EXA 407: Assessing Uncertainty and Variability in the Context of Exposure Assessment
Instructor Notes

Course Description: The purpose of this module is to teach students how to assess uncertainty and variability in the context of exposure assessment. The differences in the concepts, with regard to exposure, will be stressed. For example, variability pertains to aspects of the assessment which are judged as being known with some "certainty," but which are also known to "vary," such as body weight. On the other hand, uncertainty pertains to aspects which may or may not "vary," but for which little (or no) information is available, such as contaminant soil half-lives for fate modeling. Participants will learn about the different types of variability and uncertainty and will explore methods for analyzing, coping with, and reducing uncertainty and variability. Suggestions also will be provided for presenting the results of uncertainty analyses and variation in human exposures.

Expected Course Duration: Approximately 45 minutes

Terminal Learning Objective: Develop familiarity with the concepts of uncertainty and variability in the context of exposure assessment

Enabling Learning Objectives:

- Learn the definitions of uncertainty and variability and the differences between these concepts
- Understand the different types of variability and the factors that contribute to variability
- Understand how to analyze variability in exposure assessments
- Understand the different types of uncertainty
- Understand how to analyze, cope with, and reduce uncertainty in exposure assessments

Course Materials

- EXA 407 Reading Packet

Course Overview/List of Slides

TITLE SLIDE

- Welcome to EXA 407, uncertainty and variability in the context of exposure assessment.

What You Can Expect to Learn from this Course (Slide 1)

- In other courses in this series, we introduced the concepts of uncertainty and variability. In this course, we will explore these concepts in the context of exposure and dose calculation.
- By accounting for variability and uncertainty in your exposure assessment, it's more likely that your results will be applied correctly.
- In the first part of today's course, we'll define these two terms and briefly review the differences between them. Then, we'll address variability and uncertainty individually. We'll talk in more detail about the factors that contribute to each and ways to analyze variability and uncertainty.
- Source: (U.S. EPA, 2011)

VARIABILITY AND UNCERTAINTY IN EXPOSURE ASSESSMENT (SLIDE 2)

From Source to Receptor to Effect (Slide 3)

- While this course will focus on uncertainty and variability in the context of exposure assessment, it is important to note that these same concepts are also important in fate and transport modeling.

What Is Variability? (Slide 4)

- Variability refers to the true heterogeneity or diversity in the values for an exposure parameter.
- It's an inherent property of a population or other entity, and therefore it cannot be corrected or reduced.
- It can, however, be better characterized by collecting more data.

? What are some sources of variability that can affect the exposure estimate for a population? [For example, consider a population subject to multipathway exposures to mercury emitted from a stack.]

  - Exposure concentration and contact rates for individuals in different age groups and genders within a population, or for individuals living in different parts of the community.
  - Different body weights of age groups and genders within a population.
  - Different exposure frequencies within a population.
  - Different exposure durations and averaging times within a population.

- We'll talk more about factors like these that can contribute to variability. But first, let's define uncertainty.

- Source: EPA IRIS SOPs, Appendix C, Sections 3.0 and 4.0 ([2010]())

What is Uncertainty? (Slide 5)

- Uncertainty refers to a lack of knowledge. It's typically due to incomplete data or an incomplete understanding of a process.
- Uncertainty can often be reduced or even eliminated by collecting more or better data. When we can't eliminate or reduce uncertainty, we use approximations and assumptions.

? On the previous slide, we discussed a few examples of variability within a scenario of mercury exposure from a stack. What are some examples of uncertainty that can affect an exposure estimate?

  - Uncertainty regarding the chemical concentration in environmental media.
  - Uncertainty about what chemicals are being released from a stack.
  - Uncertainty about what the relevant exposure scenarios are.

- Let's talk a bit about the key differences between variability and uncertainty.

What is the Difference Between Variability and Uncertainty? (Slide 6)

- The difference between variability and uncertainty was discussed by the National Research Council in its 1994 report titled *Science and Judgment in Risk Assessment*. In this book, NRC emphasized the importance of distinguishing between uncertainty and variability.
- The key difference, as we mentioned previously, is that variability cannot be reduced, though it can be better characterized. Uncertainty, on the other hand, ***can*** be reduced, and in some cases, eliminated by collecting more or better data.
- You'll encounter both uncertainty and variability while conducting an exposure assessment. Sometimes, it can be hard to tease them apart.
  - Let's think about an example where a population is exposed to a pollutant through their drinking water. Water intake rates for the population are clearly important.
  - There will be ***variability*** in intake rates among members of the exposed population. For example, some people might drink more water per day than others due to their age, weight, the activities they participate in, and other factors.
  - There will also be ***uncertainty*** in the intake rate values used in the assessment. For example, it's common to use EPA exposure factors for water ingestion rates in an exposure assessment. There will likely be some uncertainty whether the data used are truly representative of the exposed population.
  - Although we cannot reduce the variability in water intake rates across a population, we can better characterize this variability by collecting more data from that population. This might also reduce some of the uncertainty associated with using a representative data set.

