, respectively. Transport and accumulation within each compartment are represented by mass balance equations that account for diffusive transport into and out of each compartment, convective mass transport within each compartment and first order degradation and adsorption to solid matrices within each compartment. The series of differential equations are solved numerically to estimate chemical masses in each compartment.

Boersma et al. (1991) evaluated the accuracy of UTAB in estimating the plant uptake and translocation of bromacil by soybean. The model satisfactorily predicted the observed chemical uptake and distribution.

C4.9 SNAPS/PLANTX

SNAPS (Simulation Model Network Atmosphere-Plant-Soil) is actually a coupled series of 3 models used to simulate soil water content, and chemical transport and fate within the soil profile and in plants (Matthies and Behrendt 1995).

The soil water model estimates soil water content by solving Richard's equation. Richard's equation is a partial differential equation relating the change in soil moisture with time to the change in the soil water velocity with depth. The equation includes a term for water loss due to uptake by plants. The soil water velocity at a given depth is proportional to the product of the hydraulic conductivity and the hydraulic gradient at that depth. The chemical transport and fate model for soil is based upon a convection-dispersion equation similar to the one used in PRZM 3.

The chemical transport and fate model for plants in SNAPS is called PLANTX (Trapp, McFarlane, and Matthies 1993; Trapp 1995).

The plant model consists of root, stem, leaf, and fruit compartments. The model numerically solves simultaneously mass balance equations for the roots, stems, leaves, and fruits.

The model simulates passive diffusive and transpiration uptake by roots from soil water and advective mass transport with transpiration and/or assimilation streams to and from the stems, leaves and fruits. It simulates first order degradation and partitioning between the aqueous phase and plant tissue in all of the compartments.

PLANTX also simulates volatilization from leaves to the atmosphere. The volatilization equation used in PLANTX and in a simplified version (PLANT) is discussed in Appendix C5.

Plant degradation and volatilization from leaves to the atmosphere were shown to be major dissipation pathways in the PLANTX modelling of carbofuran and terbuthylazine behavior in barley and wheat over the growing season (Behrendt and Bruggemann 1993). The results showed that even though the concentration of carbofuran at harvest was lower than the allowable level, peak concentrations in the vegetative period were substantially higher.

C4.10 PLANT

The PLANT model is a simplified version of the PLANTX model in which the 4 compartments within the PLANTX model (roots, stems, leaves, and fruits) are replaced by a single overall aerial plant compartment (Trapp and Matthies 1995; Trapp 1995). Uptake is represented by the product of the transpiration flow times the Transpiration Stream Concentration Factor (TSCF) times the concentration in the soil pore water. For neutral organics, the TSCF can be estimated from the octanol/water partition coefficient as described below. The single mass balance equation for the plant compartment is solved analytically to give the bulk chemical concentration in the plant.

C4.11 Soil-Plant-Air Fugacity Model

A root-stem-foliage compartment model was developed to predict residue uptake from soil and fate and transport within plants (Paterson, Mackay, and McFarlane 1994; Paterson and Mackay 1995). The model involves solving simple mass balance equations for each compartment. It is similar in many aspects to the various other plant fate models duiscussed above, but it differs in using the concept of fugacity and the ratio of fugacity capacities of different phases to estimate equilibrium partition coefficients.

The fugacity of a chemical in a phase is given by:

$$f = C / Z \quad \text{(Eq. C4-33)}$$

where

f = fugacity

C = concentration in the phase

Z = fugacity capacity

The fugacity capacity of the chemical in each phase depends upon properties of both the chemical and the phases.

Because the fugacities f_1 and f_2 of a chemical in two phases in equilibrium are equal, equilibrium partition coefficients between phases are estimated from the ratio of the fugacity capacity in each phase (Paterson and Mackay 1995):

$$K_{12} = C_1 / C_2 = f_1 Z_1 / f_2 Z_2 = Z_1 / Z_2 \quad \text{(Eq. C4-34)}$$

Like most earlier modeling efforts, the model was not designed to be used for perennial vegetation and did not include seasonal variations in temperature, precipitation, or growth rates. The results showed that K_{ow} and Henry's law constant played a key role in determining organic chemical rate of uptake, fate, and role of transport through the transpiration stream and foliar absorption from air. The authors noted that flow rates in the phloem, rates of exchange between the root and the soil, and determining when wet and dry deposition rates should be included in the mass balance were areas that needed greater elucidation.

C4.12 TRIM

The TRIM Model is currently being developed by the USEPA Office of Air Quality Planning and Standards and its contractors. The current environmental fate module is a simple compartment model that allows for first order mass transfers between compartments and first order degradation within each compartment. A mass balance ordinary differential equation and initial condition is developed for each compartment. The system of ordinary differential equations are then numerically solved simultaneously to give the chemical mass in each compartment as a function of time.

The primary purpose for developing TRIM is to generate multi-media exposure and risk assessments associated primarily with the deposition of industrial and urban air pollutants, not pesticides. The TRIM fate module does not simulate plant growth or spray drift. Its runoff extraction algorithm appears to be an improvement over the equilibrium assumed between runoff water and pore water in most models. However, soil moisture within the vadose zone is not based on Richard's equation and the fate and transport of chemicals within the vadose zone is not based on a convection dispersion equation. However, some

of the fate equations/algorithms in the TRIM fate module related to plants, worms, and wildlife may possibly be useful in developing a pesticide terrestrial exposure model.

C4.13 Plant Uptake Concentration Factors

Plant uptake of pesticide residue can occur by uptake from the soil solution or by absorption of residue volatilized from the soil. Uptake of the residue from soil solution may be a passive process whereby the residue is transported by the transpiration stream to the foliage. Such a process would allow the prediction of foliage residue levels based upon such chemical properties as K_{ow}. Pesticide solubility and soil adsorption properties would also influence bioavailability of the chemical to the plant. Root growth and diffusion may also contribute to plant uptake.

Plant root uptake of six herbicides and a systemic fungicide was described by Shone and Wood (1974) using the Root Concentration Factor (RCF) where:

RCF = (Concentration in roots-wet weight)/(Concentration in external solution) (Eq. C4-35)

For dilute solutions, RCF was independent of chemical concentration. Translocation of the chemical from the roots to the shoots was described by the Transpiration Stream Concentration Factor (TSCF) where:

TSCF = (Conc. in transpiration stream or xylem sap)/(Conc. in external solution) (Eq. C4-36)

The TSCF was independent of external solution concentration and had a maximum value of 1.0 for passive uptake. The authors noted that uptake of 2,4-dichloro-phenoxyacetic acid (2,4-D) was influenced by plant metabolic activity.

Briggs et al. (1982) reported that root accumulation of non-ionized compounds, O-methylcarbamoyloximes and substituted phenylureas, was determined by partitioning of the chemical to lipophilic root solids and uptake by the aqueous phase in the root. Lipophilic chemicals had large RCF values and the relationship reported was log (RCF-0.82) = 0.77 log K_{ow} -1.52. Translocation to shoots was a passive process and greatest for compounds with a log K_{ow} value of 1.8. The relationship was described as:

$$TSCF = 0.784 \bullet \exp\left[-\left(\log K_{ow} - 1.78\right)^2 / 2.44\right] \quad \text{(Eq. C4-37)}$$

The authors also determined first-order degradation rate values for the chemicals studied and corrected the TSCF values for degradation loss during the study.

Using a closed laboratory model ecosystem, Trapp et al. (1990) reported that plant bioconcentration of several organic chemicals was dependent upon transfer rates and the K_{ow}/K_{oc} values. Chemicals with high K_{ow} values and large enough Henry's law constants were predominantly absorbed by plant foliage from the air. Plant uptake via the transpiration stream was important for chemicals with medium K_{ow} values. Plant metabolism was important in determining foliage concentrations of given pesticides. Trapp et al. (1990) were able to model pesticide bioconcentration factors (BCF) as residue concentration in fresh plant material/ residue concentration in dry soil and reported a value of approximately 1.0 for atrazine.

A numerical and an analytical model were used to evaluate root uptake in the transpiration stream of barley (Behrendt et al., 1995). Both models were sensitive to soil sorption and degradation input parameters. Maximum residue root uptake was a function of the sorption parameter K_{oc} that was determined by the degradation rate of the pesticide.

Ryan et al. (1988) reported that compounds with log K_{ow} values of 1 to 2 would most likely result in transport of the chemical to above portions of the plant in soil systems. The researchers also indicated that compounds with half-lives of <10 days in the soil would be lost from the soil before plant uptake would result in substantial foliage concentration of the material. If active uptake is involved, the process is most likely compound specific and it would be difficult to develop general relationships to predict foliage concentrations. Absorption of pesticides by foliage is a likely process if the Henry's Constant is $>10^{-4}$ unitless and the compound is not readily degraded in the soil. Based upon the data reviewed, Ryan et al. (1988) indicated that potential plant uptake of an organic compound could be evaluated using log K_{ow}, Henry's Constant, and half-life value. Devine and Vanden Borden (1991) have summarized root uptake and root-to-shoot translocation for several herbicides.

Plant root uptake of organic chemicals was evaluated by Polder et al. (1995) with the Uniform System for the Evaluation of Substances (USES) model used in The Netherlands. The USES model was developed for rapid risk assessment of organic chemicals. Using a wider range of compounds, plant species, and plant growth stages, Polder et al. (1995) concluded that RCF and TSCF relationships described by Briggs et al. (1982) were satisfactory, but shoot concentration factors required major adjustments.

An in-depth treatment of the subject of modeling and simulation of organic chemical processes related to plant contamination was recently given by Trapp and McFarlane (1995).

APPENDIX C5

VOLATILIZATION AND PESTICIDE CONCENTRATIONS IN AIR

Pesticide doses to birds and mammals through direct inhalation of pesticide contaminated air is generally thought to be relatively small compared to pesticide doses from ingestion of food and water. Nevertheless, air inhalation could occasionally be an important exposure pathway, particularly for inhalation of volatile chemicals by terrestrial birds and mammals who spend a considerable amount of time within a plant canopy.

Pesticide residues in air are determined directly in lab and field studies and can also be estimated with the use of computer models.

The PRZM3/TEEAM models assume that pesticide concentrations in the air over bare soil or in the air over a canopy are approximately zero, but provide algorithms for estimating pesticide concentrations within the plant canopy under some conditions.

Computational methods for residues in air generally focus on volatilization fluxes from soil, water, and plants. The PRZM3/TEEAM models assume that pesticide concentrations in the air above bare soil, open water, and plant canopies are approximately equal to zero due to wind advection and turbulent dispersivity. However, the models use estimated volatilization fluxes to estimate pesticide concentrations within the plant canopy.

C5.1: Volatilization Flux at the Soil/Air Interface

To estimate pesticide concentrations in soil, PRZM3 numerically solves an advection-dispersion mass balance equation that includes sources and sinks for the pesticide on/in the soil including application, washoff, degradation, leaching, runoff, and uptake by plants.

Losses due to volatilization are not included as a sink term in the advection dispersion mass balance equation, but rather as a flux boundary condition at the soil surface.

Assuming only vertical flux, the flux at any given height is proportional to the vertical concentration gradient in air at that height (Taylor and Spencer 1990):

$$J(z,t) = -K_z \frac{\partial C_a(z,t)}{\partial z} \quad \text{(Eq. C5-1)}$$

where

K_z = molecular dispersivity coefficient in air (cm^2/day)

To develop a boundary flux equation for the soil/air interface, Jury etal 1983 assumed that a stagnant air layer of thickness w separates the bulk soil from the bulk atmosphere. Assuming that $K_z = D_a$ (molecular diffusivity in air) for a stagnant air layer and that the flux is independent of z within the stagnant layer, separating variables in equation C5-1, and integrating it from C_a =

$C_a(z=0,t)$ to $C_a = C_a(z=w,t)$ and from z = 0 to z = w, gives the following equation for volatilization flux from the soil through the stagnant air layer at the soil/air interface:

$$J_{soil(st)}(t) = \left(D_a / w\right)\left[C_a(z=0,t) - C_a(z=w,t)\right] \quad \text{(Eq. C5-2)}$$

where assuming chemical equilibrium between the soil solids, pore water, and pore air:

$$C_a(z=0,t) = \frac{C_{bulk}(z=0,t)}{\left[\left(r_s K_d / K_H\right) + \left(q_w / K_H\right) + f_g\right]}$$ (Eq. C5-3)

and where

$J_{soil(st)}(t)$ = flux from the soil through the stagnant air layer as a function of time (g/cm^2*day)

D_a = molecular diffusivity of the chemical in air (cm^2/day)

w = width of stagnant air layer over the soil/air interface (cm)

$C_a(z=0,t=t')$ = concentration in the pore air at the soil/air interface as a function of time (g/cm^3)

$C_a(z=w,t)$ = concentration in the air just above the upper boundary of the stagnant air layer as a function of time(g/cm^3)

ρ_s = bulk density of soil (g/cm^3)

K_d = soil/water equilibrium partition coefficient (cm^3 water/g soil)

K_H = "dimensionless" Henry's Law constant (actually has units of cm^3 water/cm^3 air)

Θ_w = volumetric water fraction (cm^3/cm^3)

Φ_g = volumetric air fraction

C5.2: Pesticide Concentrations in Air Within the Plant Canopy for Foliarly Applied Pesticide (PRZM3)

For bare soil having no canopy, PRZM3 assumes $C_a(z = w)$ is approximately equal to zero because of wind and atmospheric turbulence such that equation C5-2 becomes:

$$J_{baresoil(st)}(t) = \left(D_a / w\right)\left[C_a(z = 0, t)\right]$$ (Eq. C5-4)

However, as a plant canopy develops, C_a(at z = w) may increase to substantially > 0 and needs to be estimated. Assuming the canopy is neither a source or sink for pesticides (as in PRZM3) and that the flux from the soil through the canopy is independent of z within the canopy, separating variables in equation C5-1, and integrating from C_a(at z = w) to $C_a(z = h_{can}) = 0$ and from z = w to z = canopy height = h_{can} gives the flux from the soil through the plant canopy:

$$J_{soil(pc)}(t) = \frac{C_a(z = w, t)}{\int_w^{hcan} dz / K_z}$$ (Eq. C5-5)

Recall that if $C_a(z = w)$ is > 0, the flux $J_{soil(st)}$ from the soil through the stagnant air layer from z = 0 to z = w is given by equation C5-2. Assuming steady state conditions, the flux from the soil through the stagnant air layer $J_{soil(st)}$ (given by equation C5-2) can be assumed to be equal to the flux from the soil through the plant canopy $J_{soil(pc)}$ (given by equation C5-5). The assumed equality between the right sides of equations C5-2 and C5-5 can be used to solve for $C_a(z = w)$:

$$C_a(z = w, t) = \frac{C_a(z = 0, t) \bullet \int_w^{hcan} dz / K_z}{\left[\left(w / D_a\right) + \int_w^{hcan} dz / K_z\right]}$$ (Eq. C5-6)

Substituting equation C5-6 for $C_a(z=w,t)$ into equation C5-5 gives the following equation for $J_{soil(pc)}$ which is provided in the PRZM3 Manual:

$$J_{soil(pc)} = \frac{C_a(z=0,t)}{\left[\left(w / D_a\right) + \int_w^{hcan} dz / K_z\right]}$$

(Eq. C5-7)

Based primarily upon Mehlenbacher and Whitfield 1977, the PRZM3 Manual provides equations for estimating the vertical dispersivity constant $K_z(z)$ as a function of height z within the plant canopy. The function appears to be sufficiently complex to require numerical integration of the integrals in equations C5-5 through C5-7.

For foliarly applied pesticides, PRZM3 assumes that the flux through the plant canopy is due to the sum of the flux from the soil and the flux from the plants:

$$J_{tot(pc)}(t) = J_{soil(pc)}(t) + J_{pl(pc)}(t) \quad \text{(Eq. C5-8)}$$

where

$J_{tot(pc)}$ = total flux through the plant canopy from soil and plants

$J_{soil(pc)}$ = flux from the soil through the plant canopy

$J_{pl(pc)}$ = flux from plants through the plant canopy

For foliarly applied pesticides, PRZM 3 assumes that the volatilization flux per unit field area from pesticide treated leaves through the plant canopy is given by:

$$J_{pl(pc)}(t) = K_{fv} m_{pl}(t)$$ (Eq. C5-9)

where

$J_{pl(pc)}(t)$ = flux through the plant canopy from plants (g/cm^2*day)

K_{fv} = foliar volatilization rate constant (1/day)

$m_{pl}(t)$ = total mass of pesticide on/in plants per unit field area (g/cm^2 of field))

Substituting equation C5-8 for $J_{tot(pc)}$ into equation C5-1 for J and assuming the flux is independent of z within the canopy, separating variables in equation C5-1, integrating it from C(z) to C(z=h_{can}) = 0 and from any height z within the canopy to z = h_{can}, and rearranging gives the following equation for the concentration within the canopy at any height z:

$$C(z,t) = \left[J_{soil(pc)}(t) + J_{pl(pc)}(t) \right] \bullet \int_{z}^{hcan} dz / K_z$$ (Eq. C5-10)

PRZM3 assumes that the concentration within the plant canopy changes linearly such that the average concentration within the plant canopy is assumed to be approximately equal to the concentration at a height of approximately 50% of the canopy height. Therefore, to approximate the average concentration within the plant canopy for foliarly applied pesticides, PRZM3 substitutes z = 0.5 h_{can} into equation B5-10 to give the concentration within the plant canopy at 50% of the canopy height:

$$C(z = 0.5h_{can}, t) = \left[J_{soil(pc)}(t) + J_{pl(pc)}(t) \right] \bullet \int_{0.5hcan}^{hcan} dz / K_z \quad \text{(Eq. C5-11)}$$

where

$J_{pl(pc)}$ is given by equation C5-9

Equation C5-11 may provide only a somewhat crude approximation of the average concentration within the canopy because it is based upon assumptions that may not be entirely correct. The derivation of equation C5-10 (presumably from which equation C5-11 in PRZM 3 is derived) is based in part upon assuming that $J_{soil(pc)}(t)$ and $J_{pl(pc)}(t)$ are constant with respect to the height z within the canopy thereby allowing them to be treated as constants in integrating equation C5-1 with respect to z. Equation C5-9 (taken from PRZM3) gives an assumed constant flux with respect to the height z within the canopy from the plants through the plant canopy. In reality, the flux from the plants through the plant canopy may increase with height z within the canopy and therefore be a function of z. The reason is that plant leaves and/or other plant tissues above any given height z within the canopy are unlikely to contribute to the upward flux at that height. On the other hand, the flux at any given height z is likely to be a cumulative flux from all of the leaves below z.

Another possible problem with using equation C5-11 is the assumption that the concentration at half the canopy height is approximately equal to the height averaged concentration within the canopy. That approximation is based upon the assumption that the concentration changes linearly within the canopy such that dC/dz = constant. However, equation C5-1 indicates that dC/dz within the canopy will not be constant unless both the flux and vertical dispersivity coefficient are constant with respect to z. As previously discussed, it is possible that the flux from plants is a function of z for foliarly

applied pesticides. However, even if the flux could be assumed to be independent of z, the dispersivity coefficient would still be a function of z (as indicated in the PRZM manual). Consequently, it may be more appropriate to actually compute the height averaged concentration within the canopy with the following equation than to assume that it is approximately equal to $C(z=0.5h_{can},t)$:

$$\text{Height Averaged } C_a(t = t') = \frac{\int_0^{hcan} C_a(z, t = t')dz}{h_{can}} \quad \text{(Eq. C5-12)}$$

C5.3: Foliar Volatilization Equation in Plant Model (Trapp and Matthies 1995, 1997) and Relationship to Volatilization Rate Constant in PRZM 3 Equation

Trapp and Matthies (1995, 1997) have developed the PLANTX/PLANT models for estimating chemical residues in plants. The equation used in PLANTX/PLANT for estimating the rate of mass loss from plant leaves due to volatilization is (except for a sign change to reflect volatilization rather than deposition) as follows:

$$\left(\frac{dm}{dt}\right)_{volatilization} = A_{pl}\, g\left[\left(C_L / K_{LA}\right) - C_a\right] \quad \text{(Eq. C5-13)}$$

where

A_{pl} = leaf surface are (m^2)

g = conductance (m/s)

C_L = concentration in leaves (kg/m^3)

C_A = concentration in air (kg/m^3)

K_{LA} = leaf to air equilibrium partition coefficient = K_{LW}/K_H

and where

K_H = dimensionless Henry's Law constant

K_{LW} = leaf to water equilibrium partition coefficient

Assuming that C_a is << than C_L/K_{LA}, equation C5-13 from Trapp and Matthies (1995, 1997) can be approximated by:

$$\left(\frac{dm}{dt}\right)_{volatilization} = A_{pl}\, g\left(C_L / K_{LA}\right) \qquad \text{(Eq. C5-14)}$$

Recall that equation C5-9 provided in PRZM 3 for the flux from plants through the canopy is in g/cm^2 field*day. Multiplying both sides of equation C5-9 by the area of the field gives a PRZM 3 based version of the rate of volatilization loss from plants in g/day:

$$\left(\frac{dm}{dt}\right)_{volatilization} = A_s K_{fv} m_{pl}(t) \qquad \text{(Eq. C5-15)}$$

Because equations C5-14 and C5-15 both give the rate of volatilization from plants, the right sides of the equations can be equated and solved for the volatilization rate constant used in PRZM 3:

$$K_{fv} = g / \left(T_L K_{LA} \right)$$ (Eq. C5-16)

where

g = conductance (m/s)

T_L = leaf thickness

K_{LA} = leaf to air equilibrium partition coefficient = K_{LW}/K_H

Methods for estimating K_{LA} and g are discussed by Riederer (1995).

C5.4: Volatilization from Water

Volatilization rates from water typically increase with increasing Henry's Law constant, water flow, wind speed, and temperature and with decreasing molecular weight and water depth [Schwarzenbach, Gschwend, and Imboden (1993) and by Thomas (1990)].

Based upon the two film (stagnant air/stagnant water films) model of Liss and Slater as cited by Thomas (1990), the volatilization flux of a chemical from surface water is given by:

$$J_{w \leftrightarrow a} = K_{w \leftrightarrow a} \left[C_w (z = w_w) - [C_a (z = w_a) / K_H] \right]$$ (Eq. C5-17)

where

J_{wv} = volatilization flux of the pesticide from water (g/cm^2*sec)

K_{wa} = volatilization mass transfer coefficient (cm/sec)

K_H = Dimensionless Henry's Law constant

C_w = pesticide concentration in water just below the stagnant water film (g/cm^3)at z = $-w_w$

C_a = pesticide concentration in air just above the stagnant air film at z = w_a

w_a = width of stagnant air layer

w_w = width of stagnant water layer

The Henry's Law constant for a chemical can be approximately estimated by the ratio of the chemical's vapor pressure to its aqueous solubility. Measured and/or estimated values of Henry's Law constant are presented for numerous pesticides in the ARS/USDA and OPP fate property databases.

The volatilization mass transfer coefficient rate constant K_{w-a} is given by (Thomas 1990):

$$K_{w\leftrightarrow a} = \frac{k_w k_g K_H}{k_g K_H + k_w} \quad \text{(Eq. C5-18)}$$

where

k_w = water exchange coefficient (cm/s)

k_g = air exchange coefficient (cm/sec)

Equations for estimating the water exchange coefficient k_w and the air exchange coefficient k_g are presented in detail by Schwarzenbach, Gschwend, and Imboden (1993) and Thomas (1990). All of the equations depend upon the chemical's molecular diffusivity in air (D_a)or water (D_w). Most are a function of water exchange or air exchange

coefficients for reference chemicals such as O_2, CO_2, and water vapor. Most also depend upon wind velocity and/or water velocity consistent with observed increases in volatilization rates with increasing air and/or water flow.

Based upon a compilation of empirical relationships in the literature, Schwarzenbach, Gschwend, and Imboden (1993) recommend using the following equations to estimate the air k_a and water k_w exchange coefficients for slowly flowing waters such as lakes:

$$k_a = \left(0.2u_{10} + 0.3\right)\left(D_{w(chemical)} / D_{w(oxygen)}\right)^a \quad \text{(Eq. C5-19)}$$

$$k_w = \left[\left(4 \bullet 10^{-5}\right)u_{10}^2 + \left(4 \bullet 10^{-4}\right)\right]\left(D_{w(chemical)} / D_{w(oxygen)}\right)^b \quad \text{(Eq. C5-20)}$$

where

k_a = air exchange coefficient (cm/s)

k_w = water exchange coefficient

u_{10} = wind velocity 10 m above the air/water interface

D_a = molecular diffusivity in air

D_w = molecular diffusivity in water

α = empirical coefficient ranging from 0.5 to 1

β = empirical coefficient

Possible default values for α and β are 0.67 and 0.5, respectively, based upon laboratory studies by Mackay and Yeun (1983) as cited by Schwarzenbach, Gschwend, and Imboden

(1993). A mean value of 0.57 $\pm$ 0.15 for β was reported by Holmen and Liss (1984) as cited by Schwarzenbach, Gschwend, and Imboden (1993).

Equations for estimating the molecular diffusivities of chemicals in air (D_a) and in water (D_w) are discussed in detail by Schwarzenbach, Gschwend, and Imboden (1993) and by Thomas (1990). The unknown molecular diffusivities of a chemical in air and in water can be approximately estimated from its molecular weight and the known molecular diffusivities and molecular weight of a reference compound from the following equations (Schwarzenbach, Gschwend, and Imboden 1990):

$$D_{a(chemical)} = D_{a(reference)} \left(MW_{reference} / MW_{chemical} \right)^{0.5} \quad \text{(Eq. C5-21)}$$

$$D_{w(chemical)} = D_{w(reference)} \left(MW_{reference} / MW_{unknown} \right)^{0.5} \quad \text{(Eq. C5-22)}$$

To avoid confusion, note that while the terminology used above is similar to the List and Slater terminology as reported by Thomas (1990), Schwarzenbach, Gschwend and Imboden (1993) refer to the volatilization mass transfer coefficient $K_{w\text{-}a}$, the water exchange coefficient k_w, and the air exchange coefficient k_a (all in velocity units of cm/sec) as the total transfer velocity v_{total}, the stagnant water layer transfer velocity v_w, and the stagnant air layer transfer velocity v_a, respectively.

APPENDIX C6

PESTICIDE DISSIPATION KINETICS IN ENVIRONMENTAL MEDIA

This generic section on dissipation kinetics is applicable to various types of environmental media, but the concepts covered are most frequently used for soil. The concentrations referred to are generally experimental concentrations for a given bulk environmental medium, not individual phases. For example, soil concentration is for the bulk soil, not for the individual pore water, soil solids and pore air concentrations.

C6.1 Single Rate Constant Pseudo First Order Kinetics Linear Regression Model

Dissipation kinetics in environmental media are often analyzed assuming pseudo first order kinetics because of the simplicity involved and because most computer models used to estimate pesticide concentrations in environmental media require as input, pseudo first order rate constants.

