VOLUME VI: Chapter 4

EVALUATING THE UNCERTAINTY OF EMISSION ESTIMATES

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Prepared by:
Radian Corporation
Post Office Box 13000
Research Triangle Park, North Carolina 27709

Prepared for:
Quality Assurance Committee
Emission Inventory Improvement Program

DISCLAIMER

As the Environmental Protection Agency has indicated in Emission Inventory Improvement Program (EIIP) documents, the choice of methods to be used to estimate emissions depends on how the estimates will be used and the degree of accuracy required. Methods using site-specific data are preferred over other methods. These documents are non-binding guidance and not rules. EPA, the States, and others retain the discretion to employ or to require other approaches that meet the requirements of the applicable statutory or regulatory requirements in individual circumstances.

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INTRODUCTION

The quality assurance and quality control (QA/QC) procedures described in other chapters of this volume are designed to ensure that the appropriate methods and data are used, that errors in calculations or data transcriptions are minimized, and that documentation is adequate to reconstruct the estimates. It is important to recognize that the resulting quality of the emission estimates is only partly determined by adherence to a good QA program. The quality of the emission estimates is also determined by the uncertainty inherent in the estimates.

This chapter deals with the determination and evaluation of the uncertainty in emission estimates and the methodology available to do this. The goal is always to reduce uncertainty. To do so, the inventory preparer must first know the sources of bias and imprecision in the estimates; Section 2 discusses the sources of uncertainty and gives specific examples. The next step in certifying the emissions inventory is to conduct a qualitative assessment of the sources of uncertainty in the inventory. Section 3 provides an example of how this can be done. The third step is to develop subjective quality indicators for the source categories; Section 4 describes alternative approaches that produce subjective quality indicators. Finally, Section 5 describes several approaches for quantitative uncertainty analysis, arranged in order of increasing complexity.

The intended uses of the emissions data should be considered before spending significant resources on quantifying the uncertainty and reducing it. For example, if the inventory for a point source is being used to show compliance with an emissions limit, the relative accuracy is usually part of the reporting requirements. The uncertainty associated with the estimate is low.

On the other hand, a national inventory to identify and rank the relative importance of sources of a specific hazardous air pollutant (HAP) may not be as concerned with the uncertainty of specific estimates. This is especially true of smaller emissions sources. If an estimate is highly uncertain, but at worst represents only 1 percent of all the emissions, accurately quantifying the uncertainty is probably not a high priority. However, a source that is insignificant at a national level can be very important at a local level. When viewed from the local community’s perspective, high uncertainty in the estimated emissions may be unacceptable.

1.1 BACKGROUND

As discussed in Chapter 2 of this volume, the desired quality of an inventory is a function of the intended end use. If a Level IV inventory is being prepared, the users must be willing to accept that the estimates are not necessarily of the best possible quality, whereas a Level I inventory implies the highest possible data quality.

It is not always possible to achieve the desired level of quality. In some instances, the state-of-the-science may not be sufficient to provide the level of detail desired. In other situations, unforeseen problems (e.g., equipment failure, survey responses not as high as expected, activity data not available) may be encountered in the process of preparing the estimates. In any event, an important step in preparing an emissions inventory is to "qualify the data." This term means to provide an assessment of how closely the desired level of quality, or data quality objective (DQO), is met by the inventory preparer. Ideally, the target data quality can be evaluated using a quantitative data quality indicator (DQI).

When discussing the quality of an estimate, the term "uncertainty" is often used as an indicator of quality, rather than "accuracy" because there is no reasonable or practical way to determine to emission values for comparison. Confidence in an estimate is generally determined by our perception of the reliability of the underlying data and model used to generate the emissions estimate. For example, an annual boiler nitrogen oxides (NO_x) emission estimate generated using continuous emission monitor (CEM) data is generally held to be more reliable (less uncertain) than an estimate based on fuel consumption and an accepted emission factor. However, this logic implicitly assumes that the CEM is maintained properly, that QA and calibration procedures are rigorously followed, and that the data capture is near 100 percent. So, assuming that appropriate QA procedures are followed in both cases, the CEM estimate is assumed to be of higher quality (i.e., more reliable and less uncertain) than the estimate based on an emission factor.

Calculating the range, confidence interval, or other error bounds for an emission estimate is a very important tool for assessing the uncertainty of the estimate. However, these statistics are not complete measures of quality because there may be systematic errors (biases) associated with the emission estimate that are not bounded by the range or confidence interval estimates. In addition, uncertainty is due to many causes, one of which is the inherent variability in the process or processes that cause the emissions. Even if all other sources of uncertainty were removed, the variability remains. Because some processes are more variable than others, some will always have larger error bounds than others. That does not mean that the estimates are of lower quality. It does mean that we do not have as much confidence in our ability to predict the emissions at a particular point in time, but that we can confidently predict a range.

Emission inventory development and uncertainty analysis should be an iterative process. Once estimates of uncertainty are developed, the inventory preparer should review the inventory and target the significant sources with the largest uncertainty for more research. The objective of this iterative process is a minimization of overall uncertainty in the inventory. Several factors make this process difficult to implement:

- Data are not available (and not readily measurable) to quantify the uncertainty;

- The available data are insufficient to meet the data input needs of the statistical or numerical methods to be used to estimate uncertainty; and

- Reducing the uncertainty requires more resources (i.e., money and time) than are available.

The solutions to the second and third problems require the expenditure of resources that may not be available. However, the Emission Inventory Improvement Program (EIIP) has developed recommendations for methods to be used to develop better uncertainty estimates if the necessary resources are available. The EIIP recommendations for implementing uncertainty analyses are presented in the next section.

1.2 UNCERTAINTY ANALYSIS

The first step towards reducing the uncertainty associated with emission estimates is to understand and quantify the various sources of variability and inaccuracies in the data used to estimate the emissions. This analysis should include an assessment of both bias and imprecision in the estimates. When identified, bias should be eliminated while imprecision should be minimized. The remaining sources of uncertainty in the inventory should be identified and quantified if possible.

The initial task in any emissions uncertainty analysis is the definition of the analysis methodology to be used to estimate emissions uncertainty. Table 4.1-1 presents a list of eight general types of analyses that have been used or are currently being used to evaluate emissions inventory uncertainty. A brief overview of each general method, with references, is given in Table 4.1-1. Additional discussion and examples of each method are described in Sections 3 through 5 of this chapter. The inventory specialist must be aware that each of the methods in Table 4.1-1 may provide different estimates of

TABLE 4.1-1

OVERVIEW OF METHODS USED TO ESTIMATE EMISSIONS UNCERTAINTY

Methodology	References	Description	Approximate Level of Effort[a]
Qualitative Discussion	Steiner et al., 1994	Sources of uncertainty are listed and discussed. General direction of bias, and relative magnitude of imprecision are given if known.	<100 hrs
Subjective Data Quality Ratings	U.S. EPA, 1995 Saeger, 1994	Subjective rankings based on professional judgement are assigned to each emission factor or parameter.	<100 hrs
Data Attribute Rating System (DARS)	Beck et al., 1994	Numerical values representing relative uncertainty are assigned through objective methods.	<500 hrs
Expert Estimation Method	Linstene and Turoff, 1975 SCAQMD, 1982 Horie, 1988 Horie and Shorpe, 1989	Emission distribution parameters (i.e., mean, standard deviation, and distribution type) are estimated by experts. Simple analytical and graphical techniques can then be used to estimate confidence limits from the assumed distributional data. In the Delphi method, expert judgement is used to estimate uncertainty directly.	<500 hrs
Propagation of Errors Method	Mangat et al., 1984 Benkovitz, 1985 Benkovitz and Oden, 1989 Balentine et al., 1994 Environment Canada, 1994	Emission parameter means and standard deviations are estimated using expert judgement, measurements, or other methods. Standard statistical techniques of error propagation typically based upon Taylor's series expansions are then used to estimate the composite uncertainty.	<500 hrs
Direct Simulation Method	Freeman et al., 1986 Iman and Helton, 1988 Oden and Benkovitz, 1990 Efron and Tibshirani, 1991 Environment Canada, 1994 Gatz and Smith, 1995a Gatz and Smith, 1995b	Monte Carlo, Latin hypercube, bootstrap (resampling), and other numerical methods are used to estimate directly the central value and confidence intervals of individual emission estimates. In the Monte Carlo method, expert judgement is used to estimate the values of the distribution parameters prior to performance of the Monte Carlo simulation. Other methods require no such assumptions.	<1,000 hrs

TABLE 4.1-1

(CONTINUED)

Methodology	References	Description	Approximate Level of Effort[a]
Direct or Indirect Measurement (Validation) Method[b]	Pierson et al., 1990 Spellicy et al., 1992 Fujita et al., 1992 Peer et al., 1992 Mitchell et al., 1995 Claiborn et al., 1995	Direct or indirect field measurement of emissions are used to compute emissions and emissions uncertainty directly. Methods include direct measurement such as stack sampling and indirect measurement such as tracer studies. These methods also provide data for validating emission estimates and emission models.	>1,000 hrs
Receptor Modeling (Source Apportionment) Method[b]	Watson et al., 1984 Lowenthal et al., 1992 Chow et al., 1992 Scheff et al., 1995	Receptor modeling is an independent means to estimate the relative contribution of specific source types to observed air quality measurements. The method works best for nonreactive pollutants for which unique emission composition “fingerprints” exist for all significant source categories. The method provides a measure of the relative contribution of each source type but not absolute emission estimates.	>1,000 hrs
Inverse Air Quality Modeling Method[b]	Hartley and Prinn, 1993 Chang et al., 1993 Chang et al., 1995 Mulholland and Seinfeld, 1995	Air quality simulation models are used in an inverse, iterative approach to estimate the emissions that would be required to produce the observed concentrations fields.	>1,000 hrs

[a] The levels shown are a relative level of effort, including data collection. The actual effort will depend upon the scope of work implemented.

[b] These methods are described in Chapter 3, Section 9, "Emission Estimation Validation" of this volume. They can be used to develop estimates of uncertainty as well.

uncertainty when applied to the same data set. These differences range from slight to significant. A method should be chosen and applied consistently to the inventory categories. If different methods are used to develop different source groups, comparisons between the uncertainty results may not be meaningful. The overall goal of any emissions uncertainty analysis is likely to be the development of confidence limits about the mean of emission estimates from each source type analyzed. The significance level assumed for the confidence limits, generally 90 or 95 percent, is a function of the quality of the input data available and the use to which the uncertainty estimates will be put. It is up to the analyst for each study to determine the appropriate significance level for his or her study.

