**TABLE OF CONTENTS**

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## 2. VARIABILITY AND UNCERTAINTY

Accounting for variability and uncertainty is fundamental to exposure assessment and risk analysis. While more will be said about the distinction between variability and uncertainty in Section 2.1, it is useful at this point to motivate the treatment of variability and uncertainty in exposure assessment. Given that exposure and susceptibility to exposure is usually not uniform across a population, accounting for variability is the means by which a risk assessor properly accounts for risk to the population as a whole. However, a risk assessment usually involves uncertainties about the precision of a risk estimate. A heuristic distinction between variability and uncertainty is to consider uncertainty as a lack of knowledge about factors affecting exposure or risk, whereas variability arises from heterogeneity across people, places, or time.

Properly addressing variability and uncertainty will increase the likelihood that results of an assessment or analysis will be used in an appropriate manner. Characterizing and communicating variability and uncertainty should be done throughout all the components of the risk assessment process (NRC, 1994). Thus, careful consideration of the variability and uncertainty associated with the exposure factors information used in an exposure assessment is of utmost importance. Proper characterization of variability and uncertainty will also support effective communication of risk estimates to risk managers and the public.

This chapter provides an overview of variability and uncertainty in the context of exposure analysis and is not intended to present specific methodological guidance. It is intended to acquaint the exposure assessor with some of the fundamental concepts of variability and uncertainty as they relate to exposure assessment and the exposure factors presented in this handbook. It also provides summary descriptions of methods and considerations for evaluating and presenting the uncertainty associated with exposure estimates and a bibliography of references on a wide range of methodologies concerned with the application of variability and uncertainty analysis in exposure assessment. Subsequent sections in this chapter are devoted to the following topics:

2.1 Variability versus uncertainty;
2.2 Types of variability;
2.3 Addressing variability;
2.4 Types of uncertainty;
2.5 Reducing uncertainty;
2.6 Analyzing variability and uncertainty;
2.7 Literature review of variability and uncertainty analysis;
2.8 Presenting results of variability and uncertainty analyses; and
2.9 References.

There are numerous ongoing efforts in the U.S. Environmental Protection Agency (EPA) and elsewhere to further improve the characterization of variability and uncertainty. The U.S. EPA's Risk Assessment Forum has established guidelines for the use of probabilistic techniques (e.g., Monte Carlo analysis) to better assess and communicate risk (U.S. EPA, 1997a, b). The U.S. EPA's Science Policy Council is developing white papers on the use of expert elicitation for characterizing uncertainty in risk assessments. Expert judgment has been used in the past by some regulatory agencies when limited data or knowledge results in large uncertainties (NRC, 2009). The International Program on Chemical Safety (IPCS) has developed guidance on characterizing and communicating uncertainty in exposure assessment (WHO, 2008). Suggestions for further reading on variability and uncertainty include Babendreier and Castleton (2005), U.S. EPA (2008), Saltelli and Annoni (2010), Bogen et al. (2009), and Refsgaard et al. (2007).

### 2.1. VARIABILITY VERSUS UNCERTAINTY

While some authors have treated variability as a specific type or component of uncertainty, the U.S. EPA (1995), following the NRC (1994) recommendation, has advised the risk assessor to distinguish between variability and uncertainty. Variability is a quantitative description of the range or spread of a set of values. Common measures include variance, standard deviation, and interquartile range. Variability arises from heterogeneity across individuals, places, or time. Uncertainty can be defined as a lack of precise knowledge, either qualitative or quantitative. In the context of exposure assessment, data uncertainty refers to the lack of knowledge about factors affecting exposure.

The key difference between uncertainty and variability is that variability cannot be reduced, only better characterized (NRC, 2009).

We will describe a brief example of human water consumption in relation to lead poisoning to help distinguish between variability and parameter uncertainty (a particular type of uncertainty). We might characterize the variability of water consumption across individuals by sampling from a population and measuring water consumption. From

this sample, we obtain useful statistics on the variability of water consumption, which we assume here represents the population of interest. There may be similar statistics on the variability in the concentration of lead in the water consumed. A risk model may include a factor (i.e., dose response, representing the absorption of lead from ingested water to blood). The dose response may be represented by a constant in a risk model. However, knowledge about the dose response may be uncertain, motivating an uncertainty analysis. Dose response values are often relatively uncertain compared to exposure parameters. Therefore, in the above example, a high uncertainty surrounds the absorption of lead, whereas there is less uncertainty associated with the parameters of water consumption (i.e., population mean and standard deviation). One challenge in modeling dose-response uncertainty is the lack of consensus on its treatment.

