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# Uncertainties in the Norwegian Greenhouse Gas Emission Inventory

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ISBN 82-537-4808-6
ISSN 0806-2056

**Emnegruppe**
01.04.10 Air

Design: Enzo Finger Design
Print: Statistisk sentralbyrå

# Abstract

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## Uncertainties in the Norwegian Greenhouse Gas Emission Inventory

**Reports 2000/13 • Statistics Norway 2000**

The national GHG emission inventory is compiled from estimates based on emission factors and activity data and direct measurements from a few large plants. All these data and parameters will contribute to the overall inventory uncertainty. In this work the uncertainties and probability distributions of all the inventory input parameters have been assessed based on available data and expert judgements. In general there is little knowledge of the uncertainties in input parameters. Finally, the *level and trend uncertainties* of the national greenhouse gas (GHG) inventory have been estimated using methods of simulation.

The main factors influencing the inventory output (level and trend) have been identified using *sensitivity analysis* at various levels. The elasticities identify which parameters are most important for the level and trend determination. The uncertainty importances identify which parameters are most important for the uncertainty of level and trend. The uncertainty importance was identified locally by calculating the derivative of the output with respect to each input parameter and globally by simulating the correlation between these two. These two approaches give qualitatively the same results, but the ranking of sources and parameters is slightly different.

It is important for the conclusions on uncertainties and sensitivities that the analysis is performed at an appropriate level. The level should be detailed enough to reflect the actual assumptions made and give insight into where improvements could be sought. On the other hand is it important to introduce appropriate dependencies into the analysis when sub-estimates are based on the same assumptions (e.g. emission factors or activity data).

The uncertainty of the total GWP weighted greenhouse gas emissions in Norway is approximately ± 20 per cent of the level[1]. The uncertainty is dominated by the contribution from the non-$CO_2$ gases. The uncertainties of emissions of $N_2O$ from all sources (apart from fertiliser production) are particularly high (more than 100 per cent of the level of each source). $N_2O$ from agricultural soils is the main contributor to the total level uncertainty. However, reductions in this uncertainty can only be made through long term international research projects. Several of the other sources contributing to total uncertainty (like $CH_4$ from landfills and PFC from aluminium production) have been prioritised in the inventory system the last years. A major source which estimate remains to be improved is $CH_4$ from cattle.

The high level uncertainty implies that current emission estimates from several sources are likely to be recalculated in the future as the information on emission factors and estimation methodologies is likely to be improved. The high uncertainties of non-$CO_2$ gases and the risk of recalculations of historical emission estimates are obstacles to efficient reduction strategies and efficient systems of emission trading.

The uncertainty of the projected[2] trend from 1990 to 2010 is ± 4 percentage points. That is higher than the precision in the obligations. For Norway, as an example, the obligation is formulated precisely as a maximum 1 per cent increase in the same period. The sources HFC from product use, $N_2O$ from road traffic and PFC from aluminium production contribute most to the trend uncertainty. Though all these sources have been prioritised in the inventory system the last years, there are potentials for further improvements when new research data becomes available. In general more sources are important for the trend uncertainty than the level. To some extent other sources contribute to the trend uncertainty than to level uncertainty. These are emission sources changing rapidly due to abatement or large changes in activity level.

The high trend uncertainty may be an obstacle for assessing compliance with the Kyoto protocol. There is a risk that countries may adjust their sub-estimates within the uncertainty range in order to obtain a low trend estimate. Clear guidance for inventory preparation and strict control and verification systems on the national and international level are needed to avoid this.

By identifying the source estimates and individual parameters contributing mostly to the uncertainty importance of level and trend, the overall inventory uncertainty may systematically be reduced. Scientific inventory improvements, data collection and quality control procedures can then be directed towards these key source estimates.

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[1] Excluding net $CO_2$ sinks due to forest growth.

[2] Assuming an uncertainty of the projected data as if they were historical.

# Contents

# Introduction

In the Kyoto protocol countries have agreed on obligations to restrict their greenhouse gas (GHG) emissions in the period 2008-2012 with respect to the level in 1990. The Kyoto protocol will also open for emission trading and other flexible implementation mechanisms.

The estimates of emissions of GHG are mostly based on model calculations. While emissions of some of the gases ($CO_2$, $SF_6$) are quite accurately determined, emissions of other gases may be very uncertain (up to orders of magnitude). Uncertainties arise due to lack of accurate estimation data, wrong assumptions, intrinsically complicated and variable processes and data processing errors. Though the uncertainties in level estimates of these gases are high, uncertainties in the trend will be lower. The reason is that the trend estimate is partly based on the same data and assumptions in both the start and end year. However, the uncertainty in the trend estimate is large compared to the accuracy in the formulation of reduction obligations (for example one percentage point increase in the case of Norway) (Rypdal 1999).

An accurate estimate of the uncertainty in trend and level of GHG emissions is obviously important for users of the data, for example national policy makers involved in assessment of GHG abatement strategies and design of emission trading systems. Also, uncertainty figures will likely become a part of the national reporting obligations to the UNFCCC (United Nations Framework Convention on Climate Change). The uncertainty estimates may be used for comparing inventories as well as be a part of the process of assessing compliance. Finally, a GHG emission inventory contains a huge amount of data and assumptions. An assessment of uncertainties and analysis of sensitivities of input data is useful for the inventory compiler in order to give priorities with respect to reducing the inventory uncertainties in a cost-effective manner. Quality control and inventory improvements may be prioritised for the sources contributing mostly to the total uncertainty or on parameters most essential to the inventory output.

As the uncertainties in the input data may be high and their distributions may be non-normal, simple statistical theory will fail as a tool to combine the uncertainties of input data to give an assessment of the uncertainties in the complete data set. Furthermore, the statistical properties of the input data, including the true mean, the statistical variance, distribution function and correlation between parameters are in most cases not known. This report will assess the statistical properties of the input data and apply an appropriate statistical tool in order to derive the uncertainties in the combined data set. The uncertainties of the total GHG inventory and in the trend from 1990 to 2010 are estimated. These uncertainties are finally used to evaluate the contribution of each single input parameter to total uncertainty in the data set. The implications of the uncertainties are finally discussed.

# 1. Overview of the statistical problem and emission data

The greenhouse gas emission estimates are based on an emission estimation model as the emissions from very few sources can be measured directly. Consequently, the uncertainties in the emission estimates have to be derived using other methodologies than while deriving the uncertainties of an empirical data set. Furthermore, the emission model contains a vast amount of individual emission data. In order to assess the combined uncertainty we will have to reduce it (aggregate it) to a more workable dataset, without losing too much of the properties of interest.

We will below describe the steps in the design of a statistical model and the design of the emission estimation input data set which the analysis in this report is based on.

## 1.1. Statistical problem

Emission data from a source (j) and pollutant (i) are usually estimated by the basic equation:

$$Emission_{ij} = Activity\_data_{ij} * Emission\_Factor_{ij} \qquad 1.1$$

In a few cases[3] the estimation equation is more complicated than this, but in this work all emission estimation algorithms have been transferred to this form. In some cases emission data have been measured directly. These are fitted into the equation with activity data equal to 1 and an emission factor equal to the measurement output.

The total emissions of a pollutant (i) is the sum of the emissions from each source (j):

$$Emission_i = \Sigma Activity\_data_{ij} * Emission\_Factor_{ij} \qquad 1.2$$

Emissions are estimated separately for the six greenhouse gases $CO_2$, $CH_4$, $N_2O$, HFC, PFC and $SF_6$.

The total greenhouse gas emission estimate is the sum of all the pollutants (i) weighted according to their Global Warming Potential (GWP):

$$Total\_Emission = \Sigma GWP_i * Emission_i \qquad 1.3$$

All input data (both emission factors and activity data) are uncertain, and some parameters will be highly uncertain (by orders of magnitudes). In the design of a statistical model we will have to assign to each input parameter the statistical properties:

- A mean
- A measure of the spread in data (variance or standard deviation)
- A density (probability distribution)
- The degree of dependencies (or correlation) with other input parameters

As explained in chapter 2, accurate information about the values of the statistical properties of the parameters in equation 1.2 is available only in a few cases. We will instead have to derive information indirectly or based on expert judgements.

[3] Examples are road traffic, landfills and HFCs from product use.

The GWP values are fixed in the Kyoto protocol. Consequently, their uncertainties are not included in this analysis and the GWP values of each gas are assumed to be constants. Actually, however, the GWP values are highly uncertain and contribute to the total uncertainty of the inventory. The analysis is limited to anthropogenic emissions. The source *Land use change and forestry* is excluded from the analysis as definitions and methodologies to be used not yet are clarified for this source. It is, however, expected that sinks due to forest growth will be a major source of uncertainty in the Norwegian national GHG inventory.

The statistical properties of the functions in equations 1.2 and 1.3 are difficult to track analytically. This is due to the mixture of different distributions of the parameters - some of the parameters have very large variances and normal distribution would be unsuitable for them, as well as the complex dependence structure and mutual constraints within the data set. Instead, the statistical properties will be derived by means of stochastic simulations. Basically, we define a parametric simultaneous distribution of the data set as a reasonable approximation of the emission estimation model. Repeated sampling under the simulation model then gives us the various statistical properties. The methodology is explained in more detail in chapter 3 of this report.

## 1.2. Emission estimation model and emission data

### 1.2.1. The Norwegian emission model

The emission estimates are made in collaboration between Statistics Norway and the Norwegian Pollution Control Authority (SFT). Statistics Norway is responsible for collecting activity data, the development of emission models and performing the actual calculations. SFT is responsible for emission factors and emission estimates for large plants.

The emissions are estimated separately for sources related to combustion and non-combustion sources.

The emissions from energy use (combustion) are in the national emission model estimated from the following equation:

$$E_{ijklm} = \left[C_{jklm} - CPS_{jklm}\right] * EF_{ijklm} + EPS_{ijklm} \qquad 1.4$$

Where

| | | |
|---|---|---|
| $E_{ijklm}$ | = | Emission of pollutant *i* from combustion of fuel *j* in source *k* in sector *l* in municipality *m*. |
| $C_{jklm}$ | = | Consumption of fuel *j* in source *k* in sector *l* in municipality *m*. |
| $CPS_{jklm}$ | = | Consumption of fuel *j* in source *k* in point sources in sector *l* in municipality *m*. |
| $EF_{ijklm}$ | = | Emission factor for pollutant *i* from combustion of fuel *j* in source *k* in sector *l* in municipality *m*. |
| $EPS_{ijklm}$ | = | Emission of pollutant *i* from combustion of fuel *j* in source *k* in point sources in sector *l* in municipality *m*. |

Emissions from road traffic are estimated in a technical satellite model.

The *non-combustion emissions* are estimated in a free format, depending on the emission type. Emissions from landfilled waste and use of HFCs are estimated in technical satellite models. Some emissions ($N_2O$ from nitric acid production and PFCs from aluminium production) are estimated from measurements at each plant. The non-combustion emissions are assigned an emission carrier, source, sector and municipality in order to be consistent with the data set of combustion emissions.

The total emissions are the sum of the combustion and non-combustion emissions. The emission model and emission estimation methodologies of each gas are explained in detail in Flugsrud et. al. (2000).

### 1.2.2. Simplifications of the emission model

The model used to estimate the emissions explained in chapter 1.2.1. is far too detailed to be a basis for an analysis of the statistical properties. This is both due to the complexity of assessing the statistical properties of the vast number of input data and the computer time required to process the combined statistical properties. The following simplifications have been made:

- The municipality dimension has been aggregated to national level.
- The sectors and sources have been combined into the most detailed IPCC source sectors (IPCC 1997). This implies that some emission factors have been averaged.
- Some adjustments and splits have been adopted, e.g. where different pollutants from a source-sector have to be connected to different activity measures. Road traffic has been split according to rough technology (cars with and without catalytic converters).
- Energy carriers have been grouped into five main types; oil, gas, coal, waste and bio energy.
- As mentioned, emission figures based on measurements have been assigned activity data value *1* and emission factor equal to the measured emissions.
- Emissions from landfills, HFCs and some other sources have been transferred into the form of *emission factor *activity rate*, in spite of the fact that the estimates are based on more complex estimation models (e.g. taking time lag into account and using several activity data and emission factors).

### 1.2.3. Emissions in 1990 and 1997

The historical emission estimates are the official emission figures presented in 1999 (Statistics Norway 1999). The data from the national model have been converted into the IPCC source categories. Although the emission figures presented in 1999 are likely to be recalculated in the future due to better knowledge, it is expected that these recalculations in the short term only will have small effects on the main conclusions from this study. The estimates are shown in Appendix 1.

### 1.2.4. Emission projection for 2010.

According to the Kyoto protocol, Norway has to restrict its total GHG emissions by not more than 1 per cent increase from the level in 1990 in the period 2008-2012. This goal may theoretically be reached in many different ways. In order to reach the best conclusion on the uncertainty in the trend of the emissions, is it necessary as far as possible to use a realistic data set for the Kyoto target year (here approximated by 2010). For this purpose the official projected emission data will be used. The projection is taken from Ministry of Environment (1998). It is assumed a scenario where the emission obligation of 1 per cent increase is met with a certain amount of emission trading[4].

There have been some practical problems using this emission projection. Firstly, the emission projection is given at an aggregated level only. The emissions by IPCC source sectors in 2010 have been extrapolated from 1997 data taking into account planned measures and aggregated growth rate so that total emissions of each gas equals the projection.

The second problem is that since the projection was made emission estimates from some sources (mainly landfills, road traffic and HFC from product use) have been recalculated due to better estimation models and data. In these cases the growth rate of each source estimate has been assumed as in the original projection. However, this means that the total level and growth rate 1990-2010 will differ from Ministry of Environment (1998)[4].

The aggregated data and estimated trend used in the analysis is shown in table 1[5].

[4] This choice does not reflect any opinion of Statistics Norway on future emission growth or reduction strategies.

[5] Estimates as published in 1999, data are slightly different from those published and reported in 2000 due to recalculations.

**Table 1a. Total emissions of GHG in 1990, 1997 and 2010. Tonnes natural units.**

| | $CO_2$ | $CH_4$ | $N_2O$ | HFC | $SF_6$ | PFC |
|---|---|---|---|---|---|---|
| 1990 | 35 202 192 | 317 050 | 17 536 | 0.1 | 92 | 385 |
| 1997 | 41 429 600 | 350 257 | 16 335 | 44 | 21 | 219 |
| 2010 | 47 961 275 | 285 672 | 19 281 | 580 | 21 | 185 |
| GWP[6] | 1 | 21 | 310 | 2 300 | 23 900 | 6 600 |

Source: Statistics Norway and Norwegian Pollution Control Authority, Ministry of Environment (1998)

**Table 1b. Total emissions of GHG in 1990, 1997 and 2010. Mill. tonnes $CO_2$ equivalents.**

| | Total | $CO_2$ | $CH_4$ | $N_2O$ | HFC | $SF_6$ | PFC |
|---|---|---|---|---|---|---|---|
| 1990 | 52.0 | 35.2 | 6.7 | 5.4 | 0.0 | 2.2 | 2.5 |
| 1997 | 55.9 | 41.4 | 7.3 | 5.1 | 0.1 | 0.5 | 1.4 |
| 2010 | 63.0 | 48.0 | 6.0 | 6.0 | 1.3 | 0.5 | 1.2 |
| 1990-2010 (per cent change) | 21.1 | 36.2 | -9.9 | 9.9 | - | -76.8 | -51.9 |

Source: Statistics Norway and Norwegian Pollution Control Authority, Ministry of Environment (1998)

[6] For HFC and PFC average values for 1990 have been used for all years.

# 2. Determination of uncertainties in input parameters

Uncertainties in inventory data have different explanations. Processes generating emissions may be variable in time and space and consequently it will be difficult to set up an appropriate emission model and define representative emission factors. Representative emission factors (or activity data) may be inaccurate, lacking and substituted by assumptions - or emissions may not have been estimated at all. Furthermore, inventories may contain errors originating from data processing or basic data. In this analysis no distinction will be made between these types of errors, and assessed uncertainty in the model is as far as possible attributed to the emission factors. This simplification is necessary, as at this stage, there is little information on uncertainties (see below) and shortcomings of standard emission estimation models. Such simplification is, however, not desirable as separation of variability, uncertainty in data and uncertainty in models would have been useful. Furthermore, it is not theoretically justified (Cullen and Frey 1999). In the future, if uncertainties in input data become available, it would be useful to make a separate estimate of model uncertainties. It should also be emphasised that this type of analysis will not be suited for identifying data processing errors, omitted emission sources and systematic errors in general.

An emission inventory data set is not an empirical data set where the uncertainties can be derived directly from individual observations. For each of the input data in Appendix 1 we will have to assess the variance, probability distribution and possible dependencies. In a few cases we have good knowledge of this. However, for most data we will need to base the assessment on indirect sources, while in some cases it will have to be based on expert judgements. See Cullen and Frey (1999) for a justification of this type of subjective assessment of probability.

Morgan and Henrion (1990) discusses systematic approaches to assess statistical properties of input data. This frequently involves independent assessments by several experts. Given the resources allocated to the project described in this work, we have not been able to use these systematic approaches. Ongoing work within the IPCC (Intergovernmental Panel on Climate Change) will involve assessment of uncertainties of input parameters of source categories involving a broad group of experts (IPCC 1998). This process was not completed when the work described in this report was performed. For some data, e.g. $CO_2$ emission factors, the uncertainties will be limited due to mass balance considerations. For others, the range of published data may give an indication of the uncertainty. All emission data need to be positive by definition, excluding probability functions yielding negative values.