The rate of concentration change with time for a chemical following pseudo first order dissipation kinetics in/on soil, foliage, water, or air, is given by

$$\frac{dC_b}{dt} = -k_b C_b$$

(Eq. C6-1)

where

C_b = bulk chemical concentration in/on soil, foliage, water, or air (in units of mass chemical/mass of dry media for soil or foliage and mass chemical/volume of media for water or air)

k_b = pseudo-first order bulk rate constant (in units of 1/time)

A pseudo-first order constant is not an actual first order rate constant because it has incorporated into it one or more parameters (such as biomass, irradiation intensity, or pH) which can change with time. However, when those parameters approximately remain constant over the duration of the study or model simulation, a pseudo first order rate constant approximates an actual first order rate constant.

Integrating equation C6-1 gives the bulk concentration of the chemical in soil, foliage, water or air as a function of time assuming the chemical dissipates with pseudo first order kinetics:

$$C_b(t) = C_{b0} e^{-k_b t}$$

(Eq. C6-2)

Data can be fit to a single rate constant pseudo first order kinetics model using linear or non-linear regression. If linear regression is used, equation C6-2 above is ln transformed to a linear form, and the rate constant is determined by simple linear regression as follows. Taking the natural logarithm of both sides equation C6-2 gives:

$$\ln C_b(t) = \ln C_{b0} - k_b t$$

(Eq. C6-3)

The ln transformed bulk concentration ($\ln C_b$) is then plotted and linearly regressed against the time t as shown in Figure C6-1. The estimated pseudo first order dissipation rate constant is equal to the slope of the regression line. Although $\ln C_{b0}$ is generally known, a more accurate estimate of the slope and therefore the rate constant k can generally be obtained if the intercept is computed rather than forced through $\ln C_{b0}$.

By substituting $C/C_{b0} = 0.5$ and $t=t_{1/2}$ in to equation C6-3 and rearranging, it can be shown that the half-life $t_{1/2}$ and pseudo first order rate constant k are related by:

$$t_{1/2} = \ln 2 / k_b \quad \text{or} \quad k_b = \ln 2 / t_{1/2} \qquad \text{(Eq. C6-4a,b)}$$

There may be more than one pathway by which a chemical dissipates. For chemicals following pseudo first order dissipation kinetics, the overall pseudo first order dissipation rate constant k is given by:

$$k = \sum_{i=1}^{i=n} k_i$$

(Eq. C6-5)

where

k_i = pseudo first order rate constant for dissipation pathway i

n = number of dissipation pathways contributing to the overall dissipation

In cases where the dissipation of a chemical fits a single rate constant pseudo first order kinetics model over the entire study duration, a plot of the natural logarithm of the concentration (ln C) versus time will be approximately linear.

Unfortunately, the dissipation of a chemical often does not fit a single rate constant pseudo first kinetics model very well over the entire duration of the study. In such cases, a plot of the natural logarithm of the concentration (ln C) versus time will not be linear. It will often appear temporally "biphasic" with the first phase having a substantially steeper slope than the second phase (Figure C6-1). The reasons for observed "biphasic" behavior may vary and have not been firmly established. Some reasons may include some of the

chemical being gradually and irreversibly imbedded into the environmental media to a sufficient extent to inhibit dissipation processes, declines in microbiological activity over time, and the complexity of some dissipation processes such as volatilization.

C6.2 Biphasic Pseudo First Order Kinetics Linear Regression Model

Biphasic data can be fit to a number of different regression models. The most commonly used one is the biphasic linear regression model in which ln C is plotted against time. The plot is essentially divided by eye into an initial and subsequent phase representing different slopes. Linear regression of ln C versus time is then performed on both phases separately to estimate a rate constant and corresponding half-life for each phase. An example is presented in Figure C6-1, where the ln concentration versus time plot has been divided into an initial phase from $t = 0$ to $t = T_1$ and a second phase from $t = T_1$ to the end of the study at $t = T_2$. The overall pseudo first order rate constants k_1 and k_2 (one for each phase) are computed from the slopes of linear regressions performed separably on ln C versus time for the first and second phases.

The half-life corresponding to each rate constant can be computed from equation C6-4a, and is generally reported along with the duration of each phase. Note, however that the half-life corresponding to each rate constant and the duration of the phase over which the rate constant is applicable are not the same thing. The first phase can be shorter, comparable to, or longer than the initial half-life corresponding to the first phase rate constant. Likewise, the second phase can be shorter, comparable to, or longer than the second half-life corresponding to the second phase rate constant.

The resulting estimates of pseudo first order rate constants for each phase can in some cases also be used as input to some computer models. However, the biphasic regression model itself is not very realistic because it assumes the shift from one slope to another is essentially instantaneous whereas a more gradual shift in the slope is generally observed.

Consequently, it is sometimes difficult and somewhat arbitrary to determine when the first phase ends and the second phase begins.

C6.3 Non-linear Regression Models

Whenever the data do not fit a single rate constant pseudo first order kinetics linear regression model very well over the entire duration of a study, there are a large number of alternate non-linear regression models which can also be fit to kinetics data. Fortunately, the widespread availability of relatively low cost spreadsheets and statistical software has made performing non-linear regression more routine than in the past. Several of many possible alternate non-linear regression models are discussed below.

Non-linear regression models which can be used to fit observed chemical dissipation data include applying non-linear regression to the untransformed form of the single rate constant pseudo first order kinetics model, an empirical n order model, a reversible equilibrium 2 compartment model, a reversible non-equilibrium 2 compartment model, and a non-reversible non-equilibrium 2 compartment model. All of those models except the empirical n order model are also pseudo first order kinetics models.

C6.4 Single Rate Constant Pseudo First Order Kinetics Non-Linear Regression Model

As previously discussed, the single rate constant pseudo first order kinetics model $C_b(t) = C_{b0}\exp(-k_b t)$ is often ln transformed to a linear form and the data is analyzed using linear regression. In addition to allowing for simple linear regression, the ln transformation helps to stabilize any systematic increase in residuals with increasing concentration. A ln transformation also results in higher (and therefore more conservative) estimates of the half-life than non-linear regression. Consequently, ln transformations to a linear form followed by linear regression are sometimes recommended over non-linear regression on the untransformed data, particularly for data that fit reasonably well to a pseudo first order

kinetics model. However, in cases where the fit is not good using ln transformations and linear regression, non-linear regression on untransformed dat sometimes gives a better fit of the data to the single rate constant pseudo first order kinetics model. In addition, if other non-linear regression models are fit to the data, fitting the data to the single rate constant pseudo first order kinetics model using non-linear regression is more appropriate for comparative purposes.

The r^2 (0.846) for the non-linear regression of the untransformed hypothetical data set is greater than the r^2 (0.740) for the linear regression of the ln transformed data. The best fit linear regression line for the pseudo first order kinetics model is plotted in Figure C6-1 for comparison to the two best fit linear regression lines for the biphasic model. The best fit non-linear regression line for the pseudo first order kinetics model is plotted in Figure C6-2 for comparison to best fit lines for other non-linear regression models. The estimate half-life based upon the non-linear regression (15 days) is substantially shorter than the estimated half-life (32 days) based upon the linear regression of ln transformed data.

C6.5 Empirical N-Order Kinetics Non-Linear Regression Model

One empirical approach is to assume n-order kinetics:

$$\frac{dC_b}{dt} = -k_b C_b^n$$

(Eq. C6-6)

Integrating the above equation and solving for the concentration C gives:

$$C_b(t) = \left[C_{bo}^{(1-n)} - (1-n)k_b t\right]^{[1/(1-n)]}$$ (Eq. C6-7)

The rate constant k_b and the order n can be estimated by non-linear regression of C_b against t. The estimated values of k and n are the ones that minimize the sum of the squared residuals.

The times required for 50%, 75%, and 90% of the initial concentration to dissipate (DT50, DT75, and DT90 values) for an n-order kinetics model can be estimated by substituting $C_b = 0.5C_{b0}$, $C_b = 0.25C_{b0}$, and $C_b = 0.1C_{b0}$, respectively, into equation C6-7, and solving it for the time required to reach those levels:

$$DT50 = \left[C_{b0}^{(1-n)} - 0.50C_{bo}^{(1-n)}\right] / k_b(1-n) \quad \text{(Eq. C6-8)}$$

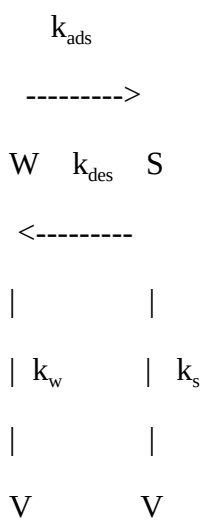
$$DT75 = \left[C_{b0}^{(1-n)} - 0.25C_{b0}^{(1-n)}\right] / k_b(1-n) \quad \text{(Eq. C6-9)}$$

$$DT90 = \left[C_{b0}^{(1-n)} - 0.10C_{b0}^{(1-n)}\right] / k_b(1-n) \quad \text{(Eq. C6-10)}$$

A non-linear regression fitting of the hypothetical data set to the empirical n-order kinetics model gave an initial concentration of 919 (as opposed to 900 monitored), a rate constant of $k = 2.33 \times 10^{-5}$, a reaction order of n = 2.26, and a $r^2 = 0.970$ (compared to $r^2 = 0.846$ and $r^2 = 0.740$ for the non-linear and linear regressions of the pseudo first order kinetics model, respectively). Note that in this example, a best fit initial concentration was computed rather than forcing the regression line through the monitored initial concentration. The best fit non-linear regression line for the n-order kinetics model is plotted in Figure C6-2.

C6.6 Reversible Non-Equilibrium 2 Compartment Non-Linear Regression Model

There are numerous non-equilibrium and equilibrium compartment non-linear regression models that can be fit to "biphasic data". One such model is the reversible non-equilibrium 2 compartment non-linear regression model depicted below:



In the reversible non-equilibrium 2 compartment non-linear regression model depicted above, mass balance derived equations for chemical dissolved in pore water and susceptible to degradation (W - pore water) and chemical reversibly adsorbed to the solid matrix and susceptible to degradation (S - sorbed) are given by:

$$\frac{dC_w}{dt} = \left(k_{des} r_s / q_w\right) C_s - \left(k_w + k_{ads}\right) C_w \quad \text{(Eq. C6-11)}$$

$$\frac{dC_s}{dt} = \left(k_{ads} q_w / r_s\right) C_w - \left(k_s + k_{des}\right) C_s \quad \text{(Eq. C6-12)}$$

where,

C_w = dissolved concentration (mass pesticide/pore water volume)

C_s = reversibly sorbed labile concentration (mass pesticide/mass solid soil or plant matrix)

Θ_w = pore water volume fraction

ρ_s = bulk density of soil or plant (dry weight mass of soil or plant/volume of soil or plant)

k_{ads} = adsorption rate constant

k_{des} = desorption rate constant

k_w = degradation rate constant for chemical dissolved in the pore water

k_s = degradation rate constant for reversibly sorbed chemical

Equations C6-11 and C6-12 must be solved simultaneously because the assumed reversible mass transfer between the 2 compartments causes the concentration in each compartment to be dependent upon the concentration in the other compartment. To solve equations C6-11 and C6-12 simultaneously, equation C6-11 is differentiated with respect to t and multiplied by ($k_s + k_{des}$), equation C6-12 is multiplied by ($k_{des}\rho_s/\Theta_w$), and the modified equations are added to give the following constant coefficient, second order homogeneous differential equation:

$$\frac{d^2 C_w}{dt^2} + D\frac{dC_w}{dt} + FC_w = 0 \qquad \text{(Eq. C6-13)}$$

where,

$$D = k_w + k_s + k_{ads} + k_{des} \qquad \text{(Eq. C6-14)}$$

$$F = k_w k_s + k_w k_{des} + k_s k_{ads} \qquad \text{(Eq. C6-15)}$$

There are 3 different general solutions to equation C6-13 depending on whether $D^2 - 4F$ is > 0, $= 0$, or < 0. As an example, for the most common case where $D^2 - 4F > 0$, the general solution to Equation B1-14 is:

$$C_w(t) = A_w \exp(r_1 t) + B_w \exp(r_2 t) \quad \text{(Eq. C6-16)}$$

where

$$r_1 = \left[-D + \left(D^2 - 4F \right)^{1/2} \right] / 2 \quad \text{(Eq. C6-17)}$$

$$r_2 = \left[-D - \left(D^2 - 4F \right)^{1/2} \right] / 2 \quad \text{(Eq. C6-18)}$$

Specific solutions of equation C6-13 for which the coefficients in the general solution (A_w and B_w in equation C6-16) are specified depend upon the initial conditions. Consider the following initial conditions at t=0:

$$C_w = C_{w0} \qquad C_s = 0 \quad \text{(Eq. C6-19)}$$

$$\frac{dC_w}{dt} = -\left(k_w + k_{ads} \right) C_{w0} \quad \text{(Eq. C6-20)}$$

Under those initial conditions, the coefficients A_w and B_w are:

$$A_w = \frac{C_{w0}\left(k_w + k_{ads} + r_2\right)}{\left(r_2 - r_1\right)} \quad \text{(Eq. C6-21)}$$

$$B_w = \frac{C_{w0}\left(k_w + k_{ads} + r_1\right)}{\left(r_1 - r_2\right)} \quad \text{(Eq. C6-22)}$$

Substituting equation C6-16 for C_w into equation C6-12 and using integrating factors to solve equation C6-12 for C_s with the initial condition $C_{s0} = 0$ gives:

$$C_s(t) = \left[\frac{k_{ads} q_w A_w}{r_s\left(r_1 + k_s + k_{des}\right)}\right]\left[\exp\left(r_1 t\right) - \exp[-(k_s + k_{des})t]\right] + \left[\frac{k_{ads} q_w B_w}{r_s\left(r_2 + k_s + k_{des}\right)}\right]\left[\exp\left(r_2 t\right) - \exp[-\left(k_s + k_{des}\right)t]\right] \quad \text{(Eq. C6-23)}$$

For a 2 compartment (pore water, solid matrix) model, the total bulk concentration $C_b(t)$ is given by:

$$C_b(t) = \left(q_w / r_s\right) C_w(t) + C_s(t) \quad \text{(Eq. C6-24)}$$

For a reversible non-equilibrium 2 compartment model, $C_w(t)$ and $C_s(t)$ are given by equations C6-16 and C6-23, respectively.

In theory, bulk concentration data $C_b(t)$ can be non-linearly regressed against sampling time t to determine numerous regression coefficients including one or more initial concentrations (depending upon the initial condition) and the pseudo first order rate constants k_w, k_s, k_{ads} and k_{des}. In reality, the accurate determination of ≥ 5 regression coefficients would require more numerous data points than are normally available. In addition, most computer models assume adsorption/desorption equilibrium and do not provide for adsorption and desorption rate constant inputs.

C6.7 Non-Reversible Non-Equilibrium 2 Compartment Model

This model is conceptually similar to the reversible non-equilibrium model, but in this model k_{des} is assumed to be zero such that there is no desorption from the solid matrix to the pore water. Setting $k_{des} = 0$ in equations B1-12 and B1-13 reduces them to:

$$\frac{dC_w}{dt} = -\left(k_w + k_{ads}\right)C_w$$

(Eq. C6-25)

$$\frac{dC_s}{dt} = \left(k_{ads}q_w / r_s\right)C_w - k_s C_s$$

(Eq. C6-26)

Because the pore water and the solid matrix are not reversibly coupled in this non-reversible non-equilibrium 2 compartment model, equations C6-25 and C6-26 do not have to be solved simultaneously. Although the concentration in the solid matrix is dependent on the concentration in the pore water, the concentration in the pore water is not

dependent on the concentration in the solid matrix in a non-reversible non-equilibrium model where there is no assumed desorption from the solid matrix.

Solving equation C6-25 for C_w with the initial condition $C_w(t=0) = C_{w0}$ gives:

$$C_w(t) = C_{w0}(t)\exp[-(k_w + k_{ads})t] \quad \text{(Eq. C6-27)}$$

Substituting equation C6-27 for C_w into equation C6-26 and using integrating factors to solve equation C6-26 for C_s with the initial condition $C_{s0} = 0$ gives:

$$C_s(t) = \left[\frac{k_{ads} q_w C_{w0}}{r_s\left(k_s - k_w - k_{ads}\right)}\right]\left[\exp[-(k_w + k_{ads})t] - \exp(-k_s t)\right] \quad \text{(Eq. C6-28)}$$

For a 2 compartment model, recall that the total bulk concentration $C_b(t)$ is given by equation C6-24. For a non-reversible nonequilibrium 2 compartment model, $C_w(t)$ and $C_s(t)$ are given by equations C6-27 and C6-28, respectively.

Substituting equation C6-27 for $C_w(t)$ and equation C6-28 for $C_s(t)$ into equation C6-24 for the bulk concentration and grouping terms gives a biexponential form for $C_b(t)$:

$$C_b(t) = \left[\frac{q_w}{r_s} + \frac{k_{ads} q_w}{r_s\left(k_s - k_w - k_{ads}\right)}\right] C_{w0} \exp[-(k_w + k_{ads})t] - \left[\frac{k_{ads} q_w}{r_s\left(k_s - k_w - k_{ads}\right)}\right] C_{w0} \exp(-k_s t)$$

(Eq. C6-29)

The bulk concentration data $C_b(t)$ can be non-linearly regressed against sampling time t to determine the regression coefficients including one or more initial concentrations (depending upon the initial condition) and the pseudo first order rate constants k_w, k_s, and k_{ads}. The estimated values of k_w, k_s and k_{ads} are the ones that minimize the sum of the squared residuals.

A non-linear regression fitting of the hypothetical data set to the non-reversible non-equilibrium 2 compartment model gave an initial pore water concentration of $C_{w0} = 4010$, an adsorption rate constant of $k_{ads} = 1.90 \text{ X } 10^{-2}$, a degradation rate constant in the pore water of $k_w = 8.48 \text{ X } 10^{-2}$, a degradation rate constant in the solid matrix of $k_s = 0$, and a $r^2 = 0.988$ (compared to $r^2 = 0.846$ and $r^2 = 0.740$ for the non-linear and linear regressions of the pseudo first order kinetics model, respectively). The best fit non-linear regression line for the non-reversible non-equilibrium 2 compartment model is plotted in Figure C6-2.

C6.8 Reversible Equilibrium 2 Compartment Non-Linear Regression Model

Note that if chemical equilibrium is assumed between the pore water and solid matrix such that $(k_{des}\rho_s/\Theta_w)C_s = (k_{ads})C_w$ and $(k_{ads}\Theta_w/\rho_s)C_w = k_{des})C_s$, the mass balance equations for each are:

$$\left(\frac{q_w M_s}{r_s}\right)\frac{dC_w}{dt} = -\left(\frac{q_w M_s k_w}{r_s}\right)C_w$$ (Eq. C6-30)

$$M_s \frac{dC_s}{dt} = -M_s k_s C_s$$ (Eq. C6-31)

where

C_w = dissolved concentration (mass pesticide/pore water volume)

C_s = reversibly sorbed labile concentration (mass pesticide/mass solid soil or plant matrix)

Θ_w = pore water volume fraction

ρ_s = bulk density of soil or plant (dry weight mass of soil or plant/volume of soil or plant)

k_w = degradation rate constant for chemical dissolved in the pore water

k_s = degradation rate constant for reversibly sorbed chemical

Assuming chemical equilibrium:

$$C_s = K_d C_w$$ (Eq. C6-32)

Substituting equation C6-32 for C_s into equation C6-31 gives:

$$M_s K_d \frac{dC_w}{dt} = -M_s K_d k_s C_w$$ (Eq. C6-33)

Adding equations C6-30 and C6-32 together and rearranging gives a total mass balance derived equation in terms of the pore water alone:

$$\frac{dC_w}{dt} = -k_m C_w \quad \text{(Eq. C6-34)}$$

where

$$k_m = \frac{q_w k_w + r_s k_s}{q_w + r_s K_d} \quad \text{(Eq. C6-35)}$$

Solving equation C6-34 with the initial condition $C_w(t=0) = C_{w0}$ gives

$$C_w(t) = C_{w0} \exp(-k_m t)$$

(Eq. C6-36)

Recall that in a 2 compartment model (pore water, solid matrix), the bulk concentration is given by equation C6-24. Substituting equation C6-35 for k_m into equation C6-36 for C_w, and equations C6-36 for C_w and equilibrium equation C6-32 for C_s in equation C6-24 for C_b gives:

$$C_b(t) = \left[\left(q_w / r_s\right) + K_d\right] C_{w0} \exp\left[-\left(\frac{q_w k_w + r_s k_s}{q_w + r_s K_d}\right) t\right] \quad \text{(Eq. C6-37)}$$

The bulk concentration data $C_b(t)$ can be non-linearly regressed against sampling time t to determine the regression coefficients including one or more initial concentrations (depending upon the initial condition), the pseudo first order rate constants k_w and k_s. The solid matrix/water equilibrium partition coefficient K_d can also be included as an additional regression coefficient or entered as a constant based upon the results of adsorption/desorption batch equilibrium studies. The estimated values of k_w, k_s and K_d are the ones that minimize the sum of the squared residuals.

When equation C6-37 is simplified, it is in the same form as equation C6-2 for the single (bulk concentration) rate constant pseudo first order kinetics model where

$$C_{b0} = \left[\left(q_w / r_s\right) + K_d\right] C_{w0} \qquad \text{(Eq. C6-38)}$$

and

$$k_b = k_m = \frac{q_w k_w + r_s k_s}{q_w + r_s K_d} \qquad \text{(Eq. C6-39)}$$

Therefore, when equation C6-37 for the reversible equilibrium 2 compartment non-linear regression model is simplified to be expressed in terms of the initial bulk concentration and an overall bulk concentration rate constant, it is identical to equation C6-2 for the single constant pseudo first order kinetics non-linear regression model. Consequently, equation C6-37 cannot provide any better fit to biphasic data than equation C6-2. However, unlike performing non-linear regression on equation C6-2, performing non-linear regression on equation C6-37 can provide separate estimates of the water (k_w) and solid matrix (k_s)

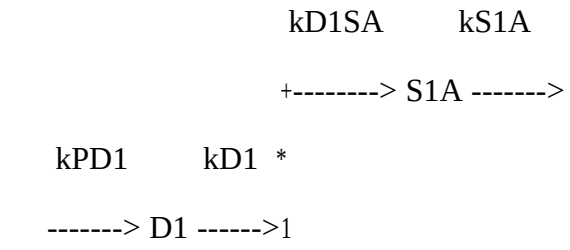
degradation rate constants as well as (if desired) for the solid matrix/water equilibrium partition coefficient K_d.

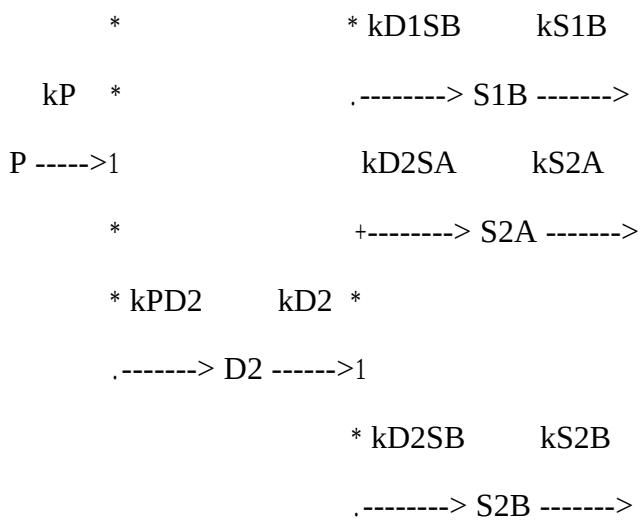
That is an important difference because some computer models such as PRZM require as input, separate values of k_w and k_s instead of k_b. However, in generating estimates of the regression coefficients, appropriate constraints should be placed on them such as setting all ≥ 0 and setting $k_w > k_s$. If only k_b is determined with the use of equation C6-2 instead of equation C6-37, default options such as assuming that both k_w and k_s are equal to k_b have been proposed. However at least in some cases, the validity of such assumptions may be poor.

C6.9 Formation and Decline Rate Constants for Major Degradates

Estimates of rate constants for the formation and decline of major degradates can be input into computer models to simulate the formation and decline of the degradates. Assuming pseudo first order kinetics, estimates of rate constants for the formation and decline of major degradates can sometimes be obtained by using nonlinear regression to fit time series data to the exponential solutions to the mass balance differential equation for each degradate.

An example is as follows: Consider a combination series and parallel degradation pathway in which the parent chemical P simultaneously degrades to primary degradates D_1 and D_2 which in turn each simultaneously degrade to secondary degradates S_{1A} and S_{1B}, and S_{2A} and S_{2B}, respectively:





Since the parent P is undergoing parallel degradation, its overall rate constant is equal to the sum of the formation rate constants for the primary degradates D_1 and D_2 (e.g., $k_P = k_{PD1} + kP_{D2}$). Since the primary degradates are also both undergoing parallel degradation, their overall decline constants are each equal to the sum of the formation constants for the secondary degradates they form (e.g., $k_{D1} = k_{D1SA} + k_{D1SB}$ and $k_{D2} = k_{D2SA} + k_{D2SB}$).

To determine formation and decline rate constants for the primary degradate D_1 and the secondary degradate S_{1A}, generate for the parent and each degradate a mass balance differential equation describing its change in concentration with time:

$$\frac{d[P]}{dt} = -k_p t \quad \text{(Eq. C6-40)}$$

$$\frac{d[D_1]}{dt} = k_{PD1}[P] - k_{D1}[D_1] \quad \text{(Eq. C6-41)}$$

$$\frac{d[S_{1A}]}{dt} = k_{D1SA}[D_1] - k_{S1A}[S_{1A}]$$ (Eq. C6-42)

At t = 0, $[P] = [P]_0$, $[D_1] = 0$, and $[S_{1A}] = 0$

The solutions to differential Equations C6-40 through C6-42 with the above stated initial conditions are as follows:

$$[P] = [P]_0 \exp(-k_P t)$$ (Eq. C6-43)

$$[D_1] = \left[\frac{k_{PD1}[P]_0}{\left(k_{D1} - k_P\right)}\right]\left[\exp(-k_P t) - \exp(-k_{D1} t)\right]$$ (Eq. C6-44)

$$[S_{1A}] = A\left[\exp(-k_P t) - \exp(-k_{S1A} t)\right] - B\left[\exp(-k_{D1} t) - \exp(-k_{S1A} t\right]$$ (Eq. C6-45)

where

$$A = \frac{k_{D1SA} k_{PD1}[P]_0}{\left(k_{D1} - k_P\right)\left(k_{S1A} - k_P\right)}$$ (Eq. C6-46)

$$B = \frac{k_{D1SA} k_{PD1} [P]_0}{\left(k_{D1} - k_P\right)\left(k_{S1A} - k_{D1}\right)}$$ (Eq. C6-47)

Note that concentrations should be in units of moles/volume rather than mass/volume to maintain the correct stoichiometric relationship between the parent, primary degradates, and secondary degradates.

