EUROPEAN TOPIC CENTRE ON AIR AND CLIMATE CHANGE (ETC/ACC)

Good Practice Guidance for CLRTAP Emission Inventories

Draft chapter for the UNECE Corinair Guidebook on Emission Inventories

To replace the

"Procedures for Verification of Emission Inventories" chapter

(Part B, verifn2)

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Contents

Section 1   Introduction

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1.1   Background

An emissions inventory is the foundation for essentially all air quality management programs. Emissions inventories are used by air quality managers in assessments of the contributions of and interactions among air pollution sources in a region, as input data for air quality models, and in the development, implementation, and tracking of control strategies. The importance of emissions inventory data increases with advances in the sophistication of the models and other analysis tools used in air quality management, and as a result, the interest in emissions verification is widespread.

This chapter on Good Practice is aimed at supporting parties to the convention in preparing inventories and reports that allow for [1]

(a)   *"the process of considering Parties' reports on emission inventories and projections, including their technical analysis and compilation; and*

(b)   *the process of verification and technical assessment, including expert review, of the emission reports and the evaluation of data quality for the purpose of the functions of the Implementation Committee (Executive Body Decision 1997/2, annex, para. 3 (c))."*

This chapter replaces a similar chapter in earlier versions of the Guidebook. A revision was needed to reflect all aspects of verification and validation, including uncertainty estimation, identification of key sources, systematic resource prioritisation and quality assurance and quality control. This review also considers the major step forward that was made in the Greenhouse Gas Inventory Program of IPCC by publication of the report "Good Practice Guidance and Management of Uncertainties" in 2000 (IPCC GPGAUM)[2]. Although the approach in this report is comparable with the one chosen in the earlier versions of the Guidebook, improved harmonization asked for a rearrangement and rephrasing of major parts of its text. This chapter thus presents an approach to inventory verification and validation that is consistent with the approach chosen in the field of Climate Change and uses the achievements in this respect also within the framework of the UNECE Convention on Long Range Transboundary Air Pollution (CLRTAP).

The table below presents the relation between the sections of this chapter and the chapters and annexes of the IPCC GPGAUM [2] report.

Sections in this document:	Related section of IPCC GPGAUM [2]
✓ Introduction & application of data	Chapter 1, Annexes 1 and 3
✓ Documentation of Data and Procedures	Chapter 8
✓ Good practice in inventory preparation - Methodological Choice	Chapter 7
✓ Uncertainty Estimates	Chapter 6 and "sector" chapters 2, 3, 4 and 5.
✓ Verification	Annex 2

This section will briefly summarize the line of thinking as described in IPCC GPGAUM as far as relevant for the UNECE/CLRTAP processes. It will define the three separate issues that are relevant with respect to inventory quality:

1) Verification and validation

2) Uncertainties; and

3) Good Practice

1.2   "Verification" and "Validation"

The purpose of verification/validation is to ensure that parties report accurately reasonable and reliable emissions data. In this paragraph we consider both the functions that should be carried out during the verification/validation process.

It is important to start by clarifying the distinction between *verification* and *validation*. In this chapter we use the following definitions, taken from the glossary of IPCC-GPGAUM[1], which are fully consistent with earlier versions of the Guidebook:

Verification	refers to the collection of activities and procedures that can be followed during the planning and development, or after completion of an inventory that can help to establish its reliability for the intended applications of that inventory. Typically, methods external to the inventory are used to check the truth of the inventory, including comparisons with estimates made by other bodies or with emission and uptake measurements determined from atmospheric concentrations or concentration gradients of these gases.
Validation	is the establishment of sound approach and foundation. In the context of emission inventories, validation involves checking to ensure that the inventory has been compiled correctly in line with reporting instructions and guidelines. It checks the internal consistency of the inventory. The legal use of validation is to give an official confirmation or approval of an act or product.

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[1] It is recommended to all user of this Guidebook to explicitly and exclusively use the terminology and definitions as presented in this Glossary.
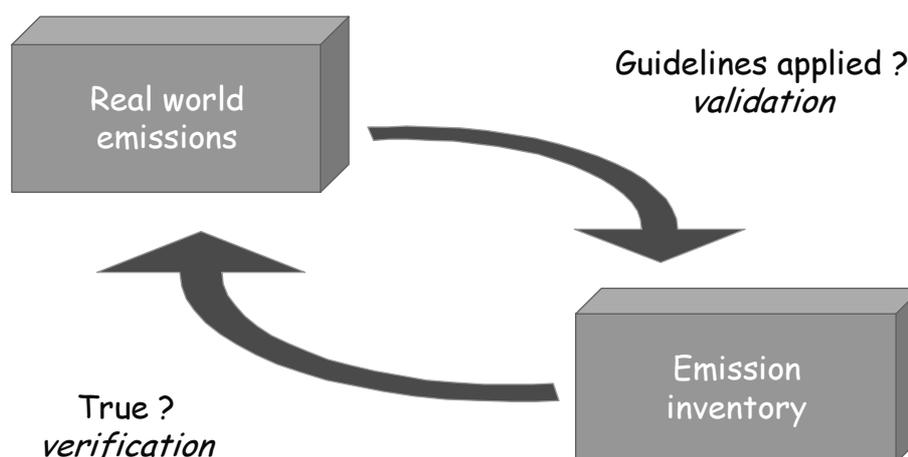
Figure 1 **Schematic representation of the concepts of validation and verification**

In Figure 1 the difference between validation and verification is schematically explained. *Validation checks whether or not the guidelines have been applied, whereas verification checks whether the data are true*. When the inventory is validated, it has been agreed that the guidelines have been correctly applied; therefore the emissions report is accepted for compliance purposes[2]. If verification then shows that the emissions report does not accurately reflect true emissions, this means that emissions determination guidelines need to be changed. But because the inventory compiler has followed programme rules, the emissions inventory and report is still accepted.

Over the long-term, verification may improve the emissions data quality and help to ensure that emissions determination methods accurately reflect true emissions. In the short-term, however, ensuring both that reporting is complete, transparent, consistent and in conformity with accepted standards, and that monitoring guidelines have been applied correctly, will give the user sufficient confidence in the possible application of the inventory in any policy process.

1.3   *Uncertainties in an emission inventory*

Uncertainty estimates are an essential element of a complete emission inventory. This concerns the ensemble of uncertainties associated with the data collected and with the aggregation thereof towards sector or national totals.

Given the uncertainty in the inventory, verification and validation of an inventory are two different aspects of the quality of an inventory. Validation is aiming at the acceptance of the inventory estimation procedures and verification is aiming at getting the true values. Tools to support these activities include quality assurance / quality control (QA/QC) and verification.

A third aspect of an emission inventory is the ensemble of uncertainties associated with the data collected and with the aggregation thereof towards sector or national totals.

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[2] The Task Force on Emissions Inventories does not decide what will be accepted for compliance purposes.

Quality aspects of emission inventories
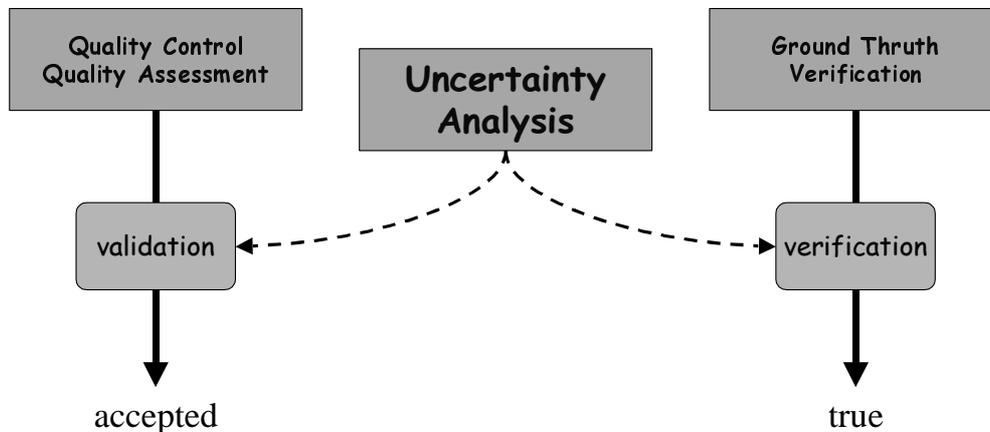
Figure 2   Uncertainty analyses to improve the quality of an emission inventory

It is important to realize that uncertainty information is not intended to dispute the validity of the inventory estimates, but to:

1) Help prioritise efforts to improve the accuracy of inventories in the future and guide decisions on methodological choice.

2) Inform users of inventory data on the scientific quality of the data, supporting them to perform uncertainty evaluations of their own applications and to consider the usability of the results of air quality models and projection studies.