1.3 EIIP RECOMMENDATIONS

The preferred and alternative methods of qualifying emissions inventory data are summarized in Table 4.1-2. Note that there are two aspects to these recommendations. The first is that all three elements--qualitative assessment, ranking, and quantitative uncertainty--are included; the second is that different methods are preferred for completing these three elements. Inventory preparers are not constrained to the combinations of elements shown in this table; rather, they should develop a plan for qualifying the data that is most suitable for the specific situation. The methods shown are the minimum recommended for the level shown.

As discussed above, the lack of necessary data is a significant limitation in the development of emission inventory uncertainty estimates. For these instances, the EIIP recommends use of ranking methods. The EIIP preferred ranking method is the Data Attribute Rating System (DARS). Because of its potential to provide significant information on emissions inventory uncertainty, the EIIP has focused on the DARS method for further development.

The DARS method addresses four major sources of uncertainty or error in both the emission factor and the activity data. Numerical scores are assigned based on predefined criteria, and a composite score is computed to provide an overall indicator of the relative quality of the estimate. While DARS does address uncertainty in a subjective way (i.e., the higher the DARS score, the more confidence or certainty we have about the estimate), it does not quantify the imprecision of the estimate. For this reason, the EIIP strongly encourages the additional use of quantitative methods to calculate confidence intervals (or other measures of the dispersion of the estimate).

For many area sources, the preferred method is to conduct a survey of facilities in the inventory region to gather more accurate activity and emissions data. The value of using this more resource-intensive approach is shown in Table 4.1-3. This table shows the estimated emissions for industrial surface coatings in the Houston area. The first two estimates were calculated using volatile organic compound (VOC) per capita and per employee factors, respectively, and then using standard speciation profiles to allocate the emissions to

TABLE 4.1-2

PREFERRED AND ALTERNATIVE METHODS FOR QUALIFYING EMISSION INVENTORY DATA

	Qualitative	Ranking[a]	Quantitative Uncertainty
Preferred (Level 1)	Provide a qualitative assessment of uncertainty, addressing bias and imprecision of key data elements; indicate direction of bias and relative magnitude of imprecision where possible. Provide any statistical measures of data dispersion that are available.	For each source contributing to the top 90% of emissions, provide a subjective relative ranking of the quality of the estimate.	Quantify the range of the estimates as a 90% confidence level for all sources.
Alternative (Level 1 or 2)	Provide a qualitative assessment of uncertainty, addressing bias and imprecision of key data elements; indicate direction of bias and relative magnitude of imprecision where possible. Provide any statistical measures of data dispersion that are available.	For each source contributing to the top 90% of emissions, provide a subjective relative ranking of the quality of the estimate.	Quantify the range of estimates at the 90% confidence level for the top 10 sources in the point, area, on-road mobile, non-road mobile, and biogenic categories.
Other Methods (Level 3)	Provide a qualitative assessment of uncertainty, addressing bias and imprecision of key data elements; indicate direction of bias and relative magnitude of imprecision where possible. Provide any statistical measures of data dispersion that are available.	Rank sources from largest to smallest; provide subjective relative ranking for as many as possible (starting with largest).	None.
Other Methods (Level 4)	Provide a qualitative assessment of uncertainty, addressing bias and imprecision of key data elements; indicate direction of bias and relative magnitude of imprecision where possible. Provide any statistical measures of data dispersion that are available.	None.	None.

[a] The EIIP preferred ranking method is DARS.

TABLE 4.1-3

COMPARISON OF UNCERTAINTY AND DATA QUALITY FOR THREE ESTIMATION METHODS FOR INDUSTRIAL SURFACE COATINGS

Method	Emissions of VOCs (tpy)	Assessment of Imprecision	DARS Score	Level of Effort (hours)
Per Capita	7423	Very high[a]	0.15	1
Per Employee	589	High[a]	0.43	200
Survey	198	±40%[b]	0.86	300

[a] Qualitative assessment.
[b] 90% confidence interval based on survey data.

individual chemical species (speciation). The third estimate was based on a survey of Standard Industrial Classification (SIC) codes included in this category. A telephone survey of 198 facilities was first used to determine what fraction of the surveyed facilities actually were sources of hazardous air pollutant (HAP) emissions. (Note: this survey was designed primarily as a survey of organic HAP emissions, but data on total VOCs were also collected. Only the VOC results are used here as an example.) The total number of facilities (416) in the SIC group was then multiplied by the survey fraction of emitting sources to give an estimate of the total number of emitting sources. A subset of 32 sites were then visited and solvent use data were collected. This information included material safety data sheets (MSDSs) documenting solvent composition and the total annual volume of solvent. From this data set, emission factors for each pollutant were developed on a per facility basis, and used with the estimated number of facilities to estimate VOC emissions in the Houston area.

The estimated VOC emissions as calculated in tons per year (tpy) by each method are given in Table 4.1-3, along with an analysis of the uncertainty, the DARS scores for each, and an estimate of the number of labor hours required for each method. As is clearly shown, the per capita estimate requires very little effort, but produces an estimate of very high uncertainty. This low-cost estimate is also shown to overestimate emissions by an order of magnitude for this case.

The second approach requires an intermediate expenditure of time but produces estimates closer to the best estimate. (For this specific example, however, the estimated emissions would have been twice as high if the number of employees had not been adjusted using the phone survey results.) The third approach targeted uncertainty in both the factor and in the activity data; while considerably more resources were required to generate this estimate, the results are dramatic both in the decrease in estimated emissions and in the increase in quality.

In this example, the higher the quality of the estimate, the lower the emissions. This will not always be the case; because the per capita and per employee factors are based on national averages, these factors will over- and underestimate emissions for specific regions (assuming that the national estimates are not biased in some way). The table does not include an assessment of possible bias. All methods potentially overestimate emissions (i.e., positive bias) because they do not account for non-air losses. However, the latter two possibly have a negative bias in that potential respondents are more likely to decline to answer when they *are* a source than when they are not.

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SOURCES OF UNCERTAINTY IN EMISSION INVENTORIES

Estimates in emission inventories are nearly always the result of modeling of one form or another. The simplest emissions modeling method is the use of an emission factor multiplied by an activity level to approximate emissions. Statistical models (such as regression models) are a more sophisticated way to achieve the same objective. Or, more complex models such as the Biogenic Emissions Inventory System (BEIS) or the Mobile Source Emissions Model MOBILE5a use detailed input data to generate emission estimates or factors. Temporal and spatial allocation of emissions may require further modeling through the use of statistical analysis or surrogate variables to distribute the emissions data or underlying activity to a grid at a specified temporal resolution. In all cases, uncertainty is associated with the development and adjustment of emission estimates.

Uncertainty in emission estimates is due to a variety of causes. First, there is inherent variability in the processes producing the emissions. For example, sulfur dioxide (SO_2) emissions from combustion sources fluctuate with the sulfur content of the fuel and the process load. For other sources, uncertainty results from variation in the environmental factors that produce the emissions (e.g., biogenic emissions vary with temperature, sunlight intensity, exposed leaf surface area, and other environmental factors). Other sources of uncertainty in emission estimates stem from the methods, models, and assumptions used to fill in our incomplete knowledge about the emission process and allow simplistic estimation of emissions from highly complex processes. Still other uncertainty comes from the measurement methods and instruments themselves. Finally, random errors--usually stemming from human errors or naturally occurring but unforeseeable events--introduce uncertainty.

The term *uncertainty* comprises two types of error in estimation: bias and imprecision. A *bias* is a consistent difference between a measurement and its true value that is not due to random chance. In an emissions inventory, bias can result from an emissions estimation process in which a systematic error occurs because some aspect of the emissions inventory process is misrepresented or is not taken into account. For example, if the emission factor for a given source category was developed from a nonrepresentative sample of source types, the emission factor will produce a biased estimate of emissions. Bias may also result due to one’s inability to obtain a comprehensive set of measurements for all conditions producing emissions (i.e., one cannot perform source sampling for all conditions under which the source may operate). A common example of bias is the use of solvent consumption as a surrogate for emissions; if the disposal of waste solvent or other nonair releases are ignored, this approach consistently overestimates emissions (i.e., positive bias).

In contrast to bias, *imprecision* in a parameter is the difference due to random error or fluctuations between a measurement and its true value. Multiple measurements of the parameter will differ, but--if the measurements are nonbiased--the measurements will cluster about the true value of the parameter. This imprecision is caused by sampling error and human error, as well as by the natural fluctuations in the process being measured. Emissions data variability results from a number of causes including temporal or spatial fluctuations in data used to estimate emissions (e.g., the temporal variation in the fuel sulfur content, heating value, and load for an industrial boiler). In addition, there are inherent differences in individual emission sources in that no two sources or operations can be exactly identical.

The factors producing uncertainty in emissions data can be separated into three general classes: variability, parameter uncertainty, and model uncertainty. This system of classifying uncertainty is based on a discussion by Finkel (1990) of uncertainty in risk assessment. In the following section, these concepts are applied to the understanding and estimation of uncertainty in emission estimates.

2.1 VARIABILITY

Variability is inherent in the process that produces emissions. If all other sources of uncertainty were removed, the inherent variability would still make it impossible to precisely specify emissions at a certain point in time and space. Some processes have very little natural variability, others have a lot. There are two major components of the variability that occur in emissions estimates and the data used to create the emissions estimates. The first component is the uncertainty introduced by variation from source to source (spatial uncertainty) and the second component is within source variation (temporal uncertainty). Table 4.2-1 presents examples of these two sources of variability in emission sources.

Source-to-source differences, such as the vehicle fleet composition between urban areas, differences in the process operation of two refineries, and differences in the physical attributes of similar boilers, introduce imprecision into estimates of emissions, emission factors, and activity data. However, even if all source-to-source uncertainty were eliminated, there would still be uncertainty in emission estimates resulting from within-source (temporal) variability. Factors such as the change in equipment operating characteristics with age, variation in fuels, load fluctuations, and maintenance history all contribute to the variability of emission estimates for a single source.