As the data set is a sum of many data with associated assumptions, wrong assumptions for parts of the dataset will frequently not be very crucial. On the other hand, it has been suggested that the mind may be biased towards systematically assessing too high or too low values. According to Morgan and Henrion (1990) the human mind has a tendency to underestimate the importance of systematic errors, so it might in general be assumed that weakly founded assessments may underestimate the uncertainties of the data.

## 2.1. Means

The true values of the activity data and emission factors are unknown. The parameters that the estimations are based on are frequently called the “best estimate”.

The best estimates are determined in the emission inventory development work and is based on Norwegian measurements, literature data or statistical surveys. Some data are based on expert judgements. See Flugsrud et. al. (2000) for an introduction to the origin of the inventory data.

It might be discussed whether these best estimates represent the mean or the median or something else. We have here assumed that the best estimate equals the mean, which in general is *not* the most probable value. Only in case of normal or any other symmetric distributions, would the two values coincide. Otherwise, how 'probable' the mean value is depends on the particular distribution in each case.

## 2.2. Standard deviation and probability density

A probability distribution model is a description of the probabilities of all possible values in a sample space (Cullen and Frey 1999). This may be represented mathematically as a probability distribution, a *probability density function*. The standard deviation is a property of this function. Further parameters may be needed in order to describe non-normal probability density functions (Cullen and Frey 1999, Morgan and Henrion 1990).

The probability densities used in this study have been divided into four types of model shapes (see Appendix 2 for an illustration):

1. Normal distribution
2. Truncated normal distribution
3. Lognormal distribution
4. Beta distribution

For low uncertainties the distributions 2-4 above approach the normal distributions. For large uncertainties the normal distribution may lead to negative values. To avoid this the distributions are, when necessary, truncated at 0, which means that there is a given probability of the value 0. The lognormal distribution and beta distribution are both asymmetrical distributions, giving a heavier tail of probabilities towards higher values. These two distributions are very similar in shape for low to medium size uncertainties. For higher uncertainties the beta distribution is more flat and the peak in the distribution is closer to the mean value. The beta distribution is, however, only defined for variables taking values between 0 and 1.

Sometimes it is not suitable or possible to specify the uncertainty in a parameter directly in terms of its standard deviation. For instance, the expert opinion might suggest that the parameter could take values within a certain range, say, between half to double of the mean. We interpret such an assessment as to imply that "the probability of the parameter taking values in the specified range equals to 0.95". Solving this equation numerically, we obtain the parameters of the relevant distribution, which then determines the corresponding standard deviation.

### 2.2.1. Activity data

The activity data are frequently statistical data based on sample surveys or censuses. The standard deviation and probability density of survey data are usually not available. However, the uncertainty of statistical data may also have contributions from errors in the population/sampling, processing errors etc. which are not properties of the data set itself. Statistics Norway does not have any investigations of uncertainties in survey data that can be utilised directly in this work.

A few activity data are indirectly derived, based on old surveys or based on expert judgements, this gives rise to additional uncertainty. Most activity data have been assumed to be normally distributed. The assessments of standard deviations are mostly based on Rypdal (1999).

The most important activity data are of course energy use. The total energy data are determined from the sales statistics (for oil) or consumer surveys (coal and fuel wood). The total energy use may for commercial fuels also be determined from *Production + Import - Export*. These two data sets are independent and the spread in data gives an indication of the statistical error. Generally, the total energy use is less uncertain than the energy use in each sector. For some sectors (e.g. the energy and manufacturing industries) the energy use is well known, while in household and service sectors the energy use is more uncertain. However, the energy use in the most uncertain sectors has been adjusted in the official energy statistics so that the sum of energy use in all sectors equals the total sales. In the analysis we have differentiated between different uncertainties in different sectors, but with restrictions to the uncertainty of the total of each fuel. Also the split between various applications of gasoline and diesel (off-road vehicles and machinery, cars equipped with catalytic converters, cars *not* equipped with catalytic converters) are assumed to be more uncertain than total consumption. Furthermore, the errors in the various energy carriers may be correlated (as respondent mix energy carriers in surveys). We have ignored this as the energy carriers in this analysis have been aggregated to main fuel categories.

A higher uncertainty has been assigned to domestic fuel for aircraft and shipping, as (especially in the case of shipping) these are difficult to distinguish from bunker fuel for international transport. These errors are assumed to be random, though unknown systematic errors could be present in the shipping sector. Also data on consumption of wood waste, black liquor and other waste used as fuel are uncertain and not completely covered by current statistics. The assessed standard deviations and corresponding probability densities are summarised in Table 2.

**Table 2. Summary of standard deviation and probability density of activity data.**

| IPCC source category | Pollutant source | Standard deviation ($2\sigma$). per cent | Density shape | Source/Comment |
|---|---|---|---|---|
| 1A1, 1A2 | Gas combustion | ± 4 | Normal | Norwegian Petroleum Directorate |
| 1A1, 1A2, 1A3, 1A4 | Oil combustion (total) | ± 3 | Normal | Spread in data |
| 1A1 | Waste combustion - Energy industries | ± 5 | Normal | Expert judgement |
| 1A2, 1A4 | Waste combustion - Other sectors | ± 30 | Lognormal | Expert judgement |
| 1A1, 1A2, 1A4 | Wood combustion - All sectors | ± 30 | Lognormal | Expert judgement |
| 1A2 | Coal and coke combustion- Industry | ± 5 | Normal | Spread in data |
| 1A3b, 1A3e | Oil, road/off-road/catalytic/non-catalytic | ± 20 | Normal | Comparisons of data |
| 1A3a | Oil combustion - Aviation | ± 20 | Normal | Expert judgement |
| 1A3d | Oil combustion - Shipping | ± 10 | Normal | Comparisons of data |
| 1A4b | Coal and coke combustion - Residential | ± 20 | Normal | Expert judgement |
| 1B1a | Mining of coal | ± 3 | Normal | Expert judgement |
| 1B2a and 1B2b | Extraction of oil and gas | ± 3 | Normal | Expert judgement |
| 1B2a | Loading of crude oil | ± 3 | Normal | Expert judgement |
| 1B2c | Flaring of natural gas | ± 4 | Normal | Norwegian Petroleum Directorate |
| 2A1 | Cement production | ± 3 | Normal | Expert judgement |
| 2B1 | Ammonia production | ± 3 | Normal | Expert judgement |
| 2B2 | Nitric acid production | - | - | Measured value |
| 2B4 | Carbide production | ± 3 | Normal | Expert judgement |
| 2C1, 2C2, 2C3 | Metal production | ± 5 | Normal | Expert judgement |
| 2F | HFCs in products | - | - | Table 3 |
| 2F | $SF_6$ in products | - | - | Table 3 |
| 4A, 4B | Animal population | ± 5-10 | Normal | Expert judgement |
| 4D | Agricultural soils - Fertiliser use | ± 5 | Normal | Agriculture authorities |
| 4D | Agricultural soils - Manure use | ± 20 | Normal | Expert judgement |
| 4D | Agricultural soils - Other activities | ± 50 | Lognormal | Expert judgement |
| 6A | Solid waste disposal | ± 20 | Normal | Expert judgement |
| 6B | Waste water treatment | ± 25 | Normal | Expert judgement |

### 2.2.2. Emission factors

The ideal of an emission factor is derived from a set of measurements, where there are no systematic errors in the measurements and the condition of which the emission factor has been derived represents the "real world". In this case the standard deviation and probability density of the emission factor may be directly derived from the empirical data which it is based on. However, this ideal of an emission factor does not exist. Only in a few cases the standard deviation and mean of the emission factors may be *approximated* from a consistent set of empirical data. Consequently, for most of the emission factors in our dataset, the standard deviation and probability density must be derived from indirect sources. One possibility, partly used in this work, is to consider the spread in published data. The weakness of this approach is that published values may origin from the same original measurements and may contain the same systematic errors due to lack of knowledge of the emission source and the same systematic errors of determination. Frequently, also a high spread may indicate a high variability in space and time, while the uncertainties of average values are lower. Hence, the assessment must frequently be based on expert judgements funded on knowledge of each particular emission source and national conditions. National source experts have contributed to the expert judgements, see Rypdal (1999).

Though the spread in data may give indications of the statistical variance, is it more difficult to derive information on the probability density of the data. The assessment of the densities is, however, in general not very crucial for the final results. If more information had been available, the emission factors could have been assigned other densities than the model shapes to better reflect the true situation[7].

The assigned values and probability densities are shown in Table 3.

[7] Evidently, if the data had been based on a perfect empirical data set, it would not have been necessary to make any assumptions about the density at all, the analysis could be based on the empirical data as they were (Efron and Tibshirani 1993).

**Table 3. Summary of standard deviation and probability density of emission factors.**

| IPCC source category | Pollutant source | Standard deviation (2σ). per cent | Density shape | Source/Comment |
|---|---|---|---|---|
| 1A1, 1A2 | $CO_2$ - Gas combustion | ± 7 | Normal | Norwegian Petroleum Directorate |
| 1A1, 1A2, 1A3, 1A4 | $CO_2$ - Oil combustion | ± 3 | Normal | Spread in data |
| 1A1, 1A2, 1A4 | $CO_2$ - Coal combustion | ± 7 | Normal | Spread in data |
| 1A2, 1A4 | $CO_2$ - Coke combustion | ± 7 | Normal | Spread in data |
| 1A1, 1A2, 1A4 | $CO_2$ - Waste combustion | ± 30 | Normal | Spread in data |
| 1A1, 1A2, 1A4 | $CH_4$ - Wood, coal, waste combustion | -50 - +100 | Lognormal | Spread in data |
| 1A3 | $CH_4$ - Oil combustion. Road traffic | -50 - +100 | Lognormal | Spread in data. Expert judgement |
| 1A1, 1A2, 1A4 | $CH_4$ - Oil combustion. Other | -50 - +100 | Truncated N | Spread in data |
| 1A3 | $N_2O$ - Oil combustion. Road traffic | -66 - +200 | Beta | Spread in data. Expert judgement |
| 1A1, 1A2, 1A4 | $N_2O$ - Oil combustion. Other | -66 - +200 | Beta | Spread in data. Expert judgement. IPCC (1997) |
| 1B2c | $CO_2$ - Flaring | ± 10 | Normal | As combustion of gas |
| 1B1a | $CH_4$ - Coal mining | -50 - +100 | Lognormal | Expert judgement. IPCC (1997) |
| 1B2a, 1B2b | $CH_4$ - Oil and gas extraction, refineries | -50 - +100 | Lognormal | Expert judgement |
| 1B2a | $CH_4$ - Oil loading | ± 40 | Lognormal | Oil company |
| 1B2c | $CH_4$ - Flaring | -50 - +100 | Lognormal | As combustion of gas |
| 1B2c | $N_2O$ - Flaring | -66 - +200 | Beta | As combustion of gas |
| 2A1 | $CO_2$ - Cement production | ± 7 | Normal | Spread in data. IPCC (1997) |
| 2B1 | $CO_2$ - Ammonia production | ± 7 | Normal | Expert judgement |
| 2B2 | $N_2O$ - Nitric acid production | ± 7 | Normal | Plants' estimate. Continous measurements |
| 2B4 | $CO_2$ - Carbide production | ± 10 | Normal | Spread in data |
| 2C1, 2C2, 2C3 | $CO_2$ - Metal production | ± 7 | Normal | Spread in data |
| 2C4 | $SF_6$ - Metal production | ± 5 | Normal | Expert judgement. Consumption of chemical |
| 2C3 | PFCs - Metal production | -30 - +50 | Lognormal | Plants estimate |
| 2F | HFCs from product use (actual emissions) | ± 50 | Lognormal | Expert judgement |
| 2F | $SF_6$ from product use | ± 60 | Lognormal | Expert judgement |
| 4A | $CH_4$ - Enteric fermentation | ± 25 | Normal | IPCC (1997) |
| 4B | $CH_4$ - Animal waste | ± 25 | Normal | IPCC (1997) |
| 4D | $N_2O$ - Agricultural soils | 2 orders of magnitude | Lognormal | Expert judgement. IPCC (1997) |
| 6A | $CH_4$, $CO_2$ - Landfilled solid waste | ± 30 | Lognormal | SFT (1999) |
| 6B | $CH_4$ - Waste water treatment | ± 70 | Lognormal | Expert judgement |

The assessed uncertainty of nitrous oxide from agricultural soils is crucial for the determination of the overall uncertainty. On the other hand, this uncertainty is not well known. The range used here (2 orders of magnitude) is based on IPCC (1997).

## 2.3. Dependencies between parameters

Some of the input parameters (emission factors and activity data) are for various reasons not independent, that means that their values are dependent (or correlated)[8]. In order to derive the statistical properties and sensitivities of the combined data set, we will have to determine which parameters are dependent and to what degree. The problem of dependencies may be solved by appropriate aggregation of the data or explicitly by modelling. In this work we have partly designed the dataset to reduce the problem as well as introduced a number of dependence assumptions into the model.

The determination of dependencies is sometimes a difficult task and requires some understanding of the data set and the assumptions it is based on. Initial estimates with variable assumptions have shown that the assumptions on dependencies generally have little effect on the final conclusions on uncertainties, but are very important for the conclusions on sensitivities. The assumptions of dependencies of data between years are, however, crucial for the determination of trend uncertainty (2.3.3).

### 2.3.1. Dependencies between activity data

The activity data, the statistical data in equation 1.2, are in principle independent. However, the same activity data may be used to estimate more than one emission source (e.g. in the agriculture sector). Also the same activity data are used for estimating more than one pollutant (especially in the case of energy emissions). The sum of

[8] The term "dependency" is used here rather than "correlation" or "covariance" as the coefficients of correlation in the cases considered are 1.

some of the energy carriers in each sector is fixed. That means that all the energy data in each source-sector for a given fuel are dependent.

More specifically the cases when activity data are assumed dependent are:
- The consumption of *oil products* in each sector. The sum of all oil products has a lower uncertainty than the consumption in each sector
- The consumption of gasoline and diesel (oil products) for the applications cars with catalytic converter, cars without catalytic converter and off-road applications. The split between the various applications is more uncertain than the total
- The number of domestic animals. The same data are used for estimation of a) methane from enteric fermentation, b) methane from manure management and partly c) nitrous oxide from agricultural soils
- Where the same activity data are used to estimate emissions of more than one pollutant.

### 2.3.2. Dependencies between emission factors

The case of dependencies between emission factors is difficult to handle correctly. In a perfect data set different emission factors from independent estimates would have been used for all the emission sources. However, as the information on $N_2O$ and $CH_4$ emissions is incomplete, frequently the same emission factors will have to be used for several emission sources. Where emission factors have been assumed equal, we have treated them as dependent in the analysis.

The following assumptions have been made:
- The $CO_2$ emission factors for each fuel type are dependent
- The methane and nitrous oxide emission factors from combustion are dependent where they have been assumed equal in the emission estimation model
- In a few cases the emission factors of different pollutants are correlated. That is in cases when $CO_2$ is oxidised from methane (oil extraction, oil loading and coal mining).

### 2.3.3. Dependencies between data in base year and end year

The assumptions made about dependencies between the two years are extremely important for the main conclusion of this analysis concerning the uncertainty of the trend from 1990 to 2010. The estimates made for the two years will to a large extent be based on the same data and assumptions.

*Activity data*

The activity data are determined independently in the two years and are in principle not dependent. Correlation could be considered in cases where activity data cannot be updated annually or where updates are based on extrapolations or interpolations of data for another year. The only case in this inventory is the area of histosols (activity data 85) where data in all years are dependent as they have been assumed equal.

This implies that we have assumed that errors in activity data are random, hence that systematic method errors are insignificant. It is, however, likely that there is a certain correlation between the activity data as they have been determined using the same methods.

*Emission factors*

Most of the emission factors are assumed unchanged from 1990 to 2010. Those that are not are all based on the same assumptions. This implies that all the emission factors are fully correlated between the two years.

This means that we have assumed that the emission factors assumed unchanged actually are unchanged from base to end year. In reality it is expected that most emission factors are changing, but the degree of change is usually not known.

# 3. The statistical modelling

## 3.1. Uncertainty estimation

Uncertainty analysis based on probabilistic analysis implies that uncertainties in model inputs are used to propagate uncertainties in model outputs. The result of the uncertainty estimation gives us the range and likelihood of various output values (Cullen and Frey 1999).

Having generated a data set according to the specified parametric simultaneous distribution of the data described in chapter 2, we may calculate any desired output defined as a function of the data. This gives us one simulated random realisation of this output, according to its marginal distribution derived from the underlying simultaneous distribution of the data. Independent repetition of the simulation gives an independent sample of the desired output according to its marginal distribution. The size of the sample is given by the number of repeated simulations, and has nothing to do with the size of the original data set. Based on such an independent and identically distributed sample, we may use the sample mean as an estimate of the mean of the output; we may also use the sample standard deviation as an estimate of the standard deviation of the output.

The simulation procedure described above is a standard application of the parametric Bootstrap (Efron and Tibshirani 1993). The precision of the estimates is determined by the sample size, which can be estimated using the following procedure. Suppose the simulated sample is of the size 1000. Resample from the simulated sample, randomly and with replacement 1000 times, gives us the second simulated sample of the same size as the first one. Repetition of the re-sampling for example 249 times would give us, altogether, 250 resamples. We then calculate the estimator 250 times based on each of these 250 re-samples. The sample deviation of these 250 estimates now gives us an estimate of the standard deviation of our estimator. In this way we may estimate the error of the Bootstrap estimator. Moreover, we may increase the number of the original Bootstrap (i.e. 1000 in this case) if we should find it to be too large to accept. Again, the technique can be found in Efron and Tibshirani (1993), and is based on the fact that the re-sampled estimates (i.e. 250 in this case) approximately follow their marginal distribution derived from the underlying simultaneous distribution of the data set.

