CHAPTER 8

METHODS FOR ASSESSMENT OF UNCERTAINTY AND SENSITIVITY IN INVENTORIES

Chapter 8 Objective: ***To describe the methods by which the uncertainy in emission inventories is assessed depicted, prioritized, and reduced, and to provide a conceptual framework for emission inventory uncertainty analysis.***

The previous chapters note that current inventories contain little information regarding uncertainties of reported emission data; however, such information is highly important to decision makers in their attempts to plan and optimize pollution-management strategies. Up to this point, this Assessment has provided little insight on how quantitative uncertainty estimates are obtained, or on how this information can be applied once it is available. The present chapter addresses these questions by providing an overview discussion of:

- Motivations for uncertainty analysis and associated applications to emission inventory information
- Basic terminology and conceptual aspects of uncertainty analysis
- Methods for performing quantitative uncertainty and sensitivity analyses of emission inventory information.

Uncertainty analysis is a complex subject and is strongly rooted in basic statistical theory. Because of this, this chapter is presented at an overview level, which is supported by a more detailed mathematical discussion in Appendix C. Even more mathematical detail is available in several references, notably the books by Morgan and Henrion (1990) and by Cullen and Frey (1999). Given this graduated level of complexity, the reader can examine this subject at progressive levels, as dictated by his or her specific needs.

8.1 MOTIVATIONS FOR UNCERTAINTY ANALYSIS

Numerous previous reports, particularly by the U.S. NRC (NRC, 1991; 2000; 2001; 2004a; 2004b), emphasize the importance of reporting uncertainties associated with emission inventory data. The 1991 report notes that the quality of current emission inventories is hampered by significant, yet poorly characterized uncertainties. The U.S. NRC (2004a) observes that inventory uncertainty analysis is usually impeded because of a perception of insufficient emission data. Ironically, this is usually the situation that exists when uncertainties are high, and uncertainty information is most critically needed.

Uncertainty quantification is useful in identifying problems and setting priorities for inventory improvement, as well as for helping decision makers to make robust decisions in the face of limited information. There remains an ongoing role for qualitative uncertainty assessments and qualitative acknowledgments of inventory limitations; however, quantitative uncertainty information is more informative for decision-making purposes. While not all uncertainties can be quantified in a convenient fashion, the 2000 NRC report advises "that a perfect assessment of uncertainty cannot be done, however, should not stop researchers from estimating the uncertainties that can be addressed quantitatively."

Several key questions that motivate the need for quantitative uncertainty analysis can be derived from the 2000 NRC report as well as from additional sources (Bloom et al., 1993; Thompson and Graham, 1996). Itemized in Box 8.1, these questions are discussed sequentially in the following paragraphs.

Box 8.1. Key Questions Decision Makers Ask That Motivate Uncertainty Analysis

- How precise do emission estimates need to be?
- What is the pedigree of the numbers used as input to inventories?
- How precise are the estimates for emission and activity factors?
- What is the uncertainty in the overall inventory?
- What are the key sources of uncertainty in the inventory?
- How should efforts be targeted to improve the precision of emission estimates?
- How significant are differences between two alternatives?
- How significant are apparent trends over time?
- How effective are proposed control or management strategies?
- Is there a systematic error (bias) in the estimates?
- Is there ongoing research that might fill critical data gaps within the near term?
- Are the estimates based upon measurements, modeling, or expert judgment?

How precise do emission estimates need to be?

The required degree of precision of an inventory will vary depending upon its intended use. For example, if the purpose of the inventory is to serve as an input to an air quality model, then the desired precision of the inventory will be dictated by the model's ability to discriminate between different emission levels in making predictions of ambient air quality. If the model is relatively insensitive to a particular pollutant's emissions, then a relatively high degree of uncertainty might be tolerated. In contrast, if the assessment objective is to detect small changes in emissions from year to year as part of a trend analysis, then a small amount of uncertainty in annual-average emissions is desired. Precision is a concept that is applicable to all model estimates and observations.

What is the pedigree of the numbers used as input to inventories?

This question deals with issues of who developed the numbers, how they were developed, and who has reviewed them. For example, have they been subject to scientific peer review? Are the numbers based upon measurements or are these preliminary estimates based upon the judgment of an analyst? The decision maker is interested in the degree of confidence assigned to a number. In the context of emission inventories, this relates to concerns over whether the data were obtained using approved or acceptable measurement techniques and whether they pertain to a random representative sample of emission sources. Alternatively, data may have been obtained using a variety of measurement methods that may not be directly comparable, and might be for non-representative conditions (e.g., best practices rather than typical operating conditions). Thus, the data may be "bad" in some way or incomplete.

How precise are the estimates for emission and activity factors?

Typically, this question could be answered in terms of absolute or relative ranges (e.g., a 95 percent probability range of plus or minus 25 percent of the mean). Examples from the literature suggest that emission inventory precision varies depending upon the pollutant, spatial scale, and temporal scale. Examples of reported uncertainties for inventories, as described later in this chapter, range from approximately plus or minus 20 percent to a factor of two or more. However, for some source categories within an inventory, the ranges of uncertainty can be much larger than this. This question can be answered at several levels of an analysis, including those for individual emission and activity factors that are inputs to an inventory.

What is the uncertainty in the overall inventory?

This question focuses on the simultaneous, combined effect of uncertainties in individual source activity and emission factors with respect to overall uncertainty of the entire inventory. This question can be answered by propagating uncertainty estimates for inventory inputs through the total inventory, an activity which can be thought of as a type of modeling analysis. Most inventories involve multiplication of activity and emission factors for individual source categories to estimate total emissions for each category, followed by summation of total emissions for each source category to arrive at a total inventory estimate. A variety of analytical or numerical methods can be applied to estimate the overall uncertainty in the inventory using a bottom-up approach. Such approaches are addressed in this chapter. Insight to this question also can be obtained from top-down approaches described in Chapter 7.

What are the key sources of uncertainty in the inventory?

This question also can be posed as: What source categories (or activity or emission factors) contribute the most to the overall uncertainty in the inventory? Identification of specific emission components helps to identify the source categories or inputs that are the largest uncertainty contributors. This insight can be used, in turn, to target resources to reduce those uncertainties that are largest and matter the most. There are various ways to answer this question, including various forms of sensitivity analysis. For example, in the context of a probabilistic uncertainty simulation for an overall inventory, various statistical methods can be used to determine which input distributions are responsible for contributing the most to the variance of the output.

How should efforts be targeted to improve the precision of emission estimates?

Knowledge of uncertainty in emission estimates helps guide additional data collection to reduce uncertainty in order to improve the precision of emission estimates. For example, the identification of key uncertainty sources can prioritize information-gathering efforts for the most important inputs. Because uncertainty results from lack of knowledge, an effective approach to its reduction is to obtain more knowledge, such as through additional measurements or the development of more precise and accurate measurement methods.

How significant are differences between two alternatives?

This question pertains to determining whether it is possible to discriminate between two alternative estimates even though they are both uncertain. For example, when comparing control strategies, does one offer a high confidence of a real emission reduction compared to a baseline even though both the estimates of baseline and controlled emissions are subject to uncertainty? This question can be answered by estimating the probability distributions for differences in emissions.

How significant are apparent trends over time?

This question pertains to evaluating the statistical significance of measured or estimated temporal changes in emissions, including long-term trends and cycles. Although formal time-series analyses are often applied for this purpose, simpler comparisons of distributions for specific time periods can also provide useful insights. For example, a probability distribution of the change in emissions from one time period to another can be used to assess the probability that emissions have increased or decreased, and the likelihood of various magnitudes of the change.

How effective are proposed control or management strategies?

This question addresses the confidence with which a standard will be met. For example, Hanna et al. (2001)

assess the uncertainty associated with estimates of predicted ambient ozone levels subject to a particular emission scenario, and Abdel-Aziz and Frey (2004) evaluate the probability of noncompliance with NAAQS for ozone based upon emission-inventory uncertainties propagated through an air quality model. A similar question might be: how likely is an exceedence of an emission budget? For this purpose, a probability distribution of estimated emissions can be compared with a point estimate of the emission budget in order to determine the probability that the emission budget will be exceeded and, if so, by how much.

Is there a systematic error (bias) in the estimates?

Systematic error, or bias, typically occurs when inferences are made on the basis of data that are not representative of the real-world situation for which an estimate is desired. For example, to estimate power plant emissions for a specific time period in a particular "target" geographic area, one should have data representative of the area's particular mix of power-plant designs, fuels, operating practices, loads, and ambient conditions. However, if data are available only for full-load operation of plants that differ somewhat in design, fuel, operation, and ambient conditions, then the average emission factors derived from the available data may differ from the "true" values for the target area. This question is difficult to answer in the absence of inventory comparisons using some type of a "ground-truth" or "reality check," which is the focus of the top-down approaches of Chapter 7. As described later in this chapter, it is possible to incorporate expert judgments regarding sources of bias. Furthermore, comparisons of probabilistic estimates with point estimates usually provide insights regarding the consistency of estimated statistical measures.

