CHAPTER 3

UNCERTAINTIES

Authors

Newton Paciornik (Brazil)

Michael Gillenwater (USA), Riccardo De Lauretis (Italy), Daniela Romano (Italy), Suvi Monni (Finland), Stephen M. Ogle (USA)

Contributing Authors

Timo Kareinen (Finland), Cody Alsaker (USA)

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3 UNCERTAINTIES

Users are expected to go to Mapping Tables in Annex 1, before reading this chapter. This is required to correctly understand both the refinements made and how the elements in this chapter relate to the corresponding chapter in the 2006 IPCC Guidelines.

3.1 INTRODUCTION

This chapter provides guidance on estimating and reporting uncertainties associated with both annual estimates of emissions and removals, and emission and removal trends over time. It also explains why uncertainty assessment is a useful means of improving emission inventories. This guidance is written primarily for inventory compilers and provides, with examples, two approaches for combining category uncertainties into uncertainty estimates for total national net emissions and trends.

3.1.1 Overview of uncertainty analysis[1]

Uncertainty assessment is an important part of the effort of compiling an inventory of anthropogenic emissions and removals of GHGs (GHG inventory) and to understand changes over time. Since the *GPG2000* report, the IPCC has adopted the concept of "*Good Practice*" in developing a GHG inventory.

In accordance with *good practice*, estimates should be *accurate* in the sense that they are neither systematically over- nor under-estimating the true emissions or removals, so far as can be judged, and they should be *precise* so far as practicable.

In the context of national GHG inventories, the purpose of the uncertainty assessment process is to qualitatively and quantitatively understand and document the causes of uncertainty in individual estimates and overall totals. The outputs of this process capture both accuracy and precision. For every value reported in an inventory there will exist an associated uncertainty. Causes of uncertainty are discussed in Section 3.1.5 of the *2006 IPCC Guidelines*.

An inventory compiler's efforts should focus on improving accuracy, meaning that estimation bias should be eliminated as far as can be judged. Figure 3.2 of the *2006 IPCC Guidelines* illustrates the difference between accuracy and precision, showing that a precise estimate is of limited value if it is not accurate.

The assessment of uncertainty is most effective while data is being collected and emission or removal estimates are calculated. The combination of quantitative uncertainty values is strongly linked to the equations used to estimate emissions and removals. Simple methods are based on equations that multiply activity data (AD) by an emission factor (EF). More generally, both AD and EF can be the result of several different parameters (see Section 3.2.3 for a discussion). For some complex methods (e.g., Tier 3), models may be used that involve numerous equations and datasets capturing a range of spatial-temporal scales. Regardless of the complexity of the method, uncertainty of the results is related to the uncertainties in the data (activity data or emission factors) used in the equations. In short, all data collected should have an associated qualitative and quantitative uncertainty assessment (see Section 3.2).

Finally, uncertainty assessment results are not absolute measures of the overall quality of the inventory. Even if the uncertainty calculation approach fully captures the complexity of the emission and removal estimation equations, the results also reflect the share of sectors and categories in each country (i.e., emission totals for some countries contain a larger fraction of emissions from categories that are inherently more uncertain). Nevertheless, uncertainty assessment is a useful tool for inventory improvement. Together with the *key category* analysis, it provides information for prioritizing methodological and data collection improvements across source and sink categories (see Section 3.1.2).

[1] The *2006 IPCC Guidelines* use the formulations "uncertainty analysis" and "uncertainty assessment" interchangeably. In this report, the formulation "uncertainty assessment" is preferably used, and the term is intended to convey an exercise that includes the investigation of quantitative and qualitative aspects. In the glossary to the Guidelines, "uncertainty analysis" is defined as only a quantitative exercise. For easier cross-reference with the *2006 IPCC Guidelines*, however, section titles using the term "analysis" have not been changed.

3.1.1a Uncertainty assessment as part of inventory management

An uncertainty assessment is used by inventory compilers to improve inventories over time. Regardless of the framework under which national GHG inventories are developed and reported, inventories are not one-time tasks. Inventories are typically reported annually, biennially, or over longer periods and are updated and extended between reports.

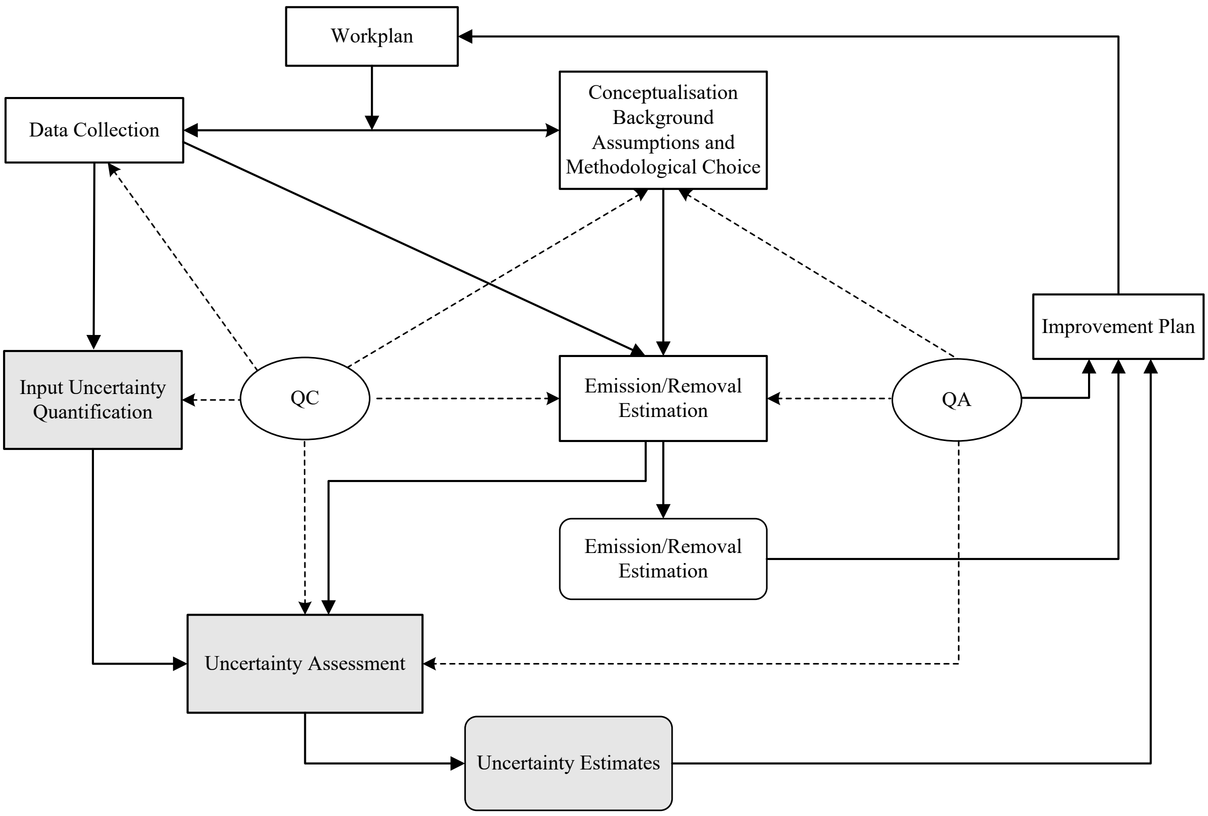
Between two reporting occasions, it is *good practice* to assess the data sources, data flows and methods used. Ideally, an inventory will be subject to Quality Assurance (QA) procedures in accordance with guidance provided in Chapter 6 of Volume 1 of the *2006 IPCC Guidelines*, as well as other review processes (e.g. reviews under the UNFCCC). Figure 1.1 in Section 1.1 of Volume 1 of the *2006 IPCC Guidelines* illustrates the steps of a typical inventory cycle, and Chapter 1 of this report covers the steps to put in place the institutional arrangements necessary to manage the process, including the organization and resources for planning and preparing an inventory. Figure 3.1 builds from Figure 3.1 in Chapter 3 of Volume 1 of the *2006 IPCC Guidelines* to show how the uncertainty assessment fits in this improvement cycle.

The process of producing an uncertainty assessment can pragmatically be divided into four parts: (1) the rigorous investigation of the likely causes of data uncertainty; (2) the development of quantitative uncertainty estimates and parameter correlations; (3) the mathematical combination of those estimates when used as inputs to a statistical model (e.g., first-order error propagation or Monte Carlo method); and (4) the selection of inventory improvement actions (improvement plan) to take in response to the results of the previous three parts.

An improvement plan will elaborate the opportunities to improve the inventory and prioritize those opportunities, taking into account the information provided in the *key category* analysis, the uncertainty assessment, the recommendations from quality assurance and verification processes (including review process), and resources available.

Particularly in relation to the uncertainty assessment, the improvement plan will investigate ways to reduce biases that have been identified and ways to enhance precision for categories with high contribution to the overall uncertainty of the inventory.

Figure 3.1 (Updated) Overall structure of a generic uncertainty assessment process



3.1.2 Overall structure of uncertainty analysis

As part of an inventory planning process, an improvement plan will identify the emission and removal categories for which changes are to be implemented in future inventories. These improvements will likely address methodological choice, as well as data specification, availability and collection. For example, a typical improvement will focus on getting better data for the same methodology (e.g. collecting country-specific data). The goal of an improvement plan is to increase the quality of the inventory.

Figure 4.1 of Volume 1 of the *2006 IPCC Guidelines* shows the steps of methodology choice, which depend on the target category for improvement, data availability, and resources requirements.

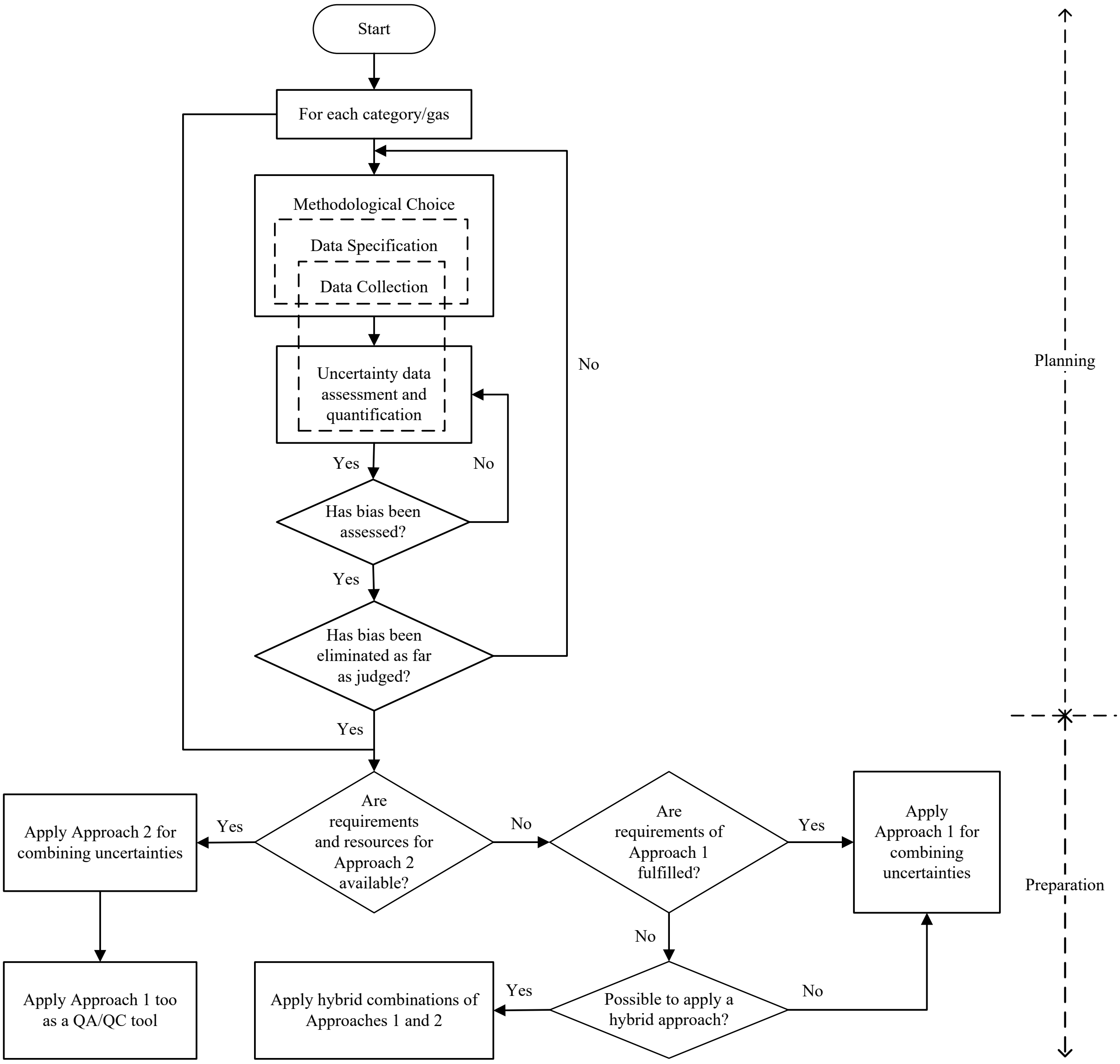
Figure 3.1a shows the general steps of an uncertainty assessment. It is important to note the strong link among these steps, especially between the data specification and collection steps and between the data collection and the quantification of data uncertainty steps.

When assessing data uncertainty, it is essential to identify the causes of uncertainty. In particular, priority should be given to identifying causes of bias, as well as potential ways to correct those biases.

Following the assessment of the uncertainty in input data used in emissions/removals estimation (e.g. activity data and emission factors), the next step is to combine or propagate the quantitative uncertainty estimates for these parameters to produce an uncertainty estimate for the source or sink category. Then these uncertainty values can be combined across all categories to determine the overall uncertainty of the total national net emissions in the inventory.

There are two approaches presented in these guidelines for combining uncertainty values. Figure 3.1a shows a simple scheme for choosing which approach to select, although it is important to note that hybrid approaches are possible where the propagation technique varies among categories. It is also important to note that even when requirements for application of approach 1 are not fully present it still can provide useful information about the uncertainty of the inventory. Because of its simplicity when compared with Approach 2, it is recommended to also apply Approach 1 as a quality assurance / quality control (QA/QC) tool when applying Approach 2.

Figure 3.1a (New) Uncertainty assessment steps description and decision tree



3.1.3 Key concepts and terminology

Definitions associated with conducting an uncertainty analysis include uncertainty, accuracy, precision and variability. These terms are sometimes used loosely and may be misunderstood. They have in fact clear statistical definitions that should be used in order to be clear about what is being quantified and reported. Several definitions are given here, in alphabetical order:

Accuracy: Agreement between the true value and the average of repeated measured observations or estimates of a variable. An accurate measurement or prediction lacks bias or, equivalently, systematic error.

Bias: Lack of accuracy. Bias (systematic error), can occur because of failure to capture all relevant processes involved or because the available data are not representative of all real-world situations, or because of instrument error.

Confidence Interval (CI): A type of interval estimate, computed from the statistics of the observed/estimated data, that might contain the true value of an unknown population parameter. The interval has an associated confidence level that quantifies the level of confidence that the parameter lies in the interval. Most commonly, the 95 percent confidence level is used.

Precision: Agreement among repeated measurements of the same variable. Better precision means less random error. Precision is independent of accuracy.

Probability density function (PDF): A function, whose value at any given sample (or point) in the sample space (the set of possible values taken by the random variable) can be interpreted as providing a relative likelihood that the value of the random variable would equal that sample.

Random errors: Random variation above or below a mean value. Random error is inversely proportional to precision. Usually, the random error is quantified with respect to a mean value, but the mean could be biased or unbiased. Thus, random error is a distinct concept compared to systematic error.