## 3.2. Sensitivity analysis

The potential importance of model inputs as contributors to variation in model outputs may be measured using a sensitivity analysis. A sensitivity analysis may be defined as *the computation of the effect of changes in input values or assumptions on the output* (Morgan and Henrion 1990).

Sensitivity analysis may be performed at several levels (Morgan and Henrion 1990)

- analysis of each factor separately, holding other factors constant (local approach)
- deterministic joint analysis, varying more than one factor at a time
- parametric analysis moving one or more input parameter across reasonable selected values
- probabilistic analysis, using correlation or other means to examine how much of the uncertainty in conclusions is attributable to which inputs (global approach)

In this work we have used both the local approach and the global approach. The approach of parametric analysis, moving one or more input parameter across reasonable selected values, was used on the national inventory in Rypdal (1999).

The advantage of the first approach is the simplicity. The shortcoming is that simultaneous effects can not be studied and that the approach not is valid for large uncertainties. The probabilistic approach, on the other hand, does not have these shortcomings. It is, however, too complex to perform on the entire data set. Consequently, this analysis is only performed including data identified as particularly important in the local approach.

The simple theory below on sensitivity measures and elasticities is mostly taken from Morgan and Henrion (1990).

We will here consider a simplified case where the total emission (E) is a function of two uncertain input estimates ($e_1$ and $e_2$).

$$E = f(e_1, e_2) \qquad 3.1$$

*E.g*, the input parameters may be estimates of source emissions, $E = e_1 + e_2$, or they may be an emission factor and an activity measure, $E = e_1 \; e_2$. The input estimates given in the inventory as the best estimates are $e_1^0$ and $e_2^0$, and the best estimate of total emission is $E^0$.

The absolute *sensitivity* ($U_s$) is defined as the rate of change of the output (E) with respect to variations in the input, evaluated at the best estimate, that is

$$U_S(e_i,E) = \left[\frac{\partial E}{\partial e_i}\right]_{E^0} \qquad 3.2$$

The sensitivities are not directly comparable between various emission sources. The normalised sensitivity (or *elasticity*) ($U_E$) is defined as the ratio of the relative change in output (E) induced by a unit relative change in input (*e*). This expression should be used for comparing the sensitivity of various parameters since it is dimensionless. It is defined as:

$$U_E(e_i,E) = \left[\frac{\partial E}{\partial e_i}\right]_{E^0} \times \frac{e_i^0}{E^0} \qquad 3.3$$

Furthermore, the degree of uncertainty may be taken into account directly. The contribution to total uncertainty, *uncertainty importance* ($U_G$), may as a simplification be expressed as

$$U_G(e_i,E) = \left[\frac{\partial E}{\partial e_i}\right]_{E^0} \times \sigma_{e_i} \qquad 3.4$$

Where

$\sigma_e$ is the standard deviation of the input parameters.

This may also be modified into a normalised uncertainty importance elasticy ($U_{GE}$), that is

$$U_{GE}(e_i,E) = U_E(e_i,E) \times \frac{\sigma_{ei}}{e_i^0} = \left[\left[\frac{\partial E}{\partial e_i}\right]_{E^0} \times \frac{e_i^0}{E^0}\right] \times \frac{\sigma_{ei}}{e_i^0} = \left[\frac{\partial E}{\partial e_i}\right]_{E^0} \times \sigma_{ei} / E^0 \qquad 3.5$$

Note that the simplified equations 3.4 and 3.5 are not valid for large uncertainties and non-normal distributions (local approach). In these cases the analysis will be more accurate based on other approaches (see global approach).

Simulation under the global approach is similar to that for uncertainty propagation earlier. After each simulated data set, we record the pair of variables of which the correlation is to be estimated. Repeated simulation now gives us a sample of pair of values. The corresponding sample correlation provides an estimate of the correlation of the two variables. Further re-samples based on the sampled pairs can be used to estimate the precision of this correlation estimator.

The elasticities tell us which input parameters contribute most to the total output. The uncertainty importance, on the other hand, tells us what input parameters contribute most to the overall inventory uncertainty. For inventory applications the uncertainty importance will be a useful parameter to rank the most important sources or input parameters with respect to their contribution to total uncertainty, that is what parts of the inventory should be improved (if possible) to reduce the overall uncertainty.

# 4. Results and discussion

This analysis gives conclusions on both uncertainties in the total emissions and trends (4.1) and on the sensitivity of the conclusions of possible errors of each input parameter (4.2).

## 4.1. Conclusions on uncertainties

### 4.1.1. Uncertainties in emission level

The estimated uncertainties of the level of total emissions and in each gas are shown in Table 4.

**Table 4. Uncertainties in emission level. Each gas and total GWP weighted emissions.**

| 1990 | μ (mean) | Fraction of total emissions | Relative standard deviation (σ/μ) | Uncertainty 2σ (per cent of mean) |
|---|---|---|---|---|
| Total | 52 mill. tonnes | 1 | 0.103 | 21 |
| $CO_2$ | 35 mill. tonnes | 0.67 | 0.017 | 3 |
| $CH_4$ | 317 ktonnes | 0.12 | 0.111 | 22 |
| $N_2O$ | 18 ktonnes | 0.11 | 0.960 | 200 |
| HFC | 0.13 tonnes | 0.00 | 0.251 | 50 |
| PFC | 385 tonnes | 0.05 | 0.203 | 40 |
| $SF_6$ | 92 tonnes | 0.04 | 0.026 | 5 |
| 2010* | μ (mean) | Fraction of total emissions | Relative standard deviation (σ/μ) | Uncertainty 2σ (per cent of mean) |
| Total | 63 mill. tonnes | 1 | 0.084 | 17 |
| $CO_2$ | 48 mill. tonnes | 0.76 | 0.018 | 4 |
| $CH_4$ | 286 ktonnes | 0.10 | 0.098 | 20 |
| $N_2O$ | 19 ktonnes | 0.09 | 0.852 | 170 |
| HFC | 580 tonnes | 0.02 | 0.255 | 50 |
| PFC | 185 tonnes | 0.02 | 0.202 | 40 |
| $SF_6$ | 21 tonnes | 0.01 | 0.043 | 9 |

* Projected data with uncertainties as if they were historical.

The estimated probability densities are shown in Appendix 3.

The total national emissions of GHG in Norway in 1990 are estimated with an uncertainty of 21 per cent of the mean. While the emission level of $CO_2$ is known as accurately as 3 per cent, all other pollutants are more uncertain. The uncertainty is particularly high for $N_2O$ (more than 150 per cent).

The uncertainty analysis of the projected data for 2010 shows a decrease in uncertainty (17 per cent of total emissions). This is only due to changes in source and pollutant mix, a higher fraction of total emissions will be $CO_2$. Possible future inventory improvements have not been taken into account.

In a former more simple analysis the uncertainty was estimated to be 11-18 per cent (Rypdal 1999). The more accurate estimate falls slightly outside this interval. The total uncertainty in the United Kingdom GHG inventory has in a comparable manner been estimated to be 19 per cent (Eggleston et al 1998). UK has a higher $CO_2$ fraction of total emissions compared to Norway, 78 per cent in 1990 and 85 per cent in 2010. It is generally expected that countries having a larger fraction of non-$CO_2$ gases will have a higher inventory uncertainty.

### 4.1.2. Uncertainties in emission trend

The estimated uncertainties of the trend of total emissions and each gas are shown in Table 5.

**Table 5. Uncertainty of emission trend. 1990-2010***

| | per cent change | Relative standard deviation | Uncertainty |
|---|---|---|---|
| | $((\mu_{2010}-\mu_{1990})*100/\mu_{1990})$ | $(\sigma/(\mu_{2010}-\mu_{1990}))$ | $2\sigma$ (per cent-point of change) |
| Total | 21 | 0.107 | 4 |
| $CO_2$ | 36 | 0.066 | 5 |
| $CH_4$ | -10 | -0.785 | 16 |
| $N_2O$ | 10 | 0.652 | 13 |
| HFC | - | 0.250 | - |
| PFC | -51 | -0.193 | 20 |
| $SF_6$ | -77 | -0.024 | 4 |

* Projected values with uncertainties as if they were historical.

No numerical assessment of the trend uncertainty was made in Rypdal (1999), but it was concluded that the trend uncertainty is likely to be higher than the precision in the commitments. This study shows that the increase from 1990 to 2010 (in the given projection scenario) is 21 ±4 per cent. Given that the remaining reductions are achieved by the means of international emission trading (assuming no uncertainty in the traded emissions), the political target increase would be 1 ±4 per cent.

PFC gases, followed by $CH_4$ and $N_2O$, have the highest trend uncertainty relative to the percentage change. Also, the total trend is less uncertain than the trend of each individual gas. This may imply that the concept of commitments based on percentage changes in GWP weighted emissions leads to less uncertainty measured in percentage points than each gas measured on its own.

The mentioned UK study has estimated the trend in GHG emissions to -6 ±4 per cent. In general, the trend uncertainty will depend on the mix of trends of various sources and the individual uncertainties. It is difficult to conclude whether the UK and Norwegian estimates of trend uncertainties are typical.

## 4.2. Sensitivity analysis

The purpose of a sensitivity analysis for an inventory compiler is to identify which individual parts of the inventory that might influence the conclusions on total GHG emission level and trend. It is expected that the variability of the output can be related to variability of a limited number of input parameters (Cullen and Frey 1990).

The conclusions that can be drawn from a sensitivity analysis are very limited if they cannot be related to uncertainties. A high value of *elasticity* for a change in input parameter/emission estimate is more serious if this input parameter/source is uncertain. Sensitivities should consequently, if possible, be related to uncertainties, either nationally derived or default uncertainties. This measure is, as explained in 3.2, called *uncertainty importance.* When interpreting the results, the elasticity and uncertainty importance should be regarded as complementary information. The elasticities give the main contributors to output and conclusions, while the uncertainty importances give the sources contributing most to total uncertainty (the sources or parameters where most is gained by reducing the uncertainty).

Two approaches have been used here, the local approach and the global approach. See section 3.2 for a description of these two approaches. Sensitivities have been evaluated for the level and trend separately.

### 4.2.1. Sensitivity of emission level

*4.2.1.1. Elasticity of emission level*

To compare the sensitivities, the standardised elasticities have been used. An elasticity of 0.1 implies that a change in an input parameter of 100 per cent indices a change in total emissions of 10 per cent.

The parameters with the highest values of elasticities (equation 3.3) have been ranked (Table 6) in order to show the most important parameters in the inventory. Activity data and emission factors are ranked separately. Parameters with elasticities higher than 0.01 have been ranked.

**Table 6. Elasticities of input parameters with respect to total output. 1990 and 2010.**

*Activity data*. Ranking of the main important parameters (elasticity > 0.01).

| 1990 | | | 2010 | | |
|---|---|---|---|---|---|
| IPCC category | Source | Elasticity | IPCC category | Source | Elasticity |
| 1A3b | Oil - Road traffic | 0.15 | 1A3b | Oil - Road traffic | 0.18 |
| 1A1c | Gas - oil and gas extraction | 0.10 | 1A1c | Gas - oil and gas extraction | 0.16 |
| 6A | Solid waste disposal | 0.07 | 1A3d | Oil - shipping | 0.07 |
| 1A3d | Oil - shipping | 0.07 | 6A | Solid waste disposal | 0.05 |
| 2C2 | Ferroalloy production | 0.06 | 2C2 | Ferroalloy production | 0.05 |
| 4D | Area of histosols etc. | 0.04 | 1B2c | Gas - flaring | 0.04 |
| 1A1b | Gas- refineries | 0.03 | 1A4b | Oil - residential | 0.03 |
| 2C3 | Aluminium production | 0.03 | 4D | Area of histosols etc. | 0.03 |
| 1A4b | Oil - residential | 0.03 | 1A1b | Gas- refineries | 0.03 |
| 4A1 | Number of cattle | 0.03 | 2C3 | Aluminium production | 0.02 |
| 1B2c | Gas - flaring | 0.03 | 1A3e | Transport (other) | 0.02 |
| 1A3e | Transport (other) | 0.02 | 4A1 | Number of cattle | 0.02 |
| 1A3a | Aviation | 0.02 | 1A3a | Aviation | 0.02 |
| 1A4a | Oil - Commercial | 0.02 | 2A1 | Cement production | 0.02 |
| 1A2f | Oil -other manufacture | 0.02 | 1A2f | Oil -other manufacture | 0.02 |
| | | | 1A4a | Oil - Commercial | 0.02 |
| | | | 1B2a | Oil loading | 0.02 |

*Emission factors.* Ranking of the main important parameters (elasticity > 0.01).

| 1990 | | | 2010 | | |
|---|---|---|---|---|---|
| IPCC category | Source | Elasticity | IPCC category | Source | Elasticity |
| 1A | $CO_2$ from oil combustion | 0.35 | 1A | $CO_2$ from oil combustion | 0.38 |
| 1A1c | $CO_2$ from natural gas combustion in oil and gas extraction | 0.10 | 1A1c | $CO_2$ from natural gas combustion in oil and gas extraction | 0.16 |
| 6A | $CH_4$ from solid waste disposal | 0.07 | 6A | $CH_4$ from solid waste disposal | 0.05 |
| 2C2 | $CO_2$ from ferroalloy production | 0.06 | 2C2 | $CO_2$ from ferroalloy production | 0.05 |
| 3C3 | PFC from aluminium production | 0.05 | 1B2c | $CO_2$ from flaring | 0.04 |
| 2B2 | $N_2O$ from nitric acid production | 0.04 | 2B2 | $N_2O$ from nitric acid production | 0.03 |
| 4D | $N_2O$ from agricultural soils (other) | 0.04 | 4D | $N_2O$ from agricultural soils (other) | 0.03 |
| 2C4 | $SF_6$ from magnesium production | 0.04 | 1A1b | $CO_2$ from refineries | 0.03 |
| 4A1 | $CH_4$ from cattle | 0.03 | 2C3 | $CO_2$ from aluminium production | 0.03 |
| 1A1b | $CO_2$ from refineries | 0.03 | 4A1 | $CH_4$ from cattle | 0.02 |
| 2C3 | $CO_2$ from aluminium production | 0.03 | 1B2a | $CH_4$ from oil loading | 0.02 |
| 1B2c | $CO_2$ from flaring | 0.03 | 1B2a | $CO_2$ from oil loading | 0.02 |
| | | | 2F | HFC from product use | 0.02 |
| | | | 2A1 | $CO_2$ from cement production | 0.02 |

The $CO_2$ emission factor for oil combustion is the single parameter with the highest influence on the total GHG emission level. Other main parameters are the amount of oil used for road traffic, the amount of natural gas used and the corresponding $CO_2$ emission factor.

There are few differences in the results for 2010 compared to 1990. The same sources have the highest values of elasticities. Gas for oil and gas extraction (both indicated by activity data and emission factor) will grow in importance. Emissions from landfills will likely decrease in importance. The elasticity of HFC use will grow much.

*4.2.1.2. Uncertainty importance of emission level*

To compare the uncertainty contributions of various parameters, the standardised uncertainty importance has been used (equation 3.5).

The parameters with the highest values of uncertainty importance have been ranked in order to show the parameters in the inventory contributing most to total uncertainty (Table 7). The number of sources listed in the table has been selected so they add up to 90 per cent of total uncertainty. It has been proposed (Flugsrud, Irving and Rypdal 1999) that these are the *key sources* in the inventory, that should be given special priority in the emission inventory development process.

**Table 7. Uncertainty importance of input parameters with respect to total level uncertainty. 1990 and 2010.**

*Activity data.* Ranking of the main important parameters (uncertainty importance ≥ 0.002).

| 1990 | | | 2010 | | |
|---|---|---|---|---|---|
| IPCC category | Source | Unc_imp | IPCC category | Source | Unc_imp |
| 6A | Solid waste disposal | 0.007 | 6A | Solid waste disposal | 0.005 |
| 1A3d | Oil - shipping | 0.004 | 1A3d | Oil - shipping | 0.004 |
| 1A1c | Gas - oil and gas extraction | 0.002 | 1A1c | Gas - oil and gas extraction | 0.003 |
| 1A3a | Oil - aviation | 0.002 | 1A3a | Oil - aviation | 0.002 |
| 1A4a | Oil - services | 0.002 | 1A4a | Oil - services | 0.002 |
| | | | 1A4b | Oil - households | 0.002 |

*Emission factors.* Ranking of the main important parameters (uncertainty importance ≥ 0.002).

| 1990 | | | 2010 | | |
|---|---|---|---|---|---|
| IPCC category | Source | Unc_imp | IPCC category | Source | Unc_imp |
| 4D | $N_2O$ from agricultural soils (other) | 0.11 | 4D | $N_2O$ from agricultural soils (other) | 0.09 |
| 4D | $N_2O$ from agricultural soils (fertiliser) | 0.04 | 4D | $N_2O$ from agricultural soils (fertiliser) | 0.03 |
| 4D | $N_2O$ from agricultural soils (manure) | 0.03 | 4D | $N_2O$ from agricultural soils (manure) | 0.02 |
| 6A | $CH_4$ from landfilled waste | 0.01 | 6A | $CH_4$ from landfilled waste | 0.007 |
| 2C3 | PFC from aluminium | 0.01 | 1A | $CO_2$ from oil combustion | 0.006 |
| 1A | $CO_2$ from oil combustion | 0.005 | 1A1c | $CO_2$ from gas - oil and gas extraction | 0.006 |
| 1A1c | $CO_2$ from gas - oil and gas extraction | 0.004 | 3F | HFC used in products | 0.005 |
| 4A | $CH_4$ from cattle | 0.003 | 1A3b | $N_2O$ from road traffic | 0.005 |
| 2C2 | $CO_2$ from ferroalloy production | 0.002 | 2C3 | PFC from aluminium | 0.004 |
| 1B2a | $CO_2$ + $CH_4$ from oil loading | 0.002 | 1B2a | $CO_2$ + $CH_4$ from oil loading | 0.003 |
| | | | 4A | $CH_4$ from cattle | 0.003 |

The values of uncertainty importance of activity data are generally lower than the emission factors. This is because the uncertainty in activity data usually is lower than in the emission factors. The amount of solid waste disposed of and the amount of oil used for domestic shipping are the main activity data influencing the uncertainty importance. The emission factors for $N_2O$ from agricultural soils are dominating the uncertainty importance. $CH_4$ from landfills and PFC from aluminium production are the next contributors.

