GHG Protocol guidance on uncertainty assessment in GHG inventories and calculating statistical parameter uncertainty

Table of Contents

Important:
The calculation of statistical parameter uncertainties is only one step towards ensuring high inventory quality. A good ranking of the uncertainty of emission data does not automatically mean that the overall data quality is good!
In order to assure good quality for the data provided in your inventory, please refer to the chapter on "Managing inventory quality" of the Corporate Accounting Standard of the GHG Protocol

1 Overview

One element of GHG emissions data quality management involves quantitative and qualitative uncertainty analysis. For example, several emissions trading proposals require that participants provide basic uncertainty information for emissions from their activities (e.g. the proposed European Emissions Allowance Trading Scheme). The GHG Protocol Initiative has developed this guidance along with a calculation tool based on Excel spreadsheets. This calculation tool automates the aggregation steps involved in developing a basic uncertainty assessment for GHG inventory data.

The purpose of this document is to describe the functionality of the tool, and to give companies a better understanding of how to prepare, interpret, and utilize inventory uncertainty assessments. The guidance on the tool is embedded in this overview. The guidance is based on the IPCC Guidelines for National GHG Inventories and should be considered as an addition to the calculation tools provided by the GHG Protocol Initiative, as well as to the chapter on Managing Inventory Quality in the standard document.

Section 2 gives a short overview on the different types of uncertainty associated with corporate GHG Inventories and specifies the limitations of the GHG Protocol Uncertainty Tool. In section 3 follows a short introduction to the approach used in the tool for presenting and aggregating statistical uncertainties. Sections 4 through 8 then provide a step by step discussion on collecting uncertainty information and aggregating it using the first order error propagation method. Section 9 provides recommendations on how to document and interpret the results of an uncertainty assessment. Finally, section 10 gives a short guidance on how to use the uncertainty tool.

2 Uncertainties associated with GHG inventories

Uncertainties associated with greenhouse gas inventories can be broadly categorized into *scientific* uncertainty and *estimation* uncertainty. Scientific uncertainty arises when the science of the actual emission and/or removal process is not sufficiently understood. For example, many of the direct and indirect emissions factors associated with global warming potential (GWP) values that are used to combine emission estimates of different greenhouse gases involve significant scientific uncertainty. Analyzing and quantifying such scientific uncertainty is extremely problematic and is likely to be beyond the scope of most company's inventory efforts.

Estimation uncertainty arises any time greenhouse gas emissions are quantified. Therefore all emission or removal estimates are associated with estimation uncertainty. Estimation uncertainty can be further classified into two types: *model* uncertainty and *parameter* uncertainty[1].

Model uncertainty refers to the uncertainty associated with the mathematical equations (i.e. models) used to characterize the relationships between various parameters and emission processes. For example, model uncertainty may arise either due to the use of an incorrect mathematical model or inappropriate parameters (i.e. inputs) in the model. Like scientific uncertainty, estimating model uncertainty is also likely to be beyond the scope of most company's inventory efforts; however, some companies may wish to utilize their unique scientific and engineering expertise to evaluate the uncertainty in their emission estimation models.[2]

Parameter uncertainty refers to the uncertainty associated with quantifying the parameters used as inputs (e.g. activity data, emission factors, or other parameters) to estimation models. Parameter uncertainties can be evaluated through statistical analysis, measurement equipment precision determinations, and expert judgment. Quantifying parameter uncertainties and then

[1] Emissions estimated from direct emission monitoring will generally only involve parameter uncertainty (e.g. equipment measurement error).
[2] Emission estimation models that consist of only activity data times an emission factor only involve parameter uncertainties, assuming that emissions are perfectly linearly correlated with the activity data parameter.

estimating source category uncertainties based on these parameter uncertainties will be the primary focus for those companies which choose to investigate the uncertainty in their emission inventories.

2.1 Limitations and purposes of uncertainty quantification

Given that only parameter uncertainties are within the feasible scope of most companies, uncertainty estimates for corporate greenhouse gas inventories will, of necessity, be imperfect. It is also not always the case that complete and robust sample data will be available to assess the statistical uncertainty in every parameter. Often only a single data point will be available for most parameters (e.g. liters of gasoline purchased or tonnes of limestone consumed). In some of these cases, companies can utilize instrument precision or calibration information to inform their assessment of statistical uncertainty. However, to quantify some of the systematic uncertainties associated with parameters and to supplement statistical uncertainty estimates, companies will usually have to rely on expert judgment.[3] The problem with expert judgment, though, is that it is difficult to obtain in a comparable (i.e. unbiased) and consistent manner across parameters, source categories, or companies.

For these reasons, almost all comprehensive estimates of uncertainty for greenhouse gas inventories will be not only imperfect but also have a *subjective* component. In other words, despite the most thorough efforts, estimates of uncertainty for greenhouse gas inventories must themselves be considered highly uncertain. Except in highly restricted cases, uncertainty estimates cannot be interpreted as objective metrics that can be used as an unbiased measure of quality to compare across source categories or different companies. Such an exception is when two operationally similar facilities use identical estimation methodologies. In these cases differences in scientific or model uncertainties can, for the most part, be ignored. Then assuming that either statistical or instrument precision data is available to estimate parameter uncertainties (i.e., expert judgment is not needed), quantified uncertainty estimates can be treated as being comparable between facilities. This type of comparability is what is aimed at in some emissions trading schemes that prescribe specific monitoring, estimation and measurement requirements. However, even here the degree of comparability depends on the flexibility that participants are given for estimating emissions, the homogeneity across facilities, as well as the level of enforcement and review of the methodologies used.