- Source: NRC Science and Judgment in Risk Assessment ([1994]())

UNDERSTANDING VARIABILITY (SLIDE 7)

- Let's talk about variability in more detail.

Factors Contributing to Exposure Variability (Slide 8)

- We talked about a few of the factors that contribute to variability in previous slides. Listed on this slide are some important factors contributing to variability among members of a population.
- These include differences that are readily apparent, like age and gender, and differences that exist between males and females, like body weight, food intake rates, and life expectancy.
- Individuals' behaviors also affect exposure.
  - For example, if a child is teething, she is more likely to put objects in her mouth, increasing some exposures.
- Location is important. If one person lives close to a highway, they might have higher exposures to particulate matter and other pollutants that are associated with traffic.
- Socioeconomic factors can contribute to exposure variability. For example, people in different socioeconomic classes might have different occupations that require different amounts of time outdoors.
- Source: EPA's Exposure Factors Handbook (2011)

Types of Variability (Slide 9)

- The Exposure Factors Handbook refers to four different types of variability: spatial, temporal, inter-individual, and intra-individual. These types are not mutually exclusive, nor are they strict definitions – but they do provide a way to think about variability.
- In addition to being relevant to exposure assessment, these types of variability are relevant to fate and transport too.
- Source: EPA's Exposure Factors Handbook (2011)

Types of Variability: Spatial Variability (Slide 10)

- Spatial variability refers to variability across locations. It can occur at the macroscale level, for example, where we examine exposure across a whole region, or at the local or microscale level, where we are looking at exposures for a specific location.
- One of the most common examples of spatial variability is geographic differences in environmental concentrations. There are often regional trends in pollutant levels as well as differences on the local scale. The variability in environmental concentrations can often be explained by the spatial variability in fate and transport processes.
- Outdoor pollutant levels can be affected on the local level by individual activities, such as driving cars or mowing a lawn. Outdoor versus indoor air concentrations is another example of spatial variability on a smaller or microscale.

- Source: EPA's Exposure Factors Handbook (2011)

Types of Variability: Temporal Variability (Slide 11)

- Temporal variability refers to variation over time. This can mean variation on a long-term or short-term basis.
- Examples of long-term variability include seasonal fluctuations in weather and amount of time per week a person spends outdoors.
- Examples of short-term variability include differences in an individual's activities at different times of the day and during the week versus on weekends. Short-term variability could also refer to differences in an industrial facility's operations during the week versus on weekends.
- Source: EPA's Exposure Factors Handbook (2011)

Types of Variability: Inter-individual Variability (Slide 12)

- Inter-individual variability refers to variability between individuals. It can be grouped into two categories: human characteristics and human behaviors.
- Human characteristics include some of the factors that we've discussed already, such as gender, age, life stage, and body weight.
- Human behaviors such as activity patterns and ingestion and inhalation rates can also vary across a population, and these can definitely affect exposure potential.
- Inter-individual variability can be related to spatial and temporal factors. For example, individuals in different locations may have different dietary patterns and engage in different activities. Similarly, individuals within a population experience different exposures with time.
  - For example, in summer, some people in a population might spend more time outdoors in swimming pools and at beaches, but other individuals might prefer to spend the summer months inside in the air conditioning.

Types of Variability: Intra-individual Variability (Slide 13)

- Intra-individual variability refers to variability within an individual. This is a function of fluctuations in an individual's physiologic or behavioral characteristics, usually over time.
  - An example of a physiologic characteristic that changes with time is body weight.
  - Behavioral characteristics that can change over time include ingestion rates and other activity patterns. Patterns of food intake change from day to day and may change significantly over an individual's lifetime. Similarly, the activities in which an individual engages will also vary daily and more significantly over a lifetime.
- Intra-individual variability can also be associated with spatial variability.

? Can you think of a situation where intra-individual variability would be associated with spatial or temporal variability?

- Spatial:
  - Dietary intake may reflect local food sources, so foods consumed could vary if a person changes residences.
- Source: EPA's Exposure Factors Handbook (2011)

ADDRESSING VARIABILITY IN AN EXPOSURE ASSESSMENT (SLIDE 14)

- We've touched on some of the factors that affect variability and the different types of variability than can affect exposure potential. Let's talk a little bit about how we can deal with variability when we do an exposure assessment.
- Remember that exposure assessments are done with a tiered approach so we are not going to choose the most complicated or labor intensive method every time.