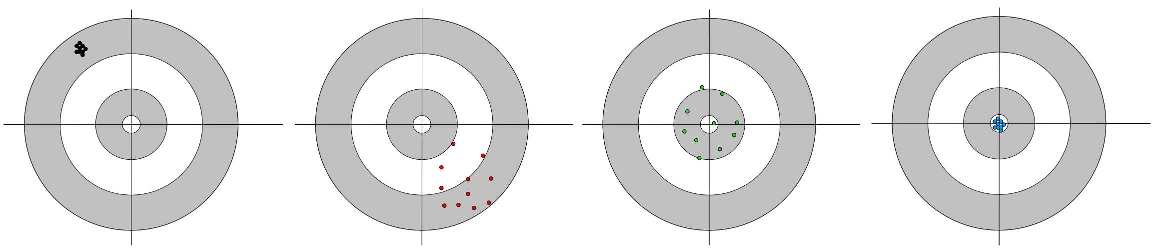
Systematic error: Another term for bias, which refers to lack of accuracy.

Uncertainty: Lack of knowledge of the true value of a variable that can be described as a PDF characterising the range and likelihood of possible values. Uncertainty depends on the analyst's state of knowledge, which in turn depends on the quality and quantity of applicable data as well as knowledge of underlying processes and inference methods.

Variability: Heterogeneity of a variable over time, space or members of a population (Morgan and Henrion 1990; Cullen and Frey 1999). Variability may arise, for example, due to differences in design from one emitter to another (inter-plant or spatial variability) and in operating conditions from one time to another at a given emitter (intra-plant variability). Variability is an inherent property of the system or of nature, and not of the analyst.

Figure 3.2 Illustration of accuracy and precision

(a) inaccurate but precise; (b) inaccurate and imprecise; (c) accurate but imprecise; and (d) precise and accurate



(a) (b) (c) (d)

Inventories should be accurate in the sense that they are neither over- nor underestimated as far as can be judged, and precise as far as practicable. Figure 3.2 provides a conceptual comparison of accuracy and precision. An accurate inventory is one that is free of bias but that could be precise or imprecise. A precise inventory may appear to have low uncertainty but if the inventory is inaccurate, then the inventory systematically over- or under-estimates the true emissions or removals. Inaccuracy, or bias, can occur because of failure to capture all relevant emissions or removal processes or because the available data are not representative of real-world situations. There is no predetermined level of precision, in part because of the inherent variability of some categories.

3.1.4 Basis for uncertainty analysis

No refinement.

3.1.5 Causes of uncertainty

No refinement.

3.1.6 Reducing uncertainty

Uncertainties should be reduced as far as is practicable during the process of compiling an inventory, and it is particularly important to ensure that the model and the data collected are fair representations of the real world. When focusing efforts to reduce uncertainty, priority should be given to those inputs to the inventory that have the most impact on the overall uncertainty of the inventory, as opposed to inputs that are of minor or negligible importance to the assessment as described in Chapter 4, Methodological Choice and Identification of Key Categories. Tools for prioritising where uncertainties should be reduced include *key category* analysis (see Chapter

4) and assessment of the contribution of uncertainties in specific categories to the total uncertainty in the inventory (see Section 3.2.3). Depending on the cause of uncertainty present, uncertainties could be reduced in seven broad ways:

- *Improving conceptualisation*: Improving the inclusiveness of the structural assumptions chosen can reduce uncertainties. An example is better treatment of seasonality effects that leads to more accurate annual estimates of emissions or removals for the AFOLU Sector.
- *Improving models*: Improving the model structure and parameterisation can lead to better understanding and characterisation of the systematic and random errors, as well as reductions in these causes of uncertainty.
- *Improving representativeness*: This may involve stratification or other sampling strategies, as set out in Section 3.2.1.2. This is particularly important for categories in the agriculture, forestry and land use parts of an inventory, but also applies elsewhere, e.g., wherever different technologies are operating within a category. For example, continuous emissions monitoring systems (CEMS) can be used to reduce uncertainty for some sources and gases as long as the representativeness is guaranteed. CEMS produces representative data at the facilities where it is used, but in order to be representative of an entire source category, CEMS data must be available for a sample or an entire set of individual facilities that comprise the category. When using CEMS both GHG emissions concentration and flow will vary, requiring simultaneous observations of both attributes.
- *Using more precise measurement methods*: Measurement error can be reduced by using more precise measurement methods, avoiding simplifying assumptions, and ensuring that measurement technologies are appropriately used and calibrated. See Chapter 2, Approaches to Data Collection.
- *Collecting more data that are measured*: Uncertainty associated with random sampling error can be reduced by increasing the sample size. Both bias and random error can be reduced by filling in data gaps. This applies both to measurements and surveys.
- *Eliminating known risk of bias*: This is achieved by ensuring instrumentation is properly positioned and calibrated (see Section 2.2 in Chapter 2), models or other estimation procedures are appropriate and representative as indicated by the decision trees and other advice on methodological choice in sectoral volumes, and by applying expert judgements in a systematic way.
- *Improving state of knowledge*: Generally, improving the understanding of the categories and the processes leading to emissions and removals can help to discover, and correct for, problems of incompleteness. It is *good practice* to continuously improve emissions and removal estimates based on new knowledge (see Chapter 5, Time Series Consistency).
- *Moving to higher tier method*: For example, Tier 1 emission factors that are considered global defaults may be biased when they are applied in a specific country where emission rates deviate by significant amounts from global defaults. Moving to a higher tier method in these cases will likely increase accuracy. Applying a higher tier method may also improve the precision of estimates, as shown in Box 3.0.

The effort to reduce uncertainty is also one that is tightly integrated with data collection and QA/QC processes. In many ways, uncertainty assessment is an in-depth approach to quality management. Both uncertainty assessment and QA/QC processes require rigorous investigation into the causes of data quality problems, especially ones that general QC checks are unlikely to identify. These problems will often involve issues of incomplete data or other systematic biases in the data, which also happen to be key issues for developing a quantitative uncertainty analysis (Gillenwater et al. 2007).

Both QA/QC and uncertainty assessment are part of a learning process. While the uncertainty assessment provides a quantification of inventory uncertainty, its primary function is to understand what causes uncertainty and how to improve inventory quality. Conversely, the outcome of QA/QC procedures may result in a reassessment of individual category or parameter uncertainty estimates (e.g. if new systematic biases in data are identified). Procedures to check quality and analyse uncertainties should work together because both processes are intended to understand the causes of uncertainty and identify potential areas of improvement (US EPA 2002).

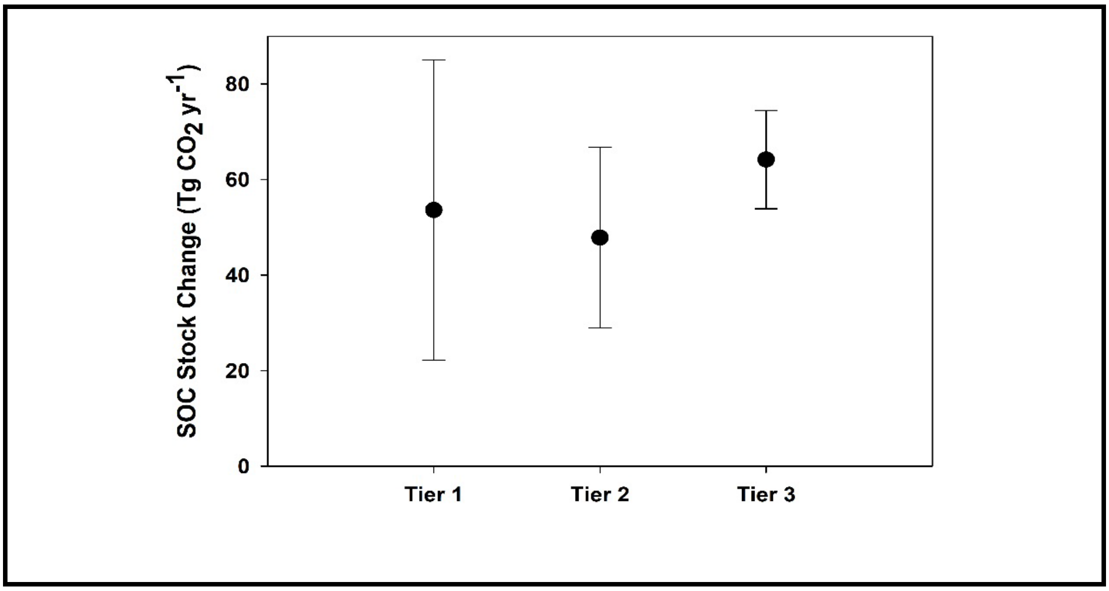
BOX 3.0 (NEW)
EXAMPLE OF REDUCING UNCERTAINTY IN A CATEGORY BY ADOPTING HIGHER TIER METHODS

Mineral soil C stock changes for *Cropland Remaining Cropland* have been estimated with all three methodological tiers for the United States, and this box provides information about how uncertainty has been reduced by moving to higher tiers. A Monte Carlo Analysis for propagating uncertainties addressing key dependencies in the underlying data, such as the relationship among the land use areas, was used for each methodological tier. As with other source categories, the Tier 1 method is relatively simple with default emission factors provided in the IPCC guidance, but does require compilation of activity data for a simple classification of lands, climate and soils. The *2006 IPCC Guidelines* provide uncertainties in emission factors, while uncertainties in land use and management data were derived from the survey data used in the inventory. For example, land use data were based on a two-stage survey design used to derive joint probability distributions for land use and land use change over the inventory time series. By moving to Tier 2, the compilers derived country-specific emission factors (i.e. stock change factors) based on experimental data from the region (Ogle et al. 2003). Specifically, the new factors were derived using a linear mixed-effect modelling approach from 46 experiments evaluating the effect of tillage management on soil carbon, 19 experiments evaluating the impact of variation in carbon input to soils, and 35 experiments evaluating the impact of land use change between native conditions and long-term cultivation. Compilers also had the option of refining the land representation and activity data into a country-specific set of climate and soil types, in addition to management classes. However, the compilers did not change the classification in this application, and so the uncertainties in activity data were the same for the Tier 1 and 2 methods. Regardless, flexibility in deriving new emission factors improved the precision of the estimates, reducing the 95 percent confidence interval for the estimated soil C stock changes from ±59% of the estimate using the Tier 1 method to a ±40% for the Tier 2 method (see Figure 3.2a, US EPA 2017).

The compilers further developed the inventory for *Cropland Remaining Cropland* with a Tier 3 method. This method was based on the Century Ecosystem Model, and later the DayCent Ecosystem Model (Ogle et al. 2010; US EPA 2017). These models incorporate a more mechanistic representation of the processes influencing soil organic matter dynamics, including water flows through the soil, crop production, organic matter decomposition, and nutrient cycling (Parton et al. 1987). With a more advanced representation of processes, the inventory was able to capture a broader suite of drivers influencing the change in soil carbon stocks. In addition, the inventory incorporated more detailed information on activity data and environmental variables, such as weather, soils, and management practices. There were additional uncertainties associated with these activity data, such as the variability in specific nitrogen fertilisation rates. Several of the main datasets, however, such as land use and cropping histories, did not differ across the three methods. In theory, Tier 3 methods allow compilers to develop a methodology that is more specific to national circumstances and in keeping with *good practice*. To address uncertainties in the emission rates (i.e., analogous to the emission factors for the Tier 1 and 2 methods), the compilers evaluated uncertainty in the Century/DayCent model predictions of soil carbon stock changes by comparing results to independent measurement data. They used these data comparisons to develop an empirical model to adjust for biases and assess precision in the inventory results (Ogle et al. 2007). More details about the uncertainty analysis are provided in Volume 4, Chapter 2, Box 2.2H. The Tier 3 inventory further constrained 95 percent confidence intervals in soil carbon stock change estimates over 5 years from a ±40% with the Tier 2 method to ±16% for the Tier 3 method (see Figure 3.2a).

Incorporating data specific to a country for estimating Tier 2 emission factors will better represent the range of cropland fields in the country. Tier 1 default factors are based on samples from a larger global population of fields, which has considerably more variation in climates, soils and other variables driving soil organic matter dynamics, and all of this variation is not relevant for an individual country. Of course, the accuracy of the Tier 2 factors also depends on an adequate sample of emission measurements in a country. For the Tier 3 method, the compilers incorporated scientific understanding of soil organic matter dynamics using the Century/DayCent model, which embodies key processes and structure that influence soil carbon stock changes. In turn, the compilers could estimate management impacts on soil carbon stock changes with more specificity to physical and biogeochemical conditions of the plant-soil environments in the country than is possible with the lower tier methods.

Figure 3.2a (New) Estimated soil organic C stock changes (Tg CO_2 eq. yr^{-1}) and 95 percent confidence intervals for Tier 1, 2 and 3 methods as applied in the national greenhouse gas inventory for the United States (US EPA 2017)



3.1.7 Implications of methodological choice

No refinement.

3.2 QUANTIFYING UNCERTAINTIES

The quantification of uncertainty will be based on the input data used in the methodology equations. The overall uncertainty of the emissions/removals will depend on the uncertainty associated with each data variable and parameter used. As such, *good practice* uncertainty assessment begins with *good practice* in data collection. Uncertainty consideration will need to be an integral part of the data collection effort, including selection of data sources and choice of methods following the guidance in Chapter 2 of Volume 1 of the *2006 IPCC Guidelines*.

Section 3.2 of Volume 1 of the *2006 IPCC Guidelines* covers the different techniques for quantifying uncertainties, which depend on the availability of information and data collection approaches. These include measured data, published information, model outputs, and expert judgement. At time, the pragmatic approach will be a combination of the techniques.

Again, it is *good practice* to follow the procedures for QA/QC according to Chapter 6 of Volume 1 of the *2006 IPCC Guidelines*. These procedures are fundamental in preventing mistakes and misreporting and misclassification errors and approach deviations.

Ultimately, the measure of uncertainty will be a 95 percent confidence interval around a point estimate for the value. To develop this information a PDF will be associated with each quantity. The development of that PDF is an essential part of the uncertainty assessment. Section 3.2.2.4 of Volume 1 of the *2006 IPCC Guidelines* provide guidance on how to select the form of PDF. The representativeness of the PDF will depend on the characteristics of the quantity, including domain (e.g., if it can have both positive or negative values, or only non-negative values), range (e.g., is the range narrow or does it cover orders-of-magnitude) and shape (e.g., symmetry). The same characteristics will be fundamental when the approaches for combining uncertainties are selected.

Where the PDF is believed to be symmetrical, the confidence interval can be conveniently expressed as plus or minus half the confidence interval width divided by the estimated value of the variable (e.g., ±10%). Where the PDF is not symmetrical, the upper and lower limits of the confidence interval need to be specified separately (e.g., -30%, +50%). In both cases, the understanding is that the confidence interval has a 95 percent probability of enclosing the true but unknown value of the emission factor, parameter, or activity data.

Box 3.0a provides some examples of appropriate estimators that the inventory compiler could use, within typical circumstances and available data, for uncertainty evaluation.

BOX 3.0A (NEW)
DIFFERENCE BETWEEN STANDARD DEVIATION AND STANDARD ERROR

The following formulas may be chosen by an inventory compiler to evaluate the uncertainty of a parameter.

A 95 percent confidence interval may be derived considering either the standard deviation (σ) or the standard error (*SE*) around the estimated parameter (μ).

Under the assumption that values are normally distributed, the uncertainty of the estimate may be expressed as:

$$\text{Uncertainty} = \pm\left(\frac{1.96 \bullet \sigma}{\mu}\right) \bullet 100\%, \text{ where:}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \mu\right)^2}$$

and

n is the number of observations

x_i are the observed values

or as:

$$\text{Uncertainty} = \pm\left(\frac{1.96 \bullet SE}{\mu}\right) \bullet 100\%, \text{ where:}$$

$$SE = \frac{\sigma}{\sqrt{n}}\ *$$

* "*n*" is used instead of "*n-1*" as an approximation for large samples.

Some considerations may help the inventory compiler choose between these two approaches.