Is there ongoing research that might fill critical data gaps within the near term?

This question, and many of the others, is fundamentally motivated by the desire not to be unpleasantly surprised or overtaken by events. For example, if new research might resolve some of the key uncertainties in the assessment, is it worth waiting until that information is available before making a decision?

Are the estimates based upon measurements, modeling, or expert judgment?

This question again pertains to the pedigree of information used to support the emission estimates. While there is typically a preference for estimates based upon directly relevant measurements, the use of models and judgments may be justified when relevant data are not available. For example, available data may not be representative and thus inferences based upon them may lead to biases. Moreover, there may be gaps in available data such that it is not possible to make empirically based estimates for some inventory inputs. In such cases, inferences could be made based upon indirect evidence such as by interpolation, extrapolation, or model analysis. Alternatively they may be derived through elicitation of subjective judgment.

8.2 BASIC TERMINOLOGY AND CONCEPTS FOR UNCERTAINTY AND SENSITIVITY ANALYSIS

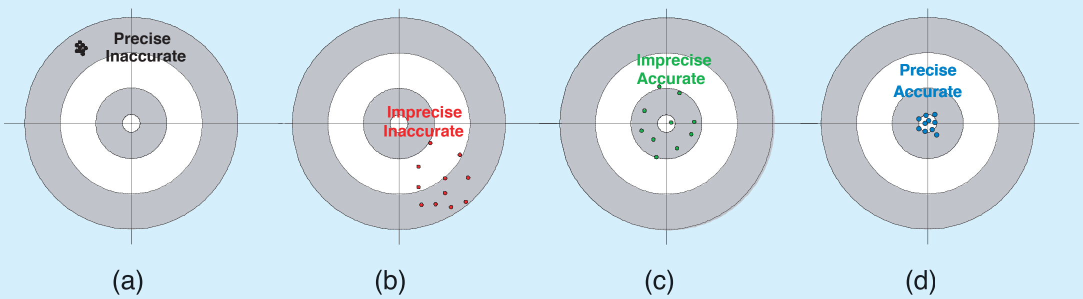
In order to further explore issues of uncertainty and sensitivity, a set of concepts and terminology is needed, as discussed here. More detail on concepts, terminology, and methodology is given in Appendix C.

Box 8.2 summarizes some basic terms that are used frequently in uncertainty analysis studies and applications. While most of these terms are straightforward, the concepts of uncertainty and sensitivity are rather involved and deserve some further elaboration at this point.

Uncertainty refers to lack of knowledge regarding the true value of a quantity. In practice, uncertainties are often expressed in the form of a probability distribution. A probability distribution describes the range and relative likelihood of different values of a quantity (e.g., emission factors, activity factors). A probability distribution can be described as either a probability density function (PDF) or a cumulative distribution function (CDF), as explained further in Box C.1 of Appendix C. As an example, Figure 8.1 shows a typical density function characterizing the uncertainty associated with an emission factor pertaining to some selected source category. A

Box 8.2. Terminology

Accuracy	Agreement between the true value and the average of repeated measured observations or estimates of a quantity. An accurate measurement or prediction lacks bias or, equivalently, systematic error.
Precision	Agreement among repeated measurements of the same quantity.
Precision vs. Accuracy	Figures a, b, c, and d illustrate the difference between precision and accuracy. Data may be accurate but not precise. In contrast, they may produce precise results but be systematically at variance with the true value.



(a) Inaccurate but Precise; (b) Inaccurate and Imprecise; (c) Accurate but Imprecise; and (d) Precise and Accurate.

Bias	A bias exists when there is a discrepancy between the true value and the average result obtained from a model or observations. Bias is also referred to as constant error or systematic error.
Random Error	The deviation of individual measurements from the average of the measurements.
Sensitivity	The influence of one or more inputs to a system on the system's output.
Uncertainty	The lack of knowledge about the true value of a quantity.
Systematic Error	An error that causes the mean of measured or predicted values to differ from the true mean. Systematic error is also referred to as bias and is also described as a lack of accuracy.
Variability	Heterogeneity of a quantity over time, space or members of a population. Variability may arise, for example, due to differences in design from one emitter to another (inter-plant or spatial variability) and in operating conditions from one time to another at a given emitter (intra-plant variability).

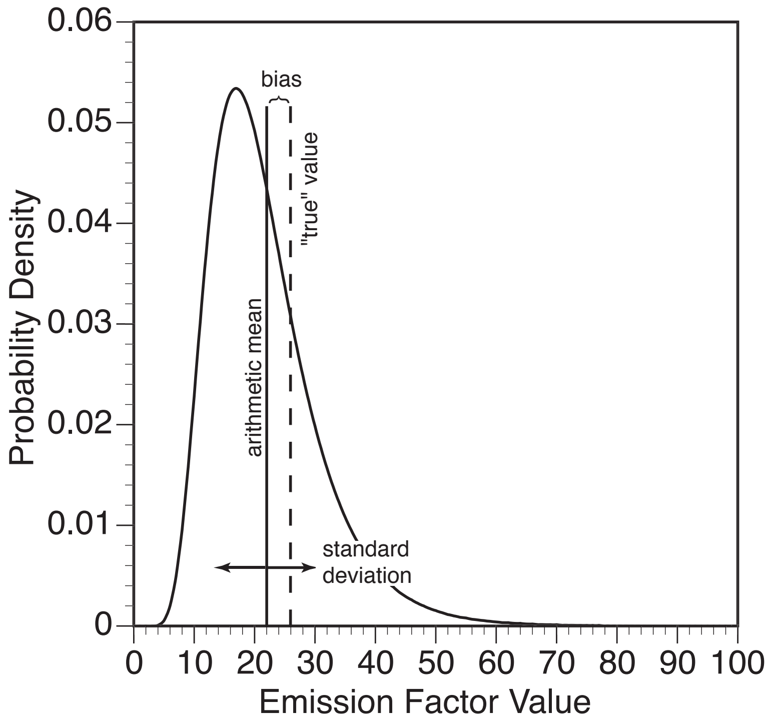


Figure 8.1. Example Probability Density Distribution, Characterizing Uncertainty of an Emission Factor for a Selected Source Category.

probability distribution can be summarized in terms of key statistics, such as the mean, standard deviation, skewness, or percentile values.

Figure 8.1 also indicates the possible presence of systematic error, or "bias" of the emission estimate in terms of the difference between the actual emission factor and the average of the estimated values. This may be compared directly with the target analogy given in Box 8.2. Bias is often difficult to quantify based upon statistical analysis of data; however, expert judgment can be used as a basis for identifying bias and developing a bias correction.

Probabilistic approaches usually begin by determining, to the extent possible, the unbiased ranges and relative likelihoods of values for individual inputs to the inventory (e.g., emission and activity factors for individual source categories), often using a variety of estimation methods, and making inferences in order to develop associated probability distributions, thus providing a quantitative mathematical characterization of uncertainty.

Once probability distributions are obtained for all cognizant sources or source classes, their collective effect on the total emission inventory's uncertainty can be calculated by propagating the ensemble of these distributions through the total system. Although numerous probabilistic techniques have been applied, the well-known Monte Carlo approach, which repeatedly takes random samples from the individual distributions and propagates them through the total inventory system, is most often used for this purpose.

Thus, uncertainty estimates are specified for the *inputs* to an inventory, and the resulting uncertainty for the *outputs* of an inventory are estimated. For this reason it is useful to consider the emission inventory output in terms of a "system" or a "model" which combines individual inputs to produce aggregated outputs, as indicated schematically in Figure 8.2. Here the model is depicted as the emission inventory computational framework, but one is not limited to this. One could for example depict the "model" as a composite of an emission inventory and an air quality model, having outputs of predicted ambient concentrations and global uncertainties associated with these predictions. Generally, uncertainties can pertain to inventory or model inputs such as emission factors, activity factors, or other inputs where the emission-factor/activity-factor paradigm is inapplicable such, for example, as the characterization of natural emissions.

