# 5.1 INTRODUCTION

Several general or cross-cutting issues need to be considered when preparing national greenhouse gas inventories of emissions and removals. This chapter provides *good practice guidance* on six such issues identified in the Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories (*GPG2000*, IPCC, 2000), building on the previous discussion to take into account the specific characteristics of the land use, land-use change and forestry (LULUCF) sector. The six issues are:

- Uncertainty Assessment: Estimates of uncertainty need to be developed for all categories in an inventory and for the inventory as a whole. *GPG2000* provides practical guidance for estimating and combining uncertainties, along with a discussion of the conceptual underpinnings of inventory uncertainty. Section 5.2, Identifying and Quantifying Uncertainties, of this chapter, discusses the key types of uncertainty in the LULUCF sector and provides specific information on how to apply the *good practice guidance* of *GPG2000* to this sector.

- Sampling: Data for the LULUCF sector often are obtained from sample surveys; for example land areas, biomass stock and soil carbon, and such data typically are used for estimating changes in land use or carbon stocks. Section 5.3, Sampling, gives *good practice guidance* for the planning and use of sample surveys for the reporting of emissions and removals of greenhouse gases at the national level. This section also gives an overview of the relationship between sampling design and uncertainty estimates.

- Key Category Analysis: Chapter 7 of *GPG2000*, Methodological Choice and Recalculation, presents the concept of key source analysis. As originally designed it applied only to source categories. Section 5.4, Methodological Choice – Identification of Key Categories, of this chapter, expands the original approach to enable the identification of key categories that are sources or sinks. *Good practice guidance* is provided on how to identify key categories for the LULUCF sector for the inventory under the UNFCCC, and additional guidance is provided for identifying key categories associated with the supplementary information provided under Articles 3.3 and 3.4 of the Kyoto Protocol.

- Quality Assurance (QA) and Quality Control (QC): A QA/QC system is an important part of inventory development, as described in Chapter 8 of *GPG2000*. Section 5.5 of this chapter describes those aspects of the QA/QC system that are needed for the LULUCF sector and provides specific *good practice guidance* on conducting Tier 2 quality control checks for this sector, building on information provided in Chapter 2, Basis for Consistent Representation of Land Areas, and Chapter 3, LUCF Sector Good Practice Guidance, of this report. QA/QC issues specific to the Kyoto Protocol are also presented.

- Time Series Consistency: Ensuring the time series consistency of inventory estimates is essential if one is to have confidence in reported inventory trends. In Chapter 7 of *GPG2000*, several methods are provided for ensuring time series consistency in cases where it is not possible to use the same methods and/or data over the entire period. In Section 5.6, Time Series Consistency and Recalculations, of this chapter, these methods are discussed with respect to specific situations that can arise in the development of emission and removal estimates for the LULUCF sector.

- Verification: Conducting verification activities can improve inventory quality as well as lead to better scientific understanding. Verification approaches and practical guidance for verifying estimates in the LULUCF sector are described in Section 5.7 of this chapter.

This chapter provides the information needed to apply *good practice guidance* in the LULUCF sector. It does not repeat all information from *GPG2000*, however. Thus, readers may wish to refer to *GPG2000* for additional background information. Specific situations in which reference to *GPG2000* may be useful are mentioned in the subsections that follow.

# 5.2 IDENTIFYING AND QUANTIFYING UNCERTAINTIES

## 5.2.1 Introduction

This section describes *good practice* in estimating and reporting uncertainties associated with estimates of emissions and removals in the LULUCF sector and shows how to incorporate the LULUCF sector into the procedure introduced in Chapter 6, Quantifying Uncertainties in Practice, of *GPG2000* for the assessment of combined uncertainties across the inventory.

The definition of *good practice* requires that inventories should be accurate in the sense that they are neither over- nor underestimated as far as can be judged, and that uncertainties are reduced as far as practicable. There is no predetermined level of precision; uncertainty is assessed to help prioritise efforts to improve the accuracy of inventories in the future and guide decisions on methodological choice. Uncertainties are also of interest when judging the level of agreement between national inventories and emission or removal estimates made by different institutions or approaches.

Inventory estimates can be used for a range of purposes. For some purposes, only the national total matters, while for others, the detail by greenhouse gas and source or sink category is important. In order to compile the data to the intended purpose, users need to understand the actual reliability of both the total estimate and its component parts. For this reason, the methods used to communicate uncertainty must be practical, scientifically defensible, robust enough to be applicable to a range of source and sink categories, methods and national circumstances, and presented in ways comprehensible to all inventory users.

There are many reasons for actual emissions and removals to differ from the number calculated in a national inventory. Some sources of uncertainty (e.g., sampling error or limitations on instrument accuracy) may generate well-defined, easily characterised estimates of the range of potential error. Other sources of uncertainty, for example systematic errors, are more difficult to identify and quantify (Rypdal and Winiwarter, 2001). This section describes how to account for both well-defined statistical uncertainties and less specific information characterising other forms of uncertainty in the LULUCF sector, and discusses the implications for the uncertainty of both the total inventory and its components.