There are few main differences in 2010 compared to 1990. The uncertainty importance of $CH_4$ from landfills (both activity and emission factor) will decrease with decreased source contribution, but will remain among the main uncertainties. Also PFC from aluminium production will decrease in importance. The uncertainty importance of HFCs will increase to 0.005, and will become a source contributing to level uncertainty. $N_2O$ from road traffic will in 2010 also be on the list of the sources contributing most to total level uncertainty.

*4.2.1.3. Uncertainty importance of emission level (global approach)*

As mentioned in chapter 3.2, compiling the uncertainty importance using the local approach has some limitations as it only considers the effect of each parameter at some fixed values of the others. The global simulation approach, on the other hand, averages this over the simultaneous distribution of all the parameters. Correlation coefficients for the sample of output values with the corresponding sample of input values were compiled with respect to the source emission estimate, and not for emission factors and activity data separately. The correlation coefficient is a measure of the effect of uncertainty in input parameters on the uncertainty in the output, averaged over all possible combinations of values of other inputs, weighted by their probabilities (Morgan and Henrion 1990).

Initial computations identified that only the correlations of the sources nitrous oxide from agricultural soils and methane from waste disposal on landfills were significant. The correlation coefficients of these parameters were further refined (Table 8).

**Table 8. Ranking of the main sources contributing to total uncertainty (correlation ≥ 0.15).**

| Source | 1990 | 2010 |
|---|---|---|
| $N_2O$ from agriculture (other) | 0.91 | 0.84 |
| $N_2O$ from agriculture (fertiliser) | 0.29 | 0.38 |
| $N_2O$ from agriculture (manure) | 0.21 | 0.24 |
| $CH_4$ from solid waste disposal | 0.17 | 0.15 |

The result are qualitatively the same as obtained using the local derivative approach, with nitrous oxide from agricultural soils, followed by methane from landfills being the sources contributing most to the total inventory uncertainty. There are only small changes from 1990 to 2010. The local approach ranks more sources (contributing to 90 per cent of total inventory uncertainty) than are found significant using the global approach.

### 4.2.2. Sensitivity of emission trend

*4.2.2.1. Elasticity of trend*

The sensitivity of the trend towards any parameter has two directions, i.e. one along the average-value of the parameter in the two years, and the other along the change in the parameter. The results below refer to change in activities and average in emission factors. This is because most emission factors are equal in the base and end year. So, for instance, an elasticity of 0.1 for an activity means that a 100 per cent increment in the change of this activity leads to a 10 per cent increment in the trend ($\mu_2$-$\mu_1$). In particular, since the change in an activity between the two years may be positive or negative, so can the elasticity for the average of an emission factor be. We have also calculated the elasticities for the average of the activities and the change in the emission factors. These give nearly the same rankings, and are therefore not shown here.

The trend elasticities are shown in Table 9.

**Table 9. Elasticity of GHG trend. 1990-2010.**

*Activity data.* Ranking of the main important parameters (elasticity > 0.01 or < 0.01).

| IPCC category | Source | Elasticity |
|---|---|---|
| 1A1c | Gas - oil and gas extraction | +0.44 |
| 1B2c | Flaring of natural gas | +0.11 |
| 1A3d | Oil - shipping | +0.10 |
| 6A | Solid waste disposal | - 0.07 |
| 1A4b | Oil - residential | +0.06 |
| 2A1 | Cement production | +0.05 |
| 1B2a | Oil loading | +0.05 |
| 1A3e | Transport (other) | +0.03 |
| 1A2c | Gas -production of chemicals | +0.02 |

*Emission factors.* Ranking of the main important parameters (elasticity > 0.01 or < 0.01).

| IPCC category | Source | Elasticity |
|---|---|---|
| 1A | $CO_2$ from oil combustion | +0.52 |
| 1A1c | $CO_2$ from natural gas combustion in oil and gas extraction | +0.44 |
| 2C4 | $SF_6$ consumption (magnesium) | - 0.15 |
| 2F | HFC consumption | +0.12 |
| 2C3 | PFC from aluminium production | - 0.12 |
| 1B2c | $CO_2$ from flaring | +0.11 |
| 6A | $CH_4$ from solid waste disposal | - 0.07 |
| 1A3b | $N_2O$ from road traffic | +0.05 |
| 2A1 | $CO_2$ from cement manufacture | +0.05 |
| 1B2a | $CH_4$ and $CO_2$ from oil loading | +0.05 |
| 2B1 | $CO_2$ from ammonia production | +0.02 |
| 1B2c | $CH_4$ and $CO_2$ from venting | - 0.02 |

Few of the activity data are very important for the trend determination. Gas used for oil and gas production is important due to the large increase from 1990 to 2010. The amount of solid waste disposed of and oil used for shipping are also important for the trend uncertainty.

Other sources are in general more important for the trend elasticity than for the level. Important sources for the level like $N_2O$ from agriculture do not influence the trend much. Other, minor sources for the level contribution, has on the other hand been added to the list; HFC from chemical use and $SF_6$ from magnesium production, PFC from aluminium production and $N_2O$ from road traffic. Emissions from all these sources are expected to be much reduced or increased in the period considered, so that their trend is different from the total trend.

*4.2.2.2. Uncertainty importance of trend*

As for the level gives the uncertainty importance information on which sub-source estimates contribute most to the total trend uncertainty. The list contains sources summing up to about 90 per cent of the trend uncertainty. These are key sources in the inventory according to the proposal in Flugsrud, Irving and Rypdal (1999).

Like the trend elasticities, may the value of trend uncertainty importance be positive or negative. Values are shown in Table 10.

**Table 10. Uncertainty importance of input parameters with respect to total trend uncertainty. 1990 and 2010.**

*Activity data*. Ranking of the main important parameters (uncertainty importance elasticity ≥ 0.01 or ≤ 0.01).

| IPCC category | Source | Unc_imp |
|---|---|---|
| 1A1c | Gas - oil and gas extraction | +0.01 |
| 6A | Solid waste disposal | - 0.01 |
| 1A3d | Oil - shipping | +0.01 |

*Emission factors*. Ranking of the main important parameters (uncertainty importance elasticity ≥ 0.01 or ≤ 0.01).

| IPCC category | Source | Unc_imp |
|---|---|---|
| 2F | HFC consumption | +0.02 |
| 1A3b | $N_2O$ from road traffic | +0.02 |
| 2C3 | PFC from aluminium production | -0.02 |
| 1A1c | $CO_2$ from natural gas combustion in oil and gas extraction | +0.01 |
| 1A | $CO_2$ from oil combustion | +0.01 |
| 1B2a | $CH_4$ from oil loading | +0.01 |
| 1B2a | $CO_2$ from oil loading | +0.01 |
| 6A | $CH_4$ from landfilled waste | -0.01 |
| 1B2c | $CH_4$ from venting | -0.00 |
| 1B2c | $CO_2$ from venting | -0.00 |
| 1B2c | $CO_2$ from flaring | +0.00 |

The trend uncertainty importance identifies HFC from product use, $N_2O$ from road traffic and PFC from aluminium production as the main sources contributing to the trend uncertainty. These are sources changing rapidly while being uncertain.

*4.2.2.3. Uncertainty importance of trend (global approach)*
In the same way as for the level, the trend uncertainty importance has been assessed globally (Table 11).

**Table 11. The correlation between changes in total emissions between 1990 and 2010 and changes in sub-estimates. Corr ≥ 0.10**

| Source | Corr |
|---|---|
| $CH_4$ from landfilled waste | 0.42 |
| $N_2O$ from road traffic | 0.32 |
| $CO_2$ from shipping | 0.30 |
| HFC consumption | 0.28 |
| PFC from aluminium production | 0.26 |
| $CO_2$ from natural gas combustion | 0.23 |
| $N_2O$ from manure | 0.12 |
| $CO_2$ from air traffic | 0.12 |
| $CO_2$ from commercial heating | 0.12 |
| $CO_2$ from residential heating | 0.12 |

The results are slightly different from the local approach. The main reason is likely that the global approach considers source estimates and not emission factors and activity data separately. In addition, the fact that this approach considers large deviations from the mean might have some influence. However, in most cases the same sources are identified, but with a slightly different ranking. Also note that more sources have a significant correlation coefficient than in the case of level determination.

## 4.3. Implications of uncertainties and sensitivities

This work has shown that the uncertainty in the national GHG inventory level is quite high, about 20 per cent of the level. The obligations of the Kyoto protocol are based on percentage reductions in emissions between the base year and commitment period (here represented by 2010). The trend from 1990 to 2010 is estimated to be 21 ±4 per cent. That implies that it is not, with the current knowledge, possible to estimate the *trend* as accurately as needed for the Kyoto protocol (exact 1 per cent increase). The uncertainty in trend is, however, far lower than the uncertainty in level. This is because some errors cancel out when percentage increases are estimated.

One consequence of the high uncertainty may be recalculations of earlier submitted estimates that may change the level and trend estimates. It is expected that estimates having high uncertainty will be improved in the future as the scientific understanding is improved. Such recalculations are allowed, and are also according to the proposal for good practice when the scientific knowledge is improved or errors have been detected (FCCC/SBSTA). This will lead to higher confidence in the estimate, but possibly also major changes. Recalculations of the level and

trend may cause several practical difficulties (see below). Another consequence of the high uncertainty could be that some countries may bias their sub-estimates within the uncertainty range to obtain a too low trend estimate. Ongoing work on developing guidelines for good practice in inventory preparation gives countries guidance on how to produce unbiased estimates (IPCC 1998).

High uncertainties in source estimates may be an obstacle for selecting the most cost-effective reduction strategies and for efficient systems of *emission trading*, as the uncertainty indicates how likely it is that the estimate will be recalculated. It is obvious that recalculations will lead to practical problems when a quota has been traded if consistency between the trading system and the inventory is a goal. High uncertainties imply more need for control and verification due to the risk of biased estimates. We here need to consider the absolute uncertainty in each emission source.

For almost all sources the source uncertainty is dominated by the uncertainty in the emission factor. Almost all sources of $CO_2$ emissions have an uncertainty less than 10 per cent of the mean. Exceptions are aircraft and shipping (about 20 per cent of the mean) as the uncertainty is higher due to the difficulty in separating domestic emissions from bunkers. Also indirect $CO_2$ sources from fugitive emissions of $CH_4$ and NMVOC have higher uncertainties. Combustion sources of $CH_4$ all have an uncertainty of 50-100 per cent. The most important sources of methane have smaller uncertainties; oil loading (40 per cent), agriculture (25 per cent) and waste (36 per cent). All sources of $N_2O$ have an uncertainty of more than 100 per cent, the agricultural sources are particularly uncertain (order of magnitude). The uncertainty of HFC emissions from use of chemicals is 50 per cent (actual emissions) and PFC from aluminium 40 per cent. Emissions of $SF_6$ from metal production are quite accurately determined (5 per cent), while the emissions from other sources have an uncertainty of 40 about per cent.

These figures give an indication of which sources that from the point of view of uncertainty are most suited for inclusion in national and international trading systems. The inclusion of the sources having higher uncertainties than 30-40 per cent can lead to practical problems due to the high risk of recalculations and a particular high demand for control and verification. The possibility of recalculations after the quota has been traded may lead to discussions about who shall bear the loss or gain (the seller, buyer or the government). In this respect also the number of trading units is of relevance. When the number of units is limited higher uncertainty is usually acceptable as more resources may, at a reasonable cost, be directed to control, verification and improvements in emissions estimation methodology compared to a situation where there is a vast amount of units.

The uncertainty importance may be seen as a measure of where inventory improvements should be sought. $N_2O$ from agricultural soils is an intrinsically uncertain source for the level determination, but reductions in uncertainty can only be made through international research projects. The next sources on the level list ($CH_4$ from landfilled waste, PFC from aluminium, $CO_2$ from combustion of oil and gas) have all recently been prioritised for inventory improvement (Flugsrud et al. 2000). For $CH_4$ from cattle Norway is using a Tier 1 (simple) method and should in the light of the high uncertainty importance improve this estimate.

The sources most important for the trend uncertainty importance (HFC from product use, $N_2O$ from road traffic and PFC from aluminium production) have all been prioritised in the inventory improvements the last years (Flugsrud et al. 2000). However, there is a further potential for improving these estimates. The future improvement of the estimate of $N_2O$ from road traffic is dependent on the availability of measurement data that are applicable for Norwegian conditions.

Compiling the uncertainty importance gives another rank of key sources in the inventory compared to the simple elasticities. The elasticities could be used to prioritise inventory quality control, as errors in these sources will have the largest impact on the inventory output. These are $CO_2$ emissions from oil and gas combustion and methane from landfilled waste.

### 4.4. Discussion of some methodological issues

Several levels of performing uncertainty analysis and sensitivity analysis on inventory data sets have been suggested (Chapter 3 and Rypdal (1999)). The simpler methods require far less resources than the detailed. Concerning uncertainty analysis, we feel that this analytical approach has been far more useful than the more qualitative approach in Rypdal (1999). The results are more accurate and has given us more confidence in some of the preliminary conclusions drawn in Rypdal (1999). In particular the analytical approach is necessary in order to draw more accurate conclusions on uncertainties in trends.

On the other hand, in order to draw conclusions on sensitivities, the simpler tools may prove to be useful. We have compiled the output of various types of approaches, in this report the local approach and global (analytical correlation based) approach, the rough sensitivity analysis in Rypdal (1999) and the proposed standardised approach to identify key sources in Flugsrud, Irving and Rypdal (1999). Basically these approaches identify the same sources as important or key, but frequently rank them differently. These differences may be due to different time horizons (historical vs projected data), detail (evaluation at the level of emission factor/activity data rather than source estimate) and, in particular, disaggregation. It is very difficult to properly define the correct disaggregation level for the analysis or to properly model correlations. For example this is essential for the ranking of the $CO_2$ from combustion related emissions and $N_2O$ from agricultural soils. These sources will rank higher in importance in an aggregated (simple) analysis than in a more disaggregated. On the other hand, in a disaggregated analysis sources may appear non-important if dependencies (due to being based on the same assumptions) are not properly introduced. We will therefore conclude that the simpler tools are useful for judging sensitivities, but when applying methods at all levels a careful interpretation is needed in order to draw the right conclusions.

A number of assumptions/restrictions on the joint data set were made in section 2.3. To check on them we have also repeated parts of the simulations under other alternatives. The results were largely similar to those presented above. To a certain extent, therefore, we believe that our main conclusions are not sensitive towards these specific assumptions. Obviously, given the scope and complexity of the phenomenon of this study, it is difficult, perhaps even impossible, to pick out all the critical elements, and assess their influences on the analysis. First of all, as explained earlier, the simulation model here has been designed to approximate the actual emission model. In a way, it is impossible to evaluate the extent, or robustness, of such a model through the model-based techniques. In order to do so we have to 'step beyond' any particular model. Verification by comparing independent measurements/estimates based on different assumptions or by comparing with atmospheric concentrations may be useful techniques (IPCC 1998). Secondly, the distribution and uncertainty of each parameter involved in the simulation model do not command the same level of confidence. It is sometimes difficult to quantify/translate the expert judgements in terms of the simulation model. Neither can failure to do so be measured objectively and completely. Indeed, we feel that these are some of the subjects which demand long term methodological developments. A possible remedy, which may turn out to be resource consuming, is to perform the analysis using several teams, and compare their results as well as approaches afterwards. In this way we hope to be able to reduce the chance of overlooking some of the various critical aspects in any single attempt.

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## Appendix 1. Emission data and parameter formats used in the study.

Note that the emission data listed are the official data from 1999. Figures published and reported in 2000 are slightly different due to some recalculations.