The overall rate constant for the parent k_P can be calculated from the non-linear regression fitting of equation C6-43 to a plot of [P] data versus time t. The formation and decline rate constants for primary degradate D_1 (k_{PD1} and k_{D1}, respectively) can be determined from the non-linear regression fitting of equation C6-44 (after substitution of the value for k_P into the equation) to a plot of $[D_1]$ versus time t. The formation and decline rate constants for the secondary degradate S_{1A} (k_{D1SA} and k_{S1A}, respectively) can be determined from the non-linear regression fitting of equation C6-45 (after substitution of the values for k_P, k_{PD1}, and k_{D1} into the equation) to a plot of $[S_{1A}]$ versus time t.

An identical procedure could be used to determine formation and decline rate constants for the other primary and secondary degradates. In addition, alternate degradation pathways could be handled with comparable procedures. If numerical methods of solution are used, equations for non-first order processes can also be developed.

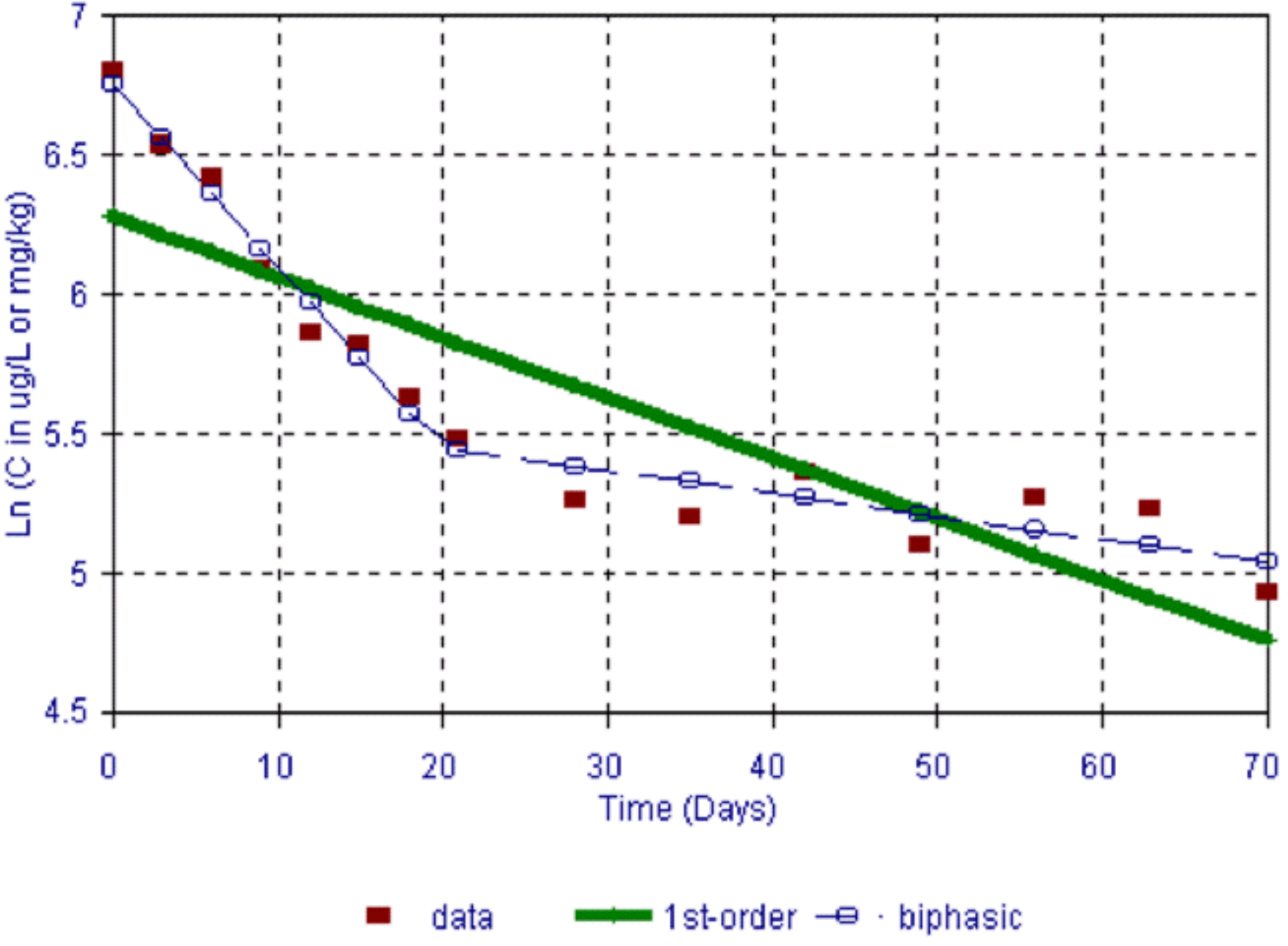


Figure C6-1. Linear regression line fits to ln concentration versus time data.

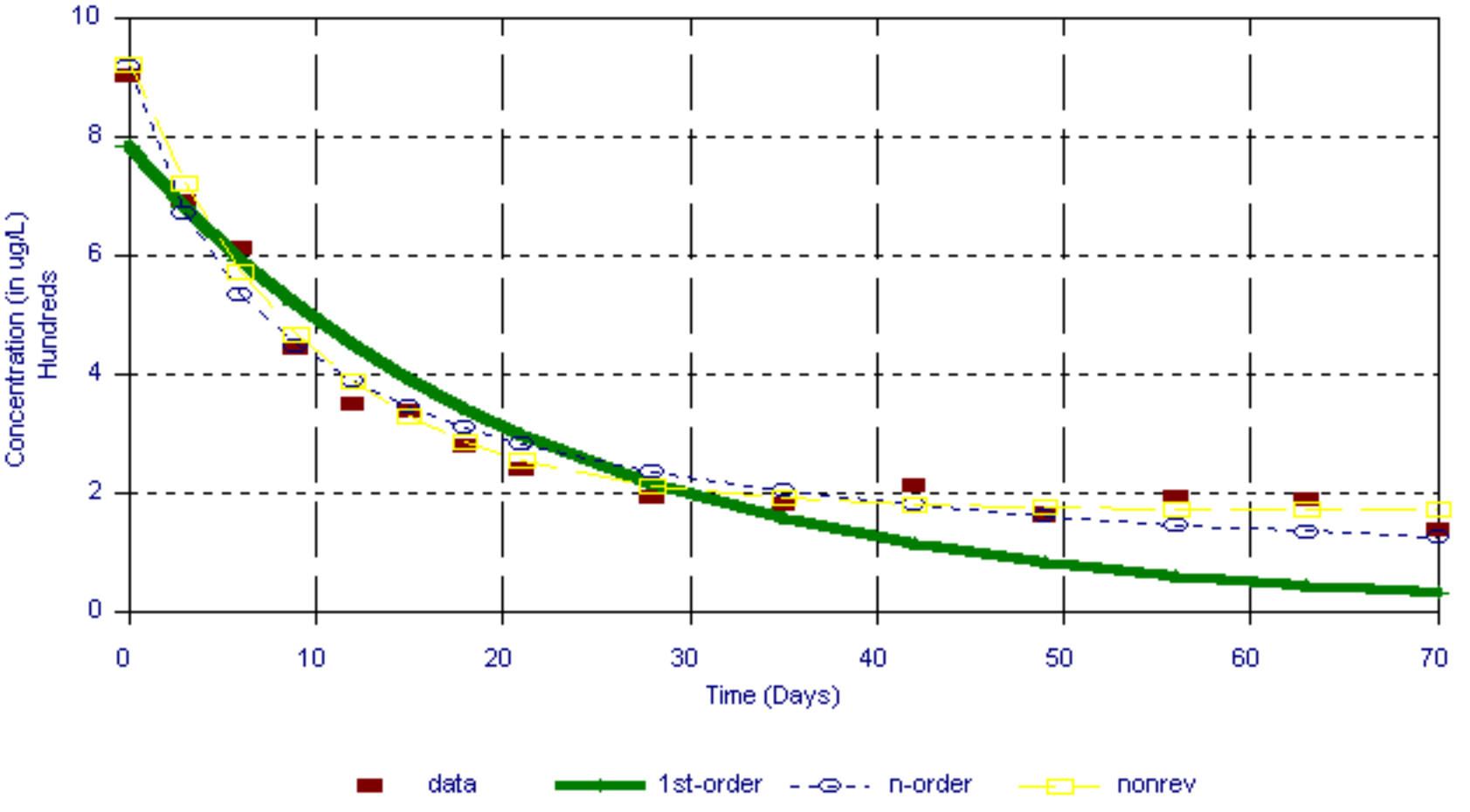


Figure C6-2. Non-linear regression line fits to concentration versus time data.

APPENDIX C7

U.S. EPA/OPP REQUIRED FATE AND/OR RESIDUE STUDIES

The Environmental Fate and Effects Division (EFED) and the Health Effects Division (HED) of the Office of Pesticide Programs (OPP) of the U.S. EPA require pesticide registrants to submit numerous pesticide studies. The results of the studies help OPP evaluate the potential exposure and risks to non-target organisms and humans associated with pesticide use. Studies of interest with respect to terrestrial exposure assessments include laboratory fate studies, field fate and residue studies, and ecological residue/effects studies.

The core environmental fate data requirements U.S. EPA/OPP/EFED imposes for the registration of pesticides in the U.S. (CFR 158) depend primarily upon the uses of the pesticide. The criteria for imposing conditionally required studies depend upon other factors as well including the physical/chemical, fate and (in some cases) the toxicity of the parent and/or major degradates. Both core and conditionally required studies are heavily oriented toward soil and water.

Pesticide residue data in the field are obtained from EFED required fate field studies, EFED required ecological residue/effects field studies, and from HED required residue studies.

C7.1 OPP/EFED Required Laboratory Fate Studies

EFED required laboratory transformation studies (study requirements vary depending upon the pesticide's use and/or characteristics) include abiotic hydrolysis, direct photolysis in water, photodegradation on soil, photodegradation in air, aerobic soil metabolism,

anaerobic soil metabolism, aerobic aquatic metabolism, and anaerobic aquatic metabolism. Laboratory transformation studies are conducted under controlled conditions generally using the radiolabeled active ingredient of one or more pesticide products. Laboratory transformation studies determine the transformation pathways of the parent and major degradates, the decline rates of the parent and the formation and decline rates of major degradates. Parental decline rates are reported as half-lives and/or DT50s. A major degradate is defined as one accounting for $\geq$ 10% of applied or present at > 0.01mg/kg (whichever is lower) at any time during any laboratory study.

EFED required laboratory mobility studies (study requirements vary depending upon the pesticide's use and/or characteristics) include adsorption/desorption batch equilibrium, soil column leaching, and volatilization from soil. The adsorption/desorption batch equilibrium study generates Freundlich adsorption and desorption binding constants and exponents for the parent and major degradates. The soil column leaching study determines the mobility of the parent and major degradates in soil columns eluted with 20 or more inches of water. The volatility from soil study determines the flux of pesticides (in mass/time*area) from soil including those incorporated as well as not incorporated into the soil.

The laboratory fish BCF study determines the accumulation and depuration of pesticides and their major degradates in whole fish, edible tissues, and non-edible tissues.

The results of the EFED laboratory fate studies are used for developing input to environmental fate and transport models. The results of laboratory fate studies are also used to develop protocols for conducting field studies.

C7.2 OPP/EFED Required Field Fate Studies

EFED required field fate studies (study requirements vary depending upon the pesticide's use and/or characteristics) include terrestrial field dissipation, aquatic field dissipation, forestry dissipation

Field fate studies are conducted under actual use conditions using one or more formulated pesticide products. In a terrestrial field dissipation study, soil cores up to 90 cm deep are collected at various sampling intervals, segmented at various widths and analyzed for parent and major degradates. Foliage is only rarely sampled. In an aquatic field dissipation study, samples of water to various depths and of sediment to a depth of 5 cm are collected at various sampling intervals and analyzed for the parent and major degradates. In a forestry dissipation study, samples of foliage, leaf litter, soil under leaf litter, exposed soil, standing (pond) water, flowing (stream) water, and sediment from water bodies are sampled at various sampling intervals and analyzed for the parent and major degradates.

In all of the different fate field studies, The dissipation of the parent and formation and decline of major degradates are generally presented tabularly and graphically as concentration versus time series for any environmental compartments for which the number of detects is sufficient to do so. The dissipation of the parent in the various environmental compartments monitored is also characterized by computed half-lives and or DT50s.

The results of field fate studies are typically not used for inputs to models because they reflect the overall dissipation of the chemical from potentially multiple dissipation pathways whereas models generally require separate inputs for different dissipation pathways. However, the results of the EFED field studies are compared to modeling outputs and are used to assess the overall environmental fate of a pesticide and its major degradates resulting from multiple dissipation pathways.

C7.3 Spray Drift Studies and the Spray Drift Task Force (SDTF)

Estimates of spray drift deposition as a function of distance downwind from the application site are necessary to predict residues on/in vegetation as well as on/in soil and in water. Spray drift droplet size laboratory and spray drift field studies are required for outdoor aerial or orchard airblast spray uses. They are also conditionally required for

outdoor ground spray or chemigation in cases where such applications may result in substantial drift.

The Spray Drift Task Force (SDTF) is a consortium of approximately 40 registrants that was formed in 1990 to (A. Jones, Clem, Thurman 1997):

(1) Conduct studies to investigate the affect of tank mixture properties, application equipment, application conditions and meteorological conditions on droplet size spectra and spray drift deposition.

(2) Develop a generic tank mixture property, droplet size distribution and spray drift deposition database that would presumably be independent of the properties of specific active ingredients.

(3) Develop or modify an existing spray drift model for use in supporting pesticide registrations under FIFRA.

The rationale for forming the SDTF was based on literature reviews that indicated (A. Jones, Clem, and Thurman 1997):

(1) Spray drift depends primarily upon the droplet size spectra, meteorological conditions, and application method, equipment, and height.

(2) The droplet size spectra depend in turn primarily upon the properties of the tank mixture, wind shear, and nozzle type, size, angle and operating pressure.

(3) The physical and chemical properties of the active ingredient had negligible effect on the physical properties of the tank mixture, the droplet size distribution, and spray drift.

The results of the SDTF research and the AGDRIFT model developed by the SDTF for estimating spray drift are currently being assessed by OPP and external peer review.

C7.4 EFED Terrestrial Ecological Residue/Effects Studies

Over a number of years, EFED has required and/or received approximately 34 terrestrial ecological residue/effects studies covering 15 pesticides. The studies involve treating fields with maximum allowed numbers of applications and application rates. Various environmental media (including soil, water, vegetation, birds, mammals, and occasionally amphibians) were sampled at various sampling intervals. The samples were analyzed for the parent and occasionally for major degradates as well. Observed effects on non-target organisms were also reported.

C7.5 HED Worker Inhalation Exposure Studies

Inhalation exposure studies are imposed by HED/OPP to determine the inhalation exposure of pesticide applicator workers (applicators and flaggers) during application and of farm workers post-application. The studies occasionally involve the collection of air grab samples and the direct determination of pesticide concentrations in the air. However, in most cases, sampling is done by test personnel wearing air pump samplers and results are reported in mass of pesticide collected in the trapping medium over the sampling interval.

Such data can presumably be converted to approximate average air concentrations over the sampling interval by dividing the mass of pesticide collected by the product of the air flow times the sampling interval. The resulting air concentrations will be total air concentrations reflecting pesticide adsorbed to particulate matter as well as pesticide in the vapor phase.

C7.6 HED Foliar Dislodgeable Residue Studies

The U.S. EPA/OPP/HED requires foliar dislodgeable residue studies for foliarly applied pesticides of concern for potential risks to humans. The results of the studies are used to help determine a safe post-application re-entry interval. Crops and/or lawn/turf are treated at maximum application rates. Foliar samples are generally collected just before application and at 1/6, 1/2, 1, 2, 4, 7, 10, 14, 21, 28, and 35 days post-application.

Although of potential use in terrestrial exposure assessments, dislodgeable residues reflect only a part of the total foliar residues ingested by a bird or mammal ingesting contaminated foliage. Furthermore, the percentage of registered pesticides for which the foliar dislodgeable residue study has been required is relatively small.

C7.7 HED Crop Residue Studies

The U.S. EPA/OPP/HED requires crop residue studies for pesticides foliarly applied to food crops. The results of the studies are used to help determine tolerances and post-harvest intervals. Crop residue studies involve the determination of total rather than dislodgeable residues and are required for a much higher percentage of registered pesticides than the foliar dislodgeable study. However, such studies rarely include more than two sampling times (immediately post-application and at the end of the proposed post-harvest interval). Indeed, many of the studies only include a sampling time at the end of the proposed post-harvest interval.

APPENDIX C8

ENVIRONMENTAL DATABASES

Types of environmental data/databases relevant to computer estimates of pesticide residues for terrestrial exposure assessments include fate, spray drift, pesticide use, crop distribution, land use, soil property, crop property and weather. Types of pesticide residue data/databases include foliar, insect, mixed media, and surface water.

C8.1 ARS/NRCS/USDA Pesticide Properties (Fate) Database

The ARS/NRCS/USDA maintains a chemical/fate pesticide properties database which lists one or more values for up to 18 chemical/fate properties for 335 pesticides. The database can be accessed and down loaded at www.arusda.gov/ppdb.html. Properties for which data are listed include hydrolysis, direct photolysis in water, photodegradation on soil, aerobic soil, anaerobic soil, and terrestrial field dissipation half-lives and/or rate constants. Other properties of interest for which data are listed include soil/water partition coefficients (K_d values), air/water partition coefficients (Henry's Law Constant values), and the octanol/water partition coefficient.

The ARS database is well maintained and reasonably up to date compared to the EFED/OPP fate database. It is of value in performing preliminary assessments of individual pesticides and preliminary comparative assessments across different chemicals. However, it should not be relied on heavily for performing more definitive assessments for regulatory purposes. The reason is that a substantial number of the studies producing the data have not been reviewed by independent parties such as the OPP/EFED. In addition, like the EFED fate database, information on the experimental media and conditions associated with the data

is minimal.

C8.2 The U.S. EPA/OPP/EFED Environmental Fate (One-Liner) Database

The U.S. EPA/OPP maintains a chemical/fate pesticide properties database that is comparable to that of the ARS/NRCS/USDA database. The U.S. EPA/OPP database has both advantages and disadvantages compared to the ARS/USDA database.

The OPP database covers more pesticides than the ARS database and includes only data that has been reviewed by OPP scientists and judged to be acceptable for use in fate and exposure assessments. Unlike the USDA/ARS/NRCS database, the U.S. EPA/OPP database does contain data from aquatic metabolism and aquatic field dissipation studies. However, it has not been as well maintained as the ARS database, and even though is covers more pesticides, it often provides less information per pesticide than the ARS database. In addition, it frequently contains errors such as failures to differentiate between Freundlich binding constants and K_d values, failure to correct reported photodegradation half-lives for dark controls, and reported half-lives and DT50s based on one or two of the data points instead of regression on all the data points.

Like the ARS database, the OPP database is of some value in performing preliminary assessments of individual pesticides and preliminary comparative assessments across different chemicals. However, it should not be relied on heavily for performing more definitive assessments for regulatory purposes.

C8.3 Spray Drift Task Force (SDTF) Database

Based upon studies conducted by the SDTF, the SDTF has developed a generic database containing data on:

1) Physical properties (dynamic surface tension, shear viscosity, extensional viscosity) of various tank mixtures that were used in droplet size distribution and spray drift deposition studies. The physical properties studied were those thought to potentially have significant affects on droplet size distributions and therefore on spray drift.

2) Wind tunnel determined droplet size distributions for numerous combinations of different tank mixtures, nozzle types, nozzle sizes, nozzle angles, nozzle pressure and windstream velocities. Most tank mixtures were aqueous based, but a few oil based mixtures were included.

3) Spray drift deposition as a function of distance for aerial spray, orchard airblast, ground spray, and chemigation with aerial spray drift trials being by far the most numerous. Spray drift trials were conducted for numerous combinations of different tank mixtures, droplet size distributions, nozzle properties, release height, boom length, airplane speed, and meteorological conditions including wind speed and direction, temperature, and relative humidity. However, no experiments were conducted under stable atmospheric conditions.

C8.4 Pesticide Use Databases and Maps

Non-proprietary estimated pesticide use data are maintained by USDA's National Agricultural Statistical Service (NASS) and the private company Resources for the Future. Downloadable information on specific pesticide uses by states and crop is available for major row crops, fruits, and vegetables at the following USDA/NASS internet address: www.usda.gov/nass/pubs/pubs.htm. The information on pesticide uses on row crops is updated yearly whereas information on pesticide uses on fruits and vegetables is updated alternately every other year.

Estimated pesticide use on a county scale is available through the Census of Agriculture which is conducted at 5 year intervals. Downloadable Census of Agriculture data can be

obtained at the following USDA/NASS internet address: www.usda.gov/census/. To help interpret the results of analyses for pesticides in water samples collected as part of the on-going National Water Quality Assessment Program (NAWQA), the USGS has used the 1992 Census of Agriculture data to generate nationwide pesticide use maps for numerous pesticides. The nationwide pesticide use maps can be downloaded from the following USGS internet address: http://water.wr.usgs.gov/pnsp/use92/.

C8.5 Crop Distribution and Land Use Databases and Maps

Estimated crop distribution on a county scale is available in the Census of Agriculture which is conducted at 5 year intervals. Downloadable Census of Agriculture data can be obtained at the following USDA/NASS internet address: www.usda.gov/census/. Down loadable maps showing 1997 nationwide distributions of major row crops, and 1992 nationwide distributions of additional row crops as well as numerous vegetables, fruits and nuts can be obtained from that internet address as well.

Nationwide information distributed separately by state on numerous factors including land use, land cover, major crops, soil properties, geographic distribution of soils, wetlands, wildlife habitats, erosion, and conservation practices/needs is available in the National Resource Inventory (NRI) which is conducted by the NRCS every 5 years. Summary tables and graphs can be downloaded at the following USDA/NRCS address: **www.nhq.nrcs.usda.gov/NRI/maps.html.**

C8.6 Soil Property and Soil Geographic Databases and Maps

The following descriptions of soil property and soil geographic databases are based primarily upon information provided by the National Resource Conservation Service (NCRS) at the following internet addresses: www.nrcs.usda.gov/. More specific information and downloadable data files from the databases can be obtained at the same internet address.

The NRCS has published thousands of soil surveys conducted throughout the United States. The area covered by each soil survey was typically that of a single county with a few exceptions such as some National Parks and Forests. To house the soil survey data, the NRCS maintains a soil attribute database (MUIR) and several related soil geographic databases. MUIR lists for > 30,000 soil series phases within the U.S., various site descriptive characteristics (such as depth to groundwater and potential crops) and up to 28 physical and chemical properties (such as horizon depth, bulk density, water capacity, and organic matter) for up to 6 vertical horizons (layers). The soil attribute database MUIR is linked to several different soil geographic databases that differ in scale (SSURGO, STATSGO, and NATSGO).

The base map of the NATSGO soil geographic database is the USDA classified Major Land Resource Area (MLRA). There are 189 MRLAs in the U.S. (excluding Alaska) and another 15 MRLAs covering Alaska. Descriptions of the MRLAs including topography, land use, crops grown, climate summaries, and the predominant soil series in each are contained in SCS Agricultural Handbook 296 entitled "Land Resource Regions and Major Land Resource Areas of the United States."

C8.7 Weather Data

Historical daily weather data collected for many years from approximately 300 hundred of the NOAA first order weather stations are maintained by the National Climatic Data Center (NCDC). The data can be downloaded from the following NOAA/NCDC internet address: www.ncdc.noaa.gov/ol/climate/climatedata.html. The data (referred to as "National Weather Service Summary of the Day" data) include 16 daily parameters which are sufficient to satisfy most model input requirements.

For use in the PRZM model, the USEPA's Center for Exposure Assessment Modeling (CEAM) maintains a weather database specifically designed for input into the PRZM

model. In the database, various MRLAs are each represented by the single NOAA first order weather closest to the centroid of the given MRLA. Information on how to obtain the MRLA based weather database can be obtained from the following USEPA/CEAM internet address: www.epa.gov/epa_ceam/wwwhtml/ceamhome.htm

C8.8 Foliar Residue Data/Databases

C8.8.1 HED Required Studies

Some foliar residue data derived from U.S. EPA/OPP/HED required foliar dislodgeable residue and crop residue data are contained in a database maintained by U.S. EPA/OPP/HED. A discussion on the types of data available from HED required studies is provided in Section 5.3.2.

C8.8.2 Hoerger and Kenaga (1972)

Hoerger and Kenaga (1972) evaluated several hundred published articles and selected 22 publications that would represent the maximum possible residue levels on vegetation. Using data compiled by Hoerger and Kenaga (1972), the Kenaga nomogram was developed by EPA to predict the maximum pesticide residue immediately following spray application to vegetation (Fig. 4352). The vegetation was categorized into six types of plants or plant parts: short range grass, long grass, leafy crop leaves, legume forages, legume pods containing seeds, and fruit.

The nomogram is based upon an assumed linear relationship between application rate and residue level on the vegetation (expressed as mg residue/kg fresh weight plant material). The Kenaga nomogram has been criticized because it is based upon fresh (instead of dry) weight, it is based upon a selective data base of high residue levels only, considers only

pesticides used prior to 1972, does not separate spray application from granular and systemic pesticides, and does not consider plant morphological differences (pubescence).

The raw data upon which the Hoerger and Kenega (1972) paper was based is not directly available. The data could be recompiled from the references they provided in their paper. However, most of the data referred to in the paper were collected in the 1950s and 1960s and include many pesticides no longer registered.

C8.8.3 Fletcher etal 1994 and the UTAB Foliar Residue Database

During the greater than 20 years following development of the Kenaga nomogram, 10 of the 27 pesticides used in the original data base were banned or no longer registered for use in the U.S. Additionally, several new pesticides were registered for use. Thus, Fletcher et al. (1994) reviewed the Kenaga nomogram using information from the UTAB data base at the University of Oklahoma and compared pesticide residue levels predicted using the Kenaga nomogram to levels reported in the literature. The UTAB data base was larger and represented more current pesticide usage than the original information used by Hoerger and Kenaga (1972). The database reportedly contains some foliar dissipation as well as day 0 residue values. Fletcher, Nellessen, and Pfleeger (1994) describe the UTAB foliar residue database as having (at that time) "42,000 individual records pertaining to over 1000 different chemicals, 65% of which are pesticides". Data were reportedly compiled from over 2100 published papers representing over 400 plant species, 95 plant families and "all major crops".

The analysis by Fletcher et al. (1994) showed that day-0 levels predicted by the nomogram were, in general, accurate with the exceptions of the fruits and legume forages categories. The recommendations were to increase the predicted residue levels for legume forages and fruits. One solution was to combine the legume forages with the leafy crops and combine the fruits with the pods category, thus, reducing the original six categories to four categories. Fletcher et al. (1994) also evaluated persistence of pesticides on vegetation

using various combinations of plant categories and pesticides. The results were consistent with exponential decay curves with the exception of systemic pesticides applied as dust or granules.