Probabilistic emission inventory evaluation efforts often apply two highly complementary components: uncertainty analysis and sensitivity analysis. Within this context uncertainty analysis involves the propagation of uncertainties in various inventory inputs through the model to characterize uncertainty in model outputs. However, without additional analysis, uncertainty analysis by itself does not

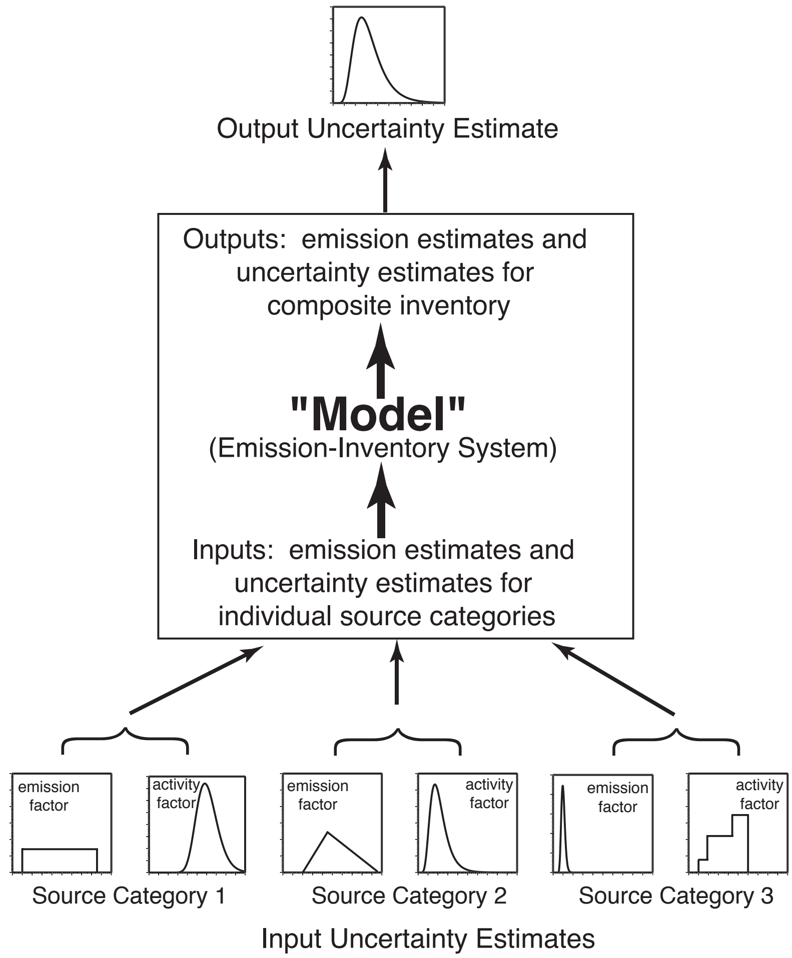


Figure 8.2. Conceptual Framework for Propagation of Uncertainty in Emission Inventory Inputs of Emission and Activity Factors for Each of k Emission Source Categories to Quantify the Uncertainty in the Estimate of Total Emissions. A variety of probability distribution models can be specified to represent uncertainty in inputs.

provide explicit information regarding which of the inputs contributed the most to the uncertainty in the output.

In contrast, *sensitivity analysis* quantifies the variation in model output that is caused by specific model inputs (e.g., Saltelli et al., 2000; Cullen and Frey, 1999). In this capacity sensitivity analysis can be used to answer the following types of questions:

- What is the rank order of importance among the model inputs?
- Are there two or more inputs to which the output has similar sensitivity, or is it possible to clearly distinguish and discriminate among the inputs with respect to their importance?
- Which inputs are most responsible for the best (or worst) outcomes of the output?
- Is the model response appropriate?

Methods of sensitivity analysis and metrics for measuring sensitivity are widely available. The most commonly used sensitivity analysis methods are often relatively simple techniques which evaluate the local linearized sensitivity of model response at a particular point in the input domain, as illustrated in Box C.2 of Appendix C. A simple type of sensitivity analysis is to evaluate the sensitivity of the system output to its various inputs in terms of a partial derivative of the output with respect to the input in question. This derivative usually takes the form of a ***sensitivity coefficient***,

$$s_i = \left(\frac{\partial(\text{output})}{\partial(\text{input i })} \right)_{\text{inputs } j \neq i} \qquad (8.1)$$

where input i might be, for example, the emission factor for Source Category 2 in Figure 8.2, and the output the total emissions of some associated pollutant species.

The simplistic sensitivity coefficient type of approach is typically used if the model inputs are treated as point estimates, often representing the "best guess" as to the true but unknown value of each input. The sensitivity analysis of point estimates is often done for the purpose of evaluating how much the model would respond to a unit change in the input. A simple variation on this approach is to vary each input individual over a possible range of its values, rather than just for a small perturbation or a change of only one unit of measure. Although conceptually simple, local sensitivity-analysis techniques typically suffer from two key shortcomings: (1) they do not take into account the simultaneous variation of multiple model inputs; and (2) they do not take into account any nonlinearities in the model that create interactions among the inputs. For example, some emission-factor models, such as BEIS or MOBILE, have nonlinear responses over portions of their domain. In particular, emissions may respond in a nonlinear way to changes in ambient temperature. Thus, a linearized sensitivity coefficient at a local point would not accurately estimate how the model responds to a change in its inputs over the entire range of values of its inputs, when several inputs are varying simultaneously.

If uncertainty analysis is thought of as a forward propagation of distributions through the model, then sensitivity analysis could be conceptualized as looking back from the output to the inputs to determine which of the inputs is most important to the range and likelihoods of the final result. For a probabilistic analysis based upon Monte Carlo simulation, a variety of statistically based methods can be used to ascertain what portion of the variation in the model output can be attributed to each of the model inputs. Depending on the functional form of the model, the resulting measures of sensitivity may be exact or may be approximate; however, even in the latter situation they are typically highly informative with regard to management and planning needs. For example, because uncertainty arises from lack of perfect knowledge of the true but typically unknown value of actual emissions, uncertainty can be reduced by obtaining better information. Therefore, insights regarding key sources of uncertainty can be used to assess priorities for collecting additional data or information in order to reduce uncertainty.

8.3 UNCERTAINTY ANALYSIS: SOURCES, TECHNIQUES, AND APPLICATIONS

This section briefly describes the key sources of uncertainty, techniques for analyzing uncertainty, and examples of uncertainty analyses applied to emission inventories, emission sub-models, and air quality models.

8.3.1 Sources of Uncertainty

Uncertainties typically derive from a number of sources, including:

- *Precision and Accuracy in Measurement Methods*. Lack of precision (random error) is usually associated with imperfections in measurement techniques or with processes that are random or statistically independent of each other. Lack of accuracy (systematic error, or bias) may originate from sources such as imperfect calibration of equipment, simplified or incorrect assumptions, and any other errors introduced in the selection and implementation of methodologies for collecting and utilizing data.
- *Variability and Sample Size*. Variability of emission sources can lead to uncertainty. For example, for vehicle or equipment emission factors, emissions from any one unit vary from time to time and place to place. Some portion of the variability might be explainable based upon factors such as age, design features, fuel

characteristics, duty cycles, ambient conditions, and others. However, even for a specific category of vehicles or equipment, such as light duty gasoline vehicles equipped with three-way catalysts, there is intra-vehicle variability over time and inter-vehicle variability within a fleet. The variability of emissions within a category and the limited sample size of measurements give rise to random sampling errors in estimation of the mean emission factor (NRC, 2000). The average emission factor, which is typically based upon the small data set available when an emission inventory is developed, is therefore subject to uncertainty (NRC, 2004b). If the emission inventory includes a large sample of specific units within a source category, then the uncertainty analysis should typically focus on uncertainty in the mean emission rate (e.g., Frey and Zheng, 2002b). However, if an emission inventory includes only one unit from a given source category, and if no site-specific emission data are available, then an assumption might be made that the individual unit is a random sample from the population of all similar units. In this latter situation, the distribution of inter-unit variability would be the appropriate estimate of uncertainty.

- *Representativeness of Data*. In the development of emission inventories, data measured from a limited number of sources may not be representative of the entire population of sources (NRC, 2000; 2004b) or the study objectives. In such situations, several judgments must be made in order to use available data to make estimates of emissions for presumably similar sources. For example, when comparing emissions sources from which test data are available to the emission sources that are within the scope of a particular inventory, judgment is needed regarding whether the feedstocks, processes, ambient conditions, operating conditions, maintenance history, and averaging time (e.g., such as for a process facility or combustion source) are sufficiently similar. This judgment will introduce uncertainty. Furthermore, emissions measured for a different duty cycle or for a different averaging time (e.g., hourly, daily, weekly, monthly, annual, etc.) may not be a reliable basis for estimating uncertainty in a particular inventory without additional analysis or judgment.

- *Dependence and Correlations*. When there is more than one uncertain quantity, it may be possible that the uncertainties are statistically or functionally dependent. Failure to properly model the dependence between the quantities can lead to uncertainty in the emission estimation, in terms of improper prediction of the variance of output variables. However, correlations typically matter only if they are sufficiently strong between two or more quantities each of which has a significant impact on the overall uncertainty of the inventory. Thus, it is not always essential to properly account for correlations even though correlations may be known to exist. It is only necessary to account for correlations if they would alter the insights provided by the analysis.

- *Lack of Empirical Basis*. This situation occurs when relevant data for inferring emissions for the source or situation of interest are absent; it can also describe situations in which emission sources or processes are overlooked because data are not available. This situation also exists when there is a need to make predictions or estimates for future emissions. Depending on the time horizon, estimates of future emissions may have to contend with the possibility of technology changes, thereby involving the need for estimates about something that has yet to be built, tested, or measured. Although it is not possible to make statistical inferences from directly relevant data in these situations, uncertainties can be represented using technically-based judgments about the range and likelihood of possible outcomes. For example, estimates of uncertainty for future emission scenarios will typically require expert judgment.