### Parameter format of data (all years)

| Source | Label | Activity | Emission Factors $CO_2$ | $CH_4$ | $N_2O$ | HFC | $SF_6$ | PFC |
|---|---|---|---|---|---|---|---|---|
| **Total Energy** | **1** | | | | | | | |
| **A Fuel Combustin Activities** | **1A** | | | | | | | |
| **1 Energy Industries** | | | | | | | | |
| a Public Electricity and Heat Prod. | 1A1a | | | | | | | |
| Oil | | 1 | | | | | | |
| Coal/Coke | | 2 | | | | | | |
| Fuel wood (waste) | | 3 | | | | | | |
| Gas | | 4 | | | | | | |
| b Petroleum Refining | 1A1b | | | | | | | |
| Oil | | 5 | | | | | | |
| Gas | | 6 | | | | | | |
| c Manufacture of Solid Fuels ++ | 1A1c | | | | | | | |
| Oil | | 7 | | | | | | |
| Gas | | 8 | | | | | | |
| **2 Manufacturing Industries and Construction** | | | | | | | | |
| a Iron and Steel | 1A2a | | | | | | | |
| Oil | | 9 | | | | | | |
| Coal/Coke | | 10 | | | | | | |
| b Non-Ferrous Metals | 1A2b | | | | | | | |
| Oil | | 11 | | | | | | |
| Coal/Coke | | 12 | | | | | | |
| Fuel wood | | 13 | | | | | | |
| Gas | | 14 | | | | | | |
| Oil (Mg prod.) | | 15 | | | | | | |
| c Chemicals | 1A2c | | | | | | | |
| Oil | | 16 | | | | | | |
| Fuel wood | | 17 | | | | | | |
| Gas | | 18 | | | | | | |
| d Pulp, Paper and Print | 1A2d | | | | | | | |
| Oil | | 19 | | | | | | |
| Coal/Coke | | 20 | | | | | | |
| Fuel wood | | 21 | | | | | | |
| e Food Processing, Beverages | 1A2e | | | | | | | |
| Oil | | 22 | | | | | | |
| Coal/Coke | | 23 | | | | | | |
| Fuel wood | | 24 | | | | | | |
| Gas | | 25 | | | | | | |
| f Other | 1A2f | | | | | | | |
| Oil | | 26 | | | | | | |
| Coal/Coke | | 27 | | | | | | |
| Fuel wood | | 28 | | | | | | |
| **3 Transport** | **1A3** | | | | | | | |
| a Civil Aviation | | 29 | | | | | | |
| b Road Transportation | 1A3b | | | | | | | |
| Catalytic | | 30 | | | | | | |
| Non-catalytic | | 31 | | | | | | |
| c Railways | | 32 | | | | | | |
| d Navigation | | 33 | | | | | | |
| e Other | | 34 | | | | | | |
| **4 Other Sectors** | | | | | | | | |
| a Commercial/Institutional | 1A4a | | | | | | | |
| Oil | | 35 | | | | | | |
| Gas | | 36 | | | | | | |
| b Residential | 1A4b | | | | | | | |
| Oil | | 37 | | | | | | |
| Coal/Coke | | 38 | | | | | | |
| Fuel wood | | 39 | | | | | | |
| c Agriculture/Forestry/Fishing | 1A4c | | | | | | | |
| Oil | | 40 | | | | | | |
| Coal/Coke | | 41 | | | | | | |
| **B Fugitive Emissions from Fuels** | | | | | | | | |
| **1 Solid Fuels** | **1B1** | | | | | | | |
| a Coal Mining | 1B1a | 42 | | | | | | |
| b Solid Fuel Transformation | 1B1b | | | | | | | |
| c Other | 1B1c | | | | | | | |
| **2 Oil and Natural Gas** | **1B2** | | | | | | | |
| a Oil (incl. refineries, gasoline distr.) | 1B2a | | | | | | | |
| Oil loading | | 43 | | | | | | |
| Gasoline distribution | | 44 | | | | | | |
| Refineries | | 45 | | | | | | |
| b Natural Gas | | 46 | | | | | | |
| c Venting and Flaring | 1B2c | | | | | | | |
| Venting | | 47 | | | | | | |
| Flaring gas | | 48 | | | | | | |
| Well testing: Flaring oil/gas | | 49 | | | | | | |

| | | | |
|---|---|---|---|
| **Total Industrial Processes** | | **2** | |
| **A Mineral Products** | | **2A** | |
| 1 Cement Production | | | 50 |
| **B Chemical Industry** | | **2B** | |
| 1 Ammonia Production | | | 51 |
| 2 Nitric Acid Production | | 2B2 | |
| | | | 52 |
| 4 Carbide Production: | Calcium carbide | | 53 |
| | Silicon carbide | | 54 |
| 5 Other | | | 55 |
| | | | 56 |
| **C Metal Production** | | **2C** | |
| 1 Iron and Steel Production | | | 57 |
| 2 Ferroalloys Production | | | 58 |
| 3 Aluminium Production | | | 59 |
| 4 $SF_6$ Used in Aluminium and Magnesium | | | 60 |
| 5 Other | | | 61 |
| | | | 62 |
| **F Consumption of HFCs and $SF_6$** | | **2F** | |
| 1 Refrigration and Air Conditioning Eq. | | | 63 |
| **G Other** | liming agriculture | | **64** |
| | liming industrial waste | | **65** |
| **Total Solvent and Other Product Use** | | **3** | |
| **A Paint Application** | | | **66** |
| **C Chemical Products, Manufacture and Processing** | | | **67** |
| **D Other** | | | **68** |
| **Total Agriculture** | | **4** | |
| **A Enteric Fermentation** | | **4A** | |
| 1 Cattle | | | 69 |
| 3 Sheep | | | 70 |
| 4 Goats | | | 71 |
| 6 Horses | | | 72 |
| 8 Swine | | | 73 |
| 9 Poultry | | | 74 |
| 10 Other | | | 75 |
| **B Manure Management** | | | |
| 1 Cattle | | | 76 |
| 3 Sheep | | | 77 |
| 4 Goats | | | 78 |
| 6 Horses | | | 79 |
| 8 Swine | | | 80 |
| 9 Poultry | | | 81 |
| 13 Other | | | 82 |
| **D Agricultural Soils** | Fertiliser | | **83** |
| | Manure | | **84** |
| | Other | | **85** |
| **Total Waste** | | **6** | |
| **A Solid Waste Disposal on Land** | | **6A** | |
| | | | 86 |
| **B Wastewater Handling** | | **6B** | |
| 1 Industrial Wastewater | | | |
| 2 Domestic and Commercial Wastewater | | | 87 |
| | | | 88 |

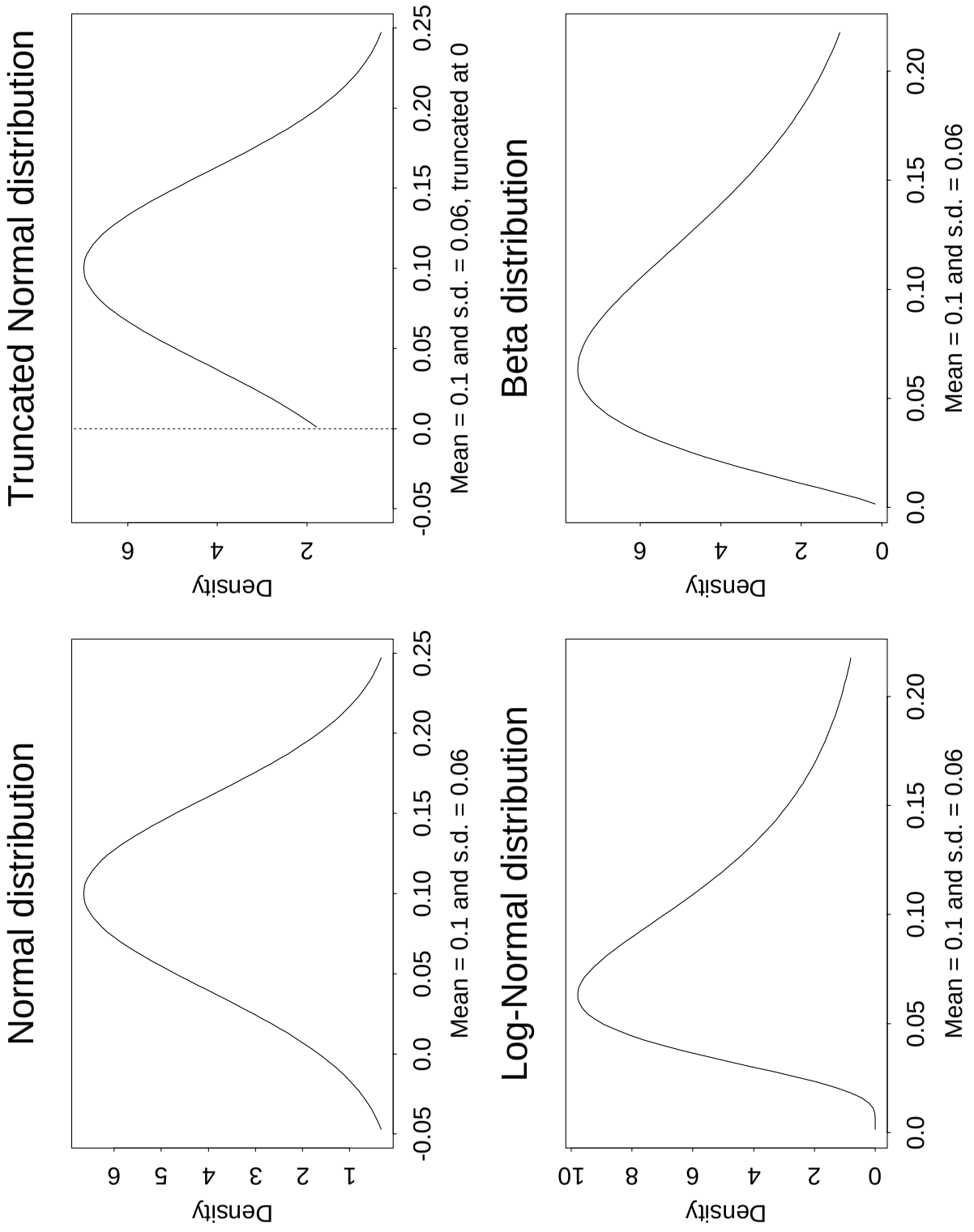
**Aggregated emission figures 1990. Tonnes.**

| | $CO_2$ | $CH_4$ | $N_2O$ | HFC | $SF_6$ | PFC |
|---|---|---|---|---|---|---|
| *Total* | *35 202 192* | *317 050* | *17 536* | *0.1* | *92* | *385* |
| **1. Total Energy** | 28 303 415 | 33 145 | 978 | 0 | 0 | 0 |
| A Fuel Combustion Activities | 26 403 131 | 13 173 | 967 | 0 | 0 | 0 |
| 1 Energy Industries | 7 408 184 | 2 257 | 62 | 0 | 0 | 0 |
| 2 Manufacturing Industries and Construction | 3 037 871 | 394 | 104 | 0 | 0 | 0 |
| 3 Transport | 13 533 111 | 3 728 | 693 | 0 | 0 | 0 |
| 4 Other Sectors | 2 423 964 | 6 793 | 108 | 0 | 0 | 0 |
| B Fugitive Emissions from Fuels | 1 900 284 | 19 972 | 11 | 0 | 0 | 0 |
| 1 Solid Fuels | 11 616 | 4 239 | 0 | 0 | 0 | 0 |
| 2 Oil and Natural Gas | 1 888 668 | 15 733 | 11 | 0 | 0 | 0 |
| **2. Total Industrial Processes** | 6 718 099 | 1 000 | 6 650 | 0.1 | 92 | 385 |
| A Mineral Products | 652 789 | 0 | 0 | 0 | 0 | 0 |
| B Chemical Industry | 1 095 875 | 1 000 | 6 650 | 0 | 0 | 0 |
| C Metal Production | 4 769 313 | 0 | 0 | 0 | 92 | 385 |
| F Consumption of Halocarbons and Sulphur Hexafluoride | 0 | 0 | 0 | 0.1 | 0 | 0 |
| G Other | 200 122 | 0 | 0 | 0 | 0 | 0 |
| **3. Total Solvent and Other Product Use** | 144 486 | 0 | 0 | 0 | 0 | 0 |
| **4. Total Agriculture** | 0 | 100 830 | 9 547 | 0 | 0 | 0 |
| A Enteric Fermentation | 0 | 86 112 | 0 | 0 | 0 | 0 |
| B Manure Management | 0 | 14 718 | 0 | 0 | 0 | 0 |
| D Agricultural Soils | 0 | 0 | 9 547 | 0 | 0 | 0 |
| **6. Waste Managment** | 36 192 | 182 076 | 361 | 0 | 0 | 0 |
| A Solid Waste Disposal on Land | 36 192 | 181 694 | 0 | 0 | 0 | 0 |
| B Wastewater Handling | 0 | 382 | 361 | 0 | 0 | 0 |

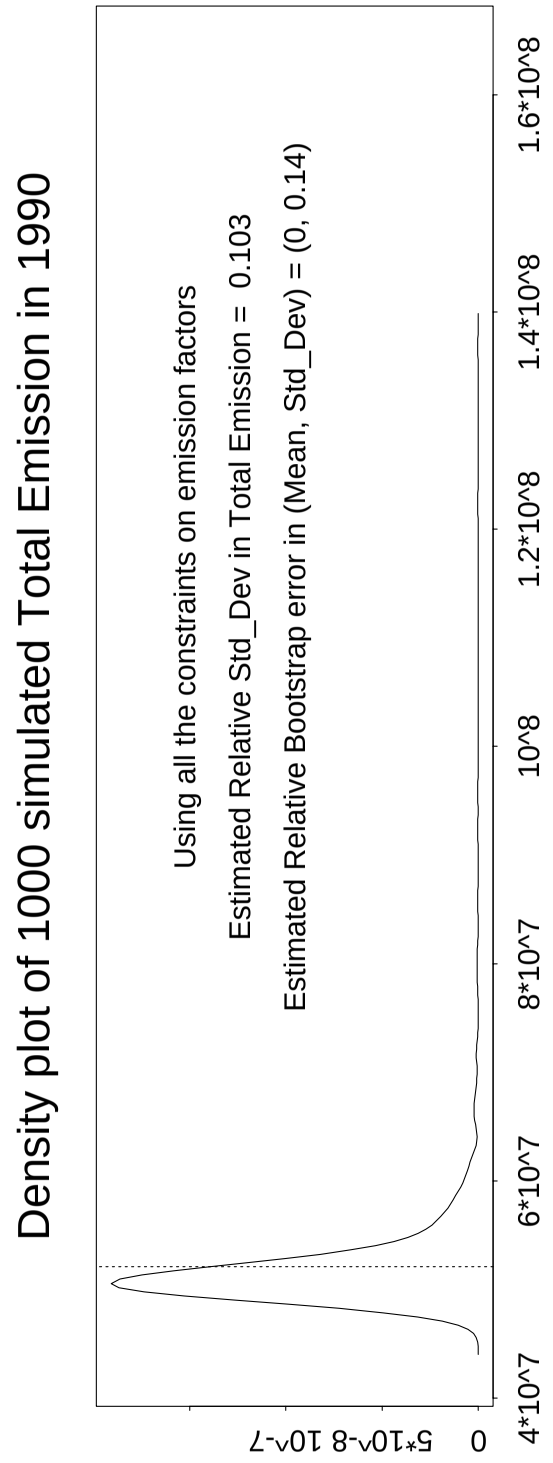
**Aggregated emission figures 2010. Tonnes.**

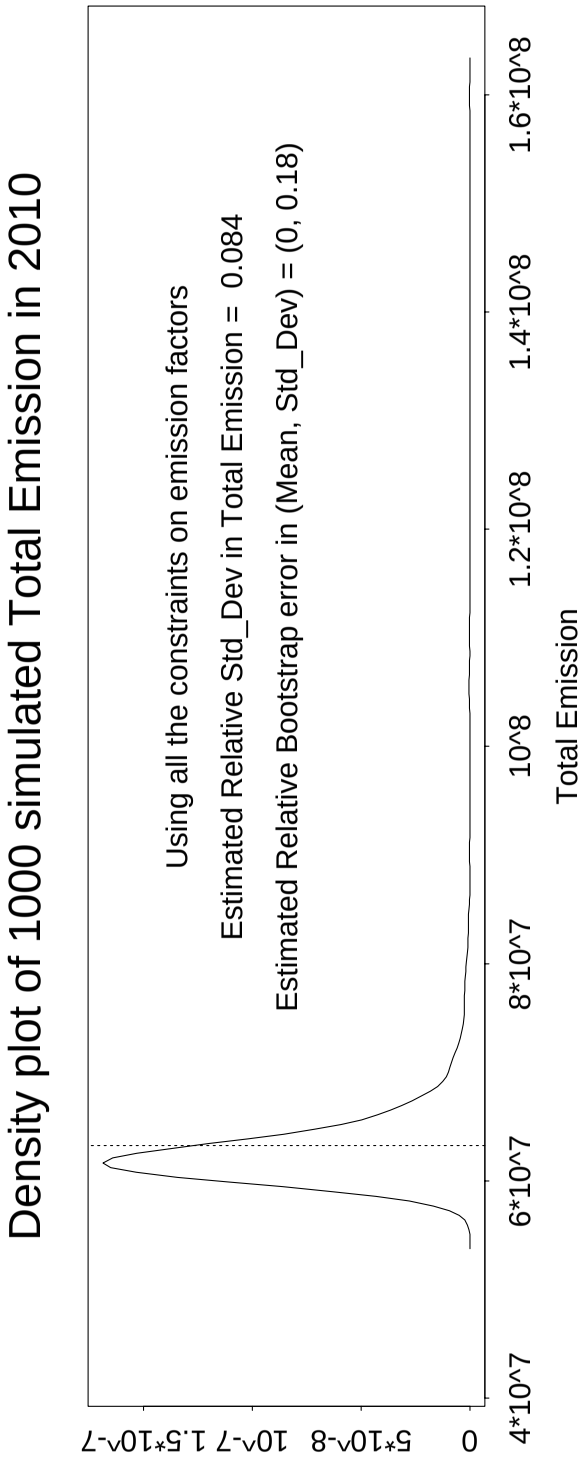
| | $CO_2$ | $CH_4$ | $N_2O$ | HFC | $SF_6$ | PFC |
|---|---|---|---|---|---|---|
| *Total* | *47 961 275* | *285 672* | *19 281* | *57.6* | *21* | *185* |
| **1. Total Energy** | 4 032 084 | 33 690 | 2 833 | 0 | 0 | 0 |
| A Fuel Combustion Activities | 36 803 251 | 14 312 | 2 812 | 0 | 0 | 0 |
| 1 Energy Industries | 12 351 602 | 4 157 | 102 | 0 | 0 | 0 |
| 2 Manufacturing Industries and Construction | 3 388 997 | 563 | 154 | 0 | 0 | 0 |
| 3 Transport | 17 888 988 | 2 324 | 2 435 | 0 | 0 | 0 |
| 4 Other Sectors | 3 173 665 | 7 267 | 120 | 0 | 0 | 0 |
| B Fugitive Emissions from Fuels | 3 522 834 | 19 378 | 21 | 0 | 0 | 0 |
| 1 Solid Fuels | 10 222 | 3 730 | 0 | 0 | 0 | 0 |
| 2 Oil and Natural Gas | 3 512 612 | 15 648 | 21 | 0 | 0 | 0 |
| **2. Total Industrial Processes** | 7 461 389 | 1 199 | 6 650 | 579.6 | 21 | 185 |
| A Mineral Products | 1 207 660 | 0 | 0 | 0 | 0 | 0 |
| B Chemical Industry | 1 379 680 | 1 199 | 6 650 | 0 | 0 | 0 |
| C Metal Production | 4 673 927 | 0 | 0 | 0 | 21 | 185 |
| F Consumption of Halocarbons and Sulphur Hexafluoride | 0 | 0 | 0 | 579.6 | 0 | 0 |
| G Other | 200 122 | 0 | 0 | 0 | 0 | 0 |
| **3. Total Solvent and Other Product Use** | 144 486 | 0 | 0 | 0 | 0 | 0 |
| **4. Total Agriculture** | 0 | 102 846 | 9 437 | 0 | 0 | 0 |
| A Enteric Fermentation | 0 | 87 834 | 0 | 0 | 0 | 0 |
| B Manure Management | 0 | 15 012 | 0 | 0 | 0 | 0 |
| D Agricultural Soils | 0 | 0 | 9 437 | 0 | 0 | 0 |
| **6. Waste Managment** | 29 316 | 147 936 | 361 | 0 | 0 | 0 |
| A Solid Waste Disposal on Land | 29 316 | 147 172 | 0 | 0 | 0 | 0 |
| B Wastewater Handling | 0 | 763 | 361 | 0 | 0 | 0 |