An incomplete understanding of the variability in a process can lead to systematic errors in estimation. For example, emissions due to the application of pesticides are highly variable.

TABLE 4.2-1

EXAMPLES OF VARIABILITY IN EMISSION SOURCE ESTIMATES

Source of Variability	Examples of Causes	Ways to Minimize Effect
Inherent variability between sources	Environmental factors vary spatially (e.g., application rate, soil moisture, ambient temperature, isolation when determining VOC emissions from a pesticide application). Hourly/daily/weekly/seasonal variations in activity (e.g., seasonal agricultural activities, business day versus weekend activities, morning/evening commute, batch processing operations). Annual variability in activity (e.g., heating and cooling demand, economic growth). Processes or activities included in the category are not uniform (e.g., product formulations vary between manufacturers, product can be produced using several processes).	Identify environmental factors responsible for variation in source emissions or activity. Make sure the averaging time of the emission factor and activity data are appropriate for temporal scale of emission estimates desired. If possible, subdivide category to create more uniform subcategories.
Inherent variability within a source	Source emissions and effectiveness of emission control systems on a source can be a function of age and maintenance history of the source. Load or production variability of a source (e.g., dry cleaning emissions depend upon demand that can vary day to day). Variation in fuel characteristics and raw materials input to an industrial process (both within-specification and outside-specification). Inherent differences in two similar pieces of equipment (i.e., no two boilers can be exactly the same).	Detail age and maintenance history of all sources. Document variability in load and production for the time scale of interest. Document fuel, raw material, and processing variability for a given source, particularly in batch processing operations. Quantify physical differences between individual pieces of equipment (e.g., type of emission control system, modifications to original equipment).

Rather than being entirely random, however, the emissions are a complex function of the volatility of the solvents in the pesticide, existing meteorological conditions, the amount and type of vegetation sprayed, the method of application, and the effect of biological organisms that can metabolize the pesticide. However, because the form and magnitude of these complex relationships are unknown, the inventory preparer tends to "be conservative" and assume that all the solvent applied is emitted. Even when an adjustment is made (e.g., assume 90 percent is emitted), that adjustment is often an expert judgement that may still produce biased results. Because adjustments that are not supported by data introduce an *unknown* bias, the tendency is to estimate high so that the direction (if not the magnitude) is known.

Most sources show some sort of temporal variation because of variability in activity patterns. For example, residential fuel consumption is higher in the winter than in the summer. Commercial or industrial activity tends to be greater on weekdays than on weekends. Other sources have variable emissions due to variability in load, operation, or fuel composition. For example, municipal solid waste combustors are characterized by spikes in SO_2 emissions that are associated with the random feed into the combustor of individual waste elements with large, and highly variable, sulfur contents. For these variable sources, activity data (i.e., fuel composition and feed rate) must be known to at least the temporal resolution required for the emission estimates in order to minimize imprecision in the emission estimates.

For many sources, the main recognized source of variability in emissions is temporal fluctuations in activity, which are usually greatest on a daily or weekly basis (e.g., weekday activity rates tend to be higher than weekend rates). Some sources vary significantly between years, particularly if emissions are driven by extreme events (e.g., chemical spills and extreme meteorological conditions).

The uncertainty due to source variability should be quantified and minimized whenever possible. Many times it is possible to attribute a portion of the emission uncertainty to a given source of variation. However, it is never possible to eliminate all imprecision in emission estimates. For example, it would not be feasible to obtain hourly use rates of dry cleaning fluids at all dry cleaning establishments in an urban area. If an estimate of the confidence interval (or other measure of dispersion) is available for a given parameter, that portion of uncertainty that is attributable to that parameter can potentially be quantified. However, other sources of variability may not be quantifiable; for example, source production data may be available on an hourly or daily basis, but detailed fuel sulfur content is known only as an annual average.

Good inventories will minimize the uncertainty due to temporal variability by ensuring that input emission factors and activity data match the scale of the inventory. If factors or activity have to be scaled up or down, adjustments must be made that account for temporal variability. Similarly, any other adjustments to the calculation to account for variability should be performed.

2.2 PARAMETER UNCERTAINTY

Parameter uncertainty is caused by three types of errors: measurement errors, sampling errors, and systematic errors (also called nonrandom error or bias). Examples of these types of parameter errors are given in Table 4.2-2.

Measurement errors occur because of the imprecision of the instrument or method used to measure the parameters of interest. Where emissions are measured directly, the measurement error of a particular method is usually known; the U.S. Environmental Protection Agency (EPA) typically uses the concept of relative accuracy to describe the performance of a measurement method (or device) with respect to an EPA Reference Method.

A more common measurement error for area sources occurs due to misclassification. For example, area source categories are frequently identified by SIC group, and the number of employees or facilities in a particular SIC group are used as the activity data. However, some SIC groups encompass a wide variety of industrial processes and activities, not all of which are really sources of emissions. This issue can still be a problem even when a survey is used to gather activity data within a SIC group if the sample design does not account for subpopulations adequately. For example, different manufacturing processes may be used to produce the same product; the ratio of emissions to employees may be different for these processes. In addition, facilities are sometimes listed under an incorrect SIC or may have more than one SIC. Any of these errors results in misclassification of data and adds to our uncertainty about the emissions estimates.

Sampling error is an important factor when one or more of the parameters (i.e., activity, factors, or emissions) are to be estimated from a sample of the population. While most people recognize the importance of an adequate sample size, obtaining an adequate sample size is often difficult. Furthermore, sample data are usually used to estimate the arithmetic mean value from which the population mean is extrapolated. This approach assumes that the underlying data are normally distributed--an assumption that is often violated (see Chapter 3, Section 7, of this volume). If the underlying data are extremely skewed, a small sample size can lead to very large errors in estimating means. Again, sampling error can be minimized if proper statistical approaches are used, QA procedures are followed, and sample sizes are adequate and properly obtained.

Systematic errors (bias) are the most problematic sources of parameter uncertainty because they are the most difficult to detect and reduce. They occur primarily because of an inherent flaw in the data-gathering process or in the assumptions used to estimate emissions. A

TABLE 4.2-2

EXAMPLES OF PARAMETER UNCERTAINTY IN EMISSION SOURCE ESTIMATES

Source of Parameter Uncertainty	Examples of Causes	Ways to Minimize Effect
Measurement errors in activity data and emission factors	Inherent random error in measurement equipment (e.g., selected anemometer is only accurate to the nearest 0.1 m/sec, air flow meter is accurate to only 10% of measured flow, CEM has relative accuracy of 12%). Monitoring equipment error tolerance too high. Misclassification of activity data (e.g., wrong area source SIC category used).	Use monitoring equipment adequate to gather data required (i.e., do not use an instrument accurate to only 1.0 ppm if 0.1 ppm levels are required). Establish and follow a data collection protocol including performance QA measurements (i.e., field blanks, duplicate samples or data entry). Verify appropriateness of all activity and emission factor data.
Sampling (random) error in activity data and emission factors	Inadequate sample size. Errors in performance of the sampling (e.g., improper probe placement in stack, misread dials, failure to follow the sampling protocol). Sampling equipment or source not in a stable or steady-state mode (i.e., monitoring equipment not at a stable temperature, source subject to load fluctuations, data collection during atypical production periods). Sampling protocol or sampling equipment inadequate to produce required resolution in collected data.	Establish sample size required to meet analytical needs as part of sampling protocol. Establish and follow a monitoring (or sampling) protocol. Audit all monitoring results to ensure compliance with proper procedures and sampling protocols. Perform a defined number of measurements as QA measurements (i.e., field blanks, duplicate samples or data entry).

TABLE 4.2-2

CONTINUED

Source of Parameter Uncertainty	Examples of Causes	Ways to Minimize Effect
Systematic errors (bias)	Inherent bias in a survey (e.g., only largest facilities are surveyed and they do not reflect activities at smaller facilities). Misclassification of data (e.g., SIC group used does not accurately define activities of facility). Incorrect assumption (e.g., assuming 100% rule compliance and ignoring rule effectiveness). Improper calibration of monitoring equipment. Sampling methodology improper for sources sampled. Use of nonrepresentative meteorological data in estimation procedures (e.g., temperature or wind speed data used are not valid for the situation).	Develop and follow a sampling or inventory development protocol. Obtain external review of methods by a qualified expert. Make sure that characteristics of the source population are understood and accounted for in the sampling or emission estimation methods. Validate all assumptions. Compare emission estimation or sampling results to similar data from other studies. Perform mass balance or other simple, common sense checks to ensure reasonableness of data.

common way that this happens is if the population to be sampled is not well defined, and a sample (thought to be random) is actually nonrandom. This is a fairly common problem for certain types of industries. For example, consider a local survey of solvent use by auto body refinishing shops. One approach would be to develop a list of facilities from business registration or other state/local business listings. However, this industry has a very large number of "backyard" operations that are not identified in these official lists. Therefore, any sample that did not recognize this fact would have systematic sampling errors.

As part of the emissions inventory development process, the goal is to reduce all known sources of bias, both across and within sources. If a bias is known to exist, then effort should be initiated to quantify and remove the bias. However, in practice this may be difficult to accomplish because of a lack of resources, data, or other factors. For example, the source testing used to develop the emission factors for a given class of sources could potentially exclude a key source type. Because this key source type would not be represented in the emission factor, the emission factor would potentially contain a known (or suspected) bias. However, resources may not be available to perform the needed source testing to develop a revised emission factor incorporating this key source type. Consequently, a known bias would exist in the emission inventory but would not be readily susceptible to elimination.

2.3 MODEL UNCERTAINTY

Model uncertainty applies to most emission estimates. In this context, a model is a simplified representation of the processes leading to the emissions. Model uncertainty stems from the inability to simulate the emission process completely due to the use of surrogate variables, exclusion of variables from the computation process, and over-simplification of emission process by the model. Table 4.2-3 presents examples of model uncertainty in emission estimates.