Most of the data presented in this handbook concern variability. Factors contributing to variability in risk include variability in exposure potential (e.g., differing behavioral patterns, location), variability in susceptibility due to endogenous factors (e.g., age, sex, genetics, pre-existing disease), variability in susceptibility due to exogenous factors (e.g., exposures to other agents) (NRC, 2009).

## 2.2. TYPES OF VARIABILITY

Variability in exposure is dependent on contaminant concentrations as well as variability in human exposure factors. Human exposure factors may vary because of an individual's location, specific exposure time, or behavior. However, even if all of those factors were constant across a set of individuals, there could still be variability in risk because of variability in susceptibilities. Variations in contaminant concentrations and human exposure factors are not necessarily independent. For example, contaminant concentrations and behavior might be correlated.

A useful way to think about sources of variability is to consider these four broad categories:

1) Spatial variability: variability across locations;
2) Temporal variability: variability over time;
3) Intra-individual variability: variability within an individual; and
4) Inter-individual variability: variability across individuals.

**Spatial variability** refers to differences that may occur because of location. For example, outdoor pollutant levels can be affected at the regional level by industrial activities and at the local level by activities of individuals. In general, higher exposures tend to be associated with closer proximity to a pollutant source, whether it is an industrial plant or related to a personal activity such as showering or gardening. Susceptibilities may vary across locations, for example, some areas have particularly high concentrations of a younger or older population.

**Temporal variability** refers to variations over time, whether long- or short-term. Different seasons may cause varied exposure to pesticides, bacteria, or indoor air pollution, each of which might be considered an example of long-term variability. Examples of short-term variability are differences in industrial or personal activities on weekdays versus weekends or at different times of the day.

**Intra-individual variability** is a function of fluctuations in an individual's physiologic (e.g., body weight), or behavioral characteristics (e.g., ingestion rates or activity patterns). For example, patterns of food intake change from day to day and may do so significantly over a lifetime. Intra-individual variability may be associated with spatial or temporal variability. For example, because an individual's dietary intake may reflect local food sources, intake patterns may change if place of residence changes. Also, physical activity may vary depending upon the season, life stage, or other factors associated with temporal variability.

**Inter-individual variability** refers to variation across individuals. Three broad categories include the following:

1) individual characteristics such as sex, age, race, height, or body weight (including any obesity), phenotypic genetic expression, and pathophysiological conditions;
2) individual behaviors such as activity patterns, and ingestion rates; and
3) susceptibilities due to such things as life stage or genetic predispositions.

Inter-individual variability may also be related to spatial and temporal factors.

## 2.3. ADDRESSING VARIABILITY

In this handbook, variability is addressed by presenting data on the exposure factors in one of the following three ways: (1) as tables with percentiles or ranges of values for various age groups or other

populations, (2) as probability distributions with specified parameter estimates and related confidence intervals, or (3) as a qualitative discussion. One approach to exposure assessment is to assume a single value for a given exposure level, often the mean or median, in order to calculate a single point estimate of risk. Often however, individuals vary in their exposure, and an exposure assessment would be remiss to exclude other possible exposure levels. Thus, an exposure assessment often involves a quantification of the exposure at high levels of the exposure factor, i.e., 90$^{th}$, 95$^{th}$, and 99$^{th}$ percentiles, and not only the mean or median exposure. Where possible, confidence limits for estimated percentiles should be provided. The U.S. EPA's approach to variability assessment is described in *Risk Assessment Principles and Practices: Staff Paper* (U.S. EPA, 2004b). Accounting for variability in an exposure assessment may be limited to a deterministic model in which high-end values are used or may involve a probabilistic approach, e.g., Monte Carlo Analysis (U.S. EPA, 1997a).

Populations are by nature heterogeneous. Characterizing the variability in the population can assist in focusing analysis on segments of the population that may be at higher risk from environmental exposure. Although population variability cannot be reduced, data variability can be lessened by disaggregating the population into segments with similar characteristics.