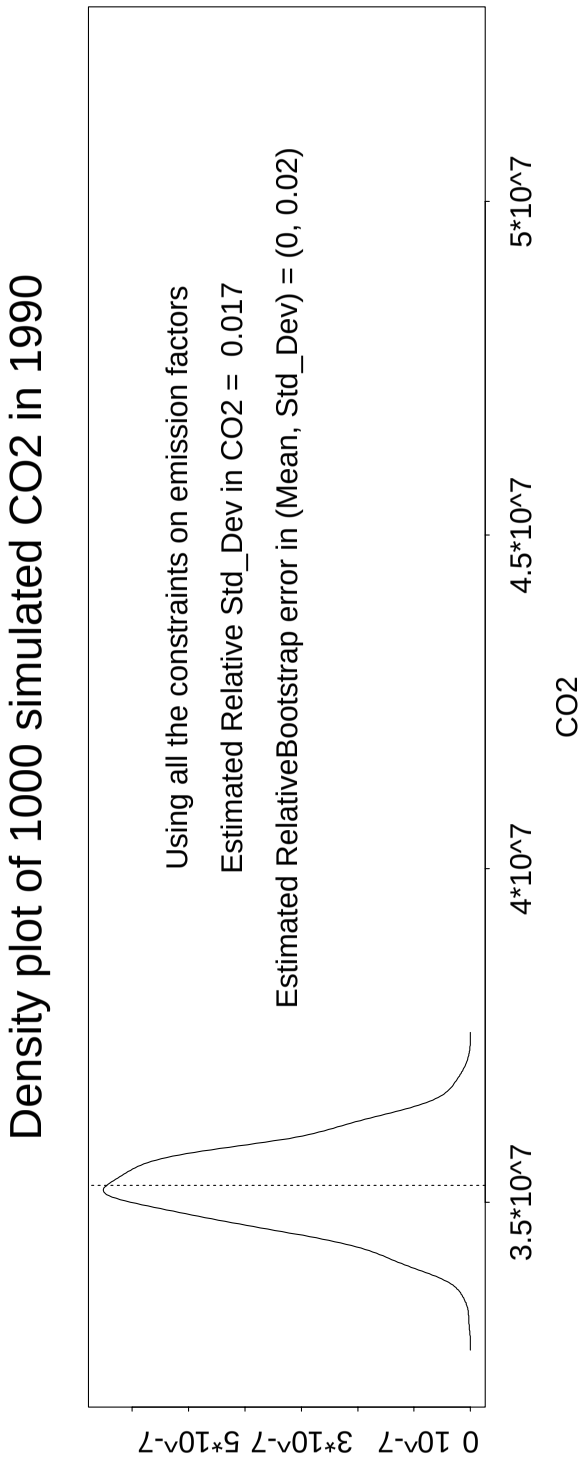
**Appendix 2. Model probability density functions**

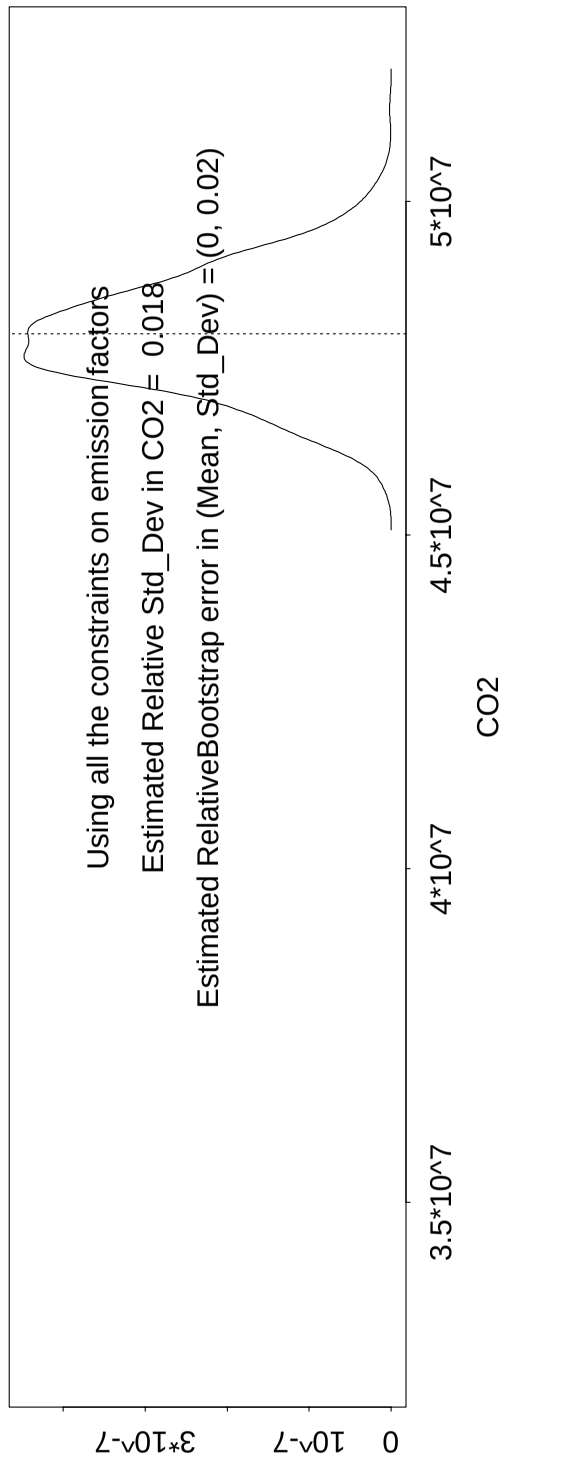


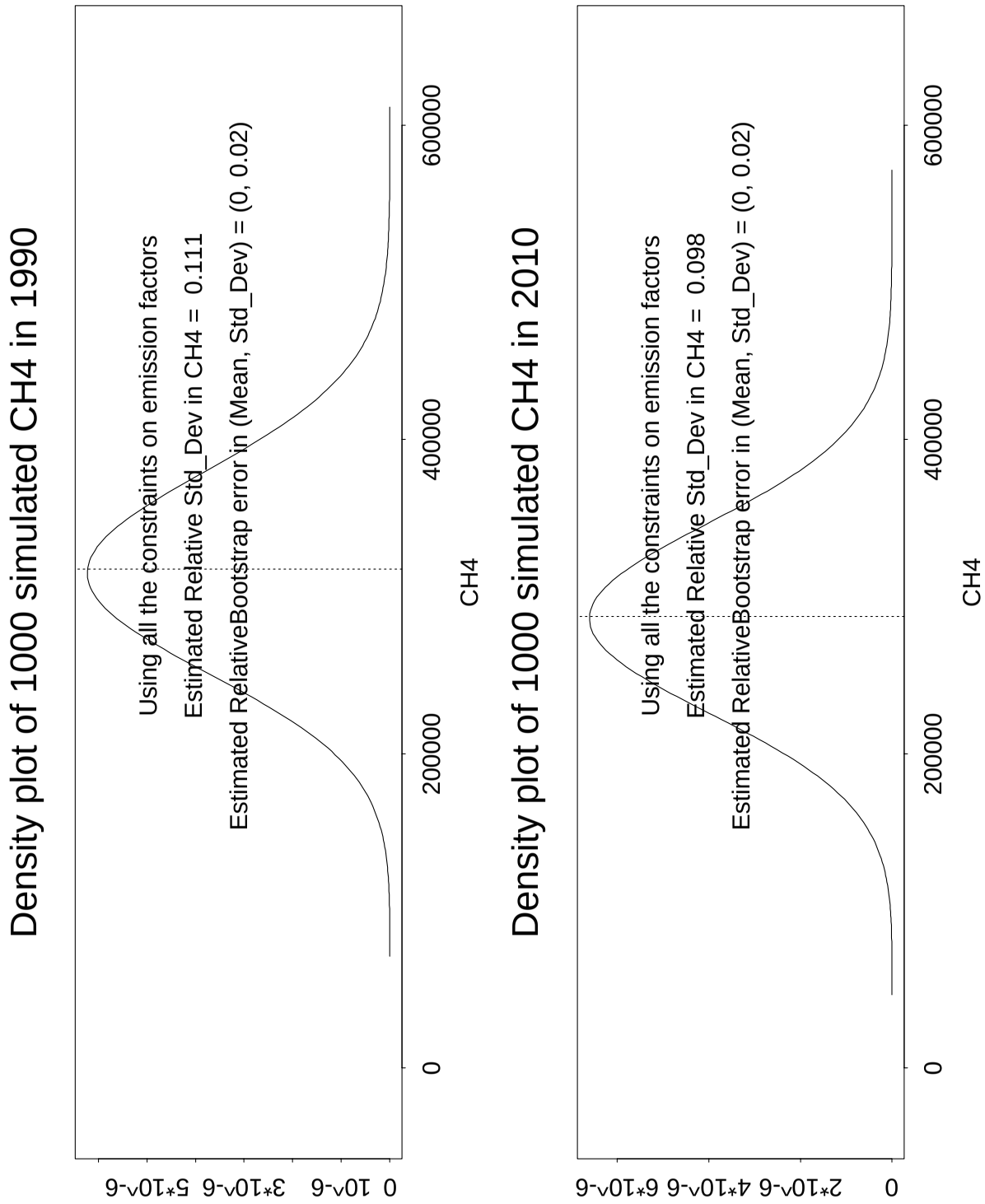
**Appendix 3. Density plots of final data set**