The standard deviation of a sample can be used to estimate the variability of the population from which the sample was drawn. For data with a normal distribution, about 95 percent of individuals will have values within 1.96 standard deviations of the mean, the other 5 percent being equally scattered above and below these limits.

When the sample mean is known, the inventory compiler is usually not ultimately interested in the mean of that particular sample, but in the mean of the population from which the sample is drawn. For instance, for a sectoral category of the inventory, in order to estimate a specific parameter (e.g. emission factor, carbon stock change factor or AD), data are usually collected with the aim to generalize from them and use the sample mean as an estimate of the average parameter for the whole category.

The sample mean will vary from sample to sample; the way this variation occurs is described by the "sampling distribution" of the mean. The variability of the mean is calculated using the standard deviation of this sampling distribution, which is defined as the standard error of the mean.

The standard error falls as the sample size increases whereas the standard deviation will tend to remain the same.

In summary, to calculate the uncertainty of a given parameter, the first step is to establish if the parameter (e.g. the mean value) is used to estimate an individual of the population (for example the case of using the average C stock of forest land to estimate the C stock of a specific stand of trees, or a subcategory if the forest land is stratified into forest types) or the entire population (when using the average C stock of forest land to estimate the C stock of the entire forest land category).

BOX 3.0A (NEW) (CONTINUED)
DIFFERENCE BETWEEN STANDARD DEVIATION AND STANDARD ERROR

In the first case, the variability (i.e. how much population values are spread) is measured using the standard deviation. In the second case the variability (i.e. how much the mean values of the samples taken from the population are spread), is measured using the standard error.

The following examples are provided for emission factors:

Case 1.

Availability of annual information to derive country-specific emission factors of a specific category/gas/fuel.

Data are collected yearly from the whole population or a representative sample(s) of the relevant category.

This situation may occur when data are collected from facilities.

In this case, the annual emission factor is calculated as the average emission factor from repeated measurements in specific years and may change over the years. Inventory compilers are interested in the variability of this average annual value.

Assuming a normal distribution of the data collected, the 95 percent confidence interval may be expressed with the standard error and the uncertainty of the estimated emission factor as:

$$\text{Uncertainty} = \pm\left(\frac{1.96 \bullet SE}{\mu}\right) \bullet 100\%$$

Case 2.

Availability of irregular information during the years used to derive country-specific emission factors of a specific category/gas/fuel.

Data are not regularly collected and the result of data collected for one single year for a specific category, which well characterizes the population, is applied to a longer period of the time series.

This situation may occur when data are sporadically collected from facilities, e.g. methane emissions and relevant activity data and parameters from landfills.

In this case, the 95 percent confidence intervals can be calculated using the standard deviation of the point estimate because, assuming the value is representative of other years, the variability of the population has to be considered. The uncertainty will be:

$$\text{Uncertainty} = \pm\left(\frac{1.96 \bullet \sigma}{\mu}\right) \bullet 100\%$$

Case 3.

Availability of annual information used to derive country-specific emission factors at an upper level than the one actually used.

This situation may occur if, for instance, an average emission factor is available and this country-specific value is applied to a specific area, e.g. carbon stock per hectare of deforested area.

As in case 2, the variability of the individuals should be considered in order to derive the 95 percent confidence intervals and the uncertainty is to be estimated as:

$$\text{Uncertainty} = \pm\left(\frac{1.96 \bullet \sigma}{\mu}\right) \bullet 100\%$$

Box 3.0b provides a formula that the inventory compiler could use to convert range (min and max) of EFs into percentage uncertainty values.

BOX 3.0B (NEW)
CONVERSION OF RANGE TO UNCERTAINTY

If a range is associated with an EF (min EF-max EF) and assuming that this range contains 95 percent of possible EF values, it is suggested to use the following formula to calculate the associated uncertainty in percentage terms:

Uncertainty lower bound Ulb = (min EF- EF)/ EF × 100 %

Uncertainty upper bound Uub = (max EF- EF)/ EF × 100 %

3.2.1 Sources of data and information

No refinement.

3.2.1.1 UNCERTAINTIES ASSOCIATED WITH MODELS

No refinement.

3.2.1.2 EMPIRICAL DATA FOR SOURCES AND SINKS AND ACTIVITY

This section describes sources of empirical data, and their implications for uncertainty, and is relevant to measured emissions data, data obtained from literature, and activity data.

UNCERTAINTY ESTIMATES OBTAINED FROM MEASURED EMISSIONS/REMOVALS DATA

No refinement.

UNCERTAINTY ESTIMATES FOR EMISSION FACTORS AND OTHER PARAMETERS OBTAINED FROM PUBLISHED REFERENCES

No refinement.

UNCERTAINTIES ASSOCIATED WITH ACTIVITY DATA

Activity data are often more closely linked to economic activity than are emission factors are. However, unlike emission factor data, there is typically no statistical sample of alternative activity data estimates readily available to fit distributions and estimate uncertainty. There are often well-established price incentives and fiscal requirements for accurate accounting of economic activity. Activity data therefore tend to have lower uncertainties and a lower correlation between years than emission factor data. Activity data are often collected and published regularly by national statistical agencies, which may have already assessed the uncertainties associated with their data as part of their data collection procedures. These previously developed uncertainty estimates can be used to construct PDFs. This information will not necessarily have been published, so it is recommended to contact the statistical agencies directly. Since economic activity data are not usually collected for the purpose of estimating greenhouse gas emissions and removals, it is *good practice* to assess the applicability of the uncertainty estimates before using them.

There are several approaches that may be helpful in assessing the uncertainty of activity data in particular circumstances:

Activity data based on complete samples **(*censuses*):** Census data are based, in principle, on counting every instance of a particular activity. A census may include systematic and random errors. Systematic errors arise through systematic undercounting or overcounting. For example, undercounting may occur due to non-responses from a sub-group of individuals with characteristics and behaviour that differ from other individuals of the population, which may lead to bias. Random errors are typically the sum of a range of commonplace errors. Random errors usually can be expected to be normally distributed and serially uncorrelated. Because activity data are usually collected by the same people, using the same processes, for each observation, systematic errors are likely to take approximately the same value each year. There are several approaches to identifying the potential uncertainty of activity data for complete samples. These approaches are often an integrated part of a QA/QC plan:

- To check for the size of random errors, look for fluctuations over time, and differential fluctuations in series that ought to be highly correlated with the data of interest.

- To check for bias errors, cross-check the data of interest with other, related information. One might, for instance, look up and down the supply chain for fuels, comparing coal production, coal import/export, and reported consumption. Or, one might study activities for which data are collected independently but which ought to be highly correlated with the data of interest, for instance reported fuel input vs. electricity output. One might also look at activity data of different frequencies (e.g., monthly, annual), if they are collected using different approaches.
- Interpretation of statistical differences, within, for instance, national energy data is an example of cross-checking. The comparison between energy-related carbon dioxide emissions derived from the IPCC reference approach is a formal cross-check with emissions estimates derived from other sources.

Census-based activity data are often 'precise but inaccurate' in the taxonomy shown in Figure 3.2, the random errors are small, but there may be larger bias errors. Cross-checking can suggest upper and lower bounds for possible bias errors, and sometimes will permit an actual estimate of the bias error. A possible bias error lurking within these bounds may often be characterised as a truncated uniform distribution: cross-checking shows that the unobservable true value must lie within a particular range, but there may be no reason to think any point within that range is more or less likely. However, because the bias errors in activity data are likely to be highly correlated, the difference between the reported value and the unknown true value is likely to be about the same every year, and this characteristic should be taken into account when estimating trend uncertainty.

***Activity data based on random samples*:** Some kinds of activity data are derived from sample surveys, for instance consumer surveys, land use surveys, or forest cover surveys. The agency conducting the sample will normally be able to advise on sampling error. If this information is unavailable, it may be possible to identify or infer the sample and population sizes and calculate sampling error directly.

The most common survey designs are simple random sampling, systematic sampling, stratified sampling, and two-stage sampling. For a simple random sampling design, a sample of n elements is selected without replacement from a population of N total elements with equal probability. For example, a survey may sample the fuel usage from 2,000,000 vehicles in a country with 80,000,000 total vehicles by randomly selecting vehicles to be included in the sample. Each sampled vehicle is multiplied by a weight of 40 (i.e., total number of vehicles divided by the number that are sampled) and summed to estimate the total fuel usage. This design is commonly used when there is little additional information known about the population.

With systematic sampling, an initial sample element is randomly selected then subsequent sampling elements are selected at equal increments, such as geographic distances apart. For example, a survey may be determining the amount of biomass C in forestlands by sampling 50 forest stands from a population 1000 stands in a country. A random location is selected for the first sample, and then additional samples are spaced at 20 km apart across all of the forestland in a country. The biomass C for each of the sampled forest stands is multiplied by a weight of 20 in this example (total number of forest stands divided by the number in the sample), and then summed to obtain the total biomass C for forestlands in the country. Systematic sampling is used to ensure a wide dispersion of samples in a geographical region.

Stratified sampling designs subdivide population into separate groups, referred to as strata. An individual stratum may be sampled using simple random sampling or systematic sampling. The differences among strata should be as heterogeneous as possible, whilst the subpopulation within a stratum should be as homogeneous as possible. For example, farms may be sampled to determine the amount of livestock manure N production by stratifying the farms according to the production systems in a country, which could be based on livestock types, products (e.g., meat, eggs, milk or other products), manure management practices, or other relevant criteria. For this example, assume that there are 15 production systems with 100 farms in each production system for a total of 1500 farms. If 10 farms are sampled in each production system, then the total amount of manure N production for each production system is estimated by multiplying each farm's value by a weight of 10 (total number of farms in a stratum, i.e., production system, divided by the number of farms in the sample for the stratum). The national total is the sum of the manure N production for the 15 production systems. In addition, individual stratum can have different sample sizes, and the weight would change in this case based on the total number of farms and number sampled in each stratum.

With a two-stage sampling design, the population is first divided into primary sampling units, and each primary sampling unit is further divided into secondary sampling units. The primary sampling units are typically selected using simple random sampling, stratified or systematic sampling, while secondary sampling units within the sampled primary sampling units are typically selected using simple random sampling. Total estimates are made for each primary sampling unit, and then combined to estimate the total for the entire population. For example, the amount of waste transported to landfills may be determined by creating primary sampling units based on random selection of provinces, and then municipalities within provinces are randomly selected for the secondary sampling units. The total amount of waste is determined for the individual provinces in the first step given the total number of municipalities in a province and the number of municipalities that are sampled. In the second step, the total waste production for the entire country is determined based on the total number of provinces and the number of provinces that are sampled. This type of sampling design may be the best approach for optimizing the precision of activity data with limited funding.

All of these designs have standard formulas that can be used to derive variances in the resulting estimates for the activity data (e.g., see Särndal et al. 1992). The estimated variances can be converted into probability distribution functions for the activity data and used to propagate uncertainty through the emissions calculations with guidance provided in Section 3.2.3 of this chapter.

3.2.1.3 EXPERT JUDGEMENT AS A SOURCE OF INFORMATION

No refinement.

3.2.2 Techniques for quantifying uncertainties

No refinement.

3.2.3 Methods to combine uncertainties

This section further elaborates on the two approaches to combine uncertainties presented in Section 3.2.3 of the *2006 IPCC Guidelines*: Approach 1, simple propagation of error equations, and Approach 2, Monte Carlo simulation. A tool for the implementation of Approach 1 is also included as an addendum.

Once the uncertainties in activity data, emission factor or other parameters for a category have been determined, they may be combined to provide uncertainty estimates for the category emissions. Once these have been determined, they may be combined to provide uncertainty estimates for the total national net emissions in any year and the overall inventory trend over time.

Two approaches for the estimation of combined uncertainties are presented in the following sections: Approach 1 uses simple error propagation equations, while Approach 2 uses Monte Carlo or similar techniques. Either Approach may be used for emission sources or sinks, subject to the assumptions and limitations of each Approach and availability of resources.

Figure 3.1a in Section 3.1.2 shows a basic step-by-step process for choosing an approach. In practice, however, the options are not always straightforward.

Approach 1 is simpler to apply but requires assumptions that frequently are not entirely met, such as lack of significant correlations among the quantities used in the inventory, uncertainties that are less than ±30% of the quantity value or uncertainties that are symmetrically distributed. Approach 2 requires more information on the probability distributions of the data involved in the calculations. As such, it also involves assumptions and more information on the underlying processes and its application depends on the capacity to acquire this information. In turn, Approach 2 may provide a more representative confidence interval for the uncertainty in the category.

Approach 2 will be particularly appropriate to use when uncertainties are large, their distribution are non-Gaussian, and algorithms are complex functions.

3.2.3.1 APPROACH 1: PROPAGATION OF ERROR

Approach 1 is based upon error propagation and is used to estimate uncertainty in individual categories, in the inventory as a whole, and in trends between a year of interest and a base year. The key assumptions, requirements, and procedures are described here.

Approach 1 should be implemented using Table 3.1, Approach 1 Uncertainty Calculation. A tool set up on a commercial spreadsheet software is provided, as an addendum to this chapter, to facilitate the implementation of Table 3.1. The table is completed at the category level using uncertainty ranges for activity data and emission factors consistent with the sectoral *good practice* guidance[2]. Different gases should be entered separately as CO_2

[2] Where estimates are derived from models, enter the uncertainty associated with the activity data used to drive the model, and enter the uncertainty associated with the model parameters instead of the emission factor uncertainty. It may be necessary to use expert judgement, or error propagation calculations associated with the model structure. If it is impractical to separate the uncertainty estimate obtained from a model for a category into separate activity and emission factor components, then enter the total uncertainty for the category in the emission factor column and assign zero uncertainty to the activity factor column.

equivalents. Categories should be disaggregated to the level where methodologies are applied and AD and EF are estimated, unless correlation between the subcategories exist.

KEY ASSUMPTIONS OF APPROACH 1

In Approach 1 uncertainty in emissions or removals can be propagated from uncertainties in the activity data, emission factor and other estimation parameters through the error propagation equation (Mandel 1984; Bevington and Robinson 1992). If correlations exist, then either the correlation can be included explicitly or data can be aggregated to an appropriate level such that correlations become less important. Approach 1 also theoretically requires that the standard deviation divided by the mean value is less than 0.3. In practice, however, the approach will give informative results even if this criterion is not strictly met and some correlations remain. Approach 1 assumes that the relative ranges of uncertainty in the emission and activity factors are the same in the base year and in year *t*. This assumption is often correct or approximately correct. If any of the key assumptions of Approach 1 do not apply, then either an alternative version of Approach 1 can be developed (e.g., see Section 3.4) or Approach 2 can be used instead.

Where the standard deviation divided by the mean is greater than 0.3 the reliability of Approach 1 can be improved. The Section 3.7.3 'Dealing with Large and Asymmetric Uncertainties in the Results of Approach 1' of the *2006 IPCC Guidelines* describes how to do this.

KEY REQUIREMENTS OF APPROACH 1

To quantify uncertainty using Approach 1, estimates of the uncertainty for each input are required, as well as the equation through which all inputs are combined to estimate an output. The simplest equations include statistically independent (uncorrelated) inputs. When inputs are known to be fully (or mostly) correlated, modified equations should be used or a preliminary step should be performed to combine these inputs before the application of the basic rules.

Uncertainty of the inputs will represent a 95 percent confidence interval expressed as a percentage of the point estimate of the input (e.g. ± 20%). When the probability distribution function is known to be asymmetrical, upper and lower limits of the confidence interval need to be specified separately (e.g., -10 %, +20%). In this case, Approach 1 will provide only a rough approximation and in order to be used the interval needs to be replaced by a symmetrical interval built using the larger of the two quantities (e.g. ±20%). When uncertainties are known to be large and asymmetrical, more elaborated techniques may be applied as described in Section 3.7.3 of the *2006 IPCC Guidelines.*

PROCEDURE OF APPROACH 1

The Approach 1 analysis estimates uncertainties by using the error propagation equation in two steps. First, the Equation 3.1 approximation is used to combine emission factor, activity data and other estimation parameter ranges by category and greenhouse gas. Second, the Equation 3.2 approximation is used to arrive at the overall uncertainty in national emissions and the trend in national emissions between the base year and the current year.