Although much of this handbook is concerned with variability in exposure, it is critical to note that there are also important variations among individuals in a population with respect to susceptibility. As noted in NRC (2009), people differ in susceptibility to the toxic effects of a given chemical exposure because of such factors as genetics, lifestyle, predisposition to diseases and other medical conditions, and other chemical exposures that influence underlying toxic processes. Susceptibility is also a function of life stages, e.g., children may be at risk of high exposure relative to adults. Susceptibility factors are broadly considered to include any factor that increases (or decreases) the response of an individual to a dose relative to a typical individual in the population. The distribution of disease in a population can result not only from differences in susceptibility, but from differing exposures of individuals and target groups in a population. Taken together, variations in disease susceptibility and exposure potential give rise to potentially important variations in vulnerability to the effects of environmental chemicals (NRC, 2009).

## 2.4. TYPES OF UNCERTAINTY

Uncertainty in exposure analysis is related to the lack of knowledge concerning one or more components of the assessment process. The U.S. EPA (1992) has classified uncertainty in exposure assessment into three broad categories: (1) scenario uncertainty, (2) parameter uncertainty, and (3) model uncertainty.

**Scenario uncertainty**

Scenario uncertainty arises from descriptive errors, aggregation errors, errors in professional judgment, and incomplete analysis. Descriptive errors are errors in information that translate into errors in the development of exposure pathways, scenarios, exposed population, and exposure estimates. Aggregation errors occur as a result of lumping approximations. These include, for example, assuming a homogeneous population, and spatial and temporal assumptions. Uncertainty can also arise from errors in professional judgment. These errors affect how an exposure scenario is defined, the selection of exposure parameters, exposure routes and pathways, populations of concern, chemicals of concern, and the selection of appropriate models. An incomplete analysis can also be a source of uncertainty because important exposure scenarios and susceptible populations may be overlooked.

**Parameter uncertainty**

Risk assessments depict reality interpreted through mathematical representations that describe major processes and relationships. Process or mechanistic models use equations to describe the processes that an environmental agent undergoes in the environment in traveling from the source to the target organism. Mechanistic models have also been developed to represent the toxicokinetic and toxicodynamic processes that take place inside the organism, leading to the toxic endpoint. The specific parameters of the equations found in these models are factors that influence the release, transport, and transformation of the environmental agent, the exposure of the target organism to the agent, transport and metabolism of the agent in the body, and interactions on the cellular and molecular levels. Empirical models are also used to define relationships between two values, such as the dose and the response. Uncertainty in parameter estimates stem from a variety of sources, including the following:

a. Measurement errors:
   1. Random errors in analytical devices (e.g., imprecision of continuous monitors that measure stack emissions).
   2. Systemic bias (e.g., estimating inhalation from indoor ambient air without considering the effect of volatilization of contaminants from hot water during showers).
b. Use of surrogate data for a parameter instead of direct analysis of it (e.g., use of standard emission factors for industrialized processes).
c. Misclassification (e.g., incorrect assignment of exposures of subjects in historical epidemiologic studies due to faulty or ambiguous information).
d. Random sampling error (e.g., variation in estimates due to who was randomly selected).
e. Non-representativeness with regard to specified criteria (e.g., developing emission factors for dry cleaners based on a sample of "dirty" plants that do not represent the overall population of plants).

**Model uncertainty**

Model uncertainties arise because of gaps in the scientific theory that is required to make predictions on the basis of causal inferences. Common types of model uncertainties in various risk assessment-related activities include the following:

a. Relationship errors (e.g., incorrectly inferring the basis of correlations between chemical structure and biological activity).
b. Oversimplified representations of reality (e.g., representing a three-dimensional aquifer with a two-dimensional mathematical model).
c. Incompleteness, i.e., exclusion of one or more relevant variables (e.g., relating asbestos to lung cancer without considering the effect of smoking on both those exposed to asbestos and those unexposed).
d. Use of surrogate variables for ones that cannot be measured (e.g., using wind speed at the nearest airport as a proxy for wind speed at the facility site).
e. Failure to account for correlations that cause seemingly unrelated events to occur more frequently than expected by chance (e.g., two separate components of a nuclear plant are both missing a particular washer because the same newly hired assembler put them together).
f. Extent of (dis)aggregation used in the model (e.g., whether to break up the fat compartment into subcutaneous and abdominal fat in a physiologically based pharmacokinetic, or PBPK, model).