Understanding the uncertainties in an emission inventory can support both the validation and verification of emission inventories (Figure 2).

Inventory practitioners understand that for many countries and source categories, emissions estimates are reasonably accurate. However, national inventories will typically also contain a wide range of emission estimates, varying from carefully measured and demonstrably complete data for some sources to order-of-magnitude estimates for others.

1.4   *Good practice*

In order to ensure that quality evaluation of an emission inventory and an emission report is possible, such an inventory and report should be compiled using "Good Practice". The IPCC GPGAUM report defines good practice as follows:

Good Practice	is a set of procedures intended to ensure that inventories are accurate in the sense that they are systematically neither over nor underestimates so far as can be judged, and that uncertainties are reduced so far as possible.

The IPCC GPGAUM definition of Good Practice covers

✓   choice of estimation methods appropriate to national circumstances,

✓   quality assurance and quality control at the national level,

✓   quantification of uncertainties and

✓   data archiving and reporting to promote transparency.

These requirements are to ensure that emissions estimates, even if uncertain, are bona fide estimates, in the sense of not containing any biases that could have been identified and eliminated, and that uncertainties have been minimized as far as possible given national circumstances. Estimates of this type would presumably be the best attainable, given current scientific knowledge and available resources.

Good practice aims to deliver these requirements by providing guidance on:

1)   Quality assurance and quality control procedures to provide

    a)   cross-checks during inventory compilation and

    b)   definition of data and information to be documented, archived and reported;

2)   Choice of estimation method within the context of this Guidebook;

3)   Quantification of uncertainties at the source category level and for the inventory as a whole, so that the resources available for research can be directed toward reducing uncertainties over time, and the improvement can be tracked.

1.5   *This chapter*

This chapter provides guidance for emission inventory compilers to enable inventory compilation according to Good Practice. The chapter should be understood in close conformity with the IPCC GPGAUM report. It does not repeat all the explanations and procedures as described therein. We therefore recommend the reader to have a copy of this report at hand, while planning, preparing and compiling an emission inventory using good practice. A copy of the GPGAUM report can be down loaded from URL: http://www.ipcc-nggip.iges.or.jp/public/gp/gpgaum.htm.

This chapter provides tools and methods the user might need for Good Practice inventory compilation.

Section 2 presents an overview of QA/QC aspects and proposes a general inventory QA/QC procedure

Section 3 deals with the planning phase of the inventory compilation and supports the selection of the most relevant sources, enabling the user to prioritise data collection efforts

Section 4 summarises the uncertainty analysis methods as described in the IPCC GPGAUM report for application in inventories under CLRTAP and its protocols

Section 5 finally gives some guidance on verification.

Section 2   Assessment and Management of Data Quality

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2.1   Introduction

The purpose of this section is to define the practice of quality control and quality assurance, as well as other techniques that may be used to assess and document the reasonableness of the emissions inventory data. Recommendations included here regarding QC / QA good practices are consistent with the IPCC GPGAUM. Excerpts from the Guidelines are included here to provide a context for discussing QC / QA activities for the CLRTAP emissions data. The reader should also obtain and read the noted chapters of the IPCC Guidelines, as they are incorporated here by reference and serve as the basis for this discussion.

In addition, this discussion describes a systematic approach that may be used to determine data quality objectives for the CLRTAP emission inventories. The approach is intended to help guide the inventory preparers in assessing and targeting the quality of the inventory data based on its anticipated uses.

2.2   Definition of QC / QA and verification

The terms 'quality control', 'quality assurance', and 'verification' are often used interchangeably, and in a non-distinct manner. The terms are distinguished here using the same definitions applied in IPCC GPGAUM, and are adopted for application to quality assessment activities for the CLRTAP inventories. (The following is taken directly from IPCC GPGAUM)

Quality Control (QC) is a system of routine technical activities, to measure and control the quality of the inventory as it is being developed. The QC system is designed to:

✓ Provide routine and consistent checks to ensure data integrity, correctness, and completeness;

✓ Identify and address errors and omissions;

✓ Document and archive inventory material and record all QC activities.

QC activities include general methods such as accuracy checks on data acquisition and calculations and the use of approved standardised procedures for emission calculations, measurements, estimating uncertainties, archiving information and reporting. Higher tier QC activities include technical reviews of source categories, activity and emission factor data, and methods.

Quality Assurance (QA) activities include a planned system of review procedures conducted by personnel not directly involved in the inventory compilation/development process. Reviews, preferably by independent third parties, should be performed upon a finalised inventory following the implementation of QC

procedures. Reviews verify that data quality objectives were met, ensure that the inventory represents the best possible estimates of emissions and sinks given the current state of scientific knowledge and data available, and support the effectiveness of the QC programme.

Verification processes are, in the present context, intended to help establish an inventory's reliability. These processes may be applied at either national or global levels of aggregation and may provide alternative information on annual emissions and trends. The results of verification processes may:

✓ Provide inputs to improve inventories;

✓ Build confidence in emissions estimates and trends;

✓ Help to improve scientific understanding related to emissions inventories.

The verification process can help evaluate the uncertainty in emissions estimates, taking into account the quality and context of both the original inventory data and data used for verification purposes. Where verification techniques are used, they should be reflected in the QC/QA plan. Improvements resulting from verification should be documented, as should detailed results of the verification process. Options or tools for verification are discussed in Annex 2 of IPCC GPGAUM.

2.3   Applying QC / QA techniques

The level of QA/QC activities should be compatible with the methods or tiers used to estimate emissions for particular source categories. Resources should be focused on priority areas, such as the key categories described in the section on 'Methodological Choice', and on priority areas identified when establishing data quality objectives. When much of an emission inventory is developed using default emission factors and aggregated activity data methods, QC procedures should focus on checking calculations and documentation. This is referred to as a "Tier 1" QC/QA approach. When national methods and data are used, instead of default data, and changes made in methods and data characteristics, a more extensive QC/QA approach should be used – this level of QC/QA is referred to as "Tier 2".

Under Tier 1, general QC procedures and a QA review of the inventory should be performed. General QC techniques focus on the processing, handling, and reporting procedures common to all inventory sources. The following table is reprinted from IPCC GPGAUM, Chpt 8, and summarises the Tier 1 General Inventory Level QC Procedures.

TIER 1 GENERAL INVENTORY LEVEL QC PROCEDURES	
QC ACTIVITY	**PROCEDURES**
Check that assumptions and criteria for the selection of activity data and emission factors are documented.	Cross-check descriptions of activity data and emission factors with information on source categories and ensure that these are properly recorded and archived.

TIER 1 GENERAL INVENTORY LEVEL QC PROCEDURES	
QC ACTIVITY	**PROCEDURES**
Check for transcription errors in data input and references.	Confirm that bibliographical data references are properly cited in the internal documentation. Cross-check a sample of input data from each source category (either measurements or parameters used in calculations) for transcription errors.
Check that emissions are calculated correctly.	Reproduce a representative sample of emissions calculations. Selectively mimic complex model calculations with abbreviated calculations to judge relative accuracy.
Check that parameter and emission units are correctly recorded and that appropriate conversion factors are used.	Check that units are properly labelled in calculation sheets. Check that units are correctly carried through from beginning to end of calculations. Check that conversion factors are correct. Check that temporal and spatial adjustment factors are used correctly.
Check the integrity of database files.	Confirm that the appropriate data processing steps are correctly represented in the database. Confirm that data relationships are correctly represented in the database. Ensure that data fields are properly labelled and have the correct design specifications. Ensure that adequate documentation of database and model structure and operation are archived.
Check for consistency in data between source categories.	Identify parameters (e.g. activity data, constants) that are common to multiple source categories and confirm that there is consistency in the values used for these parameters in the emissions calculations.
Check that the movement of inventory data among processing steps is correct.	Check that emissions data are correctly aggregated from lower reporting levels to higher reporting levels when preparing summaries. Check that emissions data are correctly transcribed between different intermediate products.
Check that uncertainties in emissions and removals are estimated or calculated correctly.	Check that qualifications of individuals providing expert judgement for uncertainty estimates are appropriate. Check that qualifications, assumptions and expert judgements are recorded. Check that calculated uncertainties are complete and calculated correctly. If necessary, duplicate error calculations or a small sample of the probability distributions used by Monte Carlo analyses.

TIER 1 GENERAL INVENTORY LEVEL QC PROCEDURES	
QC ACTIVITY	**PROCEDURES**
Undertake review of internal documentation.	Check that there is detailed internal documentation to support the estimates and enable duplication of the emission and uncertainty estimates. Check that inventory data, supporting data, and inventory records are archived and stored to facilitate detailed review. Check integrity of any data archiving arrangements of outside organisations involved in inventory preparation.
Check methodological and data changes resulting in re-calculations.	Check for temporal consistency in time series input data for each source category. Check for consistency in the algorithm/method used for calculations throughout the time series.
Undertake completeness checks.	Confirm that estimates are reported for all source categories and for all years from the appropriate base year to the period of the current inventory. Check that known data gaps that result in incomplete source category emissions estimates are documented.
Compare estimates to previous estimates.	For each source category, current inventory estimates should be compared to previous estimates. If there are significant changes or departures from expected trends, recheck estimates and explain any difference.