- *Disagreement Among Experts*. Expert opinion is often used to select appropriate values or distributions for input into an emission inventory model. For example, experts may suggest the most appropriate emission factor for a certain pollutant, or, in a Bayesian analysis, experts may supply a subjective prior distribution. Often different experts' opinions on these data and distributions may differ. Thus, there may be disagreement regarding the most appropriate values or distributions to use. Various methods are used to deal with potentially conflicting judgments regarding uncertainties. Examples include: (1) conducting the uncertainty analysis separately with each alternative set of judgments in order to determine whether insights from the analysis differ; (2) assigning weights to each judgment and performing one analysis in which the judgment is weighted; or (3) iterating the judgment and attempting to reach a consensus among experts before proceeding with an analysis.

- *Aggregation and Disaggregation*. In general, any kind of modeling involves decisions regarding aggregation or lack thereof. Aggregation refers to situations in which details are combined, such as by representing several processes or emission sources by one numerical value. Typically, aggregation results in the loss of some information regarding the details of assumptions upon which the aggregated numbers are based. Another practical example of aggregation is when emission estimates are combined from different agencies into one inventory, resulting (potentially) in loss of information regarding the source and basis of each numerical estimate that enters the inventory. In contrast, disaggregation may be required in order to convert a long-term emission estimate for a large geographic area into a shorter term estimate for a smaller area. An example of this is the development of hourly, gridded inventories for air quality modeling. To the extent that the process of aggregation results in loss of information, the range of uncertainty would typically increase, especially if the inventory was later applied to a purpose for which it was not originally developed. Similarly, the process of disaggregation may involve various assumptions and judgments, each of which is subject to uncertainty, thereby producing additional uncertainty in the disaggregated inventory.

Examination of the above features leads to the conclusion that development of probability distribution functions for inventory inputs requires a large measure of judgment and subjectivity. In addition there are several features that are not directly associated with the inputs but nevertheless affect the composite uncertainty estimates for a model output or aggregated inventory. These include:

- *Model Uncertainty.* Model uncertainty arises from model structures and inappropriate assumptions regarding emission scenarios. For example, a model based upon standardized duty cycles for mobile sources may fail to accurately and precisely estimate real-world emissions. Alternatively, structural problems could occur if emission sources are counted more than once because of ambiguity in scenario definitions. For example, a lack of clarity regarding the categorization of evaporative emissions during refueling of onroad vehicles might result in emissions being double-counted as both part of the vehicle emission inventory and part of the stationary source inventory that includes fuel service stations. Conversely, emission processes might not be counted at all if the scenario definition does not include them, such as emissions associated with startup, process upsets, and shutdown procedures. The NRC (2004b) pointed out that a major contributor to the large uncertainties in current emission inventory is the emission models used to derive the inventories. Emission models can include component models used to estimate emissions for specific source categories as well as modeling approaches for managing data in the entire inventory. Model uncertainty can be significant and is typically poorly characterized or not characterized at all (NRC, 2004b).

- *Scenario Uncertainty.* A scenario is the set of assumptions regarding the structure of the inventory and scope of geographic area, temporal averaging time, source categories, emission processes, and pollutants that are included. An emission scenario that fails to include all relevant emission sources and pollutants necessary for the desired assessment objectives would be subject to data gaps, thereby introducing uncertainty in the emission inventory (e.g., if swimming pools were omitted from an inventory of chlorine emissions). This source of uncertainty is known as scenario uncertainty (Cullen and Frey, 1999) and typically results in a bias in emission estimates. The sources of scenario uncertainty include descriptive errors, errors in professional judgment, and incomplete specification of the scenarios (U.S. EPA, 1997).

Other possible uncertainty sources include the incorrect entry or reading of emission data, misclassification of emission source categories, and improper assumptions regarding model input distributions and model formations. All of these may lead to additional uncertainty in emission estimation. Although data-entry mistakes and misclassification errors can be sources of uncertainty, these can be avoided or minimized by application of appropriate QA/QC techniques. In contrast, other types of uncertainties described above can exist even with the implementation of appropriate QA/QC procedures. This variety of sources, which are usually exceedingly difficult to characterize in mathematical form, again lead to the conclusion that good judgment is mandatory, and considerable subjectivity is involved, in establishing input uncertainties and interpreting associated global output. This is a major challenge in emission-inventory uncertainty analysis.

8.3.2 Techniques for Uncertainty Analysis

Quantitative methods for characterizing the combined effect of uncertainties in inputs on the output of a model or inventory range from relatively simple approaches to more rigorous techniques such as Monte Carlo methods and bootstrap simulation. While it is beyond the scope of this chapter to go into the details of these methods, Section C.2 of Appendix C provides an overview of the more commonly used techniques and discusses some frameworks for conducting quantitative uncertainty analysis.

As noted above, quantitative methods typically involve specifying probability distributions for inputs to an inventory, and propagating the distributions through the inventory in order to estimate the distribution of uncertainty for the total inventory. Methods for developing input distributions typically are based on empirical data, encoding of expert judgment, or some combination of both. In situations where relevant and appropriately sampled empirical data are available, a variety of statistical techniques can be used to fit a distribution to the data (e.g., Cullen and Frey, 1999). In cases where relevant data are not available, accepted protocols for encoding expert judgment can be used (e.g., Morgan and Henrion, 1990). Bayesian statistical techniques can combine information from both empirical data and expert judgment.

Once uncertainties in the inputs to the inventory have been specified, a variety of techniques can be selected to propagate the uncertainties to the inventory output. Depending on the type of input information and the model used for the inventory, an analyst may be able to choose from exact analytical solutions, approximate solutions based upon error propagation using Taylor series expansions, or numerical methods. Of the various numerical methods, Monte Carlo simulation is popular because of its flexibility. Monte Carlo simulation can be used with a wide variety of input distribution assumptions and with a wide variety of models.

Guidelines for quantification of uncertainty in emission inventories have not been developed at the national scale in the U.S., Canada, or Mexico. However, the U.S. EPA has developed guidelines for probabilistic analysis in the context of human exposure assessment (e.g., U.S. EPA, 1997). A general framework for uncertainty analysis of emission inventories has been recommended by Frey et al., 1999. Furthermore, the Intergovernmental Panel on Climate Change has developed good practice guidance for quantification of uncertainty in national greenhouse gas emission inventories (IPCC, 2000). This guidance incorporates methods for dealing with empirical data, methods for encoding expert judgment, and methods for propagating uncertainty in inventory inputs to estimate uncertainty in the total inventory.

8.3.3 Example Applications of Uncertainty Analysis

This section provides a survey of representative case study applications of uncertainty analysis to different aspects of emission estimation. For this purpose, the example applications are classified as follows: (1) direct applications refer to estimation of uncertainty for an emission inventory; (2) application for inventory sub-models refers to estimation of uncertainties for models that produce estimates of emissions for specific source categories that, in turn, are entered into an emission inventory calculation; and (3) combined emission inventory and air quality modeling refers to examples in which uncertainties in emission inventories are quantified and propagated through air quality models in order to estimate uncertainty in estimates of ambient concentrations. The key insights from these case studies are summarized.

Direct Applications

Several examples of the use of relatively simple approaches for estimation of uncertainty in emission inventories are reported by Chang et al. (1996), Van Amstel et al. (2000), Lee et al. (1997), NRDC et al. (2002), El-Fadel et al. (2001), Gschwandtner (1993), and Hanna and Wilkinson (2004). Simple approaches are typically based on limited information about input uncertainties (e.g., only the mean and standard deviation) and on approximate methods for propagating uncertainties through a model, such as using Taylor series expansion-based techniques. More complex for uncertainty estimation and propagation have also been used. For example, Frey and Zheng (2002a&b) quantified variability and uncertainty in highway vehicle emission factors based upon data used in MOBILE5b and developed probabilistic 6-month and 12-month emission inventories for a utility NO_x emission inventory for North Carolina. In these examples, empirical and parametric distributions were used to quantify variability while bootstrap simulation was employed to characterize uncertainty in emissions. Other examples are reported by Winiwarter and Rypdal (2001), Frey and Tran (1999), Allen et al. (2004), Frey and Bammi (2002), and Frey and Li (2003). Chi et al. (2004) employed bootstrap sampling, expert elicitation and Monte Carlo techniques to characterize uncertainty of nonroad emissions for Georgia, based upon the use of the U.S. EPA's NONROAD model.

Frey and Zhao (2004) characterized variability and uncertainty in urban toxic air pollutant emission inventories for Jacksonville, Florida, and Houston, Texas. Maximum likelihood estimation was used to deal with censored (non-detected) values in emission data, and bootstrap simulation in combination with maximum likelihood estimation was used to estimate uncertainty in the mean emission factors based upon data that included non-detects. An overview of this example is given in Appendix C.2.4.

Other statistical methods to quantify uncertainty in emission estimation include the use of analysis of variance (ANOVA) and time-series approaches (Abdel-Aziz and Frey, 2003; Sharma and Khare, 2000; Gleit, 1987). Bortnick and Stetzer (2002) applied ANOVA to emission inventories where they quantified uncertainty in ambient toxic air pollutant concentration data. These authors partitioned the variance of the monitored data into four components (temporal, spatial, sample collection and laboratory analysis) and concluded that temporal variability contributed most to the overall uncertainty. Khalil (1992) employed a statistical approach to estimate uncertainties in total global budgets for trace gases. Confidence limits for the total emissions were estimated.