With these limitations in mind, what should the role of uncertainty assessments be in developing GHG inventories? Uncertainty investigations can be part of a broader learning and quality feedback process. They can support a company's efforts to understand the causes of uncertainty and help identify ways of improving inventory quality. For example, collecting the information needed to determine the statistical properties of activity data and emission factors forces one to ask hard questions and to carefully and systematically investigate data quality. In addition, these investigations establish lines of communication and feedback with data suppliers to identify specific opportunities to improve the quality of the data and methods used. Similarly, although not completely objective, the results of an uncertainty analysis can provide valuable information to reviewers, verifiers, and managers for setting priorities for investments into improving data sources and methodologies. In other words, uncertainty assessment becomes a rigorous—although subjective—process for assessing quality and guiding the implementation of quality management.

2.2 Parameter uncertainties: Systematic and statistical uncertainties

The type of uncertainty most amenable to assessment by companies preparing their own inventory is the uncertainties associated with parameters (e.g. activity data, emission factors, and

[3] The role of expert judgment in the assessment of the parameter can be twofold: Firstly, expert judgment can be the source of the data that are necessary to estimate the parameter. Secondly, expert judgment can help (in combination with data quality investigations) identify, explain, and quantify both statistical and systematic uncertainties (see following section).

other parameters) used as inputs in an emission estimation model. Two types of parameter uncertainties can be identified in this context: systematic and statistical uncertainties.

Systematic uncertainty occurs if data are systematically biased. In other words, the average of the measured or estimated value is always less or greater than the true value. Biases can arise, for example, because emissions factors are constructed from non-representative samples, all relevant source activities or categories have not been identified, or incorrect or incomplete estimation methods or faulty measurement equipment have been used.[4] Because the true value is unknown, such systematic biases cannot be detected through repeated experiments and, therefore, cannot be quantified through statistical analysis. However, it is possible to identify biases and, sometimes, quantify them through data quality investigations and expert judgments. The Chapter on "Managing Inventory Quality" of the GHG Protocol Corporate Standard gives guidance on how to plan and implement a GHG Data Quality Management System. A well designed Quality Management System can significantly reduce systematic uncertainty.

Expert judgment can itself be a source of systematic biases referred to as "*cognitive biases*". Such cognitive biases are, for example, related to the psychological fact that human cognition is often systematically distorted, especially when very low or very high probabilities are involved. Cognitive biases can therefore lead to "wrong" parameter estimations when expert judgment is used in the selection or development parameter estimates. In order to minimize the risk of cognitive biases it is strongly recommended to use predefined procedures for expert elicitation. Subsection 6.1 provides some references for standardized protocols which should be consulted prior to engaging in expert elicitation.

Potential reasons for specific systematic biases in data should always be identified and discussed qualitatively. If possible, the direction (over- or underestimate) of any biases and their relative magnitude should be discussed. This type of qualitative information is essential regardless of whether quantitative uncertainty estimates are prepared because it provides the reasons why such problems may have occurred, and therefore what improvements may need to be made to resolve them. Such discussions that address the likely reasons for biases and how they may be eliminated will often be the most valuable product of an uncertainty assessment exercise.

The data (i.e. parameters) used by a company in the preparation of its inventory will also be subject to *statistical* (i.e. random) *uncertainty*. This type of uncertainty results from natural variations (e.g. random human errors in the measurement process and fluctuations in measurement equipment). Random uncertainty can be detected through repeated experiments or sampling of data. Ideally, random uncertainties should be statistically estimated using available empirical data. However, if insufficient sample data are available to develop valid statistics, parameter uncertainties can be developed from expert judgments that are obtained using an elicitation protocol as described below.

The GHG Protocol uncertainty tool is designed to aggregate statistical (i.e., random) uncertainty assuming a normal distribution of the relevant variables.

Figure 1 summarizes the different uncertainties that occur in the context of GHG inventories.

[4] It should also be recognized that biases do not have to be constant from year to year but instead may exhibit a pattern over time (e.g. may be growing or falling). For example, a company that continues to disinvest in collecting high quality data may create a situation in which the biases in its data get worse each year (e.g. changes in practices or mistakes in data collection get worse over time). Such data quality issues are extremely problematic because of the effect they can have on calculated emission trends.