TABLE 4.2-3

EXAMPLES OF MODEL UNCERTAINTY IN SOURCE EMISSION ESTIMATES

Source of Model Uncertainty	Examples of Causes	Ways to Minimize Effect
Use of surrogate variables	Surrogate variable is an incomplete representation of the activity or variable desired (e.g., factors in addition to heating degree days [HDD] contribute to the demand for space heating). Use of surrogates can mask underlying relationships between activity data and emissions.	Enhance emission models to account for more fundamental parameters. Develop emission factors based on statistically correlated surrogates. Obtain site-specific data through statistically valid surveys and with site units so that surrogate data use can be minimized.
Model simplification/ over-simplification	Data parameterized (separated into classes) rather than used as discrete values (e.g., speeds in motor vehicle emission factor models input as discrete classes, traffic network input as links and nodes). Reduction of a complex dependency to a single factor (e.g., emissions of biogenic isoprene are a complicated function of the temperature and the wavelength distribution of incoming sunlight at the leaf surface but are typically modeled as a function of ambient temperature and sunlight intensity at a single wavelength). Emission model contains an invalid representation of the process producing emissions (e.g., older versions of motor vehicle emission factor models significantly underestimated evaporative VOC emissions).	Verify the theoretical basis for all models. Validate emissions models against independent data. Use continuous variable representations where feasible and appropriate.

Most emission estimates are the product of a series of quasi-independent parameters (i.e., emission factor, activity data, control factor, temporal adjustment) of the form

$$ER_t = p_1 \times p_2 \times \ldots \times p_n \qquad (1)$$

where:

ER_t	=	Emission rate for time t;
p_i	=	Parameter used to estimates emissions, where i = 1, 2, . . ., n;
n	=	Number of parameters.

This same general equation, or linear model, applies to the simple case of an emission factor (e.g., grams per kilogram combusted) times an activity datum (e.g., number of kilograms combusted per day) as well as to the complex case where a model such as MOBILE5a or BEIS are used (although nonlinear terms may be introduced as well).

There are a number of real-world problems and complexities associated with estimating emissions uncertainty when the linear model is used to develop the emission inventory. These problems include the inherent (and generally erroneous) assumption of independence of the individual parameters, the complications inherent in obtaining temporal, spatial, and speciated estimates of emissions from average values of emissions (e.g., obtaining gridded, speciated, hourly emission estimates from annual county-wide emission estimates), the limited amount of data that may be available for validation of estimates, and the difficulty posed by temporal and spatial data dependencies in validating those estimates even when data are available.

The use of surrogate variables is common in area source methods where population or the number of employees are used as surrogates for emission activities. The uncertainty in using these surrogates is especially high when emissions for a small region (i.e., county or smaller area) are estimated using a national average factor. Local variations in activity are not necessarily accounted for by population or employment. A common example is found in large cities that have the corporate headquarters for an industry. The number of employees may be high, but all of the manufacturing may be occurring in other areas.

Per capita emission factors are often an oversimplification of emission processes. For example, the consumer/commercial solvent use factors are based on a national survey of the solvent constituents of various consumer products. From this data set, the national average consumption per person was calculated for various product groups (see Volume III, Chapter 5 of the EIIP series). These factors may not account for solvent that is not emitted because it is either disposed of (in containers) or washed down the drain; furthermore, publicly owned treatment works (POTW) or landfill emissions may include these solvents, and emissions may therefore be double-counted. The factors also do not reflect regional variation in product usage, so when used to calculate emissions on a county basis, they are likely to over- or underestimate.

Point source emissions are also often based on the use of surrogates, although usually the surrogate is very closely related to the emissive activity. Fuel consumption, for example, is a surrogate for fuel combustion in a specific type of boiler. When an emission factor is used to estimate point source emissions, the assumption is that the design, processes, and test conditions of the original boiler (from which test data were derived) are good approximations of the boiler to which the factor is being applied. The further this assumption is from reality, the more uncertainty there is regarding the accuracy of the emission estimate.

This discussion of uncertainty in emissions inventories is by no means exhaustive. More details are provided in the specific volumes and chapters for point, area, mobile, and biogenic source categories. The EIIP has sought to encourage the reduction in uncertainty in their selection of "preferred" methods wherever possible. Emission factors are usually not the best choice if reducing uncertainty is the criterion; direct or indirect measurements, surveys, and other methods targeting the specific source are preferred. Unfortunately, this is not always practical. It is important that inventory preparers recognize the sources of uncertainty, quantify it, and reduce it as much as is practical.

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3

QUALITATIVE UNCERTAINTY ANALYSIS

The simplest approach for estimating uncertainty is to discuss all known and suspected sources of bias and imprecision in the inventory. If possible, the direction (over- or underestimates) of any biases and relative magnitude (e.g., factor of two, order of magnitude) of the specific source of uncertainty should be stated. Sometimes standard deviations, confidence limits, or other statistics are available for some of the variables used to develop the inventory; if so, those statistics should be documented and their contribution to overall accuracy of the estimates should be discussed.

The qualitative uncertainty assessment can be presented in narrative form. However, tables provide a more systematic and concise method of summarizing the uncertainty. An example of a qualitative uncertainty assessment is shown in Table 4.3-1. This table is part of a report describing the results of the QA/QC procedures used during development of an inventory of emissions from offshore oil production facilities (Steiner et al., 1994). Many of the key sources of uncertainty shown are generally applicable to any inventory (e.g., survey respondent expertise and applicability/usage components). It is more important to list and discuss issues that are particularly relevant. For example, the authors of this study do a good job of describing uncertainties in their survey data.

A table such as this one is a good method for presenting the results of a qualitative assessment. One additional column that describes the direction (positive or negative) of any biases or the relative magnitude of any imprecision (if these are known) would provide additional valuable information to the assessment.

TABLE 4.3-1

SUMMARY OF UNCERTAINTIES ASSOCIATED WITH THE OCS PRODUCTION-RELATED EMISSIONS INVENTORY[a]

Inventory Component	Basis of Uncertainty	Description
Survey	Survey Respondent Expertise	Different levels of expertise of survey recipients could lead to incorrect or incomplete survey answers because of lack of understanding or incorrect interpretation.
	Unknown Answers	Some of the equipment on the platforms is very old and equipment ratings cannot be read or the equipment has been modified and manufacturers' ratings no longer are applicable.
	Incorrect Responses	Most likely some respondents did not read the directions, which could lead to aberrant or incomplete answers. Many of the problems corrected in the database were a result of incorrect units. Some of the flow rates in the survey were metered, others were not metered, and survey respondent had to guess activity levels.
	Data Entry	Even though we used a double data entry system to enter the data to minimize typographical and data omission errors, some may have occurred. In addition, some respondents had their survey responses typed onto forms by support staff, which could lead to data entry errors.
	Omitted Sources	15 percent of the companies operating platforms in the GOM contacted did not return the survey. Some of those companies may have multiple platforms. All of the major corporations operating in the Gulf returned their surveys. Some emissions sources (e.g., equipment) on the platforms may have been omitted because the survey respondent neglected to include information necessary. 6 percent of the helicopter companies contacted did not return the survey. Only the smaller helicopter companies did not return their survey. 26 percent of the vessel companies contacted did not return the survey. The companies that did not return the surveys are the smaller operations.
Emissions Methodology	Emission Factors	Emission factors represent an average population. Gulf population may not be representative of the emission factor mix.
	Fugitive Emissions	An empirical formula derived from Pacific OCS facilities was used. Gulf OCS platforms were not exactly configured as those in Pacific and product mix of oil and gas was different.
	Applicability/Usage	Even though the methodologies were reviewed for applicability, there is the possibility that a more applicable emissions methodology exists or that the methodology was applied incorrectly because of an incorrect assumption.

[a] Source: Steiner et al., 1994. OCS = outer continental shelf. GOM = Gulf of Mexico.

4

SEMIQUANTITATIVE DATA QUALITY RANKINGS

Semiquantitative ranking methodologies are relatively easy to implement and can be used where detailed data on emissions are unavailable. A drawback of their use is that it can be difficult to prevent logical inconsistencies (i.e., A > B, B > C, and C > A) because subjective criteria are applied by different people at different times. Some older methods such as those used for *AP-42* emission factors (U.S. EPA, 1995) rely on a ranking for each emission factor from A (best) to E (worst). No numerical uncertainty values are associated with each rating. Newer methods such as DARS (Beck et al., 1994) assign a numerical value to the quality of the various components of the emissions inventory and allow numerical manipulation of the uncertainty estimates of the system.

The DARS and other ranking methods are discussed below. Table 4.4-1 summarizes the preferred and alternative methods for ranking systems.

TABLE 4.4-1

PREFERRED AND ALTERNATIVE METHODS FOR RANKING SYSTEMS

Preferred	Provide DARS scores for all sources.
Alternative 1	Provide DARS scores for the largest sources (specify criteria used to identify "largest").
Alternative 2	Use a letter grade or numerical scheme to rank data quality; provide rules and rationale used to develop scores and make sure system is used consistently throughout the inventory.

4.1 DARS

The Data Attribute Rating System or DARS is currently under evaluation by the EIIP's Quality Assurance Committee (QAC). EPA originally developed DARS to assist in evaluating country-specific inventories of greenhouse gases. The system disaggregates emission estimates into emission factors and activity data, then assigns a numerical score to each of these two components. Each score is based on what is known about the factor and activity parameters, such as the specificity to the source category, spatial (geographical) congruity, measurement of estimation techniques employed, and temporal congruity. The resulting emission factor and activity data scores are combined to arrive at an overall confidence rating for the inventory.

DARS defines certain classifying attributes that are believed to influence the accuracy, appropriateness, and reliability of an emission factor or activity and derived emission estimates. This approach is quantitative in that it uses numeric scores; however, scoring is based on qualitative and often subjective assessments. DARS also disaggregates specific attributes of the data and methods utilized in development of the inventory, thus providing perspective on the reason for the overall rating.

The DARS approach, when applied systematically by inventory analysts, can be used to provide a measure of the merits of one emission estimate relative to another. The proposed inventory data rating system cannot guarantee that an emission inventory with a higher overall rating is of better quality, or more accurate, or closer to the true value. The inventory with the higher overall rating is *likely* to be a better estimate, given the techniques and methodologies employed in its development.