In contrast to general inventory (Tier 1) QC techniques, source-specific QC procedures are directed at specific types of data used in the estimation methods for individual source categories. As a result, source-specific, Tier 2, QC activities include:

✓ Emission factor QC (including emission comparisons, and order-of-magnitude checks)

✓ Activity level QC (national and site-specific)

✓ QC of uncertainty estimates

The reader is referred to IPCC GPGAUM, Chpt 8 for a full description of these Tier 2 techniques.

2.4   Documentation

The QC/QA objectives and desired time frames should be documented in a written QC/QA plan. The results of all QC/QA checks, audits, and reviews performed should also be documented in an organised manner, which can be produced for an independent review.

2.5   *Data quality objectives*

This discussion of data quality objectives is not about statistical acceptance criteria, as the term may imply, but instead is intended to guide the inventory preparer's (and the user's) perception of data quality based on how well the data performs in its anticipated use(s). It is important that the data preparer has a clear understanding of how the data will be used, including any conditions that may constrain or limit successful use of the data, as well as consequences of submitting poorly formed data for a specific analysis. This may help facilitate a decision by the data preparer to participate more actively and fully in making relevant data checks and corrections early on in the data development process. At a minimum, such a process of establishing data quality objectives can fully disclose to both data preparers and users, the expectations of the data.

Besides assessment of compliance with the protocol, it is expected that the most rigorous uses of the CLRTAP/EMEP emission inventories will be the role they serve in integrated assessment modelling. The EMEP Task Force on Integrated Assessment Modelling identifies that more interaction is needed to provide the national data needed for the integrated assessment modelling (TFIAM, April 2000)[3].

Several models are used by the different EMEP modelling centres. One of the most prevalent models is the RAINS model, implemented by the Centre for Integrated Assessment Modelling (CIAM) at IIASA (International Institute for Applied Systems Analysis). Using the RAINS model as an example, what circumstances of the emissions inventory data may constrain or limit its successful use in RAINS? Instances are described in which the RAINS modeller must first solve for missing emissions inventory data prior to using it (On-line RAINS)[4]. For instance, for missing source sectors, or sectors with incomplete emissions information, emissions data values are assumed, including:

✓ uncontrolled emission factors;

✓ process control devices and efficiencies;

✓ process specific energy (activity) scenarios; and

✓ emissions

To help refine or reduce the assumptions made about the data, while it is being used, the quality assessment of CLRTP/EMEP emission inventories should then also involve collaboration between the data developers and the users, such as the integrated assessment modellers. Establishing shared data quality objectives in a collaborative manner, and early in the data development process, may help ensure successful use of the emissions data by the models. The result of such collaboration may include a specific list of data checks that can or should be occurring as part of the emissions data development effort, and an agreement on the type of documentation useful to indicate what checks were done and those findings.   As part of the quality assessment activities, inventory data developers are encouraged to contact their EMEP modelling centres to discuss and define these data objectives.

Section 3   Good Practice in Inventory Preparation - Methodological Choice

By Kristin Rypdal,   *Statistics Norway*

3.1   Introduction

The Emission Inventory Guidebook gives for most sources a tiered methodology, at least at two levels. The simple methodology will frequently be quicker to perform, but also less accurate, than the detailed methodology. At the same time an inventory compiler has limited resources and will be unable to implement the detailed methodology for all sources. By identifying the key parameters (or sources), the inventory compiler may be able to better prioritise the inventory resources. The identification of key sources may be based on a simple sensitivity analysis. A sensitivity analysis may also be useful to test the influence of individual assumptions on the inventory conclusions. Application of sensitivity analysis for the identification of key sources is described in section 3.2.

Emissions reporting obligations for CLRTAP Protocols include the development of a time series of data usually beginning with a base-year. It is desirable that the reporting for all years are consistent (in applied estimation methods) with the base-year. If methodologies are changed and the new methodology cannot be implemented for all years, it might be difficult to maintain a consistent time series. In this case, methodologies are spliced, approximating the consistency of the time series. Options are summarised in section 3.3.

Inventory methodologies are continuously in progress. The implementation of a new methodology often has an effect on previous estimates and the whole time-series needs to be recalculated. When to recalculate is discussed in chapter 3.4.

3.2   Identification of key parameters and assumptions

As different sources have variable uncertainty, the contribution to total inventory uncertainty will vary among sources. Clearly most is gained by reducing the uncertainty in the sources contributing mostly to the overall uncertainty. In the dynamic process of improving the inventory is it consequently essential to be able to identify the sources where choice of methodology is critical for the inventory applications. Which sources that are identified as key are will vary among countries. Some sources are likely to be identified as significant in all countries, while other sources e.g. specific production processes may be absent or small in some countries and very important in others.

This chapter outlines criteria for determining key parameters (emission factors and activity data separately or measured emission levels) and describes how to apply them to national inventories. Theory is taken from IPCC GPGAUM [2], which is based on Flugsrud et al (1999) [5] and Flugsrud and Rypdal (2001) [6].

As described below the evaluation can be at the source level or at the parameter level. The evaluation is made for each gas separately (for the GHG the GWP weighted emissions).

3.2.1   Criteria for identifying key parameters

Which parameters to consider key will depend on the *inventory applications*. An accurate emission inventory shall give as correct figures as possible for the level and trend of the emissions.

For compliance assessments the trend is essential, while for scientific assessments and evaluation of the most cost-effective abatement measures, a more rigorous assessment is necessary. When emission-reporting obligations are formulated as emission ceilings, the emission level uncertainty only is relevant. A key parameter is here defined according to the main applications of inventory data:

A key parameter is a parameter that has significant influence on either the inventory total emissions or trend or their uncertainties.

Thus, parameters that contribute significantly to the total emissions and parameters contributing to rapid changing emission level should generally be considered key. Other considerations can also make a source key, such as:

• point sources (the major pollutants emitted)

• sources with a high estimated uncertainty, even if the contribution to total emission is low

• sources where national emission factors used are far lower than the information given in the 1996 Revised IPCC guidelines [7] or Emission Inventory Guidebook imply

• sources being abated when the simple methodologies not are detailed enough to detect mitigation options, and

• sources where future growth or decrease is expected

3.2.2   Sensitivity analysis

A typical inventory is based on a large number of data of which many have high uncertainties. Some of these data are likely to be more important for the inventory conclusions (level and trend) than others. According to Morgan and Henrion (1990)[8] a sensitivity analysis may be defined as *the computation of the effect of changes in input values or assumptions on the output*. It is generally expected that the variability of the output can be related to variability of a limited number of input parameters (Cullen and Frey, 1999)[9]. The purpose of a sensitivity analysis for inventory compilers is to identify which individual parts of the inventory might influence their conclusions.

A sensitivity analysis may be performed at several levels [8]:

a) analysis of each parameter separately, holding other factors constant

b) deterministic joint analysis, varying more than one factor at the time

c) parametric analysis, moving one or more input parameters across reasonable selected values

d) probabilistic analysis, using correlation or other means to examine how much uncertainty in conclusions is attributable to which inputs

All these approaches are relevant and useful for inventory applications. a) and d) can be used to identify key sources in a systematic manner, while b) and c) are in particular useful to test out the effect of assumptions or selected parameters.

3.2.3 Approaches to identify key sources

a) Sensitivity analysis - state of the art methodologies

In combination with a modelling of uncertainties is it simple to perform various types of sensitivity analysis. Both option a) and d) above can be a part of a standard analysis.

Option a) will often be based on compiling the terms elasticity and uncertainty importance as shown below. Nomenclature is based on [8]:

The elasticity:

$$U_E(e_i, E) = \left[\frac{\partial E}{\partial e_i} \right]_{E^0} \times \frac{e_i^0}{E^0} \tag{1}$$

Where E is the total emission and e_i is input parameter i

The uncertainty importance:

$$U_G(e_i, E) = \left[\frac{\partial E}{\partial e_i} \right]_{E^0} \times \sigma_{e_i} \tag{2}$$

Where σ_{ei} is the standard deviation of the input parameter e_i.