Presenting Variability (Slide 15)

- As described in EPA's *Exposure Factors Handbook*, variability in exposure parameters can be presented in several ways.
- Data can be presented in tables with percentiles or ranges of values, like those shown on the left side of this slide.
- Variability data can be presented as probability distributions like those shown on the right side of this slide. Specified parameters such as standard deviations or confidence intervals can be used to indicate the degree of variability in the estimated values.
- A third option is to discuss variability qualitatively.
- The NRC recommends four other ways to address variability in an exposure assessment. These are listed at the bottom of this slide, and they are:
  - ignore the variability,
  - disaggregate the variability,
  - use an average, minimum, or maximum value, or
  - use probabilistic or bootstrapping techniques to investigate the effects of variability.
- Let's talk about ignoring variability first.
- Sources: NRC Science and Judgment in Risk Assessment (1994); EPA's Exposure Factors Handbook (2011)

Ignoring Variability (Slide 16)

- The first method recommended by the NRC is to ignore variability. This may seem like an irresponsible approach, but in truth, EPA does not suggest that the variability be disregarded altogether. The idea here is to instead take the simplest approach and not change anything in the exposure equation to account for variability. When used correctly, this technique will not result in less accurate exposure estimates. Often, this approach is used in combination with other approaches (which, in essence, is not "ignoring" the variability).

- If we are not going to conduct evaluations of the variability in exposure data, then we need to be careful in selecting the exposure factors that we use. We also need to be clear and transparent about why we've selected the values we're using.
  - For example, for a given parameter, we could select a central tendency value that represents an average. Selecting and presenting exposures based on this value (and only this value) would not provide any information regarding exposure variability. We would in effect ignore the impact of variability, but this approach might provide an adequate estimate of typical exposure for that population, depending on the purpose of the assessment.
- This technique works best when the variability for a given parameter is relatively small, such as body weight in a population.
  - For example, EPA's assumption of 80 kg for adult body weight ignores the true variability in body weights across the U.S. population. However, this average value is likely to be correct within 25% for most adults.
- Sources: EPA's Exposure Factors Handbook (2011); NRC Science and Judgment in Risk Assessment (1994)

Disaggregating Variability (Slide 17)

- A second approach recommended by the NRC is to disaggregate variability, or to break up the data in some way so that it can be more easily characterized and quantified.
- Although we said earlier that some variability is inherent to all populations, we can better characterize the variability within the assessment context by collecting more information about the population of concern. This will help us better understand the true variability.
  - One way that variability can be disaggregated is by breaking down a population into smaller chunks – for example, into population cohorts and lifestages. We can develop different probability distributions for specific age groups, like children and adults as shown on this slide, or for males and females within each age group. The variability within each cohort will be smaller than the variability of the population as a whole.
- Similar techniques could be used by considering shorter periods of time, smaller regions, and microenvironments.
- We can also use mathematical models or equations to disaggregate variability.
  - For example, instead of using an annual average outdoor concentration of a chemical, we could fit a sine wave to the data to represent the seasonal variability. As you might remember, a sine function is a mathematical model that can be used to describe smooth, repetitive variation.
- Sources: EPA's Exposure Factors Handbook (2011); NRC Science and Judgment in Risk Assessment (1994)

Average or Minimum/Maximum (Slide 18)

- The third approach recommended by NRC (1994) is to use the average value of the distribution and the minimum or maximum (or values approaching the min or max).
- The use of a single point value to characterize a parameter value for a population requires confidence that the value was estimated reliably and that the assessor has adequately characterized the bounds of the distribution.
  - For the distribution shown here for root vegetable consumption for 40- to 69-year-olds, we could select a value up to or approaching 15 g/kg BW-day, but we wouldn't want to select, say, 20 because that's outside the assumed distribution.
- Use of a minimum or maximum value is perhaps the most common approach to coping with variability in exposure assessment. However, it can be a problem if we use this approach for several parameters.
  - For example, setting all exposure factors involved in a calculation to their maximum values will probably result in an unrealistic exposure estimate. Estimating the "reasonable maximum exposure" within a population requires good judgment in setting a limited number of exposure factors to their maximum (or minimum) values without grossly overestimating exposure.

Probabilistic or Bootstrapping Techniques (Slide 19)

- A final approach for managing variability in an exposure assessment is to use probabilistic or bootstrapping techniques.
- In the context of risk assessment, probabilistic assessments characterize the variability in risk estimates by repeated sampling of the probability distributions of variables. Then, these results are used to calculate a distribution of risk.
  - Bootstrapping can be used to estimate confidence intervals around specific exposure parameters by re-sampling from empirical distributions. This is useful when there's a lack of specific knowledge regarding the distribution for a parameter.
- We'll discuss probabilistic techniques for dealing with variability a little more after we talk about characterizing uncertainty, because the same basic methods are used for both.