Pfleeger et al. (1996) evaluated the Kenaga nomogram using 6 pesticides applied to 15 plant species in a field study. Residue levels were determined from day-0 up to day-32. The results showed that about 10% of the data for day-0 residues exceeded the Kenaga nomogram prediction levels and the researchers indicated that the forage category be combined with the leafy crops and have a higher estimated residue level. Considerable variation in pesticide residue levels in vegetation was noted even under controlled experimental conditions. The authors questioned the validity of the assumption of a linear relationship between application rate and residue level at day-0. Systemic pesticide residues in fruits were indicated as a concern because levels did not decrease over the duration of the experiment in all cases. Dusts and granules were not evaluated in the field study. The authors also noted that the Kenaga nomogram format is not suitable to adding pesticide degradation rate information because of the differences in chemical properties and dissipation rates on various vegetation types. Pfleeger et al. (1996) concluded that the Kenaga nomogram was a reasonable regulatory device if care was exercised in selecting the plant category and residue levels.

For illustrative purposes, the arithmetic means and standard deviations reported by Fletcher et. al (1994) from the UTAB database for the Hoerger and Kenega 1972 crop categories have been transformed into lognormal equivalents and used to generate theoretical lognormal distributions (See Section 3.12). However, to determine if a lognormal distribution fits the data or another type of distributions fits the data better, we will have to obtain the raw data.

The U.S. EPA/OPP does not currently have access to the UTAB database, but is currently evaluating options for gaining access to it. The U.S. EPA/OPP is also currently trying to obtain the raw data generated by Pfleeger etal (1995).

C8.8.4 Willis and McDowell (1986) Foliar Dissipation Half-lives

Willis and McDowell (1986) performed a literature review on the interception of pesticides by crops. Interception data were compiled for 15 pesticides, but only some of the data reported reflected actual interception by the plants studied (cotton, alfalfa, citrus trees, and apple trees). The rest of the interception data were for non-crop targets such as glass plates, absorbent paper, fiberglass discs, and aluminum foil.

Willis and McDowell (1986) briefly discuss factors affecting the magnitude of interception by vegetation including spray drift, droplet size, wax content of the leaves, formulations and adjuvants, and canopy cover. They also indicate that the rapid volatilization losses from foliage frequently observed during the first few minutes to hours post-application may often lead to under reporting of interception in cases where foliar samples are not collected immediately post-application.

Decreases in the droplet size distribution increase spray drift and therefore decrease the amount of chemical striking the foliage. However, that is somewhat counter balanced by leaves retaining smaller droplets to a greater extent than larger droplets.

Willis and McDowell (1986) also performed a literature review on the persistence of pesticides on foliage. In cases where a reviewed article did not contain an estimated half-life, Willis and McDowell calculated one based on tabular or graphical data and an assumption of pseudo first order kinetics. For purposes of tabular presentation and discussion, Willis and McDowell divided the pesticides for which data were reported into the following chemical family categories: organochlorines, organophosphates, carbamates, pyrethroids, and other (which consist of miscellaneous fungicides, insecticides, and herbicides).

Willis and McDowell (1986) made no attempt to explicitly differentiate between washoff, volatilization, and other dissipation pathways. However, rainfall amounts or 0 were listed

for those articles reporting rainfall and a "-" was listed for those articles that did not mention rainfall.

Willis and McDowell (1986) indicated that the following precautions should be observed in interpreting the half-lives reported in the tables.

(1) The first precaution involves the possibility that the foliar sampling may be inadequate in some cases to capture or accurately characterize the rapid volatilization which frequently occurs during the first few minutes to 1-2 days post-application. Frequent examples of inadequate foliar sampling include studies where initial foliar samples were collected 30 to 60 minutes rather than immediately post application and/or a second sample was not collected until 1-2 days post-application. In such cases, the reported foliar dissipation half-life may be substantially greater than the actual half-life.

2) The second precaution involves cases where dislodgeable residues (those extracted with aqueous solution generally reflecting only surface residues) cannot be differentiated from total residues (those extracted with organic solvents generally reflecting both surface and internal residues). In cases where an article being reviewed contained enough extraction methodology information to differentiate, Willis and McDowell indicated in the tables whether the data were for dislodgeable or total foliar residues. However, in some cases there was not enough extraction methodology information provided in the article being reviewed for Willis and McDowell to do so.

3) In reviewing the summarized half-life values, it is important to note the variability for a given pesticide-plant combination. For example, malathion on cotton had half-life values ranging from 0.3 to 6.1 days, or approximately a 20-fold difference in values. In addition, it should be noted that only foliage was considered in the review and no values were reported for fruit, seeds, pods, or roots.

Willis and McDowell (1986) discuss some of the factors affecting foliar dissipation rates. They concluded that pesticide persistence was influenced by the distribution of the residue on the foliage, plant morphological (pubescence) and chemical (waxes) properties, pesticide properties and formulation, and weather factors (temperature, wind, relative humidity, and sunlight).

Chemicals and/or formulations that are lipophilic may be able to penetrate leaves more readily and therefore be less susceptible to weathering than more hydrophilic chemicals and/or formulations. Rainfall generally increases overall dissipation rates via washoff, but in some cases may decrease overall dissipation rates by enhancing leaf penetration. Increases in the overall dissipation rate with increasing temperature and wind speed appear to be due primarily to associated increases in volatilization rates. Increases in dissipation rates with increasing intensity and/or duration of sunlight may reflect photodegradation, but may also reflect any associated increases in temperature.

For illustrative purposes, the arithmetic means and standard deviations of foliar dissipation half-lives reported by Willis and McDowell 1986 for dislodgeable and total residues for the Hoerger and Kenega 1972 crop categories have been transformed into lognormal equivalents and used to generate theoretical lognormal distributions for various chemical families (See ----). However, to determine if a lognormal distribution fits the data or another type of distribution fits the data better, we will have to use a goodness of fit test such as the Chi-square test.

C8.8.5 Beril Foliar Residue Database

The Beril foliar residue database is a compilation of mostly day 0-1 foliar residue data from over 500 international references primarily from the 1970s and 1980s. Data for numerous crops, pesticide active ingredients, and formulations are included. Data are generally expressed as mg/kg fresh weight, but are occasionally also expressed as ug/cm^2 leaf surface area.

C8.9 EFED Terrestrial Ecological Residue/Effects Study Data (Multimedia)

As previously indicated, the U.S. EPA/OPP/EFED has required and/or received approximately 34 terrestrial ecological residue/effects studies covering 15 pesticides. The studies involve treating fields with maximum allowed numbers of applications and application rates. Various environmental media (including soil, water, vegetation, birds, mammals, and occasionally amphibians) were sampled at various sampling intervals. The samples were analyzed

for the parent and occasionally for major degradates as well. Observed effects on non-target organisms were also reported.

C8.10 Insect Residue Data/Databases

See Sub-Section 3.10.6.3

C8.11 Surface Water Monitoring Databases

The STORET database maintained by the U.S. EPA/OW contains a vast amount of general water quality and pollutant monitoring data (including for various pesticides) for many sampling sites for up to > 30 years. The data have been submitted by many federal, state, academic, and private organizations. Organizations or individuals having accounts can access the STORET database directly. Other organizations and individuals can obtain data indirectly by filling out a detailed request form and submitting it electronically or by mail to the U.S. EPA. The internet site having the request form and to which the completed request form can be electronically submitted can be obtained by following menus at the general internet address www.epa.gov or at the following specific internet address: www.epa.gov/OWOW/STORET/.

The USGS National Water Quality Assessment Program (NAWQA) is an ongoing program to monitor the surface water and groundwater within 60 study units (representing 60 river basins and/or aquifers) widely spread throughout the U.S. Summaries of the NAWQA pesticide data for the first 3 years of sampling of the 20 study units in the first group are available on the internet as are downloadable raw pesticide data from some of the 20 study units within the first group. The summaries and downloadable pesticide data can be obtained by following the menus at the general USGS internet address www.usgs.gov or at the following more specific internet address: water.wr.usgs.gov/pnsp/. Although the NAWQA Program is providing a vast amount of data on pesticides in surface water, the utility of the data for terrestrial exposure assessments is somewhat limited by the data all being for flowing water instead of for ponds and lakes.

The ongoing USGS Toxic Substances Hydrology Program is also a substantial source of data on pesticides in the surface water of the Midwest, Mississippi Delta, and the Mid-Atlantic Coastal Plain. Data summaries and publication lists can be obtained by following the menus at the general USGS internet address www.usgs.gov or at the following more specific internet addresses: toxics.usgs.gov/toxics/regional/agchem-midwest.shtml, toxics.usgs.gov/toxics/regional/cotton.shtml. Although the much of the pesticide data from the Toxic Substances Hydrology Program has also focused on flowing surface water, some data have also been collected on reservoirs and lakes.

C8.12 Residues in Air Data

Literature data on pesticides in air are somewhat limited and are primarily on high use herbicides in the midwest, in California, and around the Great Lakes. As part of the background for the NAWQA Program, the USGS conducted a comprehensive literature survey for data on pesticides in the atmosphere. The results of the survey along with

discussions on factors affecting pesticide concentrations and distributions in air are presented in the following book:

Majewski MS and Capel PD. 1995. Pesticides in the Atmosphere - Distribution, trends & governing factors. Ann Arbor Press, Chelsea MI, 228 pages.

APPENDIX C9

LEVEL 1 AND 2 INTERIM ESTIMATES OF PESTICIDE CONCENTRATIONS IN ENVIRONMENTAL MEDIA

Based upon the literature reviews by Golder Associates (1997) and Jorgensen (1995), there do not appear to be any residue computer models currently available that could be used to adequately generate distributions of pesticide residues in all relevant environmental media for use in probabilistic terrestrial exposure assessments. Consequently, interim methods of estimating pesticide concentrations in environmental media must be used until an adequate model can be developed

C9.1: Interim Level 1 and 2 Estimates of Concentrations in Environmental Media

Until an adequate residue computer model for use in terrestrial exposure assessments is developed, level 3 and 4 estimates of pesticide residue concentrations in environmental media will not be performed. Interim level 1 single value estimates and level 2 distributional estimates of residues on/in soil, on/in plants, in water, and in air within the canopy can be based on existing models (PRZM, AgDRIFT, EXAMS) or on simpler mass balance models. PRZM, AgDRIFT, and EXAMS will not directly provide level 1 and 2 estimates of residues on/in surface invertebrates, subterranean invertebrates (such as worms), and vertebrates. However, estimates for invertebrates and vertebrates can be based upon the use of output from PRZM, AgDRIFT, and EXAMS as input into simple pseudo first order kinetic algorithms that can be run outside of PRZM, AgDRIFT, and EXAMS as described below.

PRZM, AgDRIFT, and EXAMS cannot be currently used to generate distributions of interest with respect to terrestrial exposure assessments using Monte Carlo simulation.

Although PRZM 3 has some Monte Carlo simulation capability, the output variables currently available in PRZM 3 for Monte Carlo simulation do not include pesticide concentrations on/in soil or plants. Neither EXAMS nor AgDRIFT currently have any Monte Carlo simulation capabilities.

PRZM 3, AgDRIFT, and EXAMS can probably be provided with adequate Monte Carlo simulation capabilities long before a new terrestrial exposure model is developed. Although they cannot currently be coupled to Monte Carlo software such as @RISK or CRYSTAL BALL, the cost of developing software to do so is probably relatively low. In fact, the FIFRA Model Validation Task Force is currently funding the development of an interface between PRZM 3 and CRYSTAL BALL. If PRZM 3, AgDRIFT, and EXAMS are provided with adequate Monte Carlo simulation capabilities, they can be used to generate interim level 1 single value estimates and level 2 distributional estimates of residues on/in soil, on/in plants, in water, and in air within the canopy until a new terrestrial exposure model is developed.

Until PRZM 3, AgDRIFT, and EXAMS are provided with adequate Monte Carlo simulation capabilities, at least two options should be considered for generating interim level 1 single value estimates and level 2 distributional estimates of residues on/in soil, on/in plants, in water, and in air within the canopy. One option is to use the current versions of PRZM 3, AgDRIFT, and EXAMS (despite their limited to no Monte Carlo simulation capabilities) to generate level 2 distributional estimates by running them deterministically over multiple years and sites. The distribution of outputs generated by running the models deterministically over multiple years and sites should adequately reflect natural year to year variations in weather at a given site and natural variability in mean values between sites.Furthermore, nonsensical combinations of inputs that are sometimes present in Monte Carlo simulations due to inadequate and/or inaccurate accounting for correlation can be avoided. However, unlike with Monte Carlo simulations, the distributional outputs will not reflect natural variability and/or measurement uncertainty in other sensitive input variables.

The other option is to use simpler mass balance based equations (discussed in greater detail below) in conjunction with deterministic outputs from AgDRIFT to generate interim level 1 single value estimates and level 2 distributional estimates of residues on/in soil, on/in plants, and in water, until PRZM 3, AgDRIFT, and EXAMS are provided with adequate Monte Carlo simulation capabilities. Such equations can be easily entered into spreadsheets and readily undergo Monte Carlo simulations with the use of Monte Carlo software such as @Risk, Crystal Ball, or DistGEN. The problems with such equations are that they are not coupled to weather, do not account for the effects of weather and hydrology on residue levels, and do not consider as many factors affecting residue levels as do PRZM 3 and EXAMS.

Many of the simple mass balance equations described below have been or will be incorporated into the bird spray exposure PARET which is described in greater detail in another section.

C9.2: Interim Equations for Bulk Pesticide Concentrations in Soil

If PRZM 3 is used, it can print out the total and dissolved pesticide mass per unit volume of soil (in g/cm^3) for each soil compartment layer at the beginning of each daily time step.

A simpler one or two soil layer model for a spray targeted field and/or a field receiving spray drift is based upon the following mass balance equation for each layer:

$$\frac{d\left[\left(A_s W_s r_s\right) C_{bs(i)}\right]}{dt} = -\left(A_s W_s r_s\right) k_s C_{bs(i)} \qquad \text{(Eq. C9-1)}$$

where

A_s = surface area of the soil (m^2)

W_s = width of the soil layer (m)

ρ_s = bulk density of the soil (kg dry weight/m^3)

$A_s W_s \rho_s$ = mass of soil (kg dry weight)

$C_{bs(i)}$ = bulk concentration of chemical in soil (mg/kg dry weight soil)

k_{bs} = overall bulk soil first order dissipation rate constant (1/day)

Equation C9-1 does not explicitly account for losses from the soil due to physical transport processes such as leaching, runoff, uptake by plants, diffusion, and volatilization. However, if the dissipation rate constants reported for field studies rather than the degradation/volatilization rate constants for lab studies are used in equation B6-1, some of those physical removal processes should be at least partially reflected in the magnitudes of the dissipation rate constants.

Because the mass of soil ($A_s W_s \rho_s$) in equation C9-1 is constant, it can be moved outside the derivative on the left side of equation C9-1, and then divided out of both sides of the equation to give:

$$\frac{dC_{bs(i)}}{dt} = -k_{bs} C_{bs(i)} \qquad \text{(Eq. C9-2)}$$

Separating variables, integrating equation C9-2 from $C_{bs(i)} = C_{bs}(t=t_i)$ to $C_{bs(i)} = C_{bs}(t=t_{i+1})$ and from $t=t_i$ from $t=t_{i+1}$, and allowing for a possible instantaneous addition at the beginning of day i+1 at $t=t_{i+1}$ due to direct application or to spray drift generates the following daily time step algorithm. The algorithm gives the concentration of chemical in soil at the beginning of day i+1 at $t=t_{i+1}$ in terms of the concentration at the beginning of the previous day i at $t=t_i$:

$$C_{bs}(t = t_{i+1}) = C_{bs(add)}(t = t_{i+1}) \bullet \exp[-k_{bs}(1\ \text{day})] \quad \text{(Eq. C9-3)}$$

where

$C_{bs}(t=t_{i+1})$ = bulk concentration of chemical in soil at the beginning of day i+1 at $t = t_{i+1}$ (mg)

$C_{bs}(t=t_i)$ = bulk concentration of chemical in soil at the beginning of day i at $t = t_i$ (mg)

$C_{bs(add)}(t=t_{i+1})$ = added concentration of chemical in soil due to direct application or to spray drift at the beginning of day i+1 at $t=t_{i+1}$

k_{bs} = overall bulk soil first order dissipation rate constant (1/day)

t_i = beginning of day i

t_{i+1} = beginning of day i+1

1 day = $(t_{i+1} - t_i)$

Equation C9-3 is applicable to a one soil layer model or to both layers of a two soil layer model. In a model not accounting for vertical movement due to leaching, a one layer model is adequate when a field receives only direct application (surface or incorporated), only spray drift, or a combination of surface direct application and spray drift. A two layer model is only necessary when a field receives both incorporated direct application to a depth of I and spray drift to an assumed depth of 1 cm (0.01 m).

For a one soil layer model with a surface direct application to the soil at $t=t_{i+1}$ and with a small incorporation of 1 cm (0.01 m) assumed to be due to natural processes, $C_{bs(add)}(t=t_{i+1})$ in equation C9-3 is given by:

$$C_{bs(add)}(t = t_{i+1}) = \left[1 - f_{\text{int}}(t = t_{i+1})\right]\left(1 - f_{sd}\right)\left[App(t = t_{i+1}) / 0.01 r_s\right] \quad \text{(Eq. C9-4)}$$

where

$f_{int}(t=t_{i+1})$ = fraction of applied chemical intercepted by foliage when applied at the beginning of day i+1 at $t=t_{i+1}$

f_{sd} = fraction of applied loss by spray drift before hitting the targeted field

$App(t=t_{i+1})$ = nominal application rate at the beginning of day i+1 at $t = t_{i+1}$ in mg chemical/m^2 field (convert from lb/acre or kg/ha)

0.01 m = assumed incorporation of surface applications due to natural process

ρ_s = bulk soil density (kg dry soil/m^3 of soil)

For a one layer model or the top layer of a two layer model receiving a spray drift application to soil at $t=t_{i+1}$ with a small incorporation of 1 cm (0.01 m) assumed to be due to natural processes, $C_{bs(add)}(t=t_{i+1})$ in equation B6-3 is given by:

$$C_{bs(add)}(t = t_{i+1}) = \left[1 - f_{\text{int}}(t = t_{i+1})\right](SD_{avg})\left[App(t = t_{i+1}) / 0.01 r_s\right] \quad \text{(Eq. C9-5)}$$

where

SD_{avg} = the average spray drift depositional fraction on a field directly downwind is given by:

$$SD_{avg} = \frac{\int_{x1}^{x2} SD(x)dx}{x_2 - x_1}$$ (Eq.

C9-6)

where

SD(x) = spray drift depositional fraction as a function of distance x downwind from the edge of a treated field (expressed as a fraction of the application rate)

x_1 = distance downwind of front edge of the field

x_2 = distance downwind of back edge of the field

For a one soil layer model or for both layers of a two soil layer model receiving an incorporated direct application at $t=t_{i+1}$ with an incorporation depth of I, $C_{bs(add)}(t=t_{i+1})$ in equation B6-3 is given by:

$$C_{bs(add)}(t = t_{i+1}) = \left(1 - fsd\right)\left[App(t = t_{i+1}) / Ir_s\right]$$ (Eq.

C9-7)

where

I = incorporation depth specified on the label (m)

If equation C9-3 is used to compute the bulk concentration in the soil layer at the beginning of day i+1 at $t=t_{i+1}$, the corresponding pore water concentration is given by:

$$C_{pw}(t = t_{i+1}) = \frac{r_s C_{bs}(t = t_{i+1})}{\left(q_w + K_d r_s + f_a K_H\right)} \quad \text{(Eq. C9-8)}$$

where

$C_{pw}(t=t_{i+1})$ = concentration in soil pore water at the beginning of day i+1 at $t=t_{i+1}$

$C_{bs}(t=t_{i+1})$ = bulk concentration in soil at the beginning of day i+1 at $t=t_{i+1}$

ρ_s = bulk density of soil

Θ_w = volumetric pore water fraction

K_d = soil/water partition coefficient

Θ_a = volumetric pore air fraction

K_H = dimensionless Henry's Law constant

C9.3: Interim Equations for Concentrations on/in Plants Without Uptake by Plants

If PRZM 3 is used, it can print out pesticide mass on the foliage per unit area of the field (m_p) at the beginning of each daily time step. However, as previously discussed, estimates of pesticide mass on foliage/area of the field (m_p) need to be converted to pesticide mass/mass of plant (C_p) to be useful for terrestrial exposure assessments. As previously discussed, the conversion can readily be made with equation C4-14 provided that the above ground biomass can be estimated at the beginning of each daily time step. Although PRZM does not estimate biomass, a biomass growth algorithm run outside of PRZM could be used to do so provided the algorithm was consistent with the canopy cover models algorithms in PRZM.

A simpler model for bulk plant concentration in a spray targeted field is based on the following mass balance equation:

$$\frac{d\left(B_{ag(i)}C_{p(i)}\right)}{dt} = -k_p B_{ag(i)} C_{p(i)} \quad \text{(Eq. C9-9)}$$

where

$B_{ag(i)}$ = above ground plant biomass as a function of time on day i (kg dry weight)

$C_{p(i)}$ = concentration of chemical on plants as a function of time on day i (mg/kg dry weight)

k_p = overall bulk plant first order dissipation rate constant (1/day)

Equation C9-9 does not explicitly account for uptake by the plant or losses from the plant due to washoff and volatilization. However, if the dissipation rate constants reported for field studies rather than the degradation/volatilization rate constants for lab studies are used in equation B6-9, the uptake and washoff processes should be at least partially reflected in the magnitudes of the dissipation rate constants.

Separating variables, integrating equation C9-9 from $B_{ag(i)}C_{p(i)} = B_{ag}(t=t_i)C_p(t=t_i)$ to $B_{ag(i)}C_{p(i)} = B_{ag}(t=t_{i+1})C_p(t=t_{i+1})$ and from $t=t_i$ from $t=t_{i+1}$, allowing for a possible instantaneous addition at the beginning of day i+1 at $t=t_{i+1}$ due to direct application or spray drift, and rearranging generates the following daily time step algorithm. The algorithm gives the concentration of chemical on/in plants at the beginning of day i+1 at $t=t_{i+1}$ in terms of the concentration at the beginning of the previous day i at $t=t_i$:

$$C_p(t=t_{i+1}) = \frac{m_{p(add)}(t=t_{i+1})}{B_{ag}(t=t_{i+1})} + \left[\frac{B_{ag}(t=t_i)}{B_{ag}(t=t_{i+1})}\right] C_p(t=t_i) \bullet \exp[-k_p(1\ \text{day})]$$

(Eq. C9-10)

where

$C_p(t=t_{i+1})$ = chemical concentration on/in plants at the beginning of day i+1 at $t=t_{i+1}$ (mg/kg dry weight)

$m_{p(add)}(t=t_{i+1})$ = mass of chemical added to plants per unit field area at the beginning of day i+1 at $t=t_{i+1}$ due to direct application or spray drift (mg/m^2 field).

$B_{ag}(t=t_i)$ = above ground plant biomass per unit field area (kg dry weight/m^2 of field)

The plant biomass at the beginning of each day can be calculated separately from one of several plant growth models including an exponential growth model and several more complex alternatives that generate characteristic sigmoidal shape plant growth curves (Jorgensen 1995).

For direct foliar application at $t=t_{i+1}$, $m_{p(add)}(t=t_{i+1})$ in equation C9-10 is given by:

$$m_{p(add)}(t = t_{i+1}) = \left[f_{\text{int}}(t = t_{i+1}) \right] \left(1 - f_{sd}\right) \left[App(t = t_{i+1}) \right] \quad \text{(Eq. C9-11)}$$

where

$f_{int(i+1)}$ = fraction intercepted by plant when chemical is applied at $t=t_{i+1}$

f_{sd} = fraction loss by spray drift before hitting the targeted field

$App_{(i+1)}$ = nominal application rate at the beginning of day i+1 at $t = t_{i+1}$ in mg chemical/m^2 (convert from lb/acre or kg/ha)

As an alternative to computing the added mass of chemical on/in plants per unit field area $m_{p(add)}(t=t_{i+1})$ for direct application from equation C9-11 and then dividing by the biomass per unit field area $B_{ag}(t=t_{i+1})$, $m_{p(add)}(t=t_{i+1})/B_{ag}(t=t_{i+1})$ can be computed from the product of the Fletcher et. al (1994) time zero foliar residues (normalized to an application rate of 1 lb ai/acre) times the application rate.

For spray drift to foliage at $t=t_{i+1}$, $m_{p(add)}(t=t_{i+1})$ in equation C9-10 is given by:

$$m_{p(add)}(t = t_{i+1}) = \left[f_{\text{int}}(t = t_{i+1}) \right] \left(SD_{avg} \right) \left[App(t = t_{i+1}) \right] \quad \text{(Eq. C9-12)}$$

where

SD_{avg} = average spray drift deposition defined by equation C9-6.

As an alternative to computing the added mass of chemical on/in plants per unit field area $m_{p(add)}(t=t_{i+1})$ for spray drift from equation C9--12 and then dividing by the biomass per unit field area $B_{ag}(t=t_{i+1})$, $m_{p(add)}(t=t_{i+1})/B_{ag}(t=t_{i+1})$can be computed from the product of the Fletcher et. al (1994) time zero foliar residues (normalized to an application rate of 1 lb ai/acre) times the application rate times the average spray drift deposition fraction for the field receiving the spray drift.

Caution should be observed in using the Fletcher etal (1994) time zero foliar values because of the large uncertainties associated with basing concentrations on a variable wet weight rather than a constant dry weight. Also, if residues on a wet weight basis are used to estimate ingestion dose, food intake must also be on a wet weight basis which may require the use of dry to wet factors (DWFs) to convert dry weight food ingestion to wet weight food ingestion.

C9.4: Interim Equations for Pesticide Concentrations on/in Plants With Uptake by Plants

To take into account uptake by plants, the one and two layer soil models previously discussed will have to have an additional layer added extending from the bottom of the incorporation depth to the bottom of the root zone. Although the concentration of the chemical in the pore water within the additional zone will be assumed to be zero, the plant will be allowed to extract water from it.

Adding a plant uptake term to plant mass balance equation C9-9 gives:

$$\frac{d\left(B_{ag(i)}C_{p(i)}\right)}{dt} = \left(\sum_{j=1}^{j=j\max(trans)}(TSCF)Q_{trans(ij)}C_{pw(ij)}\right) - k_p B_{ag(i)}C_{p(i)} \qquad \text{(Eq. C9-13)}$$

where

$C_{pw(j)}(t=t_i)$ = pore water concentration at the start of day i at $t=t_i$ in soil compartment (layer) j (g/cm^3)

$Q_{trans(ij)}$ = transpiration flow on day i from soil layer j to the roots (cm^3/day)

j = soil layer index

$j_{max(trans)}$ = the deepest soil layer from which transpiration is extracted.