An example of DARS scores for the architectural surface coatings area source category is shown in Table 4.4-2. Two alternative methods were used to estimate emissions from an urban area; one was based on a survey of paint distributors (conducted several years prior to the inventory) in the area, the other used a national per capita factor based on data from within one year of the inventory year. The more labor-intensive method gives a much higher overall DARS score. More information on considerations in using DARS scores for paints and coatings emission sources is presented in Appendix F.

EIIP members have recognized the potential utility of DARS for inventories at all levels. Among the proposed uses of DARS are:

- To identify the weakest areas of an inventory for further research and improvement;
- To use as one of several methods to quickly compare different inventories;
- To rank alternative emission estimation methods (the EIIP Area and Point Source Committees have used DARS as one of several tools to select the best method);
- To set DQO targets during the inventory planning stage; and

TABLE 4.4-2

DARS SCORES FOR ARCHITECTURAL SURFACE COATING EMISSIONS ESTIMATED BY TWO DIFFERENT METHODS

Attribute	Factor	Activity	Emissions
Local Survey			
Measurement/Method	0.7	0.9	0.63
Source Specificity	1.0	1.0	1.00
Spatial	1.0	1.0	1.00
Temporal	0.7	1.0	0.70
Composite	0.85	0.975	0.83
Per Capita Factor			
Measurement/Method	0.3	0.4	0.12
Source Specificity	1.0	0.3	0.30
Spatial	0.3	0.3	0.09
Temporal	0.7	1.0	0.70
Composite	0.575	0.5	0.30

- To provide a means of ranking inventories.

A more thorough discussion of the recommended EIIP approach for DARS is provided in Appendix F of this volume.

4.2 *AP-42* EMISSION FACTOR RATING SYSTEM

The U.S. EPA's *Compilation of Air Pollutant Emission Factors, AP-42*, is the primary reference for emission factors in the United States (U.S. EPA, 1995). Each *AP-42* emission factor is given a rating of A through E, with A being the best. A factor's rating is a general indication of the reliability, or robustness, of that factor. This rating is assigned using expert judgement. That judgement is based on the estimated reliability of the methods used to develop the factor, and on both the amount and the representative characteristics of the data.

In general, emission factors based on many observations, or on more widely accepted test procedures, are assigned higher rankings. Conversely, a factor based on a single observation of questionable quality, or one extrapolated from another factor for a similar process, is usually rated much lower. Because emission factors can be based on source tests, modeling, mass balance, or other information, factor ratings can vary greatly. In addition, there is a wide variation in the amount of QA to which each factor has been subjected.

Because the ratings do not consider the inherent scatter among the data used to calculate factors, the ratings do not imply statistical error bounds or confidence intervals about each emission factor. At most, a rating should be considered an *indicator* of the accuracy and precision of a given factor. This indicator is largely a reflection of the professional judgement of *AP-42* authors and reviewers concerning the reliability of any estimates derived with these factors.

Two steps are involved in factor rating determination. The first step is an appraisal of data quality or the reliability of the basic emission data that will be used to develop the factor. The second step is an appraisal of the ability of the factor to stand as a national annual average emission factor for that source activity. The *AP-42* rating system for the quality of the test data consists of four categories and is presented in Table 4.4-3.

The quality rating of *AP-42* data helps identify satisfactory data, even when it is not possible to extract a factor representative of a typical source in the category from those data. For example, the data from a given test may be good enough for a data quality rating of "A," but the test may be for a unique feed material, or the production specifications may be either more or less stringent than at the typical facility.

TABLE 4.4-3

AP-42 RATING SYSTEM FOR EMISSIONS TEST DATA

Rating	Description
A	Tests are performed by a sound methodology and are reported in enough detail for adequate validation.
B	Tests are performed by a generally sound methodology, but lacking enough detail for adequate validation.
C	Tests are based on an unproven or new methodology, or are lacking a significant amount of background information.
D	Tests are based on a generally unacceptable method, but the method may provide an order-of-magnitude value for the source.

The *AP-42* emission factor rating is an overall assessment of how good a factor is, based on both the quality of the test(s) or information that is the source of the factor and on how well the factor represents the emission source. Higher ratings are for factors based on many unbiased observations, or on widely accepted test procedures. For example, a factor based on 10 or more source tests on different randomly selected plants would likely be assigned an "A" rating if all tests are conducted using a single valid reference measurement method. Likewise, a single observation based on questionable methods of testing would be assigned an "E", and a factor extrapolated from higher-rated factors for similar processes would be assigned a "D" or an "E." A description of the *AP-42* emission factor quality ratings is given in Table 4.4-4.

The *AP-42* emission factor scores are of some value as indicators of the quality of emissions estimates. At best, they rate the quality of the original data as applied to estimates for that original point source. However, when applied to other sources or to groups of sources (i.e., area sources) the *AP-42* factor score is less meaningful because it does not consider how similar the original source and the modeled source(s) are, and it does not address the quality of the activity data at all.

4.3 OTHER GRADING SYSTEMS

A review of inventory quality rating systems was recently completed for the EPA (Saeger, 1994). Several systems similar to the *AP-42* system are described.

TABLE 4.4-4

AP-42 RATING SYSTEM FOR EMISSION FACTORS[a]

Ranking	Quality Rating	Discussion
A	Excellent	Factor is developed from A- and B-rated source test data taken from many randomly chosen facilities in the industry population. The source category population is sufficiently specific to minimize variability.
B	Above Average	Factor is developed from A- or B-rated test data from a "reasonable number" of facilities. Although no specific bias is evident, it is not clear if the facilities tested represent a random sample of the industry. As with an A rating, the source category population is sufficiently specific to minimize variability.
C	Average	Factor is developed from A-, B-, and/or C-rated test data from a reasonable number of facilities. Although no specific bias is evident, it is not clear if the facilities tested represent a random sample of the industry. As with the A rating, the source category population is sufficiently specific to minimize variability.
D	Below Average	Factor is developed from A-, B-, and/or C-rated test data from a small number of facilities, and there may be reason to suspect that these facilities do not represent a random sample of the industry. There also may be evidence of variability within the source population.
E	Poor	Factor is developed from C- and D-rated test data, and there may be reason to suspect that the facilities tested do not represent a random sample of the industry. There also may be evidence of variability within the source category population.

[a] Source: U.S. EPA, 1995.

A method used in Great Britain is based on letter ratings assigned to both emission factors and the activity data. The combined ratings are then reduced to a single overall score following an established protocol. The emission factor criteria for the letter scores are similar to those applied in the U.S. EPA's approach and scores for the activity data are based largely on the origin of the data. Published data either by a government agency or through an industry trade association are assigned C ratings and extrapolated data based on a surrogate would receive an E rating.

The Intergovernmental Panel on Climate Change (IPCC) uses a rating scheme in its guidelines for reporting of greenhouse gas emissions. The IPCC system incorporates an assessment of completeness and of overall data quality in a code. Table 4.4-5 shows the codes used for each of four characteristics. These codes are entered in an inventory review table (such as the one shown in Figure 2.4-1, Chapter 2 of this volume).

4.4 GEIA RELIABILITY INDEX

The Global Emissions Inventory Activity (GEIA) group is a consortium of research institutions that is attempting to develop common data sets for use in developing global emissions inventories. Data are supplied to this group from many different sources. The person supplying the data is asked to categorize it into one of three reliability categories of <50 percent, 50-100 percent, or >100 percent that represent the estimated error in the data.

This categorization relies entirely in the subjective judgements of the data originator. If a system like this is used, the inventory developer should clearly define each category and provide a rationale for the assignment of each category. This type of approach may be most useful as a relative indicator for categories within a given inventory (particularly if used in combination with a qualitative assessment as described above). Without some standardization of the reliability category definitions, this method is not suitable for comparisons between inventories.

TABLE 4.4-5

DATA QUALITY CODES RECOMMENDED BY THE IPCC[a]

Estimates		Quality		Documentation		Disaggregation	
Code	Meaning	Code	Meaning	Code	Meaning	Code	Meaning
Part	Partly estimated	H	High confidence in estimation	H	High (all background information included)	1	Total emissions estimated
All	Full estimate of all possible sources	M	Medium confidence in estimation	M	Medium (some background information included)	2	Sectoral split
NE	Not estimated	L	Low confidence in estimation	L	Low (only emission estimates included)	3	Subsectoral split
IE	Estimated but included elsewhere						
NO	Not occurring						
NA	Not applicable						

[a] Source: Intergovernmental Panel on Climate Change (IPCC), 1995.

5

QUANTITATIVE UNCERTAINTY ANALYSIS

This section describes several methods for generating statistically based uncertainty estimates. They differ from previous methods in that they give quantitative, or numerical, estimates of the error associated with emission estimates. Table 4.5-1 summarizes the preferred and alternative methods for conducting quantitative uncertainty analysis. As discussed in the introduction to this chapter, the intended uses of the emissions data should be considered before spending significant resources on quantifying the uncertainty associated with the estimates.

TABLE 4.5-1

PREFERRED AND ALTERNATIVE METHODS FOR QUANTIFYING UNCERTAINTY

Preferred	Use expert judgment (based on as much data as are available) to estimate standard deviation (or coefficient of variation) and distribution for key variables for each source type or category. Conduct probabilistic modeling (e.g., Monte Carlo), accounting for dependencies between variables.
Alternative 1	Develop standard deviations (as above), assume independence, and use error propagation to estimate uncertainty limits.
Alternative 2	Use Delphi Method or other survey of experts to generate upper and lower bounds in estimates.

5.1 EXPERT ESTIMATION METHOD

In general, information on the distributional nature of emissions data is required for a quantitative analysis. These data include the type of distribution that best fits the data, and values of the key distribution parameters (i.e., mean or median and variance) are generally unavailable. Typically, no information is available to define the distribution of activity data as being normal, lognormal, or some other distribution, and there are no estimates of mean or standard deviation of the parameter of concern. The most readily available source of data for use in emission uncertainty analysis is "expert judgement." Consequently, experts are asked to estimate key parameters associated with an emission inventory such as the qualitative lower and upper bounds of an emission estimate or the shape of a particular parameter distribution.

One approach is the highly formalized Delphi method (Linstene and Turoff, 1975) in which the opinion of a panel of experts working separately but with regular feedback converges to a single answer. The Delphi approach does not require an assumption of either independence or distribution of the underlying emissions data and is a very powerful technique when used properly and is focused on the "right" question. However, its capability is limited by the quality of the "experts" selected and the care with which the analysis protocol is followed. The work at the South Coast Air Quality Management District (SCAQMD, 1982) is an example of application of a simple Delphi technique to assess uncertainty in a large-scale inventory.