This may also be modified into a normalised quantity, the "uncertainty importance elasticity" (U_{GE}), that is

$$U_{GE}(e_i, E) = U_E(e_i, E) \times \frac{\sigma_{e_i}}{e_i^0} = \left[\left[\frac{\partial E}{\partial e_i} \right]_{E^0} \times \frac{e_i^0}{E^0} \right] \times \frac{\sigma_{e_i}}{e_i^0} = \left[\frac{\partial E}{\partial e_i} \right]_{E^0} \times \frac{\sigma_{e_i}}{E^0} = \tag{3}$$

If uncertainty estimates are available, the best option to identify key parameters is to compile the uncertainty importance. Sources can then be ranked by decreasing value of uncertainty importance. For the greenhouse gases it is suggested to rank sources until 90 % of the total uncertainty is accounted for [2], [5], [6]. This value is probably appropriate as a rule of thumb for other pollutants as well.

When using the state of the art methodologies it is possible to assess separately the contribution from emission factors and activity data.

b) Sensitivity analysis - simplified approaches

Uncertainties in inventory data are often not known. The simplified approach proposed can be used to assess the key sources without specific knowledge of uncertainties. The assessment can be made with the aid of a spreadsheet in a quite short time. The level (detail) of analysis is very important, see section 1.3.3.

For the greenhouse gases the approach given in [2] is recommended.

The approach below is suggested for the other pollutants.

It is assumed that for a given pollutant the uncertainty of each source is approximately equal. If this assumption not is valid, one of the state of the art approaches must be used. The simple approach is applicable on the source level only.

Level evaluation

The recommended approach is to list and rank the contribution from each source (fraction of total emission) until 95 % of the total emission is accounted for. In addition, possible additional sources accounting for more than 1% of total emissions should individually be included. This simply means that the largest sources are the key sources.

Trend evaluation

The trend elasticity with respect to source emissions level can be expressed as [6]

$$U_E(e_i^0, T) = U_S(e_i^0, T) \times e_i^0 = \frac{e_i^0}{E_0} \times (t_i - T) \qquad 4)$$

Where t_i is the source trend and T is the total trend.

When goals are formulated as percentage reductions the recommended approach is to list and rank the contribution from each source according to this equation until 90 % of total the total values is accounted for. In addition to the largest sources, the sources with highly changing trend will be identified as key.

When goals are expressed as emission ceilings, key parameters can be evaluated by ranking the absolute changes in source level. However, the large sources will usually dominate the changes in absolute terms so the results will likely be quite similar to the level evaluation.

c) Correlations and level of analysis

The output of a sensitivity analysis is obviously very dependent on the level of aggregation of the analysis. Several of the input data may be correlated for instance if they are assumed equal, based on the same basic data or restricted for example by a top down distribution. In the detailed approaches such dependencies may be modelled. In a simplified analysis the dataset will need to be aggregated to a level where correlations are eliminated. A detailed analysis is the best in order to properly assess what parameters actually are key (which may be masked by aggregation).

For the GHG a suitable level of analysis was suggested in IPCC GPGAUM. This level of aggregation has been suggested to avoid dependencies, but may mask some information.

For the other gases the starting point of analysis should be SNAP level 2or 3 with a rough fuel split. Further aggregation should be made to get rid of dependencies for example in the case of SO_2 where the same emission factors may have been used for many sources.

When analysing the trend it should be taken into account that the same emission factors often are used for both the start and end year, which implies that they should be treated as correlated. Activity data are often assumed independent in such an analysis. Measured emission data may also be considered independent if there not are any apparent systematic errors.

3.2.4   Practical consequences

For greenhouse gas inventories decision trees have been proposed guiding the inventory compiler to choose the correct level of methodology [2]. Such decision trees have not been made for the LRTAP gases. However, the same principle can be followed for all types of pollutants. In principle, the detailed methodology (or a state-of-the-art national methodology) should be selected for key sources. For non-key sources a simpler methodology is appropriate. If a methodology not proposed in the Emission Inventory Guidebook is used, this methodology (and emissions factors) should be properly documented.

An emission inventory is based on a large number of assumptions. An inventory compiler will often feel uneasy about many of these. Performing a simple sensitivity analysis is extremely useful for testing out the effects of the various assumptions made in the inventory on the level and trend. Obviously, if the conclusions are sensitive to an assumption made more work should be prioritised for that particular assumption while an assumption that proves to have a minor effect could be left as it is.

3.3   Splicing of methodologies

The option of splicing of methodologies implies that consistency of a data time series is approximated without using the same methodology for every year.

The methodologies below are not ranked; they may all be applicable depending on data and circumstances. It may be a good idea check out several of the splicing methods suggested below for consistency. No clear distinction is made between splicing due to discontinuity of input data and other problems using the same method for every year.

In general, few of the splicing methodologies are valid when technical conditions are changing throughout the time series e.g. as abatement is introduced. These can only be captured by using a complete methodology or have to be corrected for ad hoc.

The methodologies below are taken from [2] and [5], these reports also provide more details and examples.

a) Overlap

Whenever the methodology is changed, the output from the new and old method should be compared, both the level and trend. If the new methodology cannot be used for all years, an option is to use the overlap deviation to adjust the time-series. If x_o is the base year, and if the first year with estimate from the new methodology is m, the new emission estimate for this year is y_m, and the original estimate x_m, then a revised emission estimate for the base year may be expressed as

$$x_0^* = x_0 \times \frac{y_m}{x_m}$$

This simple method follows from the following three requirements to the revised estimates:

1. Estimates with the new methodology are assumed to be most correct in all years of overlap between methods.

2. There should be no break in the time series between the revised original estimates and the new methodology, *i.e*, the combined time series is consistent.

3. The revised time series should be a simple scaling of the estimates from the original method. This is equivalent to assuming that the new methodology would give the same trend for the period as the original method (as yearly percent changes).

The third requirement may be inappropriate for some sources. For example, the difference between the new and original estimates might be assumed to be constant. In this case, the revised estimate for the base year should be estimated as

$$x_0^{**} = x_0 + (y_m - x_m)$$

If there is more than one year of overlap between the new and the original methodologies, the first two requirements leads to the conclusion that only the first year of overlap should be used for recalculation. If we relax the second requirement and accept a break in the time series, we can reformulate the first expression, replacing the simple ratio y_m/x_m with an average over the overlap period (n is the last year with estimates from both methodologies):

$$x_0^{***} = x_0 \cdot \left(\sum_{i=m}^{n} y_i \bigg/ \sum_{i=m}^{n} x_i \right)$$

It seems to be a conflict between the wishes on one hand to get a consistent time series without breaks, and on the other hand to use all information from the overlap of the methodologies (a break in time series is not according to good practice). However, if the trend is the same in both methodologies, *i.e.*, they differ only in level, then both methods for recalculating x_o will give the same result. If the difference in trend between the methodologies can be ascribed to random errors, then using only one year as the basis for rescaling may lead to bias, and the last expression using the average ratio should be used. If the trends are very different, then it may be more appropriate to use one of the extrapolation techniques described below.

b) Extrapolations and interpolations

If the methodology is too resource demanding to perform every year an option is to perform a complete calculation for some years and interpolate for the years in between. The interpolation could be arithmetic, but preferable simple corrections for variations in activity level should be made.

If an estimate for the base year not is feasible it may be extrapolated from the estimate most close in time using rate of change of activity and possibly other corrections. See "surrogate extrapolations" below for an equivalent description.

c) Surrogate extrapolations

When data are missing to estimate the emissions in the base year, surrogate extrapolations may be a useful technique. Data here can be activity data or measurements. The reason for missing data may be a changed data collection systems that has led to a non consistent time series, new data collection that does not include the inventory base year or former data collection that has been stopped. The extrapolation technique may also be used when the methodology is too resource demand to perform every year.

The technique relies on the possibility to find a statistical source that explains the time variations of the emission source in the best way. This is not necessarily the activity data actually used for the estimation (as this could be missing).

$$y_0 = y_i \times \frac{s_i}{s_0}$$

Where y is the emission estimate and s is the surrogate statistical parameter.

Care should be taken to find the best statistical parameter and it is recommended to try various options and compare the results. It is also possible to weight several of the options.

3.4   Recalculations

Application of new data, methodologies, and correction of data will often change earlier estimates. This is called recalculations. Recalculations based on better information will clearly improve the scientific value of the inventory, it may, however, also cause problems when assessing compliance for environmental protocols. How to deal with recalculations when reporting to the various protocols is finally a policy decision.

When reporting GHG data to UNFCCC the rules for recalculations have been described in [2] based on recommendations from the *Subsidiary Body on Technological and Scientific Advice* (SBSTA). These can in short be summarised saying that countries shall always recalculate when information is available to increase the inventory quality. It is possible that inventories will be "frozen" in the first commitment period from 2008-2012, so that recalculations no longer are allowed in this period.

