ANNEX 1

CONCEPTUAL BASIS FOR UNCERTAINTY ANALYSIS

CO-CHAIRS, EDITORS AND EXPERTS

Co-chairs of the Expert Meeting on Cross-sectoral Methodologies for Uncertainty Estimation and Inventory Quality

Taka Hiraishi (Japan) and Buruhani Nyenzi (Tanzania)

REVIEW EDITOR

Richard Odingo (Kenya)

Expert Group: Conceptual Basis for Uncertainty Analysis

CO-CHAIRS

Ian Galbally (Australia) and Newton Paciornik (Brazil)

AUTHORS OF BACKGROUND PAPERS

Ian Galbally (Australia), Newton Paciornik (Brazil), and Milos Tichy (Czech Republic)

CONTRIBUTORS

Wiley Barbour (USA), Leandro Buendia (IPCC-NGGIP/TSU), Franck Jacobs (Antigua), Naoki Matsuo (Japan), Richard Odingo (Kenya), Daniela Romano (Italy), and Milos Tichy (Czech Republic)

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ANNEX 1 CONCEPTUAL BASIS FOR UNCERTAINTY ANALYSIS

A1.1 INTRODUCTION

A structured approach to the development of a methodology to estimating inventory uncertainty is needed. The requirements include:

- A method of determining uncertainties in individual terms used in the inventory;
- A method of aggregating the uncertainties of individual terms to the total inventory;
- A method of determining the significance of year to year differences and long term trends in the inventories taking into account the uncertainty information;
- An understanding of the likely uses for this information which include identifying areas requiring further research and observations and quantifying the significance of year to year and longer term changes in national greenhouse gas inventories;
- An understanding that other uncertainties may exist, such as those arising from inaccurate definitions that cannot be addressed by statistical means.

This Annex is concerned with the basis for concepts used elsewhere in this report to discuss uncertainties in greenhouse gas inventories. Some issues concerned with uncertainties in inventories requiring further research are discussed at the end of this annex.

A1.2 STATISTICAL CONCEPTS

There is a number of basic statistical concepts and terms that are central to the understanding of uncertainty in greenhouse gas inventories. These terms have common language meanings, specific meanings in the statistical literature and in some cases other specific meanings with regard to uncertainty in inventories. For definition, the reader is referred to the Glossary in Annex 3; the definitions in SBSTA-UNFCCC (1999); and the International Standards Organisation Guide to Uncertainty (ISO, 1993).

The process of estimating uncertainties in greenhouse gas inventories is based on certain characteristics of the variable of interest (input quantity) as estimated from its corresponding data set. The ideal information includes:

- The arithmetic mean (mean) of the data set;
- The standard deviation of the data set (the square root of the variance);
- The standard deviation of the mean (the standard error of the mean);
- The probability distribution of the data;
- Covariances of the input quantity with other input quantities used in the inventory calculations.

A1.2.1 Expressing uncertainty

An important aspect of an uncertainty analysis concerns the ways on how to express the uncertainties associated with individual estimates or the total inventory. The *Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories* (*IPCC Guidelines*) specify the following: '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 (Robinson, 1989) or the Monte Carlo technique (Eggleston, 1993). Otherwise, the range will have to be assessed by national experts.'

This statement indicates that the confidence interval is specified by the confidence limits defined by the 2.5 percentile and 97.5 percentile of the cumulative distribution function of the estimated quantity. Put another way, the range of an uncertain quantity within an inventory should be expressed such that: (i) there is a 95%

probability that the actual value of the quantity estimated is within the interval defined by the confidence limits, and (ii) it is equally likely that the actual value, should it be outside the range quoted, lies above or below it.

A1.2.2 Individual sample, mean value and confidence interval

A key issue in the compilation of uncertainties within inventories is the distinction between the standard deviation of the data set and the standard deviation of the sample mean. The uncertainty associated with the information being analysed (emission rate, activity data or emission factor) can be either the standard deviation of the sample population or the standard deviation of the sample mean, depending on the context (ISO 1993).

The standard deviation of the mean, known also as the standard error of the mean, is the standard deviation of the sample data set divided by the square root of the number of data points. The standard deviation and variance of the data set do not change systematically with the number of observations, but the standard deviation of the mean decreases as the number of observations increase. Within much statistical and physical science literature the standard deviation of the mean is known as the standard error of the mean, but the ISO (1993) recommends the use of the term standard deviation of the mean for this quantity.

The use of the standard deviation to estimate the limits of the confidence interval (in this case the 95% confidence interval) is directly dependent on the probability distribution of the data set or the probability function chosen to represent the data set. For some probability distributions, including those discussed later, there are analytical relationships that relate the standard deviation to the required confidence intervals. Some examples are given in Annex 3 (Glossary), and ISO (1993). Usually, a normal distribution is assumed for the variable under consideration; in this case, the confidence limits are symmetric about the mean. For a 95% confidence interval, the confidence limits are approximately 2 standard deviations of the variable, above and below the mean.

It is probable that in many circumstances, the quantification of uncertainties for the input variables of the inventory will involve analyses of small amounts of data combined with expert judgement. For this reason it is important to review the information content of small data sets. There are useful studies of the amount of information on uncertainties contained in data sets with a small number of observations (Manly, 1997; Cullen and Frey, 1999). The term examined is the 95% confidence interval of the estimate of a standard deviation. This is the uncertainty in the estimate of the standard deviation: essentially, how the standard deviation might vary from one set of observations to another where both sets of observations are made on the same quantity. Cullen and Frey (1999) have presented data from which the limits of the 95% confidence interval of the standard deviation have been derived for a normally distributed variable where the sample used to calculate the standard deviation has a given number of observations. The limits of the 95% confidence interval for repeated determinations of the standard deviation are:

- 7 observations: 0.64 and 2.2 times the standard deviation estimated from a very large number of observations;
- 20 observations: 0.76 and 1.5 times the standard deviation estimated from a very large number of observations;
- 100 observations: 0.88 and 1.2 times the standard deviation estimated from a very large number of observations.

A similar analysis of the uncertainty in estimates of confidence intervals has been done on synthetic data samples for non-normal distributions using the bootstrap technique (Manly, 1997) with similar results to those above. What these calculations emphasise is that very large numbers of observations are required to precisely estimate the variance, standard deviation and standard error of the mean of any quantity. Essentially, the confidence intervals estimated from small numbers of observations via a variance (and an assumed probability distribution) have uncertainties associated with them, and in these cases, further observations may either increase or decrease these calculated uncertainty limits. Ultimately, large numbers of observations will decrease the uncertainty limits of the standard deviation.

A1.2.3 Choosing the appropriate measure of uncertainty

The following are two hypothetical worked examples illustrating the choice of the standard error of the mean and the standard deviation of the data set as the appropriate uncertainty:

In the first case, the emission factor for a greenhouse gas from biomass burning in savanna has been measured on 9 individual occasions and varies between 0 and $6 \bullet 10^{-3}$ kg kg^{-1} (mass emitted per unit mass of biomass burned) with an arithmetic mean and standard deviation of the data set of $2 \bullet 10^{-3}$ kg kg^{-1} and $1 \bullet 10^{-3}$ kg kg^{-1} respectively, sometimes written as $2 \pm 1 \bullet 10^{-3}$ kg kg^{-1}. The emission factor used for that year in the IPCC inventory algorithm is the arithmetic mean, and the uncertainty appropriate to the inventory must be based on the standard error of the mean, which is $1 \bullet 10^{-3} / \sqrt{9}$ kg kg^{-1} or $3.3 \bullet 10^{-4}$ kg kg^{-1}, a factor of three smaller than the standard deviation. The mean and 95% confidence interval is then encompassed by $2 \pm 0.7 \bullet 10^{-3}$ kg kg^{-1}.