Expert judgement outside a formal Delphi framework is also used to estimate emissions uncertainty. In these methods, which can be relatively simplistic to highly structured, one or more experts make judgements as to the values of specific distributional parameters for a number of sources. For example, Horie (1988) used graphical techniques to estimate confidence limits once estimates of upper and lower limits of emissions were developed through expert judgement. Dickson and Hobbs (1989) applied three separate methods, including Horie’s, to estimate the confidence limits for a number of source categories after developing estimates of the uncertainty parameters based upon questionnaires filled out by a panel of emission inventory experts.

Table 4.5-2 presents a portion of the results of Dickson and Hobbs. This table presents alternative estimates of uncertainty in VOC emissions in the San Joaquin Valley for 1985 using the lognormal method of Mangat et al. (1984), the probability method of Horie (1988), and the error propagation method as implemented by Benkovitz (1985), which is discussed in the next section. The estimates of uncertainty for emission factors and activity data for each individual source type were obtained through a polling of experts. Once these data were compiled and processed, a simple Monte Carlo simulation was used to estimate uncertainty in the entire inventory for the Mangat and Horie approaches. For the error propagation method, estimates of overall inventory uncertainty were obtained directly through error propagation. For most categories (only four are presented in the table), the lognormal and error propagation methods yield similar results with slightly larger differences produced using the probability method.

All three of these methods require the assumptions of independence of the activity data and emission factors, assumptions that are not often met. In addition, each method makes the explicit assumption of normality (or lognormality) of the emissions data. A consequence of

TABLE 4.5-2

COMPARISON OF VOC EMISSION UNCERTAINTY ESTIMATES DERIVED USING THREE ALTERNATIVE UNCERTAINTY ESTIMATION METHODS[a]

VOC Area Source Category	Median Emission Estimate (Med)			90% Upper Confidence Limit (UCL_{90})			Relative Percentage Difference[b] [(UCL_{90}-Med)/Med*100]		
	LN	P	EP	LN	P	EP	LN	P	EP
On-Road Motor Vehicles	30	29	29	35	41	36	17	41	22
Surface Coating	9.2	9.6	9.1	11	16	11	18	63	18
Pesticide Use	21	22	21	25	27	26	19	25	22
Oil Production	150	150	140	200	190	200	33	27	37
All Sources	210	210	200	260	260	260	23	21	27

[a] Source: Dickson and Hobbs, 1989. Emissions are for 1985 for the San Joaquin Valley and units are in thousands of tons per year.
[b] Computed prior to rounding median and upper confidence limits to two significant figures.

LN Lognormal Method of Mangat et al., 1984.
P Probability Method of Horie, 1988.
EP Error Propagation Method, Benkovitz, 1985.

a violation of any of these basic assumptions is that the uncertainty estimates that result are typically biased low. The fact that emissions data often violate these assumptions is a major weakness in most simple emission uncertainty estimation methodologies such as the three listed in Table 4.5-2. A strength of these methods, however, is their relatively low implementation cost when compared to the next two methods discussed in this section. In many circumstances, reasonable estimates of uncertainty for a multicounty or regional inventory can be developed for less than 2,000 hours of effort.

Note that these methods are different from the GEIA reliability index (and other ranking systems) discussed in the previous section. While all rely on expert judgement, the methods described in this section rely on sampling expert opinions and using that data to develop statistical indicators.

5.2 PROPAGATION OF ERROR METHOD

Error propagation methods follow traditional statistical methodology to estimate the composite error introduced by the joint action of a number of individual factors each with their own uncertainty. These error propagation methods are based upon the twin assumptions that:

- Emission estimates are equal to the product of a series of parameters; and
- Each of the parameters is independent (i.e., no temporal or spatial correlations among the parameters).

A good example of an error propagation analysis used to estimate emissions uncertainty in a large-scale emissions inventory is the National Acid Precipitation Assessment Program (NAPAP, 1991). For NAPAP, Benkovitz (1985) used a Taylor's series expansion of the equation describing the variance of a series of products to develop an analytic closed-form to an otherwise intractable problem. In particular, the assumption of independence allows the variance of multiplicative products to be expressed in terms of the individual variances. There is general agreement that the uncertainty in the NAPAP inventory is underestimated, in part because of the incorrect assumption of independence of the emission parameters used in the NAPAP error propagation analysis (EPA, 1986).

The IPCC proposes that this approach be used only when the ranges in the emission factor and uncertainty do not exceed more than 60 percent above or below the mean emission estimate. The uncertainty in each component (i.e., the factor and activity) is first established using classical statistical analysis (Chapter 3, Section 7 of this volume), probabilistic modeling (described in next section), or the formal expert assessment methods (described in the previous section). Figure 4.5-1 presents an excerpt from the IPCC guidelines (IPCC,

TABLE A1-1
UNCERTAINTIES DUE TO EMISSION FACTORS AND ACTIVITY DATA

1	2	3	4	5
Gas	**Source category**	**Emission factor** U_E	**Activity data** U_A	**Overall uncertainty** U_T
CO_2	Energy	7%	7%	10%
CO_2	Industrial Processes	7%	7%	10%
CO_2	Land Use Change and Forestry	33%	50%	60%
CH_4,	Biomass Burning	50%	50%	100%
CH_4	Oil and Nat. Gas Activities	55%	20%	60%
CH_4	Coal Mining and Handling Activities	55%	20%	60%
CH_4	Rice Cultivation	3/4	1/4	1
CH_4	Waste	2/3	1/3	1
CH_4	Animals	25%	10%	25%
CH_4	Animal waste	20%	10%	20%
N_2O	Industrial Processes	35%	35%	50%
N_2O	Agricultural Soils			2 orders of magnitude
N_2O	Biomass Burning			100%

Note: Individual uncertainties that appear to be greater than ± 60% are not shown. Instead judgement as to the relative importance of emission factor and activity data uncertainties are shown as fractions which sum to one.

A1.2 Procedures for Quantifying Uncertainty

Estimating Uncertainty of Components

To estimate uncertainty by source category and gas for a national inventory, it is necessary to develop information like that shown in Table A1-1, but specific to the individual country, methodology and data sources used. In scientific and process control literature the 95 per cent (± 2) confidence limit is often regarded as appropriate for range definition. Where there is sufficient information to define the underlying probability distribution for conventional statistical analysis, a 95 per cent confidence interval should be calculated as a definition of the range. Uncertainty ranges can be estimated using classical analysis (see Robinson) or the Monte Carlo technique (in Eggleston, 1993). Otherwise the range will have to be assessed by national experts.

FIGURE 4.5-1. RECOMMENDED IPCC PROCEDURES FOR QUANTIFYING UNCERTAINTY (SOURCE: IPCC, 1995)

If possible ranges should be developed separately for

- emission factors (and other assumptions in the estimation method) (column 3 of Table A1-1).
- socio-economic activity data (column 4 of Table A1-1)

Combining Uncertainties

It is necessary to derive the overall uncertainty arising from the combination of emission factor and activity data uncertainty. IPCC/OECD suggest that emission factor and activity data ranges are regarded as estimates of the 95 per cent confidence interval, expressed as a percentage of the point estimate, around each of two independent components (either from statistically based calculations or informal *ex ante* judgements).

On this interpretation (for quoted ranges extending not more than 60 per cent above or below the point estimate) the appropriate measure of overall *percentage* uncertainty U_T for the emissions estimate would be given by the square root of the sum of the squares of the *percentage* uncertainties associated with the emission factor (U_E) and the activity data (U_A). That is, for each source category:

$$U_T = \pm\sqrt{\left(U_E^2 + U_A^2\right)}; \text{ so long as } |U_E|,\ |U_A| < 60\%\ ^1$$

For individual uncertainties greater than 60 per cent the sum of squares procedure is not valid. All that can be done is to combine limiting values to define an overall range, though this leads to upper and lower limiting values which are asymmetrical about the central estimate[2].

Estimated total emission for each gas is of course the summation ΣC_i where C_i is the central estimate of the emission of the gas in the source category. The appropriate measure of *uncertainty* in total emissions in emissions units (not percentages) is then:

$$E = \pm(1/100)\cdot\sqrt{\left(\Sigma U_{T,i}^2 \cdot C_i^2\right)}$$

where $U_{T,i}$ is the overall percentage uncertainty for the source category of the gas from Table A1-1. Source categories for which symmetrical limiting values cannot be defined (because $|U_E|$ or $|U_A|$ exceeds 60 per cent) cannot sensibly be treated in this way. The uncertainty might be handled by reporting that total emissions from gas X are estimated to be Y Mt, of which Y_1 Mt had an estimated uncertainty of $\pm E_1$ Mt and Y_2 Mt had a range of uncertainty between - L Mt and + U Mt.

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[1] The 60% limit is imposed because the rule suggested for U_T requires σ to be less than about 30% of the central estimate, and we are interpreting the quoted range as $\pm 2\sigma$

[2] If uncertainties due to the emission factor and the activity data are ± E% and ± A% respectively, and the upper and the lower limits of overall uncertainty are U% and L% respectively, then U% = (E+A+E·A/100) and L% = (E+A-E·A/100).

FIGURE 4.5-1. CONTINUED

A1.3 Implications

If the assumptions in Table A1.1 are correct then typical uncertainties in national emissions estimates range between:

- ± 10% for CO_2 from fossil fuels although this may be lower for some countries with good data and where source categories are well defined (IPCC, 1993; von Hippel et al., 1993)
- ± 20% and ± 100% for individual methane sources (though the overall error might be ± 30%)
- perhaps two orders of magnitude for estimates of nitrous oxide from agricultural soils

These uncertainties will affect the level of quantitative understanding of atmospheric cycles of greenhouse gases that can be derived using the summation of inventories.

The situation is less critical for monitoring emissions mitigation options, because the profile of the emissions time series will be relatively insensitive to revisions to the emissions estimation methodology. However very different levels of uncertainty for different gases will be inevitable for some time to come, and this will need to be recognised in any move towards a comprehensive approach to greenhouse gas mitigation.

