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Monte Carlo analysis of uncertainties in the Netherlands greenhouse gas emission inventory for 1990–2004

Andrea Ramírez [a,*], Corry de Keizer [a], Jeroen P. Van der Sluijs [a], Jos Olivier [b], Laurens Brandes [b]

[a] Copernicus Institute, Utrecht University, Heidelberglaan 2 3584 CS Utrecht, The Netherlands
[b] The Netherlands Environmental Assessment Agency, Postbus 303 3720 AH Bilthoven, The Netherlands

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ABSTRACT

This paper presents an assessment of the value added of a Monte Carlo analysis of the uncertainties in the Netherlands inventory of greenhouse gases over a Tier 1 analysis. It also examines which parameters contributed the most to the total emission uncertainty and identified areas of high priority for the further improvement of the accuracy and quality of the inventory. The Monte Carlo analysis resulted in an uncertainty range in total GHG emissions of 4.1% in 2004 and 5.4% in 1990 (with LUCF) and 5.3% (in 1990) and 3.9% (in 2004) for GHG emissions without LUCF. Uncertainty in the trend was estimated at 4.5%. The values are in the same order of magnitude as those estimated in the Tier 1. The results show that accounting for correlation among parameters is important, and for the Netherlands inventory it has a larger impact on the uncertainty in the trend than on the uncertainty in the total GHG emissions. The main contributors to overall uncertainty are found to be related to N_2O emissions from agricultural soils, the N_2O implied emission factors of Nitric Acid Production, CH_4 from managed solid waste disposal on land, and the implied emission factor of CH_4 from manure management from cattle.

1. Introduction

In its 2000 report the Intergovernmental Panel on Climate Change (IPCC) established guidelines that prescribe how uncertainties in National Greenhouse Gas Inventory Reports (NIR) should be analyzed and reported (IPCC, 2000). The guidance offers countries a choice between simplified uncertainty analysis that uses error propagation equations (Tier 1), and a comprehensive Monte Carlo based analysis on a more detailed level of aggregation (Tier 2). In its NIR, the Netherlands annually reports uncertainties according to the Tier 1 method. A first Tier 2 analysis was carried out for the Netherlands for the 1999 emissions (Olsthoorn and Pielaat, 2003) in order to explore the viability of Tier 2. That study concluded that there was no need to repeat a Tier 2 every year because it was unlikely that uncertainties would change quickly over the years.

In the framework of a continuous improvement of the Netherlands emission inventory, recently the way in which emissions are calculated has been changed substantially. This has led to recalculations, also for the reference year 1990, which have been included in the NIR and the Common Reporting Format (CRF) for 2005. The Tier 1 analysis shows substantial differences in calculated uncertainty in GHG emissions before and after the recalculations. Consequently, substantial changes in outcome due to improvements in inventory methodology are expected for Tier 2 outcomes as well. Furthermore, the earlier Tier 2 study could not easily be compared to the Tier 1 study for the same year because the aggregation level differed significantly and the uncertainty assumptions were not harmonized across the two studies. This made it impossible to get a clear insight into the added value of a Tier 2 (more particularly, of accounting for

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* Corresponding author. Tel.: +31 30 2537639; fax: +31 30 2537601.
E-mail address: c.a.ramirez@uu.nl (A. Ramírez).

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correlations and including non-normal distributions) compared to a Tier 1. In addition, there has been little exploration of the effect of correlations, whereas the possibility to include correlations it is widely seen as one of the main advantages of Tier 2. Finally, it should be noted that for the NIR the Netherlands uses an improved version of Tier 1 by taking into account an extra term of the taylor series. It is expected that this improvement diminishes the differences in outcome between Tier 1 and Tier 2 but to explore that, a Monte Carlo analysis is needed at a comparable aggregation level and using the same assumptions for uncertainty ranges as the Tier 1 study where possible. In this context, the objective of the present study is four-fold:

- To perform a Monte Carlo analysis of uncertainties in the NIR, accounting for all known correlations and using similar assumptions for uncertainty ranges as the Tier 1;
- To obtain insight into the differences in outcomes between the improved Tier 1 used annually in the Netherlands NIR and the Tier 2;
- To obtain insight into how the Netherlands Tier 2 and the Netherlands assumptions for uncertainty ranges in activity data and emission factors relate to Tier 2 studies performed in other European countries;
- To provide advice regarding the necessity and frequency of future Tier 2 studies for the Netherlands.