Recalculations have traditionally been encouraged when reporting to LRTAP. However, the former generation of protocols was based on percentage reductions. The

new generation of protocols is based on emission ceilings[3]. Any decision on whether or not recalculations should be encouraged (or should be allowed at all) has not been taken. Some options for consideration by LRTAP policy groups may be:

- Not to allow recalculations (this will mean that inventories not necessarily are based on the best scientific information as methodologies cannot be changed nor errors corrected).

- To report two data sets, one "frozen" and one recalculated (will be extremely confusing and will also require far more work for the inventory compilers)

- To have a mechanism to adjust emission ceilings when necessary recalculations have been performed (is that feasible?)

- To encourage recalculations and accept the consequences (that will probably mean that recalculations only are made one way...)

We note however, that in order to meet the goal in the reporting instructions to produce complete, accurate and consistent inventories it sometimes will be needed to change the methodology used, and to obtain consistency, also change previously submitted estimates. Such methodological improvements, when leading to changes in emission estimates, will mean that obligations are easier or harder to meet. It is however in both cases good practice to always change the methodology whenever the overall inventory completeness, accuracy and consistency can be improved. This may be the case when new scientific results become available, when the methodology applied is not according to GP or when gross errors in the inventory have been detected.

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[3] For HM and POPs the targets are more general, that the emission level in 2010 shall not exceed the one in 1990.

Section 4   Uncertainty Estimates[4]

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4.1   Introduction

The "Draft Guidelines for Estimating and Reporting Emission Data" [1] request in article 14:

> "*Parties should estimate the uncertainties of their inventories using the best methodologies (see para. 8 above) available to them, taking account of guidance provided by the EMEP/CORINAIR Guidebook.*"

This section will provide guidance in this respect, based on the achievements within the Greenhouse Gas Inventory Programme of IPCC.

The IPCC GPGAUM[2] report states that a structured approach to estimate inventory uncertainty is needed. Such an approach includes:

✓ A method of determining uncertainties in individual terms used in the inventory;

✓ A method of aggregating the uncertainties of individual terms to the total inventory;

✓ A method of determining the significance of year to year differences and long term trends in the inventories taking into account the uncertainty information;

✓ An understanding of the likely uses for this information which include identifying areas requiring further research and observations and quantifying the significance of year to year and longer term changes in inventories;

✓ An understanding that other uncertainties may exist, such as those arising from inaccurate definitions that cannot be addressed by statistical means.

Chapter 6 of [2] presents a comprehensive overview of these issues in the context of a greenhouse gas inventory. This section will give some additional guidance to the GPGAUM report with special reference to the application within a CLRTAP / EMEP emission inventory. Please refer to the GPGAUM report for definitions and explanations of all concepts and quantities.

4.2   Expressing uncertainty

An important aspect of an uncertainty analysis concerns the ways on how to express the uncertainties associated with individual estimates or the total inventory. It is recommended to use the same quantity to express uncertainty in a CLRTAP inventory as required in a greenhouse gas inventory, namely the 95 % confidence interval.

This 95 % confidence interval is specified by the confidence limits defined by the 2.5 percentile and 97.5 percentile of the cumulative distribution function of the estimated

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[4] This section makes a broad use of the concepts and texts of the GPGAUM report.

quantity. Put another way, the range of an uncertain quantity within an inventory should be expressed such that:

✓ there is a 95% probability that the actual value of the quantity estimated is within the interval defined by the confidence limits, and

✓ it is equally likely that the actual value, should it be outside the range quoted, lies above or below it.

In practical terms, the 95 % confidence interval for a normal distribution lies between ± 2 standard deviations around the mean. Therefore, when uncertainties are not too large (standard deviations less than 30 % of the mean value), the (cumulative) distribution function of the estimated quantity might be assumed to be normal and the 95 % confidence can be estimated as being two times the standard deviation.

4.3   Quantifying uncertainties

4.3.1   Variables and parameters

The bulk of an emission inventory is compiled by collecting activity data and appropriate emission factors according to

$$Emission_{pollutant} = \sum_{activitiess} Activity\ rate_{activity} \times Emission\ factor_{activity,pollutant} \tag{1}$$

Although for some sectors the equation to be used to estimate emissions is more complicated than a simple multiplication of a-variable (*Activity rate_{activity}*) and a parameter (*Emission factor_{activity, pollutant}*), in this section we present for reasons of simplicity, the quantification methods and principles using this simple equation. In case of a more complicated algorithm, the calculation becomes also more complicated but not essentially different.

4.3.2 Methods

For emission estimation both variables, and-parameters quantitative uncertainty ranges are needed to enable a quantitative uncertainty analysis as proposed here. This paragraph copies some essential parts from the GPGAUM report on this issue.

a) Measurements

In some cases, periodic emission measurements may be available at a site. If these measurements can be linked to representative activity data, which of course is crucial, then it is possible to determine a site-specific emission factor, together with an associated probability density function to represent annual emissions.

This can be a complex task. To achieve representativeness it may be necessary to partition (or stratify) the data to reflect typical operating conditions. For example:

✓ *Start-up and shut down can give different emission rates relative to activity data*. In this case, the data should be partitioned, with separate emission factors and probability density functions derived for steady state, start-up and shut down conditions.

✓ *Emission factors can depend on load*. In this case, the total emissions estimation and uncertainty analysis may need to be stratified to take account of load, expressed, for example, as percentage of full capacity. This could be done by regression analysis and scatter plots of the emission rate against likely controlling variables (e.g. emissions *versus* load) with load becoming part of the activity data needed.

✓ *Measurements taken for another purpose may not be representative*. For example, methane measurements made for safety reasons at coalmines and landfills may not reflect total emissions. In such cases, the ratio between the measured data and total emissions should be estimated for the uncertainty analysis.

If the data sample size is large enough, standard statistical goodness-of-fit tests can be used, in combination with expert judgement, to help in deciding which probability density function to use for describing variability in the data (partitioned if necessary) and how to parameterise it. However, in many cases, the number of measurements from which to make an inference regarding uncertainty will be small. Typically, as long as there are three or more data points, and as long as the data are a random representative sample of the quantity of interest, it is possible to apply statistical techniques to estimate the values of the parameters of many two-parameter distributions (e.g. normal, lognormal) that can be used to describe variability in the data set (Cullen and Frey, 1999)[9]. With small sample sizes, there will be large uncertainties regarding the parameter estimates that should be reflected in the quantification of uncertainty for use in the emissions inventory. Furthermore, it is typically not possible to rely on statistical methods to differentiate goodness-of-fit of alternative parametric distributions when sample sizes are very small[9]. Therefore, considerable judgement is required in selecting an appropriate parametric distribution to fit to a very small data set. In situations where the coefficient of variation is less than approximately 0.3, a normal distribution may be a reasonable assumption (Robinson, 1989)[10]. When the coefficient of variation is large and the quantity is non-negative, then a positively skewed distribution such as a lognormal one may be appropriate. Guidance on the selection of distributions is provided in Annex 1, Conceptual Basis for Uncertainty Analysis, and the use of expert judgements in this context is outlined below.

b) Literature and other documented data

When site-specific data are unavailable, good practice will usually be to develop emission estimates using average emission factors drawn from references consistent with this Guidebook. These factors will have been measured under particular circumstances that are judged to be typical. There will be uncertainties associated with the original measurements, as well as with the use of the factors in circumstances other than those associated with the original measurements.

It is a key function of good practice guidance for each source category to guide the choice of emission factors to minimise this second source of uncertainty to the extent possible. Where such emission factors are used, the associated uncertainties should be estimated from:

✓ *Original research including country-specific data*: For measurement-based emission factors, the data from the original measurement programme may enable an assessment of the uncertainty and possibly the probability density function. Well-designed measurement programmes will provide sample data that cover the range of types of plants and their maintenance, size and age, so that the factors and their uncertainties can be used directly. In other cases, expert judgement will be needed to extrapolate from the measurements to the full population of plants in that particular source category.

✓ *This Guidebook*: the source category-specific guidance in this Guidebook (methodological chapters, section 10 in each activity description) also indicates, wherever possible, the uncertainty ranges likely to be associated with using these factors.

Unless clear evidence to the contrary is available, the probability density functions are assumed to be normal. However, the inventory agency should evaluate the representativeness of the default for its own situation. If the default is judged to be unrepresentative and the source category is important to the inventory, improved assumptions based upon expert judgement should be developed.

c) Expert judgement

When empirical data are lacking, estimates of uncertainty in emission factors or direct emission measurements will need to be based on expert judgement. Experts are people who have special skills or knowledge in a particular field. A judgement is the forming of an estimate or conclusion from information presented to or available to the expert.

It is important to select appropriate experts with respect to the emission inventory inputs for which uncertainty estimates are needed.

The goal of expert judgement here is to develop a probability density function, taking into account relevant information such as:

✓ Is the emission source similar to other sources? How is the uncertainty likely to compare?

✓ How well is the emission process understood? Have all possible emission sources been identified?