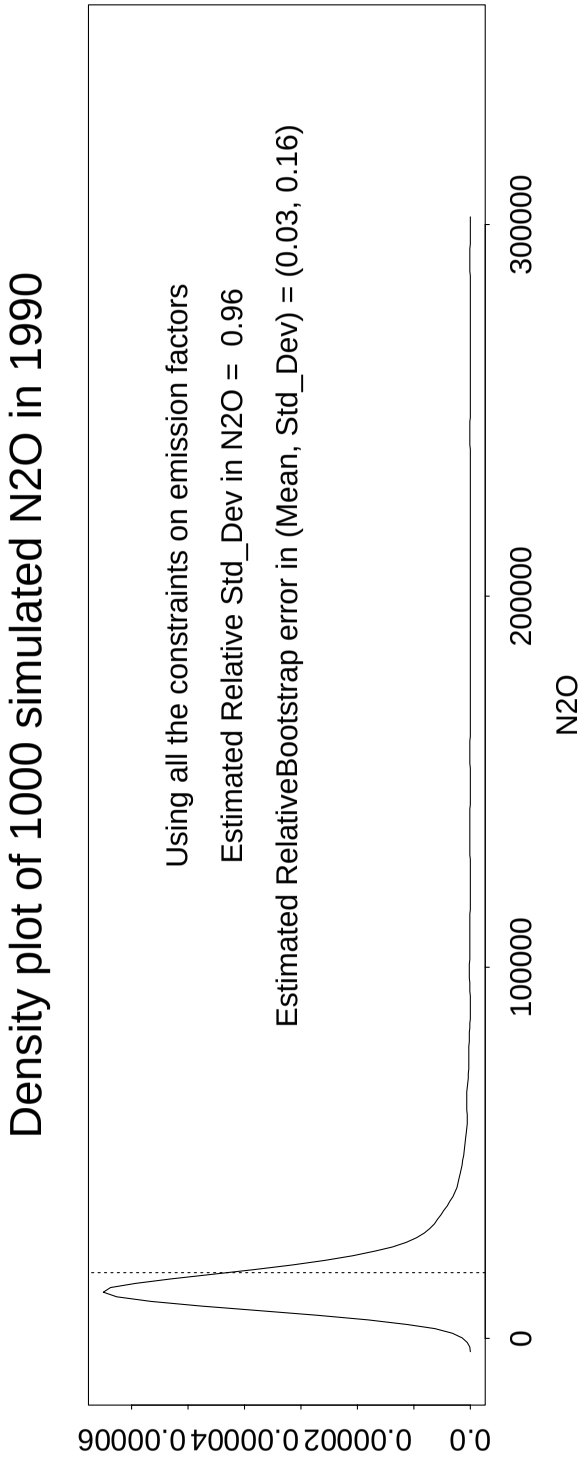


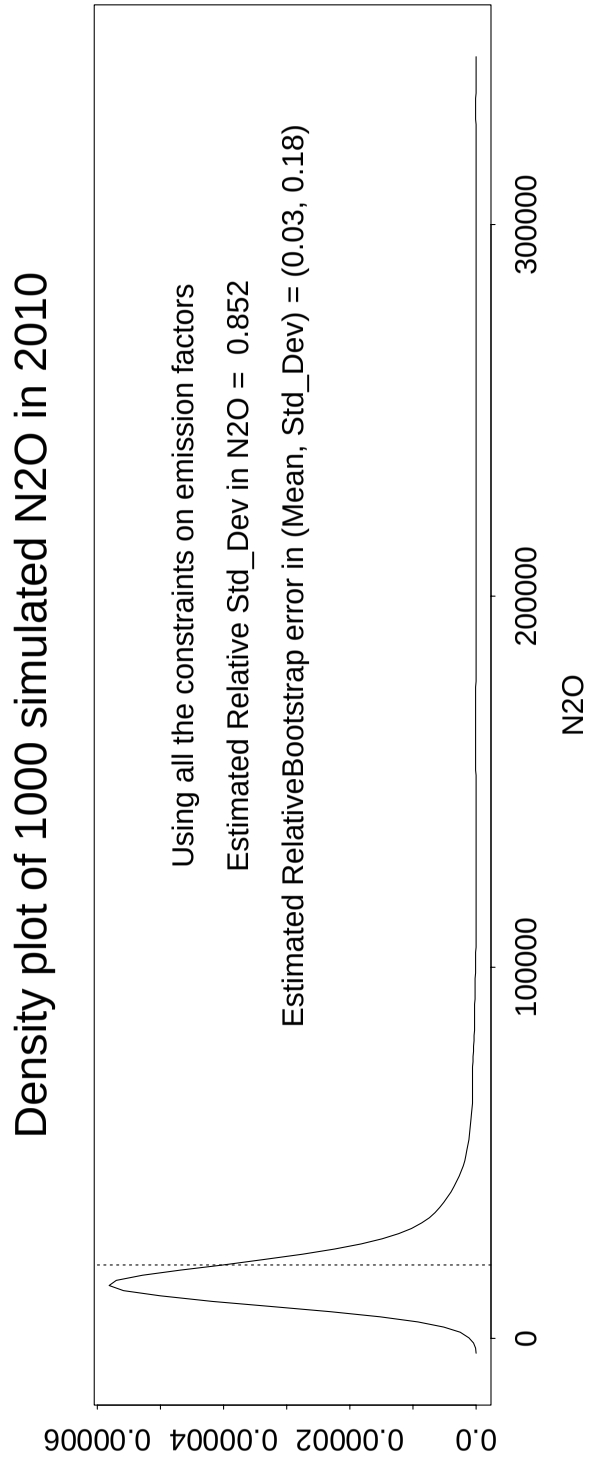



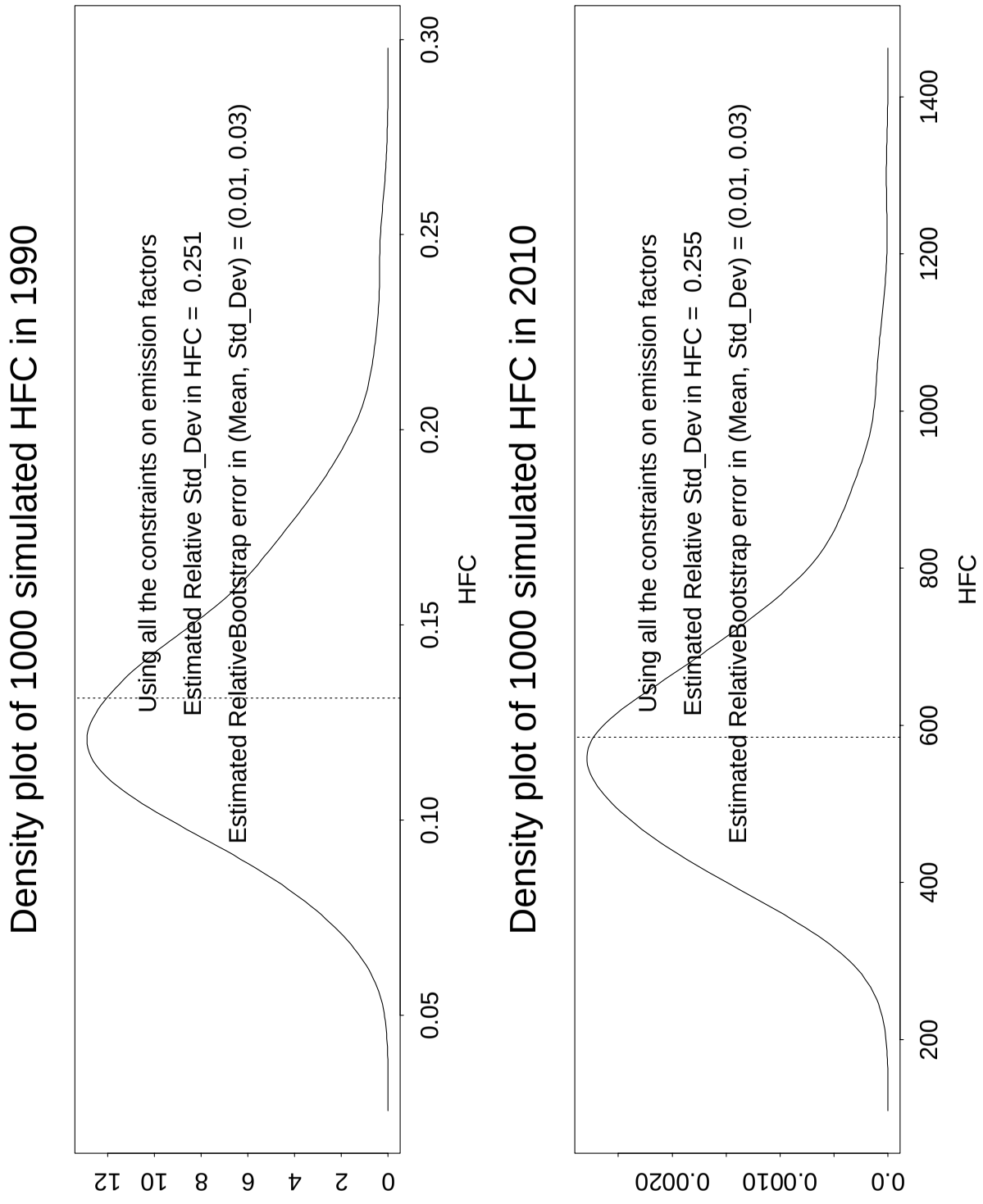

Density plot of 1000 simulated CO2 in 1990
Using all the constraints on emission factors
Estimated Relative Std_Dev in CO2 = 0.017
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0, 0.02)
0
10^-7
3*10^-7
5*10^-7
3.5*10^7
4*10^7
4.5*10^7
5*10^7
CO2

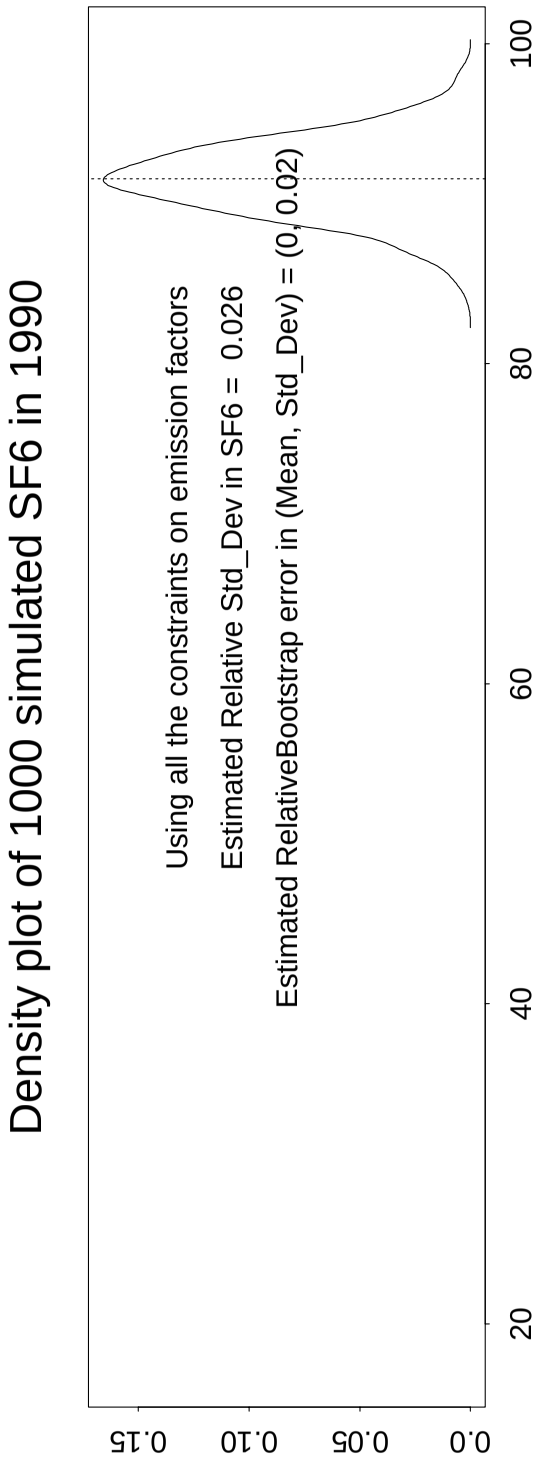

Density plot of 1000 simulated CO2 in 2010
Using all the constraints on emission factors
Estimated Relative Std_Dev in CO2 = 0.018
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0, 0.02)
0
10^-7
3*10^-7
3.5*10^7
4*10^7
4.5*10^7
5*10^7
CO2

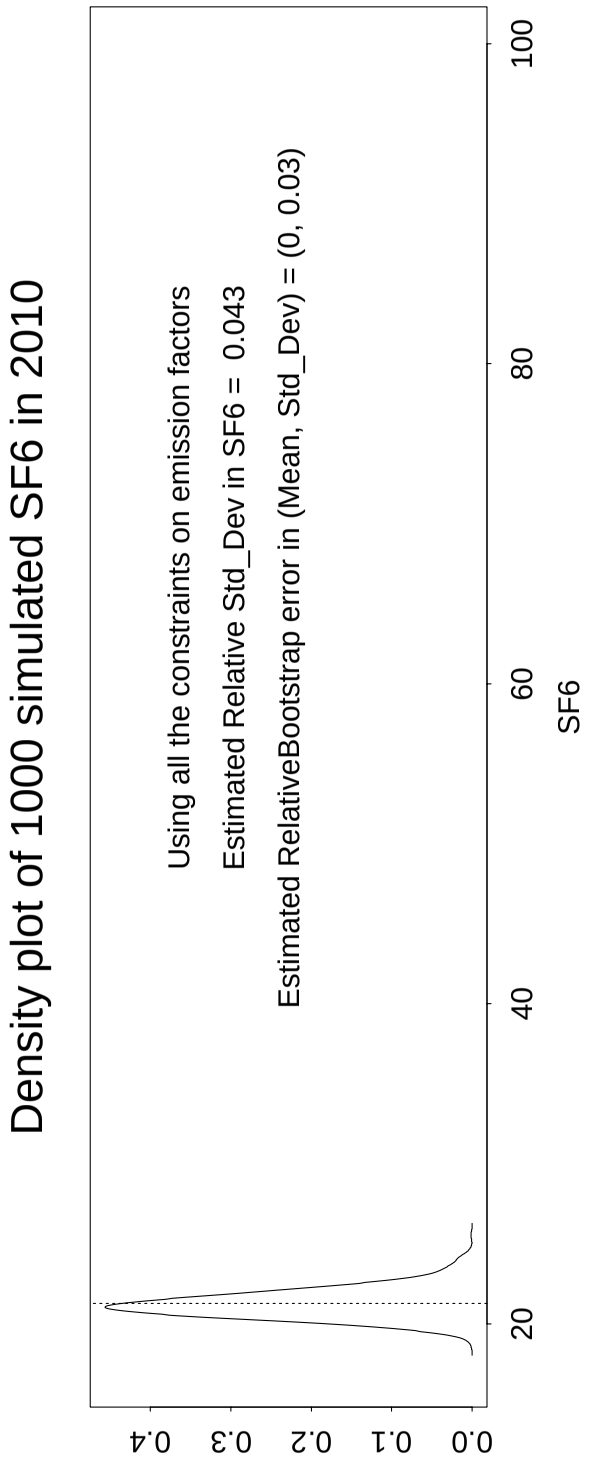

Density plot of 1000 simulated CH4 in 1990
Using all the constraints on emission factors
Estimated Relative Std_Dev in CH4 = 0.111
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0, 0.02)
0 10^-6 3*10^-6 5*10^-6
0 200000 400000 600000
CH4
Density plot of 1000 simulated CH4 in 2010
Using all the constraints on emission factors
Estimated Relative Std_Dev in CH4 = 0.098
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0, 0.02)
0 2*10^-6 4*10^-6 6*10^-6
0 200000 400000 600000
CH4

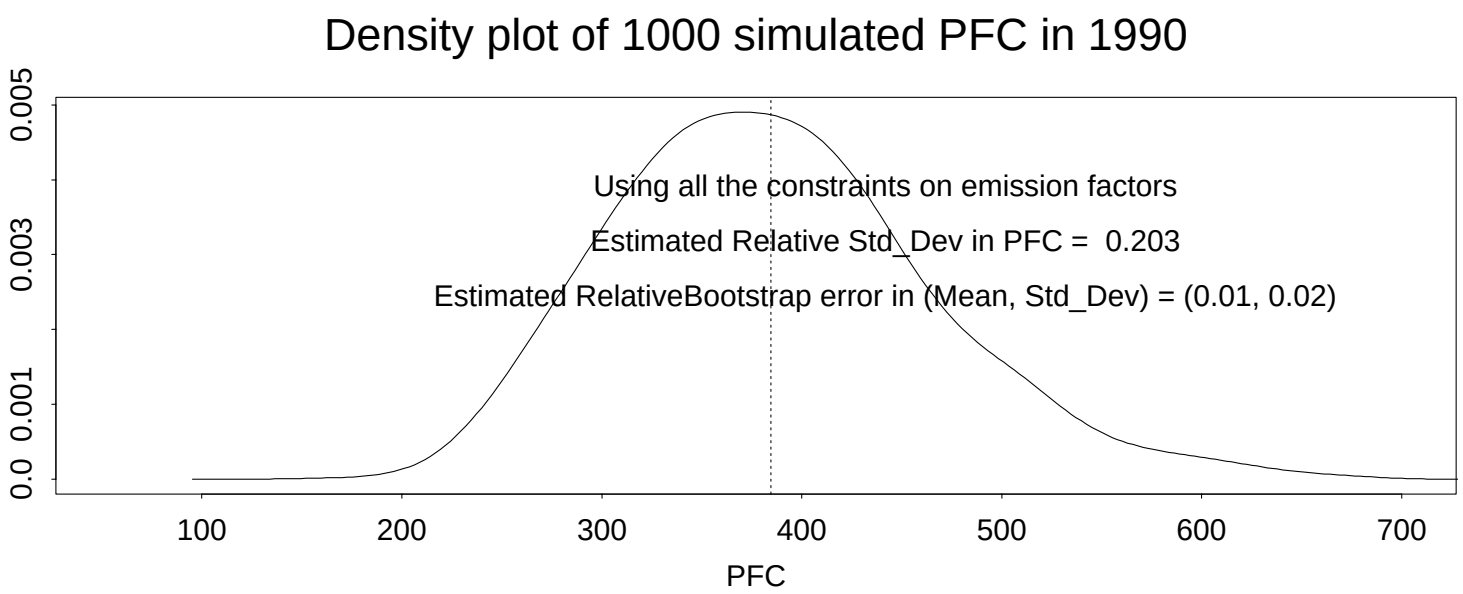

Density plot of 1000 simulated N2O in 1990
Using all the constraints on emission factors
Estimated Relative Std_Dev in N2O = 0.96
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0.03, 0.16)
0.0
0.00002
0.00004
0.00006
0
100000
200000
300000
N2O

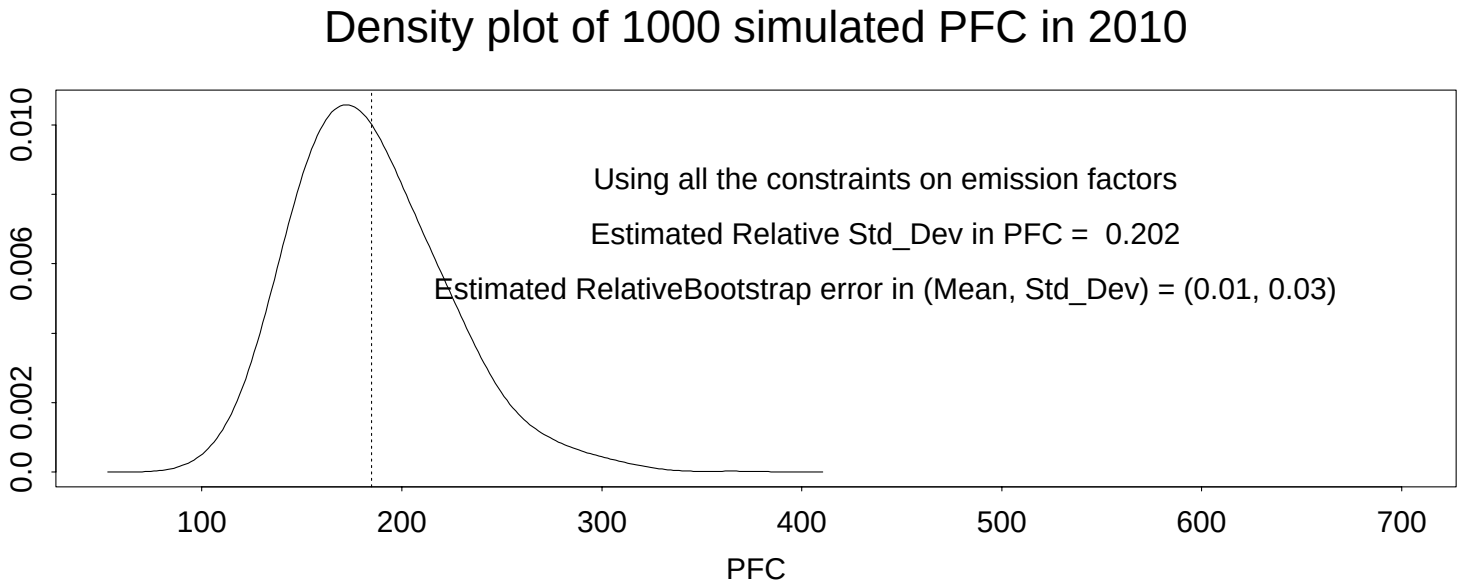

Density plot of 1000 simulated N2O in 2010
Using all the constraints on emission factors
Estimated Relative Std_Dev in N2O = 0.852
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0.03, 0.18)
0.0
0.00002
0.00004
0.00006
0
100000
200000
300000
N2O

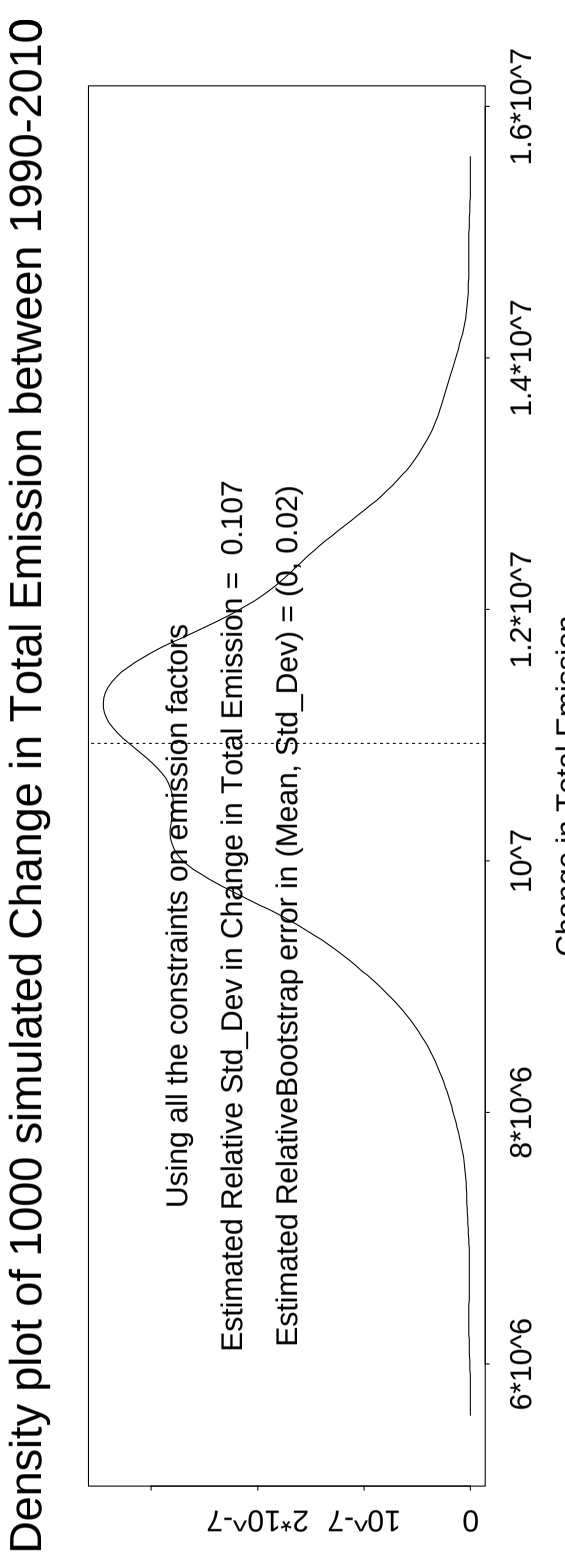

Density plot of 1000 simulated HFC in 1990
Using all the constraints on emission factors
Estimated Relative Std_Dev in HFC = 0.251
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0.01, 0.03)
0
2
4
6
8
10
12
0.05
0.10
0.15
0.20
0.25
0.30
HFC
Density plot of 1000 simulated HFC in 2010
Using all the constraints on emission factors
Estimated Relative Std_Dev in HFC = 0.255
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0.01, 0.03)
0.0
0.0010
0.0020
200
400
600
800
1000
1200
1400
HFC