The second case involves a component of an inventory, for which there is a single estimate for a particular year that has been calculated on more than one occasion. Such recalculations have occurred as a result of changes in agreed methodology, during audits of the inventory, or as a result of the emergence of new data. In this case, it is the standard deviation of the sample set that is appropriate and not the standard deviation of the mean.

An illustration of this point may be made using a set of national estimates of waste to landfill given in Table A1.1. These are the activity data needed to calculate greenhouse gas emissions from waste.

TABLE A1.1
NATIONAL ESTIMATES OF MASS OF WASTE TO LANDFILL FOR THE YEAR 1990

Source and year of estimate	Mass (kilotonnes)
Technology Commission, 1991	12,274
Consultant 1994	11,524
National inventory 1994	14,663
National inventory revision 1995	16,448
National inventory revision 1996	12,840
Academic review 1995	22,000
Mean	**14,958**
Standard deviation	**3,883**

We note that the mean and the 95% confidence interval based on the standard error of the mean of the six estimates is 14,958 $\pm$3,107. However, in the case, where the 1996 inventory estimate is used, only a single estimate is used and the uncertainty appropriate for inventory is calculated from the standard deviation of the data set.

Specifically, based only on the evidence in Table A1.1, the 95% confidence interval associated with the 1996 estimate should be two standard deviations, namely 12,840 $\pm$ 7,610. As it is a single estimate, a re-evaluation of the data is needed. This happens because the 1996 estimate is not the mean value of many independent determinations.

Choosing the appropriate measure of uncertainty depends on the context of the analysis. If only one data point per inventory period is available, the uncertainty range should be based on the probability density function of the population if this is known or can be derived from other sources. The choices made should be reviewed as part of the expert review process for the inventory.

A1.2.4 Probability functions

When multiple determinations are made of a quantity that is an input to the inventory, a set of data is obtained that has variability. The issue is how to represent this variability in a compact way. One approach is to determine the following summary statistics (ISO, 1993; Cullen and Frey, 1999):

- Arithmetic mean;

- Variance;
- Skewness (asymmetry of the distribution);
- Kurtosis (peakedness of the distribution).

However, when focusing on the determination of uncertainty limits on the input data in terms of frequency (the 95% confidence limits) additional information about the data set is needed as well as summary statistics. This additional information can be obtained by representing the data as a probability distribution, either cumulative or as a density distribution (ISO, 1993; Cullen and Frey 1999). This is the approach adopted in Chapter 6, Quantifying Uncertainties in Practice. An empirical cumulative distribution provides a relationship between the percentiles and the data.[1] A percentile is the percentage of values in the data set that are less than or equal to a given value of the quantity.

For the subsequent task of calculating the propagation of errors in a complex system (using either analytical or computational approaches), empirical probability distributions are unwieldy. The common approach is to replace the empirical distribution with an analytical function, either a cumulative distribution function (CDF) or a probability density function (PDF) which is the first derivative of the CDF. These functions are, in fact, the first component of a model of the uncertainty process. Also, they are only an approximation to the real data. These probability functions are essential for two aspects of the uncertainty work. The functions are required for (i) the propagation of uncertainties and (ii) for the determination of the confidence interval of the quantity being considered.

There are many probability functions available in the statistical literature and often representing particular situations from the physical world. Examples of such functions and the situations they represent are:

- The normal distribution – human heights;
- The lognormal distribution – concentrations of chemicals in the environment.

These functions can also be expressed in truncated forms to represent the situation when there are known physical limits on the possible range of the data.

Other distributions are used to represent the absence of information on the processes. Examples are:

- The uniform distribution – all values in a given range have equal probability;
- The triangular distribution – upper and lower limits and a preferred value in this range are assigned.

The issue of identifying which function best fits a set of data can be difficult. One approach is to use the square of the skewness and the kurtosis to define functional forms that can fit the data (Cullen and Frey, 1999). The function is then fitted to the data by least squares fit or other means. Tests are available to assess the goodness of fit, including the chi-squared test and others (Cullen and Frey, 1999). In many cases, several functions will fit the data satisfactorily within a given probability limit. These different functions can have radically different distributions at the extremes where there are few or no data to constrain them, and the choice of one function over another can systematically change the outcome of an uncertainty analysis. Cullen and Frey (1999) reiterate the advice of previous authors in these cases that *it must be knowledge of the underlying physical processes that governs the choice of a probability function.* What the tests provide, in the light of this physical knowledge, is guidance on whether this function does or does not satisfactorily fit the data.

A1.2.5 Good practice guidance for selecting a probability density function

The criteria of comparability, consistency and transparency in emission inventories, as defined earlier, are best met when:

- The minimum number of probability functions are used;
- These probability functions are well known and well based.

Such probability functions would be the default probability functions.

[1] A key point with regard to both data sets and their representation as empirical cumulative probability distributions is that no information is available on the likely values of the quantity for percentile probabilities either less than 50/*n*, or greater than (100-50/*n*) where *n* is the number of observations. In fact the probability data in the tails are very uncertain.

The criteria of accuracy are met when either:

- The default probability functions provide a good fit to the data; or
- A more appropriate probability function is used in the event that either the default probability functions fail to provide a good fit to the data or there is compelling scientific evidence to use another probability function.

The following *good practice guidance* describes how inventory agencies can meet these criteria:

(i) Where empirical data are available, the first choice should be to assume a normal distribution of the data (either in complete or truncated form to avoid negative values, if these would be unrealistic), unless the scatter plot of the data suggests a better fit to another distribution;

(ii) Where expert judgement is used, the distribution function adopted should be normal or lognormal as in (i), supplemented by uniform or triangular distributions as described in Annex 3;

(iii) That other distributions are used only where there are compelling reasons, either from empirical observations or from expert judgement backed up by theoretical argument.

A1.2.6 Characterising probability density functions for uncertainty analyses

The characteristics of PDFs that are relevant to the quantification and aggregation of uncertainties associated with quantities included in national greenhouse gas inventories, are:

- The mathematical form of the PDF;
- The parameters required as input values to specify the PDF;
- The relationships between these parameters that specify the PDF and available data about the quantity being described;
- The mean, variance and standard error of the mean, calculated from the data set that are used to determine the parameters of the PDF.

In selecting the input values and the PDF, the inventory compiler must distinguish between occasions where the appropriate uncertainty is the standard deviation or confidence intervals of the data set, or the appropriate uncertainty is the standard error of the mean value.

As previously mentioned, the wrong choice of the measure used to estimate the uncertainty would lead to spurious results.

A1.3 SOURCES OF UNCERTAINTY IN INVENTORIES

Some sources of uncertainty are addressable by statistical means, others are outside the scope of statistics (ISO 1993).