Exposure Modeling with APEX (Slide 20)

- In EXA 402, we talked about the use of exposure models to estimate dose and risk for people. Let's look specifically at one of those models, APEX, and see how using it, or other exposure models like it, helps us to better account for variability in exposure.
- APEX, or Air Pollution EXposure model, was created to support development of the National Ambient Air Quality Standards, or NAAQS. The flow chart on this slide shows in detail what type of information goes in to APEX to model exposure.
- At the top left, you'll see that we first define the study area and provide both meteorology data and air pollution concentration data. APEX can estimate concentrations in geographic areas down to the census block level. To develop the NAAQS, EPA uses

AERMOD to model pollutant concentrations in geographic areas. These are then used as inputs to APEX.

- Next, we identify the population of interest. Using census data for our geographic area, we identify which people live there, their ages, genders, and races, their commuting habits, and the characteristics of their homes. APEX creates simulated individuals by sampling from activity diaries compiled by EPA and U.S. census data.
  - In creating the simulated individuals, it's difficult to tease out the variability versus uncertainty in the model because the populations may vary.

? What are some of the types of variability you see modeled in APEX?
  - Spatial, temporal, inter-individual.

APEX Activity Modeling (Slide 21)

- APEX then creates a sequence of activities for each of the simulated people for the duration of the simulation. The activities vary by day of the week and season of the year, and they're consistent for the person. For example, one simulated adult might drive to work in a car each day weekday, commuting 25 miles each way. He might have a desk job and have a relatively low activity rate during the day, but he might also be an avid runner and spend an hour running outside every afternoon, inhaling a lot more than normal during that hour.
- A different simulated individual might be a child that walks to school, plays outside for recess, and then comes home to a house without air conditioning where the windows are open for many days of the year.
- The resulting collection of activity patterns that APEX compiles is intended to reflect the variability across the population.
- And because of the way APEX samples from the activity diaries, intra-individual variability is also captured.

Concentrations and Exposures in APEX (Slide 22)

- Using the input meteorology data and the air concentrations in each census block for the region of interest, APEX creates a mass balance to determine the concentration in each microenvironment (school, work, home, shopping). The mass balance is affected by the pollutant concentration outside, the penetration of the pollutant from the exterior to the interior, and the ventilation rates for the environment.
- Then, for each simulated individual, APEX calculates an hourly exposure concentration based on the time spent in the microenvironment and the concentration of the pollutant in that environment.
- For the entire modeled population, APEX estimates the population exposure.
- So putting all of this together, the model can account for spatial, temporal, and intra- and inter-individual variability.

UNDERSTANDING UNCERTAINTY (SLIDE 23)

- Now that we have a better understanding of variability in the context of exposure assessment, let's move on to discuss uncertainty.

Types of Uncertainty (Slide 24)

- EPA's *Exposure Assessment Guidelines* specify three broad types of uncertainty commonly encountered when conducting exposure assessments: scenario uncertainty, parameter uncertainty, and model uncertainty.
- Identification of the sources of uncertainty in an exposure assessment is the first step towards potentially reducing or ideally eliminating uncertainty.
- It should be noted that classification of uncertainty into these three categories is not as strict as it may seem. In practice, these uncertainties may arise in overlapping areas.
    - For example, let's say that we have a specific data set that we'll use to determine the numerical inputs for our exposure model. In this case, we may have to deal with parameter uncertainty, because there is uncertainty about the approaches used to measure the source data. We may also have to deal with model uncertainty, because the model we've selected might not be appropriate for the exposure scenario.

(click mouse to highlight blue "Scenario Uncertainty" circle.)

- Let's talk a little bit more about each of these types of uncertainty. We'll start with our discussion of Scenario Uncertainty.
- Sources: EPA Exposure Assessment Guidelines (1992); EPA EFH (2011); IPCS Uncertainty and Data Quality in Exposure Assessment Parts 1 and 2 (2008)

Scenario Uncertainty (Slide 25)

- Scenario uncertainty refers to uncertainty regarding missing or incomplete information that is needed to fully define exposure and dose. In other words, it's uncertainty that's present because you are not able to fully characterize the exposure scenario you're evaluating.
- Sources of scenario uncertainty can usually be attributed to incomplete descriptions of key information.
    - This might include the physical and chemical properties and sources of the chemical of concern; the population of concern, including activity pattern data; spatial and temporal information.
- There are four main sources of scenario uncertainty: descriptive errors, aggregation errors, errors in professional judgment, and incomplete analysis.
- Let's dig into these sources of scenario uncertainty in a little more detail.
- Sources: EPA Exposure Assessment Guidelines (1992); IPCS Uncertainty and Data Quality in Exposure Assessment Parts 1 and 2 (2008)