A1.4 References

(IPCC) Intergovernmental Panel on Climate Change (1992), *Climate Change 1992: The Supplement to the IPCC Scientific Assessment.*

The method for combining errors in a multiplicative chain are given in many statistical textbooks, but note Jennifer Robinson's discussion (On uncertainty in the computation of global emissions from biomass burning, *Climatic Change*, 14, 243-262) about the difficulties which arise at high coefficients of variation.

H S Eggleston (1993), "Uncertainties in the estimates of emissions of VOCs from Motor Cars." Paper presented at the *TNO/EURASAP Workshop on the Reliability of VOC Emission Databases*, June 1993, Delft, The Netherlands.

IPCC (1993), "Preliminary IPCC national GHG inventories: in depth review." Report presented at the *IPCC/OECD Workshop on National GHG Inventories*, October 1993, Bracknell, UK.

von Hippel et al. (1993), "Estimating greenhouse gas emissions from fossil fuel combustion", *Energy Policy*, 691-702, June 1993.

FIGURE 4.5-1. CONTINUED

1995). [Note that the nomenclature used in the IPCC example is not always consistent with EIIP terms. In particular, "point estimate" refers to the statistical concept of a single number that may be an average or an engineering judgement; it does not refer to "point sources" or single facilities.]

An example of the input data used in an error propagation analysis for the Grand Canyon Visibility Transport Commission emissions inventory is given in Table 4.5-3 (Balentine et al., 1994). In this study, Balentine et al. used expert judgement to estimate emissions uncertainty for all significant source classes and then developed refined estimates of uncertainty for nine source categories using error propagation methodology. Emissions from each source category were assumed to be a multiplicative function of the underlying emission parameters. For each of the nine categories for which refined uncertainty estimates were made, estimates of the coefficient of variation of each emission parameter contributing to the uncertainties were developed based upon the analysis of surrogate parameters and expert judgement. Including data acquisition (but not inventory development), this study required less than 300 staff hours to complete.

For the example source category given in Table 4.5-3 (industrial and commercial fuel combustion), the emission estimate, and hence uncertainty, was assumed to be a function of the number of sources, the distillate oil demand, the average sulfur content, and the variability in the *AP-42* emission factor. Application of the error propagation method with the data in Table 4.5-3 yields an overall composite coefficient of variation of approximately 40 percent, estimated as the square root of the sum of the square of the individual coefficients of variation. Again, this method requires the generally poorly met assumptions of independence and normal (lognormal) distribution of the individual emission parameters.

5.3 DIRECT SIMULATION METHOD

Direct simulation methods are statistical methods in which the uncertainty and confidence limits in emission estimates are directly computed using statistical procedures such as Monte Carlo (Freeman et al., 1986), bootstrap and related resampling techniques (Efron and Tibshirani, 1991), and Latin hypercube approaches (Iman and Helton, 1988). A major benefit of these statistical procedures is that the lack of independence in emission parameters is not a limitation. If set up and performed properly, the analysis methodology explicitly accounts for any dependencies as part of the statistical formulation of the problem.

The common Monte Carlo technique is a powerful direct simulation method. Freeman et al. (1986) applied this technique to evaluate uncertainty in the input parameters, including emissions, in an air quality model. Environment Canada (1994) applied the methodology to estimate uncertainty in greenhouse gas emissions for Canada. Table 4.5-4 presents the Environment Canada Monte Carlo results for carbon dioxide (CO_2) emissions in Canada.

TABLE 4.5-3

ESTIMATED COEFFICIENT OF VARIATION FOR PARAMETERS USED IN ESTIMATING SO_2 EMISSIONS FROM INDUSTRIAL AND COMMERCIAL SOURCES[a]

Parameter	Source	Discussion	Coefficient of Variation (%)
Number of industrial and commercial sources	Dickson et al., 1992	Variation in day-specific emissions from annual day emissions for 33 facilities in Wisconsin.	15
Distillate oil demand	Oil and Gas Journal, 1992, 1993, and 1994	1992-1994 quarterly variability in nontransportation distillate fuel demand.	5
Distillate oil average sulfur content	El-Wakil, 1984	Average sulfur content for No. 2 and No. 6 fuel oils.	25
Emission factor variability	Assumption based on *AP-42*, Table 1.3-1; EPA, 1985	*AP-42* uncertainty in emission factor given as an "A" rating.	20

[a] Source: Balentine et al., 1994.

The estimated uncertainty in emissions in individual source categories varied from 5 percent for diesel fuel combustion to 40 percent for coal combustion. Because the Environment Canada study made the assumption of independence between parameters, the resultant uncertainty estimates should be considered lower limits.

One limitation of the Monte Carlo approach is that a distribution type and distribution values for each emission parameter must be specified. Typically, expert judgement is required to make some or all the estimates of distribution type and parameters. A second limitation (but also a strength because it gets around the assumption of independence) is that all underlying dependencies between the various parameters must be accounted for when formulating the model. These dependencies can be taken into account during randomization of each parameter because the same random number can be used to estimate multiple parameters that are correlated (e.g., if population is a factor in multiple emission parameters, the same random number can be used to estimate each factor that is dependent on population rather than allowing use of independent random numbers).

The Latin hypercube methodology (Iman and Helton, 1988) has evolved from the Latin square methodology (Cox, 1958) commonly used for planning and analyzing field

TABLE 4.5-4

ESTIMATES OF UNCERTAINTY OF CO_2 EMISSIONS IN CANADA PRELIMINARY 1990 CO_2 ESTIMATES IN KILOTONNES[a]

Source Group	At 95% Confidence Level		
	Range of Emissions (Rounded) From/To	Range Width	Overall Uncertainty (± %)
Industrial Processes			
• Cement Process Only	4,700/6,000	1,300	(12)
• Lime & Other	1,900/2,600	700	(15)
Inorganics	5,100/7,300	1,800	(18)
• Stripped Natural Gas	9,900/18,400	8,500	(30)
• Non Energy Use			
Subtotal	23,350/32,254	8,903	(16)
Fuel Combustion			
• Power Generation	89,000/99,000	10,000	(5)
• Residential	38,000/43,000	5,000	(6)
• Commercial	22,500/25,500	3,000	(6)
• Industrial/Steam	72,500/85,500	13,000	(8)
• Agriculture	2,280/2,680	400	(8)
• Public Administration	1,900/2,200	300	(8)
• Refinery Use	12,500/18,700	6,200	(20)
• Oil & Gas Production	22,700/34,000	11,300	(20)
• Pipeline	6,000/7,400	1,400	(10)
• Coal	240/560	320	(40)
• Miscellaneous	200/500	300	--
Subtotal	282,409/304,074	21,666	(4)
Transportation			
• Gasoline	73,900/81,600	7,700	(5)
• Jet Fuels	11,900/14,500	2,600	(10)
• Diesel	44,900/49,700	4,800	(5)
• Natural Gas & Propane	1,500/1,900	400	(10)
Subtotal	135,024/144,540	9,515	(3.5)
Overall Total	448,185/473,467	25,283	(3)

[a] Source: Table 4.2.1-1 in Environment Canada, 1994.

measurements. A typical application of the Latin square approach would be an agricultural experiment examining the role of application of *n* alternative pesticides to *m* plant varieties in an effort to determine the combination that maximizes crop yield.

In the Latin hypercube approach, the methodology is expanded beyond the simple two-dimensional relationship to higher dimensions with multiple parameters and potential interactions. In an example involving emission estimates, the data set may consist of stack test measurements of emissions from industrial boilers and three of the variables included are the boiler type, load, and control device. Using the Latin hypercube approach, the internal relationship between load, boiler type, and control device would be approximated by the various random samples selected from the data set. This approach allows one to estimate directly the uncertainty of the parameter of interest (i.e., emission rate) as a function of the causative factors examined.

The numerical method developed by Oden and Benkovitz (1990) allows one to estimate uncertainty in the typical situation in which autocorrelations and covariances that occur in the parameters responsible for producing emissions. Using their methodology, it is possible to estimate the uncertainty accounting for the lack of independence between the parameters and to determine what this lack of independence contributes to the overall uncertainty.

Resampling methodologies such as the bootstrap method (Efron and Tibshirani, 1991) involve performing random sampling (with replacement) from a data set in order to estimate some statistical parameter such as the standard error or variance. For a small data set, a direct computation of the parameter of interest can be highly uncertain given the small sample size or may not even be possible because there is no simple formula with which to compute the value. However, in bootstrap and other resampling methods, resampling with replacement both increases the effective size of the data set and allows direct estimation of parameters of interest. While there are difficulties in applying resampling techniques to emissions data because they are temporally correlated, recent work by Carlstein (1992) has allowed bootstrap techniques to be applied in situations with temporally correlated data.

The major drawback of the direct simulation methodologies is the computationally intensive nature of the techniques. However, as computing costs decrease with the advent of increasingly more powerful desktop computers, this limitation is becoming less important as a selection criteria for an uncertainty estimation methodology. Because of the complexity of the statistical analyses required, staff members with advanced degrees in statistics are typically involved in studies using direction simulation methods to estimate uncertainty. Also, the level of effort required can approach (or exceed) 1,000 staff hours depending upon the complexity of the analysis and the data collection required.

5.4 OTHER METHODS

In addition to the above methods, direct and indirect field measurement, receptor modeling, and inverse air quality modeling can be used to produce estimates of uncertainty (or relative uncertainty) in emission inventories. However, such methods can provide significantly more information than estimates of uncertainty. Each can produce emission estimates completely independent of standard emission computation methods. Typically, these other methods are very labor and data intensive, and can easily require 1,000 staff hours or more to collect the required data and perform the analysis.

Because these emission estimates are independent, they can be used as an independent verification of the emission estimates. This potential role in validating emission estimates is perhaps the most important use of information resulting from application of these methods. A detailed discussion of each method is given in Chapter 3, Section 9 of this volume.

6

REFERENCES

Balentine, H.W., R.J. Dickson and W.R. Oliver. 1994. *Development of Uncertainty Estimates for the Grand Canyon Visibility Transport Commission Emissions Inventory.* Radian Corporation Technical Memorandum, Sacramento, California. December.