Note that the present study is not a full-blown Tier 2 analysis but merely a Monte Carlo analysis at the Tier 1 aggregation level and using data and uncertainty assumptions from the Tier 1 study. A full-blown Tier 2 analysis would require a much more detailed emission model, implementing the Monte Carlo analysis using emission factors of individual fuels and processes, whereas at the Tier 1 aggregation level implied emission factors are used. Many correlations can be modeled much more adequately at a Tier 2 aggregation level, but the data required for a full-blown Tier 2 were not available for this project. It should also be emphasized that the NIR covers only those GHG emissions that are regulated under the Kyoto protocol. This mismatch between “real” anthropogenic GHG emissions and the subset covered by the Kyoto protocol is outside the scope of this study. It should also be emphasized that the inventory method developed by the IPCC is taken for granted in this uncertainty analysis. For instance, uncertainties in the so-called “global warming potentials” that are used to calculate CO_2-equivalents for emissions of non-CO_2 GHG are not included in the present analysis, and the model structure uncertainty (Refsgaard et al., 2006) is not assessed in this study. The scope of the present uncertainty analysis is mainly limited to uncertainty in activity data and emission factors. The present study is thus a partial uncertainty assessment. For a more comprehensive approach to uncertainty assessment and communication we refer to Janssen et al. (2005).

2. Methodology

A Monte Carlo analysis has been applied to the calculations used to estimate GHG emissions in the Netherlands. The analysis is performed for the Kyoto base year (1990/1995) and for 2004. The probability distribution functions (PDF) of the activity data and emission factors for each sub-sector are inputs into an emission model. The model calculates the distribution function for the emissions of each sub-sector, sector and the country by GHG type (CO_2, CH_4, N_2O, F-gas). Basic data for the emission calculations has been extracted from detailed background information of the Dutch NIR as provided by the Netherlands Environmental Assessment Agency (PBL). The level of sector aggregation was determined by the level of aggregation used in the Tier 1 analysis. The software package @Risk was used to assess the propagation of uncertainties in the emission model. In general terms, emissions are calculated by applying an emission factor to an appropriate activity statistic. The PDF assumed for the emission factors and activity data were based on the uncertainty ranges used in the existing Tier 1 analysis, complemented with expert judgment by experts from the PBL. In line with IPCC guidelines, normal distributions were used as the standard type in this study for parameters considered having a symmetrical uncertainty distribution and a limited range relative to the mean value (coefficient of variation $< 30\%$ for parameters that cannot be negative). We took into account non-Gaussian PDFs where appropriate. Log normal distributions were used for parameters with non-negative values and a standard deviation as reported in the TIER 1 was equal or greater than 30%. For parameters where it is possible to identify a range of possible values but is not possible to decide which value is more likely to occur, we used uniform distributions. When we had some certainty about the most expected value and the minimum and maximum of the range, but the shape of the distribution was not precisely known a triangular distribution was used. Furthermore in this paper we have considered three types of correlation factors: i) fully correlated ($r = 1$), when for instance a fuel has the same emission factor between sectors and/or between years; ii) independent ($r = 0$); and iii) partially correlated. In the latter case we have considered a $r = 0.75$, when for instance, implied emission factors between years for a given fuel diverge by less than 10%. We assume that the divergence is caused by a small change in the mix of fuels (since the same fuels mix is assumed to be present, the implied emission factors between the years are correlated). We assigned a correlation factor of 0.5 when, for instance, a fuel has an emission factor that between years diverge in the range of 10–40%. When the same fuel has emission factors that diverge by more than 40% (between years or between sectors), we assume this to be no correlated. The correlation factors used only reflect our qualitative understanding of the relations. A sensitivity analysis will be performed to assess their influence in the robustness of the results. A detailed overview of the PDFs, uncertainties and known correlations used in our analysis can be found in Ramírez et al. (2006). Following the IPCC Tier 2 method (IPCC, 2000), uncertainties in the trend emissions were calculated in absolute and in relative terms, and a key source analysis was undertaken.