Although difficult to quantify, model uncertainty is inherent in risk assessment that seeks to capture the complex processes impacting release, environmental fate and transport, exposure, and exposure response.

## 2.5. REDUCING UNCERTAINTY

Identification of the sources of uncertainty in an exposure assessment is the first step in determining how to reduce uncertainty. Because uncertainty in exposure assessments is fundamentally tied to a lack of knowledge concerning important exposure factors, strategies for reducing uncertainty often involve the application of more resources to gather either more or targeted data. Example strategies to reduce uncertainty include (1) collecting new data, (2) implementing an unbiased sample design, (3) identifying a more direct measurement method or a more appropriate target population, (4) using models to estimate missing values, (5) using surrogate data, (6) using default assumptions, (7) narrowing the scope of the assessment, and (8) obtaining expert elicitation. The best strategy likely depends on a combination of resource availability, time constraints, and the degree of confidence necessary in the results.

## 2.6. ANALYZING VARIABILITY AND UNCERTAINTY

There are different strategies available for addressing variability and uncertainty that vary in their level of sophistication. The level of effort required to conduct the analysis needs to be balanced against the need for transparency and timeliness.

Exposure assessments are often developed in a tiered approach. The initial tier usually screens out the exposure scenarios or pathways that are not expected to pose much risk, to eliminate them from more detailed, resource-intensive review. Screening-level assessments typically examine exposures on the high end of the expected exposure distribution. Because screening-level analyses usually are included in the final exposure assessment, it may contain scenarios that differ in sophistication, data quality, and amenability to quantitative expressions of variability or uncertainty. Several approaches can be used to analyze uncertainty in parameter values. When uncertainty is high, for example, an assessor

may set order-of-magnitude bounding estimates of parameter ranges (e.g., from 0.1 to 10 liters for daily water intake). Another method may involve setting a range for each parameter as well as point estimates for certain parameters determined by available data or professional judgment.

A sensitivity analysis can be used to determine which parameters and exposures have the most impact on an exposure assessment. General concepts in sensitivity analysis are described in Saltelli et al. (2008). The International Program on Chemical Safety proposes a four-tier approach for addressing uncertainty and variability (WHO, 2006). The four tiers are similar to those proposed in U.S. EPA (1992) and include the use of default assumptions; a qualitative, systematic identification and characterization of uncertainty; a qualitative evaluation of uncertainty using bounding estimates, interval analysis, and sensitivity analysis; and a more sophisticated one- or two-stage probabilistic analysis (WHO, 2006).

Practical considerations regarding an uncertainty analysis include whether uncertainty would affect the results in a non-trivial way; an issue might be addressed by an initial sensitivity analysis in which a range of values are explored. An initial analysis of this sort might be facilitated by use of Microsoft Excel. Probabilistic risk analysis techniques are becoming more widely applied and are increasing in the level of sophistication. Bedford and Cooke (2001) describe in more detail the main tools and modeling techniques available for probabilistic risk analysis (Bedford and Cooke, 2001). If a probabilistic approach is pursued, another consideration is the choice of a software package. Popular software packages for Monte Carlo analysis range from the more general: Fortran, Mathematica, R, and SAS to the more specific: Crystal Ball, @Risk (Palisade Corporation), RISKMAN (PLG Inc.), and SimLab (Saltelli et al., 2004).

Increasingly, probabilistic methods are being utilized to analyze variability and uncertainty independently as well as simultaneously. It is sometimes challenging to distinguish between variability and parameter uncertainty in this context as both can involve the distributions of a random variable. For instance, parameter uncertainty can be estimated by the standard error of a random variable (itself a function of variability). Note that in this case, increasing the sample size necessarily reduces the parameter uncertainty (i.e., standard error).

More sophisticated techniques that attempt to simultaneously model both variability and uncertainty by sampling from their respective probability distributions are known as two-stage probabilistic analysis, or two-stage Monte Carlo analysis, which is discussed in great detail in Bogen and Spear (1987), Bogen (1990), Chapter 11 and Appendix I-3 of NRC (1994), and U.S. EPA (2001). These methods assume a probabilistic distribution for certain specified parameters. Random samples are drawn from each probabilistic distribution in a simulation and are used as input into a deterministic model. Analysis of the results from the simulations characterizes either the variability or uncertainty (or both) of the exposure assessment.