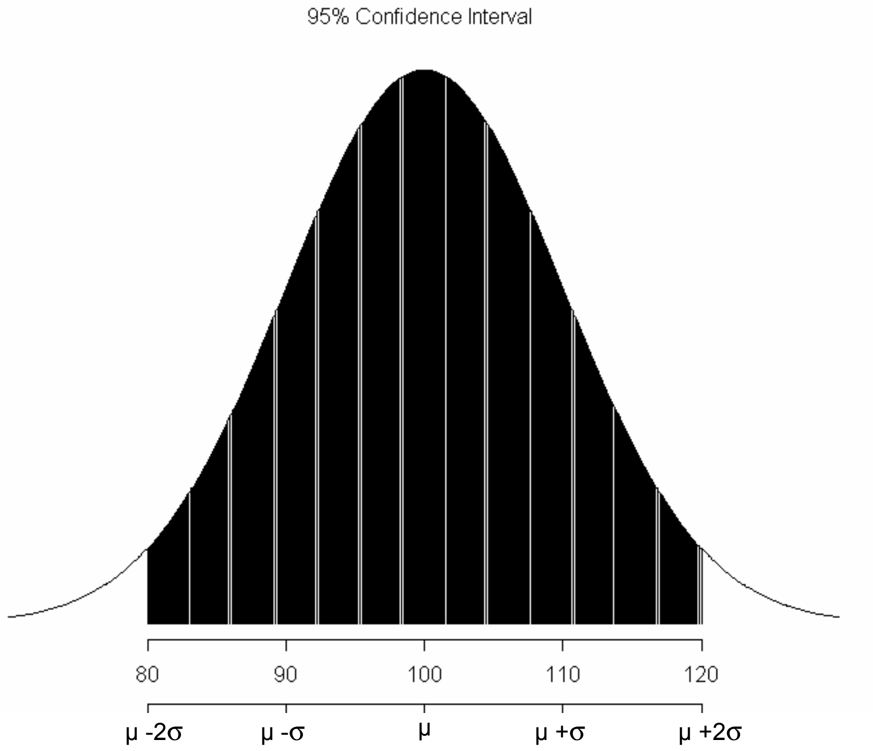
Ideally, emission and removal estimates and uncertainty ranges would be derived from source-specific measured data. Since it is not practical to measure every emission source or sink category in this way, some of the estimates are based on the known characteristics of typical sites taken to be representative of the population of all sites. This approach introduces additional uncertainties, because it must be assumed that the entire population behaves, on average, like the sites that have been measured. Random sampling of a target population allows quantitative estimation of uncertainties. Large systematic errors (implying biased estimates) can occur in cases where an estimate with known precision is based on a population which is different from the population where the estimate is to be applied. In practice, expert judgement will often be necessary to define the uncertainty ranges.

The pragmatic approach for producing quantitative uncertainty estimates in this situation is to use the best available estimates − a combination of the available measured data, model outputs, and expert judgement. The methods proposed in this section can therefore be used with the category-specific default uncertainty ranges discussed in Chapters 2 to 4 in this report, and also allow for new empirical data to be incorporated as they become available.

Consistent with Chapter 6 of *GPG2000* (Quantifying Uncertainties in Practice), uncertainties should be reported as a confidence interval giving the range within which the underlying value of an uncertain quantity is thought to lie for a specified probability. The *IPCC Guidelines* suggest the use of a 95% confidence interval, which is the interval that has a 95% probability of containing the unknown true value. This may also be expressed as a percentage uncertainty, defined as half the confidence interval width divided by the estimated value of the quantity (see Box 5.2.1). The percentage uncertainty is applicable when either the underlying probability density function is known or when a sampling scheme or expert judgement is used. Furthermore, this notion can be readily used to identify the categories for which efforts to reduce uncertainty should be prioritised.

This section is consistent with Chapter 6 and Annex 1 (Conceptual Basis for Uncertainty Analysis) of *GPG2000*, while providing additional information on how to assess uncertainties in the LULUCF sector. Much of the discussion focuses on issues related to $CO_2$ emissions and removals, which were not addressed in the previous report. Uncertainty estimates for emissions of non-$CO_2$ gases can also be prepared, following the guidance from Chapter 6 of *GPG2000*. Methods to combine uncertainties are described in Section 5.2.2, practical considerations for quantifying uncertainties in input data in Section 5.2.3, an example of an uncertainty analysis for the LULUCF sector is presented in Section 5.2.4, and Section 5.2.5 addresses reporting and documentation issues. Because of the importance of well-designed sampling programmes to reduce uncertainties when preparing LULUCF inventories for many countries, specific guidance on the design of sampling programmes for land areas and biomass stock, as well as guidance on assessment of associated uncertainties is provided separately in Section 5.3.

**BOX 5.2.1**
**EXAMPLE OF UNCERTAINTY EXPRESSION**




In the *GPG2000*, the percentage uncertainty is defined as:

$$\% \text{ uncertainty } = \frac{\frac{1}{2}(95\% \text{ Confidence Interval width})}{\mu} \times 100$$

For this example:

$$\% \text{ uncertainty} = \frac{\frac{1}{2}(4\sigma)}{\mu} \times 100 = \frac{2\sigma}{\mu} \times 100 = \frac{20}{100} \times 100 = 20\%$$

Where:

$\sigma$ = standard deviation

$\sigma = \sqrt{\text{variance}} = 10$

$\mu$ = the mean of the distribution

Note that this uncertainty is twice the relative standard error (in %), a commonly used statistical estimate of relative uncertainty.

## 5.2.2 Methods to Combine Uncertainties

Estimated carbon stock changes, emissions and removals arising from LULUCF activities have uncertainties associated with area or other activity data, biomass growth rates, expansion factors and other coefficients. This section describes how to combine these uncertainties at the category level and how to estimate the uncertainty in level and trend in the inventory as a whole. It assumes that the uncertainties of the various input data estimates are available, either as default values given in Chapters 2, 3 and 4 of this report, expert judgement, or estimates based of sound statistical sampling (Section 5.3).

In *GPG2000*, two methods for the estimation of combined uncertainties are presented: a Tier 1 method using simple error propagation equations, and a Tier 2 method using Monte Carlo or similar techniques. Both methods are applicable when dealing with the LULUCF sector. However, some specific considerations have to be highlighted, because net emissions can be negative if both emissions and removals are taken into account. Inventory agencies may also apply national methods for estimating the overall uncertainty, e.g., error propagation methods that avoid the simplifying approximations associated with the Tier 1 method. In this case, it is *good practice* to clearly document such methods.

Use of either Tier 1 or Tier 2 will provide insight into how individual categories and greenhouse gases contribute to the uncertainty in total emissions in any given year, and to the trend in total emissions between years. Being spreadsheet based, the Tier 1 method is easy to apply, and it is *good practice* for all countries to undertake an uncertainty analysis according to Tier 1. Inventory agencies may also undertake uncertainty analysis according to Tier 2 or national methods. The uncertainty estimates of the LULUCF sector can be combined with the uncertainty estimates of the non-LULUCF sector (derived using the *good practice* methods outlined in *GPG2000*) to obtain the total inventory uncertainty.