Uncertainty of an Annual Estimate

The error propagation equation[3] yields two convenient rules for combining uncorrelated uncertainties under addition and multiplication:

Where uncertain quantities are to be combined by multiplication a simple equation (Equation 3.1) can then be derived for the uncertainty of the product, expressed in percentage terms. This rule is approximate for all random variables. Under typical circumstances, this rule is reasonably accurate as long as the percentage uncertainty is less than approximately 30%. This rule is not applicable to division.

EQUATION 3.1 (UPDATED)
COMBINING UNCERTAINTIES – APPROACH 1 – MULTIPLICATION

$$U_{total} = \sqrt{U_1^2 + \ldots U_i^2 + \ldots + U_n^2}$$

Where:

[3]As discussed more extensively in Annex 1 of the *Good Practice Guidance and Uncertainty Management* (*GPG2000*, IPCC, 2000), and in Annex I of the *Revised 1996 IPCC Guidelines* (Reporting Instructions) (*1996 IPCC Guidelines*, IPCC, 1997).

U_{total} = the percentage uncertainty in the product of the quantities (half the 95 percent confidence interval divided by the total and expressed as a percentage)

U_i = the percentage uncertainties associated with each of the quantities

Where uncertain quantities are to be combined by addition or subtraction, a simple equation (Equation 3.2) can be derived for the uncertainty of the sum, expressed in percentage terms[4]. This rule is exact for uncorrelated variables.

EQUATION 3.2 (UPDATED)
COMBINING UNCERTAINTIES – APPROACH 1 – ADDITION AND SUBTRACTION

$$U_{total} = \frac{\sqrt{(U_1 \bullet x_1)^2 + \ldots + (U_i \bullet x_i)^2 + \ldots + (U_n \bullet x_n)^2}}{|x_1 + \ldots + x_i + \ldots + x_n|}$$

Where:

U_{total} = the percentage uncertainty in the sum of the quantities (half the 95 percent confidence interval divided by the total (i.e., mean) and expressed as a percentage)

x_i = quantities to be combined; x_i may be a positive or a negative number

U_i = the percentage uncertainties associated with each of the quantities

The GHG Inventory is principally the sum of products of emission factors, activity data and other estimation parameters. Therefore, Equations 3.1 and 3.2 can be used repeatedly to estimate the uncertainty of the total inventory. In practice, uncertainties found in inventory categories vary from a few percent to orders of magnitude and may be correlated. This is not consistent with the assumptions of Equations 3.1 and 3.2 that the variables are uncorrelated, and with the assumption of Equation 3.2 that the coefficient of variation is less than about 30 percent, but under these circumstances, Equations 3.1 and 3.2 may still be used to obtain an approximate result.

Applying Approach 1 (level) in practice

Simple methods for estimation of the emissions of a category are usually based on the multiplication of activity data (AD) by an emission factor (EF). In many cases, it will be a reasonable assumption that these values are uncorrelated. The uncertainty associated with the emissions can then be calculated by Equation 3.2a:

EQUATION 3.2A (NEW)
COMBINING UNCERTAINTIES – APPROACH 1 – AD • EF

$$U_{emissions} = \sqrt{U_{AD}^2 + U_{EF}^2}$$

More generally, both AD and EF can be the result of several different parameters and this frequently occurs for the EF (e.g. EF = a • b • c). The uncertainty of the EF will be calculated as:

[4] The option for expressing uncertainties in percent terms allows the results to be presented in a user-friendly way. However, caution should be exercised in the interpretation of the results in cases where the point estimate is very small when compared with the size of the confidence interval (e.g. a sector or inventory where removals and emissions are of similar sizes). Moreover, in the unique case the sum of negative quantities is equal to the sum of positive ones, the denominator in the Equation 3.2 is equal to "0" and the formula has no sense. In that case, the uncertainty should be expressed just as half the 95 percent confidence interval (±1.96σ).

EQUATION 3.2B (NEW)
COMBINING UNCERTAINTIES – APPROACH 1 – EF = A •B • C

$$U_{EF} = \sqrt{U_a^2 + U_b^2 + U_c^2}$$

The uncertainties associated with the emissions for each subcategory will be combined to obtain the uncertainty associated with a whole category and further combined to obtain the uncertainty of the whole inventory. In these steps, the uncertainties are combined through addition and therefore Equation 3.2 should be applied.

Particular attention should be given to the correlation in this step. The subcategories can be highly correlated, because either the AD are derived from the same source or the EFs have parameters in common. A special situation occurs when an input is entirely dependent on a set of other inputs. As noted in the *2006 IPCC Guidelines* this could occur, for example, if residential fuel is estimated as the difference between total consumption and usage in the transportation, industrial, and commercial sectors. Similarly, in the AFOLU sector, when land transitions are assessed, total area transitions depend on the total area of the country, resulting in less degrees of freedom for the variables.

Approach 1 has limitations to the consideration of correlation as it only allows for full correlation or independency between the variables. Still broad sensibility can be implemented, either for correlation between variables in the same year or different years. This flexibility is included in the tool for the implementation of Approach 1 included in the addendum. It is important to note that in the case of full correlation among categories, aggregation of these categories is the recommended procedure. When information is lacking for either uncertainties of AD or EF for subcategories of a category, pre-processing by expert judgement may be necessary to either provide individual values to the subcategories or recommend their aggregation. Where partial correlations are known to exist and are relevant, Approach 2 is recommended.

BOX 3.1A (NEW)
EXAMPLE OF UNCERTAINTY CALCULATION: CH_4 EMISSIONS FROM MANURE MANAGEMENT

In accordance with the Tier 1 methodology described in Chapter 10 (Section 10.4) of this Methodology Report, CH_4 emissions from manure management are estimated applying the equation below:

$$CH_{4(mm)} = \left[\sum_{T,S} \left(N_{(T)} \bullet VS_{(T)} \bullet AWMS_{(T,S)} \bullet EF_{(T,S)} \right) / 1000 \right]$$

Where:

$CH_{4(mm)}$ = CH_4 emissions from Manure Management in the country, kg CH_4 yr^{-1}

$N_{(T)}$ = number of head of livestock species/category *T* in the country

$VS_{(T)}$ = annual average VS excretion per head of species/category *T*, kg VS $animal^{-1}$ yr^{-1}

$AWMS_{(T,S)}$ = fraction of total annual VS for each livestock species/category *T* that is managed in manure management system *S* in the country, dimensionless

$EF_{(T,S)}$ = emission factor for direct CH_4 emissions from manure management system *S,* by animal species/category in the country, g CH_4 kg VS^{-1} in manure management system *S*

In addition, $VS_{(T)}$ is evaluated by the equation:

$$VS_{(T)} = VS_{rate(T)} \bullet \frac{TAM_{(T)}}{1000} \bullet 365$$

Where:

$VS_{rate(T)}$ = default VS excretion rate, kg VS (1000 kg animal mass)$^{-1}$ day^{-1}

$TAM_{(T)}$ = typical animal mass for livestock category *T*, kg $animal^{-1}$

Essentially, by these equations, the CH_4 emissions are estimated by a sum of products of parameters and, as such, Equations 3.1 and 3.2 apply and could be successively used, always under usual assumptions. The parameters may be classified as AD or EF, although this is not really necessary and sometimes artificial.

To estimate the uncertainty, a point estimate and a confidence interval are necessary for each of the parameters. In some cases, it may be difficult to develop simple confidence intervals, particularly in cases where calculations are not linear (e.g. when using the gross energy intake (GE) from the agricultural enteric fermentation Tier 2). As an example, the formulas are applied for the Tier 1 method for calculation of methane emissions from manure management from dairy cows. Data are from Volume 4, Chapter 10 and Monni et al. 2007. Three types of manure management systems (pasture, slurry and solid storage) are considered.

$$CH_4 = \left[\sum_{i=1}^{3} \left(N_{dairy} \bullet VS_{dairy} \bullet AWMS_{dairy,i} \bullet EF_{dairy,i} \right) / 1000 \right]$$

Data:			
	N_{dairy}	= 350 000	(-3%, +3%)
	VS_{dairy}	= 7.5 kg/t animal mass/day	(-20%, +20%)
	TAM_{dairy}	= 570 kg	(-4%, +4%)
	$EF_{dairy,pasture}$	= 0.60 g CH_4/kg VS	(-30%, +30%)
	$EF_{dairy, slurry}$	= 33.8 g CH_4/kg VS	(-30%, +30%)
	$EF_{dairy, solid}$	= 3.2 g CH_4/kg VS	(-30%, +30%)
	$AWMS_{dairy,pasture}$	= 0.28	(-20%,+20%)
	$AWMS_{dairy, slurry}$	= 0.25	(-20%,+20%)
	$AWMS_{dairy, solid}$	= 0.47	(-20%,+20%)

BOX 3.1A (NEW) (CONTINUED)
EXAMPLE OF UNCERTAINTY CALCULATION: CH_4 EMISSIONS FROM MANURE MANAGEMENT

It is important to note that AWMS fractions are not independent quantities (as $AWMS_1+AWMS_2+AWMS_3=1$). Before calculating the uncertainty, $AWMS_{dairy,3}$ needs to be replaced by $(1-AWMS_{dairy,1}-AWMS_{dairy,2})$.

The terms of the resulting equation will not be all independent and this contradicts the assumptions behind Equations 3.1 and 3.2. To correctly consider the correlation between the values of $AWMS_i$, Approach 2 is recommended to be used. Nonetheless, due to the overwhelming effect of liquid manure management systems in the calculation of the emission factor, in this case, the simplifying assumption can be applied.

The results of application of Approach 1 are shown below:

Point estimates for CH_4:

$CH_{4,pasture} = 0.09$ Gg $\quad CH_{4,slurry} = 4.61$ Gg $\quad CH_{4,solid} = 0.82$ Gg

$CH_{4,Total} = 5.53$ Gg

Recalling that:

$$CH_{4,pasture} = \left[N_{dairy} \bullet VS_{rate,dairy} \bullet TAM_{dairy} \bullet AWMS_{dairy,pasture} \bullet EF_{dairy,pasture} \bullet 365/10^6 \right]$$

$$U\left(CH_{4,pasture}\right) = \sqrt{U^2_{N_{dairy}} + U^2_{VS_{rate,dairy}} + U^2_{TAM_{dairy}} + U^2_{AWMS_{dairy,pasture}} + U^2_{EF_{dairy,pasture}}}$$

In the example:

$$U\left(CH_{4,pasture}\right) = \sqrt{9+400+16+400+900} = 41.5\%$$

Similarly:

$$U\left(CH_{4,slurry}\right) = U\left(CH_{4,solid}\right) = 41.5\%$$

And then:

$$U(CH_4) = \frac{\sqrt{\left(41.5 \bullet 0.09\right)^2 + \left(41.5 \bullet 4.61\right)^2 + \left(41.5 \bullet 0.82\right)^2}}{5.53} = 35.22\%$$

To compare this result with the result of Approach 2, two cases of Monte Carlo simulation have been developed, assuming normal distribution for all parameters. In the first case, the correlation between the share of systems (AWMS) was disregarded. In the second case, the correlation between the systems was taken into consideration. The results obtained were:

Case without correlations: $U_{MC} = 37.21$ $\quad$ Case with correlations: $U_{MC2} = 36.41$

The results show that if correlation is disregarded the uncertainty result is higher than when the correlation is considered and that in this example, Approach 1 underestimates the uncertainty.

It is interesting to note that, although the result of Approach 2 will be more accurate than the result of Approach 1, the result of Approach 1, in this example, is not too far apart from the result of Approach 2 due to the minor role of the two AWMS systems that were correlated in the calculation of the emission factor. However, this will not always be the case, depending on the data and their distribution. Nevertheless, Approach 1 would still qualify as a tool for QA/QC and for helping in prioritizing improvements to the inventory if there are not enough data and resources for using Approach 2.

Uncertainty in the Trend

The trend of the net emissions of a category is expressed as a percentage calculated in relation to the emissions in the base year. The uncertainty in the trend will be a function of the uncertainties of the emissions in both the base year and the current year. As a direct consequence, the uncertainty of the trend will be a function of the uncertainties of the activity data and the emission factors at both these points in time.

Similar to the level uncertainty, Approach 1 for the trend uncertainty applies a simple propagation method based on the uncertainties of the input data (activity data and emission factors) for both the base year and the current year. In addition to the assumptions already described, the approach for calculating the trend uncertainty requires assumptions on data correlation between the base year and the current year.

In general, emission factors (and other estimation parameters) uncertainties will tend to be correlated between years while activity data will tend to be uncorrelated between years. The basic approach presented assumes full correlation between emission factors in the base year and the current year and independence between activity data in the base year and the current year. The method allows for change in case the activity data for a category is fully correlated between years or emission factor for a category is independent between years reflecting national circumstances. However, as for the level approach, the method does not provide for partial correlations.

The uncertainty in the trend in total emissions from the country is estimated as:

EQUATION 3.2C (NEW)
APPROACH 1 - TREND UNCERTAINTY

$$U_T = \sqrt{\sum_i (U_{Te,i}^2 + U_{Ta,i}^2)}$$

Where:

U_T = uncertainty in the trend in total emissions from the country

$U_{Te,i}$ = trend uncertainty introduced by the uncertainty associated with the emission factor of the category/gas i

$U_{Ta,i}$ = trend uncertainty introduced by the uncertainty associated with the activity data of the category/

gas i

It is important to note that while the level uncertainty is reported as a confidence interval expressed as percentage uncertainties in relation to the point estimate, the uncertainty of the trend is reported as a confidence interval expressed in percentage points to be added to or subtracted from the trend estimation. For example, if the emissions for year *t* are 10 Gg and the result of the level uncertainty is ±2%, the confidence interval for the emissions will be [9.8, 10.2]. Differently, if the trend in the emissions is 10% between the base year and year *t* and the result of the trend uncertainty is ±2%, this means that the confidence interval for the trend will be [8%, 12%].

In order to know how the uncertainty of the emission factors and activity data affects the trend in the emissions Type A and Type B sensitivities need to be developed as follows:

- *Type A sensitivity*: the change in the difference in overall emissions between the base year and the current year, expressed as a percentage, resulting from a 1 percent increase in emissions or removals of a given category and gas in both the base year and the current year.

EQUATION 3.2D (NEW)
CALCULATION OF TYPE A SENSITIVITY

$$A_x = \left| \frac{0.01 \bullet E_{x,t} + \sum_i E_{i,t} - \left(0.01 \bullet E_{x,BY} + \sum_i E_{i,BY}\right)}{\left(0.01 \bullet E_{x,BY} + \sum_i E_{i,BY}\right)} \bullet 100 - \frac{\sum_i E_{i,t} - \sum_i E_{i,BY}}{\sum_i E_{i,BY}} \bullet 100 \right|$$

Where:

A_x = the type A sensitivity for category/gas x

$E_{i,t}$ = emissions/removals for category/gas i in the year t

$E_{i,BY}$ = emissions/removals for category/gas i in the base year

- *Type B sensitivity*: the change in the difference in overall emissions between the base year and the current year, expressed as a percentage, resulting from a 1 percent increase in emissions or removals of a given category and gas in the current year only.

EQUATION 3.2E (NEW)
CALCULATION OF TYPE B SENSITIVITY

$$B_x = \left| \frac{100 \bullet 0.01 \bullet E_{x,t}}{\sum_i E_{i,BY}} \right|$$

Where:

B_x = the type B sensitivity for category/gas *x*

$E_{x,t}$ = emissions/removals for category/gas *x* in the year *t*

$E_{i,BY}$ = emissions/removals for category/gas *i* in the base year

Under the assumption that the emission factors are fully correlated, variation in the base year emission factor will correspond to the same variation in the current year emission factor. Hence, the emission factor uncertainty will be propagated to the trend through a Type A sensitivity.