Furthermore, the expert judgments and assumptions taken into account in this research have been compared to the uncertainty assumptions (and their underpinnings) used in Tier 2 studies by other European countries:

Table 1
Pedigree matrix for emission monitoring

Scale value	Proxy	Empirical basis	Methodological rigour	Validation
4	Exact measure	Large sample of direct measurements	Best available practice	Compared with independent measurements of same variable
3	Good fit or measure	Small sample of direct measurements	Reliable method commonly accepted	Compared with independent measurements of closely related variable
2	Well correlated	Modelled/derived data	Acceptable method limited consensus on reliability	Compared with measurements not independent
1	Weak correlation	Educated guesses/rule of thumb estimates	Preliminary methods, unknown reliability	Weak/indirect validation
0	Not clearly related	Crude speculation	No discernable rigour	No validation

Note that the columns are independent (Risbey et al., 2001, Van der Sluijs et al., 2005).

Austria (Winiwarter and Orthofer, 2000; Winiwarter and Rypdal, 2001), Flanders (Boogaerts and Starckx, 2004), Finland (Monni and Suri, 2003; Monni et al., 2004; Statistics Finland, 2005), Norway (Rypdal and Zhang, 2000) and the United Kingdom (Baggott et al., 2005). Note that since the comparison was to be used to evaluate the ranges used in the Dutch TIER analysis, the aggregation level of the European TIER-2 analyses has been kept similar to the aggregation level of the TIER-1 analysis that is used in the Dutch NIR.

Finally, a pedigree assessment has been carried out for the most sensitive emission factors and activity data to systematically assess strengths and weaknesses in their knowledge base. Pedigree analysis is part of the NUSAP system[1](Funtowicz and Ravetz, 1990; Van der Sluijs et al., 2005; Risbey et al., 2005; Refsgaard et al., 2006). It conveys an evaluative account of the production process of a quantity and indicates different aspects of the underpinning of the numbers and scientific status of the knowledge base where it stems from. Pedigree is expressed by means of a set of pedigree criteria to assess these different aspects (Table 1). We carried out a quick and dirty pedigree scoring for the 15 inputs of the emission model that have the highest contribution to the uncertainty in the output, both for the total GHG emissions in 2004 and for the trend uncertainty. In total, five experts were involved in the pedigree scoring. Results from the pedigree analysis and the Monte Carlo sensitivity analysis were combined in a so-called Diagnostic Diagram (Van der Sluijs et al., 2005a) mapping pedigree and sensitivity of key uncertain inputs. This kind of figure reveals the weakest critical links in the knowledge base of the emission monitoring system with respect to the overall emissions, and helps in the setting of priorities for improvement of the monitoring.

3. Results

3.1. Monte Carlo analysis

Table 2 shows a comparison of the results of the Monte Carlo analysis and the Tier 1 for the total and for each type of GHG emitted in the Netherlands. The results show that there is a slight change for the mean emissions between the Monte Carlo and the Tier 1, which is the result of the asymmetrical PDF's attributed to some variables in the model. The resulting uncertainties of the Monte Carlo analysis for the total emissions and for each type of GHG are in the same order of magnitude as those obtained by the Tier 1 analysis, although a somewhat higher trend uncertainty was found. The Monte Carlo analysis also generates PDFs for each outcome of the model. As an example, Fig. 1[2] shows the PDF obtained from the Monte Carlo analysis for the total Dutch GHG emissions in the Netherlands.

3.2. Importance analysis

The @Risk software allows carrying out a variance decomposition to show to what degree the variance in a total emission can be attributed to variance in the various inputs of the calculation. This allows ranking the uncertain inputs according to their importance. Fig. 2 shows a so-called tornado graph for the total Netherlands' GHG emission in 2004 as calculated for the base case[2]. In this kind of figure, the regression sensitivity is used as metric for sensitivity[3].

The Monte Carlo sensitivity analysis shows that the main contributors to uncertainty in emissions and in the trend are related to N_2O emissions from agricultural soils. Other important factors are the N_2O implied emission factor of Nitric Acid Production, CH_4 from managed solid waste disposal on land, and the implied emission factor of CH_4 from manure management from cattle. In the Tier 1 study, a similar ranking of sources was made according to their contribution to the uncertainty in total national emissions[4]. The Tier 1 top 10 sources contributing most to total annual Tier 1 uncertainty in 2004 are given in Table 3.