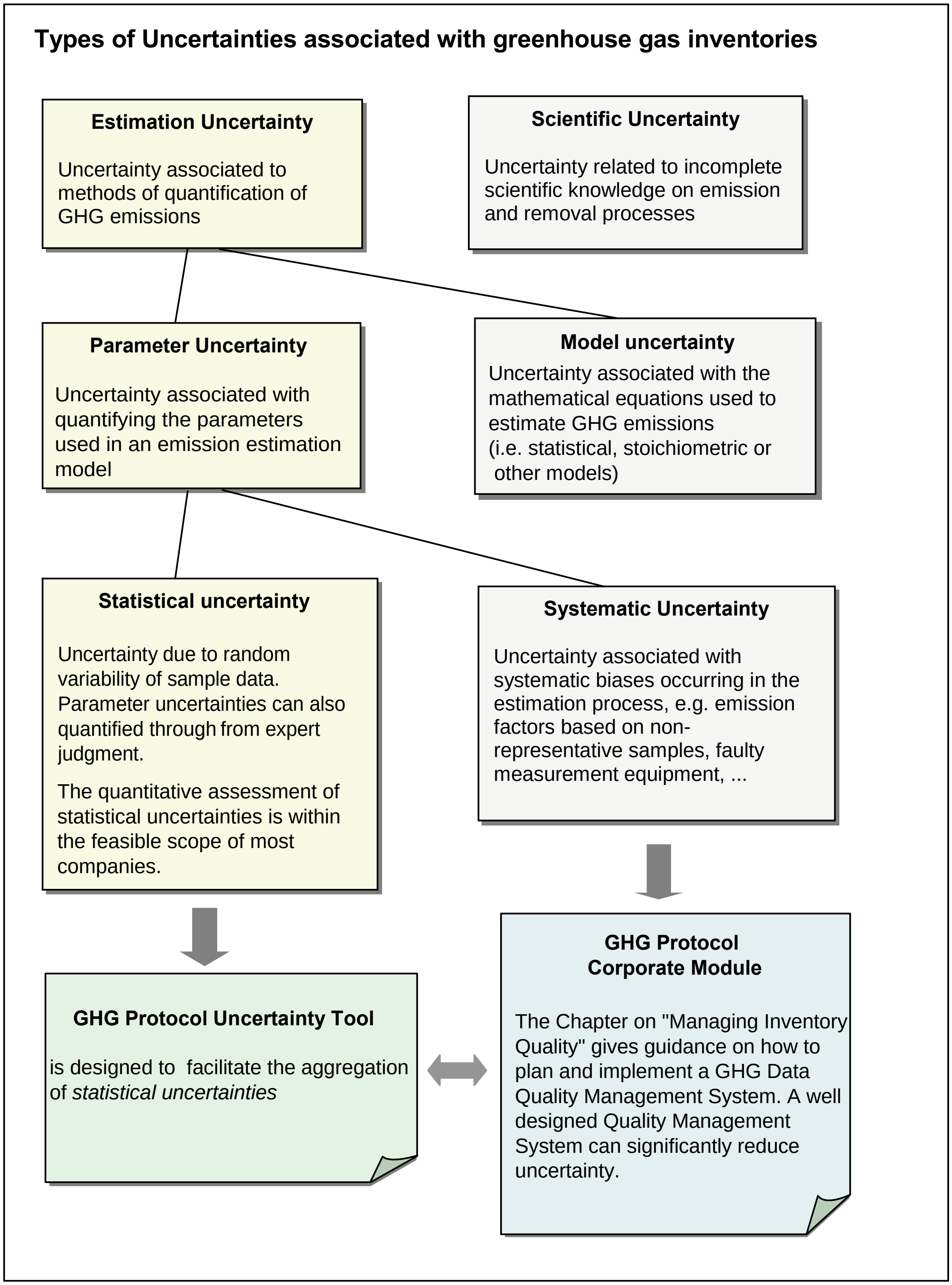

Figure 1: types of uncertainties associated with greenhouse gas inventories

The following guidance concentrates on a process to assess statistical (or inherent) uncertainties, as their quantitative assessment is within the feasible scope of most companies, and the GHG Protocol Uncertainty Tool is designed to facilitate the aggregation of this type of uncertainty.

3 Aggregating statistical uncertainty

Measurement uncertainty is usually presented as an *uncertainty range,* i.e. an interval expressed in +/- percent of the mean value reported (e.g. 100t +/- 5%)
Once sufficient information on the parameter uncertainty ranges has been collected (see Section 6) and a company wishes to combine its parameter uncertainty information using a fully quantitative approach, it has two main choices of mathematical techniques.

- The first order error propagation Method (Gaussian Method)[5]
- Methods based on a Monte Carlo Simulation[6]

The GHG Protocol Uncertainty Tool presented in this guidance uses the first order error propagation method. This method should however only be applied if the following assumptions are fulfilled:

- The errors in each parameter must be normally distributed (i.e. Gaussian),
- There must be no biases in the estimator function (i.e. that the estimated value is the mean value)
- The estimated parameters must be uncorrelated (i.e. all parameters are fully independent).
- Individual uncertainties in each parameter must be less than 60% of the mean

A second approach is to use a technique based on a Monte Carlo simulation, that allows uncertainties with any probability distribution, range, and correlation structure to be combined, provided they have been suitably quantified. The Monte Carlo technique can be used to estimate the uncertainty of single sources as well as to aggregate uncertainties for a site or company.

Although the Monte Carlo technique is enormously flexible, in all cases computer software is required for its use. Several simulation software packages are commercially available (e.g. @Risk or Crystal Ball).

As the GHG Protocol Tool for uncertainty aggregation is based on the first order propagation method, the following guidance will always refer to this method. Further Guidance on the use of the Monte Carlo technique is available from the IPCC Good Practice Guidance or EPA's Quality Control/Quality Assurance Plan (see references below).

[5] This approach corresponds to Tier 1 of the IPCC Good Practice Guidance and Uncertainty Management
[6] This approach corresponds to Tier 2 of the IPCC Good Practice Guidance and Uncertainty Management

4 The Uncertainty estimation and aggregation process

Figure 2 gives an overview of the process to follow for the assessment of **statistical uncertainties** in Greenhouse Gas Accounting using the first order error propagation technique. The GHG Protocol Uncertainty tool is designed to support the uncertainty analyst with the aggregation and ranking of the different uncertainties. The process is divided into 5 different steps, which will be explained in more detail below.