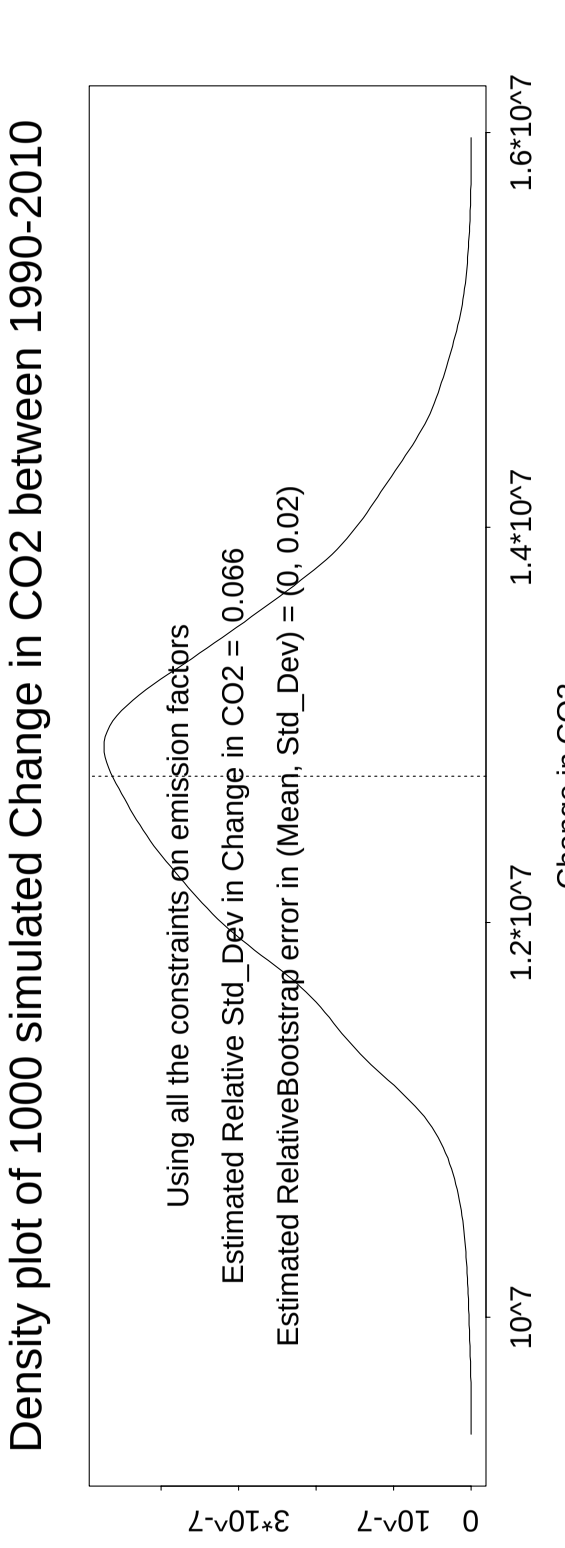

Density plot of 1000 simulated SF6 in 1990
Using all the constraints on emission factors
Estimated Relative Std_Dev in SF6 = 0.026
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0, 0.02)
0.0
0.05
0.10
0.15
20
40
60
80
100
SF6

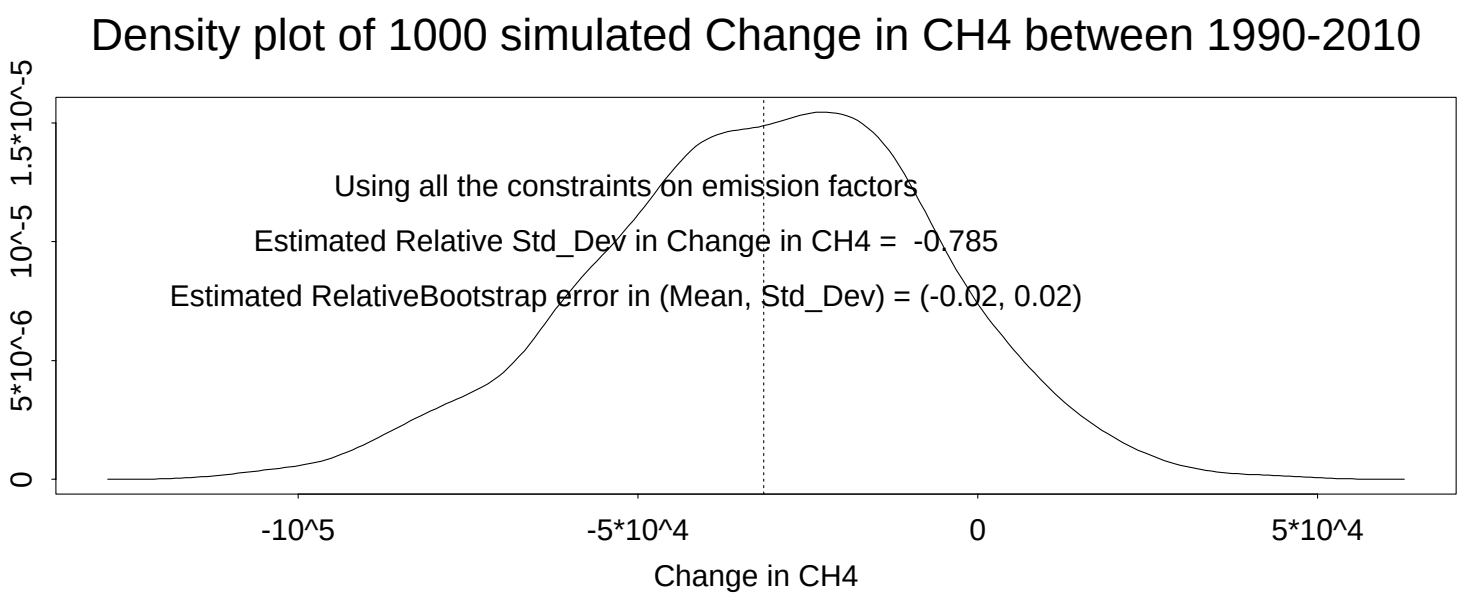

Density plot of 1000 simulated SF6 in 2010
Using all the constraints on emission factors
Estimated Relative Std_Dev in SF6 = 0.043
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0, 0.03)
0.0
0.1
0.2
0.3
0.4
20
40
60
80
100
SF6

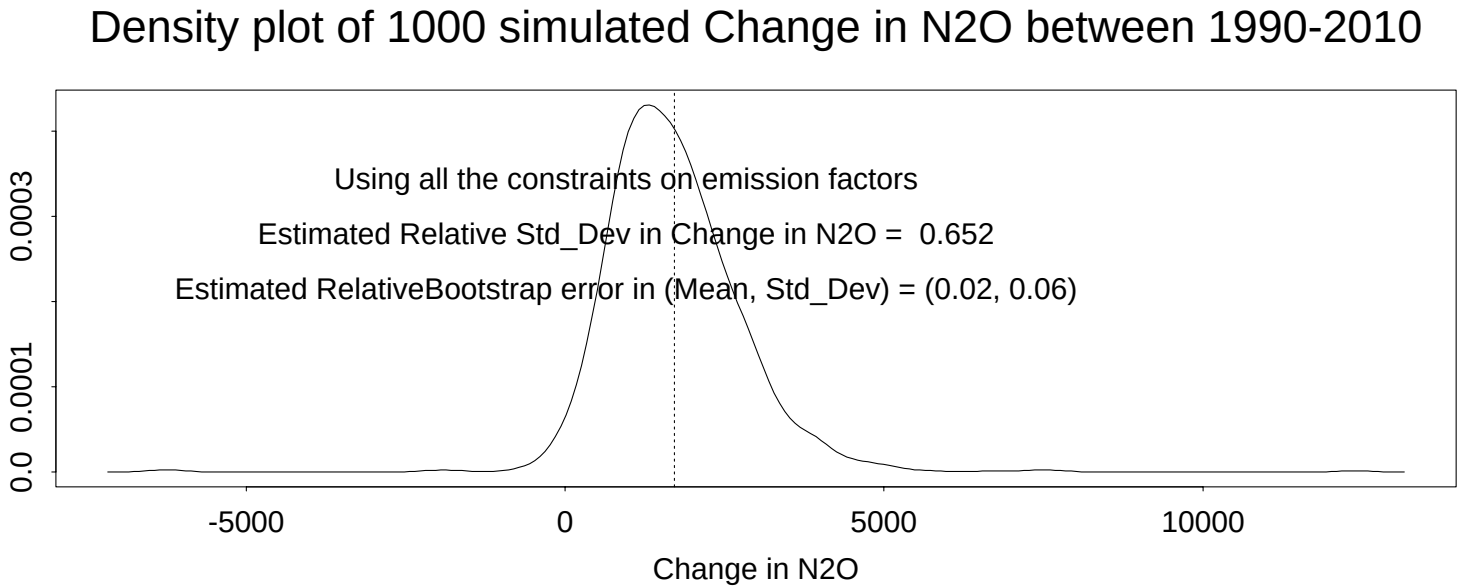

Density plot of 1000 simulated PFC in 1990
Using all the constraints on emission factors
Estimated Relative Std_Dev in PFC = 0.203
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0.01, 0.02)
0.0
0.001
0.003
0.005
100
200
300
400
500
600
700
PFC

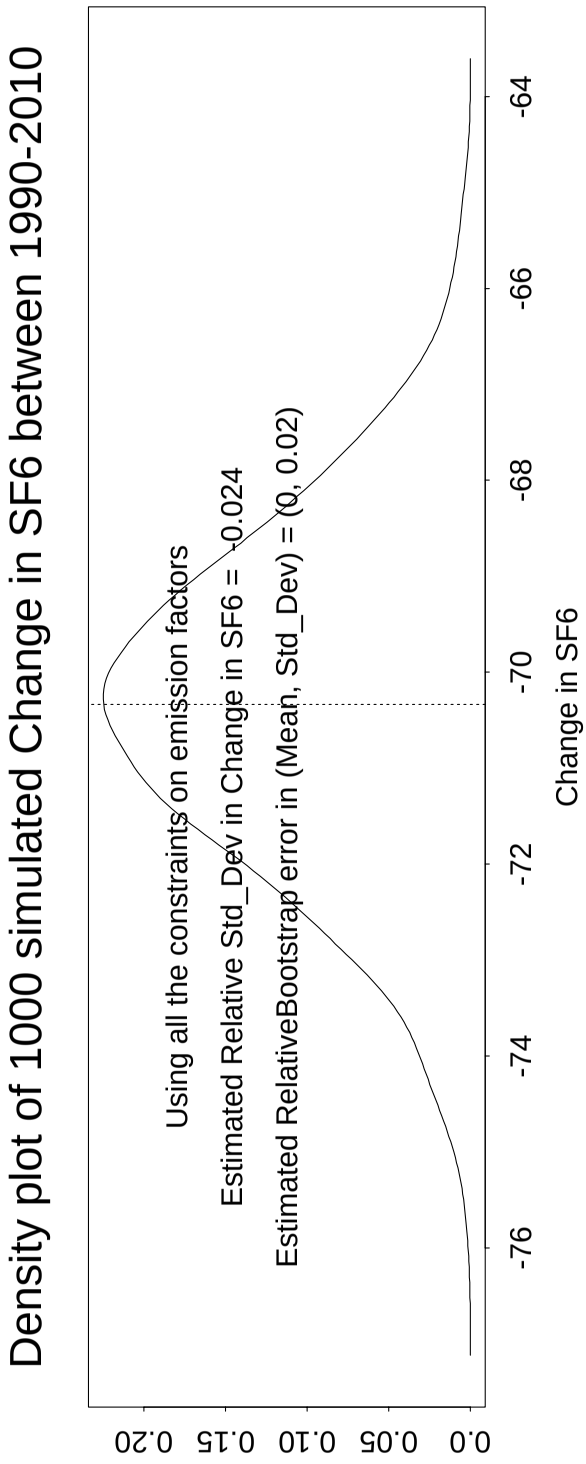

Density plot of 1000 simulated PFC in 2010
Using all the constraints on emission factors
Estimated Relative Std_Dev in PFC = 0.202
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0.01, 0.03)
0.0
0.002
0.006
0.010
100
200
300
400
500
600
700
PFC

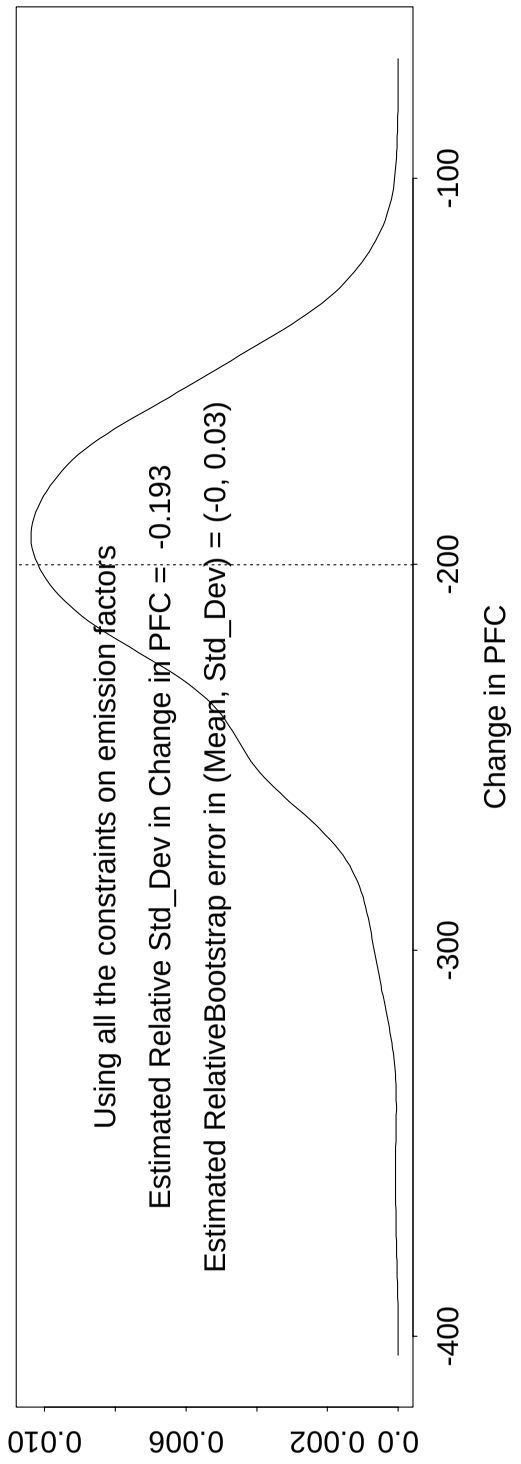

Density plot of 1000 simulated Change in Total Emission between 1990-2010
Using all the constraints on emission factors
Estimated Relative Std_Dev in Change in Total Emission = 0.107
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0, 0.02)
0
10^-7
2*10^-7
6*10^6
8*10^6
10^7
1.2*10^7
1.4*10^7
1.6*10^7
Change in Total Emission


Density plot of 1000 simulated Change in CO2 between 1990-2010
Using all the constraints on emission factors
Estimated Relative Std_Dev in Change in CO2 = 0.066
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0, 0.02)
0
10^-7
3*10^-7
10^7
1.2*10^7
1.4*10^7
1.6*10^7
Change in CO2


Density plot of 1000 simulated Change in CH4 between 1990-2010
Using all the constraints on emission factors
Estimated Relative Std_Dev in Change in CH4 = -0.785
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (-0.02, 0.02)
0
5*10^-6
10^-5
1.5*10^-5
-10^5
-5*10^4
0
5*10^4
Change in CH4


Density plot of 1000 simulated Change in N2O between 1990-2010
Using all the constraints on emission factors
Estimated Relative Std_Dev in Change in N2O = 0.652
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0.02, 0.06)
0.0
0.0001
0.0003
-5000
0
5000
10000
Change in N2O


Density plot of 1000 simulated Change in SF6 between 1990-2010
Using all the constraints on emission factors
Estimated Relative Std_Dev in Change in SF6 = -0.024
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (0, 0.02)
0.0
0.05
0.10
0.15
0.20
-76
-74
-72
-70
-68
-66
-64
Change in SF6


Density plot of 1000 simulated Change in PFC between 1990-2010
Using all the constraints on emission factors
Estimated Relative Std_Dev in Change in PFC = -0.193
Estimated RelativeBootstrap error in (Mean, Std_Dev) = (-0, 0.03)
0.0
0.002
0.006
0.010
-400
-300
-200
-100
Change in PFC

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