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[1] NUSAP stands for Numeral, Unit Spread Assessment, Pedigree. It provides a notational system and systematic approach to uncertainty assessment and communication.

[2] The PDF obtained for the emissions without LUCF looks quite similar and therefore is not shown in this paper.

[3] The regression sensitivity or Standard B coefficient is a metric that indicates how sensitive the model output is to a change in the input. The standard B coefficient has a value between −1 and +1. A standard B coefficient of for example +0.17 means that a +1 standard deviation increase in that input causes a +0.17 standard deviation increase in the output.

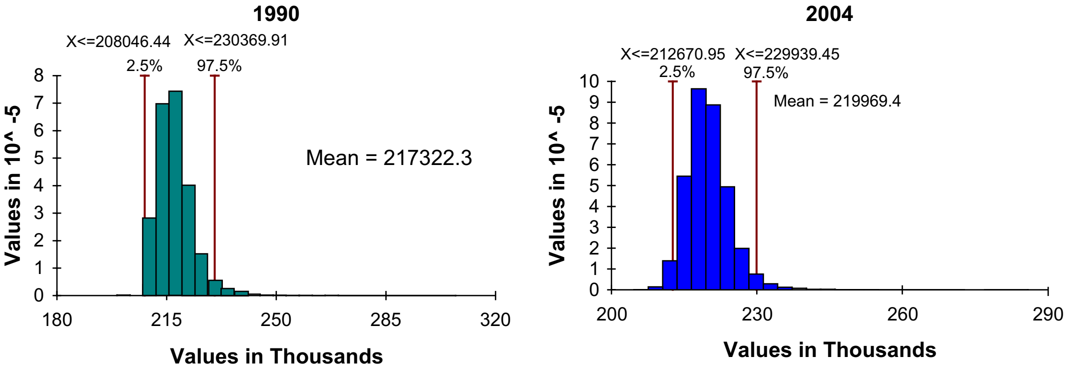
[4] Using 'Combined Uncertainty' as percentage of total national emissions in 2004 as metric for importance.

Table 2
Comparison of the results of Monte Carlo analyses and the TIER 1 analysis for the total emissions in the Netherlands, by type of greenhouse gas

	With LUCF[a]			Without LUCF[a]		
	1990	2004	Trend	1990	2004	Trend
Total GHG emissions						
Emissions (mean) [Gg CO_2 eq.]-Monte Carlo	217322	219969	2647 (1.3)[d]	214434	217211	2777(1.3)[d]
2σ [%]-Monte Carlo	5.4	4.1	379(4.5)[e]	5.3	3.9	355(4.5)[e]
Emissions (mean) [Gg CO_2 eq.]-Tier 1	216394	219845	3451	213493	217077	3584
2σ [%]-Tier 1	4.5 (6.0)[f]		(3.3)[e]	4.5 (6.0)[f]		(3.3)[e]
Total CO_2 emissions						
Emissions (mean) [Gg CO_2 eq.]-Monte Carlo	161892	182291	20399(9.4)[d]	158975	179516	20542 (9.6)[d]
2σ [%]-Monte Carlo	2.2	2.1	16 (1.6)[e]	1.5	1.5	15.1 (1.6)[e]
Emissions (mean) [Gg CO_2 eq.]-Tier 1	161482	182158	20676	158587	179397	20810
2σ [%]-Tier 1	2.5 (5.0)[f]		(2.1)[e]	2.5 (5.0)[f]		(2.1)[e]
Total CH_4 emissions[b]						
Emissions (mean) [Gg CO_2 eq.]-Monte Carlo				25464	17445	−8019 (−3.7)[d]
2σ [%]-Monte Carlo				18.7	15.1	61.2 (2.2)[e]
Emissions (mean) [Gg CO_2 eq.]-Tier 1				25437	17453	−7984
2σ [%]-Tier 1				18 (25)[f]		(1.4)[e]
Total N_2O emissions						
Emissions (mean) [Gg CO_2 eq.]-Monte Carlo	23231	17986	−3245 (−1.5)[d]	21262	17999	−3263 (−1.5)[d]
2σ [%]-Monte Carlo	46.7	42.0	240.3 (3.4)[e]	46.2	42.0	235.3 (3.4)[e]
Emissions (mean) [Gg CO_2 eq.]-Tier 1	21226	17992	−3234	21219	17985	−3234
2σ [%]-Tier 1	45 (50)[f]		(2.1)[e]	45 (50)[f]		(2.0)[e]
Total F emissions[b,c]						
Emissions (mean) [Gg CO_2 eq.]-Monte Carlo				8734	2252	−6483(−3.0)[d]
2σ [%]- Monte Carlo				21.1	28.1	30 (0.9)[e]
Emissions (mean) [Gg CO_2 eq.]-Tier 1				8250	2242	−6278
2σ [%]-Tier 1				28 (50)[f]		(0.4)[e]