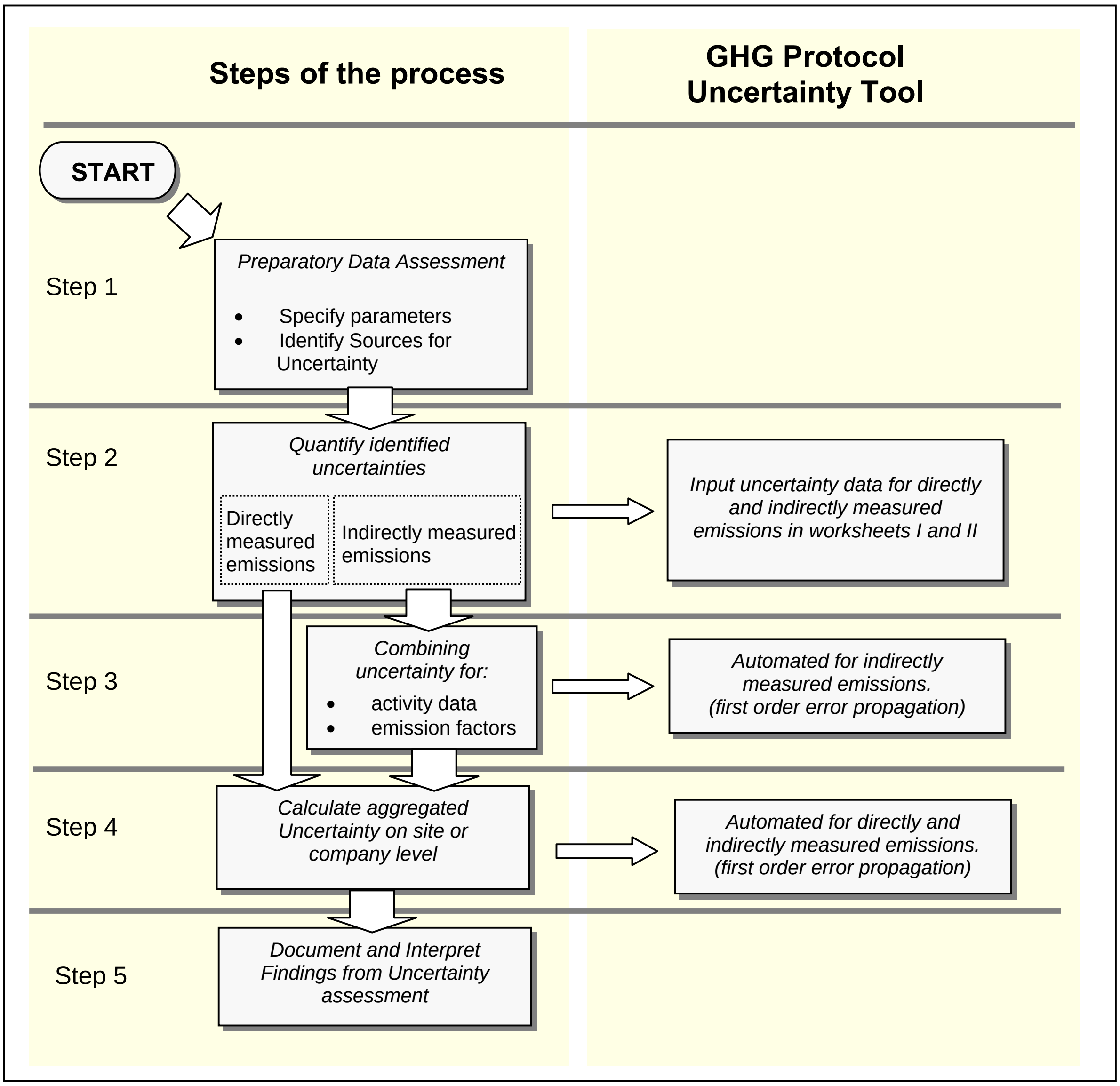

Figure 2: Process for estimating and aggregating parameter uncertainty for GHG inventories

5 Preparatory Data Assessment (Step 1)

As in any uncertainty assessment, it should be made clear that (a) what is being estimated (i.e., GHG emissions) and (b) what are the likely causes of the uncertainties identified and quantified.

GHG emissions can be measured either directly or indirectly. The indirect approach usually involves the use of an estimation model (e.g., activity data and an emission factor), while the direct approach requires that emissions to the atmosphere be measured directly by some form of instrumentation (e.g., continuous emissions monitor).

As the data used in the direct or indirect measurement of GHG emissions are subject to random variation there is always statistical uncertainty associated with the resulting emission estimates. A well designed data quality management system can help reduce the uncertainty in data. Please refer to Chapter 8 “Managing Inventory Quality” of the GHG Protocol Corporate Inventory Module for guidance on how to establish a good quality management system.

The level at which uncertainty data are collected should generally be at the same level at which the actual estimation data are collected. Usually an uncertainty assessment is more precise if you start the assessment at the lowest level where data are collected and then aggregate them on the plant- and company-level.

6 Quantifying statistical uncertainties on the source level (Step 2)

Statistical uncertainty in the context of GHG inventories is usually presented by giving an uncertainty range expressed in a percentage of the expected mean value of the emission. This range can be determined by *calculating the “confidence limits”,* within which the underlying value of an uncertain quantity is thought to lie for a specified probability (see section 6.2 for further discussion). Another possibility is to *consult experts* within the company to give an estimation of the uncertainty range of the data used. [7]

In practice the uncertainty assessment will probably be based on a combination of both approaches: Where a large sample of directly or indirectly measured emission data is available, it is possible to calculate the statistical uncertainty using specific statistical methods. For other parameters, where data are insufficient for a statistical analysis, expert judgment will be necessary to estimate an uncertainty range. This expert judgment can be supplemented by determining the precision of any measurement equipment used in the collecting of inventory data. The collection of uncertainty information, whether from sample data, measurement equipment precision determinations, or expert judgment, is best performed in conjunction with an a company’s overall quality management system in which investigations are performed into the quality of the data collected for estimating greenhouse gas emissions (see the chapter on “Managing Inventory Quality” of the corporate accounting Standard of the GHG Protocol).