✓ Are there physical limits on how much the emission factor can vary? Unless the process is reversible it cannot emit less than zero, and this may constrain a very wide uncertainty range. Mass balance considerations or other process data may place an upper limit on emissions.

✓ Are the emissions consistent with atmospheric concentrations? Emissions are reflected in atmospheric concentrations at site-specific and larger scales and again this may limit the possible emission rates.

A degree of expert judgement is required even when applying classical statistical techniques to data sets, since one must judge whether the data are a representative random sample and, if so, what methods to use to analyse the data. This may require both technical and statistical judgement. Interpretation is especially needed for data

sets that are small, highly skewed or censored. The formal methods for obtaining data from experts are known as expert elicitation.

The IPCC GPGAUM report proposes a protocol for expert elicitation. The use of this protocol is strongly recommended to minimise misunderstandings between inventory compiler and the expert and to avoid unintentional bias.

4.3.3   Default uncertainty ranges

a) Activity data

Activity data are usually derived from (economic) statistics, including energy statistics and balances, economic production rates, population data etc.. It is possible that these agencies have already assessed the uncertainties associated with their data as part of their data collection procedures. These uncertainties can be used to construct probability density functions.

In some cases uncertainty data for activity rates are not easily available. Since any uncertainty analysis needs quantitative input, quantitative uncertainty ranges are needed. The table below proposes indicative ranges that could be applied in all cases where no independent data are available.

Data source	Error range	Remarks
The national (official) statistics	-	The official statistics of a country will in principle be assumed to be "fixed" data, with no uncertainty. In fact however for energy data an indication of the uncertainties could be derived from the entry under "Statistical Differences" representing the mismatch between production and consumption.
An update of last year's statistics, using gross economic growth factors	2-5 %	The economic system of a county will probably not shift more than a few percent between successive years. Hence, if an update of last year's data is used, an uncertainty of a few percent seems reasonable
IEA Energy statistics	OECD: 2 - 3 % non-OECD: 5 - 10 %	The International Energy Agency (IEA) publishes national energy statistics for many countries. For OECD countries these statistics will ideally be equal to the official energy statistics. For other countries the uncertainties could be expected to be in the order of 5 to 10 % (educated guess)
UN Data bases	5 - 10 %	These data might have a similar uncertainty as the ones provided by IEA
Default values other sectors and data sources.	30 - 100 %	

The table proposes for the uncertainty range, when official statistics are used, a value of 0 %. This can of course not be a true uncertainty range. The value here is given to

facilitate for selection of a certain range. It is recommended to always use experts' opinions to make the final selection.

b) Emission factors

In many cases uncertainty ranges for emission factors are rather difficult to obtain. The table below represents an application of the concepts of qualitative data rating schemes for all pollutants of concern in the guidebook. The Table is organised by major SNAP code groupings. It is important to note that any such qualitative summary is subjective and individual opinions will differ.

MAIN SNAP CATEGORY	SO_2	NO_x	VOC	CO	NH_3	HM/POP	CO_2	CH_4	N_2O
1. public power, cogeneration and district heating	A	B	C	B		D	A	C	E
2. commercial, institutional & residential combustion	B	C	C	C		E	B	C	E
3. industrial combustion	A	B	C	B		D	A	C	E
4. industrial processes	B	C	C	C	E	E	B	D	D
5. extraction & distribution of fossil fuels	C	C	C	C		E	D	D	
6. solvent use			B			E[1]			
7. road transport	C	C	C	C	E	E[2]	B	C	E
8. other mobile sources and machinery	C	D	D	D		E	C	D	D
9. waste treatment	B	B	B	C		D	B	C	E
disposal activities	C	C	C	C	E	E	C	D	E
10. agriculture activities		D	D	D	D	E	C	D	E
11. nature	D[3]	D	D	E	E	E[3]	D	E	E

[1]   In some cases, solvents may be toxic compounds
[2]   Rating representative of typical pollutant source category combination; some specific cases may have higher ratings
[3]   Natural sources could be contributed from volcanoes and other geothermal events

The letter grade ratings are primarily applicable to the estimation approaches for emissions inventory preparation that rely on emission factors and estimates of activity indicators. In all cases, the application of more direct approaches based on measurement would receive higher quality ratings.

The application of these subjective ratings for the aggregated source category groupings represented by the major SNAP code groupings can be misleading in some specific cases. For example, the rating specified for heavy metals/persistent organic pollutants for road transport is listed as E to apply in general to the understanding of the contribution of these pollutants from mobile sources. In fact, for the specific case of lead from mobile sources, the emission factors and emissions estimates are known with significantly more confidence. In such an analysis at that level of disaggregation, lead from mobile sources would receive a B rating. Also at this level of aggregation

several source category pollutant combinations are irrelevant in that emissions of the pollutant from that source category are zero or so minimal as to be of little or no importance.

Definitions of the ratings are presented in the table below. This table also proposes default error ranges associated with each quality rating. The error ranges are obtained from the EU Guidance Report on Supplementary Assessment under EC Air Quality Directives, where they have been defined for application in air quality models.

Rating	Definition	typical error range
A	An estimate based on a large number of measurements made at a large number of facilities that fully represent the sector	10 to 30 %
B	An estimate based on a large number of measurements made at a large number of facilities that represent a large part of the sector	20 to 60 %
C	An estimate based on a number of measurements made at a small number of representative facilities, or an engineering judgement based on a number of relevant facts	50 to 150 %
D	An estimate based on single measurements, or an engineering calculation derived from a number of relevant	100 to 300 %
E	An estimate based on an engineering calculation derived from assumptions only	order of magnitude

4.4   Aggregating uncertainties

Once the uncertainties in the source categories have been determined, they may be combined to provide uncertainty estimates for the entire inventory in any year and the uncertainty in the overall inventory trend over time.

The error propagation equation, as discussed more extensively in Annex 1 of this report, and in Annex I of the *IPCC Guidelines* (Reporting Instructions), yields two convenient rules for combining uncorrelated uncertainties under addition and multiplication:

1) *Rule A:* Where uncertain quantities are to be combined by addition, the standard deviation of the sum will be the square root of the sum of the squares of the standard deviations of the quantities that are added with the standard deviations all expressed in absolute terms (this rule is exact for uncorrelated variables).

   Using this interpretation, a simple equation can be derived for the uncertainty of the sum, that when expressed in percentage terms becomes:

$$U_{total} = \frac{\sqrt{(U_1 \bullet x_1)^2 + (U_2 \bullet x_2)^2 + ... + (U_n \bullet x_n)^2}}{x_1 + x_2 + ... + x_n} \tag{2}$$

   Where:

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

x_i and $U_i$are the uncertain quantities and the percentage uncertainties (half the 95% confidence interval) associated with them, respectively.

2) *Rule B*: Where uncertain quantities are to be combined by multiplication, the same rule applies except that the standard deviations must all be expressed as fractions of the appropriate mean values (this rule is approximate for all random variables).

A simple equation can also be derived for the uncertainty of the product, expressed in percentage terms:

$$U_{total} = \sqrt{U_1^2 + U_2^2 + ... + U_n^2}$$
(3)

Where:

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

U_i are the percentage uncertainties (half the 95% confidence interval) associated with each of the quantities.

The inventory is principally the sum of products of emission factors and activity data. Therefore, Rules A and B can be used repeatedly to estimate the uncertainty of the total inventory.

In practice, uncertainties found in inventory source categories vary from a few percent to orders of magnitude, and may be correlated. This is not consistent with the assumptions of Rules A and B that the variables are uncorrelated with a standard deviation of less than about 30% of the mean, but under these circumstances, Rules A and B may still be used to obtain an approximate result. Alternatively, a stochastic simulation (the Monte Carlo method) can be used, that can combine uncertainties with any probability distribution, range, and correlation structure, provided they have been suitably quantified. Thus, two tiers for uncertainty analysis are described below:

1) *Tier 1*: Estimation of uncertainties by source category using the error propagation equation via Rules A and B, and simple combination of uncertainties by source category to estimate overall uncertainty for one year and the uncertainty in the trend.

2) *Tier 2*: Estimation of uncertainties by source category and in the overall inventory by stochastic simulation for one year and the uncertainty in the trend.

In most cases a quantitative indicator of inventory uncertainty will be enough and the resource intensive application of a Monte Carlo analysis can be avoided. Paragraph 0 will present this Tier 1 approach for CLRTAP pollutants in a simple calculation scheme.