### 5.2.2.1 TIER 1 – SIMPLE PROPAGATION OF ERRORS

The Tier 1 method for combining uncertainties is based on the error propagation equation introduced in Section A1.4.3.1 (Error Propagation Equation) in the Annex 1 (Conceptual Basis for Uncertainty Analysis) of *GPG2000*. Practical guidance on how to apply the Tier 1 method for uncertainty analysis of emission estimates is provided in Section 6.3.2 (Tier 1 – Estimating Uncertainties by Source Category with Simplifying Assumptions) of *GPG2000*.

For the estimation of trend uncertainties, the method described in Section 6.3.2 of *GPG2000* can be used when emissions and removals are summed. Table 6.1, Tier 1 Uncertainty Calculation and Reporting, of *GPG2000* can also be applied with the implementation of a Tier 1 uncertainty calculation including the LULUCF sector.

Equation 5.2.1 can be used to estimate the uncertainty of a product of several quantities, e.g., when an emission estimate is expressed as the product of an emission factor and activity data. It applies where there is no significant correlation among data and where uncertainties are relatively small (standard deviation less than about 30% of the mean). The equation can also be used to give approximate results where uncertainties are larger than this. Where significant correlation exists, Equation 5.2.1 can be modified based on the equation provided in Section A1.4.3.1 of *GPG2000*, or the data can be aggregated following the guidance in Box 5.2.2 in this section and the paragraphs on dependence and correlation in Section 5.2.2.2.

**EQUATION 5.2.1**
**ESTIMATING CATEGORY UNCERTAINTIES (TIER 1)**

$$U_{total} = \sqrt{U_1^2 + U_2^2 + ... + U_n^2}$$

Where:

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

$U_i$ = percentage uncertainties associated with each of the quantities, $i = 1, \ldots, n$

**BOX 5.2.2**
**LEVEL OF AGGREGATION OF THE TIER 1 ANALYSIS**

Correlation among input data to the uncertainty analysis often exists. Examples are cases where the same activity data or emission factors are used in several estimates that are to be added in a later step. Often, these correlations cannot be detected statistically, especially if default values or coarse area statistics are used. However, a qualitative assessment of the likely correlation can still be made by evaluating, e.g., whether or not estimates are derived from the same source or if there are other logical dependencies that would cause the errors of different estimates to deviate in the same direction (if the correlation is positive). One possibility to avoid the correlation due to such dependencies is to aggregate the source/sink categories to a level where they are eliminated. For example, the emission factors for all carbon pools on a certain land-use class can be added before they are multiplied with activity data. This aggregation gives more reliable results overall, although it results in some loss of detail in reporting on uncertainties. Table 5.4.2 of Section 5.4 gives guidance on aggregation level for key category analysis that also may be applied for the Tier 1 uncertainty analysis.

Where uncertain quantities are to be combined by addition or subtraction, as when deriving the overall uncertainty in national estimates, Equation 5.2.2 can be used. Equation 5.2.2 is adapted from Equation 6.3 in *GPG2000*. However, the inclusion of LULUCF sector in the analysis can result in the summing of emissions and removals, the latter considered with a negative sign; therefore, the absolute value of the sum of all category estimates should be used in the denominator.

**EQUATION 5.2.2**
**OVERALL UNCERTAINTY IN NATIONAL EMISSIONS (TIER 1)**

$$U_E = \frac{\sqrt{(U_1 \bullet E_1)^2 + (U_2 \bullet E_2)^2 + \cdots + (U_n \bullet E_n)^2}}{\left|E_1 + E_2 + \cdots + E_n\right|}$$

where:

$U_E$ = percentage uncertainty of the sum

$U_i$ = percentage uncertainty associated with source/sink *i*

$E_i$ = emission/removal estimate for source/sink *i*

As with Equation 5.2.1, Equation 5.2.2 assumes that there is no significant correlation among emission and removal estimates and that uncertainties are relatively small. However, it still can be used to give approximate results where uncertainties are relatively large. Where significant correlation exists and the level of correlation is known, Equation 5.2.1 can be modified based on the equation provided in Section A1.4.3.1 in Annex 1 of *GPG2000*. Otherwise, categories should be aggregated, if possible (see Box 5.2.2), or Monte Carlo analysis (Tier 2) may be used.

### 5.2.2.2 ESTIMATING UNCERTAINTIES BY CATEGORY USING MONTE CARLO ANALYSIS (TIER 2)

Monte Carlo analysis is suitable for detailed category-by-category Tier 2 assessment of uncertainty. This section expands guidance on Monte Carlo analysis given in Chapter 6 of *GPG2000* by providing guidance specific to the LULUCF sector. *GPG2000* should be consulted as background, although some of the material from Chapter 6 is reproduced here.

Monte Carlo analysis is especially useful where extensive country-specific land use data exist. It can handle varying degrees of correlation (both in time and between categories) and can be used to assess uncertainty in complex models as well as simple ‘management factor (or emissions factor) times activity data’ calculations. A general description of the Monte Carlo method can be found in Fishman (1996), and statistical software packages are readily available – some of which include Monte Carlo algorithms that are very user-friendly. Winiwarter and Rypdal (2000) and Eggleston *et al*. (1998) provide examples of Monte Carlo analysis applied to national greenhouse gas inventories to estimate uncertainties both in overall emissions and emissions trends. Ogle *et al*. (2003) document a Monte Carlo analysis of uncertainty for the agricultural soil portion of the

LULUCF carbon inventory in the United States. A brief example of the application of Monte Carlo analysis is provided in Box 5.2.3 based on Ogle *et al*. (2003).

## BACKGROUND ON MONTE CARLO ANALYSIS

Monte Carlo analyses are designed to select random values for estimation parameters and activity data from probability distribution functions (PDF), and then calculate the corresponding change in carbon (or carbon equivalent) stocks. This procedure is repeated many times to provide a mean value and a range of uncertainty (i.e., a PDF for the emissions and removals) resulting from variability in model input variables as represented by PDFs. Monte Carlo analyses can be performed at the category level, for aggregations of categories or for the inventory as a whole.

Variability in the input variables is quantified in probability distribution functions, describing the pattern of possible values for the variable. PDFs may need truncation if certain thresholds are known to occur in the input variables. For example, estimates of base soil carbon could be small but would never be negative (soils can not have less than 0 percent carbon), therefore a distribution that would otherwise take negative values would need to be truncated at 0, although both negative and positive numbers are meaningful in cases such as where a process can lead to either a sink or a source term.