Sources of Scenario Uncertainty: Descriptive Errors (Slide 26)

- We'll talk about descriptive errors first. These are errors in the basic information regarding exposure pathways, scenarios, and populations of concern.
- Examples include mistakes in identifying the current producers of a chemical, uses of a chemical, and properties of a chemical. Another example might be leaving out an important population cohort, such as children, because the assessor didn't realize that the chemical of concern is found in children's toys.
- All of this information influences how a population could be exposed to a chemical.
- Source: EPA Exposure Assessment Guidelines (1992)

Sources of Scenario Uncertainty: Aggregation Errors (Slide 27)

- Aggregation errors arise as a result of lumping together information to the extent that we overlook important differences within an exposed population or contaminated area.
    - For example, we could incorrectly assume that a population is homogenous. This could lead to assumptions of similar dietary habits or other activity patterns that affect exposure potential.
    - Another example of aggregation is assuming steady-state conditions across different locations or at different times when the conditions are not actually the same.

Source: EPA Exposure Assessment Guidelines (1992)

Sources of Scenario Uncertainty: Errors in Professional Judgment (Slide 28)

- Because professional judgment is used throughout the exposure assessment process, there are plenty of opportunities to make incorrect assumptions.
    - For example, if we do not accurately define the exposure scenario, we might not be able to accurately identify the population of concern or the relevant exposure routes and pathways, or even the chemical of concern. Of course, this clearly overlaps with scenario uncertainty. In this case, errors in professional judgment are related to scenario uncertainty.
- An exposure assessor must also identify the appropriate models to conduct the exposure assessment. This could include environmental fate and transport models or human exposure models.
- In terms of fate and transport modeling, errors in professional judgment might be easier to identify. An assessor might have to select a value for a parameter based on little or no site-specific data.
- Source: EPA Exposure Assessment Guidelines (1992)

Sources of Scenario Uncertainty: Incomplete Analysis (Slide 29)

- An analysis that's not complete could be a source of a lot of uncertainty in an exposure assessment.
- For example, if we leave out an important exposure pathway or an important lifestage, we might underestimate exposure significantly.
- Although it's hard to quantify this type of uncertainty, we should always include a rationale for excluding known potential exposure scenarios and identify and discuss the estimated uncertainty associated with excluding them.
- We should also explain whether the decision to exclude exposure scenarios was based on data, analogs (like using results from an animal study to predict human effects), or professional judgment.
- If the uncertainty is high, the assessor should consider performing a "what if" analysis.
    - For example, let's say we're conducting an assessment of exposure to a chemical discharged to water. If we believe the main exposure pathway is through ingestion of contaminated surface water, we might not estimate dermal exposures that could occur through swimming or showering while using this water. In this case, we would want to comment on why we think the dermal pathway is not important. Or, we might want to conduct a screening-level assessment of dermal exposure.
- Source: EPA Exposure Assessment Guidelines (1992)

Types of Uncertainty (Slide 30)

- Now that we've discussed these four sources of scenario uncertainty, let's move on to the next type of uncertainty: parameter uncertainty.

Parameter Uncertainty (Slide 31)

- Parameter uncertainty refers to uncertainty regarding a specific parameter value used in an exposure assessment, such as ingestion rates. Parameter uncertainty is also important to take into account in fate and transport modeling, but is not further discussed in this module.
- Values for parameters are typically estimated from measurements or samples from a larger population. As we talked about in a previous course, EPA provides numerical values for some exposure parameters in the *Exposure Factors Handbook.*
- Because the values used in our exposure scenario or model will directly affect the exposure estimate, it is important to try to identify the potential sources of parameter uncertainty. Uncertainty can result from small samples sizes, imprecise measurements, samples that are not representative, or data from a study that's poorly designed.
- In EPA's Exposure Assessment Guidelines, parameter uncertainty is attributed to four sources: measurement errors, sampling errors, variability, and uncertainty surrounding the type of data included in your assessment.
- Let's talk some more about these four areas.

- Sources: EPA Exposure Assessment Guidelines (1992); IPCS Uncertainty and Data Quality in Exposure Assessment Parts 1 and 2 (2008); EPA Exposure Factors Handbook (2011)

Sources of Parameter Uncertainty: Measurement Errors (Slide 32)

- Measurement errors are mistakes associated with anything that's measured, including an exposure concentration itself. These errors can be random or systematic.
- Random errors result from imprecision in the measurement process. For example, there could be measurement error associated with a questionnaire on use of a specific consumer product. Measurement error would result if use was under- or over-reported in the questionnaire.
- Random measurement errors can be compounded by variability. Using the same example, the variability in the use of a consumer product can be compounded by random error introduced by use of the questionnaire.
- Systematic error is a bias or tendency away from the true value. The average of the measurements of an exposure parameter may differ from its true value. We call the difference between the average of the measurements and its true value "bias." Bias may result from incorrect calibration of the measurement tool or from systematic over- or under-reporting in questionnaires.
- Source: EPA Exposure Assessment Guidelines (1992); IPCS Uncertainty and Data Quality in Exposure Assessment Parts 1 and 2 (2008)