Uncertainty in inventories arises through at least three different processes:

- Uncertainties from definitions (e.g. meaning incomplete, unclear, or faulty definition of an emission or uptake);
- Uncertainties from natural variability of the process that produces an emission or uptake;
- Uncertainties resulting from the assessment of the process or quantity, including, depending on the method used,: (i) uncertainties from measuring; (ii) uncertainties from sampling; (iii) uncertainties from reference data that may be incompletely described; and (iv) uncertainties from expert judgement.

Uncertainties due to poor definitions are related to completeness and attribution to source categories and should be eliminated as far as possible before undertaking uncertainty analysis.

Uncertainties from natural variability are inherent to the emission process and can be assessed by statistical analysis of representative data.

Uncertainties that arise due to imperfect measurement include:

- Personal bias in measuring, recording and transmitting information;
- Finite instrument resolution or discrimination threshold;
- Inexact values of measurement standards and reference materials;
- Inexact values of constants and other parameters obtained from external sources and used in the data-reduction algorithm (e.g. default values from the *IPCC Guidelines*);
- Approximations and assumptions incorporated in the measurement method and estimation procedure;
- Variations in repeated observations of the emission or uptake or associated quantity under apparently identical conditions.

While continuous emission measurements can reduce overall uncertainty, it usually has limited application on the evaluation of GHG emissions. Periodic and random sampling are more frequently employed, introducing further uncertainties like:

- *Random sampling error*. This source of uncertainty is associated with data that are a random sample of a finite sample size and typically depends on the variance of the population from which the sample is extracted and the size of the sample itself (number of data points).
- *Lack of representativeness.* This source of uncertainty is associated with lack of complete correspondence between conditions associated with the available data and the conditions associated with real world emissions or activity. For example, emissions data may be available for situations in which a plant is operating at full load but not for situations involving start-up or load changes. In this case, the data are only partly relevant to the desired emission estimate.

Uncertainties due to expert judgement cannot, by definition, be assessed by statistical means since expert judgements are only used where empirical data are sparse or unavailable. However, expert judgements, provided they are treated according to the practical procedures summarised here and in Chapter 6, Quantifying Uncertainties in Practice, can be combined with empirical data for analysis using statistical procedures.

All of these sources of uncertainty need to be accounted for in the assessment of uncertainties in inventories.

The International Standards Organisation (ISO, 1993) stresses that with 'natural materials' the uncertainty due to sampling and due to the requirement to obtain a representative sample can outweigh the uncertainties due to the measurement technique. Sampling issues apply to the evaluation of inventory uncertainties. The achievement or failure to obtain representative sampling directly affects the uncertainty in an inventory. The overall problem of determining the uncertainty in these inventories is a mixture of a statistical problem in error analysis and a problem in matching the statistical and inventory concepts to occurrences in the real world.

A1.4 ASSESSMENT, RECORDING AND PROPAGATION OF UNCERTAINTIES IN INVENTORIES

A1.4.1 Determination and recording of uncertainties in input data

The measure of every physical quantity that is input data into the inventory algorithms has some associated uncertainty. In some select cases, such as the ratio of molecular weights, the uncertainty is negligible for the purposes of the inventory, but in almost all other cases, the uncertainty requires evaluation.

There are several underlying principles that govern *good practice* with regard to the estimation of uncertainties in input data for inventories. The ideal situation is that there are hundreds of measurements of the input quantity and the confidence intervals can be estimated by classical statistical methods. However, in most cases, there are few or no data available. Four types of information that can be used to varying degrees to deal with specific situations are:

- Available measurements of the quantity;
- Knowledge of extreme values of the quantity;

- Knowledge of the underlying processes regulating the quantity and its variance;
- Expert judgement.

The collection and recording of information about the uncertainty in input data is critical to the success and transparency of the uncertainty analysis. Box A1.1 lists the information required for an extensive and transparent uncertainty analysis which is consistent with *good practice*. In practical terms, the full information may not be available and expert judgement may be required.

BOX A1.1
DESIRABLE INFORMATION FOR EACH INPUT QUANTITY IN A NATIONAL GREENHOUSE GAS INVENTORY FOR A TRANSPARENT UNCERTAINTY ANALYSIS

(i)	Name of the quantity;
(ii)	Units;
(iii)	A description of the spatial, temporal and system domain that this quantity represents;
(iv)	Input value of the quantity;
(v)	Specification of whether this is a mean value from a set of data or a single observation;
(vi)	Specification of whether the uncertainty required is the standard deviation of the sample mean or the standard deviation of the population;
(vii)	Size of the sample or number of estimates of the quantity available;
(viii)	The estimate of the standard deviation of the sample mean or the estimate of the standard deviation of the population;
(ix)	Estimates of the variance of the quantity from knowledge about the controlling factors and processes influencing the quantity;
(x)	Upper and lower limits to the values of the quantity based on scientific analyses and expert judgement;
(xi)	The preferred probability density function;
(xii)	The input parameters to specify the probability density function;
(xiii)	Succinct rationale explaining the basis or cause of the uncertainty;
(xiv)	References to the source of expert judgement and data used in this tabulation;
(xv)	Documentation of the peer review of the analysis.

A1.4.1.1 EXPERT JUDGEMENT

In situations where it is impractical to obtain reliable data or where existing inventory data lack sufficient statistical information, it may be necessary to elicit expert judgements about the nature and properties of the input data. Experts may be reluctant to provide quantitative information regarding data quality and uncertainty, preferring instead to provide relative levels of uncertainty or other qualitative inputs. Elicitation protocols, discussed in Chapter 6, Quantifying Uncertainties in Practice, may be helpful in overcoming these concerns, and if necessary the experts should be made aware of the existence of IPCC default uncertainty ranges which would be used in the absence of their judgements.

The use of expert judgement to make these quantitative uncertainty estimates is acceptable, provided it takes into account all the available data and involves reasoned formation of opinions by someone with special knowledge or experience with the particular quantity being examined, and provided that the judgement is documented and can be explained with sufficient clarity to satisfy outside scrutiny (Cullen and Frey, 1999). The key requirement in making estimates of uncertainty by expert judgement or otherwise, is that all the possible sources of uncertainty are considered.

Frequently, there are few observations from which to determine input data into these inventories, and so there must be considerable reliance on expert judgement. There should be a recognition that the results of quantitative uncertainty analyses for inventories provide, at best, an estimate of their uncertainty, but that there are also substantial uncertainties attached to these confidence intervals.

A1.4.2 Representative sampling, algorithms and covariance

Issues of representative sampling and the development of adequate algorithms to represent emissions are closely linked. The issue of representative sampling arises because the inventory must capture all of the emissions (or uptake) within the national border and over the period of the inventory. However, measurements are limited by time and space. The emissions of the different activities are calculated as the product of activity data and the related emission factor. The data for both of these variables have to be representative of the reality of the spatial and temporal domain considered. An emission factor is considered representative if it is calculated as the weighted average of all the emission factors related to all the different typologies of processes or products, where the weights are the percentages that different productions/products are of the total. Activity data can be considered representative if they include all of the activities in the period considered. There are many cases in which activity data and emission factors are not available for a region or for a specific category of process so there is a need to estimate emissions using emission factors determined in a different region or different category of processes. This is the process of extrapolation. Otherwise, it may be possible to calculate the values using proxy variables. Whenever extrapolation or proxy variables are used, an evaluation of the representativeness of the values chosen is needed. The data are more representative and so more accurate if a similar condition or similar process is used.