EQUATION 3.2F (NEW)
TREND UNCERTAINTY DUE TO EMISSION FACTOR

$$U_{Te,i} = A_i \bullet U_{EF,i}$$

Where:

$U_{Te,i}$ = trend uncertainty introduced by the uncertainty associated with the emission factor of the category/gas *i*

A_i = the Type A sensitivity for category/gas *i*

$U_{EF,i}$ = uncertainty of the emission factor for category/gas *i*

Under the assumption that the activity data in the base year and the current year are independent, both the uncertainties have to be taken into consideration. Hence, the activity data uncertainty will be propagated to the trend through a Type B sensibility that shows the sensitivity to a random uncertainty error in the emissions estimate. The additional factor of √2 is introduced because an uncorrelated uncertainly might affect either the base year or the current year.

EQUATION 3.2G (NEW)
TREND UNCERTAINTY DUE TO ACTIVITY DATA

$$U_{Ta,i} = B_i \bullet U_{AD,i} \bullet \sqrt{2}$$

Where:

$U_{Ta,i}$ = trend uncertainty introduced by the uncertainty associated with the activity data of the category/ gas *i*

B_i = the Type B sensitivity for category/gas *i*

$U_{AD,i}$ = uncertainty of the activity data for category/gas *i*

Worksheet for Approach 1 Uncertainty Calculation

The columns of Table 3.2, Approach 1 Uncertainty Calculation, are labelled A to Q and contain the following information, of which the derivation of key equations is given in Section 3.7.1 in Section 3.7, Technical Background Information.

- A shows the sector of the IPCC category.
- B shows the code of the IPCC category.
- C shows the name of the IPCC category.
- D shows the greenhouse gas.
- E and F are the inventory estimates in the base year and the current year[5] respectively, for the category and gas specified in Columns C and D, expressed in CO_2 equivalents.
- G and I contain the uncertainties for the activity data and emission factors respectively, derived from a mixture of empirical data and expert judgement as previously described in this chapter, entered as half the 95 percent confidence interval divided by the mean and expressed as a percentage. The reason for halving the 95 percent confidence interval is that the value entered in Columns G and I corresponds to the familiar plus or minus value when uncertainties are loosely quoted as 'plus or minus *x* percent', so expert judgements of this type can be directly entered in the spreadsheet. If uncertainty is known to be highly asymmetrical, enter the larger percentage difference between the mean and the confidence limit.
- H indicates if the uncertainty in activity data is correlated across years.
- J indicates if the uncertainty in emission factor is correlated across years.
- K is the combined uncertainty by category derived from the data in Columns G and I using the error propagation equation (Equation 3.2). The entry in Column K is therefore the square root of the sum of the squares of the entries in Columns G and I.
- L shows the uncertainty in Column K as a percentage of total national emissions in the current year. The entry in each row of Column L is the square of the entry in Column K multiplied by the square of the entry in Column F, divided by the square of total at the foot of Column F. The value at the foot of Column L is an estimate of the percentage uncertainty in total national net emissions in the current year, calculated from the entries above using Equation 3.1. This total is obtained by summing the entries in Column L and taking the square root.
- M shows how the percentage difference in emissions between the base year and the current year changes in response to a one percent increase in category emissions/removals for both the base year and the current year. This shows the sensitivity of the trend in emissions to a systematic uncertainty in the estimate (i.e., one that is correlated between the base year and the current year). This is the Type A sensitivity as defined above.
- N shows how the percentage difference in emissions between the base year and the current year changes in response to a one percent increase in category emissions/removals in the current year only. This shows the sensitivity of the trend in emissions to random error in the estimate (i.e., one that is not correlated, between the base year and the current year). This is the Type B sensitivity as described above.
- O shows the uncertainty introduced into the trend in emissions by emission factor uncertainty. If the uncertainty in emission factors is correlated between years (J = Y) the result is the product of the information in Columns M and I. If the emission factor uncertainties are not correlated between years (J = N) then the entry in Column N should be used in place of that in Column M and the result multiplied by $\sqrt{2}$.
- P shows the uncertainty introduced into the trend in emissions by activity data uncertainty. If the uncertainty in activity data is not correlated between years (H = N) the result is the product of the information in Columns N and G multiplied by $\sqrt{2}$. If the activity data uncertainties are correlated between years (H = Y) then the entry in Column M should be used in place of that in Column N and the $\sqrt{2}$ factor does not then apply.
- Q is an estimate of the uncertainty introduced into the trend in national emissions by the category in question. Under Approach 1, this is derived from the data in Columns O and P using Equation 3.2. The entry in Column Q is therefore the sum of the squares of the entries in Columns O and P. The total at the foot of this column is an estimate of the total uncertainty in the trend, calculated from the entries above using the error propagation equation. This total is obtained by summing the entries in Column Q and taking the square root. The uncertainty in the trend is a *percentage point* range relative to the inventory trend. For example, if the current year emissions are 10 percent greater than the base year emissions, and if the trend uncertainty at the foot of Column Q is reported as 5 percent, then the trend uncertainty is 10% ±5% (or from 5% to 15% increase) for the current year emissions relative to the base year emissions.

[5] The current year is the most recent year for which inventory data are available.

- Explanatory footnotes go at the bottom of the table and give documentary references of uncertainty data (including measured data) or other relevant comments.

An example of the spreadsheet with all the numerical data completed is provided in Section 3.6, Approach 1 uncertainty calculation example. Details of this approach are given in Section 3.7.1 and derivation of the uncertainty in the trend is in Section 3.7.2.

TABLE 3.2 (UPDATED)
APPROACH 1 UNCERTAINTY CALCULATION

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
Inventory sector	IPCC category code	IPCC category name	GHG	Base year emissions or removals	Year *t* emissions or removals	Activity data uncertainty	AD uncertainty correlated across years?	Emission factor / estimation parameter uncertainty	EF uncertainty correlated across years?	Combined uncertainty	Contribution to Variance by Category in Year *t*	Type A sensitivity	Type B sensitivity	Uncertainty in trend in national emissions introduced by emission factor / estimation parameter uncertainty	Uncertainty in trend in national emissions introduced by activity data uncertainty	Uncertainty introduced into the trend in total national emissions
				Input data	Input data	Input data Note A	Input data Default: N	Input data Note A	Input data Default: Y	$\sqrt{G^2 + I^2}$	$\frac{K \bullet F^2}{\sum F^2}$	Note B	$\left\| \frac{F}{\sum E} \right\|$	If J = Y $M \bullet I$ If J = N $N \bullet I \bullet \sqrt{2}$	If H = N $N \bullet G \bullet \sqrt{2}$ If H = Y $M \bullet G$	$O^2 + P^2$
				Gg CO_2 equivalent	Gg CO_2 equivalent	%	Y/N	%	Y/N	%		%	%	%	%	%
e.g. Energy	e.g. 1.A.1	e.g. Energy Industries Fuel 1	CO_2													
e.g.	e.g. 1.A.1	e.g. Energy Industries Fuel 2	CO_2													
Etc...	Etc.	Etc...	…													
Total				$\sum E$	$\sum F$						$\sum L$					$\sum Q$
										Percentage uncertainty in total inventory:	$\sqrt{\sum L}$				Trend uncertainty:	$\sqrt{\sum Q}$

Note A: If only total uncertainty is known for a category (not for emission factor and activity data separately), then:

- If uncertainty is correlated across years, enter the uncertainty into Column I, and enter 0 in Column G; it is suggested to assume correlation across years if some of the parameters used in the estimates are the same in both years or derived from the same source.
- If uncertainty is not correlated across years, enter the uncertainty into Column G, and enter 0 in Column I; it is suggested to assume no correlation between years if the estimates for the two years are independent from each other, for example based on independent measurements.

Note B: Absolute value of:

$$\frac{0.01 \bullet F_x + \sum F_i - \left(0.01 \bullet E_x + \sum E_i\right)}{0.01 \bullet E_x + \sum E_i} \bullet 100 - \frac{\sum F_i - \sum E_i}{\sum E_i} \bullet 100$$

Where:

E_x, F_x = entry from row *x* of the table from the corresponding column, representing a specific category

ΣE_i, ΣF_i = sum over all categories (rows) of the inventory of the corresponding column

3.2.3.2 APPROACH 2: MONTE CARLO SIMULATION

No refinement.

3.2.3.3 HYBRID COMBINATIONS OF APPROACHES 1 AND 2

No refinement.

3.2.3.4 COMPARISON BETWEEN APPROACHES

No refinement.

3.2.3.5 GUIDANCE ON CHOICE OF APPROACH

No refinement.

3.3 UNCERTAINTY AND TEMPORAL AUTOCORRELATION

No refinement.

3.4 USE OF OTHER APPROPRIATE TECHNIQUES

No refinement.

3.5 REPORTING AND DOCUMENTATION

No refinement.

3.6 EXAMPLES

The section further elaborates on the two approaches to combine uncertainties presented in Section 3.2.3 of the *2006 IPCC Guidelines*: Approach 1, simple propagation of error equations, and Approach 2, Monte Carlo simulation. A tool for the implementation of Approach 1 is also included as an addendum.

Two examples of uncertainty estimates for inventories are described, one based upon Finland's GHG inventory (Statistics Finland 2018), and the other one on Italy's GHG inventory (ISPRA 2018).

The example of Table 3.4 is based upon Approach 1, and is shown in the general format of Approach 1 worksheet (Table 3.2).

TABLE 3.4 (UPDATED) EXAMPLE OF AN APPROACH 1 UNCERTAINTY ANALYSIS FOR FINLAND (BASED ON STATISTICS FINLAND 2018) Note: The aggregation level and uncertainty estimates are country-specific and do not represent recommended uncertainties or level of aggregation for other countries.													
A	B	C	D	E	F	G	H	I	J	K	L	M	N
IPCC category code	IPCC category name	Gas	Base year emissions or removals	Year t emissions or removals	AD uncertainty	EF/ estimation parameter uncertainty	Combined uncertainty	Contribution to variance by category in year t	Type A sensitivity	Type B sensitivity	Uncertainty in trend in national emissions introduced by EF / estimation parameter uncertainty	Uncertainty in trend in national emissions introduced by AD uncertainty	Uncertainty introduced into the trend in total national emissions
			Gg CO_2 eq	Gg CO_2 eq	%	%	%		%	%	%	%	%
1.A.1	Energy Industries, Liquid	CO_2	2,616.21	2,256.04	3.0	2.5	4	0.077	0.014	0.039	0.14	0.17	0.047
1.A.1	Energy Industries, Liquid	CH_4	1.11	1.07	3.0	35.0	35	0.000	0.000	0.000	0.00	0.00	0.000
1.A.1	Energy Industries, Liquid	N_2O	23.29	23.02	3.0	40.0	40	0.001	0.000	0.000	0.01	0.00	0.000
1.A.1	Energy Industries, Solid	CO_2	9,640.06	8,952.07	0.9	1.3	2	0.199	0.063	0.156	0.29	0.20	0.122
1.A.1	Energy Industries, Solid	CH_4	2.73	2.30	0.9	50.0	50	0.000	0.000	0.000	0.00	0.00	0.000
1.A.1	Energy Industries, Solid	N_2O	41.72	45.49	0.9	55.0	55	0.006	0.000	0.001	0.02	0.00	0.000
1.A.1	Energy Industries, Gaseous	CO_2	2,636.23	2,315.52	0.9	0.5	1	0.006	0.015	0.040	0.01	0.05	0.003
1.A.1	Energy Industries, Gaseous	CH_4	1.23	1.13	0.9	55.0	55	0.000	0.000	0.000	0.00	0.00	0.000
1.A.1	Energy Industries, Gaseous	N_2O	15.04	14.06	0.9	50.0	50	0.000	0.000	0.000	0.00	0.00	0.000
1.A.1	Energy Industries, Other fossil	CO_2	1.00	507.16	10.0	15.0	18	0.083	0.009	0.009	0.19	0.13	0.051
1.A.1	Energy Industries, Other fossil	CH_4	0.00	0.66	9.0	60.0	61	0.000	0.000	0.000	0.00	0.00	0.000
1.A.1	Energy Industries, Other fossil	N_2O	0.01	6.41	9.0	55.0	56	0.000	0.000	0.000	0.01	0.00	0.000
1.A.1	Energy Industries, Peat	CO_2	3,949.51	4,797.50	2.0	2.0	3	0.183	0.046	0.084	0.24	0.24	0.112
1.A.1	Energy Industries, Peat	CH_4	2.99	6.18	2.0	60.0	60	0.000	0.000	0.000	0.00	0.00	0.000
1.A.1	Energy Industries, Peat	N_2O	33.44	61.89	2.0	60.0	60	0.014	0.001	0.001	0.05	0.00	0.002
1.A.1	Energy Industries, Biomass	CH_4	1.75	16.29	4.5	55.0	55	0.001	0.000	0.000	0.01	0.00	0.000
1.A.1	Energy Industries, Biomass	N_2O	2.94	113.34	4.5	55.0	55	0.039	0.002	0.002	0.11	0.01	0.012
1.A.2	Manufacturing industries and construction, Liquid	CO_2	4,861.59	3,182.02	2.0	1.2	2	0.055	0.009	0.056	0.09	0.16	0.034

TABLE 3.4 (UPDATED) (CONTINUED)
EXAMPLE OF AN APPROACH 1 UNCERTAINTY ANALYSIS FOR FINLAND (BASED ON STATISTICS FINLAND 2018)
Note: The aggregation level and uncertainty estimates are country-specific and do not represent recommended uncertainties or level of aggregation for other countries.

A	B	C	D	E	F	G	H	I	J	K	L	M	N
IPCC category code	**IPCC category name**	**Gas**	**Base year emissions or removals** Gg CO_2 eq	**Year t emissions or removals** Gg CO_2 eq	**AD uncertainty** %	**EF/ estimation parameter uncertainty** %	**Combined uncertainty** %	**Contribution to variance by category in year t**	**Type A sensitivity** %	**Type B sensitivity** %	**Uncertainty in trend in national emissions introduced by EF / estimation parameter uncertainty** %	**Uncertainty in trend in national emissions introduced by AD uncertainty** %	**Uncertainty introduced into the trend in total national emissions** %
1.A.2	Manufacturing industries and construction, Solid	CH_4	1.63	0.42	1.7	25.0	25	0.000	0.000	0.000	0.00	0.00	0.000
1.A.2	Manufacturing industries and construction, Solid	N_2O	44.93	28.24	1.7	50.0	50	0.002	0.000	0.000	0.00	0.00	0.000
1.A.2	Manufacturing industries and construction, Gaseous	CO_2	2,198.58	1,326.27	1.6	0.4	2	0.005	0.002	0.023	0.00	0.05	0.003
1.A.2	Manufacturing industries and construction, Gaseous	CH_4	1.20	0.73	1.6	40.0	40	0.000	0.000	0.000	0.00	0.00	0.000
1.A.2	Manufacturing industries and construction, Gaseous	N_2O	14.64	9.58	1.6	45.0	45	0.000	0.000	0.000	0.00	0.00	0.000
1.A.2	Manufacturing industries and construction, Other fossil	CO_2	100.64	387.08	5.5	8.0	10	0.014	0.006	0.007	0.08	0.05	0.009
1.A.2	Manufacturing industries and construction, Other fossil	CH_4	0.13	0.36	5.5	40.0	40	0.000	0.000	0.000	0.00	0.00	0.000
1.A.2	Manufacturing industries and construction, Other fossil	N_2O	0.63	3.22	5.5	30.0	31	0.000	0.000	0.000	0.00	0.00	0.000
1.A.2	Manufacturing industries and construction, Peat	CO_2	1,475.86	940.32	2.0	2.0	3	0.007	0.002	0.016	0.00	0.05	0.002
1.A.2	Manufacturing industries and construction, Peat	CH_4	1.06	0.66	2.0	55.0	55	0.000	0.000	0.000	0.00	0.00	0.000
1.A.2	Manufacturing industries and construction, Peat	N_2O	15.43	7.34	2.0	60.0	60	0.000	0.000	0.000	0.00	0.00	0.000

TABLE 3.4 (UPDATED) (CONTINUED)
EXAMPLE OF AN APPROACH 1 UNCERTAINTY ANALYSIS FOR FINLAND (BASED ON STATISTICS FINLAND 2018)
Note: The aggregation level and uncertainty estimates are country-specific and do not represent recommended uncertainties or level of aggregation for other countries.