Sources of Parameter Uncertainty: Sampling Errors (Slide 33)

- The purpose of sampling is to make an inference about the "whole."
    - For example, to characterize a feature of an entire population, we could take measurements from a subset of individuals from that population.
- Therefore, it is very important that the subset be representative of the whole.
- In determining the representativeness of the subset, we have to consider the reason why the data on the subset were generated. If the purpose of the study is not consistent with the purpose of our assessment, it's more likely that sampling errors might be introduced into our assessment.
    - In the conceptual example shown on this slide, a subset of the population has been sampled to determine the typical "color." Unfortunately, blue – which is the most common color in the whole population – is underrepresented in the sample.
- As a real-life example, let's go back to the survey conducted to determine how often a cleaning product is used. If the survey is voluntary and the only people who respond are people who used the product, the results will not be representative of the entire population, including those people who ***don't*** use the product. The survey results would probably overestimate product use. This would be a systematic error.

- ? Sampling errors can obviously also affect our fate and transport modeling if the samples we base our analysis on are not the most representative. Has anyone had an experience with this in the field?
- Sources: EPA Exposure Assessment Guidelines (1992); IPCS Uncertainty and Data Quality in Exposure Assessment Parts 1 and 2 (2008)

Sources of Parameter Uncertainty: Characterization of Variability (Slide 34)

- Another possible contributor to parameter uncertainty is the assessor's inability to characterize the true variability in a population.
- As we discussed in the first part of this course, there are four types of variability that we have to consider: temporal, spatial, and intra- and inter-individual variability.
- Failure to accurately capture and account for variability can result in an exposure estimate that's not representative.
- Source: EPA Exposure Assessment Guidelines (1992)

Sources of Parameter Uncertainty: Data Type Uncertainty (Slide 35)

- Scenario-specific data are usually not available for all parameters in an exposure assessment. As a result, we might have to rely on surrogate or generic data. We'll need to apply expert judgment to select the most representative data. Data type uncertainty is a lack of knowledge about whether the data used in an assessment are appropriate – that is, are they the correct "type."
    - For example, we could use fish consumption data from the Exposure Factors Handbook for recreational fishers to characterize the fish consumption behavior in another population that's not included in the Handbook if we think they are similar populations.
- Evaluating representativeness is important.
    - In this example, the types and amounts of fish consumed by the recreational population might not be comparable to the types and amounts of fish consumed by the other population. This introduces data type uncertainty.
- In some cases, an assessor might call on an expert to apply his professional judgment to select appropriate surrogate data. In this case, it's still possible to introduce uncertainty if the expert is biased, or if the expert's not as good as you think he is.
    - One way to get around this is expert elicitation. This involves obtaining input and advice from multiple experts using methods designed to avoid bias and maximize accuracy.
- Defaults can also be used when we don't have scenario-specific data. This approach is often used in screening assessments. The uncertainty surrounding these values depends on the quality of the data set used to derive the defaults and their applicability to the situation of interest.

- Sources: EPA Exposure Assessment Guidelines (1992); IPCS Uncertainty and Data Quality in Exposure Assessment Parts 1 and 2 (2008) ; EPA Exposure Factors Handbook (2011)

Types of Uncertainty (Slide 36)

- We've now discussed scenario and parameter uncertainty – two of the three types of uncertainty. Let's move on to the third and final type of uncertainty we'll cover, which is model uncertainty.

Model Uncertainty (Slide 37)

- Model uncertainty refers to uncertainty resulting from gaps in scientific knowledge that is required to make predictions.
- As you learned in EXA 405, exposure models and fate and transport models use mathematical relationships, ranging from simple static equations to complex, dynamic algorithms, to describe the relationship between input parameters and responses to changes in these inputs.
- However, the use of models in an exposure assessment introduces additional uncertainties. Primary sources of model uncertainty include relationship errors, modeling errors, and selection of an incorrect model. Let's talk about these.
- Sources: EPA Exposure Assessment Guidelines (1992); IPCS Uncertainty and Data Quality in Exposure Assessment Parts 1 and 2 (2008)

Sources of Model Uncertainty: Relationship Errors, Modeling Errors, and Model Selection (Slide 38)

- Relationship errors result from drawing incorrect conclusions from correlations, or disregarding correlations that might exist.
  - For example, when we use a model that estimates dietary intake for a population, we have to remember that the type of food eaten on a given day is not independent of the food eaten on the previous or subsequent day.
- Modeling errors result from a failure to consider exposure parameters, or an oversimplification of the model used to represent the exposure scenario.
  - Using the example of a dietary intake model, the same model would need to account for water consumed both as drinking water and water used in food preparations. Failure to account for either of these sources of water could be an oversimplification.
- It is also important, of course, to select the correct model – without that, you'll probably get the wrong answer, regardless of how good the inputs of the model are.
- Some of the considerations related to use of a model are listed here. They include boundaries, dependencies, assumptions, level of detail, extrapolation, and implementation and technical aspects.