The following subsection provides some references on the assessment of uncertainties through expert elicitation (subsection 6.1). Subsection 6.2 gives some guidance on calculating the uncertainty range of specific parameters from sample data by using the statistical t-test.

6.1 Guidance for Expert elicitation

In order to avoid cognitive biases that can occur when experts are consulted to estimate uncertainty ranges or the probability function of parameters for the uncertainty assessment, the use of an “expert elicitation protocol” is highly recommended. In the context of this guidance, an elicitation protocol refers to the set of procedures to be used by the uncertainty analysts who

[7] If the latter approach is chosen, it has to be made clear that a normal distribution of the errors is assumed otherwise the error propagation method and therefore the uncertainty tool should not be used.

interviews experts for purposes of developing quantitative uncertainties of the input variables and, thereby, of the inventory estimates of source categories.

An example of a well-known protocol for expert elicitation is the Stanford/SRI protocol. The *IPCC Good Practice Guidance in National Greenhouse Gas* as well as the *US-EPA Procedures Manual for Quality Assurance/Quality Control and Uncertainty Analysis* give a good overview on the how to set up an Expert elicitation process for country data that apply also for GHG inventories on the company level.

6.2 Calculation of uncertainty by using sample data

Parameter uncertainties can also be estimated by using statistical methods to calculate the confidence interval for a parameter from sampling intervals, variations among samples, and instrument calibration. This section describes a simple statistical method for the calculation of the uncertainty range by using the sample data. The estimation of a confidence interval using the t-statistic, which is presented here, can be applied for the estimation of uncertainties of directly measured emissions as well as those associated with activity data and emission factors (i.e., indirect measurement). This method is based on the assumption that the distribution of measurement data converges to a normal distribution, which is normally – in the absence of major systematic biases – the case.

It is important to note that this method is a very general one, and depending on the situation there may be more appropriate, but more complicated, statistical methods to be applied.[8] For a sample with *n* measurements the method presented here requires 5 steps:

1. Choice of a confidence level
   The "confidence level" determines the probability, that the true value of emission is situated within the identified uncertainty range. In natural science and technical experiments it is often standard practice to chose the confidence levels 95% or 99,73%. The IPCC suggests a confidence level of 95% as an appropriate level for range definition. *The used confidence level should always be reported*.

2. Determine the t-factor t (also referred to as the (1-α/2)-fractile of the t-distribution, as the standard error that is to be estimated follows a t-distribution). This can be done by using the table 1, provided below (Annex 1 of this guidance provides a table for t-factors with a larger range of n and different confidence levels):

Number of measurements (n)	t-factor (t) for confidence level:	
	95%	99,73%
3	4,30	19,21
5	2,78	6,62
8	2,37	4,53
10	2,26	4,09
50	2,01	3,16
100	1,98	3,08
∞	1,96	3,00

Table 1: t-factors for the 95% and 99,73% confidence level

3. Calculate the sample average $\bar{x}$ and the sample standard deviation s:

   $\bar{x} = \frac{1}{n}\sum_{k=1}^{n} x_k$, for a sample with n different measurements, and

[8] For further explanation on the use and applicability of such methods see for example ISO (1993)

$$s = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(x_k - \bar{x})^2}$$

4. Calculate the value of $\frac{s \cdot t}{\sqrt{n}}$

5. Calculate the resulting Interval: $\left[\bar{x} - \frac{s \cdot t}{\sqrt{n}}; \bar{x} + \frac{s \cdot t}{\sqrt{n}}\right]$

The interval can then easily be transformed into the uncertainty range expressed in a +/- percent value.

Such statistical tests are usually performed by using computer software. All statistical software packages and spreadsheet applications can easily be programmed to perform these calculations.

7 Combining uncertainties for indirectly measured single-source emissions (Step 3)

The likely causes of *uncertainty with direct measurement* are generally related to the measurement techniques used. Methods with a high degree of variability will typically lead to a high degree of statistical uncertainty in the final estimates.

In the case of *indirect measurement* the uncertainties are related to the *activity data,* and the *emission factor*. There are several ways to quantify the uncertainty range in these parameters:

1. Run statistical tests on one or several sets of sample data (e.g. by the method explained in section 6.2).
2. Determine the instrument precision of any measurement equipment used, especially for activity data.
3. Consulting experts within the company to give an estimation of the uncertainty range of the data used as explained in Section 6.1.
4. Use third-hand uncertainty ranges (e.g. the IPCC-data provided in the second worksheet of the uncertainty tool). This approach is the least useful, as it not specific to the data generated by the reporting company.

For activity data—and to a lesser extent the emission factors, which depend directly on the used technology—it is recommended to use method one or two.