The significance of these examples is two-fold. First, they demonstrate that a wide range of methodologies can be applied, depending on study objectives and availability of information. Second, the information produced in these examples is useful in answering the types of questions posed by decision makers described in Section 8.1. For example, each of these case studies provides insight regarding the quantifiable range of uncertainty in emission estimates for individual sources and for inventories and regarding the pedigree and quality of emission estimates.

Applications for Inventory Sub-Models

Frequently composite emission inventories contain sub-model components such as, for example, mobile-source emission models and natural emission models (e.g., MOBILE, NONROAD, BEIS3). Although current sub-models of this type rarely incorporate online uncertainty analysis, a few examples exist to illustrate that uncertainty analysis can be incorporated as an integral technique with such emission inventory components.

One of these efforts, which is currently in an emerging stage, is the MOVES mobile-source sub-modeling framework, which is being designed to incorporate an uncertainty analysis component (U.S. EPA, 2002). MOVES is expected to replace both MOBILE and NONROAD, neither of which contain online uncertainty analysis. This effort is considered to be particularly timely and appropriate because several studies of MOBILE have identified significant ranges of uncertainty in fleet-average emission estimates (Guensler, 1993; Guensler and Leronard, 1997; Chatterjee et al., 1997). Frey and Zheng (2002a) derived estimates of uncertainty in basic emission rates, speed correction, temperature correction, and Reid vapor pressure for a specific MOBILE 5b LDV technology group (port-fuel and throttle body injection vehicles). Uncertainty in the-fleet average emission factor was as much as -90% to +280% when correction factors for alternative driving cycles, temperature, and Reid vapor pressure were applied. Although most of the reported efforts have dealt with onroad emissions sources, Frey and Bammi (2002) have characterized uncertainty in nonroad vehicle and equipment emission factors.

A second effort to incorporate uncertainty analysis into a sub-model component is the Integrated Environmental Control Model (IECM) developed by Carnegie Mellon University for the U.S. Department of Energy (Rubin et al., 1997). The IECM incorporates a probabilistic simulation capability, and provides performance, emission, and cost estimates for user-specified power-plant configurations using site-specific plant parameters and fuel characteristics. The IECM has the capability to explicitly quantify uncertainty in calculated results including emission estimates. The IECM enables the user to accept default specifications of uncertainty for inputs or to provide user-specified probabilistic inputs. The IECM allows the user to choose either Monte Carlo simulation or Latin hypercube sampling to propagate uncertainties through the model in order to estimate uncertainty in emission rates and other outputs.

Combined Emission Inventory and Air Quality Modeling

Emission inventories are often used as inputs to air quality models, and it is well known that errors in emission inventories can have a significant influence on model-predicted pollutant concentrations (e.g., Guenther et al., 2000; Placet et al., 2000; Russell and Dennis, 2000; Sawyer et al., 2000). Because of this, several past studies have examined the uncertainties of air quality model predictions as influenced by uncertainties in their emission-inventory inputs.

Hanna et al. (1998), for example, used expert elicitation to estimate typical uncertainties in 109 input parameters for the Urban Airshed Model (UAM-IV) including emissions, meteorological conditions, boundary conditions, and chemical rate constants; they propagated uncertainties using Monte Carlo simulation to quantify uncertainty in ozone predictions for the 6-8 July 1998 episode in New York City. The results indicate that the variability in anthropogenic VOC emissions had most impact on the uncertainty in predicted ozone concentrations. Hanna et al. (2001) later applied a similar analysis to the Ozone Transport Assessment Group domain. They addressed uncertainties in 128 input variables including emissions, initial and boundary conditions, meteorological variables, and chemistry. Through the use of sensitivity analysis, the authors were able to pinpoint key sources of uncertainty and to estimate the effect of control strategies on ambient ozone levels in the face of uncertainty. Simulation results include base-case uncertainty estimates for ozone concentrations and estimates of differences in ozone concentrations resulting from emission reduction strategies. Uncertainty was lower for estimates of differences in concentration than for absolute estimates of total concentration, thus implying more confidence in estimating changes than in estimating absolute values.

Moore and Londergan (2001) applied a probabilistic approach to quantify uncertainties in the differences of predicted ozone between a base and a control scenario in which Latin hypercube sampling was employed. They propagated uncertainties in 168 model inputs for emissions, chemistry, meteorology and boundary conditions. Lognormal and normal distributions were used based on expert judgment to describe the input uncertainties. Assessment of the uncertainty in the difference between two alternatives enables assessment of the likelihood that one alternative will perform better than another in the face of uncertainty. Bergin et al. (1999) used Monte Carlo simulation with Latin hypercube sampling to propagate uncertainties in 51 model parameters through the California/Carnegie Institute of Technology air quality model. Uncertainties in onroad CO emissions were quantified based on remote sensing measurements.

Uncertainties for other emissions were estimated based on expert judgment. The study concluded that uncertainties in motor vehicle emissions contributed most to uncertainties in ozone concentrations. This example illustrates that uncertainty analysis can help pinpoint priorities where reductions in uncertainty (e.g., via more or better data collection) would be most useful.

Abdel-Aziz and Frey (2004) propagated uncertainty of hourly utility NO_x emissions through a photochemical air quality model to estimate the uncertainty in the maximum 1-hour and 8-hour ozone concentrations for Charlotte, North Carolina, modeling domain using a Monte Carlo simulation. They took into account statistical dependencies between power plant units (inter-unit variability) as well as temporal autocorrelation for each individual unit (intra-unit variability). Simulation results included the probability of exceeding each of two different ambient air quality standards in each grid cell during the time frame of a simulated air quality episode. This case study illustrates the ability to deal with complex dependencies among inputs while producing results that could inform decisions regarding whether addition emission control is needed, despite the existence of uncertainty in the estimates.

Key Insights from Uncertainty Analysis

Several key insights can be gleaned from the various analyses and studies described above. One of the most important of these is that it is usually far more efficient and less resource-intensive to conduct uncertainty analyses when they are incorporated directly into the emission inventory methodology, rather than conducted after the fact (e.g., Frey and Zheng, 2002a,b). A key difficulty in this respect is finding the original data used to develop a point estimate inventory or estimate average emission factors. The time required to assemble databases when original data could not be found is substantial. When data are found, they are typically poorly documented.

Because emission inventories typically involve inputs that must be nonnegative, uncertainties in inputs often are positively skewed (cf. Figure 8.1), and in these cases normality assumptions are not valid. Thus, the mean of the distribution is often greater than the mode and median. When positively skewed distributions are propagated through a model, especially one that involves multiplication, the output also tends to be positively skewed. Thus, interactions among inputs, plus the positive skewness of inputs, can lead to situations in which the mean emission rate is larger than the point estimate of emissions from a point estimate analysis. This suggests that failure to consider the interactions among simultaneous uncertainties can be a source of bias (underestimation) in some emission models.

Visualization of data used to develop an inventory is highly informative to choices of empirical or parametric distribution models for quantification of variability or uncertainty. It is important to correctly determine whether inter-unit variability or uncertainty in the mean is the relevant basis for characterizing uncertainty, since the range can differ substantially between the two. Uncertainty estimates based upon fitting parametric distributions to data might be sensitive to the choice of parametric distribution models if there is variation in the goodness-of-fit among the alternatives. However, in such cases, there is typically a preferred best fit. When several alternative models provide equivalent fits, results are not sensitive to the choice of the model. The quantifiable portion of uncertainty attributable to random sampling error can be large and should be accounted for when using emission factors and inventories.

The ranges of variability and uncertainty are typically much greater as averaging time decreases. Intra-unit dependence in hourly emissions is significant for some sources (e.g., power plants), including hourly and daily lag effects. Inter-unit dependence in emissions is important for some sources, such as multiple units at one power plant. These types of dependencies can be quantified statistically, such as with time series models. Even for sources with CEMS data, there is uncertainty regarding predictions of future emissions that can be informed by analysis of historical data.

Many of the case examples demonstrate that it possible to combine multiple methods (e.g., statistical analysis, expert elicitation) into one assessment, and that there are varying levels of detail and sophistication from which to choose a methodology appropriate to a particular assessment objective.

Typically, analysts who have conducted uncertainty analysis report that systematically thinking about uncertainties leads to a better understanding of the strengths and weaknesses of an assessment. Overall, uncertainty analysis helps improve the characterization of the state of knowledge of emissions, thereby better informing decisions and avoid unpleasant surprises that would have occurred had uncertainty been ignored.

8.4 SENSITIVITY ANALYSIS

Sensitivity analysis is useful for answering several of the key questions given in Section 8.1.3, and can play an important role in emission inventory development and analysis (e.g., Russell and Dennis, 2000). This section briefly describes the roles of sensitivity analysis, techniques for sensitivity analysis, and example applications.