A	B	C	D	E	F	G	H	I	J	K	L	M	N
IPCC category code	**IPCC category name**	**Gas**	**Base year emissions or removals**	**Year t emissions or removals**	**AD uncertainty**	**EF/ estimation parameter uncertainty**	**Combined uncertainty**	**Contribution to variance by category in year t**	**Type A sensitivity**	**Type B sensitivity**	**Uncertainty in trend in national emissions introduced by EF / estimation parameter uncertainty**	**Uncertainty in trend in national emissions introduced by AD uncertainty**	**Uncertainty introduced into the trend in total national emissions**
			Gg CO_2 eq	Gg CO_2 eq	%	%	%		%	%	%	%	%
1.A.3a	Domestic aviation, Liquid	CH_4	0.14	0.08	5.0	60.0	60	0.000	0.000	0.000	0.00	0.00	0.000
1.A.3a	Domestic aviation, Liquid	N_2O	3.14	1.52	5.0	150.0	150	0.000	0.000	0.000	0.00	0.00	0.000
1.A.3b	Road transportation, Diesel oil	CO_2	4,923.47	7,796.64	1.0	1.5	2	0.196	0.088	0.136	0.29	0.19	0.120
1.A.3b	Road transportation, Diesel oil	CH_4	13.66	2.97	1.0	60.0	60	0.000	0.000	0.000	0.00	0.00	0.000
1.A.3b	Road transportation, Diesel oil	N_2O	65.48	57.94	1.0	140.0	140	0.065	0.000	0.001	0.20	0.00	0.040
1.A.3b	Road transportation, Motor gasoline	CO_2	5,884.29	4,047.77	2.0	2.0	3	0.130	0.014	0.071	0.20	0.20	0.080
1.A.3b	Road transportation, Motor gasoline	CH_4	93.20	12.27	2.0	60.0	60	0.001	0.001	0.000	0.02	0.00	0.000
1.A.3b	Road transportation, Motor gasoline	N_2O	88.26	13.62	2.0	150.0	150	0.004	0.001	0.000	0.05	0.00	0.003
1.A.3b	Road transportation, Gaseous	CO_2	0.00	5.35	3.0	0.5	3	0.000	0.000	0.000	0.00	0.00	0.000
1.A.3b	Road transportation, Gaseous	CH_4	0.00	0.09	3.0	60.0	60	0.000	0.000	0.000	0.00	0.00	0.000
1.A.3b	Road transportation, Gaseous	N_2O	0.00	0.11	3.0	150.0	150	0.000	0.000	0.000	0.00	0.00	0.000
1.A.3b	Road transportation, Biomass	CH_4	0.00	0.83	1.0	45.0	45	0.000	0.000	0.000	0.00	0.00	0.000
1.A.3b	Road transportation, Biomass	N_2O	0.00	3.36	1.0	120.0	120	0.000	0.000	0.000	0.01	0.00	0.000
1.A.3c	Railways, Liquid	CO_2	191.10	63.71	2.0	1.5	3	0.000	0.001	0.001	0.00	0.00	0.000
1.A.3c	Railways, Liquid	CH_4	0.27	0.09	2.0	60.0	60	0.000	0.000	0.000	0.00	0.00	0.000
1.A.3c	Railways, Liquid	N_2O	1.45	0.31	2.0	150.0	150	0.000	0.000	0.000	0.00	0.00	0.000
1.A.3d	Domestic navigation, Liquid	CO_2	441.29	403.21	10.0	1.0	10	0.016	0.003	0.007	0.01	0.10	0.010

TABLE 3.4 (UPDATED) (CONTINUED)
EXAMPLE OF AN APPROACH 1 UNCERTAINTY ANALYSIS FOR FINLAND (BASED ON STATISTICS FINLAND 2018)

Note: The aggregation level and uncertainty estimates are country-specific and do not represent recommended uncertainties or level of aggregation for other countries.

A	B	C	D	E	F	G	H	I	J	K	L	M	N
IPCC category code	**IPCC category name**	**Gas**	**Base year emissions or removals**	**Year t emissions or removals**	**AD uncertainty**	**EF/ estimation parameter uncertainty**	**Combined uncertainty**	**Contribution to variance by category in year t**	**Type A sensitivity**	**Type B sensitivity**	**Uncertainty in trend in national emissions introduced by EF / estimation parameter uncertainty**	**Uncertainty in trend in national emissions introduced by AD uncertainty**	**Uncertainty introduced into the trend in total national emissions**
			Gg CO_2 eq	Gg CO_2 eq	%	%	%		%	%	%	%	%
1.A.3d	Domestic navigation, Biomass	N_2O	0.00	0.04	12.5	130.0	131	0.000	0.000	0.000	0.00	0.00	0.000
1.A.3e	Other Transportation, Gaseous	CO_2	2.20	9.16	20.0	0.5	20	0.000	0.000	0.000	0.00	0.00	0.000
1.A.3e	Other Transportation, Gaseous	CH_4	0.00	0.01	20.0	60.0	63	0.000	0.000	0.000	0.00	0.00	0.000
1.A.3e	Other Transportation, Gaseous	N_2O	0.01	0.05	20.0	60.0	63	0.000	0.000	0.000	0.00	0.00	0.000
1.A.4	Other sectors, Liquid	CO_2	6,987.63	3,293.46	6.5	0.7	7	0.460	0.010	0.057	0.06	0.53	0.282
1.A.4	Other sectors, Liquid	CH_4	26.29	16.18	6.5	25.0	26	0.000	0.000	0.000	0.01	0.00	0.000
1.A.4	Other sectors, Liquid	N_2O	54.96	23.11	6.5	40.0	41	0.001	0.000	0.000	0.02	0.00	0.001
1.A.4	Other sectors, Solid	CO_2	46.47	9.32	18.0	0.9	18	0.000	0.000	0.000	0.00	0.00	0.000
1.A.4	Other sectors, Solid	CH_4	2.79	0.08	18.0	65.0	67	0.000	0.000	0.000	0.00	0.00	0.000
1.A.4	Other sectors, Solid	N_2O	0.57	0.09	18.0	55.0	58	0.000	0.000	0.000	0.00	0.00	0.000
1.A.4	Other sectors, Gaseous	CO_2	102.35	137.63	7.0	0.3	7	0.001	0.001	0.002	0.00	0.02	0.001
1.A.4	Other sectors, Gaseous	CH_4	0.26	0.18	7.0	40.0	41	0.000	0.000	0.000	0.00	0.00	0.000
1.A.4	Other sectors, Gaseous	N_2O	0.56	0.74	7.0	40.0	41	0.000	0.000	0.000	0.00	0.00	0.000
1.A.4	Other sectors, Other fossil	CO_2	0.22	0.00	10.0	15.0	18	0.000	0.000	0.000	0.00	0.00	0.000
1.A.4	Other sectors, Other fossil	CH_4	0.00	0.00	10.0	60.0	61	0.000	0.000	0.000	0.00	0.00	0.000
1.A.4	Other sectors, Other fossil	N_2O	0.00	0.00	10.0	60.0	61	0.000	0.000	0.000	0.00	0.00	0.000
1.A.4	Other sectors, Peat	CO_2	121.64	223.78	8.5	1.7	9	0.004	0.003	0.004	0.01	0.05	0.002
1.A.4	Other sectors, Peat	CH_4	1.48	2.72	8.5	130.0	130	0.000	0.000	0.000	0.00	0.00	0.000

TABLE 3.4 (UPDATED) (CONTINUED) EXAMPLE OF AN APPROACH 1 UNCERTAINTY ANALYSIS FOR FINLAND (BASED ON STATISTICS FINLAND 2018) Note: The aggregation level and uncertainty estimates are country-specific and do not represent recommended uncertainties or level of aggregation for other countries.													
A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**N**
IPCC category code	**IPCC category name**	**Gas**	**Base year emissions or removals** Gg CO_2 eq	**Year t emissions or removals** Gg CO_2 eq	**AD uncertainty** %	**EF/ estimation parameter uncertainty** %	**Combined uncertainty** %	**Contribution to variance by category in year t**	**Type A sensitivity** %	**Type B sensitivity** %	**Uncertainty in trend in national emissions introduced by EF / estimation parameter uncertainty** %	**Uncertainty in trend in national emissions introduced by AD uncertainty** %	**Uncertainty introduced into the trend in total national emissions** %
1.A.5	Other energy, Liquid	CO_2	1,042.74	849.98	15.0	1.7	15	0.163	0.005	0.015	0.04	0.31	0.100
1.A.5	Other energy, Liquid	CH_4	2.97	1.85	15.0	45.0	47	0.000	0.000	0.000	0.00	0.00	0.000
1.A.5	Other energy, Liquid	N_2O	7.88	6.08	15.0	50.0	52	0.000	0.000	0.000	0.00	0.00	0.000
1.A.5	Other energy, Solid	CO_2	1.17	0.00	20.0	1.0	20	0.000	0.000	0.000	0.00	0.00	0.000
1.A.5	Other energy, Solid	CH_4	0.00	0.00	20.0	60.0	63	0.000	0.000	0.000	0.00	0.00	0.000
1.A.5	Other energy, Solid	N_2O	0.01	0.00	20.0	60.0	63	0.000	0.000	0.000	0.00	0.00	0.000
1.A.5	Other energy, Gaseous	CO_2	55.86	258.30	20.0	0.5	20	0.027	0.004	0.005	0.00	0.13	0.016
1.A.5	Other energy, Gaseous	CH_4	0.08	0.35	20.0	60.0	63	0.000	0.000	0.000	0.00	0.00	0.000
1.A.5	Other energy, Gaseous	N_2O	0.30	1.39	20.0	60.0	63	0.000	0.000	0.000	0.00	0.00	0.000
1.A.5	Other energy, Peat	CO_2	23.97	0.00	10.0	2.0	10	0.000	0.000	0.000	0.00	0.00	0.000
1.A.5	Other energy, Peat	CH_4	0.28	0.00	10.0	60.0	61	0.000	0.000	0.000	0.00	0.00	0.000
1.A.5	Other energy, Peat	N_2O	0.14	0.00	10.0	60.0	61	0.000	0.000	0.000	0.00	0.00	0.000
1.A.5	Other energy, Biomass	CH_4	0.35	0.62	10.0	60.0	61	0.000	0.000	0.000	0.00	0.00	0.000
1.A.5	Other energy, Biomass	N_2O	0.25	0.12	10.0	60.0	61	0.000	0.000	0.000	0.00	0.00	0.000
1.B.2	Oil and Natural gas and other emissions from energy production	CO_2	111.49	104.15	55.0	20.0	59	0.037	0.001	0.002	0.05	0.14	0.023
1.B.2	Oil and Natural gas and other emissions from energy production	CH_4	10.86	32.98	25.0	100.0	103	0.011	0.000	0.001	0.08	0.02	0.007

TABLE 3.4 (UPDATED) (CONTINUED)
EXAMPLE OF AN APPROACH 1 UNCERTAINTY ANALYSIS FOR FINLAND (BASED ON STATISTICS FINLAND 2018)

Note: The aggregation level and uncertainty estimates are country-specific and do not represent recommended uncertainties or level of aggregation for other countries.

A	B	C	D	E	F	G	H	I	J	K	L	M	N
IPCC category code	**IPCC category name**	**Gas**	**Base year emissions or removals**	**Year t emissions or removals**	**AD uncertainty**	**EF/ estimation parameter uncertainty**	**Combined uncertainty**	**Contribution to variance by category in year t**	**Type A sensitivity**	**Type B sensitivity**	**Uncertainty in trend in national emissions introduced by EF / estimation parameter uncertainty**	**Uncertainty in trend in national emissions introduced by AD uncertainty**	**Uncertainty introduced into the trend in total national emissions**
			Gg CO_2 eq	Gg CO_2 eq	%	%	%		%	%	%	%	%
2.A.3	Glass production	CO_2	20.98	2.12	5.0	3.0	6	0.000	0.000	0.000	0.00	0.00	0.000
2.A.4	Other process uses of carbonates	CO_2	63.14	138.90	4.5	2.5	5	0.001	0.002	0.002	0.00	0.02	0.000
2.B.1	Ammonia production	CO_2	92.95	0.00	3.0	15.0	15	0.000	0.001	0.000	0.00	0.00	0.000
2.B.2	Nitric acid production	N_2O	1,591.63	218.32	3.0	15.0	15	0.011	0.012	0.004	0.08	0.02	0.007
2.B.11a	Phosphoric acid production	CO_2	24.54	33.05	7.0	0.0	7	0.000	0.000	0.001	0.00	0.01	0.000
2.B.10	Hydrogen production	CO_2	116.22	937.85	5.0	3.0	6	0.030	0.015	0.016	0.07	0.12	0.018
2.B.11b	Limestone and dolomite use	CO_2	36.52	81.71	5.0	3.0	6	0.000	0.001	0.001	0.00	0.01	0.000
2.C.1	Iron and steel production	CO_2	1,966.62	2,170.99	4.0	0.0	4	0.075	0.019	0.038	0.00	0.21	0.046
2.C.1	Iron and steel production	CH_4	0.00	0.00	3.0	20.0	20	0.000	0.000	0.000	0.00	0.00	0.000
2.C.8	Other Metal Industry	CO_2	8.91	17.19	5.0	0.0	5	0.000	0.000	0.000	0.00	0.00	0.000
2.D.1	Lubricant use	CO_2	207.53	73.65	20.0	7.0	21	0.002	0.001	0.001	0.01	0.04	0.001
2.D.1	Lubricant use	CH_4	0.28	0.10	20.0	60.0	63	0.000	0.000	0.000	0.00	0.00	0.000
2.D.1	Lubricant use	N_2O	1.69	0.60	20.0	60.0	63	0.000	0.000	0.000	0.00	0.00	0.000
2.D.2	Paraffin wax use	CO_2	10.17	25.04	20.0	100.0	102	0.006	0.000	0.000	0.03	0.01	0.001
2.D.4	Other non energy products	CO_2	0.00	8.28	20.0	2.0	20	0.000	0.000	0.000	0.00	0.00	0.000
2.F.1	Refrigeration and air conditioning	HFCs	0.01	1,340.07	20.0	0.0	20	0.713	0.023	0.023	0.00	0.66	0.438
2.F.1	Refrigeration and air conditioning	PFCs	0.00	0.91	20.0	0.0	20	0.000	0.000	0.000	0.00	0.00	0.000

TABLE 3.4 (UPDATED) (CONTINUED)
EXAMPLE OF AN APPROACH 1 UNCERTAINTY ANALYSIS FOR FINLAND (BASED ON STATISTICS FINLAND 2018)
Note: The aggregation level and uncertainty estimates are country-specific and do not represent recommended uncertainties or level of aggregation for other countries.