Through the implementation of computationally efficient Markov Chain Monte Carlo algorithms like Metropolis-Hastings, Bayesian methods offer an alternative approach to uncertainty analysis that is attractive in part because of increasing usability of software. For more on Bayesian methods, see Gelman et al. (2003), Gilks et al. (1995), Robert and Casella (2004).

The U.S. EPA has made significant efforts to use probabilistic techniques to characterize uncertainty. These efforts have resulted in documents such as the March 1997 *Guiding Principles for Monte Carlo Analysis* (U.S. EPA, 1997a), the May 1997 Policy Statement (U.S. EPA, 1997b), and the December 2001 Superfund document *Risk Assessment Guidance for Superfund: Volume III—Part A, Process for Conducting Probabilistic Risk Assessment* (U.S. EPA, 2001).

## 2.7. LITERATURE REVIEW OF VARIABILITY AND UNCERTAINTY ANALYSIS

There has been a great deal of recent scholarly research in the area of uncertainty with the widespread use of computer simulation. Some of this research also incorporates issues related to variability. The purpose of the literature review below is to give a brief description of notable developments. Section 2.9 provides references for further research.

Cox (1999) argues that, based on information theory, models with greater complexity lead to more certain risk estimates. This may only be true if there is some degree of certainty in the assumptions used by the model. Uncertainties associated with the model need to be evaluated (NRC, 2009). These methods were discussed in Bogen and Spear (1987), Cox and Baybutt (1981), Rish and Marnicio (1988), and U.S. EPA (1985). Seiler (1987) discussed the analysis of error propagation with respect to general mathematical formulations typically found in risk assessment, such as linear combinations, powers of one variable, and multiplicative normally distributed variables. Even for large and uncertain errors, the

formulations in Seiler (1987) are demonstrated to have practical value. Iman and Helton (1988) compared three methodologies for uncertainty and sensitivity analysis: (1) response surface analysis, (2) Latin hypercube sampling (with and without regression analysis), and (3) differential analysis. They found that Latin hypercube sampling with regression analysis had the best performance in terms of flexibility, estimate-ability, and ease of use. Saltelli (2002) and Frey (2002) offer views on the role of sensitivity analysis in risk assessment, and Frey and Patil (2002) compare methods for sensitivity analysis and recommend that two or more different sensitivity assessment methods should be used in order to obtain robust results. A Bayesian perspective on sensitivity analysis is described in Greenland (2001), who recommends that sensitivity analysis and Monte Carlo risk analysis should begin with specification of prior distributions, as in Bayesian analysis. Bayesian approaches to uncertainty analysis are described in Nayak and Kundu (2001).

Price et al. (1999) review the history of the inter-individual variability factor, as well as the relative merits of the sensitive population conceptual model versus the finite sample size model in determining the magnitude of the variability factor. They found that both models represent different sources of uncertainty and that both should be considered when developing inter-individual uncertainty factors. Uncertainties related to inter-individual and inter-species variability are treated in Hattis (1997) and Meek (2001), respectively. And Renwick (1999) demonstrates how inter-species and inter-individual uncertainty factors can be decomposed into kinetic and dynamic defaults by taking into account toxicodynamic and toxicokinetic differences. Burin and Saunders (1999) evaluate the robustness of the intra-species uncertainty factor and recommend intra-species uncertainty factoring in the range of 1-10.

Based on Monte Carlo analysis, Shlyakhter (1994) recommends inflation of estimated uncertainties by default safety factors in order to account for unsuspected uncertainties.

Jayjock (1997) defines uncertainty as either natural variability or lack of knowledge and also provides a demonstration of uncertainty and sensitivity analysis utilizing computer simulation. Additional approaches for coping with uncertainties in exposure modeling and monitoring are addressed by Nicas and Jayjock (2002).