In this case, $j_{max(trans)}$ must be ≤ 2 or ≤ 3 depending on whether a 2 or 3 layer soil model is being used. The relative transpiration contribution of each soil layer j on day i ($Q_{trans(ij)}$) to the overall transpiration on day i ($Q_{trans(i)}$) will depend on several factors including the root mass/area distribution, the soil moisture content relative to the wilting point, the depth of

the layer, and to what extent higher layers satisfied the transpiration demand (Carsel etal 1997).

The uptake term in equation C9-13 is a multiple layer version of ones in the PRZM 3, PLANTX, and PLANT models.

The total transpiration on day i ($Q_{trans(i)}$) as well as well as the transpiration extracted from each soil layer j on day i ($Q_{trans(ij)}$) will increase with increasing biomass and leaf area index. In a daily time step model, increases in transpiration can be reflected at the beginning of each day while still assuming that the transpiration remains constant during any given day. Consequently, during any given day i, the uptake term in equation C9-13 can be considered constant such that:

$$\frac{d\left(B_{ag(i)}C_{p(i)}\right)}{dt} = \left(\frac{dm}{dt}\right)_{up} - k_p B_{ag(i)} C_{p(i)} \quad \text{(Eq. C9-14)}$$

where

$$\left(\frac{dm}{dt}\right)_{up} = \sum_{j=1}^{j=j\max(trans)} (TSCF) Q_{trans(ij)} C_{pw(i)} \quad \text{(Eq. C9-15)}$$

Separating variables, integrating equation C9-14 from $B_{ag(i)}C_{p(i)} = B_{ag}(t=t_i)C_p(t=t_i)$ to $B_{ag(i)}C_{p(i)} = B_{ag}(t=t_{i+1})C_p(t=t_{i+1})$ and from $t=t_i$ from $t=t_{i+1}$, allowing for a possible instantaneous addition at the beginning of day i+1 at $t=t_{i+1}$ due to direct application or

spray drift, and rearranging generates the following daily time step algorithm. The algorithm gives the concentration of chemical on/in plants at the beginning of day i+1 at $t=t_{i+1}$ in terms of the concentration at the beginning of the previous day i at $t=t_i$:

$$C_p(t = t_{i+1}) = \frac{m_{p(add)}(t = t_{i+1})}{B_{ag}(t = t_{i+1})} + \left[\frac{\left(dm/dt\right)_{up}}{k_p B_{ag(i)}(t = t_{i+1})}\right] \bullet \left[1 - \exp[-k_p(1\ \text{day})]\right] + \left[\frac{B_{ag}(t = t_i)}{B_{ag}(t = t_{i+1})}\right] C_p(t = t_i) \bullet \exp[-k_p(1\ \text{day})]$$

(Equation C9-16)

C9.5: Interim Equations for Pesticide Concentrations in Dew

In a more sophisticated residue model, mass balance differential equations for residues in the dew, on/in plants, in soil and in any other environmental media with which they reversibly transfer chemical mass would be solved simultaneously. In addition, the decrease in dew volume would be taken into account. However, for a daily time step model in which the dew is assumed to form at the beginning of each day, but only last for a small fraction of the day, the equilibrium calculation provided above using an average dew volume should suffice for interim estimates.

Assuming equilibrium between the chemical dissolved in dew water and the bulk concentration of the chemical on/in plants, and desorption of x chemical mass from the plant to the dew water,

$$C_p(t = t_{i+1}) - \left[x_{dew} / A_s B_{ag}(t = t_{i+1})\right] = K_{p/w}\left(x_{dew} / A_L D_{dew}\right) \quad \text{(Eq. C9-17)}$$

where

$C_p(t=t_{i+1})$ = bulk concentration in plant at the beginning of day i+1 at $t = t_{i+1}$ in mg/kg dry weight plant

x_{dew} = chemical mass desorbed from plant tissue to dew water (mg)

$B_{ag}(t=t_{i+1})$(kg dry weight/m^2 field)

A_s = field area (m^2)

$K_{p/w}$ = plant to water equilibrium partition coefficient

A_L = leaf area (m^2)

D_{dew} = dew depth (m)

Solving equation C9-17 for x_{dew} gives

$$x_{dew} = \frac{A_s A_L D_{dew} B_{ag}(t = t_{i+1})}{\left[A_L D_{dew} + K_{p/dew} A_s B_{ag}(t = t_{i+1})\right]} \quad \text{(Eq. C9-18)}$$

$$C_{dew}(t = t_{i+1}) = x_{dew} / A_L D_{dew} \quad \text{(Eq. C9-19)}$$

Substituting equation C9-18 for x_{dew} into equation C9-19 gives:

$$C_{dew}(t = t_{i+1}) = \frac{A_s B_{ag}(t = t_{i+1})}{\left[A_L D_{dew} + K_{p/dew} A_s B_{ag}(t = t_{i+1})\right]} \quad \text{(Eq. C9-20)}$$

C9.6: Interim equations for Concentrations in Puddles Assuming Constant Puddle Depth

Assuming equilibrium between the sediment and puddle water and that the depth of the puddle water remains constant with time, coupled simple pseudo first order decline mass balance equations for puddles and sediment are given by:

$$A_{pud} D_{pud} \frac{dC_{pud(i)}}{dt} = -A_{pud} D_{pud} (k_{pud} + k_{volatil}) C_{pud(i)} \quad \text{(Eq. C9-21)}$$

$$A_{pud} D_{sed} r_{sed} \frac{dC_{sed}}{dt} = -A_{pud} D_{sed} r_{sed} k_{sed} C_{sed(i)} \quad \text{(Eq. C9-22)}$$

where

A_{pud} = surface area of the puddle in the field (m^2)

D_{pud} = puddle depth (m)

k_{pud} = first order degradation rate constant for dissolved chemical in the puddles (1/day)

k_{volat} = first order volatilization rate constant for dissolved chemical in the puddles (1/day)

$C_{pud(i)}$ = concentration in the puddle as a function of time on day i (mg/m^3)

D_{sed} = depth of sediment assumed to interact and to be in equilibrium with the puddle water column (m)

ρ_{sed} = bulk density of the sediment (kg dry sediment/m^3)

k_{sed} = first order dissipation rate constant for chemical on/in sediment (1/day)

$C_{sed(i)}$ = concentration on/in sediment as a function of time on day i (mg/kg dry weight)

Assuming the chemical dissolved in the puddle water and adsorbed to the underlying sediment are in equilibrium:

$$C_{sed\,(i)} = K_{sed\,/\,pud} C_{pud\,(i)} \quad \text{(Eq. C9-23)}$$

Differentiating equation C9-23 with respect to time gives:

$$\frac{dC_{sed\,(i)}}{dt} = K_{sed\,/\,pud} \frac{dC_{pud\,(i)}}{dt} \quad \text{(Eq. C9-24)}$$

where

$K_{sed/pud}$ = equilibrium sediment/water partition coefficient (L/kg)

Substituting equation C9-23 for $C_{sed(i)}$ and equation C9-24 for $dC_{sed(i)}/dt$ in equation C9-22 gives:

$$A_{pud} D_{sed} r_{sed} K_{sed/pud} \frac{dC_{pud(i)}}{dt} = -A_{pud} D_{sed} r_{sed} k_{sed} K_{sed/pud} C_{pud(i)} \quad \text{(Eq. C9-25)}$$

Adding equations C9-21 and C9-25 and rearranging gives the overall mass balance equation for the puddle/sediment system in terms of the puddle concentration:

$$\frac{dC_{pud(i)}}{dt} = -k_m C_{pud(i)} \quad \text{(Eq. C9-26)}$$

where

$$k_m = \frac{\left(k_{pud} + k_{volatil}\right) D_{pud} + k_{sed} K_{sed/pud} D_{sed} r_{sed}}{D_{pud} + K_{sed/pud} D_{sed} r_{sed}} \quad \text{(Eq. C9-27)}$$

Separating variables, integrating equation C9-26 from $C_{pud(i)} = C_{pud}(t=t_i)$ to $C_{pud(i)} = C_{pud}(t=t_{i+1})$ and from $t=t_i$ from $t=t_{i+1}$, allowing for a possible instantaneous application to the puddles at the beginning of day i+1 at $t=t_{i+1}$, and allowing for instantaneous adsorption by sediment of part of what is added to the puddle generates the following daily time step algorithm. The algorithm gives the dissolved concentration in puddle water at the beginning of day i+1 at $t=t_{i+1}$ in terms of the dissolved concentration in puddle water at the beginning of the previous day i at $t=t_i$:

$$C_{pud}(t = t_{i+1}) = \frac{m_{pud(add)}(t = t_{i+1}) - x_{ads}}{A_{pud} D_{pud}} + C_{pud}(t = t_i) \bullet \exp[-k_m(1\ \text{day})]$$

(Equation C9-28)

where

$C_{pud}(t=t_{i+1})$ = dissolved concentration in puddle at the beginning of day i+1 at $t = t_{i+1}$ in mg/m^3

$m_{pud(add)}(t=t_{i+1})$ = chemical mass added to puddle at beginning of day i+1 at $t=t_{i+1}$ due to direct application or spray drift (mg)

x_{ads} = mass of chemical adsorbed from puddle water by sediment immediately after application to the puddles

$C_{pud}(t=t_i)$ = concentration in puddle at the beginning of day i at $t = t_i$ in mg/m^3

$k_{overall}$ = overall dissipation rate constant in puddle and sediment (1/day)

1 day = $t_{i+1} - t_i$

Assuming equilibrium partitioning of the chemical dissolved in puddle water with chemical adsorbed to sediment to an interaction sediment depth of D_{sed}, the mass of chemical adsorbed (x_{ads}) from puddle water by sediment immediately after any application to the puddles is computed as follows:

Based upon the assumed equilibrium,

$$\frac{x_{ads}}{A_{pud} D_{sed} r_{sed}} = \frac{K_{sed/pud}\left[m_{add}(t = t_{i+1}) - x_{ads}(t = t_{i+1})\right]}{A_{pud} D_{pud}}$$

(Eq. C9-29)

Solving equation C9-29 for $x_{ads}(t=t_{i+1})$ gives

$$x_{ads}(t = t_{i+1}) = \frac{D_{sed}\, r_{sed}\, K_{sed/pud}\, m_{add}(t = t_{i+1})}{D_{pud} + D_{sed}\, r_{sed}\, K_{sed/pud}} \quad \text{(Eq. C9-30)}$$

For direct application to the puddle at $t=t_{i+1}$ (assuming puddles are only formed outside the canopy cover), the $m_{pud(add)}(t=t_{i+1})$ in equations C9-28 through C9-30 is given by:

$$m_{pud\,(add)}(t = t_{i+1}) = \left(1 - f_{sd}\right) A_{pud}\left[App(t = t_{i+1})\right] \quad \text{(Eq. C9-31)}$$

where

f_{sd} = fraction loss by spray drift before hitting the targeted field

$App_{(i+1)}$ = nominal application rate at the beginning of day i+1 at $t = t_{i+1}$in mg chemical/m^2(convert from lb/acre or kg/ha)

For spray drift to the puddle at $t=t_{i+1}$ (assuming puddles are only formed outside the canopy cover), the $m_{pud(add)}(t=t_{i+1})$ in equations B6-28 through B6-30 is given by:

$$m_{pud\,(add)}(t = t_{i+1}) = \left(SD_{avg}\right) A_{pud}\left[App(t = t_{i+1})\right]$$ (Eq.

C9-32)

where

SD_{avg} = average spray drift deposition defined by equation C9-6.

Estimating the initial concentration in the puddle depends upon how the chemical is assumed to be first introduced to the puddle. If the puddle is formed over uncontaminated soil, the chemical will be first introduced to the puddle by direct application or spray drift at some time $t=t_{add\text{-}pud}$. In such a case the initial concentration in the puddle C_{pud0} when the puddle first receives a direct application or spray drift at $t=_{add\text{-}pud}$ can be estimated from the following equations:

$$C_{pud}(t = t_{add-pud}) = \frac{m_{add}(t = t_{add-pud}) - x_{ads}(t = t_{add-pud})}{A_{pud} D_{pud}}$$ (Eq.

C9-33)

where

$$x_{ads}(t = t_{add-pud}) = \frac{D_{sed}\, r_{sed}\, K_{sed/pud}\left[m_{add}(t = t_{add-pud})\right]}{D_{pud} + D_{sed}\, r_{sed}\, K_{sed/pud}}$$ (Eq.

C9-34)

Note that equation C9-34 was obtained by substituting $t=t_{add\text{-}pud}$ for $t=t_{i+1}$ in equation B6-30.

If the puddle is formed at $t=t_{form\text{-}pud}$ over contaminated soil, the following desorption equations can be used to estimate the initial concentration in the puddle C_{pud0} when the puddle is formed at $t=t_{form\text{-}pud}$:

Based upon the assumed equilibrium,

$$\frac{m_{sed}(t = t_{form-pud}) - x_{des}(t = t_{form-pud})}{A_{pud} D_{sed} r_{sed}} = \frac{K_{sed/pud}\left[x_{des}(t = t_{form-pud})\right]}{A_{pud} D_{pud}} \quad \text{(Eq. C9-35)}$$

Solving equation C9-35 for $x_{des}(t=t_{form\text{-}pud})$ gives:

$$x_{des}(t = t_{form-pud}) = \frac{D_{pud} m_{sed}(t = t_{form-pud})}{D_{pud} + K_{sed/pud} D_{sed} r_{sed}} \quad \text{(Eq. C9-36)}$$

The initial puddle concentration is given by

$$C_{pud\,0}(t = t_{form-pud}) = \frac{x_{des}(t = t_{form-pud})}{A_{pud} D_{pud}} \quad \text{(Eq. C9-37)}$$

where

$x_{des}(t=t_{form\text{-}pud})$ is given by equation C9-36

C9.7: Interim Equations for Pesticide Concentrations in Puddles Assuming A Linear Decrease in Puddle Depth

Assuming even a simple linear decrease in puddle volume greatly increases the complexity of estimates of concentrations in puddles compared to assuming the puddle volume remains constant (as was previously done). Assuming equilibrium between the sediment and puddle water and that the volume of the puddle water linearly decreases with time due to infiltration and evaporation, coupled simple pseudo first order decline mass balance equations for puddles and sediment are given by:

$$A_{pud}\frac{d\left(D_{pud(i)}C_{pud(i)}\right)}{dt} = -\left[A_{pud}D_{pud(i)}(k_{pud} + k_{volatil}) + A_{pud}I_{\inf il}\right]C_{pud(i)} \quad \text{(Eq. C9-38)}$$

$$A_{pud}D_{sed}r_{sed}\frac{dC_{sed(i)}}{dt} = -A_{pud}D_{sed}r_{sed}k_{sed}C_{sed(i)} \quad \text{(Eq. C9-39)}$$

If both sides of equation C9-38 were divided by A_{pud}, the right side of the equation would be identical to the first 3 terms on the right side of the puddle mass balance equation in TEEAM.

Because the puddle depth (but not the puddle area) as well as the concentration in the puddle are functions of time, the derivative on the left side of equation C9-38 can be expanded to give:

$$A_{pud}\left(D_{pud(i)} \frac{dC_{pud(i)}}{dt} + C_{pud(i)} \frac{dD_{pud(i)}}{dt} \right) =$$
$$-\left[A_{pud} D_{pud(i)} \left(k_{pud} + k_{volat} \right) + A_{pud} I_{\inf il} \right] C_{pud(i)}$$

(Eq. C9-40)

Assuming the puddle depth linearly decreases with time:

$$D_{pud(i)}(t_i < t \le t_{i+1}) = D_{pud}(t = t_i) - k_{\inf il\&evap}\left(t - t_i\right)$$

(Eq. C9-41)

Therefore,

$$\frac{dD_{pud(i)}}{dt} = -k_{\inf il\&evap}$$

(Eq. C9-42)

Substituting equation C9-42 for $dD_{pud(i)}/dt$ into equation C9-40 gives:

$$A_{pud}\left(D_{pud(i)} \frac{dC_{pud(i)}}{dt} - k_{\inf il\&evap} C_{pud(i)} \right) =$$
$$-\left[A_{pud} D_{pud(i)} \left(k_{pud} + k_{volatil} \right) + A_{pud} I_{\inf il} \right] C_{pud(i)}$$

(Eq. C9-43)

Assuming equilibrium and substituting $dC_{sed(i)}/dt = K_{sed/pud} dC_{pud(i)}/dt$ and $C_{sed(i)} = K_{sed/pud} C_{pud(i)}$ into equation C9-39 gives:

$$A_{pud} D_{sed} r_{sed} K_{sed/pud} \frac{dC_{pud(i)}}{dt} = -A_{pud} D_{sed} r_{sed} K_{sed/pud} k_{sed} C_{pud(i)} \quad \text{(Eq. C9-44)}$$

Adding equations C9-43 and C9-44 and rearranging gives the overall mass balance equation for the puddle/sediment system in terms of the puddle concentration:

$$\frac{dC_{pud(i)}}{dt} = -\left(\frac{at+b}{pt+q}\right) C_{pud(i)} \quad \text{(Eq. C9-45)}$$

where

$$a = k_{\text{inf\&}evap}(k_{pud} + k_{volatil}) \quad \text{(Eq. C9-46)}$$

$$b = k_{\text{inf\&}evap} - \left[\left(D_{pud}(t=t_i) + k_{\text{inf\&}evap} t_i\right)\left(k_{pud} + k_{volat}\right) + I_{\text{inf}il} + D_{sed} r_{sed} K_{sed/pud} k_{sed}\right]$$

(Equation C9-47)

$$p = -k_{\text{inf\&}evap} \quad \text{(Eq. C9-48)}$$

$$q = D_{pud}(t=t_i) + k_{\text{inf\&}evap} t_i + D_{sed} r_{sed} K_{sed/pud} \quad \text{(Eq. C9-49)}$$

Separating variables, integrating equation B6-45 from $C_{pud(i)} = C_{pud}(t=t_i)$ to $C_{pud(i)} = C_{pud}(t=t_{i+1})$ and from $t=t_i$ from $t=t_{i+1}$, allowing for a possible instantaneous application to the puddles at the beginning of day i+1 at $t=t_{i+1}$, and allowing for instantaneous adsorption by sediment of part of what is added to the puddle generates the following daily time step algorithm. The algorithm gives the dissolved concentration in puddle water at the beginning of day i+1 at $t=t_{i+1}$ in terms of the dissolved concentration in puddle water at the beginning of the previous day i at $t=t_i$:

$$C_{pud}(t = t_{i+1}) = \frac{\left[m_{add}(t = t_{i+1}) - x_{ads}\right]}{A_{pud} D_{pud}} + \left(\frac{pt_{i+1} + q}{pt_i + q}\right)^{\frac{bp-aq}{p^2}} \bullet C_{pud}(t = t_i) \bullet \exp[a(1\text{ day}) / p] \quad \text{(Eq. C9-50)}$$

C9.8: Interim Level 1 and 2 Estimates of Pesticide Concentrations in a Pond

When AgDRIFT, PRZM3 and EXAMS are provided with adequate Monte Carlo simulation capabilities, they can be used to generate interim level 1 and 2 estimates of dissolved pesticide concentrations in ponds. AgDRIFT and PRZM3 will provide estimates of pesticide loadings to the pond and EXAMS will be used to estimate the resulting pesticide concentrations in the pond.

Until AgDRIFT, PRZM3, and EXAMS are provided with adequate Monte Carlo simulation capabilities, GENEEC (which is currently used by OPP/EFED as a screening model in aquatic risk assessments) can be used to generate interim level 1 and 2 estimates of dissolved pesticide concentrations in ponds. GENEEC is also a component of PARET and is described along with PARET in a separate Section.

C9.9:Interim Level 1 and 2 Estimates of Pesticide Concentrations in Air Within the Canopy

Interim level 1 estimates of average pesticide concentrations in air within the plant canopy can be generated with PRZM3. When the Monte Carlo output variable capability of PRZM 3 is expanded to include pesticide concentrations in air, level 2 estimates can also be generated with PRZM 3.

C9.10: Interim Level 1 and 2 One Compartment Vertebrate Mass Balance Model

The overall contaminant mass balance differential equation for a one compartment vertebrate model is given by:

$$\frac{d\left(W_{v(i)}C_{v(i)}\right)}{dt} = \left(\frac{dm}{dt}\right)_{\text{int}\,ake} - \left(k_{depur} + k_{metab}\right)W_{v(i)}C_{v(i)} \qquad \text{(Eq. C9-51)}$$

where

$C_{V(i)} = C_V(t_{i+1}<t<t_i)$ = bulk concentration in the vertebrate as a function of time on day i from $t=t_i$ to $t=t_{i+1}$ (mg/kg body weight)

$W_V(t=t_i)$ = vertebrate mass (body weight) at the beginning of day i at $t=t_i$ (kg)

$(dm/dt)_{intake(i)}$ = rate of total contaminant intake on day i from food ingestion, water ingestion, inhalation, and dermal contact (mg/day)

$k_{depuration}$ = pseudo first order depuration rate constant (1/day)

k_{metab} = pseudo first order metabolic rate constant for the contaminant (1/day)

Equation C9-51 is in the form

$$\frac{d\left(W_{v(i)}\right)}{dt} = K_{1(i)} - K_2 W_{v(i)} C_{v(i)} \quad \text{(Eq. C9-52)}$$

where

$$K_{1(i)} = \left(\frac{dm}{dt}\right)_{\text{int}\,ake(i)} \quad \text{(Eq. C9-53)}$$

$$K_2 = k_{depur} + k_{metab} \quad \text{(Eq. C9-54)}$$

Separating variables in equation C9-52, integrating from $W_{v(i)}C_{v(i)} = W_v(t=t_i)C_v(t=t_i)$ to $W_{v(i)}C_{v(i)} = W_v(t=t_{i+1})C_v(t=t_{i+1})$ and from $t=t_i$ from $t=t_{i+1}$, and rearranging generates the following daily time step algorithm. The algorithm gives the concentration of chemical in the vertebrate at the beginning of day i+1 at $t=t_{i+1}$ in terms of the concentration at the beginning of the previous day i at $t=t_i$:

$$C_v(t = t_{i+1}) = \frac{K_{1(i)}}{K_2 W_v(t = t_{i+1})}\left[1 - \exp[-K_2(1\ \text{day})]\right] + \frac{W_v(t = t_i)}{W_v(t = t_{i+1})} C_v(t = t_i) \bullet \exp[-K_2(1\ \text{day})] \quad \text{(Eq. C9-55)}$$

C9.11: Interim Equations for Concentrations in Surface and Foliar Dwelling Insects

The mathematical form of equation C9-55 for vertebrates should also be applicable for foliar and soil surface dwelling insects except the mass balance should reflect pesticide on as well as in the insect. Therefore, if a direct or spray drift application occurs in field j on day i+1, an additional application term (equivalent to that reaching the insect) should be added to the right side of the equation to reflect deposit of pesticides on to the organism:

$$C_{insect}(t = t_{i+1}) = \frac{m_{insect(add)}(t = t_{i+1})}{W_{insect}(t = t_{i+1})} + \frac{K_1}{K_2 W_{insect}(t = t_{i+1})}\left[1 - \exp[-K_2(1\ \text{day})\}\right] + \frac{W_{insect}(t = t_i)}{W_{insect}(t = t_{i+1})} C_{insect}(t = t_i) \bullet \exp[-K_2(1\ \text{day})]$$

(Equation C9-56)

For direct application and spray drift at $t=t_{i+1}$ to an insect on foliage, the $m_{insect(add)}(t=t_{i+1})$ in equation C9-56 is given respectively by:

$$m_{insect(add)}(t = t_{i+1}) = \left(1 - f_{sd}\right)\left[f_{int}(t = t_{i+1})\right]\left[A_{insect}\right]\left[App(t = t_{i+1})\right] \quad \text{(Eq. C9-57)}$$

$$m_{insect(add)}(t = t_{i+1}) = \left(SD_{avg}\right)\left[f_{int}(t = t_{i+1})\right]\left[A_{insect}\right]\left[App(t = t_{i+1})\right] \quad \text{(Eq. C9-58)}$$

where

f_{int} = fraction intercepted by plant when chemical is applied at $t=t_{i+1}$

f_{sd} = fraction loss by spray drift before hitting the targeted field

App = nominal application rate at the beginning of day i+1 at $t = t_{i+1}$ in mg chemical/m^2(convert from lb/acre or kg/ha)

A_{insect} = area of insect exposed to pesticide deposition

SD_{avg} = average spray drift deposition defined by equation C9-6

For direct application and spray drift at $t=t_{i+1}$ to an insect on uncovered bare soil, the $m_{insect(add)}(t=t_{i+1})$ in equation C9-56 is given respectively by:

$$m_{in\sec t(add)}(t = t_{i+1}) = \left(1 - f_{sd}\right)\left[A_{in\sec t}(t = t_{i+1})\right]\left[App(t = t_{i+1})\right] \quad \text{(Eq. C9-59)}$$

$$m_{in\sec t(add)}(t = t_{i+1}) = \left(SD_{avg}\right)\left[A_{in\sec t}\right]\left[App(t = t_{i+1})\right] \quad \text{(Eq. C9-60)}$$

For direct application and spray drift at $t=t_{i+1}$ to an insect on canopy covered bare soil, the $m_{insect(add)}(t=t_{i+1})$ in equation C9-56 is given respectively by:

$$m_{in\sec t(add)}(t = t_{i+1}) = \left(1 - f_{sd}\right)\left[1 - f_{\text{int}}(t = t_{i+1})\right]\left[A_{in\sec t}\right]\left[App(t = t_{i+1})\right] \quad \text{(Eq. C9-61)}$$

$$m_{in\sec t(add)}(t = t_{i+1}) = \left(SD_{avg}\right)\left[1 - f_{\text{int}}(t = t_{i+1})\right]\left[A_{in\sec t}\right]\left[App(t = t_{i+1})\right] \quad \text{(Eq. C9-62)}$$

C9.12: Interim Equations for Concentrations in Worms and Subterranean Insects

Earthworms can possibly act as a substitute for other soil invertebrates and subterranean insects. Earthworms are often assumed to be in equilibrium with the bulk contaminant concentration in the soil or the pore water concentration (Sample et. al 1997):

$$C_{worm} = K_{worm/soil} C_{bulk-soil} \quad \text{(Eq. C9-63)}$$

$$C_{worm} = K_{worm/pw} C_{pw} \quad \text{(Eq. C9-64)}$$

Worms ingest contaminated soil as well as uptake contaminants from pore water and can move between vertical soil compartments (layers) j (Bird, Cheplick, and Brown 1991). Worms presumably tend to spend more time in soil layers with somewhat intermediate soil moisture than in excessively dry layers or in excessively wet layers where oxygen exclusion or depletion may occur. However, there is no hydrology component in this interim model to estimate soil moistures for different layers. Therefore, within the vertical extent of their movement, we will assume that on any given day i, the ratio of time worms spend in any given soil compartment (layer) j to the entire day will be equal to the ratio of the thickness of soil compartment (layer) j to the vertical extent of their movement. Therefore, in weighing the relative contributions of different soil compartments (layers) with different concentrations in soil to the contaminant intake of the worm on day i, we will use ($\Delta z_j/D_{worm}$) as weighing factors where Δz_j = the thickness of soil compartment (layer) j and D_{worm} = deepest vertical extent of their movement.