PDFs can be based on field data, expert judgement, or a combination of the two and can be linked to account for interdependencies, notably correlations across time or between gases for activity data and correlations among management factors. If these interdependencies are not taken into account, the estimated uncertainty may be too large or too small depending on the correlations, and the results are less meaningful.

After constructing PDFs, a Monte Carlo analysis is conducted as an iterative process. A set of input values are selected at random within each PDF, after that the model is run with those values producing an estimate for the output of interest, and then the process is repeated many times over and over, providing a PDF for the inventory estimate as a whole.

## ESTIMATING UNCERTAINTIES IN LEVELS AND TRENDS

As with all methods, Monte Carlo analysis only provides satisfactory results if it is properly implemented, and the results will only be valid to the extent that the input data, including PDFs, correlations, and any expert judgements, are sound. The Monte Carlo approach consists of five clearly defined steps. Only the first two steps require effort from the user, the remainder being handled by the software package.

Step 1: Specify uncertainties in the input variables. This includes estimation parameters and LULUCF activity data, their associated means and probability distribution functions (PDFs), and any correlations. The uncertainties can be assessed following the guidance in Section 5.2.3 (Practical Consideration for Quantifying Uncertainties of Input Data) and Section 5.2.4 (Example of Uncertainty Analysis) of this chapter. For guidance on assessment of correlations, see below.

Step 2: Set up software package. The emission inventory calculation, the PDFs, and the correlation values should be set up in the Monte Carlo package. The software performs the subsequent steps. In some cases, the inventory agency may decide to set up its own programme to run a Monte Carlo simulation; this can be done using statistical software.

Step 3: Select input values. Input values will normally be the *good practice* estimates applied in the calculation. This is the start of the iterations. For each input data item, a number is randomly selected from the PDF of that variable.

Step 4: Estimate carbon stocks. The variables selected in Step 3 are used to estimate carbon stocks for the base year and the current year (i.e., beginning and end of the inventory period; year $t{-}20$ and year $t$) based on input values.

Step 5: Iterate and monitor results. The calculated total from Step 4 is stored, and the process then repeats from step 3. The mean of the totals stored gives an estimate of the carbon stock, and the variability represents uncertainty. Many repetitions are needed for this type of analysis. The number of iterations can be determined in two ways: by setting the number of model runs, a priori, such as 10,000 and allowing the simulation to continue until reaching the set number, or by allowing the mean to reach a relatively stable point before terminating the simulation.

The Monte Carlo method can also be used to estimate uncertainties in the trend (changes between two years) resulting from LULUCF activities. The procedure is a simple extension of that described previously. The Monte Carlo analysis needs to be set up to estimate stocks for both years simultaneously. The procedural steps are the same as described above, except for variations in Step 1 and 2:

Step 1: The same procedure as described above, except that it needs to be done for both the base year and the current year, and consequently additional interdependencies must be considered. For many LULUCF categories, the same emission factor will be used for each year (i.e., the emission factors for both years are 100% correlated). Activity data for land use and emissions are often correlated across time, and this will need to be represented in the model as well.

Step 2: The software package should be set up as previously described, except that the PDFs will need to capture the relationship between carbon stocks in the base year and current year. Where the input data are assumed to be 100% correlated between years (as will be the case for many LULUCF estimation parameters), the same random number is used to generate the emission factor values from the PDF in both years.

### SPECIFYING PROBABILITY DISTRIBUTIONS FOR INVENTORY INPUTS

Data used in an uncertainty analysis can be derived from field trials or from expert judgement. These data need to be synthesized in such a way as to produce the probability distribution functions. Some key questions to ask regarding the data include:

- Are the data representative of management practices and other national circumstances?
- What is the averaging time associated with the data set, and is it the same as for the assessment?

Usually, available data will represent an annual average for an estimation parameter or an annual total for activity data.

Monte Carlo simulation requires that the analyst specifies probability distributions (see Fishman 1996) that reasonably represent each model input for which the uncertainty is to be quantified. The probability distributions may be based on advice in Chapter 3 of this report, or be obtained by a variety of methods, including statistical analysis of data, or the elicitation of expert judgement as described in Chapter 6 of *GPG2000*. A key consideration is to develop the distributions for the input variables to the emission/removal calculation model so that they are based upon consistent underlying assumptions regarding averaging time, location, and other conditioning factors relevant to the particular assessment (e.g., climatic conditions influencing agricultural greenhouse gas emissions). See also Section 5.2.3 (Practical Considerations for Quantifying Uncertainties of Input Data) for further guidance.

### ASSESSING THE CONTRIBUTION OF EACH INVENTORY INPUT TO OVERALL UNCERTAINTY

Ideally, the amount of effort devoted to characterizing uncertainty in an inventory input should be proportional to its importance to the overall uncertainty assessment. It would not be a good use of limited resources to spend large amounts of time exhaustively collecting data and expert judgements for a source/sink category that has little effect on overall uncertainty. Thus, countries are encouraged to identify which inputs to particular categories are particularly significant with respect to the overall uncertainty of the inventory as a mean to prioritise improvements. Similarly, it would be a shortcoming of an assessment not to devote reasonable resources to quantifying the uncertainties associated with the inputs to which the overall uncertainty in the inventory is highly sensitive. Thus, many analysts suggest an approach in which the first iteration of uncertainty analysis is an assessment of the main sources of uncertainty. This information will enhance the assessment of overall uncertainty and can be very useful in documentation. Methods for assessing the importance of each input are described in references such as Morgan and Henrion (1990), Cullen and Frey (1999), and others. See also Section 5.4 (Methodological Choice − Identification of Key Categories).

### SPECIFYING DEPENDENCE AND CORRELATION AMONG INVENTORY INPUTS

A key issue that should be considered by analysts when setting up a probabilistic analysis is whether there are dependencies or correlations among model inputs. Ideally, it is preferable to define the model so that the inputs are as statistically independent as possible. Therefore, rather than trying to estimate uncertainties separately for each LULUCF subcategory, it may be more practical to estimate uncertainty for aggregated categories, for which good estimates and cross-checks may be available. Dependencies, if they exist, may not always be important to the assessment of uncertainties. Dependencies among inputs will matter only when they exist between two inputs to which the uncertainty is particularly sensitive and when the dependencies are sufficiently strong. In contrast, weak dependencies among inputs, or strong dependencies among inputs to which the uncertainty in the inventory is insensitive, will be of relatively little importance to the analysis. Of course, some interdependencies are important and failure to account for those relationships can result in misleading results.