[a] : The numbers presented in this table are hyper precise. Because the inputs we received were hyper precise as well, we were not able to determine the proper number of significant digits.
[b] : LUCF does not contribute to emissions in this category.
[c] : The base year for this category is 1995.
[d] : The value outside the brackets is the absolute difference between the emissions in the base year and 2004, while the value inside is the relative change compared to the 1990 emission and is a percentage.
[e] : The value outside the brackets reflects the uncertainty (2σ) in the absolute difference between the emissions in the base year and 2004, while the value inside is the trend uncertainty (2σ) relative to the emissions in the base year.
[f] : The value in brackets is suggested in the TIER-1 if dependencies among the variables were taken into account.

If we compare the top 15 from the Monte Carlo sensitivity analysis for the total GHG emissions in 2004 to the top 10 of the Tier 1 analysis for the same year, we see that they are to a large extend in agreement. In comparing the results one should be aware that the Monte Carlo analysis distinguished for most sources between activity data and emission factor. The Tier 1 ranking only takes the contribution of the entire source together. This explains why the IPCC



Year	Minimum	Maximum	Mean	Mode	Std Deviation	Variance	Skewness	Kurtosis
1990	199152.0	307182.1	217322.3	211931.6	5862.2	34364960.0	1.710	13.706
2004	204664.3	281685.7	219969.4	216021.1	4456.5	19860110.0	1.205	8.464

Fig. 1. PDFs of the trend between the base year and 2004 in the total GHG emissions in the Netherlands (in Gg CO_2-eq).

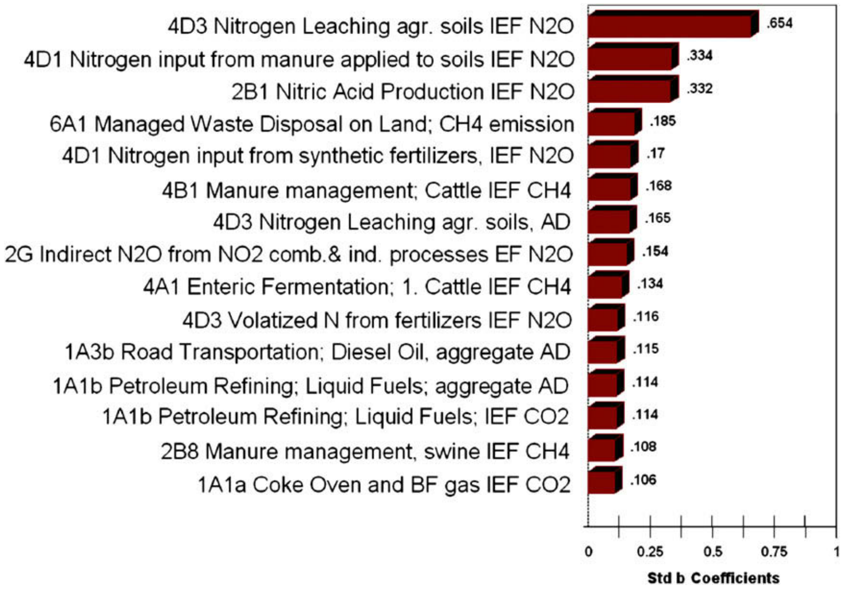


Fig. 2. Regression sensitivity for total GHG emissions in the Netherlands in 2004, without LUCF.

category 1A4a (4th in the Tier 1 ranking) is not in the top 15 from the Monte Carlo sensitivity chart.