As explained above, indirectly measured emissions are typically calculated by multiplying an activity factor and an emission factor, for example:

- Electricity purchased *times* a factor for generation CO_2/kWh
- Tons of cement sold *times* a factor of CO_2/ton cement.
- Rental sedan miles driven *times* a factor of CO_2/vehicle mile

Uncertainty is compounded by this multiplication*; the resulting emissions estimate will be less certain than its least certain component* (this phrase is called the *compounded uncertainty principle*). For example, a firm may compile a highly certain total of kiloWatt-hours (kWh) from its electrical bills, however, the best available CO_2/kWh factor for generation and transmission may be a national grid annual average, which may poorly reflect seasonal and hourly fluctuations in generation fuel mix corresponding to the firm's load profile. The kWh measurement has 'high' certainty, but the CO_2 factor could easily be off by 20%.

For companies that characterize uncertainty numerically, a sum of squares approach may be used to calculate the confidence interval for the product of two or more factors[9]. This approach is only valid if the uncertainties follow a normal distribution and if the individual uncertainties are less than 60%. If this assumption is being made, and deemed valid, the company should state it in their analysis.

The relative confidence interval (the plus or minus *percent*) of the product is the square root of the sum of the squares of the relative (*percent*) confidence intervals of each factor.

$$\sqrt{a^2 + b^2}$$

Multiplying Uncertainties: where: (A +/- a%) X (B +/- b%) = C +/- c%

with $c = \sqrt{a^2 + b^2}$

The above equation shows how companies that have assessed the individual uncertainty ranges of each factor could apply the compounded uncertainty principle.[10] It is however important to note that for individual uncertainties greater than 60% the sum of squares procedure is not valid.

This formula is incorporated in the first worksheet of the uncertainty calculation tool, which is designed to facilitate the process steps 3 and 4 of the uncertainty estimation and aggregation process for indirectly measured emissions.

[9] The relatively simple formulas presented here are defensible when no factor in a multiplication is raised to a power, and when a normal distribution of probabilities within the confidence interval is assumed. For information on handling more complex situations, see EPA, Emission Inventory Improvement Project Volume VI: Quality Assurance/Quality Control, at www.epa.gov/ttn/chief/eiip/techrep.htm *Chapter 4 covers all approaches to inventory uncertainty analysis, or* Frey, H. et al. Quantitative Analysis of Variability and Uncertainty in Emissions Estimates, at www4.ncsu.edu/~frey/freytech.html *Evaluation of uncertainties in activity levels and emission factors, both stationary and mobile sources*.

[10] The above presented method implies the assumption that statistical variance of both factors may compensate each other. If the individual uncertainties are derived from very small samples it is therefore more accurate to use the so called method of linear error propagation. For the here presented problem – the combination of uncertainties of activity data and emission factors – that means simply adding up the *absolute* values of the individual uncertainties.

8 Quantifying uncertainty for sub-totals and totals of single-sources (Step 4)

If the parameter uncertainty for single sources in an inventory has been assessed, companies can determine uncertainty estimates for subtotals and totals, using a *weighted average approach*. The additive uncertainty can be estimated using a calculation method outlined below. Numeric uncertainties are combined using root-sum-of-squares techniques, using the absolute values to adjust for the relative weight of each parameter or estimate.

Adding Uncertainties: where: (C +/- c%) + (D +/- d%) = E +/- e%

$$e = \frac{\sqrt{(C \times c)^2 + (D \times d)^2}}{E}$$

Example:
An inventory has two sources of CO_2 calculated as 110 ± 4% and 90 ± 24% tonnes. The inventory total is then 200 tonnes with an uncertainty of:

$$u = \frac{\sqrt{4.4^2 + 21.6^2}}{110 + 90} = \frac{22.04}{200} \approx \pm 11\%$$

The aggregation of uncertainties using this approach is facilitated by the GHG protocol uncertainty tool, which provides automated worksheets for directly and indirectly measured emissions.

9 Documenting and Interpreting an Uncertainty Assessment (Step 5)

The final step in an uncertainty assessment can often be the most important. A great deal of effort can be expended by a company in collecting information and data for a quantified uncertainty assessment and implementing a model – such as the GHG Protocol's uncertainty tool – to aggregate parameter uncertainties across source categories and the entire inventory. However, all that effort can result in little benefit if steps are not also taken to carefully document and interpret findings throughout the process so that they can lead to real improvements in the quality of data collected and the inventory as a whole. The integration of a company's uncertainty assessment efforts with the implementation of its overall quality management system can help solve this problem. In addition, the reporting of basic results from uncertainty investigations (e.g., data on equipment measurement precision) is required by several emerging and existing emissions trading schemes (e.g. the proposed European Emissions Allowance Trading Scheme or the UK Trading Scheme).

During the process of collecting data on parameters for an uncertainty assessment (e.g., statistical, equipment precision, or expert judgment) it is critical that steps be taken to document and explain, in detail, the likely causes of the various uncertainties identified and specific recommendations regarding how they can be reduced. Although the first order error propagation approach used in the Protocol's uncertainty tool cannot address systematic biases in data, when such biases are identified in the course of an uncertainty assessment or ongoing data quality management processes, they should also be documented.

When interpreting the results from a quantitative uncertainty assessment, it is important to keep in mind the limitations of the approach used. Although it can provide a useful "first order" appraisal, the first order error propagation approach requires many assumptions that may not be entirely appropriate given the characteristics of a particular activity within a company. The proper interpretation of uncertainty requires a discussion of such limitations and ample caveats for any quantitative uncertainty estimates produced. Interpretations also require a thorough discussion of the causes of the uncertainties identified – including biases as well as measurement precision – whether or not these uncertainties were quantified for use in a model. At a minimum, the interpretation of an uncertainty assessment may exclude a quantitative analysis of uncertainty or summarized rankings, especially if they are believed to present an incomplete picture of an inventory. However, inventories should always include a detailed qualitative discussion of the likely causes of uncertainties and related recommendations for data quality improvements.