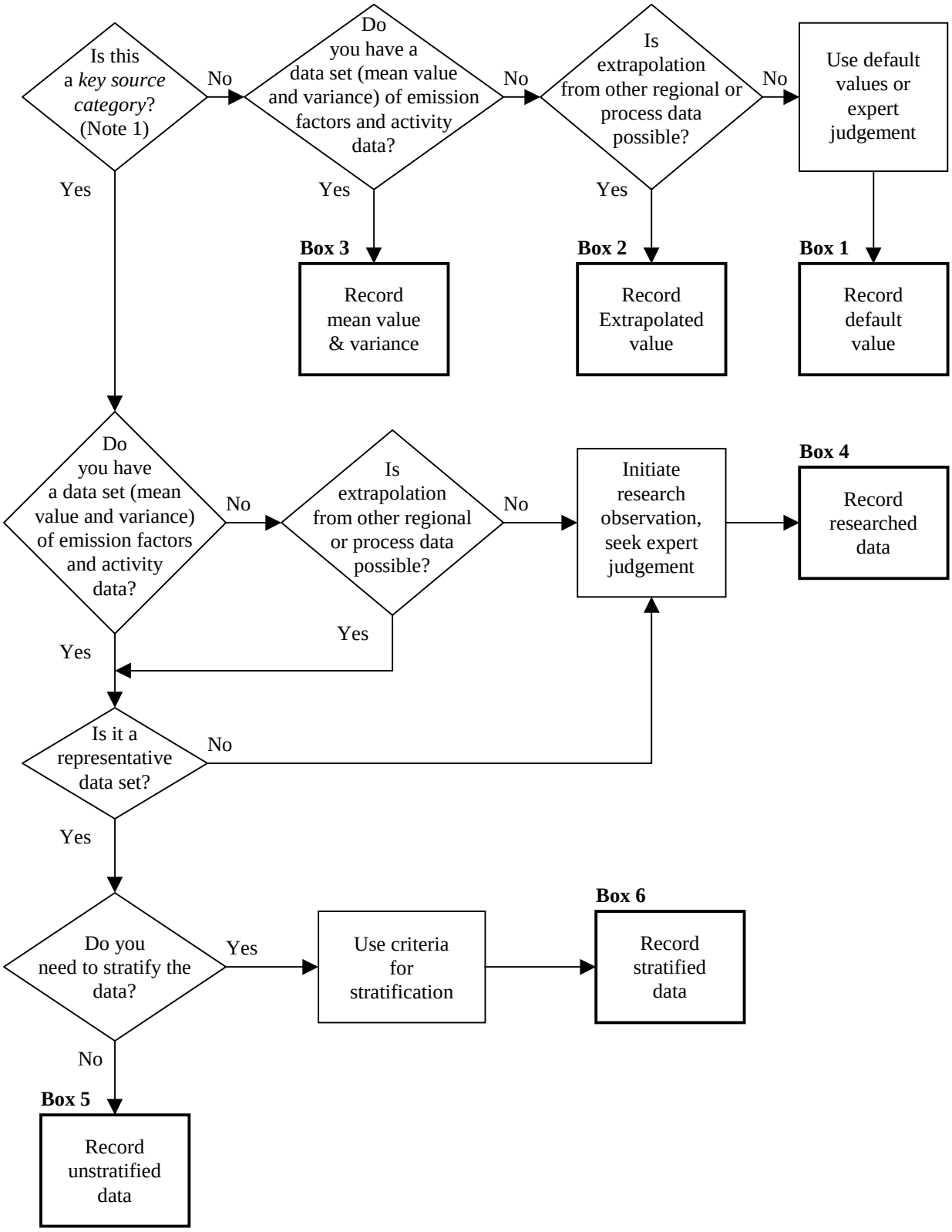
There are statistical methods to estimate the uncertainty associated with extrapolation provided the available data arise from random sampling. However, in the cases of national inventories, it is rare that data come from random sampling. Consequently, in view of the heterogeneous nature of greenhouse gas emissions and uptakes, the key issue with regard to extrapolation is that of the uncertainty associated with unrepresentative or representative sampling. For example, extrapolation of a known emission rate derived from irrigated rice to a countryside including rainfed rice will result in high uncertainty. In contrast, it is possible to stratify the activity data in the country into irrigated and rainfed rice and produce a far more reliable analysis. In the biosphere, homogeneity is rarely present and use of stratification is a powerful technique to manage and reduce the uncertainty in inventory estimates.

If there are sufficient resources, it may be possible to undertake a monitoring campaign and design a stratified sample of measurements choosing the most appropriate variables to stratify the sample (products, processes, plants, territory, population). The whole set of data can be used to estimate the probability density function and summary statistics. Then statistical tools can be used to calculate bias of the mean and variance, confidence intervals and the distribution of the errors. When data are missing at a regional level, it is possible to extrapolate information from existing literature provided that care is taken to choose data coming from sources with similar characteristics to those being estimated. In this case, expert judgement is needed.

This activity/process involves a minimal set of procedures outlined in the decision tree in Figure A1.1.

Firstly, one needs to ascertain whether or not the data are for a key emission source category (as described in Chapter 7, Methodological Choice and Recalculation). If the source category is not a key source then the use of the existing data set, extrapolated values, default values, or expert judgement is appropriate and these data can be recorded. If the source category is a key source then either there will be an existing complete data set, or it is possible to extrapolate a data set, or there is a need to initiate observations or gather data. Then there is a need to test the data set for representativeness which could require stratification (for refinement/improvement of accuracy). Finally, all data need to be recorded. These pathways are presented in Figure A1.1. It is necessary to consider the averaging time of the data versus the averaging time of the inventory, and the geographic applicability of the data. For example, data for a given emission factor may be based upon short-term (e.g. hourly, daily) measurements taken in one country under conditions that might be specific to that location, but there may be a need to use this data to estimate both annual emissions and their uncertainty in a different country. The analyst is encouraged to use reasonable judgements and methods to develop an appropriately representative estimate of uncertainty as input to an emission inventory. Such adjustments, although not always perfect, are preferable to using a non-representative data set. A corollary of this is that there is a burden on the analyst to justify the assumptions used in a particular assessment, and to be careful about using ‘defaults’ that in fact may not be directly applicable in a given situation.

Figure A1.1 A Flow Chart and Decision Tree for Actions Concerning the Representativeness of Data



Note 1: A *key source category* is one that is prioritised within the national inventory system because its estimate has a significant influence on a country's total inventory of direct greenhouse gases in terms of the absolute level of emission, the trend in emissions, or both. (See Chapter 7, Methodological Choice and Recalculation, Section 7.2, Determining National Key Source Categories.)

In most cases, it is impossible to directly measure a significant portion of the emissions in a source category over a significant part of the year for a country. What is required for the inventory is the sum of the emissions and uptakes over the entire country and the whole inventory year whereas what is directly measured are the emissions and uptakes for a time much less than a year and for an area much smaller than the national domain. The observed emission is only a sub-set of the required inventory and so a method of extrapolation of the emissions is required.