For the trend uncertainty the differences in ranking are bigger. Only four source categories in the Tier 1 top 10 were also identified in the Monte Carlo (MC) top 15: 4D3 (rank 1, 2, 6 and 13), 6A1 (rank 3), 1A1b (rank 12) and 4D1 (rank 4, 5, 8 and 11). If we look beyond the top 15 of the Monte Carlo analysis, three more sources from the Tier 1 top 10 are identified: 1A3b (rank 17 in MC), 1A4b (rank 22 and 24 in MC) and 1A4c gases (rank 23 in MC). Again, the fact that the Monte Carlo analysis distinguishes between activity data and emission factor is the main explanation, whereas the accounting for correlations in the Monte Carlo analysis may be another explanation for the differences in rankings found.

Table 3
Reported 10 most contributing sources to total annual Tier 1 uncertainty in the total Dutch GHG emissions, 2004

	Category	Gas	Combined. uncertainty[a] (%)
1	4D3. Indirect N_2O emissions from nitrogen used in agriculture	N_2O	3.0
2	4D1. Direct N_2O emissions from agricultural soils	N_2O	1.4
3	2B2. Nitric acid production	N_2O	1.3
4	1A4a. Stationary combustion: Other Sectors: commercial/ Institutional, gases	CO_2	1.0
5	6A1. Emissions from solid waste disposal sites	CH_4	1.0
6	4B1. Emissions from manure management: cattle	CH_4	0.7
7	1A1b. Stationary combustion: Petroleum Refining: liquids	CO_2	0.6
8	2G. Indirect N_2O from NO_2 from combustion and industrial processes	N_2O	0.6
9	4A1. Emissions from enteric fermentation in domestic livestock: cattle	CH_4	0.5
10	1A3b. Mobile combustion: road vehicles: diesel oil	CO_2	0.4

[a] As % of the total Dutch emissions in 2004. Source: NIR 2006.

3.3. *Uncertainty in the knowledge base (pedigree analysis and diagnostic diagrams)*

The results of the pedigree analysis for the 10 inputs of the emission model that have the highest contribution to the uncertainty in the output are presented in Table 4 (pedigree averaged over the experts). Pedigree scores can be classified as low (between 0 and 1.3) medium (between 1.4 and 2.6) or high (2.7–4). The higher the score the lower the uncertainty in the knowledge base. With the results from the pedigree analysis and the Monte Carlo sensitivity analysis we have mapped two independent characterizations of uncertainty in the inputs of the emission monitoring. The rank correlations from the Monte Carlo assessment express the sensitivity to inexactness in input data whereas pedigree expresses the quality of the underlying knowledge base of these data, in view of its empirical and methodological limitations. We have mapped these two types of inputs into a diagnostic diagram in order to reveal the weakest critical links in the knowledge base of the emission monitoring system and to help in the setting of priorities for improvement the accuracy and quality of the emission inventory. Fig. 3 presents the diagnostic diagram for the total 2004 GHG emissions. A combined ranking based on pedigree and sensitivity can be made by scanning the diagnostic diagram from the top right corner to the bottom left corner. It follows from the diagram that for the uncertainty in total GHG emission improvements in our knowledge of the *emission factors* for categories 4D3 (indirect N_2O emissions from agricultural soils), 4D1 (direct N_2O emissions from agricultural soils), 2G (indirect N_2O from combustion and industrial processes) and 4B1 (emissions from manure management: cattle) might be given the highest priority. Inspection of Table 4 shows that the main problem in the knowledge base of these categories is in the validation and empirical basis.

4. Discussion of results

In this section the results of this study are discussed by comparing the uncertainties obtained and correlations used with respect to those reported by European countries and a range of scenarios to further explore robustness of the base case.