8.4.1 Roles of Sensitivity Analysis

The roles of sensitivity analysis include: (1) evaluation and verification of emission inventory models; (2) identification of key sources of variability and uncertainty; and (3) evaluation of the importance of key assumptions in the inventory structure.

Emission inventory model verification is a process of making sure that the model properly calculates emissions from various sources. If a model responds in an unacceptable way to changes in one or more inputs, then troubleshooting efforts can be focused to identify the source of the problem. For example, if a significant increase in activity factor does not lead to appropriate increase in the emission inventory, efforts need to be focused on fixing problems with the emission-inventory model structure. Model validation ideally involves comparison of model results to independent observations from the system being modeled. Generally, complete validation is not possible because of lack of sufficient observational data. Cullen and Frey (1999) discuss partial validation of a model when observational data are available for only a part of the modeling domain. Sensitivity analysis can be used to help develop a "comfort level" with a particular model. If the model response is reasonable from an intuitive or theoretical perspective, then the model users may have some comfort with the qualitative behavior of the model even if the quantitative precision or accuracy is unknown. Saltelli (2002) discusses the role of sensitivity analysis in model evaluation and how to make use of sensitivity analysis to verify or validate a model. Russell and Dennis (2000) discuss the application of sensitivity analysis to air quality model evaluation and verification.

Identification of key variability and uncertainty sources often can be aided by application of sensitivity analysis methods, in combination with probabilistic analysis techniques. Even though an emission inventory may involve many uncertain inputs, it is often the case that only a few of these contribute substantially to total uncertainty. Therefore, as a means for conserving resources devoted to an analysis, sensitivity analysis can be used concurrently with the process of developing input assumptions to continually refine the identification of key uncertainty sources and to prioritize information-gathering efforts for the most important inputs.

Evaluation of key assumptions in the inventory structure can also be aided by sensitivity-analysis applications. For example, independence among model inputs is a commonly employed assumption. Using sensitivity analysis, it is possible to evaluate whether the assumption is reasonable. For example, bounding analyses can be performed in which the inputs of interest are assumed to be independent versus assumed to be completely correlated. If the results and insights from the analysis do not change irrespective of which assumption is made, then the issue of correlation is unimportant. Frey and Zhao (2003) demonstrated that correlation between uncertain emission factors for hazardous air pollutants was typically unimportant for several inventories. Furthermore, sensitivity analysis can be used to determine whether simplifying assumptions or judgments in the absence of empirical data have a significant influence on results. Frey and Zhao (2003) demonstrated, for example, that assumptions regarding weighting factors for emissions of different processes within a source category were unimportant to an overall assessment of urban-scale emissions because the source categories were also unimportant to the overall uncertainty estimate.

8.4.2 Techniques for Sensitivity Analysis

Methods of sensitivity analysis and metrics for measuring sensitivity are widely available. They can be classified as *screening methods* or *refined methods* depending on their level of accuracy, and as *local* or *global*, depending on their scope of coverage of the sample space for model inputs. Some methods are model-dependent in that they involve assumptions regarding model form, whereas other methods are model-independent. Although refined, global, and model-independent methods typically provide the most robust insights regarding key sources of uncertainty, they are often more difficult to apply than screening and local sensitivity analysis methods. Section C.3 of Appendix C provides an overview of methods for sensitivity analysis. Saltelli et al. (2000, 2004), Cullen and Frey (1999), and Frey, Mokhtari, and Zheng (2004) provide more detail regarding sensitivity analysis methods.

There are simple sensitivity analysis methods that work well for linear models, such as nominal range sensitivity analysis, but that may not be robust to model characteristics such as nonlinearity, thresholds, interactions, and different types of inputs (e.g., categorical, continuous). These latter characteristics may be present in some kinds of emissions models. In the context of a probabilistic simulation of uncertainties using Monte Carlo or similar methods, typically used methods for sensitivity analysis include correlation coefficients, regression techniques, ANOVA, and categorical and regression trees (CART).

The choice of an appropriate sensitivity analysis method depends on the objectives of the analysis, the characteristics of the model, and other considerations such as ease of implementation and resource availability to conduct the analysis (e.g., Frey, Mokhtari, and Zheng, 2004). For example, when the objective of sensitivity analysis is to identify key sources of uncertainty and apportion variance in an output to individual inputs, the choice of methods further depends on model characteristics. If a model is linear, correlation methods and regression analysis methods are appropriate. If the model is nonlinear, ANOVA or other methods capable of dealing with interactions are better choices. When there are categorical inputs, CART may be more appropriate. When the objective of sensitivity analysis is to identify factors contributing to high emissions in order to develop control strategies, ANOVA and CART should be considered since these methods can provide insight into conditions that lead to high emissions.

Although no guidance is available specifically for the application of sensitivity analysis to emission inventory development and air quality modeling, guidance documents are available on sensitivity analysis applied to other quantitative analysis fields such as risk assessment. For example, the U.S. Department of Agriculture sponsored work to identify and evaluate methods for sensitivity analysis (e.g., Frey and Patil 2002; Frey, Mokhtari, and Danish, 2003) and development of a guidance document on the application of sensitivity analysis methods to food-safety risk process models (Frey, Mokhtari, and Zheng, 2004). The latter study discusses the various objectives for performing sensitivity analysis, identifies key factors to be considered in the selection and application of sensitivity analysis methods, and discusses the interpretation and communication of results from sensitivity analysis.

The U.S. EPA (2001) provides guidance on how sensitivity analysis can be applied to identify important exposure or risk factors as part of risk assessment of Superfund sites. The role of sensitivity analysis in probabilistic risk assessment is discussed. Common sensitivity analysis methods such as correlation and regression methods, graphical methods such as scatter plots, and the use of these methods in the risk assessment are introduced via example case studies.

Saltelli et al. (2004) provide a guide regarding application of sensitivity analysis methods to scientific modeling. A review of the state-of-the-art in sensitivity analysis is presented and a guide regarding selection of appropriate methods for evaluating model performance and key inputs is provided with example applications.

8.4.3 Example Applications

Sensitivity analysis has been used to evaluate emission models. For example, Kear and Niemeier (2002) evaluated the sensitivity of exhaust emission rates to vehicle population and mileage accrual data for the CARB mobile source emission model, EMFAC 2001 V2.08. Sensitivity analyses also have been performed to evaluate the relative importance of model inputs in MOBILE models such as average speed, ambient temperature, fuel property and I/M parameters. Heiken et al. (1994) assessed the sensitivity of model outputs to alternative fuel formulations for exhaust emission rate, evaporative system pressure and evaporative basic emission rates. Fox (1996) evaluated the contributions of key model inputs (e.g., temperature, Reid vapor pressure, average speed) to emission factor estimates for MOBILE 6. Chatterjee et al. (1997) analyzed key travel-related inputs (e.g., speed, VMT, vehicle classification, operating-model fraction) and assessed the sensitivity of model outputs to these variables.

Sensitivity analysis has been applied to the development of emission inventories to identify key sources of variability and uncertainty. For example, Frey and Zheng (2002a,b) used sensitivity studies to identify key sources of variability and uncertainty in developing a probabilistic emission inventory for utility NO_x emissions and key contributors (e.g., speed correction factor, temperature correction factor, base emission rate and Reid vapor correction factor) to the uncertainty in highway vehicle emission factors. Frey and Zhao (2003) performed sensitivity studies to identify key source of uncertainty in developing probabilistic a toxic air pollutant emission inventory for Houston, Texas, and Jacksonville, Florida. Sax and Isakov (2003) used sensitivity analysis to determine the importance of different roadway classifications, speed, emission factor and other sources contributing to uncertainty of onroad emission estimates. In most of these example applications, sample or rank correlations and regression were the most commonly used methods to identify key contributors to uncertainty in the emission estimates.

Sensitivity analysis also has been used in air quality modeling to investigate how emission-control strategies affect atmospheric air quality and to quantify the sensitivity of air quality model results to uncertainty in emission input or other input parameters (e.g., chemical reaction rates). For example, Morris et al. (2004) investigated how ozone concentration is sensitive to emission-reduction scenarios for controlling anthropogenic VOC versus NOx emissions. Odman et al. (2002) calculated sensitivities of modeled air quality concentrations and deposition fluxes to various emission inputs. Bullock et al. (1998) used scatter plots to analyze model sensitivity to uncertainties in mercury emissions. Bergin et al. (1999) evaluated the effects of uncertainty in air parcel trajectory, emissions, rate constants, deposition affinities, mixing height, and atmospheric stability on the predictions from a photochemical air pollution model by using regression analysis, with the help of scatter plots to determine the relationship (linear or nonlinear) between the model output variables and uncertain inputs. Mendoza-Dominguez and Russell (2000) linked sensitivity analysis of air quality models with an inverse modeling technique to help identify improvements in estimates of emission strength, pattern, and composition of various source categories. Chock et al. (1995) investigated the sensitivity of UAM results for test fuels to uncertainty in light-duty vehicle and biogenic emissions and alternative chemical mechanisms. Jiang et al. (1997) evaluated the sensitivity of ozone concentrations to VOC and NO_x emissions in the Lower Frasier Valley. Other examples include investigations of the sensitivity of model-predicted predicted ozone concentrations to rate parameters of chemical mechanisms (e.g., Gao et al., 1996; Yang et al., 1996), and the sensitivity model-predicted pollutant concentrations to key model inputs, particularly emissions and meteorology (e.g., Kumar and Russell, 1996; Kuklin and Seinfeld, 1995; Seinfeld, 1988).