The method of extrapolation is based on the algorithms in the *IPCC Guidelines* and knowledge of the input quantities throughout the country and over the inventory year. As interest in greenhouse gas emissions has only recently emerged, the measurements necessary to quantify the emissions have been made at only a limited number of locations under a limited range of conditions. The algorithm used for emission estimation is an approximation that includes only the major variables apparent from the available measurements and generally accounts for only a limited amount of the variance in the available data. At the same time many possibly important sources of covariance in the actual emissions disappear from the inventory calculations because of incomplete knowledge of the emission process.

An efficient method to collect further representative data and to simultaneously improve the quality of the algorithms is to conduct a programme of stratified sampling of the emissions and relevant supporting information. Stratified sampling is a common statistical technique (Cochran, 1963).

There are several steps in stratified sampling. The first step involves identifying variables (environmental, technological etc.) that are known to have a significant influence on the emissions in question. Knowledge about the influence of these variables can come from laboratory studies, theoretical modelling, field observations and elsewhere. Having identified the key variables, one must estimate the cumulative distributions for these variables over the inventory domain. Finally, one must check if the available observations constitute a representative sample from these distributions. If not, the distributions can be divided into strata, and a sampling programme designed and undertaken to get representative data. These representative data can be used to revise the emission algorithm. An emission algorithm based on a representative data set is an essential prerequisite for high inventory quality.

An example is presented to illustrate these issues about representative data. The example concerns the emissions of nitrous oxide (N_2O) from fertiliser application to dry land crops. Most of the data used to construct the current IPCC Inventory algorithm and default global emission factor comes from northern hemisphere temperate cropping systems. Bouwman (1996) presented an excellent systematic analysis of the data (available at that time) on the N_2O emissions arising from fertiliser application and derived an algorithm based solely on the amount of fertiliser nitrogen applied and an emission factor. However, as Bouwman (1996) acknowledged, soil science indicates that there are other key factors that can contribute to the variance in emissions including soil temperature, soil fertility, the frequency and amount of rainfall and waterlogging of the soil, and fertiliser composition. A consequence is that the emission factor, derived mainly from northern hemisphere temperate cropping systems may not be appropriate in hot tropical climates where the relevant environmental variables, such as soil temperature and rainfall frequency are entirely different from those in temperate latitudes. When the IPCC algorithm and emission factor (which are based on the best available data) are applied in tropical regions the resulting emission estimates may be unintentionally biased. The potential bias arises from the lack of adequate emission data in the tropics. Thus there is a problem concerning the representativeness of the underlying data for N_2O emissions from fertiliser application. What is needed, where there is a lack of representative data for a key emission or uptake, is the establishment of appropriate measurement, in this case of emissions of N_2O from fertiliser application in the tropics, and afterwards a review of the algorithm and emission factor. In some cases such as this, the global default emission factors should be replaced by regional ones, if more appropriate. This process of reviewing the representativeness of the data and acting to fill key data gaps should lead to a substantial increase in confidence of an inventory estimate. This is a key issue for reducing uncertainty in inventories and represents *good practice*. This example is only one of many cases where the representativeness of key data could be improved.

An associated issue concerning uncertainty and the review of algorithms, is that there may be considerable unexplained variance in an algorithm developed from a data set. This unexplained variance should be represented in uncertainty estimates for each parameter in the algorithm, including the exponents. Subsequent uncertainty analysis must include allowance for these uncertainties.

Stratified sampling is a useful technique in situations where covariance between activity data and emission factors is present. Covariance is reduced by stratifying activity data and emission factors into carefully selected sets. This approach has already been applied extensively within the IPCC inventory methodology.

Some numerical packages for Monte Carlo propagation of errors include covariances in their calculations, and require as input, the correlation matrix between all input quantities. Hence, it is important to have methods of either estimating these correlations or of circumventing the need for them.

The issue that arises in inventory compilation, and particularly in this step of calculation of uncertainty in an emission estimate, is the determination of the likely value of the covariance, or the related correlation coefficient between the various input quantities, in this case between the various activities and also between the activities and their associated emission factors. There is need for evaluation of these correlation coefficients for a range of inventory categories: stationary combustion, mobile sources, fugitive emissions, industrial processes, agriculture and land use change and forestry. Knowledge of correlation is required irrespective of the method used for the calculation of uncertainties, either the propagation of errors equation or the Monte Carlo method.

An example of a possible correlation between activity and emission factor for a single source category occurs when there is an elevated emission on start up of the equipment. In this case, there is an association of low local activity or frequent short periods of activity (in time or space) with high emissions, and fewer longer periods of local activity with lower emissions, this being negative correlation.

Similarly, with methane (CH_4) from animals, there will be a correlation between total animal numbers and average bodyweight over the course of the year which can produce a covariance affecting the animal CH_4 emissions. The effect of this covariance on the emissions can be minimised by disaggregating the calculations according to animal age and season of the year.

A1.4.3 Propagation of uncertainties

There are many methods that can be used for the propagation of uncertainties including those under the general descriptions of analytical methods, approximation methods and numerical methods. For the purpose of propagating uncertainties in national greenhouse gas inventories, we discuss two general methods: the approximation method based on a first order Taylor series expansion, often referred to as the error propagation equation, and the numerical Monte Carlo method.

A1.4.3.1 Error propagation equation

In the first approach, an uncertainty in an emission can be propagated from uncertainties in the activity and the emission factor through the error propagation equation (Mandel 1984, Bevington and Robinson 1992). This method is presented in the current *IPCC Guidelines* where the conditions imposed for use of the method are:

- The uncertainties are relatively small, the standard deviation divided by the mean value being less than 0.3;
- The uncertainties have Gaussian (normal) distributions;[2]
- The uncertainties have no significant covariance.

Under these conditions, the uncertainty calculated for the emission rate is appropriate. The method can be extended to allow for covariances.

The error propagation equation is a method of combining variances and covariances for a variety of functions, including those used in inventories. In this approach, non-linear equations can be expanded using the Taylor expansion. This approach provides an exact solution for additive linear functions and an approximation for products of two terms. Most emission inventories are sums of emissions, E, that are the products of activity data, A, and emission factors, F. Assuming that both quantities have some uncertainty, such inventory equations are non-linear with respect to uncertainty calculations. Therefore the error propagation equation provides only an approximate estimate of the combined uncertainty that is increasingly inaccurate for larger deviations. Systematic error caused by neglecting this non-linearity in inventories can be assessed case by case. The method is very inaccurate with respect to functions containing inverse, higher power or exponential terms (Cullen and Frey, 1999). Terms can be included to allow for the effects of covariance.

When the activity and emission factor are mutually independent, their variances for a single source category can be combined according to Equation A1.1.

[2] In fact, this condition that the uncertainties have Gaussian (normal) distributions is not necessary for the method to be applicable.

EQUATION A1.1

$$\sigma_E^2 = \sigma_A^2 F^2 + \sigma_F^2 A^2$$

Where σ_E^2 is the emission variance, σ_A^2 is the variance of the activity data, σ_F^2 is the variance of the emission factor, A is the expected value of the activity data, and F is the expected value of the emission factor.