Based on the previous paragraph, one possible mass balance equation for worms would be:

$$\frac{dC_{worm(i)}}{dt} = \sum_{j=1}^{j=j\max(worm)} \left(\Delta z_j / D_{worm}\right)\left(k_{up(pw)}\right)\left[q_{pw(j)}(t=t_i)\right]\left(A_s \Delta z_j\right) C_{pw(j)}(t=t_i)/W_w$$

$$+ \sum_{j=1}^{j=j\max(worm)} \left(\Delta z_j / D_{worm}\right)\left(dM_{soil(ingest)}/dt\right) C_{bulk(j)}(t=t_i)/W_w - \left(k_{depur} + k_{metab}\right) C_{worm}$$

(Equation C9-65)

where

$C_{worm(i)} = C_{worm}(t_{i+1}<t<t_i)$ = bulk concentration in the worm as a function of time on day i from $t=t_i$ to $t=t_{i+1}$

W_{worm} = worm mass (body weight)

$j_{max(worm)}$ = deepest layer worms go to

Δz_j = thickness of soil compartment (layer) j (cm)

D_{worm} = deepest vertical extent of movement (cm)

k_{up} = rate of soil pore water uptake (1/day)

$\Theta_{pw(j)}(t=t_i)$ = volumetric water content of soil compartment (layer) j at the beginning of day i at $t=t_i$

A_s = area of the field (cm^2)

$C_{pw(j)}(t=t_i)$ = concentration in the pore water of soil compartment (layer) j at the beginning of day i at $t=t_i$ (g/cm^3)

$dM_{s(ingest)}/dt$ = soil ingestion rate (g/day)

$C_{sbulk(j)}(t=t_i)$ = bulk soil concentration in soil compartment (layer) j at the beginning of day i at $t=t_i$

k_{depur} = depuration rate constant (1/day)

k_{metab} = metabolic rate constant (1/day)

Note that

$$D_{worm} = \sum_{j=1}^{j=j\max(worm)} \Delta z_j \quad \text{(Eq. C9-66)}$$

Also note that to calculate C_{pw} from $C_{s(bulk)}$ or $C_{s(bulk)}$ from C_{pw}, it can shown from mass balance considerations that:

$$C_{soil(bulk)} = \left(\frac{q_{pw}}{r_s} + K_d + \frac{f_a K_H}{r_s} \right) C_{pw} \quad \text{(Eq. C9-67)}$$

and

$$C_{pw} = \frac{r_s C_{soil(bulk)}}{q_{pw} + K_d r_s + f_a K_H} \quad \text{(Eq. C9-68)}$$

where

ρ_s = bulk density of soil

Θ_w = volumetric pore water fraction

K_d = soil/water partition coefficient

Θ_a = volumetric pore air fraction

K_H = dimensionless Henry's Law constant

Equation C9-65 is in the form

$$\frac{dC_{worm(i)}}{dt} = K_{1(i)} - K_2 C_{worm(i)} \qquad \text{(Eq. C9-69)}$$

where

$$K_{1(i)} = \sum_{j=1}^{j=j\max(worm)} \left(\Delta z_j / D_{worm}\right)\left(k_{up(pw)}\right)\left[q_{pw(j)}(t = t_i)\right]\left(A_s \Delta z_j\right) C_{pw(j)}(t = t_i) / W_w$$
$$+ \sum_{j=1}^{j=j\max(worm)} \left(\Delta z_j / D_{worm}\right)\left(dM_{soil(ingest)} / dt\right) C_{bulk(j)}(t = t_i) / W_w$$

(Equation C9-70)

and

$$K_2 = k_{depur} + k_{metab}$$

(Eq. C9-71)

Separating variables in equation C9-69, integrating from $C_{worm(i)} = C_{worm}(t=t_i)$ to $C_{worm(i)} = C_{worm}(t=t_{i+1})$ and from $t=t_i$ from $t=t_{i+1}$, and rearranging generates the following daily time step algorithm. The algorithm gives the concentration of chemical in the worm at the beginning of day i+1 at $t=t_{i+1}$ in terms of the concentration at the beginning of the previous day i at $t=t_i$:

1 $$C_{worm}(t = t_{i+1}) = \frac{K_{1(i)}}{K_2}\left[1 - \exp[-K_2(1\ \text{day})\right] + C_{worm}(t = t_i) \bullet \exp[-K_2(1\ \text{day})]$$

2 (Equation C9-72)

3 where $K_{1(i)}$ and K_2 are given be equations C9-70 and C9-71, respectively.

APPENDIX C 10

RISKS TO BIRDS FROM THE USE OF CHLORPYRIFOS ON APPLES: AN EXAMPLE USING ECOFRAM APPROACHES

OBJECTIVE

- The aim of this section is to illustrate the use of some of the approaches proposed by ECOFRAM. In particular:
  - ⇒ The use of the daily dose equations at varying Levels of Refinement
  - ⇒ The use of generic field data to estimate distributions of pesticide residues on invertebrates
  - ⇒ The use of hypothetical distributions to help decide whether a variable has sufficient influence to be worth measuring in field studies.
  - ⇒ The use of radio-tracking data to estimate empirical distributions for the proportion of food obtained from treated areas
  - ⇒ Methods for extrapolating acute toxicity between species and estimating species sensitivity distributions
  - ⇒ The use of Monte Carlo simulations for risk characterization
  - ⇒ The definition and use of ‘acceptability thresholds’
  - ⇒ The use of sensitivity analysis to assess the relative influence of different inputs
  - ⇒ How all these elements fit together into a practical assessment process.

- The example uses data relating to the use of chlorpyrifos in UK apple orchards, and is presented in a sequential fashion introducing progressive refinements as might be done in a regulatory assessment. ***The example is for illustration only and should not be interpreted as a formal assessment.***

PROBLEM FORMULATION

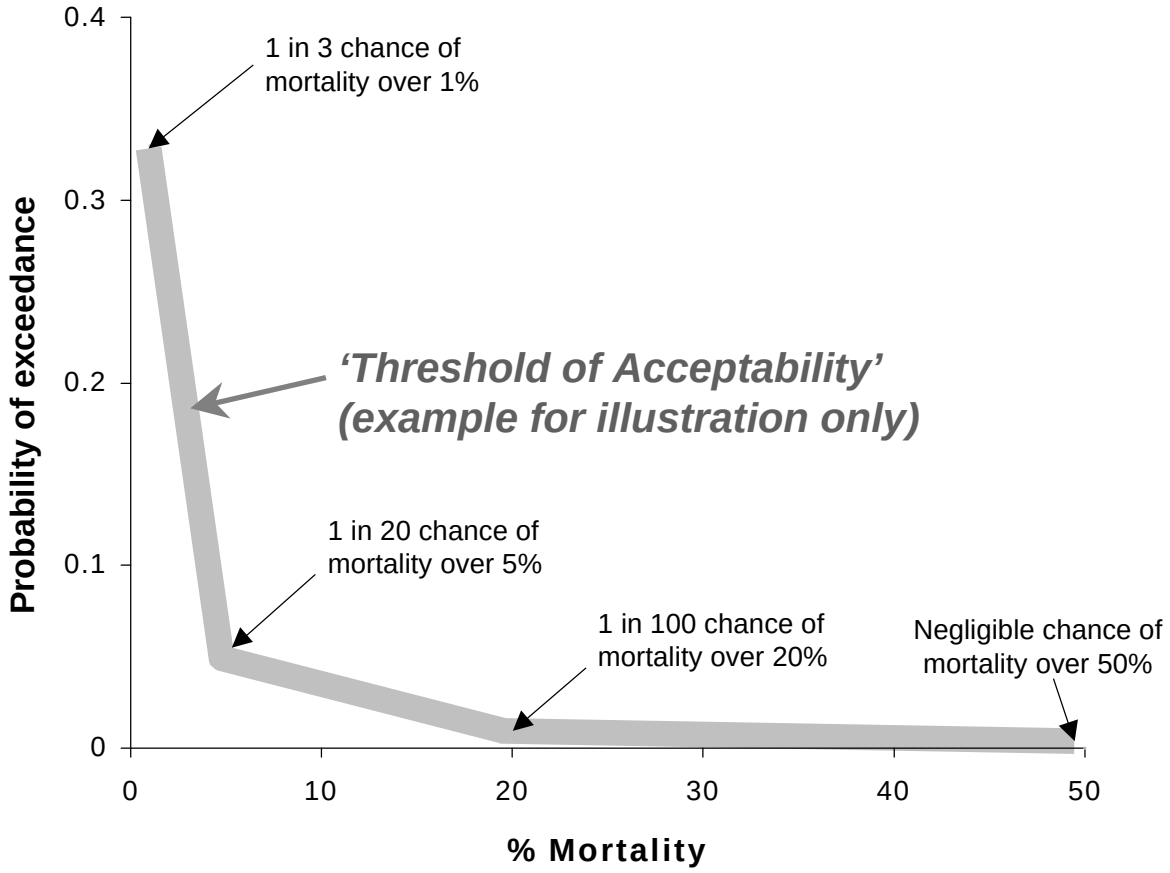
- The example focuses on risks to birds from the use of **chlorpyrifos in apple orchards in the United Kingdom**, applied by air-blast sprayer at 0.96 kg/ha.
- **The focal species** for the example is the **blue tit (Parus caeruleus)**, a small insectivorous bird which is common in orchards in the UK.
- **The Assessment Endpoint** for the example is the **Percent Mortality of Adult birds**.
- **The Scope** of the example is limited to considering **Acute lethal effects, Exposure via the Dietary route only, and Exposure periods of One Day**. This is purely to provide a relatively simple basis for illustrating the ECOFRAM approaches. *A proper risk assessment should take account of other effects and timescales, as indicated by the ECOFRAM report.*
- ECOFRAM recommends that the acute oral LD50 should be used to assess effects of short-term exposures in the order of minutes to hours, and that a (modified) dietary LC50 should be used for longer term exposures. However, this example uses the LD50 as the measure of sensitivity for exposures estimated over one day.

Defining the threshold of acceptability

- Section 6 proposes that a 'threshold of acceptability' be defined at the start of the assessment, both to interpret the results at each stage and to assist in deciding whether and how to refine the assessment.
- For example, it might be decided that a 1 in 3 chance of 1% mortality was at the limit of acceptable risk, but that only a 1 in 20 chance could be tolerated for mortality of 5% or more. These simple probability statements can be plotted as points on a graph of Probability of Exceedance vs. % Mortality, as in Figure 1.
- A small number of points are sufficient to draw a line marking the approximate position of the threshold of acceptability. The line is shown as a broad grey area because of its subjective and approximate nature.
- **The points and threshold shown in Figure 1 are purely illustrative.** In practice, very careful consideration would be required to define them, as discussed in Section 6. This might

take account of ecological factors (e.g. population stability and resilience) and other issues such as the economic and agricultural benefits of the pesticide.

Figure 1. The use of simple subjective probability statements to define a threshold of acceptability. Different thresholds might be defined for different assessment endpoints. The positions of the points and threshold shown here are examples for illustration only.



Exposure model

Chapter 3, equation 3.3-7:

$$\text{One day dose}_{\text{dietary (day i)}} = \sum_{k=1}^{k=N_k} (PT_i)(TFIR_i)(PD_{ik})(FDR_{ik})\left[1-(AV_i)\right]C_{ik} \,/\, W$$

(variable names are defined in the table below).

- This example explores variation in sensitivity, and in PT and C, but not the other exposure variables.
- This example does not consider exposure by any route other than the ingestion of contaminated food.

INITIAL DETERMINISTIC ASSESSMENT

- The inputs used for the initial assessment are shown in the following table. The 'Levels of Refinement' correspond to those discussed in Sections 2 to 6 of the ECOFRAM report.

Variable	Level of Refinement	Input
PT_i – Proportion of food obtained from treated area on day *i*	1	1 – all food from treated area.
$TFIR_i$ – Total food ingestion rate on day *i*	1	3.3g dry weight – estimated using Nagy's (1987) equation for passerine birds.
PD_{ik} – Proportion of diet comprising food type *k*	1	1 – feeds exclusively on food type with highest pesticide concentrations (small insects).
FDR_{ik} – Fresh to dry weight ratio for food type *k* on day *i*	1	5 – based on water content of about 80% by weight.
AV_i – Avoidance of contaminated food on day *i*	1	0 – no avoidance.
C_{ik} – Concentration of pesticide on food type *k* on day *i*	1	116 mg/kg – residues on small insects assumed similar to 'maximum' estimates used by US EPA, based on Fletcher et al. (1994), and adjusted for pesticide application rate of 0.96 kg/hectare.
W – body weight of bird	1	13.3g – mean from Dunning (1993).
LD50	1	Single study for bobwhite quail.
Probit slope of LD50	1	

- Most of the exposure inputs are highly conservative (i.e. are more likely to over-estimate rather than under-estimate risk). PT, PD, AV are based on literal worst-case assumptions,

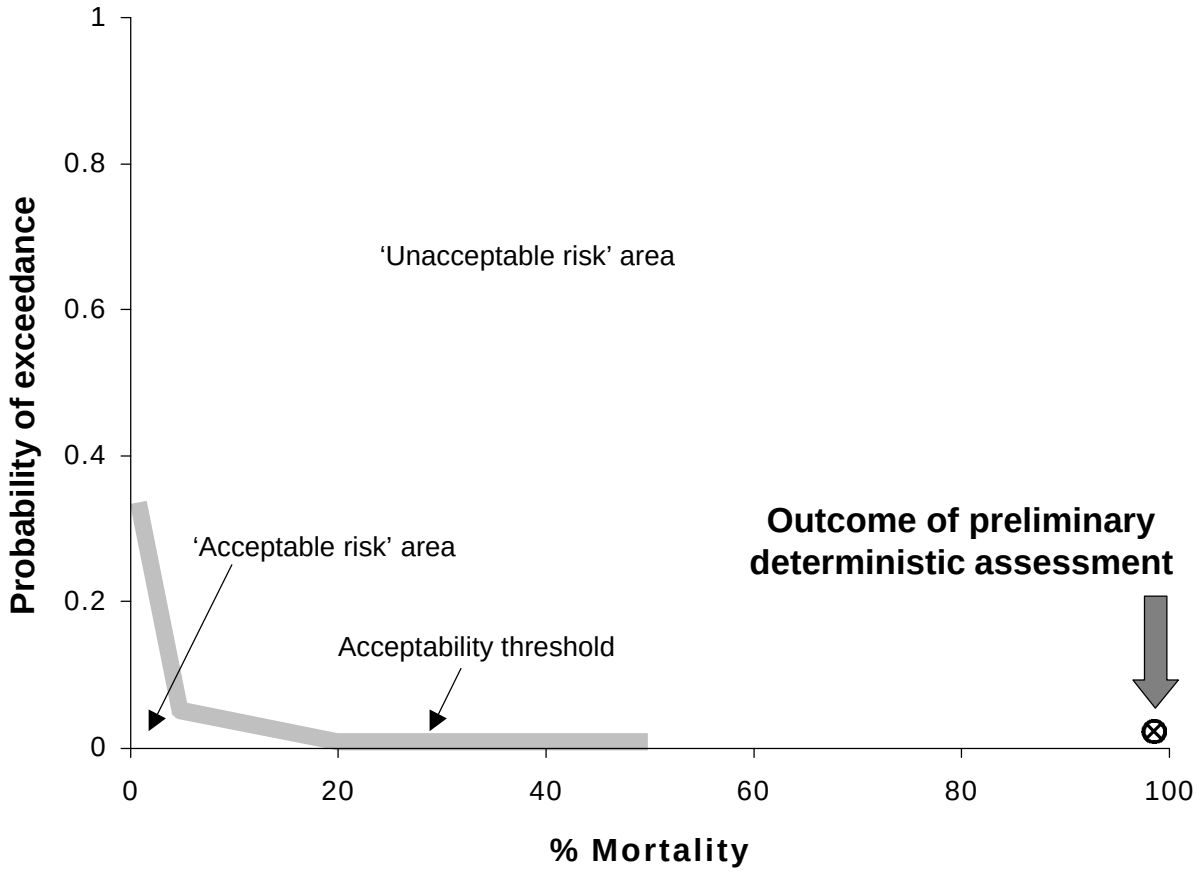
while C is based on a value tending to worst case (around the 95 percentile for residues immediately after application). TFIR, FDR and W are averages.

- The exposure estimate should therefore be very conservative – actual exposures of this magnitude could conceivably occur, but should be very rare.
- A summary of results from 41 LD50 studies was available for the example. It was decided to use a bobwhite quail study in the initial assessment, as this is the most likely species if only one study were available (e.g. for a new pesticide). There were several bobwhite studies but only one provided a slope for the technical active ingredient, so this study was selected.
- The 5th percentile of the distribution of species sensitivities was estimated from the bobwhite quail LD50 using the method developed for ECOFRAM (Figure 4.5.5, output number 1). The one-sided 95% left confidence limit was also estimated (ECOFRAM Figure 4.5.5, output number 2).
- The exposure and sensitivity estimates were combined in two ways: as a Risk Quotient (RQ = dose/sensitivity), and as the % mortality estimated using the probit relationship and the slope reported from the bobwhite quail study.

LD50 estimate used	Risk Quotient	% Mortality
Reported value (bobwhite quail)	4.5	99.9 %
Estimated 5th percentile of the distribution of species sensitivities	20	100 %
One-sided 95% left confidence limit of the estimated 5th percentile of the distribution of species sensitivities	141	100 %

- These results can be compared to the threshold of acceptability as shown in Figure 2. All three estimates are effectively 100% mortality, placing them at the right-hand end of the x-axis.
- The probability associated with these estimates is not quantified at this stage of the assessment. However, as both the exposure and sensitivity estimates are conservative, the probability is likely to be very small, so the result is plotted at a probability close to zero.

Figure 2.



- Figure 1 shows the risk is very uncertain at this stage of the assessment. If the true risk curve is very shallow, or the current inputs are very over-conservative, then the true risk may in fact fall below the threshold. However, the position of the current estimate clearly leaves open the possibility that the risk curve exceeds the threshold by a large margin, so further refinement of the assessment is appropriate.

PROBABILISTIC ASSESSMENT

Methods

- The examples were computed using Excel and @Risk software.

- In most cases, a two-stage Monte Carlo simulation was used, representing 1000 populations each comprising 1000 individuals. Exposure and individual tolerance varied *within* populations, but species sensitivity (LD50 and slope) was only varied *between* populations.
- In the first stage, 1000 iterations of the exposure model were computed to provide 1000 estimates of the one-day dose (mg/kg/day), representing the exposure of 1000 individual birds.
- In the second stage, 1000 iterations were computed in which values were drawn for the median and slope of the LD50. Individual tolerances were computed for the 1000 individuals using the method from Section 4.4.3.1 and a list of 1000 z-scores drawn from a standard Normal distribution (this list was generated once and used repeatedly throughout the example). In each iteration, the 1000 individual tolerances were compared with the 1000 doses calculated in stage 1. Individuals for which dose exceeded tolerance were assumed to have died.
- The percentage mortality was calculated for each population, and the overall output was a distribution of percentage mortalities for 1000 populations. This distribution was used to compute an exceedance curve, showing the estimated probability with which each level of mortality was exceeded.
- The two-stage Monte Carlo was repeated 7 times with different inputs, referred to below as Models 1-6 and 8. Model 7 used a one-stage Monte-Carlo, in order to carry out a sensitivity analysis covering inputs in both stages of the two-stage method (see later).
- The input variables were assumed to be independent in every simulation.

Model 1

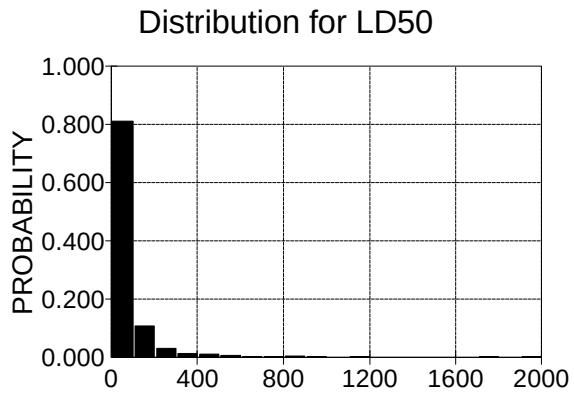
The first model used the same inputs as the initial deterministic assessment, but using a two-stage Monte Carlo simulation to obtain an exceedance curve instead of point estimates for risk.

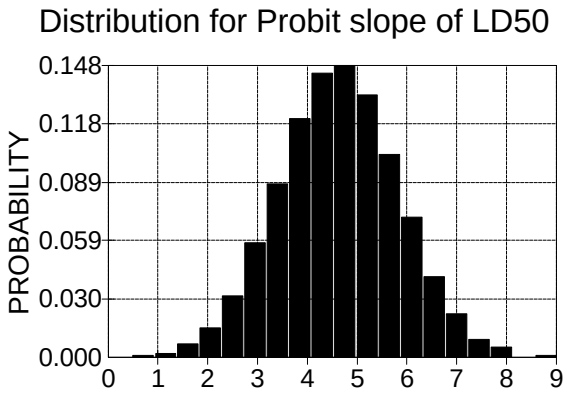
Inputs table

Variable	Level of Refinement	Input
PT_i	1	1
$TFIR_i$	1	3.3g dry weight
PD_{ik}	1	1
FDR_{ik}	1	5
AV_i	1	0
C_{ik}	1	116 mg/kg
W	1	13.3g
LD50	1	Lognormal distribution estimated from one study for bobwhite quail and method of Section 4.5.4.
Probit slope of LD50	1	Normal distribution estimated from slope and standard error for the same bobwhite quail study, as suggested in Section 4.5.7 (option I C).

Input distributions

Figure 3. In these and subsequent histograms of input distributions, the figures show the distribution of values generated in the simulations rather than the distribution functions from which they were generated.

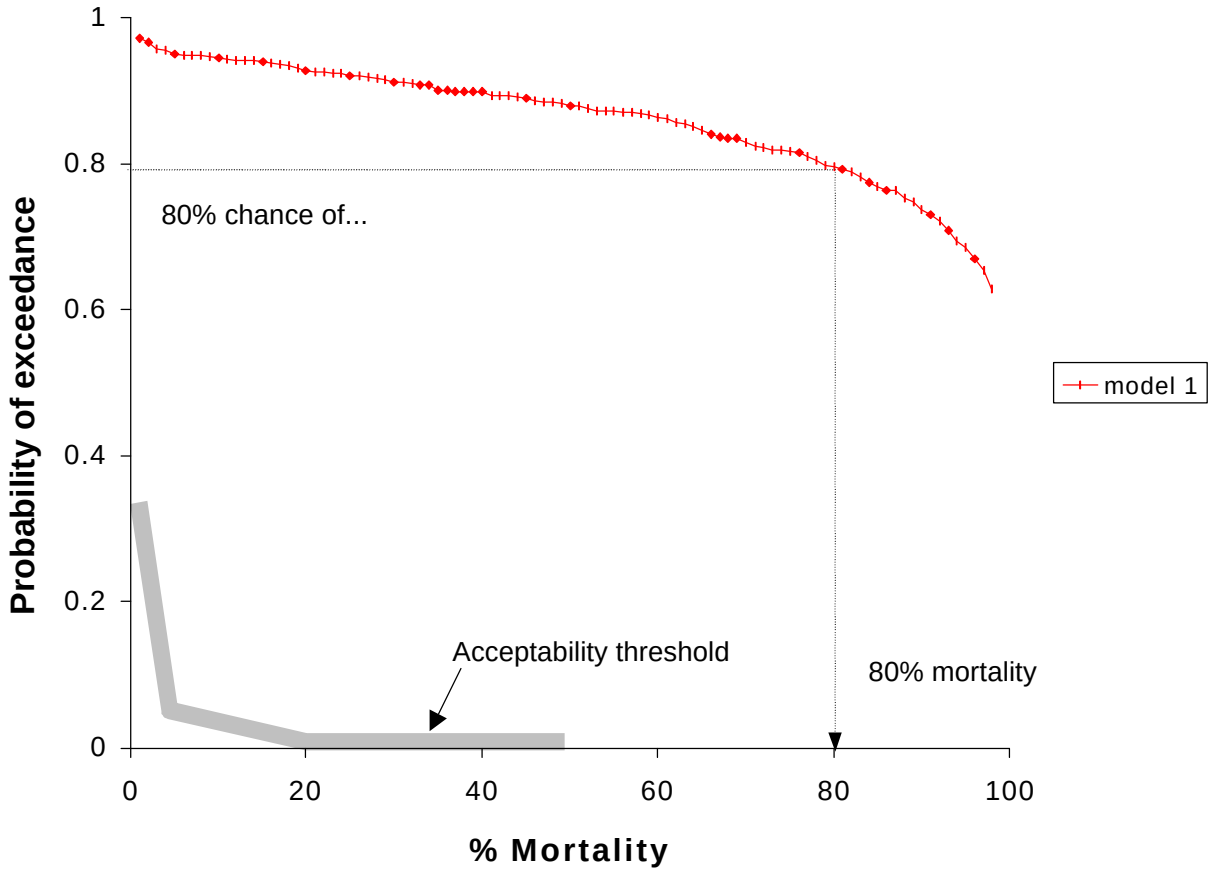




- Note that the dose was deterministic in this model, as in the initial assessment, and was estimated as 143.9 mg/kg. It can be seen from Figure 3 that the dose exceeded the LD50 for over 80% of the simulations.

Output

Figure 4.



Interpretation

- The risk curve at this stage greatly exceeds the threshold. Further refinement is clearly appropriate.

Model 2

- It was decided to utilise a second LD50 study in the next stage, but to make no change to the exposure assessment.

- A mallard study was selected, as this would most commonly be available for a pesticide with 2 studies. A slope was available from only one of the available mallard studies, so this study was selected.