Tier 1 method does not account for correlation and dependency between source categories that may occur because the same activity data or emission factors may be used for multiple estimates. Correlation and dependency may be significant for fossil fuels because a given fuel is used with the same emission factor across several sub-categories, and if (as is sometimes the case) total consumption of a fuel is better

known than consumption disaggregated by source category, hidden dependencies will exist within the statistics because of the constraint provided by overall consumption. Dependency and correlation can be addressed by aggregating the source categories to the level of overall consumption of individual fuels before the uncertainties are combined. This entails some loss of detail in reporting on uncertainties but will deal with the dependencies where they are thought to be significant (e.g. where the uncertainties in fossil fuel emissions when aggregated from the source category level are greater than expected)

4.5   *Uncertainties in trends*

An emission factor that over or underestimates emissions in the base year will probably do so in subsequent years. Therefore, uncertainties due to emission factors will tend to be correlated over time. The Tier 1 uncertainty aggregation method, as proposed by GPGAUM is in principle able to deal with this issue.

Trend uncertainties are estimated using two sensitivities:

1. *Type A sensitivity*: the change in the difference in overall emissions between the base year and the current year, expressed as a percentage, resulting from a 1% increase in emissions of a given source category and gas in both the base year and the current year.
2. *Type B sensitivity*: the change in the difference in overall emissions between the base year and the current year, expressed as a percentage, resulting from a 1% increase in emissions of a given source category and gas in the current year only.

Conceptually, Type A sensitivity arises from uncertainties that affect emissions in the base year and the current year equally, and Type B sensitivity arises from uncertainties that affect emissions in the current year only. Uncertainties that are fully correlated between years will be associated with Type A sensitivities, and uncertainties that are not correlated between years will be associated with Type B sensitivities.

IPCC GPGAUM suggests that emission factor uncertainties will tend to have Type A sensitivities, and activity data uncertainties will tend to have Type B. However, this association will not always hold and it is possible to apply Type A sensitivities to activity data, and Type B sensitivities to emission factors to reflect particular national circumstances. Type A and Type B sensitivities are simplifications introduced for the analysis of correlation.

Once the uncertainties introduced into national emissions by Type A and Type B sensitivities have been calculated, they can be summed using the error propagation equation (Rule A) to give the overall uncertainty in the trend.

4.6 *The Tier 1 uncertainty aggregation scheme*

The calculation scheme reproduced below is an adaptation of the spreadsheet scheme as presented in the IPCC GPGAUM report [2].

Tier 1 Uncertainty Calculation and Reporting

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
NRF sector	Pollutant	Base year emissions	Year t emissions	Activity data uncertainty	Emission factor uncertainty	Combined uncertainty	Combined uncertainty as % of total national emissions in year t	Type A sensitivity	Type B sensitivity	Uncertainty in trend in national emissions introduced by emission factor uncertainty	Uncertainty in trend in national emissions introduced by activity data uncertainty	Uncertainty introduced into the trend in total national emissions	Emission factor quality indicator	Activity data quality indicator	Expert judgement reference numbers	Footnote reference number
		Input data	Input data	Input data	Input data	$\sqrt{E^2+F^2}$	$\dfrac{G \bullet D}{\sum D}$	Note B	$\dfrac{D}{\sum C}$	$I \bullet F$ Note C	$J \bullet E \bullet \sqrt{2}$ Note D	$\sqrt{K^2+L^2}$	Note E	Note E		
		Mg	Mg	%	%	%	%	%	%	%	%	%				
1a																
1b																
…	…															
Etc.																
		$\sum C$	$\sum D$				$\sqrt{\sum H^2}$					$\sqrt{\sum M^2}$				
Total																

Note A

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

✓ If uncertainty is correlated across years, enter the uncertainty into column F, and enter 0 in column E;

✓ If uncertainty is not correlated across years, enter the uncertainty into column E and enter 0 in column F.

Note B

$$\frac{0.01 \bullet D_x + \sum D_i - (0.01 \bullet C_x + \sum C_i)}{(0.01 \bullet C_x + \sum C_i)} \bullet 100 - \frac{\sum D_i - \sum C_i}{\sum C_i} \bullet 100$$

Note C

In the case where no correlation between emission factors is assumed, sensitivity B should be used and the result multiplied by √2:

$$K_x = J_x \bullet F_x \bullet \sqrt{2}$$

Note D

In the case where correlation between activity data is assumed, sensitivity A should be used and the √2 is not required:

$$L_x = I_x \bullet E_x$$

Note E

Please use the following abbreviations:
D – IPCC source category default
M – measurement based
R – national referenced data

The columns of the table are labelled A to Q and contain the following information:

✓ A and B show the NFR source category and pollutant.

✓ C and D are the inventory estimates in the base year and the current year[5] respectively, for the source category and gas specified in columns A and B, expressed in CO_2 equivalents.

✓ E and F contain the uncertainties for the activity data and emission factors respectively, derived from a mixture of empirical data and expert judgement as previously described in this chapter, entered as half the 95% confidence interval divided by the mean and expressed as a percentage. The reason for halving the 95% confidence interval is that the value entered in columns E and F then corresponds to the familiar plus or minus value when uncertainties are loosely quoted as 'plus or minus x%', so expert judgements of this type can be directly entered in the spreadsheet. If uncertainty is known to be highly asymmetrical, enter the larger percentage difference between the mean and the confidence limit.

✓ G is the combined uncertainty by source category derived from the data in columns E and F using the error propagation equation (Rule B). The entry in column G is therefore the square root of the sum of the squares of the entries in columns E and F.

✓ H shows the uncertainty in column G as a percentage of total national emissions in the current year. This is a measure of the degree of uncertainty introduced into the national emissions total by the source category in question. The entry in each row of column H is the entry in column G multiplied by the entry in column D, divided by the total at the foot of column D. The total at the foot of column H is an estimate of the percentage uncertainty in total national emissions in the current year, calculated from the entries above using Rule A. This total is obtained by summing the squares of all the entries in column H and taking the square root.

✓ I shows how the percentage difference in emissions between the base year and the current year changes in response to a one percent increase in source category emissions in both the base year and the current year. This shows the sensitivity of the trend in emissions to a systematic uncertainty in the emissions estimate (i.e. one that is correlated between the base year and the current year). This is the Type A sensitivity as defined above. Appendix 6A.1 provides the derivation for the formula for the entries in column I.

✓ J shows how the percentage difference in emissions between the base year and the current year changes in response to a one percent increase in source category emissions in the current year only. This shows the sensitivity of the trend in emissions to random error in the emissions estimate (i.e. one, that is not correlated, between the base year and the current year). This is the Type B sensitivity as described above. The formula for the entries in column J is derived in Appendix 6A.

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

✓ K uses the information in columns I and F to show the uncertainty introduced into the trend in emissions by emission factor uncertainty, under the assumption that uncertainty in emission factors is correlated between years. If the user decides that the emission factor uncertainties are not correlated between years then the entry in column J should be used in place of that in column I and the result multiplied by $\sqrt{2}$. The formula for the entries in column K is derived in Appendix 6A.

✓ L uses the information in columns J and E to show the uncertainty introduced into the trend in emissions by activity data uncertainty, under the assumption that uncertainty in activity data is not correlated between years. If the user decides that the activity data uncertainties are correlated between years then the entry in column I should be used in place of that in column J and the $\sqrt{2}$ factor does not then apply. The formula for the entries in column L is derived in Appendix 6A.

✓ M is an estimate of the uncertainty introduced into the trend in national emissions by the source category in question. Under Tier 1, this is derived from the data in columns K and L using Rule B. The entry in column M is therefore the square root of the sum of the squares of the entries in columns K and L. The total at the foot of this column is an estimate of the total uncertainty in the trend, calculated from the entries above using the error propagation equation. This total is obtained by summing the squares of all the entries in column M and taking the square root. The formula for the entries in column M and the total at the foot of column M is shown in Appendix 6A.1.

✓ Columns N to Q are used for indicators and cross-referencing to footnotes.

✓ N contains D, M or R, depending on whether the emission factor uncertainty range is based on default (D) information in source category guidance, measurements (M) made for the purpose or national referenced (R) information.

✓ O contains D, M or R, depending on whether the activity data uncertainty range is based on default information in sector guidance, measurements made for the purpose or national referenced information.

✓ P contains the reference numbers of any expert judgements used to estimate uncertainties in this source category.

✓ Q contains the number of an explanatory footnote to go at bottom of table to identify documentary reference of uncertainty data (including measured data) or other comments relevant to the line.

4.7   Reporting uncertainties

The "Draft Guidelines for Estimating and Reporting Emission Data" [1] request in article 26:

> "*When reporting emissions, the level of uncertainty associated with these data and their underlying assumptions should also be reported. The methodologies used for estimating uncertainties should be indicated in a transparent manner. Parties are encouraged to report quantitative information on uncertainties, where this is available.*"

In accordance with the guidance in the GPGAUM report, the uncertainties could be reported in a table analogous to the one given in paragraph 4.6. The draft Reporting Guidelines do not include a specific requirement in this respect.