Many of the case study examples indicate that a relatively small number of inputs often contribute substantially to uncertainty in a model output. This observation can be used to limit debate over inputs that are of little consequence to an assessment objective, and to enable time and effort to be devoted to more fruitful discussions on those inputs that matter the most. Similarly, when basing inputs on expert judgments, only those disagreements that really matter to the decision need become the focus of further discussion and evaluation.

The examples mentioned here illustrate the diversity of objectives, methods, and applications of sensitivity analysis in the context of emission inventories. Sensitivity analysis is shown to provide useful insights regarding model behavior, key sources of uncertainty, emission control strategies, and priorities for reducing uncertainties.

8.5 CONCLUSIONS AND RECOMMENDATIONS

The discussions within this chapter combine with those of preceding chapters to produce three important conclusions with regard to emission-inventory uncertainties, their analysis, and their application. These conclusions are directly related to key recommendations of this Assessment, and are discussed sequentially below.

1. A well designed uncertainty analysis should be an essential part of the design and assessment of alternative air quality management strategies. Any decision process is more robust when uncertainties are acknowledged and taken into account. Application of uncertainty and sensitivity analysis becomes increasingly important when modern, risk-based protocols are applied to air quality decision analysis. Accordingly, this Assessment strongly recommends incorporation of quantitative uncertainty estimation into the development of all future emission inventory and air quality management strategies.

2. Most current emission inventories and emission-inventory components do not contain embedded uncertainty or sensitivity analyses, nor do they include quantified measures of uncertainty. In view of the previous conclusion this is not an acceptable situation, and this Assessment recommends that it be corrected, particularly in future inventories. It is important to note that uncertainty analysis is less resource-intensive when it is incorporated into emission inventory development, rather than conducted post hoc.

3. Although numerous techniques for uncertainty and sensitivity analysis are available, no clear guidance for application of these techniques exists for the specific case of emission inventories. Such guidance is badly needed, in order to provide a consistent and systematic basis for developing the embedded uncertainty analyses recommended above. Accordingly, this Assessment strongly recommends that Canada, the United States, and Mexico cooperate to create a central guidance document for emission inventory uncertainty analysis, including a definitive framework for applying such analyses.

REFERENCES FOR CHAPTER 8

Abdel-Aziz, A., Frey, H.C. 2003. Quantification of Hourly Variability in NO_x Emissions for Baseload Coal-Fired Power Plants. Journal of the Air & Waste Management Association 53(11), 1401-1411.

Abdel-Aziz, A., Frey, H.C. 2004. Propagation of Uncertainty in Hourly Utility NO_x Emissions through a Photochemical Grid Air Quality Model: A Case Study for the Charlotte, NC Modeling Domain, Environmental Science and Technology, Accepted pending minor revisions 11/03.

Allen, D. Murphy, C., Kimura, Y., Vizuete ,W. 2004. Variable Industrial VOC Emissions and Their Impact on Ozone Formation in the Houston-Galveston Area, 13th Annual Emission Inventory Conference, Clearwater, FL.

Bergin, M., Noblet, G., Petrini, K., Dhieux, J., Milford, J., Harley, R. 1999. Formal Uncertainty Analysis of a Lagrangian Photochemical Air Pollution Model, Environmental Science and Technology 33, 1116-1126.

Bloom, D.L., Byrne, D.M., Andreson, J.M. 1993. Communicating Risk to Senior EPA Policy-Makers: A Focus Group Study, Prepared by Bloom Research and the Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency, Research Triangle Park, NC.

Bortnick, S.M., Stetzer, S. L. 2002. Sources of Variability in Ambient Air Toxics Monitored Data, Atmospheric Environment 36, 1783-1791.

Bullock, O.R., Brehme, K.A., Mapp, G.R. 1998. Lagrangian modeling of mercury air emission, transport and deposition: An analysis of model sensitivity to emissions uncertainty, Science of the Total Environment 213 (1-3), 1-12 1998.

Chang, W., Cardelino, C., Chang, M. 1996. The Use of Survey Data to Investigate Ozone Sensitivity to Point Sources, Atmospheric Environment 30(23), 4095-4099.

Chatterjee A., Miller, T., Philpot, J., Wholley, T., Guensler, R., Hartgen, D., et al. 1997. Improving Transportation Data for Mobile Source Emission Estimates, NCHRP Report 394, National Academies Press, Washington, DC.

Chi, T.R., Unal, A., D. Tian, Russell, A. 2004. Uncertainty of NONROAD Emissions in Georgia, 13th Annual Emission Inventory Conference, Clearwater, FL.

Chock, D.P., Yarwood, G., Dunker, A.M., et al. 1995. Sensitivity of Urban Airshed Model Results for Test Fuels to Uncertainties in Light-Duty Vehicle and Biogenic Emissions and Alternative Chemical Mechanisms- Auto Oil Air Quality Improve Research Program, Atmospheric Environment 29(21): 3067-3084.

Cullen, A.C., Frey, H.C. 1999. The Use of Probabilistic Techniques in Exposure Assessment: A Handbook for Dealing with Variability and Uncertainty in Models and Inputs. Plenum, New York.

El-Fadel, M., Zeinati, M., Ghaddar, N., Mezher, T. 2001. Uncertainty in Estimating and Mitigating Industrial Related GHG Emissions, Energy Policy, 29, 1031-1043.

Fox, J.W. 1996. Air Pollution Abatement: Quantifying Automobile Emissions, Ph.D. Thesis, Department of Mechanical Engineering, Massachusetts Institute of Technology, Cambridge, MA.

Frey, H.C., Bharvirkar, R., Zheng, J. 1999. Quantitative Analysis of Variability and Uncertainty in Emissions Estimation, Prepared by North Carolina State University for the U.S. Environmental Protection Agency, Research Triangle Park, NC.

Frey, H.C., and Zhao, Y. 2004. Quantification of Variability and Uncertainty for Air Toxic Emission Inventories With Censored Emission Factor Data, Environmental Science and Technology, 38(22), 6094-6100.

Frey, H.C., Bammi, S. 2002. Quantification of Variability and Uncertainty in Lawn and Garden Equipment NO_x and Total Hydrocarbon Emission Factors, Journal of the Air & Waste Management Association 52(4), 435-448.

Frey, H.C., Li, S. 2003. Quantification of Variability and Uncertainty in AP-42 Emission Factors: Case Studies for Natural Gas-Fueled Engines, Journal of the Air & Waste Management Association 53(12), 1436-1447.

Frey, H.C., Mokhtari, A., Danish, T. 2003. Evaluation of Selected Sensitivity Analysis Methods Based Upon Applications to Two Food Safety Risk Process Models, Prepared by North Carolina State University for Office of Risk Assessment and Cost-Benefit Analysis, U.S. Department of Agriculture, Washington, DC.

Frey, H.C., Mokhtari, A., Zheng, J. 2004. Recommended Practice Regarding Selection, Application, and Interpretation of Sensitivity Analysis Methods Applied to Food Safety Risk Process Models, Prepared by North Carolina State University for Office of Risk Assessment and Cost-Benefit Analysis, U.S. Department of Agriculture, Washington, DC.

Frey, H.C., Patil, S.R. 2002. Identification and Review of Sensitivity Analysis Methods, Risk Analysis, 22 (3), 553-578.

Frey, H.C., Tran, L.K. 1999. Quantitative Analysis of Variability and Uncertainty in Environmental Data and Models: Volume 2 Performance, Emissions, and Cost of Combustion-Based NO_x Controls for Wall and Tangential Furnace Coal-Fired Power Plants. Report No. DOE/ER/30250--Vol. 2, Prepared by North Carolina State University for the U.S. Department of Energy, Germantown, MD.

Frey, H.C., Zhao Y. 2003. Development of Probabilistic Emission Inventories of Benzene, Formaldehyde And Chromium for the Houston Domain, Prepared by North Carolina State University for U.S. Environmental Protection Agency, Research Triangle Park, NC.

Frey, H.C., Zheng, J. 2002a. Quantification of Variability and Uncertainty in Utility NOx Emission Inventories, Journal of the Air & Waste Management Association 52(9), 1083-1095.

Frey, H.C., Zheng, J. 2002b. Probabilistic Analysis of Driving Cycle-Based Highway Vehicle Emission Factors, Environmental Science and Technology 36(23), 5184-5191.

Gao. D., Stockwell, W.R., Milford, J.B. 1996. Global Uncertainty Analysis of a Regional-scale Gas-Phase Chemical Mechanism, Journal of Geophysical Research 101, 9107-9119.