Distributional risk assessment should be employed when data are available that support its use. Fayerweather et al. (1999) describe distributional risk assessment, as well as its strengths and weaknesses. Exposure metrics for distributional risk assessment using log-normal distributions of time spent showering (Burmaster, 1998a), water intake (Burmaster, 1998c), and body weight (Burmaster, 1998b; Burmaster and Crouch, 1997) have been developed. The lognormal distribution provides a succinct mathematical form that facilitates exposure and risk analyses. The fitted lognormal distribution is an approximation that should be carefully evaluated. One approach is to compare the lognormal distribution with other distributions (e.g., Weibull, Gamma). This is the approach used by Jacobs et al. (1998) and U.S. EPA (2002) in developing estimates of fish consumption and U.S. EPA (2004a) and Kahn and Stralka (2009) for estimates of water ingestion. These estimates were derived from the Continuing Survey of Food Intake by Individuals (CSFII), which was a Nationwide statistical survey of the population of the United States conducted by the U.S. Department of Agriculture. The CSFII collected extensive information on food and beverage intake from a sample that represented the population of the United States, and the sample weights provided with the data supported the estimation of empirical distributions of intakes for the entire population and various target populations such as intake distributions by various age categories. Kahn and Stralka (2008) used the CSFII data to estimate empirical distributions of water ingestion by pregnant and lactating women and compared the results to those presented by Burmaster (1998c). The comparison highlights the differences between the older data used by Burmaster and the CSFII and the differences between fitted approximate lognormal distributions and empirical distributions. The CSFII also collected data on body weight self-reported by respondents that supported the estimation of body-weight distributions by age categories, which are presented in Kahn and Stralka (2009). Detailed summary tables of results based on the CSFII data used by Kahn and Stralka (2009) are presented in Kahn (2008) personal communication (Kahn, 2008).

When sensitivity analysis or uncertainty propagation analysis indicates that a parameter profoundly influences exposure estimates, the assessor should, if possible, develop a probabilistic description of its range. It is also possible to use estimates derived from a large-scale survey such as the CSFII as a basis for alternative parameter values that may be used in a sensitivity analysis. The CSFII provides the basis for an objective point of reference for food and beverage intake variables, which are critical components of many risk and exposure assessments. For example, an assumed value for a mean or upper percentile could be compared to a

suitable value from the CSFII to assess sensitivity. Deterministic and probabilistic approaches to risk assessment are reviewed for non-carcinogenic health effects in Kalbelah et al. (2003), with attention to quantifying sources of uncertainty. Kelly and Campbell (2000) review guidance for conducting Monte Carlo analysis and clarify the distinction between variability and uncertainty. This distinction is represented by two-stage Monte Carlo simulation, where a probability distribution represents variability in a population, while a separate distribution for uncertainty defines the degree of variation in the parameters of the population variability distribution. Another example of two-stage Monte Carlo simulation is given in Xue et al. (2006). Price et al. (1997) utilize a Monte Carlo approach to characterize uncertainties for a method aimed at estimating the probability of adverse, non-cancer health effects for exposures exceeding the reference dose. Their method relies on general toxicologic information for a compound, such as the no-observed-adverse-effect-level dose (NOAEL). Semple et al. (2003) examine uncertainty arising in reconstructed exposure estimates using Monte Carlo methods. Uncertainty in PBPK models is discussed in Simon (1997) and Bois (2010). Slob and Pieters (1998) propose replacing uncertainty factors with probabilistic uncertainty distributions and discuss how uncertainties may be quantified for animal NOAELs and extrapolation factors. Zheng and Frey (2005) demonstrate the use of Monte Carlo methods for characterizing uncertainty and emphasize that uncertainty estimates will be biased if contributions from sampling error and measurement error are not accounted for separately.

Distributional biometric data for probabilistic risk assessment are available for some exposure factors. Empirical distributions are provided in this handbook when available. If the data are unavailable or otherwise inadequate, expert judgment can be used to generate a subjective probabilistic representation. Such judgments should be developed in a consistent, well-documented manner. Morgan et al. (1990) and Rish (1988) describe techniques to solicit expert judgment, while Weiss (2001) demonstrates use of a Web-based survey.

Standard statistical methods may be less cumbersome than a probabilistic approach and may be preferred, if there are enough data to justify their use and they are sufficient to support the environmental decision needed. Epidemiologic analyses may, for example, be used to estimate variability in human populations, as in Peretz et al. (1997), who describe variation in exposure time. Sources of variation and uncertainty may also be explored and quantified using a linear regression modeling framework, as in Robinson and Hurst (1997). A general framework for statistical assessment of uncertainty and variance is given for additive and multiplicative models in Rai et al. (1996) and Rai and Krewski (1998), respectively. Wallace and Williams (2005) describe a robust method for estimating long-term exposures based on short-term measurements.