Dependencies can be assessed by evaluating the correlation among the input variables through statistical analyses. For example, Ogle *et al*. (2003) accounted for dependencies in tillage management factors, which were estimated from a common set of data in a single regression-type model, by determining the covariance between factors for reduced tillage and no-till management, and then using that information to generate tillage factor values with appropriate correlation during a Monte Carlo simulation. Box 5.2.3 discusses this study in more detail. One should consider the potential for correlations among input variables and focus on those that would likely have the largest dependencies (e.g., applying management factors for the same practice in different years of an inventory, or correlations among management activities from one year to the next). Additional discussions and examples are given in Cullen and Frey (1999) and Morgan and Henrion (1990). These documents also contain reference lists with citations to relevant literature.

**BOX 5.2.3**

**TIER 2 UNCERTAINTY ASSESSMENT FOR CHANGES IN AGRICULTURAL SOIL C IN THE U.S.A**

Ogle *et al*. (2003) have performed a Monte Carlo analysis for assessing the changes in carbon in agricultural soil in the United States. The method in the *IPCC Guidelines* requires inputs for management factors (i.e., the quantitative coefficients representing the change in soil organic carbon following a land use or management change), reference carbon stocks (i.e., the amount of soil organic carbon in the soils under the baseline condition), and the land use and management activity data. The management factors were estimated from about 75 published studies using linear mixed effect models. PDFs were derived for the management effect at a depth of 30 cm following 20 years since its implementation. Reference stocks were estimated using the National Soil Survey Characterization Database of the United States department of agriculture – national resource conservation service (USDA-NRCS) with carbon stock estimates from about 3700 soil samples across the United States. PDFs were based on the mean and variance from the samples, taking into account the spatial autocorrelation due to clumped distribution patterns. The land use and management activity data were recorded in the National Resources Inventory (NRI; USDA-NRCS), which tracks agricultural land management at more than 400,000 points in the United States and supplemented with data on tillage practices from the Conservation Technology Information Center (CTIC). The Monte Carlo analysis was implemented using a commercially available statistical software package and code developed by U.S. analysts. Their analysis accounted for interdependencies between estimation parameters that were derived from common datasets. For example, factors for set-aside lands and land-use change between cultivated and uncultivated conditions were derived from a single regression analysis using an indicator variable for set-asides, and hence were interdependent. Their analysis also accounted for interdependencies in land use and management activity data. When simulating input values, factors were considered completely interdependent from the base year and current year in the inventory because the effect of management was assumed not to change during the inventory period. As such, factors were simulated with identical random seed values. In contrast, reference carbon stocks for the various climates by soil zones used in the IPCC analysis were simulated independently, with different random seeds, because stocks for each zone were constructed from separate sets of data. U.S. analysts chose to use 50,000 iterations for the Monte Carlo analysis. Ogle *et al*. (2003) estimated that mineral soils gained an average of 10.7 Tg C $yr^{-1}$ between 1982 and 1997, with a 95% confidence interval ranging from 6.5 to 15.2 Tg C $yr^{-1}$. In contrast, organic soils lost an average of 9.4 Tg C $yr^{-1}$, ranging from 6.4 to 13.3 Tg C $yr^{-1}$. Further, Ogle *et al*. (2003) found that the variability in management factors contributed 90% of the overall uncertainty for final inventory estimates of soil carbon change.

## 5.2.3 Practical Considerations for Quantifying Uncertainties of Input Data

Before uncertainties in an inventory category can be assessed, information on the uncertainties of the input data is needed. Chapter 3 of this report provides guidance on the uncertainties related to the choice of methods (tiers) and uncertainties in default parameters. For key categories, it is *good practice* to make an independent assessment of the uncertainty associated with the data used in order to prepare the national estimates. The following sections provide general guidance on some of the issues that should be considered for the three methodological tiers described in Chapter 3, and issues associated with the Kyoto Protocol described in Chapter 4.

Chapter 2 describes the sources of uncertainty likely to be encountered in determining land areas associated with land use and land-use change activities. These depend on national circumstances, and on how countries specifically apply the three approaches, or the mix of approaches, used to categorise land area. Given the differences in national approaches, it is difficult to give general quantitative advice, although Table 2.3.6 in Chapter 2 provides illustrative ranges and advice on how to reduce uncertainties associated with the land classification. The advice in Chapter 2 is relevant to all tiers addressed in the following three subsections.

#### QUANTIFYING UNCERTAINTIES WHEN ESTIMATES OF EMISSIONS AND REMOVALS ARE BASED ON TIER 1 METHODS

Tier 1 methods to estimate emissions and removals from the LULUCF sector use country-specific area estimates (land area and changes in land area by categories) and default values of estimation parameters needed to calculate the source/sink strength of a specific category. The uncertainty associated with Tier 1 methods will likely be high because the suitability of the available default parameters to a country's circumstances is not known. The application of default data in a country or region that has very different characteristics from those of the source data can lead to large systematic errors (i.e., highly biased estimates of emissions or removals). A qualitative uncertainty estimation of the default values used in Tier 1 or the verification approaches described in Section 5.7 can help to identify potential bias of the estimates.

Ranges of uncertainty estimates for default estimation parameters are given in Chapter 3. Estimates of uncertainties in other estimation parameters (e.g., harvest data) have to be based on national sources or expert judgment reflecting national circumstances. Uncertainties in estimating the areas associated with land use and land-use change activities are obtained as described above. Overall uncertainty estimates for the LULUCF sector are obtained by combining uncertainties as described in Section 5.2.2 (Methods to Combine Uncertainties).