Gleit, A. 1987. SO_2 Emissions and Time Series Models II,. Journal of the Air Pollution Control Association 37(12), 1445-1447.

Gschwandtner, G. 1993. Trends and Uncertainties in Anthropogenic VOC and NO_x Emissions, Journal of Water, Air and Soil Pollution 67, 39-46.

Guensler, R. 1993. Vehicle Emission Rate and Average Vehicle Operating Speeds, Ph.D. dissertation, University of California, Davis, CA.

Guensler, R., Leronard, J.D. 1997. Mobile5a Confidence Intervals for Average Speed Emission Rates, School of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA.

Guenther, C., Geron, T., Pierce, B., Lamb, P., Harley, R. 2000. Natural Emissions of Non-methane Volatile Organic Compounds, Carbon Monoxide, and Oxides of Nitrogen from North America, Atmospheric Environment 34(12-14), 2205-2230.

Hanna, S., Wilkinson, J. 2004. Analytical Estimation of Uncertainties in Biogenic Emissions Calculated by BEIS3 due to Uncertainties in Model Inputs and Parameters, 13th Annual Emission Inventory Conference, Clearwater, FL.

Hanna, S.R., Lu, Z., Chang, J.C., Fernau, M., and Hansen, D.A. 1998. Monte Carlo Estimates of Uncertainties in Predictions by a Photochemical Grid Model (UAM-IV) due to Uncertainties in Input Variables, Atmospheric Environment 32(21), 3619-3628.

Hanna, S.R., Lu, Z., Frey, H.C., Wheeler, N., Vukovich, J., Arunachalam, S., Fernau, M., Hansen, D.A. 2001. Uncertainties in Predicted Ozone Concentrations due to Input Uncertainties for the UAM-V Photochemical Grid Model Applied to the July 1995 OTAG Domain, Atmospheric Environment 35(5), 891-903.

Heiken, J., Fieber, J.J., Shepard, S.B., Cohen, J.P., Pollack, A.K., Whitten, G.Z. 1994. Investigation of MOBILE5a Emission Factors: Assessment of Exhaust and Nonexhaust emission Factor Methodologies and Oxygenate Effects, Health and Environmental Department, API Pub. No. 4603, Prepared by System Applications International, San Rafael, CA for American Petroleum Institute.

IPCC. 2000. Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories. National Greenhouse Gas Inventories Program, Intergovernmental Panel on Climate Change, Geneva

Jiang, W.M., Singleton, D.L., Hedley, M., et al. 1997. Sensitivity of ozone concentrations to VOC and NO_x emissions in the Canadian Lower Fraser Valley, Atmospheric Environment 31(4), 627-638.

Kear, T., Niemeier, D. 2002. Sensitivty of Composite Exhaust Emission Rates to Vehicle Population and Mileage Accrual Assumptions, TRB 2003 Annual Meeting, CA.

Khalil, M.K. 1992. A Statistical Method for Estimating Uncertainties in the Total Global Budget of Atmospheric Trace Gases, Journal of Environmental Science and Health, A27(3), 755-770.

Kuklin, A., Seinfeld, J.H. 1995. Emissions Reductions Needed to Meet the Standard for Ozone in Southern California: Effect of

Boundary Conditions, Journal of the Air & Waste Management Association 45, 899-901.

Kumar, N., Russell, A. G. 1996. Multiscale Air Quality Modeling of the Northeastern United States, Atmospheric Environment 30, 1099-1116.

Lee, D.S., Kholer, I., Grobler, E., Rohrer, F., Sausen, R., Klenner, L., Oliver, J.G.J., Dentener, F.J., Bouwman, A.F. 1997. Estimation of Global NO_x Emissions and Their Uncertainties, Atmospheric Environment 1735-1749.

Mendoza-Dominguez, A, Russell, A.G. 2000. Iterative inverse modeling and direct sensitivity analysis of a photochemical air duality model, Environmental Science and Technology 34, 4974-4981, C1.

Moore, G., Londergan, R. 2001. Sampled Monte Carlo Uncertainty Analysis for Photochemical Grid Models, Atmospheric Environment 35, 4863-4876.

Morgan, M.G., Henrion, M. 1990. Uncertainty: A Guide to Dealing With Uncertainty in Quantitative Risk and Policy Analysis. Cambridge University Press, Cambridge, NY.

Morris, R.E., Mansell, G., Tai, E. 2004. Air Quality Modeling Analysis for the Denver Early Action Ozone Compact: 2007 Emission Reduction Sensitivity Modeling, Prepared by ENVIRON International Inc. for Colorado Department of Health and Environment, Novada, CA.

National Resources Defense Council (NRDC), Coalition for Environmentally Responsible Economics (CERES) and Public Service Enterprise Group (PSEG), Benchmarking Air Emissions of the 100 Largest Electric Generation Owners in the U.S. -2000; at C Page. http://www.ceres.org/reports/issue_reports.htm.

NRC. 1991. Rethinking the Ozone Problem in Urban and Regional Air Pollution, National Research Council, National Academies Press: Washington, DC.

NRC. 2000. Modeling Mobile Source Emissions, National Research Council, National Academies Press, Washington, DC.

NRC. 2001. Evaluating Vehicle Emissions Inspection and Maintenance Programs, National Academies Press, Washington, DC.

NRC. 2004a. Research Priorities for Airborne Particulate Matter (IV). Continuing Research Progress, National Academies Press, Washington, DC. ISBN 0-309-09199-3.

NRC. 2004b. Air Quality Management in the United States, National Academies Press, Washington, DC.

Odman, T., Boylan J., Wilkinson, J.G., Russell, A.G., et al. 2001. SAMI Air Quality Modeling, Final Report, Prepared by Depart of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA.

Placet, M., Mann, C.O., Gilbert, R.O., Niefer, M.J. 2000. Emissions of Ozone Precursors from Stationary Sources: A Critical Review, Atmospheric Environment 34, 2183-2204.

Rubin, E.S., Kalagnanam, J.R., Frey, H.C., Berkenpas, M.B. 1997, Integrated Environmental Control Concepts for Coal-Fired Power Plants, Journal of the Air & Waste Management Association, 47(11),1180-1188.

Russell, A., Dennis, R. 2000. NARSTO critical review of photochemical models and modeling, Atmospheric Environment 34 (12-14), 2283-2324.

Saltelli, A., Chan, K., Scott, M., eds. 2000. Sensitivity Analysis, Probability and Statistics Series. John Wiley & Sons, New York.

Saltelli, A. 2002. Making Best Use of Model Evaluations to Compute Sensitivity Indices, Computer Physics Communication, 145(2), 280-297.

Saltelli, A. Tarantola, Campolongo, F. 2004. Sensitivity Analysis in Practice: A Guide to Assess Scientific Models, Wiley Press.

Sawyer R.F., Harley, R.A., Cadle, S.H., Norbeck, J.M., Slott, R., Bravo, H.A. 2000. Mobile sources critical review: 1998 NARSTO assessment, Atmospheric Environment 34, 2161-2181.

Sax, T., Isakov, V. 2003. A case study for assessing uncertainty in local-scale regulatory air quality modeling applications, Atmospheric Environment 37, 3481-3489.

Seinfeld, J.H. 1988. Ozone Air Quality Models: A Critical Review, Journal of the Air Pollution Control Association 38, 616-645

Sharma, P., Khare, M. 2000. Real-Time Prediction of Extreme Ambient Carbon Monoxide Concentrations due to Vehicular Exhaust Emissions Using Univariate Linear Stochastic Models, Transportation Research Part D, 5, 59-69.

Thompson, K.M., Graham, J.D. 1996. Going Beyond the Single Number: Using Probabilistic Risk Assessment to Improve Risk Management, Human and Ecological Risk Assessment 2(4):1008-1034.

U.S. EPA. 1997. Guiding Principles for Monte Carlo Analysis, U.S. Environmental Protection Agency, EPA/630/R-97/001, March 1997.

U.S. EPA. 2001. Risk Assessment Guidance for Superfund: Volume III - Part A, Process for Conducting Probabilistic Risk Assessment, EPA 540-R-02-002, Office of Emergency and Remedial Response.

U.S. EPA. 2002. Draft Design and Implementation Plan for EPA's Multi-Scale Motor Vehicle and Equipment Emission System (MOVES), EPA420-P-02-006, Office of Transportation and Air Quality.

Van Amstel, A., Olivier, J.G.J., Russenaars, P., eds. 2000. Monitoring of Greenhouse Gases in the Netherlands: Uncertainty and Priorities for Improvement, Proceedings of a National Workshop: Bilthoven, The Netherlands.

Winiwarter, W., Rypdal, K. 2001. Assessing the Uncertainty associated with National Greenhouse Gas Emission Inventories: A Case Study for Australia, Atmospheric Environment 35, 5425-5440.

Yang, Y.J., Stockwell, W.R., Milford, J.B. 1996. Effect of Chemical Product Yield Uncertainties on Reactivities of VOCs and Emissions from Reformulated Gasolines and Methanol Fuels, Environmental Science and Technology 30, 1392-1397.