- Sources: EPA Exposure Assessment Guidelines (1992); IPCS Uncertainty and Data Quality in Exposure Assessment Parts 1 and 2 (2008)
- (See pp 19-22 in IPCS)

CLASS ACTIVITY (SLIDE 39)

- Let's put what you've just learned into practice.

Class Activity: Source to Effect Continuum (Slide 40)

- Here, we illustrate the concept of the "source to effect continuum" in exposure assessment. Starting at the top left corner of the diagram and moving downward, we see the stressor domain, the fate and transport of a source leading to the environmental concentrations, and exposure to the receptor. The stressor reaches a target dose within the receptor causing a biological event and effecting a specific outcome.

Class Activity: London Smog of 1952 (Slide 41)

- Now, let's apply the concepts of uncertainty and variability in the context of the source-to-effect continuum and a well-known exposure scenario: The Great Smog of 1952 in London, England.
  - From December 5th through 9th of 1952, a dense smog settled over London due to a combination of atmospheric conditions and increased coal burning during the winter months.

? What are some examples of uncertainty and variability in the:

- Source/stressor?
  - Spatial variability in the area of fog, quantitative uncertainty in types of air pollutants (particulate matter, NO_x, etc.) and point sources, quantitative uncertainty in level of air pollutants
- Fate and transport?
  - Quantitative uncertainty in rate of deposition of the particulate matter to soil, variability in wind patterns to carry smog or particulates, model uncertainty in determining the transport of particulates
- Environmental concentration?
  - Temporal variability in amount of time smog lingered in the environment
- Exposure?
  - Qualitative uncertainty in the amount of time that individuals spent outdoors, activity engaged in
- Target dose?
  - Variability in deposition of particulate matter into an individual's lungs based on breathing rate
- Biological event?

    - Uncertainty in the amount of inhaled particulate matter to trigger respiratory or cardiac effects
  - Effect/outcome in the receptor?
    - Inter-individual variability in susceptibility to smog (asthmatics, older, younger populations would be more susceptible)
- For further reading: Bell ML, Davis DL (2001), Reassessment of the Lethal London Fog of 1952: Novel Indicators of Acute and Chronic Consequences of Acute Exposure to Air Pollution.

ADDRESSING UNCERTAINTY IN AN EXPOSURE ASSESSMENT (SLIDE 42)

- Let's talk briefly about ways to address and potentially reduce uncertainty.

Why Address Uncertainty in Exposure Assessments? (Slide 43)

- EPA policy and memoranda require clarity, transparency, reasonableness, and consistency in risk assessment. Addressing uncertainty in our assessments helps us fulfill these requirements. EPA's Exposure Assessment Guidelines outline seven reasons why uncertainty should be addressed in exposure assessments.
  - An analysis of uncertainty demonstrates our level of understanding and confidence in our exposure estimate.
  - It allows us to combine the uncertainties from different sources and levels of data quality.
  - An uncertainty analysis can provide context for evaluating the results of our assessment. It can help us determine how confident we are in our answers.
  - We might be able to **improve** the quality of our best estimate by identifying and exploring areas of uncertainty.
  - Results of an uncertainty analysis can **inform** decision makers about the reliability of results and potentially help us decide where to spend resources to acquire more data in an effort to reduce uncertainty.
  - A careful analysis can **guide** the process of refining the exposure estimate.
  - Finally, assessors are responsible for presenting not only the quantitative results of an analysis, but also carefully explaining how the assessment was conducted. In other words, the assessment must be transparent. An analysis of uncertainty can **increase** transparency by showing some of the limitations of the analysis.
- Let's talk now about ***how*** you can characterize uncertainty, either qualitatively or quantitatively.
- Source: EPA Exposure Assessment Guidelines (1992)

Qualitative and Quantitative Uncertainty Analysis (Slide 44)

- In both qualitative and quantitative uncertainty analyses, we need to identify the sources of uncertainty, whether they are scenario, parameter, or model uncertainties.

- We can qualitatively describe scenario, parameter, and model uncertainty. Our focus in quantitative uncertainty analysis is generally on parameter uncertainty since we usually qualitatively assess scenario uncertainty. Model uncertainty can be either addressed qualitatively or quantitatively.