In addition to the use of defaults and quantitative analysis, exposure and risk assessors often rely on expert judgment when information is insufficient to establish uncertainty bounds (NRC, 2009). There are, however, some biases introduced during expert elicitation. Some of these include availability, anchoring and adjustment, representativeness, disqualification, belief in "law of small numbers," and overconfidence (NRC, 2009). Availability refers to the tendency to assign greater probability to commonly encountered or frequently mentioned events (NRC, 2009). Anchoring and adjustment is the tendency to be over-influenced by the first information seen or provided (NRC, 2009). Representativeness is the tendency to judge an event by reference to another (NRC, 2009). Disqualification is the tendency to ignore data or evidence that contradicts strongly held convictions (NRC, 2009). The belief in the "law of small numbers" is to believe that small samples from a population are more representative than is justified (NRC, 2009). Overconfidence is the tendency of experts to belief that their answers are correct (NRC, 2009).

## 2.8. PRESENTING RESULTS OF VARIABILITY AND UNCERTAINTY ANALYSES

The risk assessor is advised to distinguish between variability of exposure and associated uncertainties. A risk assessment should include three components involving elements of variability and uncertainty: (1) the estimated risk itself (X), (2) the level of confidence (Y) that the risk is no higher than X, and (3) the percent of the population (Z) that X is intended to apply to in a variable population (NRC, 1994). This information will provide risk managers with a better understanding of how exposures are distributed over the population and of the certainty of the exposure assessment.

Sometimes analyzing all exposure scenarios is unfeasible. At minimum, the assessor should describe the rationale for excluding reasonable exposure scenarios; characterize the uncertainty in these decisions as high, medium, or low; and state whether

they were based on data, analogy, or professional judgment. Where uncertainty is high, a sensitivity analysis can be used to estimate upper limits on exposure by way of a series of "what if" questions.

Although assessors have historically used descriptors (e.g., high-end, worst case, average) to communicate risk variability, the 1992 *Guidelines for Exposure Assessment* (U.S. EPA, 1992) established quantitative definitions for these risk descriptors. The data presented in this handbook are one of the tools available to exposure assessors to construct the various risk descriptors. A thorough risk assessment should include particular assumptions about human behavior and biology that are a result of variability. A useful example is given in NRC (1994):

> "…a poor risk characterization for a hazardous air pollutant might say 'The risk number R is a plausible upper bound.'" A better characterization would say, "The risk number R applies to a person of reasonably high-end behavior living at the fenceline 8 hours a day for 35 years."

In addition to presenting variability in exposure, frequently, exposure assessments include an uncertainty analysis. An exposure assessment will include assumptions about the contaminant, contaminant exposure routes and pathways, location, time, population characteristics, and susceptibilities. Each of these assumptions may be associated with uncertainties. Uncertainties may be presented using a variety of techniques, depending on the requirements of the assessment, the amount of data available, and the audience. Simple techniques include risk designations, i.e., high, medium, or low (un)certainties. Sophisticated techniques may include quantitative descriptions of the uncertainty analysis or graphical representations.

The exposure assessor may need to make many decisions regarding the use of existing information in constructing scenarios and setting up the exposure equations. In presenting the scenario results, the assessor should strive for a balanced and impartial treatment of the evidence bearing on the conclusions with the key assumptions highlighted. For these key assumptions, one should cite data sources and explain any adjustments of the data.

The exposure assessor should describe the rationale for any conceptual or mathematical models. This discussion should address their verification and validation status, how well they represent the situation being assessed (e.g., average versus high-end estimates), and any plausible alternatives in terms of their acceptance by the scientific community.

To the extent possible, this handbook provides information that can be used in a risk assessment to characterize variability, and to some extent, uncertainty. In general, variability is addressed by providing probability distributions, where available, or qualitative discussions of the data sets used. Uncertainty is addressed by applying confidence ratings to the recommendations provided for the various factors, along with detailed discussions of any limitations of the data presented.

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