When the variables are correlated, but the uncertainties are small, then the following approach is valid. The covariance, cov(x,y), between two variables can be derived from their correlation coefficient, r_{xy}, and the standard deviations as follows:

EQUATION A1.2

$$\mathrm{cov}(x, y) = r_{xy}\sigma_x\sigma_y$$

Equation A1.1 is expanded to:

EQUATION A1.3

$$\sigma_E^2 = \sigma_A^2 F^2 + \sigma_F^2 A^2 + 2r_{AF}\sigma_A\sigma_F AF$$

Inspection of Equation A1.3 shows that the variance of the product can, in the extreme case, double or go to zero if the correlation between the two components approaches its extreme values of +1.0 and –1.0 and the coefficients of variation are of equal value. In practical terms, correlation between emission factors and activity data should be dealt with by stratifying the data or combining the categories where covariance occurs, and these are the approaches adopted in the advice on source specific *good practices* in Chapter 6, Quantifying Uncertainties in Practice.

To estimate the uncertainty of an estimate which results from the sum of independent sources E_1 and E_2 where $E = E_1 + E_2$, one can apply the error propagation equation presented in Equation A1.4.

EQUATION A1.4

$$\sigma_E^2 = \sigma_{E_1}^2 + \sigma_{E_2}^2$$

If the source categories (or sinks) are correlated, the error propagation equation provided in Equation A1.4 does not hold and Equation A1.5 should be applied.

EQUATION A1. 5

$$\sigma_E^2 = \sigma_{E_1}^2 + \sigma_{E_2}^2 + 2r_{E_1E_2}\sigma_{E_1}\sigma_{E_2}E_1E_2$$

Once the summation exceeds two terms and covariance occurs, the use of the Monte Carlo approach is preferable where resources are available.

A1.4.3.2 MONTE CARLO APPROACH

Numerical statistical techniques, particularly the Monte Carlo technique, are suitable for estimating uncertainty in emission rates (from uncertainties in activity measures and emission factors) when:

- Uncertainties are large;
- Their distribution are non-Gaussian;
- The algorithms are complex functions;
- Correlations occur between some of the activity data sets, emission factors, or both.

Uncertainties in emission factors or activity data or both are often large and may not have normal distributions. In these cases, it may be difficult or impossible to combine uncertainties using the conventional statistical rules. Monte Carlo analysis can deal with this situation. The principle is to perform the inventory calculation many times by electronic computer, each time with the uncertain emission factors or model parameters and activity data chosen randomly (by the computer) within the distribution of uncertainties specified initially by the user. This process generates an uncertainty distribution for the inventory estimate that is consistent with the input uncertainty distributions on the emission factors, model parameters and activity data. The method is very data and computing time intensive, but is well suited to the problem of propagating and aggregating uncertainties in an extensive system such as a national greenhouse gas inventory. More detailed descriptions and applications of this method are presented in Annex 3, Glossary, and in Bevington and Robinson (1992), Manly (1997) and Cullen and Frey (1999).

A1.4.4 Propagation of uncertainties in the whole inventory

The task of propagation of uncertainties in the inventory, after the individual uncertainties for each class of emission are estimated, is simpler than the task of propagation of uncertainties in algorithms, because only addition and subtraction are used in aggregating the emissions and uptakes.

In aggregating uncertainties, two different processes occur. Firstly, there is the aggregation of emissions of a single gas which obeys the rules of propagation of uncertainties already discussed. The other case is the aggregation of uncertainties from several gases. In this case, the emissions and uptakes must be reduced to a common scale, and the process for this is the use of global warming potentials (GWPs). However, for the gases nitrogen oxides (NO_x), carbon monoxide (CO), and volatile organic compounds (VOCs) there is no IPCC accepted GWP. Consequently, the emissions and uptakes of these gases cannot be included in an aggregated uncertainty for an emissions inventory. Furthermore, it should be kept in mind that GWP values have a rather important uncertainty associated with them and that an overall scientific appraisal of the total equivalent emission should take this into account.

As some of the variables to be aggregated are non-Gaussian, have large variances, and are correlated with other variables, the use of a Monte Carlo approach to the aggregation of uncertainty is the preferred approach. The application of this method to inventory uncertainty calculations is presented in Chapter 6, Quantifying Uncertainties in Practice.

There is the option, as a working approximation, to estimate the overall uncertainty in an inventory using the Central Limit theorem (Cullen and Frey 1999). The assumptions relevant to the Central Limit theorem are:

- The number of emission and uptake terms are large;
- No single term dominates the sum;
- The emissions and uptakes are independent.

If this is the case then the sum of the variances of all the terms equals the variance of the total inventory, and the distribution of the total emissions is normal. Thus the interval defined by approximately two standard deviations either side of the mean is the 95% confidence interval of the inventory. As noted above this approach is a gross approximation. Its use in aggregating uncertainties is an option for use at the Tier 1 of an inventory uncertainty system. The simplified spreadsheet approach to uncertainty analysis described in Chapter 6 uses this approach.

A1.4.5 Covariance and autocorrelation

The subsequent discussions assume that the uncertainty propagation calculations are carried out by a Monte Carlo procedure.

The emissions (or uptake) estimates of two components of the inventory are represented by the functions $E_1(t)$ and $E_2(t)$ where t is the year of the inventory estimate. These estimates have uncertainties represented by $\delta_1(t)$ and $\delta_2(t)$ respectively.

There are at least four significant sources of covariance in the overall inventory. These arise from:

- Use of common activity data for several emissions estimates (as occurs in the suite of gases from combustion);

- Mutual constraints on a group of emission estimates (such as a specified total fuel usage or total manure production which provides input to a number of processes);
- The evolution of activities and emission factors associated with new processes, technology etc. decoupling the uncertainties from one time period to the next;
- External drivers that affect a suite of emissions or uptakes (economic, climatic, resource based).

For the purpose of calculating uncertainties, we are only interested in covariance between the uncertainties represented by $\delta_1(t)$ and $\delta_2(t)$. While covariance does occur between $E_1(t)$ and $E_2(t)$ and such covariance is relevant to the issues of understanding and projecting emissions and uptakes, it is not of primary relevance to the issue of aggregating uncertainties etc. Therefore of these four sources of covariance, the first three are central to determining uncertainties. The first source of covariance, the use of common activities over a range of inventory components occurs particularly when several gases are emitted from the same process, such as in fossil fuel combustion or biomass burning. The use of the same activity in two different emission estimates will lead to a positive covariance between two emission estimates. One effective way to remove this source of covariance is to combine the equations into a single formula, having one activity and the sum of several emission factors (expressed in CO_2 equivalent).

The second type of covariance occurs when there is a mutual constraint on a set of activities or emission factors, where a total activity is entered and proportions for each treatment pathway are prescribed to divide this activity amongst several emissions processes and algorithms. An example of this is the proportioning of animal manure between different manure waste management systems. In this case, the system can be over specified if all proportions and their uncertainties are solved simultaneously. The appropriate method of removing the covariance is to leave one of the proportions unspecified, and to determine it by the difference between the other proportions and the total fraction. This removes the necessity to specify the correlation of other terms with the residual component. However, if there are correlations between the specified proportions or between the specified proportions and the total activity, these need to be quantified and used in the uncertainty propagation calculations.