When documenting the results from the quantitative portion of an uncertainty assessment, these results can be ranked using a summary scale. A typical, although arbitrary, scale is given below in Table 2. These ordinal values are based on quantitative confidence intervals, as a percentage of the estimated or measured value, in which the true value is likely to exist.[11]

Data Accuracy	Interval as Percent of Mean Value
High	+/- 5%
Good	+/- 15%
Fair	+/- 30%
Poor	More than 30 %

Table 2: Data Accuracy rating and corresponding intervals used in the GHG Protocol uncertainty tool

The GHG Protocol's uncertainty tool automatically assigns ranks based on the scale given in Table 2 at several levels:

i) The level of individual data for directly measured emissions
ii) The level single sources for indirectly measured emissions
iii) The sub-total and total level

Use of such an "ordinal" ranking is often criticized, as there is a significant loss of information in the transformation of quantified uncertainty into a qualitative ranking. Therefore, it is essential that thorough documentation accompany such rankings that caveat the limitations in the underlying quantitative assessment and describe the primary causes of uncertainty.

Table 3 provides certainty rankings – and brief descriptions of conditions under which they are likely to be found – that are typically the best attained by facilities and firms that have recently assembled emissions inventories. Poorer data and the lack of an effective quality management system are likely to lead to lower rankings. It is highly recommended that a rigorous data quality management system be implemented as discussed in the chapter on "Managing Inventory Quality"8 in the Corporate Accounting Standard of the GHG Protocol.

[11] Likeliness is generally defined by a 95 percent two-tailed probability. In other words, the true value of an estimate with a "fair" ranking has a 95% probability of being within +/- 30% of the estimated value.

Major Emissions Category Subtotal	Best Attainable Certainty Ranking
On-site fuel combustion, stationary sources	• High – Delivery records and bills make measurement easy and accurate; carbon content is almost standard so emissions factors are accurate. (Carbon per tonne coal varies; using an average default factor for coal may yield a Good total)
Process Emissions	• High - mass balance calculations combined with accurate input records can yield highly accurate totals. • Fair or Poor if by-products are calculated from production totals times industry average factors. Leaks of unmeasured gasses are a problem.
Directly-controlled vehicles	• High if complete fuel use records are tallied and multiplied by fuel factors. • Fair if distance by equipment type is multiplied by average fuel use per distance factors. • Poor if distance is only roughly estimated.
Electricity use	• High if one fuel is used for generation, or if marginal generation fuel can be matched to facility load profile. • Fair if annual average is used for a grid with multiple fuel sources. • Fair or Poor if electricity use is not metered and must be estimated from equipment and time of use.
In-bound freight, Out-bound freight	• Good if a few well-documented modes or routes are used, • Otherwise fair at best.
Employee job-related travel	• Fair if miles are accurately tallied. • Poor if trips are roughly categorized as short or long, etc.
Waste disposed to landfill	• Good if recovery systems are in place and most CH4 is collected, • Otherwise fair at best (waste amounts may be well measured, but composition of waste and decomposition conditions may vary widely).

Table 3: certainty ranking for common emission sources

10 Using the GHG Protocol Uncertainty Tool

10.1 Calculation steps for Worksheet 1 "aggregation - indirect measurement"

To calculate the aggregated uncertainty for indirectly measured emissions, you need to determine the activity data, the GHG emission factor and the respective uncertainty ranges. The Spreadsheet automates the Steps 3 and 4 of the uncertainty aggregation process and assigns an uncertainty ranking corresponding to table 2 of this guidance.

Data Input :

1. Enter the activity data in column A. Specify the unit in which fuel use data is measured in column B, e.g. metric tons, GJ, gallons, ….
2. Enter the estimated uncertainty ranges of the activity data expressed in +/- percent of the mean value in column C.
3. Enter the emission factor in column D. The emission factor must be compatible to activity data input, and be calculated for kg CO_2. Example: If the use of a fuel is measured in GJ, the emission factor should also be expressed in kg CO_2/GJ. As a reminder to this important fact you can enter the Unit of the emission factor in Column E.

4. Enter the estimated uncertainty ranges of the emission factor expressed in +/- percent of the mean value in column F.
5. Columns G and H show the calculated CO_2 emission in kg and metric tonnes.

Step 3: Combining uncertainties for activity data and emission factors (automated)

6. Column I provides the uncertainty range for the indirectly measured single source emissions.
7. Column J provides automatically the certainty ranking of the single source emissions according table 2 of this guidance.

Step 4: Calculate aggregated uncertainty for all indirectly measured emissions (automated)

8. The field in Column I below the Data entry Section provides the aggregated uncertainty for all indirectly measured emissions (Columns K and L show the result of intermediate calculations for control purposes.
9. The field in Column J below the Data entry Section provides automatically the certainty ranking for the aggregated indirectly measured emissions according table 2 of this guidance.

10.2 Calculation steps for Worksheet 2 “aggregation - direct measurement”

Data Input :

1. Enter the reported GHG emissions in kg for each directly measured single source in Column A.
2. Enter the estimated uncertainty ranges of the reported GHG emissions expressed in +/- percent of the mean value in column B.
3. Column C provides automatically the certainty ranking of the single source emissions according table 2 of this guidance.