#### QUANTIFYING UNCERTAINTIES WHEN ESTIMATES OF EMISSIONS AND REMOVALS ARE BASED ON TIER 2 METHODS

Tier 2 methods described in Chapter 3 make use of country specific data within the framework established at Tier 1. In this case it is *good practice* to assess the uncertainty of these data given national circumstances. These data are often only broadly defined, presumably with very little stratification according to climate/management/disturbance categories. Mostly, they will be assessed in top-down approaches on the basis of cross-referenced background values, or combined estimates from non-representative data sources including expert judgement. It is *good practice* to assess uncertainty estimates for such default values using literature evaluation, expert judgement or comparisons with countries with similar conditions. By tracing the original data, it might be possible to improve the uncertainty assessment. Uncertainties in estimating the areas associated with land use and land-use change activities are obtained as described in the opening to Section 5.2.3. For emission factors (for example of wetlands or non-$CO_2$ trace gases from biomass burning), countries may have direct measurements from a few samples for certain reporting categories. Overall uncertainty estimates are then obtained by combining uncertainties as described in Section 5.2.2.

#### QUANTIFYING UNCERTAINTIES WHEN ESTIMATES OF EMISSIONS AND REMOVALS ARE BASED ON TIER 3 METHODS

In Tier 3, extensive and representative country-specific information on carbon stock changes (in forestry, for example, gains by growth, and losses by harvest, as well as losses due to natural mortality or disturbance) is used in estimates of emissions and removals. In this case, the uncertainty of all estimation parameters entering the calculation, including possible systematic errors, should be assessed. Uncertainties in estimating the areas associated with land use and land-use change activities are obtained as already described. While the random error component can be quantified in bottom-up approaches using in-situ inventory information (see Section 5.3 on sampling), the systematic error requires additional focus. The specific errors introduced by e.g., sampling and model conversions have to be considered (Lehtonen *et al*., 2004). It is *good practice* to combine all error components (random and systematic) for each parameter (including expansion and conversion factors), and to combine the corresponding uncertainty estimates for the emission and removal estimates for each category (see also specific recommendations on assessing the uncertainty of estimates from sample based surveys in Section 5.3).

Depending on the national Tier 3 approach, the important driving factors for the carbon cycle might be identified and parameterised in the subsections of Section 3.2.1. This allows for the application of dynamic models for extrapolation and verification purposes (see Section 5.7 on verification). Therefore, special attention should be paid to uncertainties of estimates based on models (Box 5.2.4).

**BOX 5.2.4**
**UNCERTAINTIES OF ESTIMATES BASED ON MODELS**

Models used in inventory construction can range from purely empirical/statistical relationships to detailed process based models. In practice, most models are constructed with elements of both. There are many issues to consider in quantifying the uncertainties in the estimates produced by these models. A few general comments can be made although it is beyond the scope of this document to review all relevant models. Overall uncertainty in models can be derived from two main components: uncertainty in the structure of the model and uncertainty in the parameter values. The first source of uncertainty is difficult to quantify. Comparison with observational field data can indicate that either the structure of the model or the parameter values or both are incorrect (Oreskes *et al.*, 1984). It is therefore important to test the validity of the models, and to use only models that are validated for the intended purpose. If a model is not well validated, a validation programme should complement its use. The uncertainty associated with parameter values can be more easily quantified by combining statistical estimates or expert judgments of parameter uncertainty with sensitivity, or Monte Carlo analysis. A sensitivity analysis should be performed before a model is used so as to determine its usefulness for prediction. A model that is highly sensitive to a parameter with high uncertainty may not be the best choice for inventory purposes. Given that the model structure is adequate, the final point to consider is the uncertainty of estimates produced by models. In this case, there are typically two error components to consider: uncertainty due to parameter uncertainty and uncertainty due to inherent variation in the population that cannot be captured by the model. When making these estimates, both sources of uncertainty should be considered in any calculation.

#### QUANTIFYING UNCERTAINTIES WHEN ESTIMATES OF EMISSIONS AND REMOVALS ARE BASED ON SUPPLEMENTARY REQUIREMENTS OF THE KYOTO PROTOCOL

The general methods to combine uncertainties as described in Section 5.2.2 (Methods to Combine Uncertainties) can also be applied in the reporting of estimates under the Kyoto Protocol. However, some of the major factors influencing the uncertainties might be different. For example, the overall uncertainty of the inventory of the LULUCF sector might be more sensitive to uncertainties in detection of land-use categories and changes within them for categories under Articles 3.3 and 3.4 of the Kyoto Protocol. In addition, the net-net accounting which is required for the reporting for agriculture-related activities, introduces some specific issues, which are addressed in more detail in Sections 4.2.4.2 and 4.2.8.1. For example, the uncertainty in the base year estimate may be different from that of the commitment period. On the other hand, there are special requirements for methodological choice for the reporting according under the Kyoto Protocol (as described in Chapter 4). It is necessary for reporting purposes to conduct separate uncertainty assessments for activities under Articles 3.3 and 3.4 of the Kyoto Protocol. The requirements and level of detail of the analysis is described in Section 4.2.4.3 of Chapter 4.

## 5.2.4 Example of uncertainty analysis

Chapter 6 , Quantifying Uncertainties in Practice, gives a general example on how uncertainties can be combined in its Appendix 6A.2. This approach can also be used for LULUCF sector provided all LULUCF calculations are expressed as products of area (or other activity data) and emission or removal factors. Since LULUCF estimates are in general approximately proportional to area more complex estimation procedures than multiplying activity data with a single emission factor can all be expressed in this form, with uncertainties associated with the equivalent emission or uptake factor estimated by expert judgement or by using the standard relationships for error propagation.

In this section an example is given that illustrates the steps for the Tier 1 uncertainty assessment, applied for the LULUCF Tier 1 approach using two typical activities. It considers a simple case where carbon stock changes, emissions and removals are estimated for two sub-categories within the forest land category: i) forest land that remains as forest land, and ii) the conversion of forest land to grassland. Non-$CO_2$ gases and emissions from soils are not considered here. The example concentrates on simple numerical estimates of uncertainty, not taking into account correlations between input parameters.

The estimation involves four steps.

Step 1: Estimate emissions or removals related to each activity; forest land remaining as forest, and conversion from forest to grassland.

Step 2: Assessment of uncertainties related to both activities.

Step 3: Assessment of the total uncertainties from the LULUCF sector.