A	B	C	D	E	F	G	H	I	J	K	L	M	N
IPCC category code	**IPCC category name**	**Gas**	**Base year emissions or removals**	**Year t emissions or removals**	**AD uncertainty**	**EF/ estimation parameter uncertainty**	**Combined uncertainty**	**Contribution to variance by category in year t**	**Type A sensitivity**	**Type B sensitivity**	**Uncertainty in trend in national emissions introduced by EF / estimation parameter uncertainty**	**Uncertainty in trend in national emissions introduced by AD uncertainty**	**Uncertainty introduced into the trend in total national emissions**
			Gg CO_2 eq	Gg CO_2 eq	%	%	%		%	%	%	%	%
2.G.3	N_2O from product uses	N_2O	64.49	24.56	10.0	0.0	10	0.000	0.000	0.000	0.00	0.01	0.000
2.H.3	Other Industrial process and product use	HFCs	0.01	2.81	17.0	0.0	17	0.000	0.000	0.000	0.00	0.00	0.000
2.H.3	Other Industrial process and product use	PFCs	0.21	3.53	50.0	0.0	50	0.000	0.000	0.000	0.00	0.00	0.000
2.H.3	Other Industrial process and product use	SF_6	7.48	36.62	50.0	0.0	50	0.003	0.001	0.001	0.00	0.05	0.002
3.A.1	Enteric fermentation	CH_4	2,422.95	2,104.60	19.0	0.0	19	1.588	0.013	0.037	0.00	0.99	0.974
3.A.2	Manure management	CH_4	369.61	460.86	40.0	0.0	40	0.337	0.004	0.008	0.00	0.46	0.207
3.A.2	Manure management	N_2O	285.06	284.62	120.0	0.0	120	1.158	0.002	0.005	0.00	0.84	0.711
3.C.4	Direct soil emissions	N_2O	3,313.75	3,031.32	55.0	0.0	55	27.603	0.021	0.053	0.00	4.12	16.938
3.C.5	Indirect emissions	N_2O	482.72	381.44	270.0	0.0	270	10.533	0.002	0.007	0.00	2.54	6.463
3.C.1.b	Field burning of agricultural residues	CH_4	3.07	1.94	55.0	0.0	55	0.000	0.000	0.000	0.00	0.00	0.000
3.C.1.b	Field burning of agricultural residues	N_2O	0.95	0.60	45.0	0.0	45	0.000	0.000	0.000	0.00	0.00	0.000
3.C.2	Liming	CO_2	642.01	265.58	0.0	20.0	20	0.028	0.002	0.005	0.03	0.00	0.001
3.C.3	Urea Application	CO_2	5.35	2.77	0.0	30.0	30	0.000	0.000	0.000	0.00	0.00	0.000
3.B.1.a	Forest Land remaining Forest Land	CO_2	-22,635.99	-35,773.51	30.0	0.0	30	1143.772	0.407	0.624	0.00	26.49	701.843
3.B.1.b	Land converted to Forest Land	CO_2	-1.30	-332.35	75.0	0.0	75	0.617	0.006	0.006	0.00	0.62	0.379

TABLE 3.4 (UPDATED) (CONTINUED)
EXAMPLE OF AN APPROACH 1 UNCERTAINTY ANALYSIS FOR FINLAND (BASED ON STATISTICS FINLAND 2018)
Note: The aggregation level and uncertainty estimates are country-specific and do not represent recommended uncertainties or level of aggregation for other countries.

A	B	C	D	E	F	G	H	I	J	K	L	M	N
IPCC category code	**IPCC category name**	**Gas**	**Base year emissions or removals**	**Year t emissions or removals**	**AD uncertainty**	**EF/ estimation parameter uncertainty**	**Combined uncertainty**	**Contribution to variance by category in year t**	**Type A sensitivity**	**Type B sensitivity**	**Uncertainty in trend in national emissions introduced by EF / estimation parameter uncertainty**	**Uncertainty in trend in national emissions introduced by AD uncertainty**	**Uncertainty introduced into the trend in total national emissions**
			Gg CO_2 eq	Gg CO_2 eq	%	%	%		%	%	%	%	%
3.B.3.b	Land converted to Grassland	CO_2	179.16	235.92	130.0	0.0	130	0.934	0.002	0.004	0.00	0.76	0.573
3.B.4.a	Wetlands remaining Wetlands	CO_2	1,357.80	1,961.93	150.0	0.0	150	86.005	0.021	0.034	0.00	7.26	52.774
3.B.4.b	Land converted to Wetlands	CO_2	65.46	137.84	120.0	0.0	120	0.272	0.002	0.002	0.00	0.41	0.167
3.B.5.a	Settlements remaining Settlements	CO_2	0.00	0.00	0.0	0.0	0	0.000	0.000	0.000	0.00	0.00	0.000
3.B.5.b	Land converted to Settlements	CO_2	870.53	570.66	75.0	0.0	75	1.819	0.002	0.010	0.00	1.06	1.116
3.D.1	Harvested Wood Products	CO_2	-2,951.60	-3,642.41	50.0	0.0	50	32.938	0.035	0.064	0.00	4.50	20.211
3.C.4	N fertilization	N_2O	20.56	17.28	10.0	200.0	200	0.012	0.000	0.000	0.02	0.00	0.000
3.C.4	Drainage, rewetting and other management soils	CH_4	1,533.39	918.77	100.0	100.0	141	16.766	0.001	0.016	2.27	2.27	10.288
3.C.4	Drainage, rewetting and other management soils	N_2O	1,218.24	1,212.39	100.0	100.0	141	29.194	0.009	0.021	2.99	2.99	17.914
3.C.4	Mineralization	N_2O	29.06	37.97	10.0	200.0	200	0.057	0.000	0.001	0.08	0.01	0.006
3.C.5	Indirect N_2O emissions	N_2O	2.24	3.25	100.0	0.0	100	0.000	0.000	0.000	0.00	0.01	0.000
3.C.1.d	Biomass Burning	CO_2	3.89	3.52	10.0	70.0	71	0.000	0.000	0.000	0.01	0.00	0.000
3.C.1.d	Biomass Burning	CH_4	4.90	0.68	10.0	70.0	71	0.000	0.000	0.000	0.00	0.00	0.000
3.C.1.d	Biomass Burning	N_2O	0.47	0.08	10.0	70.0	71	0.000	0.000	0.000	0.00	0.00	0.000
4.A	Solid Waste Disposal	CH_4	4,327.75	1,639.59	34.0	0.0	34	3.086	0.013	0.029	0.00	1.38	1.894
4.B	Biological Treatment of Solid Waste	CH_4	25.75	62.55	9.0	55.0	56	0.012	0.001	0.001	0.08	0.01	0.007

TABLE 3.4 (UPDATED) (CONTINUED)
EXAMPLE OF AN APPROACH 1 UNCERTAINTY ANALYSIS FOR FINLAND (BASED ON STATISTICS FINLAND 2018)

Note: The aggregation level and uncertainty estimates are country-specific and do not represent recommended uncertainties or level of aggregation for other countries.

A	B	C	D	E	F	G	H	I	J	K	L	M	N
IPCC category code	**IPCC category name**	**Gas**	**Base year emissions or removals**	**Year t emissions or removals**	**AD uncertainty**	**EF/ estimation parameter uncertainty**	**Combined uncertainty**	**Contribution to variance by category in year t**	**Type A sensitivity**	**Type B sensitivity**	**Uncertainty in trend in national emissions introduced by EF / estimation parameter uncertainty**	**Uncertainty in trend in national emissions introduced by AD uncertainty**	**Uncertainty introduced into the trend in total national emissions**
			Gg CO_2 eq	Gg CO_2 eq	%	%	%		%	%	%	%	%
5.B	Indirect emissions	CO_2	166.22	52.88	16.0	0.0	16	0.001	0.001	0.001	0.00	0.02	0.000
Total			**57,289.89**	**31,733.14**				**1933.33**					**1185.31**
						Percentage uncertainty in total inventory		**44.0**				**Trend uncertainty**	**34.4**

Step-by-step example for Approach 2 based on the Italian GHG Inventory (CH_4 emissions from enteric fermentation in the Agriculture sector) is provided below (ISPRA 2018). This example focuses on the process of obtaining the data for all parameters involved and the analysis of results. CH_4 emissions are estimated by a Tier 2 approach (for cattle and buffalo) and Tier 1 approach for other livestock species.

Step 1

A list of selected parameters used in the CH_4 emission factors estimation process is indicated in Table 3.6. For each parameter, the choices of distributions and underlying assumptions are described with identification whether they were modeled by Monte Carlo.

TABLE 3.6 (NEW)
LIST OF SELECTED PARAMETERS FOR ESTIMATING CH_4 EMISSION FACTORS FOR ENTERIC FERMENTATION (BASED ON ISPRA 2018)

Parameter	Description	Monte Carlo assessment	Range	Source
Animal number	Average annual population within a country by animal species (include all livestock categories)	Yes	The uncertainty associated with populations vary depending on the source, but should be within ±20%. The National Institute of Statistics has estimated an uncertainty of 5-6%. Uncertainty assumed based on expert judgment (ISPRA) amounts to 10%	IPCC 2006; National Institute of Statistics; ISPRA
Milk production	Average daily milk production (dairy cattle and buffalo)	Yes	Expert judgment, assumed the same value as for animal population (10% uncertainty)	ISPRA
Methane conversion factor (Y_m)	Y_m is the fraction of gross energy in feed converted to methane (dairy cattle and buffalo)	Yes	IPCC expert group judgment assumed for dairy cattle and buffalo a conversion factor equal to 6.5% ±1%	IPCC 2006
Weight	Live-weight data should be collected for each animal sub-category (dairy and non-dairy cattle and buffalo)	Yes	Expert judgment, assumed the same value as for animal population (10% uncertainty)	ISPRA
Percent animal grazing	Animals graze open range land or hilly terrain and expend significant energy to acquire feed (dairy cattle and buffalo)	Yes	Expert judgment; assumed that 10% of animals are grazing, while fraction of grazing animals calculated based on national statistics makes up about 5% (uncertainty 50%)	ISPRA
Fat content, percent by weight	Fat content of milk is required for dairy cattle and buffalo	Yes	Expert judgment, assumed the same value as for animal population (10% uncertainty)	ISPRA

TABLE 3.6 (NEW) (CONTINUED) **LIST OF SELECTED PARAMETERS FOR ESTIMATING CH_4 EMISSION FACTORS FOR ENTERIC FERMENTATION (BASED ON ISPRA 2018)**				
Parameter	**Description**	**Monte Carlo assessment**	**Range**	**Source**
Percent giving birth	Percent of females that give birth in a year for dairy cattle and buffalo	Yes	Expert judgment, assumed 5% of uncertainty	ISPRA
Feed digestibility (DE)	The proportion of energy in the feed not excreted in the feces is known as feed digestibility, expressed as a percentage (dairy cattle and buffalo)	Yes	Default 12-20% of uncertainty. Expert judgement 18% of uncertainty	IPCC 2006 ISPRA
EF for Tier 1 approach	The EF is assumed for an animal category for an entire year (365 days): Swine (sows and other swine), sheep, goats, horses, mules and asses, rabbits	Yes	All estimates have an uncertainty of -50%, +30%. EFs estimated using the Tier 1 method are unlikely to be known more accurately than +30% and may be uncertain to +50%. Assumed 50% of uncertainty	IPCC 2006 ISPRA
Dry matter intake (DMI)	DMI establishes the amount of nutrients available to an animal for health and production. Important for the formulation of diets	Yes	The same default 12-20% of uncertainty as for DE. Assumed 20% of uncertainty	IPCC 2006 ISPRA
Coefficient for NE_m (CF_i)	Coefficient for calculating NE_m	No		
Coefficient for NE_a (Ca)	Coefficient corresponding to animal's feeding situation	No		
Weight gain (kg/d)	Average weight gain (or loss) per day, kg/d (for cattle and buffalo)	No		
NE_m	= Net energy required by the animal for maintenance (Equation 10.3, *2006 IPCC Guidelines*), MJ/day	No		
NE_a	= Net energy for animal activity (Equation 10.4, *2006 IPCC Guidelines*), MJ/day	No		
NE_g	= Net energy needed for growth (Equation 10.6, *2006 IPCC Guidelines*), MJ/day	No		
NE_l	= Net energy for lactation (Equation 10.8, *2006 IPCC Guidelines*), MJ/day	No		
NE_p	= Net energy required for pregnancy (Equation 10.13, *2006 IPCC Guidelines*), MJ/day	No		

TABLE 3.6 (NEW) (CONTINUED) LIST OF SELECTED PARAMETERS FOR ESTIMATING CH_4 EMISSION FACTORS FOR ENTERIC FERMENTATION (BASED ON ISPRA 2018)				
Parameter	**Description**	**Monte Carlo assessment**	**Range**	**Source**
Gross energy (GE)	= Amount of energy (MJ/day) an animal needs for maintenance and for activities such as growth, lactation, and pregnancy (Equation 10.16, *2006 IPCC Guidelines*)	No		

For each parameter, the choice of distribution and distribution parameters (mean, median, range etc.) is based on actual information if available (literature, distribution of measurements, past data information) or/and expert judgment. The shape of distribution may vary from the classical normal or lognormal distributions to more sophisticated ones. Whenever assumptions or constraints on variables are known, this information is reflected on the choice of type and shape of distributions (e.g. variability, asymmetry and multimodal).

Examples of selected distributions for some parameters are shown in Figure 3.8a.

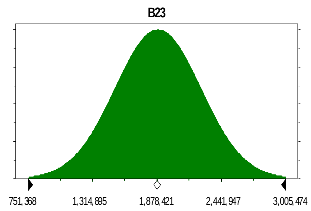
Figure 3.8a (New) Examples of selected distribution functions (based on ISPRA 2018)

Assumption: Number of dairy cattle

Normal distribution with parameters:

Mean	1,878,421
Standard Dev.	375,684

Selected range is from -Infinity to +Infinity

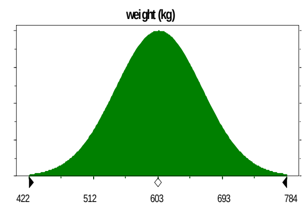


Assumption: Weight (kg)

Normal distribution with parameters:

Mean	603
Standard Dev.	60

Selected range is from 0 to +Infinity

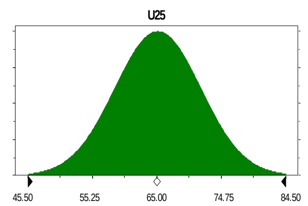


Assumption: Digestibility of feed

Normal distribution with parameters:

Mean	65
Standard Dev.	6.5

Selected range is from 0 to 84.44

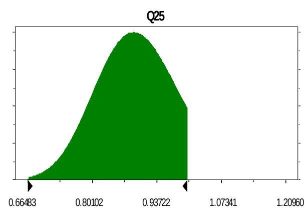


Assumption: Portion of cows giving birth

Normal distribution with parameters:

Mean	0.90123
Standard Dev.	0.09012

Selected range is from 0 to 1



Step 2

A description of the statistics resulting from the Monte Carlo analysis is reported in Table 3.7.

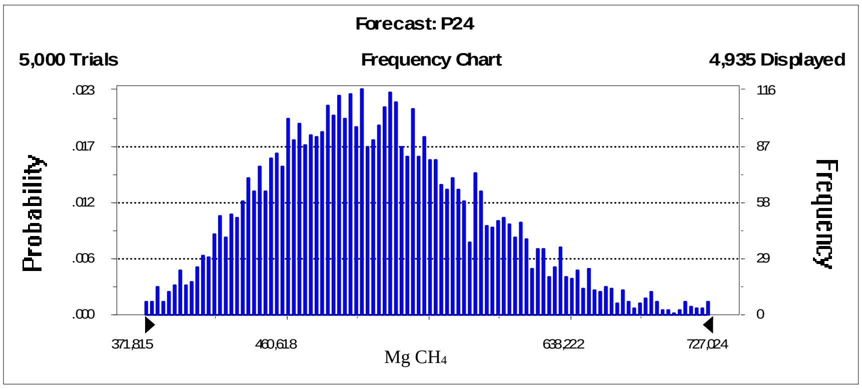
TABLE 3.7 (NEW)
STATISTICS OF THE MONTE CARLO ASSESSMENT FOR CH_4 EMISSIONS FROM ENTERIC FERMENTATION, 2009 (BASED ON ISPRA 2018)

Index	Value
Trials	5,000
Mean	519,226
Median	512,480
Standard Deviation	71,264
Range Minimum	340,639
Range Maximum	869,092
Uncertainty (%)	**-21.8; +31.7**

The application of Approach 1 uncertainty assessment to this category, considering an uncertainty value equal to ±3% for activity data and a default uncertainty value of ±20% (for emission factors based on Tier 2 methodology), results in an overall uncertainty equal to ±20.2% at category level.