Section 5   Verification

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                                       Assessment TNO-WUR

5.1   Introduction

Verification checks whether the emission inventory is true. Tools to perform a
verification involves techniques that make comparisons between emission estimates
and some other known quantity that is related either directly to the emission source or
indirectly to the underlying process that results in emissions. The following tools can
be used for verification purposes: (i) survey analysis, (ii) monitoring analysis, (iii)
comparison with other inventories, (iv) forward air quality modelling and (v) inverse
air quality modelling. In this revised Guidebook information on survey analysis and
monitoring analyses has been included from the former Guidebook. The brief
discussion of other tools for verification is taken from a study by Van Aardenne
(2001) [11] in which a framework is proposed for a systematic analysis of uncertainties.

This chapter describes a brief overview of the different tools that can be applied for
verification purposes for a more detailed description of tools see [11] or specific
references in the text.

5.2   Survey analysis

Some common methodologies for estimating emissions from area source emission
categories rely on a per-capita, per-employee, per area emission factor. While these
approaches may be adequate for estimating national or regional emissions, they may
introduce bias when applied to specific locations or during specific time periods.
Statistical sampling techniques can identify the population of establishments in a
specific industry that need to be sampled in detail to provide useful statistical results
on the regional and temporal characteristics of that activity. The results of a statistical
sampling based on these principles could be applied to develop regionally specific
emission or allocation factors that depend on population density, economic
demography, or the distribution of employment by major industrial and commercial
sectors.

5.3   Monitoring analysis

Monitoring analyses include three principal types of measurement activities: direct
source testing, indirect source testing and ambient measurements. All monitoring
programs are expensive to implement and should be well planned and executed to
maximise the data recovery and to ensure the collection of high-quality measurement
data. It is possible, in some cases, to apply measurement data that is routinely
collected as part of a government- sponsored air quality management program and
data that is routinely collected by individual facilities related to process operation and

efficiency, to an emissions verification exercise. Whenever a monitoring program is considered, a thorough review of all existing measurement data should be completed and the program should be designed to make use of these data whenever possible. The following table summarises some of the monitoring activities that have been used to help verify emissions estimates.

MONITORING TYPES, EXAMPLES, AND USES FOR EMISSIONS INVENTORIES		
Monitoring Class	Examples of Monitoring Programs	Uses of the Data for Emissions Inventories
Direct Measurements	• In process emissions measurements • Process operating parameters • Random sampling of process units or potential leak tests	• Comparison to estimated values • Identification of ranges of application estimates (operating parameters, emissions factors) • Specification of fugitive emissions or process leaks
Indirect Measurements	• Remote measurement systems: FTIR, UV, Gas Filter Correlation • Ambient VOC/NO_x ratio studies	• Comparison of estimated emission rates with near source concentrations • Estimation of emission factors for sources that do not have stacks or vents
Ambient Studies	• Tunnel Studies • Aircraft Studies • Upwind-downwind difference studies • Receptor Modelling	• Identification of obvious weaknesses in procedures or underestimation of emissions • Checking of ambient impacts of sources or mixtures of sources • Identification of principal emissions sources in a region

5.4   Comparison with other inventories

When comparing emission inventories that have been constructed independently from each other, the difference between emission inventories could be used to verify whether the emission inventory is an accurate representation of the true emission [11]. Verification is in theory possible but only when information on the accuracy of one of the emission inventories is available. The reason for independency of the emission inventories is the facts that agreement is easily found between two inventories when the same activity data and emission factors are used. This principle has been applied by Van Amstel et al. (1999)[12]. In their study, emission estimates of greenhouse gases calculated by country for the year 1990 using the EDGAR database have been compared with National Communications of several countries. In some cases the reasons for the differences was clear and lead to conclusions about either the EDGAR or national emission estimates (e.g. different emission factors, different activity data, gaps in inventories).

5.5   *Forward air quality modelling*

In forward air quality modelling an emission inventory is used as input into an atmospheric dispersion model, which calculates the atmospheric concentration of the pollutant [11]. When accurate atmospheric concentration measurements are available, the difference between model result and observation can be used as an indicator whether the emission inventory is an accurate representation of the true emission. An example of such a study is the work performed by Iversen (1993)[13]. By using scatter plots of measured versus calculated concentrations, comparison of yearly averaged modelled and measured concentrations, comparison of both measured and modelled concentrations with emissions estimates per grid cell and calculation of variation in measured concentrations from year to year, Iversen attempted to diagnose model error, emission error or inaccurate measurement as cause for the difference between EMEP/MSC-W acid deposition model calculations and EMEP measurement network observations for NO_2, SO_2 and sulphate in the period 1985-1989. One of the important aspects with this tool for verification is the distinction between uncertainty in the model, measurement or emission inventory.

5.6   *Inverse air quality modelling*

In inverse modelling atmospheric concentrations are used as input into an atmospheric dispersion model to calculate the emissions needed to reproduce the observed concentrations [11]. Comparison of the 'back-casted' emission estimates with the emission inventory can be used to 'verify' whether the emission inventory is an accurate representation of the true emission. Inverse modelling studies have been applied both on a global, regional and national scale. Hein et al. (1997)[14] have used inverse modelling with a three-dimensional transport model to analyse the global methane budget. They describe inverse modelling as an optimisation problem of the difference between calculated and observed concentrations. The solution to this optimisation provides emission patterns that result in an optimal agreement between calculated and observed concentrations, the so-called 'back-casted' emission estimates. Other examples on a regional scale can be found in Seibert (2000)[15] or in Vermeulen et al. (1999)[16] on a national scale.

References

[1] *DRAFT GUIDELINES FOR ESTIMATING AND REPORTING EMISSION DATA*, prepared by the Task Force on Emission Inventories and Projections in cooperation with the secretariat

[2] **J. Penman, D. Kruger, I. Galbally, T. Hiraishi, B. Nyenzi, S. Emmanul, L. Buendia, R. Hoppaus, T. Martinsen, J. Meijer, K. Miwa and K. Tanabe** (Eds), 2000, *Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories* , IPCC National Greenhouse Gas Inventories Programme, Published for the IPCC by the Institute for Global Environmental Strategies, Japan, ISBN 4-88788-000-6

     Available via URL: http://www.ipcc-nggip.iges.or.jp/public/gp/gpgaum.htm

[3] **TFIAM**, April 2000. *UNECE Convention on Long-Range Transboundary Air Pollution. Task Force on Integrated Assessment Modelling*. Report on the 25th Meeting. April 2000.

[4] On-line RAINS (2000).   Internet access to the RAINS Databases (http://www.iiasa.ac.at/~rains/). VOC Database. Additional Comments. October 8, 2000.

[5] **Flugsrud, K., Irving, W., Rypdal, K**., 1999. *Methodological Choice in Inventory Preparation. Suggestion for Good Practice Guidance*. Documents 1999/19. Statistics Norway.

[6] **Rypdal, K. and Flugsrud, K.** (2001), *Sensitivity analysis as a tool for systematic reductions in GHG inventory uncertainties*. Environmental Science & Policy, Vol 4., 117-135

[7] **IPCC/OECD/IEA** (1997), *Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories*. OECD, Paris.

[8] **Morgan, M.G., Henrion, M**. (1990). *Uncertainty. A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. Cambridge University Press. ISBN 0-521-42744-4.

[9] **Cullen, A.C., Frey, H.C**. (1999). Probabilistic Techniques in Exposure Assessment. A Handbook for Dealing with Variability and Uncertainty in Models and Inputs. ISBN 0-306-45957-4. Plenum Press. New York: London.

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

[11] **Van Aardenne, J.A**. (2001) Uncertainty in emission inventories: sources and assessment, Chapter 4, PhD. Thesis Wageningen University, In prep.

[12] **Van Amstel, A., J. Olivier and L. Janssen** (1999), *Analysis of the differences between national inventories and an Emissions Database for Global Atmospheric Research (EDGAR)*, Environmental Science and Policy 2, 275-293.

[13] **Iversen, T.** (1993) *Modelled and measured transboundary acidifying pollution in Europe-Verification and trends*, Atmospheric Environment 27A, 889-920.

[14] **Hein, R., P.J. Crutzen and M. Heimann** (1997), *An inverse modelling approach to investigate the global atmospheric methane cycle,* Global Biogeochemical Cycles, Vol. 11., No. 1, p43-76.

[15] **Seibert, P.** (2000)*, Inverse modelling of sulphur emissions in Europe based on Trajectories,* Inverse Methods in Global Biogeochemical Cycles Geophysical Monograph 114., pp. 147-154.

[16] **Vermeulen, A.T., R. Eisma, A. Hensen, J. Slanina** (1999), *Transport model calculation of NW-Europe methane emissions,* Environmental Science and Policy, 2, 315-324.