Step 4: Combination of LULCF uncertainties with other source categories.

### Step 1: Estimate emissions or removals for each activity

Before conducting an uncertainty assessment, estimates of the carbon stock change are prepared for both subcategories: forest land remaining forest land and forest land converted to grassland. These estimates should be prepared following the detailed guidance in Chapters 3 of this report.

#### *Forest Land Remaining Forest Land*

Section 3.2.1.1.1.1 in Chapter 3 gives two methods for estimating carbon stock changes in biomass; in this example we only apply Method 1 which requires the biomass carbon loss to be subtracted from the biomass increment (Equation 3.2.2):

$$\Delta C_{FF\,LB} = (\Delta C_{FF_G} - \Delta C_{FF\,L})$$

where:

$\Delta C_{FF\,LB}$ = annual change in carbon stocks in living biomass (includes above- and belowground biomass) on forest land remaining forest land, tonnes C $yr^{-1}$

$\Delta C_{FF_G}$ = average annual increase in carbon due to biomass growth (also called biomass increment), tonnes C $yr^{-1}$

$\Delta C_{FF\,L}$ = annual average decrease in carbon due to biomass loss, tonnes C $yr^{-1}$.

To simplify the example we assume that there is no biomass loss, so that $\Delta C_{FF\,L} = 0$. Hence in this example, $\Delta C_{FF\,LB} = \Delta C_{FF_G}$ . The biomass increment $\Delta C_{FF_G}$ is calculated according to Equation 3.2.4 as:

$$\Delta C_{FF_G} = \sum_{ij} (A_{ij} \bullet G_{TOTAL\,ij}) \bullet CF$$

where:

$\Delta C_{FF_G}$ = average annual increase in carbon due to biomass increment in forest land remaining forest land by forest type and climatic zone, tonnes C $yr^{-1}$

$A_{ij}$ = area of forest land remaining forest land, by forest type ($i$= 1 to $n$) and climatic zone ($j$=1 to $m$), ha

$G_{TOTAL\,ij}$ = annual average increment rate in total biomass in units of dry matter by forest type ($i$= 1 to $n$) and climatic zone ($j$=1 to $m$), , tonnes d.m. $ha^{-1}$ $yr^{-1}$

CF = carbon fraction, tonnes C (tonnes d.m.)$^{-1}$ (default value 0.5, with 2% uncertainty)

In this example, the area of forest land remaining as forest is assumed to be 10 million hectares. Assume further that there is only one forest type and one climatic zone, so that $n = m = 1$, which simplifies the expression of $\Delta C_{FF_G}$ above to be:

$$\Delta C_{FF_G} = A \bullet G_{TOTAL} \bullet CF$$

where $G_{TOTAL}$ is now the annual average increment rate in total biomass, averaged over the whole land area. In general, the value for $G_{TOTAL}$ can be calculated from Equation 3.2.5 in Section 3.2.1.1.1.1 for each forest type and climatic zone, taking into account the parameter values in Annex 3A.1.[1] In the present example, a default value of 3.1 tonnes d.m. $ha^{-1}$ $yr^{-1}$, with a default percent uncertainty of 50%, is given for $G_{TOTAL}$, so for the average annual increase in carbon stock due to biomass increment on forest land remaining forest land is:

$$\Delta C_{FF\,LB} = \Delta C_{FF_G} = 10{,}000{,}000 \bullet 3.1 \bullet 0.5 \text{ tonnes C } yr^{-1} = 15{,}500{,}000 \text{ tonnes C } yr^{-1}$$

#### *Forest Land Converted to Grassland*

The basic method for Tier 1 to estimate carbon stock changes in biomass due to conversion of forest land to grassland is given in Section 3.4.2.1.

[1] Default values for the average annual aboveground biomass $G_W$ and the root-to-shoot ratio R entering Equation 3.2.5 can be found in Annex 3A.1, in Tables 3A.1.5, 3A.1.6 and 3A.1.8 (for R).

Equation 3.4.13 gives the annual carbon stock change from the conversion of forest land into grassland, assuming the year of conversion, as:

$$\Delta C_{LG_{LB}} = A_{Conversion} \bullet (C_{Conversion} + C_{Growth})$$
$$C_{Conversion} = C_{After} - C_{Before}$$

where:

$\Delta C_{LG_{LB}}$ = Annual change in carbon stocks in living biomass as a result of land use conversion to grassland from some initial land use, tonnes C $yr^{-1}$

$A_{Conversion}$ = Annual area of land converted to grasslands from some initial use, ha $yr^{-1}$

$C_{Conversion}$ = Carbon stocks removed when lands are converted from some initial use to grassland, tonnes C $ha^{-1}$

$C_{Growth}$ = Carbon stocks from one year of growth of grassland vegetation after conversion, tonnes C $ha^{-1}$

$C_{After}$ = Carbon stocks in biomass immediately after conversion to grassland, tonnes C $ha^{-1}$

$C_{Before}$ = Carbon stocks in biomass immediately before conversion to grassland, tonnes C $ha^{-1}$

If the default values are expressed as biomass per hectare, it will be necessary to convert to carbon using CF of 0.5 as a default, with an uncertainty for CF of 2%.

In this example, the area of forest converted to grassland is 500 hectares. The emission factors and the associated uncertainties are provided in Chapter 3.2.1.1.2 and Table 3.4.9 in Section 3.4.2.1 of Chapter 3. For this example we assume that:

$C_{F_{LB}}$ = $C_{Before}$ = 80 tonnes C $ha^{-1}$, with percent uncertainty of 24%

$C_{After}$ = 0 tonne C $ha^{-1}$, with percent uncertainty of 0%

$C_{G_{LB}}$ = $C_{Growth}$ = 3 tonnes C $ha^{-1}$, with percent uncertainty of 60%

Replacing the above values in the equation gives:

$$\Delta C_{LG_{LB}} = A_{FG} \bullet (-C_{F_{LB}} + C_{G_{LB}})$$
$$= 500 \text{ ha} \bullet (-80 + 3) \text{ tonnes C ha}^{-1} = -38{,}500 \text{ tonnes C}$$

## Step 2: Assessment of uncertainties for each activity

### *Forest Land Remaining Forest Land*

The uncertainty associated with estimated forest land area must be determined based on expert judgement. If the estimate is based on national surveys with designed statistical sampling (see Section 5.3, Sampling and Table 2.3.6 in Chapter 2) then statistical methods can be used to calculate the uncertainty.