The probability density function resulting from the Monte Carlo assessment is shown in the Figure 3.8b.

Figure 3.8b (New) Probability density function from Monte Carlo assessment (based on ISPRA 2018)

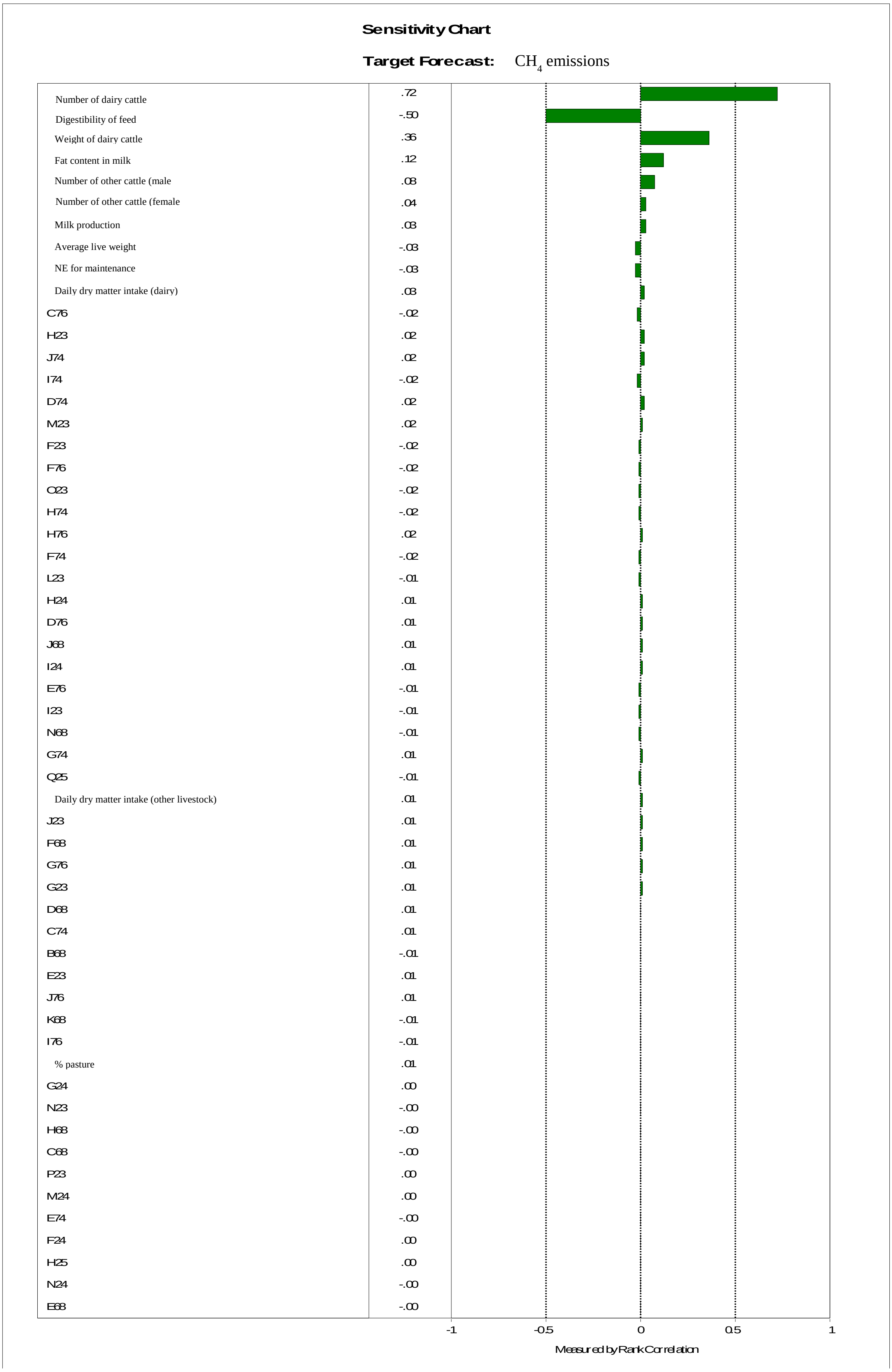


Step 3

The most relevant parameters for the uncertainty of CH_4 emissions from enteric fermentation, measured by the rank correlation coefficient have been individuated from the application of Monte Carlo. These are the number of dairy cattle, digestibility and the weight of animals. As far as feasible, it is important to reduce the associated uncertainty.

The results of this analysis are shown in the Figure 3.8c.

Figure 3.8c (New) Sensitivity chart from Monte Carlo assessment (based on ISPRA 2018)



3.7 TECHNICAL BACKGROUND INFORMATION

No refinement.

3.7.1 Approach 1 variables and equations

No refinement.

3.7.2 Approach 1 – details of the equations for trend uncertainty

No refinement.

3.7.3 Dealing with large and asymmetric uncertainties in the results of Approach 1

No refinement.

3.7.4 Methodology for calculation of the contribution to uncertainty

No refinement.

References

References copied from the 2006 IPCC Guidelines

Abdel-Aziz, A., and Frey, H.C. (2003). 'Development of Hourly Probabilistic Utility NO_x Emission Inventories Using Time Series Techniques: Part I-Univariate Approach', *Atmospheric Environment*, 37:5379-5389 (2003).

Ang, A. H-S., and Tang, W.H., (1975). *Probability Concepts in Engineering Planning and Design, Volume 1.* John Wiley and Sons, New York.

Ang, A. H-S., and Tang, W.H., (1984). *Probability Concepts in Engineering Planning and Design, Volume 2: Decision, Risk, and Reliability*. John Wiley and Sons, New York.

Baggott, S.L., Brown, L., Milne, R., Murrells, TP., Passant, N., Thistlethwaite, G., Watterson, J.D. (2005) *"UK Greenhouse Gas Inventory, 1990 to 2003: Annual Report for submission under the Framework Convention on Climate Change",* April 2005. pub AEA Technology, UK ref AEAT/ENV/R/1971.

Barry, T.M. (1996), Recommendations on the testing and use of pseudo-random number generators used in Monte Carlo analysis for risk assessment*, Risk Assessment*, 16(1): 93-105.

Bevington, P.R. and Robinson, D.K. (1992). *Data Reduction and Error Analysis for the Physical Sciences*. McGraw-Hill: New York.

Cohen A.C. and Whitten B. (1998). *Parameter Estimation in Reliability and Life Span Models*, M. Dekker: New York.

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

D'Agostino, R.B. and Stephens, M.A. (eds.) (1986). *Goodness-of-Fit Techniques*, Marcel Dekker, New York.

Efron, B. and Tibshirani, R.J. (1993). *An Introduction to the Bootstrap*, Chapman and Hall, New York.

Eggleston, S., *et al*. (1998). Treatment of Uncertainties for National Greenhouse Gas Emissions, Report AEAT 2688-1 for DETR Global Atmosphere Division, AEA Technology, Culham, UK.

Evans, J.S., Graham J.D., Gray, G.M., and Sielken Jr, R.L. (1994). "A Distributional Approach to Characterizing Low-Dose Cancer Risk," *Risk Analysis*, 14(1): 25-34 (February 1994).

Falloon, P. and Smith, P. (2003). Accounting for changes in soil carbon under the Kyoto Protocol: need for improved long-term data sets to reduce uncertainty in model projections. *Soil Use and Management*, 19, 265-269.

Frey, H.C. (2003), "Evaluation of an Approximate Analytical Procedure for Calculating Uncertainty in the Greenhouse Gas Version of the Multi-Scale Motor Vehicle and Equipment Emissions System," Prepared for Office of Transportation and Air Quality, U.S. Environmental Protection Agency, Ann Arbor, MI, May 30, 2003.

Frey, H.C. (2005), "Comparison of Approach 1 and Approach 2," January 2005, unpublished analysis done for this Chapter. Chapter 3: Uncertainties *2006 IPCC Guidelines for National Greenhouse Gas Inventorie*s 3.65 Gelfand, A. E. (1996). *Gibbs Sampling, The Encyclopedia of Statistical Sciences* (editors: Kotz J., Reed C. and Banks D.), John Wiley and Sons, New York, 283-292.

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

Frey, H.C. and Rhodes, D.S. (1996). "Characterizing, Simulating, and Analyzing Variability and Uncertainty. An Illustration of Methods Using an Air Toxics Emissions Example," *Human and Ecological Risk Assessment: an International Journal*, 2(4): 762-797 (December 1996).

Frey, H.C. and Rubin, E.S. (1991). *Development and Application of a Probabilistic Evaluation Method for Advanced Process Technologies*, Final Report, DOE/MC/24248-3015, NTIS DE91002095, Prepared by Carnegie-Mellon University for the U.S. Department of Energy, Morgantown, West Virginia, April 1991, 364p.

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

Frey, H.C., Zheng, J., Zhao, Y., Li, S., and Zhu, Y. (2002). Technical Documentation of the AuvTool Software for Analysis of Variability and Uncertainty, Prepared by North Carolina State University for the Office of

Research and Development, U.S. Environmental Protection Agency, Research Triangle Park, NC. February 2002

Hahn, G.J., and Shapiro, S.S. (1967) *Statistical Models in Engineering*, Wiley Classics Library, John Wiley and Sons, New York.

Holland, D.M and Fitz-Simons, T. (1982) "Fitting statistical distributions to air quality data by the maximum likelihood method," *Atmospheric Environment*, 16(5):1071-1076.

Hora, S.C. and Iman, R.L. (1989). Expert opinion in risk analysis: The NUREG-1150 methodology, *Nuclear Science and Engineering*, 102: 323-331.

IPCC (1997). Houghton, J.T., Meira Filho, L.G., Lim, B., Tréanton, K., Mamaty, I., Bonduki, Y., Griggs, D.J. and Callander, B.A. (Eds). *Revised 1996 IPCC Guidelines for National Greenhouse Inventories*. Intergovernmental Panel on Climate Change (IPCC), IPCC/OECD/IEA, Paris, France.

IPCC (2000). Penman, J., Kruger, D., Galbally, I., Hiraishi, T., Nyenzi, B., Emmanuel, S., Buendia, L., Hoppaus, R., Martinsen, T., Meijer, J., Miwa, K., and Tanabe, K. (Eds). *Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories*. Intergovernmental Panel on Climate Change (IPCC), IPCC/OECD/IEA/IGES, Hayama, Japan.

ISO (1993). "Guide to the Expression of Uncertainty in Measurement (GUM)" prepared by ISO, IEC, BIPM, IFCC, OIML, IUPAC, IUPAP and published by ISO, Switzerland in 1993.

Kirchner, T.B. (1990). Establishing modeling credibility involves more than validation, Proceedings, On the Validity of Environmental Transfer Models, Biospheric Model Validation Study, Stockholm, Sweden, October 8-10.

Manly, B.F.J. (1997). *Randomization, Bootstrap, and Monte Carlo Methods in Biology, Second Edition*, Chapman and Hall.

McCann, T.J. and Associates, and Nosal, M. (1994). Report to Environmental Canada Regarding Uncertainties in Greenhouse Gas Emission Estimates, Calgary, Canada.

Merkhofer, M.W. (1987). Quantifying judgmental uncertainty: Methodology, experiences, and insights, *IEEE Transactions on Systems, Man, and Cybernetics*. 17(5): 741-752.

Mokhtari, A., Frey H.C. and Zheng J. (2006). "Evaluation and recommendation of sensitivity analysis methods for application to Stochastic Human Exposure and Dose Simulation (SHEDS) models," *Journal of Exposure Assessment and Environmental Epidemiology*, Accepted December 2, 2005, In press.

Monni, S., Syri, S. and Savolainen I. (2004). 'Uncertainties in the Finnish greenhouse gas emission inventory'.*Environmental Science and Policy* 7, pp.87-98.

Monte, L, Hakanson, L., Bergstrom, U., Brittain, J. and Heling, R. (1996). Uncertainty analysis and validation of environmental models: the empirically based uncertainty analysis. *Ecological Modelling*, 91, 139-152.

Morgan, M.G., and Henrion, M. (1990). *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*, Cambridge University Press, New York.

NARSTO (2005). Improving Emission Inventories for Effective Air Quality Management Across North America, NARSTO, June 2005.

NCRP (National Council on Radiation Protection and Measurements). (1996). A Guide for Uncertainty Analysis in Dose and Risk Assessments Related to Environmental Contamination, NCRP Commentary No. 14, Bethesda, MD.

Ogle, S.M., Breidt, F.J., Eve, M.D. and Paustian, K. (2003). Uncertainty in estimating land use and management impacts on soil organic carbon storage for U.S. agricultural lands between 1982 and 1997. *Global Change Biology* 9: 1521-1542.

Smith, A.E, Ryan, P.B. and Evans J.S. (1992). The effect of neglecting correlations when propagating uncertainty and estimating the population distribution of risk, *Risk Analysis*, 12: 467-474.

Spetzler, C.S., and von Holstein, S. (1975). Probability Encoding in Decision Analysis, *Management Science*, 22(3).

Statistics Finland. (2005). *Greenhouse gas emissions in Finland 1990-2003. National Inventory Report to the UNFCCC*, 27 May 2005.

USEPA (1996). Summary Report for the Workshop on Monte Carlo Analysis, EPA/630/R-96/010, Risk Assessment Forum, U.S. Environmental Protection Agency, Washington, DC.

References newly cited in the 2019 Refinement

US EPA (2002) Procedures manual for Quality Assurance/Quality Control and Uncertainty Analysis.

US EPA (2017) Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2015.

Gillenwater, M., Sussman, F., Cohen, J (2007) Practical Policy Applications of Uncertainty Analysis for National Greenhouse Gas Inventories. *Water, Air & Soil Pollution: Focus* **7**: 451-474.

ISPRA, 2018. *Greenhouse gas emissions in Italy 1990-2016. National Inventory Report under the UNFCCC and the Kyoto Protocol, April 2018 (https://unfccc.int/documents/65681).*

Monni, S., Perälä, P., Kristina, R. (2007) Uncertainty in Agricultural CH_4 and N_2O Emissions from Finland - Possibilities to Increase Accuracy in Emission Estimates. *Mitigation and Adaptation Strategies for Global Change*. **12**: 545-571.

Ogle, S. M., Breidt, F.J., Easter, M., Williams, S., Killian, K., and Paustian, K. (2010) Scale and Uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model. *Global Change Biology* **16**: 810-820.

Ogle, S. M., Breidt, F.J., Easter, M., Williams, S., and Paustian, K. (2007) An Empirically based approach for estimating uncertainty associated with modeling carbon sequestration in soils. *Ecological Modelling* **2005**: 453-463.

Ogle, S. M., Eve, M.D, Breidt, F.J., Paustian, K. (2003) Uncertainty in estimating land use and management impacts on soil organic carbon storage for US agroecosystems between 1982 and 1987. *Global Change Biology* **9**: 1521-1542.

Parton, W.J., Schimel, D.S., Cole, C.V., Ojima, D.S. (1987). Analysis of factors controlling soil organic matter levels in Great Plains grasslands. *Soil Sci. Soc. Am. J.* **51**, 1173-1179.

Särndal, C.-E., Swensson, B & Wertman, J. (1992) Model assisted survey sampling. *Springer-Verlag* **Springer Series**.

Statistics Finland, 2018. *Greenhouse gas emissions in Finland 1990-2016. National Inventory Report under the UNFCCC and the Kyoto Protocol, 15 April 2018. (https://unfccc.int/documents/65334).*