The third type of covariance arises when new measurement techniques, new methods of recording data, or new technologies remove existing uncertainties and introduce new uncertainties, reducing the degree of autocorrelation of the series over time. Autocorrelations will be high when technology, measurement techniques and the gathering of statistics are unchanging, and low when they change. Engineering and social sciences have a wealth of information to contribute on these rates of change (Grübler *et al.*, 1999). Now that the records of national inventories are approaching a decade in length, there is a need for analysis of these covariances.

A1.4.6 Systematic compilation of uncertainty in inventory components

The key features of *good practice* for the determination of uncertainty in an individual greenhouse gas emission or uptake in an inventory have been presented in the previous sections. These are presented in Box A1.2.

There is need for revision of the IPCC standard reporting tables to include information on uncertainties. In the summary tables, the information recorded could be limited to confidence intervals with limits at 2.5% and 97.5% respectively. The full information described in Boxes A1.1 and A1.2 should be recorded. The practice of uncertainty analysis in inventories is presented in detail in Chapter 6, Quantifying Uncertainties in Practice.

A1.5 APPLICATIONS

A1.5.1 Significance of year to year differences and trends in inventories

A major component of uncertainty analysis for inventories is the determination of year to year and longer-term differences in national emissions.

If two years, t_1 and t_2, in a time series are considered, the difference in the total emissions between these years can be represented using the symbols defined in Section A1.4.5 above, by:

EQUATION A1.6

$$\Delta E(t_1 - t_2) = E(t_1) - E(t_2)$$

and the variance of the difference is defined by:

EQUATION A1.7

$$\sigma^2_{\Delta E} = \sigma^2_{E_1} + \sigma^2_{E_2} - 2\,\mathrm{cov}(\delta E_1, \delta E_2)$$

or

EQUATION A1.8

$$\sigma^2_{\Delta E} = \sigma^2_{E_1} + \sigma^2_{E_2} - 2r_{\delta E_1 \delta E_2}\sigma_{E_1}\sigma_{E_2}$$

Where

$E_1 = E(t_1)$
$E_2 = E(t_2)$

Thus if the autocovariance or autocorrelation function of the estimated uncertainties in the inventory is known, then the significance of year to year differences can be determined. (Note that the term autocovariance is to autocorrelation as covariance is to correlation.) To estimate the correlation of the uncertainty between years in the total inventory, one may consider the addition of two autocorrelated series representing two of the many uncertainty components of the inventory. The autocovariance of the combined series includes the autocovariances of the individual terms plus a component to allow for the time lagged covariance between the two components of the inventory. For any evaluation beyond two terms, the use of a Monte Carlo analysis is recommended.

BOX A1.2
KEY FEATURES OF GOOD PRACTICE FOR THE DETERMINATION OF UNCERTAINTY IN EMISSION AND UPTAKE ESTIMATES

(i) Use of available observations and expert judgement to determine uncertainty in input quantities;

(ii) Systematic and transparent recording of this input data;

(iii) Examination of the available emission data to determine if representative sampling has occurred;

(iv) Design of further sampling and revision of parameters, default values and algorithms for key source categories if representative sampling has not taken place;

(v) Use of sectoral *good practice guidelines* to choose a probability density function to represent the data;

(vi) Evaluation of any significant correlations (covariances) between input quantities;

(vii) Propagation of uncertainties by the approximation method if the uncertainties are small and have Gaussian distributions; otherwise

(viii) Propagation of uncertainties by Monte Carlo method where resources are available; and

(ix) Recording of uncertainty.

Enting (1999) has presented a similar analysis for the uncertainty in the trend in a quantity over a specified time interval. As an example, consider emissions E(t), E(t + Δt), in two different years of a time-series separated by Δt years. The variance of the trend over this time period is given by:

EQUATION A1.9

$$\mathrm{var}(\Delta E) = 2\sigma_E^{\,2}(1 - r_{\delta E}(\Delta t))$$

This demonstrates that the uncertainty in the emission trend is smaller for positively autocorrelated estimated uncertainties, than for random uncertainties of equivalent size. There is a need for studies on autocorrelations of estimated uncertainties in inventories as well as of cross correlations of estimated uncertainties within one inventory year and between subsequent inventory years for related emissions and uptakes.

A1.5.2 Splicing of methods

In some cases as the compilation of national inventories continue, there will be a need to change the algorithm used for the calculation of a particular emission or uptake. This may come about either because of improved knowledge about the form of the algorithm or because of some change in the availability of activity data. In these cases, the best approach is to recalculate previous years' inventories using the new methods. In some cases, this will not be possible, and some means of 'splicing' or combining estimates prepared using different approaches into a consistent time series will be required. The statistical theory underlying *good practice* is described below, and practical guidance on how to apply this in inventories is found in Chapter 7, Methodological Choice and Recalculation. The emissions (or uptake) estimates by the two methods are represented by the functions P(t) and Q(t) where t is the year of the inventory estimate. In any particular year when both estimates are available, there will be a difference, and the task of splicing is to examine the difference. There are three likely possibilities: the two emissions estimates may differ by a constant amount, the two emissions estimates may be proportional to each other, or, they may be related by both a constant difference and a proportional term. In the case analysed here, the near constant difference is considered. (A similar analysis can be performed for the two other cases. In fact with the third case, a form of linear regression analysis is appropriate.)

The uncertainty in the difference between the two emission estimates at time t can be expressed as:

EQUATION A1.10

$$\text{uncertainty} = \delta\Delta_{P-Q}(t)$$

$$\text{where } \Delta_{P-Q}(t) = P(t) - Q(t)$$

The ideal situation is to determine this difference for many years, along with the uncertainty of the mean difference taking into account the uncertainties in P and Q. An overbar indicates the multiyear average of the difference over the years t_1–t_2 and δ indicates the uncertainty of this mean difference. In this case, an acceptable series of estimates can be made up by splicing the series P(t) and Q(t) by correcting Q(t) back to P(t) by adding $\overline{\Delta_{P-Q}}(t)$ as averaged over the period t_1 to t_2. A change in the estimation technique can be either an improvement or a diminishment in the quality of an estimate. If it is demonstrated that Q(t) is an improvement then Q(t) corrected back to P(t) should be used as long as possible. That is P(t) should be used up until t_1, and $Q(t) + \overline{\Delta_{P-Q}}(t)$ thereafter. Conversely, if P(t) is preferred, it should be used up until t_2 etc.

In practice in a national inventory, three situations may arise. There may be no years of overlap between P(t) and Q(t); there may be a limited number of years of overlap which are inadequate for the process of refinement of the difference between the two series as discussed above; and there may be sufficient number of years of overlap.

In the first two cases, some additional information is required to determine the effectiveness of the splicing. Several approaches may be possible. These are:

- Identify other locations (countries) where very similar time series exist and use these data to develop a global or regional estimate of the mean difference $\overline{\Delta_{P-Q}}(t)$ gathering all available data until $\delta\overline{\Delta_{P-Q}}(t)$ decreases to an acceptably small uncertainty, or all data sources are exhausted.
- When all data sources are exhausted and $\delta\overline{\Delta_{P-Q}}(t)$ is still above the cut off criterion, accept the time series noting that the time series, from beginning to end has an additional uncertainty that arises because of the uncertainty in the difference between the two series.
- Where there is no overlap of data, nor any data available from elsewhere, other splicing techniques are needed. One possibility is the use of time series techniques (Box and Jenkins, 1970) to forward forecast P(t) and to back forecast in time Q(t) and to see if in the immediate years around the splice, these forecasts agree with the other data set to within the 95% confidence interval. If so the splice could be accepted, if not then a discontinuity in the emissions (or uptake) estimates would have to be recorded. In both these cases, the

uncertainty applied throughout the time series would, at minimum, be the combined uncertainty arising from each of the estimates P(t) and Q(t).