In this example, it is assumed that the area of managed forest comes from administrative records. The agency that compiles them used a *good practice* method and an uncertainty in the area estimates of 20%, based on expert judgement.

The uncertainty of the annual biomass growth depends on the uncertainty of input parameters. If the country is using default parameters, uncertainty will be high and can be only roughly estimated with expert judgment (see Chapter 3). If the annual growth in biomass is calculated according to Equation 3.2.4 and converted to carbon with CF, then the uncertainty estimate of the growth in biomass carbon ( $U_{\Delta C_{FF_G}}$ ) is obtained as:

$$U_{\Delta C_{FF_G}} = \sqrt{U_{A_{FF}}^2 + U_{G_{TOTAL}}^2 + U_{CF}^2}$$

If we define $U_{GC_{TOTAL}}$ as the percentage uncertainty of the annual biomass growth in terms of carbon per unit area (i.e., the combined uncertainty of $G_{TOTAL} \bullet CF$), then:

$$U_{GC_{TOTAL}} = \sqrt{U_{G_{TOTAL}}^2 + U_{CF}^2}$$

$$U_{GC_{TOTAL}} = \sqrt{50\%^2 + 2\%^2} = 50.04\%$$

Before the combined uncertainties of the activity information $A_{FF}$ (area of forest land remaining forest land) and the emission factor (annual biomass growth in terms of carbon, $GC_{TOTAL}$) can be calculated, it must be determined whether they are correlated. In this example, the inputs are derived from independent sources, and it is reasonable to assume that they are not correlated. Consequently, Equation 5.2.1 can be used to give the $U_{\Delta C_{FF_G}}$ as:

$$U_{\Delta C_{FF_G}} = \sqrt{U_{A_{FF}}^{\;2} + U_{GC_{TOTAL}}^{\;2}}$$

$$= \sqrt{20\%^2 + 50.04\%^2} = 53.8\%$$

where:

$U_{\Delta C_{FF_G}}$ = percent uncertainty of the change in carbon stock

$U_{A_{FF}}$ = percent uncertainty of the forest land area estimates

### *Forest land converted to Grassland*

It is also necessary to estimate the uncertainty associated with the carbon stock change resulting from land-use change. Depending on the source, type and density of the data, statistical error estimates might not be possible, and expert judgement will be used. In this example, since the carbon stock immediately after the conversion $C_{After}$ is assumed to be zero with certainty, the uncertainty of the carbon stock change, as calculated with Equation 3.4.13, has three components: the uncertainty in carbon stock immediately before the conversion $U_{C_F}$, (F = Forest), the uncertainty in carbon stock of grassland vegetation after the conversions $U_{C_G}$, (G = Grassland) and the uncertainty associated with the estimate of the area that has been converted $U_{A_{FG}}$. Using Equation 5.2.2 and the example values for the carbon stocks and uncertainties as given in Step 1 above, the percent uncertainty of the carbon stock change per hectare $U_\Phi$ is estimated as:

$$U_\Phi = \frac{\sqrt{(U_{C_F} \bullet C_F)^2 + (U_{C_G} \bullet C_G)^2}}{|C_F + C_G|}$$

$$= \frac{\sqrt{(24\% \bullet (-80))^2 + (60\% \bullet 3)^2}}{|-80+3|} = 25\%$$

The total uncertainty for biomass carbon stock change for this simplified example of land-use change is then calculated using Equation 5.2.1, combining the uncertainty in carbon stock change per hectare with the uncertainty in the estimate of the converted area, which – in our example – is assumed to be 30%. Hence:

$$U_{\Delta C_{FG}} = \sqrt{U_{A_{FG}}^{\;2} + U_\Phi^{\;2}}$$

$$= \sqrt{30\%^2 + 25\%^2} = 39\%$$

### Step 3: Assessment of the total uncertainties from the LULUCF sector

In this simple example, the uncertainty of the LULUCF Sector is estimated by combining the uncertainty of the estimates of the two activities. Uncertainties for a real world case with more category estimates can be combined in the same way.

| Total uncertainty for this example | | |
|---|---|---|
| Land-Use Category | Estimate of the associated carbon stock change (tonne C yr $^{-1}$) | $U_{\Delta C}$ |
| Forest Land Remaining as Forest | 15 500 000 | 53.8% |
| Forest Land Converted to Grassland | -38 500 | 39% |
| Total | 15 461 500 | 54% |

The overall uncertainty is then estimated from Equation 5.2.2 to be:

$$U_{TOTAL} = \frac{\sqrt{(53.8\% \bullet 15500000)^2 + (39\% \bullet (-38500))^2}}{\left|15500000 + (-38500)\right|} = 54\%$$

The overall uncertainty from these two LULUCF activities, when expressed as percent uncertainty is 54%. The uncertainty expressed as the relative standard error of the estimate is obtained by dividing the percent uncertainty by 2. It should be noted that the formula implies correlations among the estimates due to the reliance on identical conversion and expansion factors for both activities. In practice, however, this correlation may be small. If not, the calculations should be done for independent samples, e.g., during Tier 2 uncertainty analysis (such as Monte Carlo).

**Step 4: Combination of LULUCF uncertainties with other source categories**

Finally, the uncertainty estimate for the LULUCF sector can be combined by uncertainty estimates for other source categories using either a Tier 1 or Tier 2 method.

## 5.2.5 Reporting and documentation

The general advice on reporting given in *GPG2000* is also applicable for the LULUCF sector. The result of a Tier 1 uncertainty analysis for the LULUCF sector can be reported adding the lines for the relevant LULUCF categories to Table 6.1 in Section 6.3 in Chapter 6 of *GPG2000*, with taking the guidance given in Section 6.3.2 of *GPG2000* into account.

According to *GPG2000*, the analysis can be performed using $CO_2$ equivalent emissions calculated using global warming potentials (GWP) specified by COP3, Decision 2/CP.3.[2]

[2] The methodology is also generally applicable using other weighting schemes.