4.1. Comparison of uncertainties obtained with respect to those reported by several European countries

The results of Monte Carlo analyses reported by different European countries are compared with the results of this study in order to assess whether the level of uncertainty obtained in this study for the Netherlands is at the same level. Results are shown in Table 5[5]. The comparison shows that the uncertainty in the total Dutch GHG emissions is at a similar level as the uncertainties reported by Flanders, Finland and the random uncertainty reported by Austria. The uncertainties in the total GHG emissions in the United Kingdom, Finland with LUCF, Norway and Austria (including the systematic uncertainties) are much larger than the values found for the Netherlands. The large uncertainty in the total GHG emissions in the United Kingdom stems from the very large uncertainty in the total N_2O emissions, which is in turn caused by uncertainties in the sub-sectors Nitric Acid production (2σ: 230%), N_2O emissions from agricultural soils (2σ: 341%) and N_2O emissions from wastewater handling (2σ : 215%). The large uncertainty in Austria stems from the assumed large systematic uncertainties and a larger share of non-CO_2 GHG emissions. In Finland, the sector LUCF explains a large uncertainty in the total CO_2 emissions. The Norwegian uncertainties for all types of gases are larger; also the share of non-CO_2 GHG emissions is larger. We conclude that major differences in the uncertainty of the total GHG emissions of the countries studies stem from the differences in magnitude of the uncertainty in the total N_2O emissions, which vary between around 40 and 230%. Also the relative share of non-CO_2 gases in the total GHG emissions, especially N_2O is key to the explanation.

4.2. Comparison of correlations used with respect to other European studies

One of the main differences between a TIER 1 and a Monte Carlo analysis is that correlations among variables can be accounted for. In this study, we have looked at the correlations assumed between PDFs of activity data and emission factors within a given year by country and correlations assumed between different years (i.e. the base year and the year of study). Main results of comparing the different assumptions used in the different European Tier 2 studies are:

- Most countries, including the Netherlands, fully correlate activity data, when it is used to calculate more than one emission. This is the case for example for number of animals, which are used both for calculating enteric fermentation and manure management.
- Emission factors are correlated if for instance the same fuel is present in more subcategories.
- The activity data is, in most cases, not correlated between base year and end year. Exceptions are histosols in Norway, peat production areas in Finland, solid and other waste and cement production in Austria.
- The emission factors between base year and end year are fully correlated in all countries except for some situations in the UK. The exceptions in the UK are related to the level of aggregation and the reference to specific studies for instance methane emissions for open cast and coal storage.
- Most studies lack a full description of the correlations used and, based on the information reported, it seems that correlations are not fully taken into account in the studies examined.

4.3. Sensitivity analysis

In order to test the robustness of the results of the Monte Carlo analysis, we have run a series of nine scenarios. All scenarios include the category LUCF unless it is explicitly stated otherwise. Most of the scenarios are based on information supplied by expert knowledge from the PBL and/or discussions with the 'advisory panel'. In this paper we present the results of 3 out of the 9 scenarios developed (for detailed results of all scenarios we refer to Ramírez et al., 2006).

4.3.1. Changing the assumed uncertainty and PDF in the CO_2 emission factor of natural gas

The combustion of natural gas accounted for more than 35% of the total Dutch GHG emissions in 2004. In 1990 natural gas mainly came from the Dutch gas field in Slochteren. This gas has a stable composition and the uncertainty in the CO_2 emission factor (56.1 kg/GJ) has been reported as 1%. This value is also used as the emission

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[5] For Austria the values with LUCF include both random and systematic uncertainties, while without LUCF the results shown only include the results from the random uncertainties.

Table 4
Regression sensitivity (Std. b coefficient), average pedigree scores (scale 0–4, see Table 1) and standard deviation (in brackets) in pedigree scores for the 10 inputs that contribute the most to the uncertainty in total 2004 greenhouse gas emissions in the Netherlands