Practical approaches to splicing are discussed in Chapter 7, Methodological Choice and Recalculation.

A1.5.3 Sensitivity analyses and the setting of national inventory research priorities

Given the objective of reducing uncertainties in an inventory, priorities for further research should be established based on three main characteristics:

- The importance of the source category or sink;
- The size of the uncertainty in the emission and uptake;
- The research cost and the expected benefit, measured as an overall reduction in the uncertainty of the inventory.

The importance of the source category should be established using the criteria described in Chapter 7, Methodological Choice and Recalculation. Among source categories of equal magnitude, priority should be given to those with larger uncertainties or greater effect on the trend.

For each source category, the options for research will depend on the origins of the uncertainty. In most cases, there are a number of variables that determine the activity and the emission factor. Priority should be given to those quantities which influence the overall uncertainty most. Among the research options, further stratification of the emissions and uptakes can lead to great benefit. In fact, many current default values are defined for a wide range of conditions which necessarily leads to large confidence intervals.

In the present context, the research cost includes financial cost, time involved and other components that cannot always be quantified.

There are sophisticated computational techniques for determining the sensitivity of a model (such as an inventory) output to input quantities. These methods rely on determining a sensitivity coefficient, λ, that relates the aggregated emissions E_T to an input quantity (or parameter) which in this case is represented by *a*. These methods determine the coefficient as:

Equation A1.11

$$\lambda = \partial E_T / \partial a$$

Some software packages for Monte Carlo analyses have an option for such analysis. This approach has been used for atmospheric chemical systems involving tens to hundreds of chemical reactions (NAS, 1979; Seinfeld and Pandis, 1998). However, one difference between these chemical models and greenhouse gas inventories is the state of knowledge. Chemical models generally represent a closed system with conservation of mass, well-defined relationships and a suite of rate constants that mostly have been well quantified. There is much less knowledge about the extent of interactions, and values of quantities and parameters in greenhouse gas inventories.

There are other approaches that may fill the need for providing input on measurement and research priorities for inventory development. It is possible to develop simpler methods, using broad assumptions, to provide indication of research priorities. The advantage of these simpler schemes is that they can be used by all inventory compilers. Such information on research and measurement priorities arises from the evaluations of representative sampling as discussed in Section A1.4.2, Representative sampling, algorithms and covariances, the uncertainty analysis in Chapter 6, Quantifying Uncertainties in Practice, and Chapter 7, Methodological Choice and Recalculation, and from the *good practice guidance* for each sector (see Chapters 2 to 5). These various inputs combined with the expert judgement of inventory compilers provide the best guide to priorities for inventory development.

A1.6 RESEARCH REQUIREMENTS

While some of the assumptions that underpin IPCC inventories are self evident and already have been examined, the systematic investigation of the set of assumptions that underpin these inventories would facilitate a structured

approach to the identification of uncertainties and the design of experiments to test and refine these assumptions. This work includes issues of definition and the theoretical basis of emission algorithms. Such work would strengthen the coupling of understanding, and exchange of information, between IPCC inventories and studies of the global cycles of trace gases incorporated in IPCC Working Group 1, to the benefit of both activities.

One currently unresolved aspect of the reporting of emissions and uptakes is the number of significant digits recorded (numerical precision). The approach in ISO (1993) is that the numerical values of the estimate and its standard deviation should not be given with an excessive number of digits. The Canadian National Greenhouse Gas Inventory has adopted the practice of only reporting data to the number of significant digits commensurate with the uncertainty of the inventory estimates. If care is taken to maintain this association throughout the inventory, it is possible to clearly visualise the uncertainty of the values and the difference between the uncertainty associated with the emissions from each source category. The other approach is to define the minimum unit for reporting as a fixed quantity, then inventories from all countries and all components of these inventories are reported with the same numerical unit. In practical terms there are probably advantages in this approach for ease of auditing the tables, but this issue will require further discussion.

REFERENCES

Bevington, P. R. and Robinson, D. K. (1992). *Data Reduction and Error Analysis for the Physical Sciences*. WCB/McGraw-Hill Boston USA, p. 328.

Bouwman, A.F. (1996). 'Direct emission of nitrous oxide from agricultural soils'. *Nutrient Cycling in Agroecosystems*, 46, pp. 53-70.

Box, G.E.P. and Jenkins, G.M. (1970). *Time Series Analysis forecasting and control*. Holden-Day, San Francisco, USA, p. 553.

Cochran, W.G. (1963). *Sampling Techniques*. 2nd edition, John Wiley & Sons Inc., New York, p. 411.

Cullen, A.C. and H.C. Frey, H.C. (1999). *Probabilistic Techniques in Exposure Assessment*, Plenum Publishing Corp., New York, USA, p. 335.

Eggleston, S. (1993). Cited in IPCC (1996) *Revised Guidelines for National Greenhouse Gas Inventories*, op. cit.

Enting, I.G. (1999). *Characterising the Temporal Variability of the Global Carbon Cycle.* CSIRO Technical Paper No 40, CSIRO Aspendale, Australia, p. 60.

Grübler, A., N. Nakićenović, N. and Victor D.G. (1999). 'Dynamics of energy technologies and global change', *Energy Policy*, 27, pp. 247-280.

IPCC (1996). *Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventoires: Volumes 1, 2 and 3.* J.T. Houghton et al., IPCC/OECD/IEA, Paris, France.

ISO (1993). *Guide to the Expression of Uncertainty in Measurement.* International Organisation for Standardiszation, ISBN 92-67-10188-9, ISO, Geneva, Switzerland, p.101.

Mandel, J. (1984). *The Statistical Analysis of Experimental Data*. Dover Publications New York, USA, p. 410.

Manly, B.F.J. (1997). *Randomization, Bootstrap and Monte Carlo Methods in Biology*. 2nd edition, Chapman & Hall, p. 399.

NAS (1979). *Stratospheric Ozone Depletion by Halocarbons: Chemistry and Transport.* Panel on Stratospheric Chemistry and Transport, National Academy of Sciences, Washington D.C., USA, p.238.

Robinson, J.R. (1989). 'On Uncertainty in the Computation of Global Emissions for Biomass Burning'. *Climatic Change*, 14, pp. 243-262.

Seinfeld, J.H. and Pandis, S.N. (1998). *Atmospheric Chemistry and Physics.* John Wiley and Sons, New York, USA, p. 1326.

Subsidiary Body for Scientific and Technological Advice (SBSTA), United Nations Framework Convention on Climate Change (1999). *National Communications from Parties included in Annex 1 to the Convention, Guidelines for the Preparation of National Communications, Draft conclusions by the Chairman.* FCCC/SBSTA/1999/L.5, p. 17.