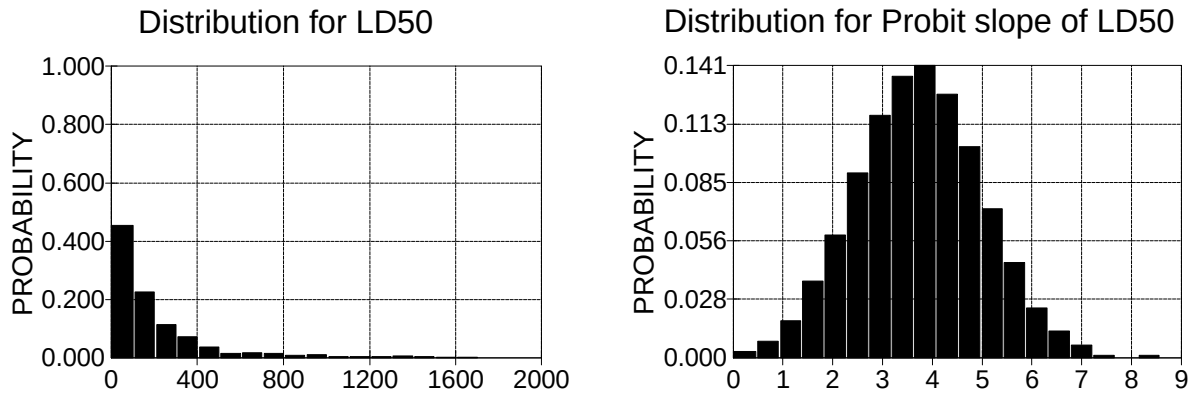
Inputs table

Variable	Level of Refinement	Input
PT_i	1	1
$TFIR_i$	1	3.3g dry weight
PD_{ik}	1	1
FDR_{ik}	1	5
AV_i	1	0
C_{ik}	1	116 mg/kg
W	1	13.3g
LD50	2*	Lognormal distribution estimated from one study for bobwhite quail and one for mallard, and the method of Section 4.5.4.
Probit slope of LD50	2*	Normal distribution estimated from slopes for the same bobwhite quail and mallard studies, as suggested in Section 4.5.7 (option II A).

* these inputs have moved up a Level of Refinement from the previous assessment.

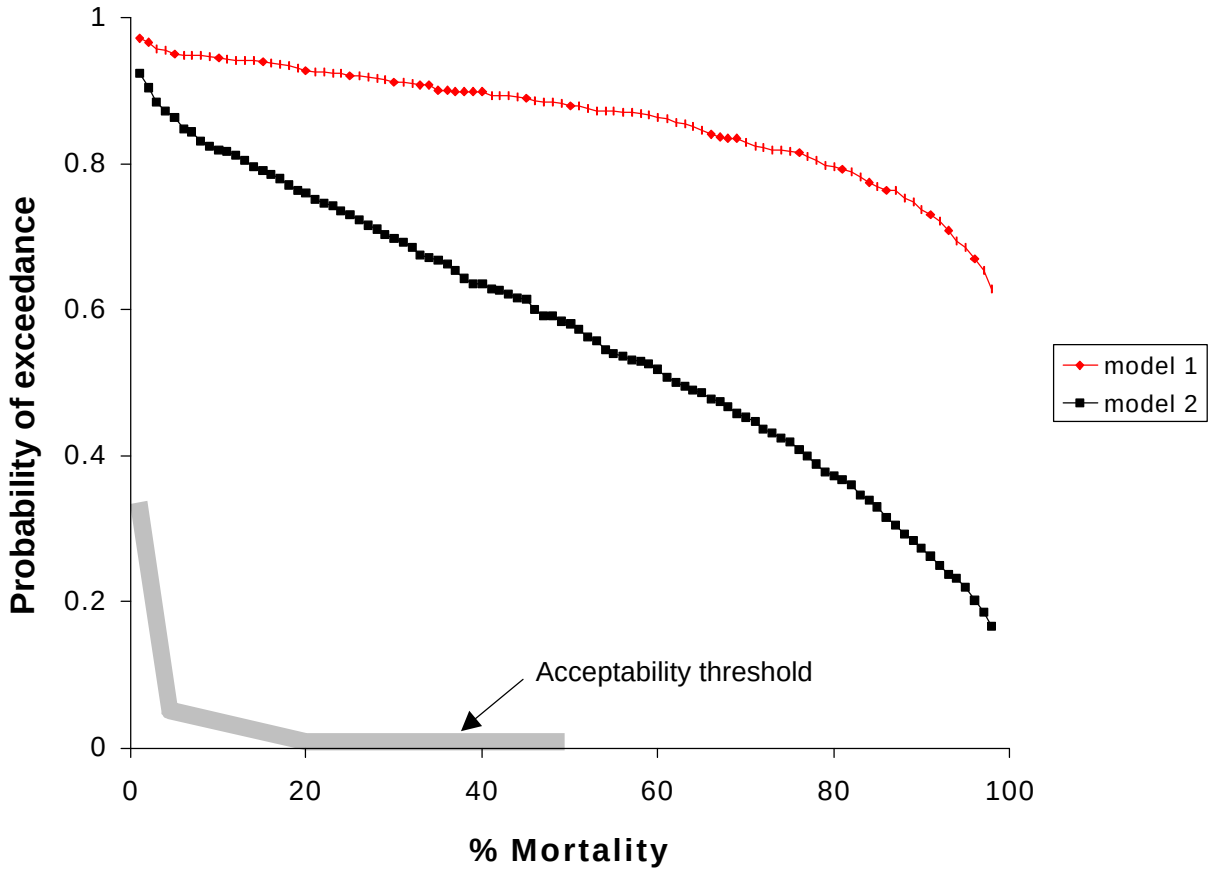
Input distributions

Figure 5.



Output

Figure 6.



Interpretation

- The second LD50 (mallard) was very much higher than the first (bobwhite), so the estimated mean of the sensitivity distribution increased markedly compared to Model 1. Consequently, the risk curve has moved down by a substantial amount.
- However, the risk curve is still way above the acceptability threshold. It seems clear that reducing uncertainty about the LD50 will not bring the risk within threshold. However, the exposure assessment is still highly conservative, so it is appropriate to examine the effects of relaxing some of the worst-case assumptions on exposure.

Model 3

- It was decided to start refining the exposure assessment by introducing a distribution for the concentration of pesticide on insects, based on empirical data from field studies (insert reference to Appendix *** containing these?).
- Only the 4 studies relating to applications to orchards (apples and citrus) were used: it is assumed that all were air-blast applications though this is unconfirmed for 2 studies. None was for chlorpyrifos. Insects were collected using pitfall traps. Biases which may affect these data are discussed in Appendix ***.
- It should be noted that there are large differences between the levels found in the 4 studies, but the cause of this is unknown. This variation needs to be examined further to decide the best way to extrapolate to chlorpyrifos and other pesticides.
- In view of the differences between studies it was decided to use the pooled data to generate a General distribution using RiskView software. This in effect adopts the shape of the empirical distribution rather than fitting a standard distribution such as the lognormal.

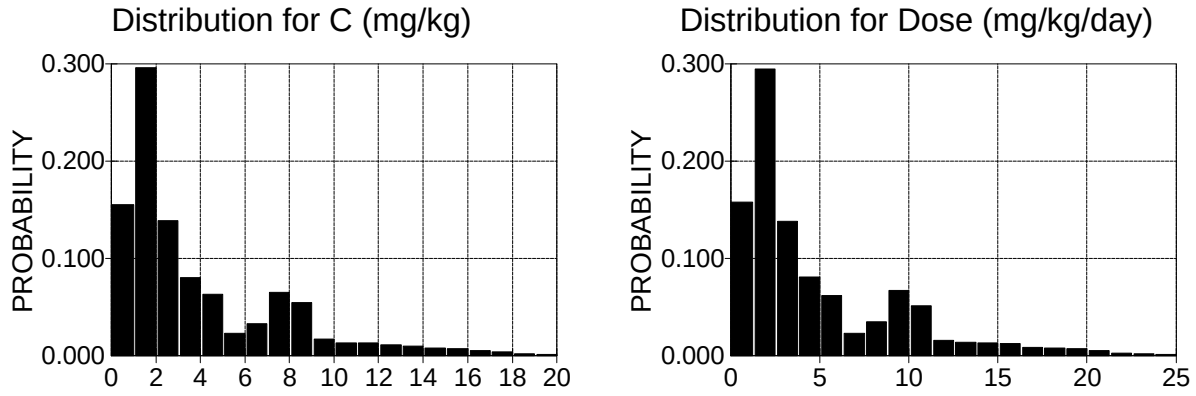
Inputs table

Variable	Level of Refinement	Input
PT_i	1	1
$TFIR_i$	1	3.3g dry weight
PD_{ik}	1	1
FDR_{ik}	1	5
AV_i	1	0
C_{ik}	3*	General distribution based on 4 field studies measuring residues in insects for pesticides other than chlorpyrifos.
W	1	13.3g
LD50	2	Lognormal distribution as in Model 2.
Probit slope of LD50	2	Normal distribution as in Model 2.

* these inputs have moved up a Level of Refinement from the previous assessment.

Input distributions

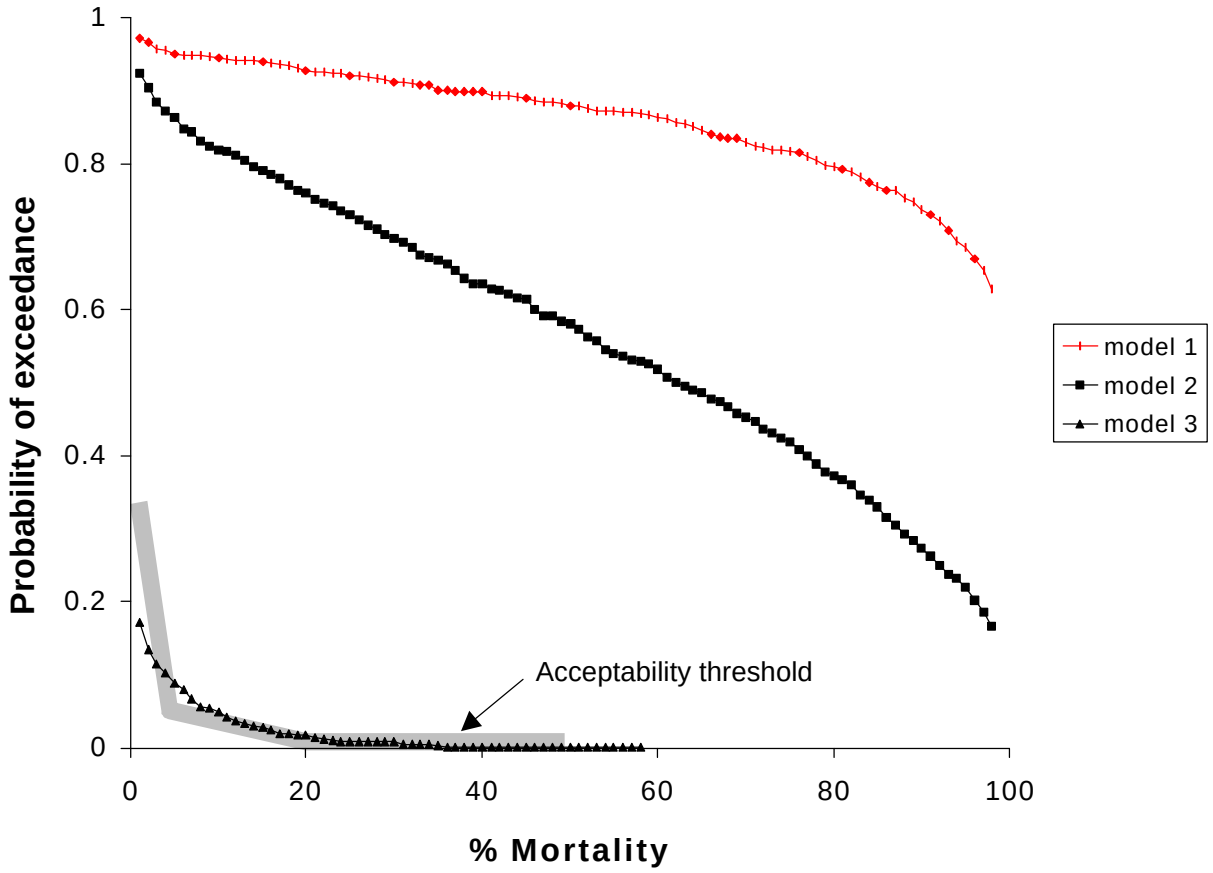
Figure 7.



- Note that the maximum concentration found in the field studies was much lower than the 'maximum' estimate used in Models 1 and 2 (116 mg/kg).
- The distribution for dose (output from stage 1 of Monte Carlo) mirrors the distribution for C, because the other exposure inputs are fixed values.

Output

Figure 8.



Interpretation

- The use of a distribution for C has greatly reduced the risk estimates, and the curve for Model 3 exceeds only part of the acceptability threshold. The result indicates less than a 1 in 3 chance of >1% mortality, but over a 1 in 20 chance of >5% mortality. Further refinement is therefore appropriate.

Model 4

- Only two LD50 studies were used in Models 2-3. In fact, LD50 data were available for 17 species. It was therefore decided to use these to develop a refined estimate of the species sensitivity distribution for Model 4. Probit slopes were only available for 3 species.

- The LD50 data showed some deviations from the Lognormal distribution (see later) and was poorly fitted by the Log-logistic, so again a General distribution was fitted using RiskView.

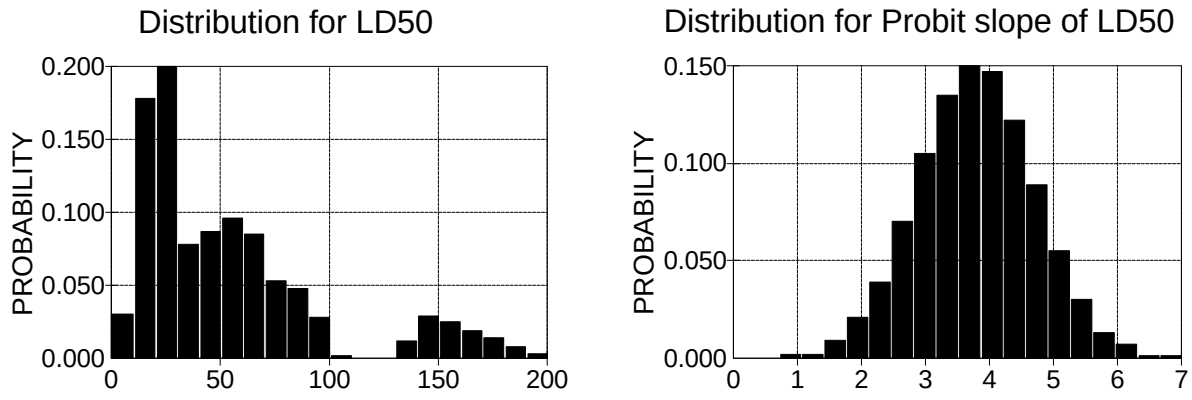
Inputs table

Variable	Level of Refinement	Input
PT_i	1	1
$TFIR_i$	1	3.3g dry weight
PD_{ik}	1	1
FDR_{ik}	1	5
AV_i	1	0
C_{ik}	3	General distribution as in Model 3.
W	1	13.3g
LD50	3*	General distribution fitted to LD50s for 17 species.
Probit slope of LD50	3*	Normal distribution based on slopes from studies for bobwhite, mallard and chicken.

* these inputs have moved up a Level of Refinement from the previous assessment.

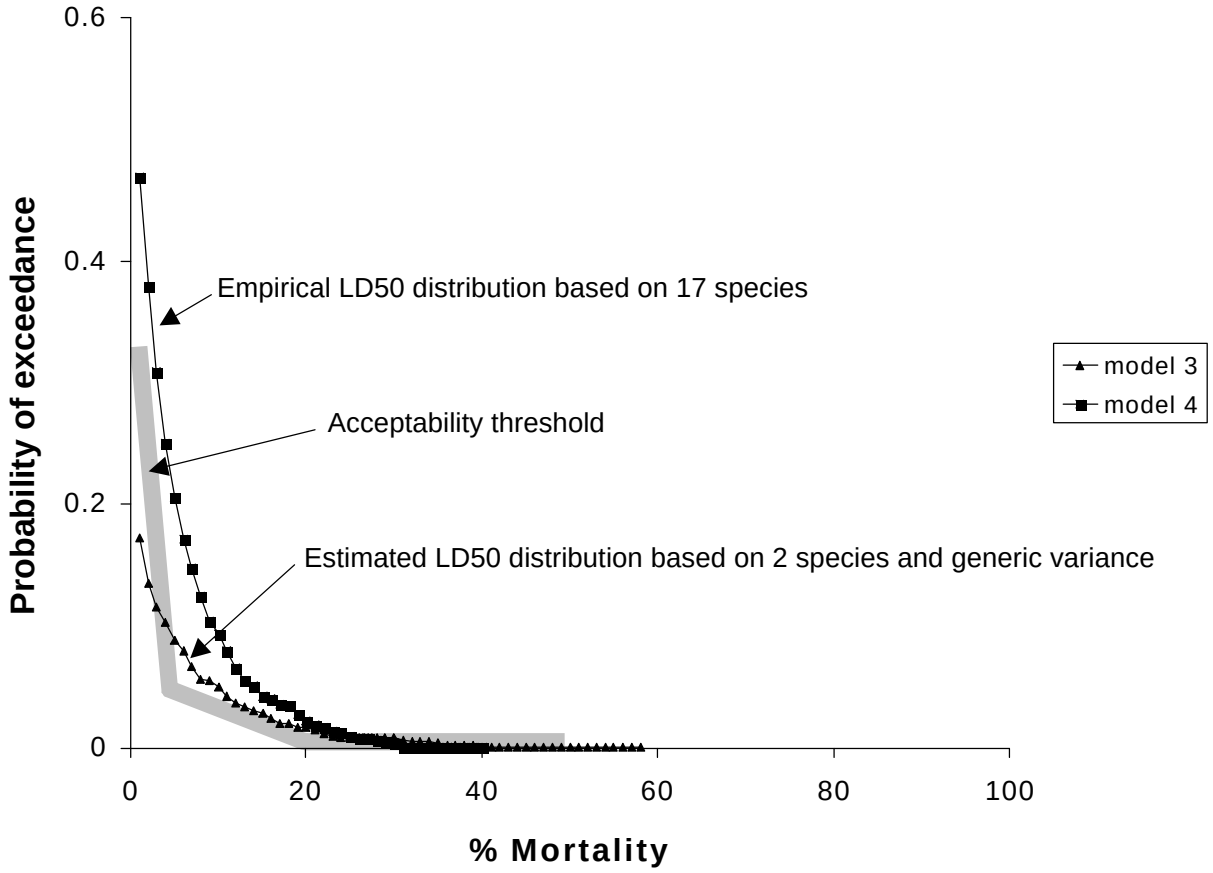
Input distributions

Figure 9.



Output

Figure 10.



Interpretation

- The results show *higher* risk in Model 4 than Model 3. This occurs because the distribution based on 2 LD50s underestimated the general range of species sensitivities, due to the very high LD50 for mallard.

- The mallard study used in Models 2 and 3 was the highest result out of a total of 41 studies for 17 species, including 6 studies giving lower values for mallard. It had been selected for Model 2 because it was the only mallard study from which a slope was available. If the full dataset was being considered in a real assessment (e.g. a regulatory review), this study would have been identified as an outlier and examined more closely. However, such an outlier could in principle occur even in a small dataset (e.g. for a new pesticide). In this case it might not

have been identified as an outlier and would have significantly biased the risk assessment, as is apparent from Figure 10.

- Sensitivity distributions are therefore estimated from the full dataset in all subsequent models.
- There is still a need to refine the assessment, as Model 4 is more reliable than Model 3 and clearly exceeds the acceptability threshold.

Model 5

- The final variable considered for refinement in this example is PT – the proportion of food obtained from the treated area. So far it has been assumed that PT = 1, i.e. birds obtain all their food in the treated area.
- Obtaining reliable field data on PT would be very costly. Before committing to such expense, it would be desirable to check the possible influence of PT in reducing risk. This is done in Model 5 by trying a hypothetical distribution in which all values of PT between 0 and 1 are considered equally likely (a uniform distribution).

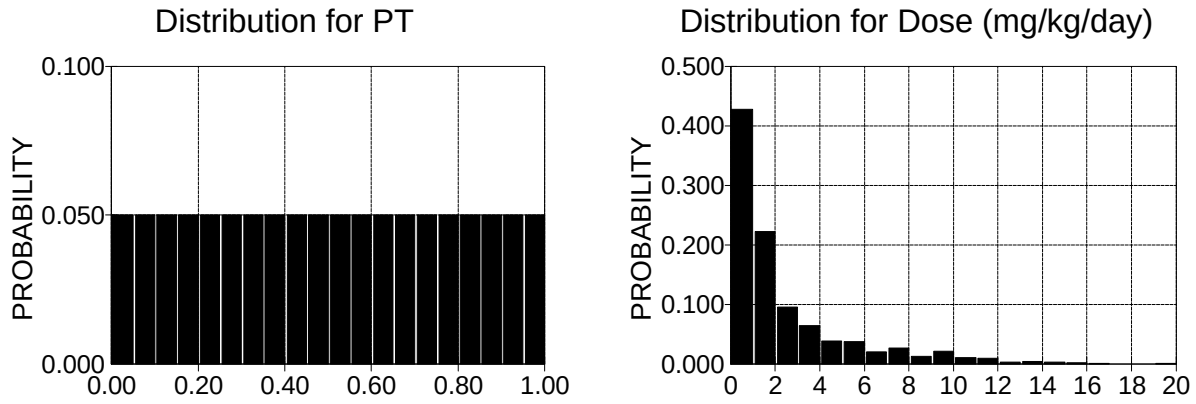
Inputs table

Variable	Level of Refinement	Input
PT_i	2*	Uniform distribution between 0 and 1.
$TFIR_i$	1	3.3g dry weight
PD_{ik}	1	1
FDR_{ik}	1	5
AV_i	1	0
C_{ik}	3	General distribution as in Model 3.
W	1	13.3g
LD50	3	General distribution for 17 species.
Probit slope of LD50	3	Normal distribution based on 3 species.

* these inputs have moved up a Level of Refinement from the previous assessment.

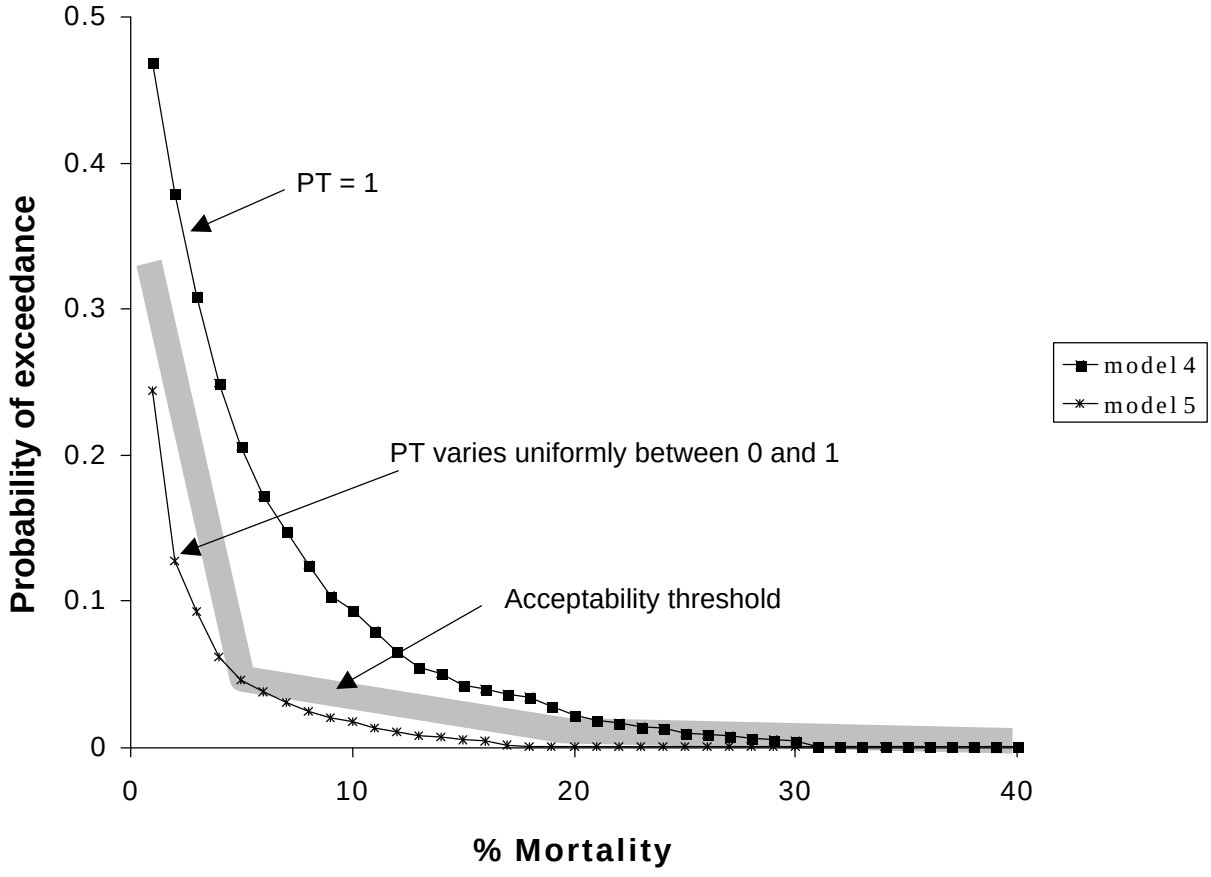
Input histograms

Figure 11.



Output

Figure 12.



Interpretation

- Using a uniform distribution for PT brings the risk curve just below threshold. This distribution is purely hypothetical so the result cannot be relied upon as it stands. It may therefore be worth investing in field studies to obtain reliable data on PT for relevant species in relevant scenarios.
- In practice, consideration would be given to refining other exposure variables before committing to costly field studies on PT.

Model 6

- In fact, data on PT is already available from field studies of blue tits in UK orchards (Crocker et al. 1998). 23 individuals were tracked continuously in 8 orchards for periods of 1-2 hours. The total time monitored per individual ranged from 76 minutes to 719 minutes: 17 were monitored for 6 hours or more. The time for each individual was divided into that spent inside the orchards, and that spent in adjacent, non-orchard habitat. Time spent in the orchard was expressed as a percentage of total time to provide estimates of PT.
- A General distribution was fitted to the field data using RiskView.
- See Section 3.3.3 and Appendix C1 for detailed discussion of the many issues and possible biases affecting the use of field data to estimate PT. These would require very careful consideration in a formal risk assessment.

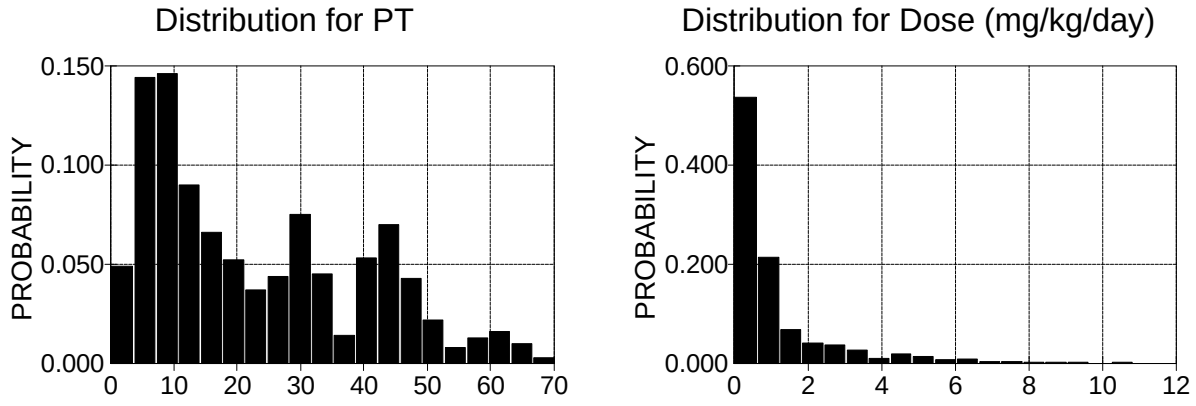
Inputs table

Variable	Level of Refinement	Input
PT_i	4*	General distribution fitted to radio-tracking data for 23 blue tits.
$TFIR_i$	1	3.3g dry weight
PD_{ik}	1	1
FDR_{ik}	1	5
AV_i	1	0
C_{ik}	3	General distribution as in Model 3.
W	1	13.3g
LD50	3	General distribution for 17 species.
Probit slope of LD50	3	Normal distribution based on 3 species.