- How do we address uncertainty qualitatively versus quantitatively?
  - For qualitative analysis, we can accomplish this by answering some questions that will help characterize uncertainty:
    - What is the level of uncertainty in influential parameters?
    - What data gaps exist?
    - Were any subjective decisions made? Are there instances where we had to use professional judgment?
    - There may be other controversial sources of uncertainty that we need to identify. We should also look at the impact of the subjectivity of the choices we've made. For example, resource limitations may have dictated choice of models, and the impacts of these choices need to be evaluated. What is the impact of the choices made?
- In an ideal world, we would repeat this process until the output of the uncertainty analysis satisfied all stakeholders, but in reality, we know that time and money are limiting factors.
- Time and money also affect the quantitative analysis we can perform.
- Our quantitative analysis can assess both uncertainty and the impact of variability in the data set.
- To do this we can use non-probabilistic approaches as well as probabilistic ones like those we've already discussed.
- Let's start by discussing a common non-probabilistic approach – sensitivity analysis.
- Source: IPCS Uncertainty and Data Quality in Exposure Assessment Parts 1 and 2 (2008)

Sensitivity Analysis (Slide 45)

- In a sensitivity analysis, the assessor changes one variable and leaves the other variables constant to determine the effect of changing that one variable on the outcome of the equation. These results are useful to identify which variables have the greatest effect on model output.
- The graph on this slide is a tornado plot. It shows an elasticity analysis for the estimation of risk associated with exposure to dioxin over a lifetime for a given scenario. The green bars are parameters used in the fate and transport model. You can see that mixing height, emission factor, and wind speed were some of the most influential parameters, as shown at the top of the figure.
- The yellow bars represent parameters used in the calculation of dose and risk. Body weight, among others, is an influential parameter.
- Finally, the blue bars are for parameters in the farm food chain biotransfer model that uses outputs of the fate and transport model to estimate concentrations in produce and

livestock consumed by people. For this, the metabolism factor, especially for the cattle, was very influential.

- Source: EPA's Risk and technology review (RTR) risk assessment methodologies : For review by the EPA's Science Advisory Board, case studies, MACT I petroleum refining sources, Portland cement manufacturing [(2009), EPA-452/R-09-006]

Probabilistic Approaches to Uncertainty Analysis (Slide 46)

- As we learned previously, probabilistic methods characterize variability and uncertainty by repeated sampling of probability distributions of parameters in the exposure equation.
- The most commonly used probabilistic approach is the Monte Carlo technique, described in detail in EPA's Guiding Principles for Monte Carlo Analysis.
- In this approach, probability density functions are assigned to each exposure parameter.
- Values for each parameter are selected based on the probability distributions of each parameter and inserted into the exposure equation. This process is repeated many times.
- The result is a distribution of predicted values that reflects the overall uncertainty in the inputs for the calculation.
- Sources: EPA Exposure Assessment Guidelines (1992); EPA Guiding Principles for Monte Carlo Analysis (1997)

Monte Carlo Analysis (Slide 47)

- There are strengths and complications to the Monte Carlo technique.
- The major strength is that the approach is generally applicable. There are no restrictions on the form of the input distribution and the computations are relatively straightforward.
- However, there are some drawbacks and precautions related to using Monte Carlo methods.
    - First, it's critical that we have confidence in the distributions of values used for each parameter.
    - We must know the relationships – that is, the correlations – between parameters or know which parameters are independent.
    - Changing the distribution for one parameter can require that the entire simulation be run again, so it's sometimes difficult to assess the sensitivity of the results to the input distributions.
    - In addition, the results of a standard Monte Carlo analysis don't tell the assessor which variables are the most important contributors to uncertainty.
- A Monte Carlo analysis provides a classic example of GIGO – garbage in, garbage out. The outputs look "valid," interesting, and powerful, but they'll have no bearing on reality if parameter distributions are invalid, correlations between parameters are ignored, and if the model itself is flawed.
- Sources: EPA Exposure Assessment Guidelines (1992); EPA Guiding Principles for Monte Carlo Analysis (1997)

CONCLUSION (SLIDE 48)

- Let's wrap things up.

Conclusion (Slide 49)

- During the last 45 minutes, we have learned to differentiate between uncertainty and variability.
    - Variability refers to true heterogeneity or diversity, and is an inherent property of a population.
    - Uncertainty refers to a lack of knowledge due to incomplete data.
    - Variability cannot be reduced, only better characterized by collection of more or better data. Uncertainty can be reduced or even eliminated by collecting more or better data.
- We have also discussed the importance of addressing uncertainty and variability in exposure assessment and several ways that we can qualitatively and quantitatively do this.

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