Step 4: Calculate aggregated uncertainty for all indirectly measured emissions (automated)

4. The field in Column B below the Data entry Section provides the aggregated uncertainty for all measured emissions
5. The field in Column C below the Data entry Section provides automatically the Certainty ranking for the aggregated directly measured emissions according table 2 of this guidance.

10.3 Worksheet 3 “aggregated uncertainty”

Worksheet 3 aggregates automatically the uncertainty ranges of the directly and indirectly measured emissions:

Step 4: Calculate aggregated uncertainty for all entered emissions (automated)

1. The grey field “aggregated uncertainty” provides the aggregated uncertainty for all measured emissions
2. The colored field “Uncertainty Ranking” provides automatically the Certainty ranking for the aggregated directly measured emissions according table 2 of this guidance.

11 For further Information

Detailed guidance and information on assessing uncertainty – including approaches to developing quantitative uncertainty estimates and eliciting judgments from experts – can be found in chapter 6 of the IPCC’s Good Practice Guidance and the EPA’s Procedures Manual for Quality Assurance/Quality Control and Uncertainty Analysis (see references).

12 References

EPA (1996-1997) *Quality Assurance Procedures*. Emission Inventory Improvement Program (EIIP) Document Series, Volume 6. U.S. Environmental Protection Agency. Download at <http://www.epa.gov/ttnchie1/eiip/techreport/volume06/index.html>

EPA (2002), *Background on the U.S. Greenhouse Gas Inventory Process,* U.S. Environmental Protection Agency, Office of Atmospheric Programs, EPA 430-R-02-007A. Download at <http://yosemite.epa.gov/oar/globalwarming.nsf/content/ResourceCenterPublicationsGHGEmissions.html>

EPA (2002), *Procedures Manual for Quality Assurance/Quality Control and Uncertainty Analysis*, U.S. Environmental Protection Agency, Office of Atmospheric Programs, EPA 430-R-02-007B. Download at <http://yosemite.epa.gov/oar/globalwarming.nsf/content/ResourceCenterPublicationsGHGEmissions.html>

IPCC (2000) *Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories*. Intergovernmental Panel on Climate Change. Download at <http://www.ipcc-nggip.iges.or.jp/public/gp/gpgaum.htm>

IPCC/OECD/IEA (1997) *Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories. The Reference Manual*. Intergovernmental Panel on Climate Change, Organisation for Economic Co-operation and Development, and International Energy Agency. Download at http://www.ipcc-nggip.iges.or.jp/public/gl/invs1.htm

ISO (1993) *Guide to the Expression of Uncertainty in Measurement,* International Organization for Standardization, Geneva, Switzerland.

13 Acknowledgements

The GHG Protocol team would like to thank Markus Ohndorf, Swiss Federal Institute of Technology Zurich, Center for Economic Research, for programming the uncertainty tool and Markus Ohndorf and Michael Gillenwater for co-authoring the guidance document.

Many sincere thanks also go to Brad Upton (NCASI), Duncan Noble (FiveWinds International), Einar Telnes (DNV), Jochen Mundinger (University of Cambridge, UK), Kamala Rajamani Jayaraman (ICF Consulting), Manuela Ojan (Toyota Europe), Manuele de Gennaro (Swiss Federal Institute of Technology Zurich, Center for Economic Research), Matthias Gysler (Federal Office for Energy, Switzerland) and Pierre Boileau (Environment Canada) for reviewing the draft tool and guidance and providing very helpful and insightful comments.

Annex: t-factor for several different confidence levels

No of measurements n	**t-factor for Confidence Level**					
	68.27[a]	**90**	**95**	**95.45** [a]	**99**	**99.73** [a]
2	1.84	6.31	12.71	13.97	63.66	235.8
3	1.32	2.92	4.3	4.53	9.92	19.21
4	1.2	2.35	3.18	3.31	5.84	9.22
5	1.14	2.13	2.78	2.87	4.6	6.62
6	1.11	2.02	2.57	2.65	4.03	5.51
7	1.09	1.94	2.45	2.52	3.71	4.9
8	1.08	1.89	2.36	2.43	3.5	4.53
9	1.07	1.86	2.31	2.37	3.36	4.28
10	1.06	1.83	2.26	2.32	3.25	4.09
11	1.05	1.81	2.23	2.28	3.17	3.96
12	1.05	1.8	2.2	2.25	3.11	3.85
13	1.04	1.78	2.18	2.23	3.05	3.76
14	1.04	1.77	2.16	2.21	3.01	3.69
15	1.04	1.76	2.14	2.2	2.98	3.64
16	1.03	1.75	2.13	2.18	2.95	3.59
17	1.03	1.75	2.12	2.17	2.92	3.54
18	1.03	1.74	2.11	2.16	2.9	3.51
19	1.03	1.73	2.1	2.15	2.88	3.48
20	1.03	1.73	2.09	2.14	2.86	3.45
25	1.02	1.71	2.06	2.11	2.8	3.34
30	1.02	1.7	2.05	2.09	2.76	3.28
35	1.01	1.7	2.03	2.07	2.73	3.24
40	1.01	1.68	2.02	2.06	2.71	3.2
50	1.01	1.68	2.01	2.05	2.68	3.16
100	1.005	1.66	1.98	2.025	2.63	3.08
∞	1	1.645	1.96	2	2.576	3

[a] For a quantity z described by a normal distribution with expectation μ_z and standard deviation σ, the interval $\mu_z \pm k\sigma$ encompasses p = 68.27, 95.45, and 99.73 percent of the distribution for k = 1, 2, and 3, respectively.