* these inputs have moved up a Level of Refinement from the previous assessment.

Input histograms where appropriate. Incl. Intermediate outputs – dose, LD50

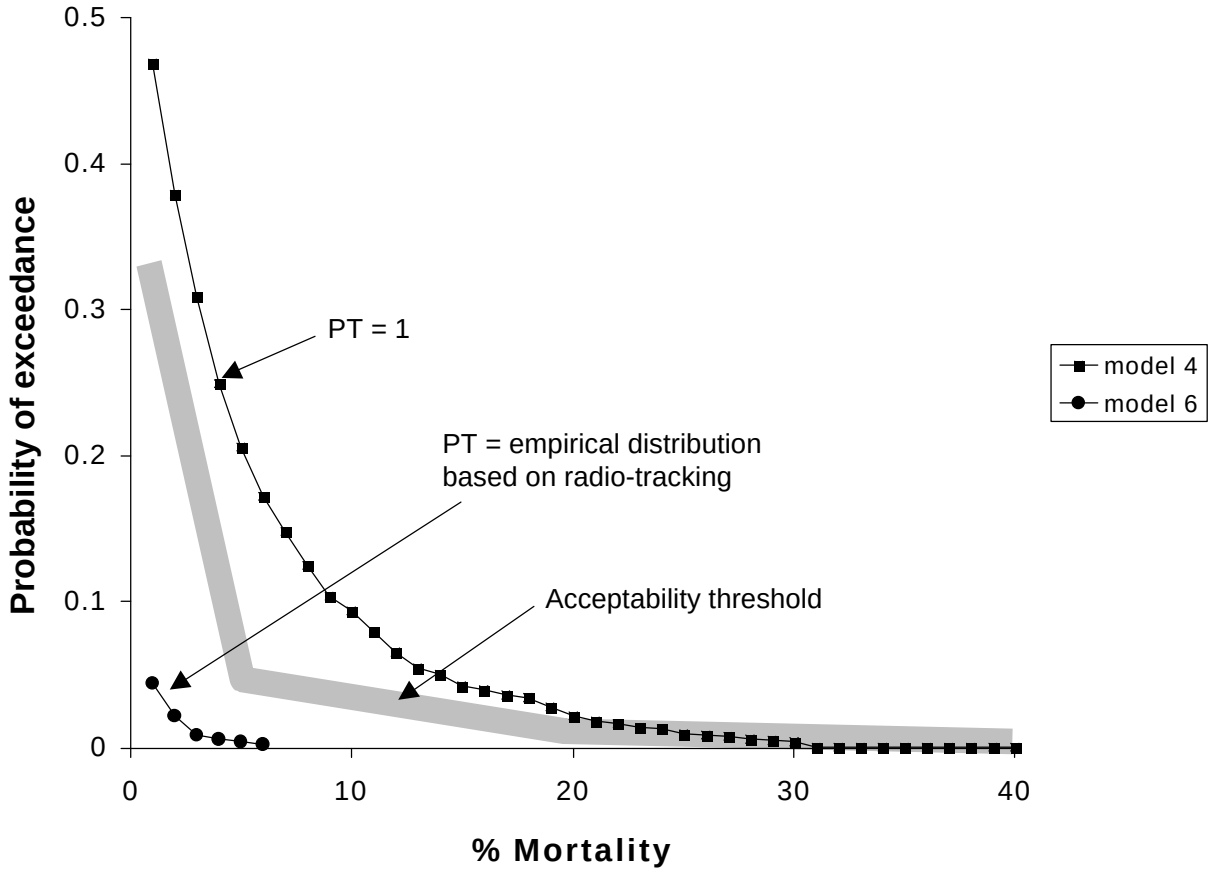
Figure 13.



- Note that PT is expressed as a percentage in Figure 13 but was used as a fraction in the simulations.

Output

Figure 14.



Interpretation

- The risk curve for Model 6 is well below the acceptability threshold. For example, the results indicate a 1 in 50 chance that mortality will exceed 2%.
- The actual risk could be higher or lower, and more or less variable. Lower, because input values for PD and AV in the exposure assessment remain conservative. Higher, because Models 1-6 have not considered exposure in the drift zone. More variable, because the exposure assessment still uses fixed averages for TFIR, FDR and W.
- In a formal assessment, the assessor would need to consider the possible influence of all these factors and perhaps address them with further refinements to the models.

- If the assessor were satisfied with the Model, the input data and the definition of the threshold of acceptability, then the result in Figure 14 would indicate that the risk is acceptable for timescale and assessment endpoint being considered. No further refinement of the assessment would then be necessary.
- The assessor would still need to consider other assessment endpoints (e.g. reproductive effects), other timescales (e.g. exposure over more than one day) and other focal species (e.g. omnivorous or herbivorous birds). The assessment process would be repeated for each combination of endpoint, timescale and focal species. These combinations would require assessment to varying Levels of Refinement, depending on whether the initial assessments produced results to the left of the acceptability threshold.
- As noted in Section 6, risk mitigation could be considered as an alternative to refining the assessment at any stage. The effect of the proposed mitigation could be incorporated into the assessment model to examine its effectiveness in bringing the risk curve below the threshold of acceptability.

SENSITIVITY ANALYSIS

- The division of the Monte Carlo simulations into two stages in Models 1-6 means that @Risk reports sensitivity analyses for only the exposure variables in stage one, and only the LD50 and slope in stage 2. To obtain statistics on the relative influence of all the inputs, Model 6 was repeated as a single stage Monte Carlo analysis in Model 7. The inputs were the same as those for Model 6 (see table above).
- The simulation was run for 10,000 iterations, in effect representing 10,000 individuals with varying exposures and species sensitivities. The output for each individual was the probability of death. The mean probability of death was 0.0026, close to the mean percentage mortality from Model 6 (0.23).
- Sensitivity analyses were conducted using regression and rank correlation statistics provided by @Risk (Figures 15 and 16).

Figure 15.

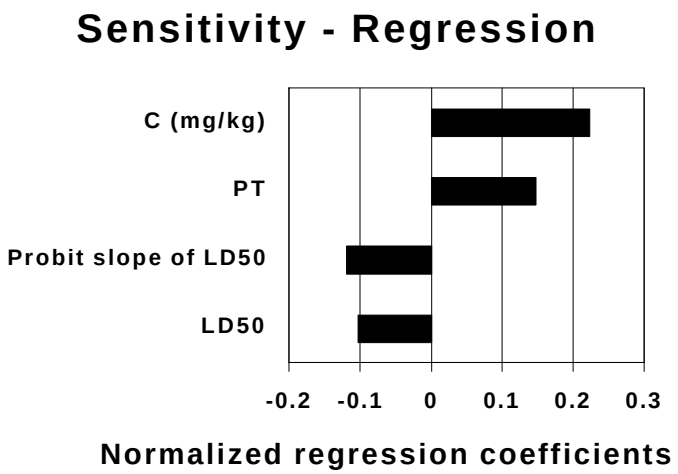
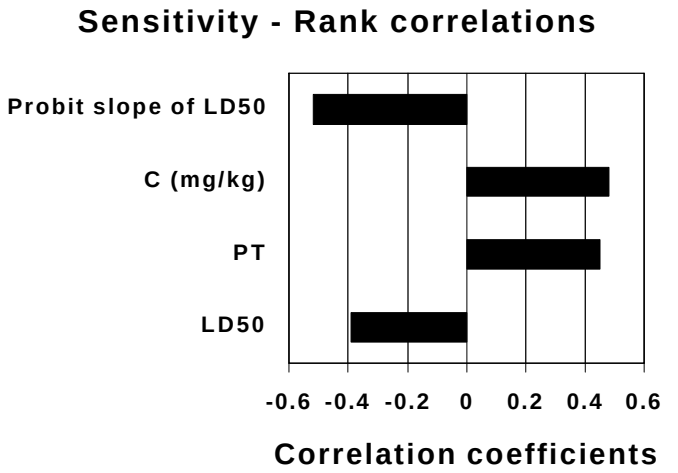


Figure 16.



- All 4 of the variables examined probabilistically have a substantial influence on the risk outcome. Overall, the exposure variables (PT and C) and effects variables had broadly similar influence. The order of priority differs between the regression and correlation analyses as the former responds less to non-linear relationships

- C has slightly more influence than PT on both measures (regression and correlation). This emphasises the need for closer examination of the reliability of the extrapolation from of invertebrate residue data between pesticides, as mentioned above. It also suggests that if an assessment requires refinement to Level 4 it may be more cost-effective to focus field studies

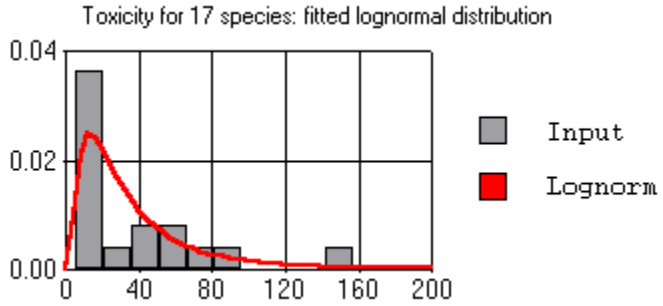
on C than on PT. On the other hand, once PT is measured for a given habitat scenario it can be applied to any pesticide used in that situation.

- The probit slope has slightly more influence than the median LD50 in Model 7. This presumably occurs because the predicted mortality is far from 50% in nearly all the iterations of Model 7. In Models 1 and 2 the average mortality was 82% and 56% respectively, and the slope had much less influence than the median LD50. In Models 3-6 the average mortalities were between 0.23 % and 3.13%, and the slope had more influence although still not as much as the median.

ALTERNATIVE DISTRIBUTIONS

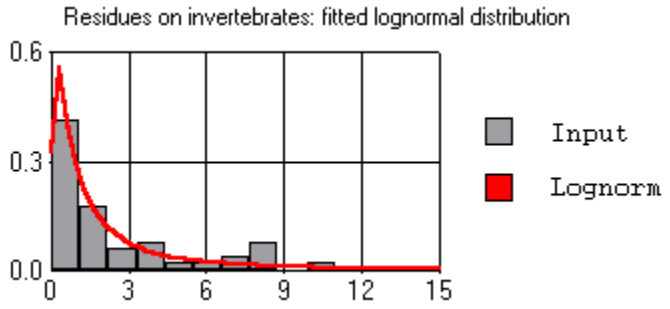
- Alternative distributions were considered for the LD50, C and PT, using BestFit software.

Figure 17.



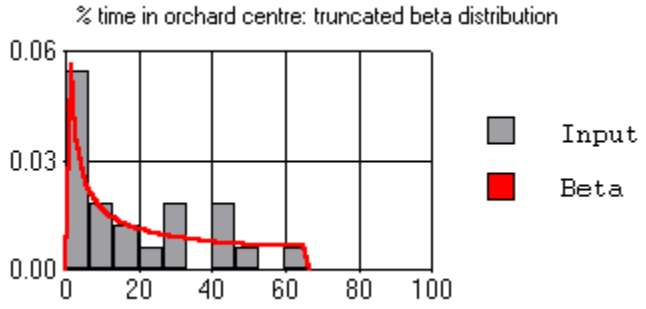
- The Lognormal and Log-logistic distributions are often used for toxicity data. The Lognormal fits chlorpyrifos well, but the fitted values for the Log-logistic differed significantly from the raw data. Nevertheless, the Lognormal under-estimates the frequency of toxicities in the range 10-20mg/kg, and over-estimates the frequency of toxicities between 20 and 40mg/kg (Figure 17). If the peaks and troughs in the raw data reflect real deviations from the Lognormal rather than sampling error, then the fitted distribution will lead to underestimation of risk. However, it is possible that the deviations are an artefact caused by the choice of dosing levels in up-and-down tests: this is an issue that needs further consideration (Section 4).

Figure 18.



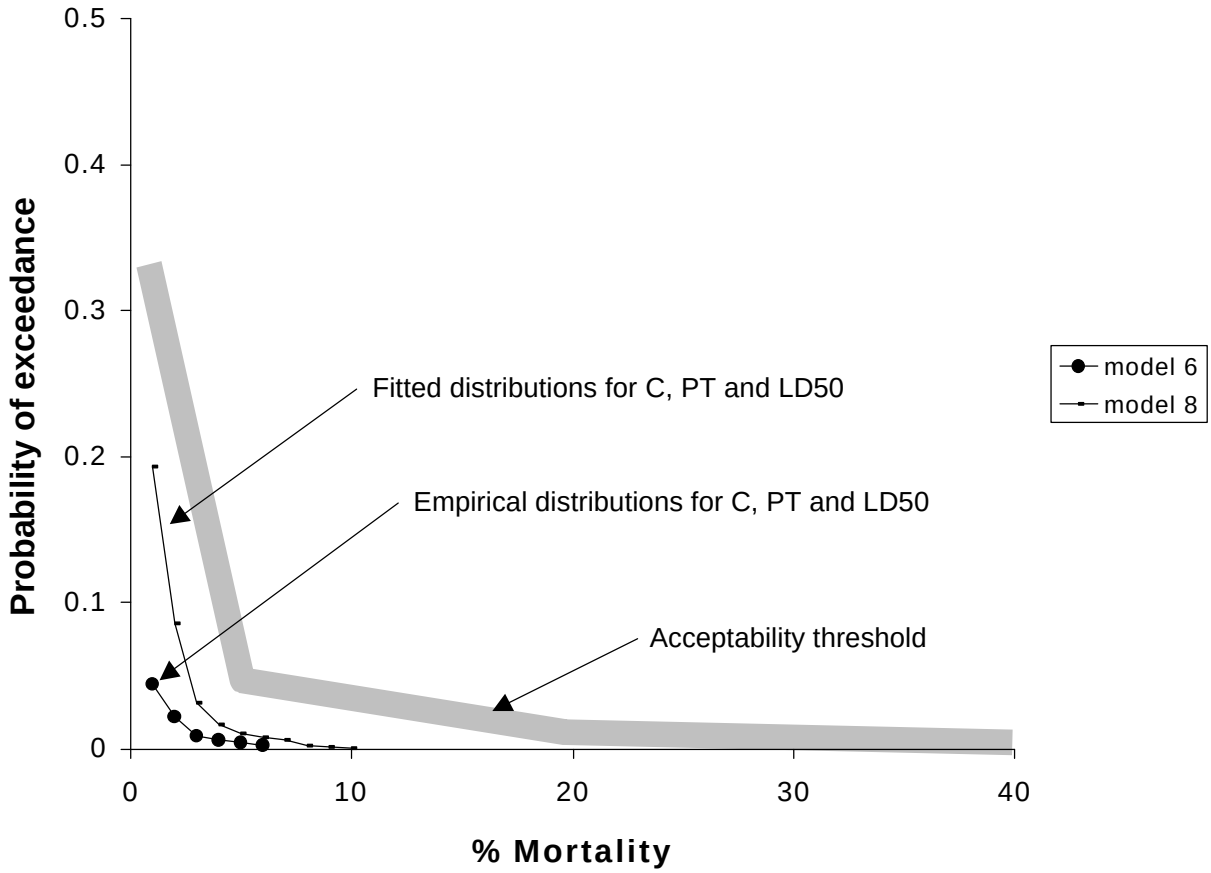
- The Lognormal distribution provides a good fit to the field data for C. However, as already mentioned, there were significant differences between the 4 contributing studies, and this was responsible for the small peak between 6 and 9 mg/kg.

Figure 19.



- The Beta distribution truncated at the observed maximum provided the best fit to PT. Truncating the distribution at 1 (100%) would be more conservative.

Figure 20.



- The fitted distributions from Figures 17-19 were used in Model 8, which was in other respects the same as Model 6. The results show a somewhat increased risk in Model 8. Further simulations using different combinations of the standard and General distributions would be required to analyse how the choice of distributions influences the risk outcome. These results emphasise the importance of care in choosing distributions.

REFERENCES

Crocker, D R, Prosser P, Tarrant K A, Irving P A, Watola G, Chandler-Morris S A, Hart J, Hart A D M. 1998. Improving the assessment of pesticide risks to birds in orchards. Objective 1: Use of radio-tracking to monitor birds' use of orchards. CSL Report No. EH18/02. Central Science Laboratory, York, UK.

Dunning J B. 1993. CRC Handbook of avian body masses. CRC Press, Boca Raton.

Fletcher J S, Nellessen J E, Pfleeger T G. 1994. Literature review and evaluation of the EPA food-chain (Kenaga) nomogram, an instrument for estimating pesticide residues on plants. Environ. Toxicol. Chem. 13: 1383-1391.

Nagy K A. 1987. Field metabolic rate and food requirement scaling in mammals and birds. Ecol. Monogr. 57: 111-128.

APPENDIX D1

TECHNICAL NOTES FOR CHAPTER 4

Following are some mathematical details of results claimed in Chapter 4.

Note 1. Generation of a random tolerance based on the probit model. The formula given above is,

$$\text{random tolerance} = LD_{50} * 10^{(z / \text{slope})}$$

where z has the N(0,1) distribution. The formula just given is derived as follows. The base-10 logarithms of tolerances are assumed to have a normal distribution with parameters:

$$\text{mean}=\log(LD_{50}); \text{ standard deviation}=1/\text{slope}.$$

To sample from this normal distribution we, drawing a random number z from the the N(0,1) distribution. That value is transformed to a normal deviate with the desired mean and variance:

$$\log(LD50) + (1/\text{slope})*z$$

This result is transformed back to the dose scale using the inverse-log function. The formula given follows from standard operations involving logarithms and antilogarithms.

Note 2. Formal equivalence of two algorithms for generating random mortality decisions. To generate random numbers from a distribution with CDF $F(x)$, as required

for Algorithm 2, one algorithm would be the inverse-CDF method: The random tolerance would be given by

$F^{-1}(U)$ where U has a U(0,1) distribution. However, comparing $F^{-1}(U)$ to exposure d is equivalent to comparing $F(d)$ to U (Algorithm 1). This argument applies to any dose-response function that can be interpreted as a CDF, i.e., a dose-response that is increasing with the value of its argument, from zero to one.

Because Algorithm 1 does not require inversion of the CDF, it appears that it is never necessary to invert the CDF. Algorithm 2 is suggested when sampling from the tolerance distribution does not require inversion of the CDF, as common algorithms for generating random numbers from a normal or lognormal distribution.

Note 3. Correlation of the probit slope and median effective dose. Using standard methods (see Stuart and Ord, 1985, Section 10.5), the following expression can be derived for the asymptotic correlation between the slope (b) and the log of the LD50 (say m), when the probit parameters are estimated using maximum likelihood:

$$\text{corr.}[\, b,\, m\,] \;=\; \frac{\bar{x} - m}{b} \sqrt{\frac{\text{variance of } b}{\text{variance of } m}}$$

Thus a correlation of zero is obtained if the log of the LD50 precisely equals $\bar{x}$, a weighed average of the doses (see Finney, 1971, Ch. 4). The correlation will tend to be positive if the LD50 is in the lower range of doses tested and negative if the LD50 is in the upper range of doses tested. Because a good design is to place the LD50 towards the center of the range of doses; it seems possible that the correlation will often be small.

This formula represents the correlation of statistical errors for the two parameters when they are estimated from a single data set. In practice we may be concerned with the correlation of the parameters over studies.

APPENDIX E1

An Individual-Based Model for Predicting Population Effects from Exposure to Environmental Contaminants

Kenneth R. Dixon and Samuel R. Anderson

1 Introduction

2 IBMOD is a simple individual-based growth model that is species specific. The model uses
3 probabilities for fecundity and survival on each individual in separate age classes. IBMOD will
4 simulate the growth of a population and display graphs of the output for the species. There are two
5 parts to the program: IBMOD.EXE is used to model the data, and IBMGRAPH.EXE is used to
6 display the results.

7 Source Code

8 The model was programmed by Sam Anderson using Borland's C++ v4.5, Borland's Turbo
9 Assembler, and Borland's DOS Power Pack (16 and 32 bit DPMI enhancements). He also developed
10 a statistical library in C and included functions from this library in the model. All code is in C except
11 hook functions that check for ctrl-break during execution. This code was written in assembly.

12 Model Description

13 The model first reads a species specific data file to gather the probabilities for reproduction, survival
14 of each age class, number of males and females in the age class, along with probabilities for sex ratio
15 and offspring survival. The fecundity probabilities form a cumulative probability distribution used
16 to create a specific number of offspring per individual. The model calculates the population size by

summing the number of individuals in all age classes. Several output graphs are generated by IBMOD, including a plot of the population over time for each run, a plot of all populations over combined runs, and a mean and standard deviation for all runs.

IBMOD starts with the first age class and determines the fecundity probability for each individual in the age class at time step t1. We assumed that individuals in age class 1 do not reproduce. Therefore the sample Species.DAT specifies that individuals in age class 1 have a 100% probability of having 0 offspring. The fecundity is estimated using a cumulative probability distribution to determine the number of offspring each individual could have. The model tracks the frequency of births occurring and will display graphs of the measured and predicted fecundity by age class.

Note that the probabilities specified in the species file must add up to 1.0.

IBMOD then calculates the survival of each offspring in the current age class. Survivors of this calculation are moved into age class 1 at time step t+1.

IBMOD then calculates the survival of each individual in the current age class (offspring excluded). The survivors of this calculation are moved into (age class + 1), at time step t+1. Each age class is processed in the current time step, and survivors graduate into the next highest age class at time step t+1.

Note that the last age class members have a 0.0 percent probability of survival. Members of the last age class cannot graduate to a higher class, because there isn't one to graduate to.

The process is repeated for each time step on all age classes.

The output file IBMOD will generate will have a .OUT extension. This file will contain statistics on fecundity and survival for each run. The beginning of the output file will contain notes on how the various results are obtained.

After all runs, and age classes for all time steps are completed, IBMOD will display statistics on the population for the simulation. Minimum, maximum, standard deviation, variance, and normal probability are displayed for the population of all age classes combined over time. Graphs are also provided for the combined age class population data.

IBMOD tracks females and males in populations by age class at each time step. The model also tracks the number born and survival by sex and age class.

The model assumes that all females can, according to the fecundity distribution, reproduce. There is one limitation. There must be at least one male in the age class.

The species input file has two more parameters for tracking mixed sex populations. The first is for the initial number of females in each age class. The second parameter is for the sex ratio in each age class. This parameter is used for calculating how many offspring are female.

Example

A simulation was run for 100 time steps, using artificial population data, to illustrate the model. The population had six age classes of both sexes, including newborn offspring. Probabilities were assigned to reproduction (Figure 1) and survival (Figure 2) for each age class. The survival of newborn offspring was set to 0.65 for each age class. The newborn sex ratio was set to 0.50 for each age class. The initial number of individuals in each age class was set for both males and females (Figure 3).

Results of the simulation predict that the male population will increase from 103 at time t1 to 539 at time t100 (Figure 4). This model yields output comparable to an aggregated population model such as a Leslie Matrix model, but allow for individual responses in reproduction and survival to exposure to environmental contaminants.

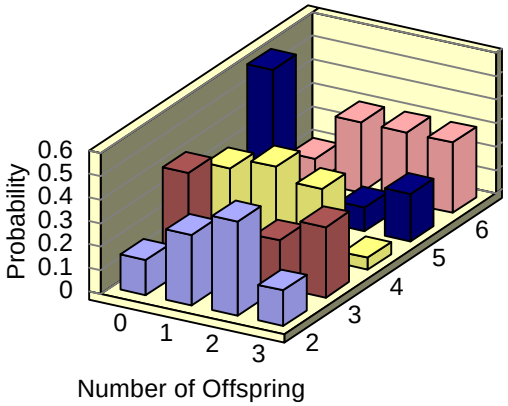


Figure 1. Probability of from zero to three offspring occurring during one time period for age classes two through six.

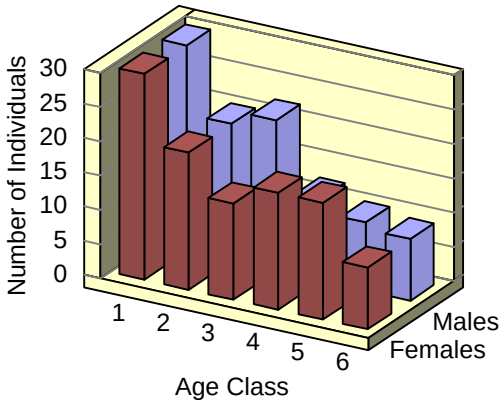


Figure 3. Initial number of individuals in each age class for male and females.

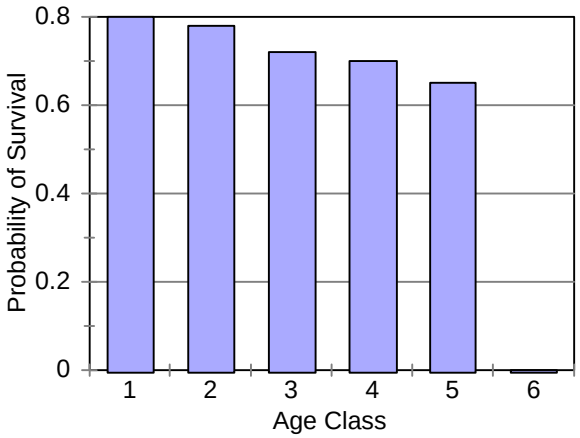


Figure 2. Probability of survival for each of six age classes.

1

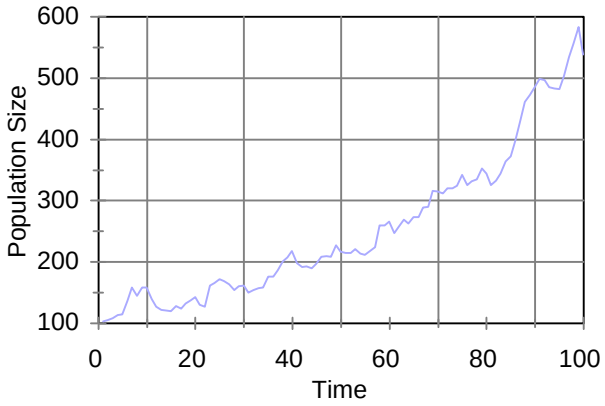


Figure 4. Predicted population size for males over time.