Beck, L., R. Peer, L. Bravo, and Y. Yan. 1994. *A Data Attribute Rating System.* Presented at the Air & Waste Management Association's Emission Inventory Conference, Raleigh, North Carolina.

Benkovitz, C.M. 1985. *Framework for Uncertainty Analysis of the NAPAP Emissions Inventory*. U.S. Environmental Protection Agency, Air and Energy Engineering Research Laboratory. EPA/600/7-85/036. Research Triangle Park, North Carolina.

Benkovitz, C.M. and N.L. Oden. 1989. Individual Versus Averaged Estimates of Parameters used in Large Scale Emissions Inventories. *Atmospheric Environment* 23:903-909.

Carlstein E. 1992. Resampling techniques for stationary time series: Some recent developments. In: *The IMA Volumes in Mathematics and its Applications: New Directions in Time Series Analysis I.* Springer-Verlag, New York.

Chang, M., C. Cardelino, W. Chameides, and W. Chang. 1993. *An iterative procedure to estimate emission inventory uncertainties.* Presented at The Regional Photochemical Measurement and Modeling Studies Meeting of the Air & Waste Management Association at San Diego, California. November.

Chang, M., C. Cardelino, D. Hartley, and W. Chang. 1995. *Inverse Techniques for Developing Historical and Future Year Emission Inventories.* Presented at The Emission Inventory: Programs and Progress Specialty Conference of the Air & Waste Management Association, Research Triangle Park, North Carolina. October 11-13.

Chow, J.C., J.G. Watson, D.H. Lowenthal, P.A. Soloman, K.L. Magliano, S.D. Ziman, and L.W. Richards. 1992. PM_{10} Source Apportionment in California's San Joaquin Valley. Atmospheric Environment 26A:3335-3354.

Claiborn, C., A. Mitra, G. Adams, L. Bamesberger, G. Allwine, R. Kantamaneni, B. Lamb, and H. Westberg. 1995. Evaluation of PM_{10} Emission Rates from Paved and Unpaved Roads using Tracer Techniques. *Atmospheric Environment* 29:1075-1089.

Cox, D.R. 1958. *Planning of Experiments*. John Wiley and Sons, Inc., New York, pp. 35-44.

Dickson, R.J., and A.D. Hobbs. 1989. *Evaluation of Emission Inventory Uncertainty Estimation Procedures.* Paper 89-24.08, presented at the 82nd Annual Meeting of the Air & Waste Management Association, Anaheim, California.

Dickson, R.J., K.K. Mayenkar, and J. Laas. 1992. *Increasing the Accuracy of Hourly Emission Estimates Using Day-Specific Data in the Lake Michigan Ozone Study*. Paper 92-87.04, presented at the 85th Annual Meeting of the Air & Waste Management Association, Kansas City, Missouri.

El-Wakil, M.M. 1984. *Power Plant Technology*. McGraw-Hill, Inc., New York, New York. p. 149.

Efron, B., and R. Tibshirani. 1991. Statistical Data Analysis in the Computer Age. *Science* 253:390-395.

Finkel, A.M. 1990. *Confronting Uncertainty in Risk Management - A Guide for Decision-Makers*. Center for Risk Management, Resources for the Future, Washington, D.C.

Freeman, D.L., R.T. Egami, N.F. Robinson, and J.G Watson. 1986. A Method for Propagating Measurement Uncertainties through Dispersion Models. *Journal of the Air Pollution Control Association* 36:246-253.

Fujita, E.M., B.E. Croes, C.L. Bennett, D.R. Lawson, F.W. Lurmann, and H.H. Main. 1992. Comparison of Emission Inventory and Ambient Concentration Ratios of CO, NMOG, and NO_x in California's South Coast Air Basin. *Journal of the Air & Waste Management Association 42(3):264-276.*

Gatz, D.F., and L. Smith. 1995a. The Standard Error of a Weighted Mean Concentration - I. Bootstrapping vs Other Methods. *Atmospheric Environment* 29:1185-1193.

Gatz, D.F., and L. Smith. 1995b. The Standard Error of a Weighted Mean Concentration - I. Estimating Confidence Intervals. *Atmospheric Environment* 29:1195-1200.

Hartley, D., and R.J. Prinn. 1993. Feasibility of Determining Surface Emissions of Trace Gases Using an Inverse Method in a Three-Dimensional Chemical Transport Model. *Journal of Geophysical Research.* 98:5183-5197.

Horie, Y. 1988. *Handbook on Procedures for Establishing the Uncertainties of Emission Estimates.* Prepared for the California Air Resources Board Research Division, by Valley Research Corporation, ARB Contract A5-184-32. Sacramento, California. February.

Horie, Y., and A.L. Shorpe. 1989. *Development of Procedures for Establishing the Uncertainties of Emission Estimates.* Paper 89-24.7. Presented at the 82nd Annual Air & Waste Management Association Meeting, Anaheim, California, June.

Iman, R.L., and J.C. Helton. 1988. An Investigation of Uncertainty and Sensitivity Analysis Techniques for Computer Models. *Risk Analysis* 8:71-90.

Intergovernmental Panel on Climate Change (IPCC). 1995. *IPCC Guidelines for National Greenhouse Gas Reporting Instructions.* IPCC WGI Technical Inventories, Volume 1: Support Unit, Bracknell, United Kingdom.

Linstene, H.A., and M. Turoff. 1975. *The Delphi Method, Techniques and Applications.* Edited by Linstene and Turoff. Addison - Wesley Publishing Company.

Lowenthal, D.H., J.C. Chow, J.G. Watson, G.R. Neuroth, R.B. Robbins, B.P. Shafritz, and R.J. Countess. 1992. The Effects of Collinearity in the Ability to Determine Aerosol Contributions from Diesel- and Gasoline-Powered Vehicles using the Chemical Mass Balance Model. *Atmospheric Environment* 26A:2341-2351.

Mangat, T.S., L.H. Robinson, and P. Switzer. 1984. *Medians and Percentiles for Emission Inventory Totals.* Presented at the 77th Annual Meeting of the Air Pollution Control Association, San Francisco, California. June.

Mitchell, W.J., J.C. Suggs, and E.W. Streib. 1995. A Statistical Analysis of Stationary Source Compliance Test Audit Data. *Journal of the Air & Waste Management Association* 45:83-88.

Mulholland, M., and J.H. Seinfeld. 1995. Inverse Air Pollution Modelling of Urban-Scale Carbon Monoxide Emissions. *Atmospheric Environment* 29:497-516.

National Acid Precipitation Assessment Program. 1991. *Acidic Deposition: State of Science and Technology; Volume I - Emissions, Atmospheric Processes, and Deposition.* ISBN 0-16-036144-3. P.M. Irving, ed. Washington, D.C.

Oden, N.L., and C.M. Benkovitz. 1990. Statistical Implications of the Dependence Between the Parameters Used for Calculations of Large Scale Emissions Inventories. *Atmospheric Environment* 24A:449-456.

Oil and Gas Journal. Annual Forecast and Review, July 27, 1992, p. 63; July 26, 1993, p. 51, July 25, 1994, p. 55.

Peer, R.L., and D.L. Epperson, D.L. Campbell., and P. von Brook. 1992. *Development of an Empirical Model of Methane Emissions from Landfills.* United States Environmental Protection Agency, Air and Energy Engineering Laboratory, EPA-600/R-92-037, Research Triangle Park, North Carolina.

Pierson, W.R., A.W. Gertler and R.L. Bradow. 1990. Comparison of the SCAQS Tunnel Study with Other On-Road Vehicle Emission Data. *Journal of the Air & Waste Management Association.* 40(11):1495-1504.

Saeger, M. 1994. *Procedures for Verification of Emissions Inventories, Final Report*. Prepared for Emissions Inventory Branch, Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency, Research Triangle Park, North Carolina (EPA Contract No. 68-D3-0030).

Scheff, P.A., R.A. Wadden, D.M. Kenski, and J. Chang. 1995. *Receptor Model Evaluation of the SEMOS Ambient NMOC Measurements.* Paper 95-113C.03. Presented at the 88th Annual Meeting of the Air Pollution Control Association, San Antonio, Texas. June.

South Coast Air Quality Management District (SCAQMD). 1982. *Uncertainty of 1979 Emissions Data, Chapter IV: 1983 Air Quality Management Plan Revision, Appendix IV-A; 1979 Emissions Inventory for the South Coast Air Basin, Revised October 1982.* Planning Division, El Monte, California. October.

Spellicy, F.L., J.A. Draves, W.L. Crow, W.F Herget, and W.F. Buchholtz. 1992. *A Demonstration of Optical Remote Sensing in a Petrochemical Environment.* Presented at the Air & Waste Management Association Specialty Conference on Remote Sensing, Houston, Texas. April 6-9.

Steiner, C.K.R., L. Gardner, M.C. Causley, M.A. Yocke, and W.L. Steorts. 1994. Inventory Quality Issues Associated with the Development of an Emissions Inventory for the Minerals Management Service Gulf of Mexico Air Quality Study. In: *The Emission Inventory: Perception and Reality*. Proceedings of an International Specialty Conference, VIP-38. Air & Waste Management Association, Pittsburgh, Pennsylvania.

Environment Canada. *Uncertainties in Canada's 1990 Greenhouse Gas Emission Estimates, A Quantitative Assessment.* Prepared by T.J. McCann & Associates. Unpublished report. Ottawa, Ontario, March, 1994.

U.S. EPA. 1986. *Estimation of Uncertainty for the 1980 NAPAP Emission Inventory.* U.S. Environmental Protection Agency, Air and Energy Engineering Research Laboratory, EPA/600/S7-86/055. Research Triangle Park, North Carolina.

U.S. EPA. 1985-1993. *Compilation of Air Pollutant Emission Factors, Volume I: Stationary Point and Area Sources, Fourth Edition and Supplements, AP-42.* U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards. Research Triangle Park, North Carolina.

U.S. EPA. 1995. *Compilation of Air Pollutant Emission Factors, Volume I: Stationary Point and Area Sources, Fifth Edition, AP-42.* U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards. Research Triangle Park, North Carolina.

Watson, J.G., J.A. Cooper, and J.J. Huntzicker. 1984. The Effective Variance Weighing for Least Squares Calculations Applied to the Mass Balance Receptor Model. *Atmospheric Environment* 18:1347-1355.

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