Rank	IPCC Cat	Description	Std. b coeffi.	Avg. proxy	Avg. emp.	Avg. meth.	Avg. val.	Avg. pedigree
1	4D3	Agricultural Soils; indirect emissions N implied emission factor	0.654	1.3 (0.6)	**1.3** (0.6)	1.7 (0.6)	**0.3** (0.6)	1.2
2	4D1	Agricultural Soils; direct soil emissions; implied emission factor N_2O	0.334	1.7 (0.6)	2 (0)	2.3 (0.6)	1.7 (**1.5**)	1.9
3	2B2	B. Chemical industry; Nitric Acid Production; implied emission factor N_2O	0.332	3 (**1.0**)	3.3 (0.6)	3 (0)	2.3 (**1.2**)	2.9
4	6A1	Solid waste disposal; Managed Waste Disposal on Land; CH_4 emission factor	0.185	1.5 (0.7)	2 (0)	2.5 (0.7)	**1** (0)	1.8
5	4D1	Agricultural Soils; Direct soil emissions; Synthetic Fertilizers; implied emission factor N_2O	0.17	1.7 (**1.2**)	2 (0)	2.3 (0.6)	1.7 (**1.5**)	1.9
6	4B1	Manure management; Cattle. Implied emission factor CH_4	0.168	2 (0)	2 (1)	2 (0)	2 (1)	2
7	4D3	Agricultural soils; Indirect emissions: Nitrogen Leaching and Run-off; N from fertilizers, Activity data	0.165	1.5 (0.7)	2 (0)	2.5 (0.7)	1.5 (0.7)	1.9
8	2G	G. Other; Indirect N_2O from combustion and industrial processes, emission factor N_2O	0.154	1.7 (0.6)	**1.3** (0.6)	1.7 (0.6)	0.7 (**1.2**)	1.3
9	4A1	Enteric Fermentation; Cattle; implied emission factor CH_4	0.134	2 (0)	2.7 (0.6)	3 (0)	2.7 (0.6)	2.6
10	4D3	Agricultural soils; Indirect emissions; Atmospheric Deposition; Volatized N; Implied emission factor N_2O	0.116	**1** (0)	**1.3** (0.6)	1.7 (0.6)	**0.3** (0.6)	1.1

Note. Pedigree scores between 0 and 1.3 are marked in bold as well as very high standard deviations (>1).

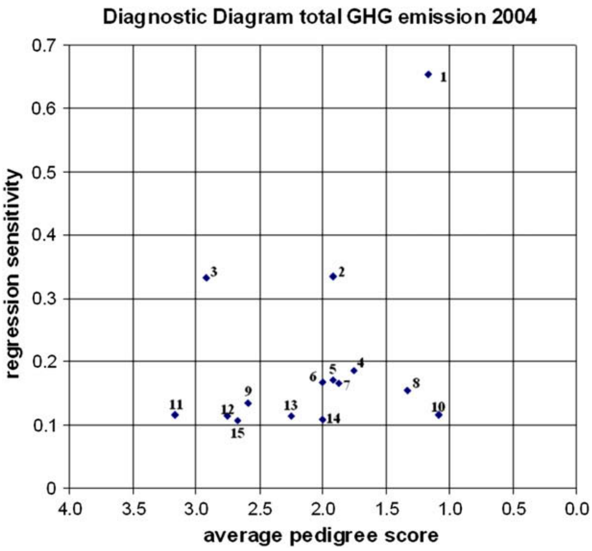

Fig. 3. Diagnostic diagram for 2004 greenhouse gas emissions in the Netherlands. The numbers of the inputs plotted correspond to the rank number in Table 4.

factor in the NIR 2005. In the final version of the NIR 2006 a new emission factor of 56.8 kg/GJ has been introduced based on detailed new information on the average gas composition[6]. For this scenario it has been considered that the emission factor for 2004 could have a different uncertainty range than in 1990. Hence we examine the effect on the results of changing the shape of the PDF within a larger uncertainty range (−1 to +3%). We consider two variants, one in which the uncertainty is asymmetric and positively skewed accounting for the fact that there is relatively more high calorific gas in 2004 than in 1990 (i.e. triangular PDF) and one that examined the effect of the uncertainty having a uniform PDF.

The results show negligible differences in the mean of the total Dutch GHG emissions. The uncertainty ranges for the total GHG emissions only show a very small increase in the uniform variant (from 4.05% in the base case to 4.11 %).

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[6] Since 1990, increasing amounts of natural gas from small fields have been used. Natural gas from these small fields has a higher calorific value. In addition, an increasing amount of gas with a different composition than the Slochteren gas has been imported. As a result, since 1990 natural gas used in the Netherlands has a composition with a higher variability.

Table 5
Comparison of uncertainties in Tier 2 analyses

Country	Category	With LUCF					Without LUCF				
		Total	CO_2	CH_4	N_2O	F	Total	CO_2	CH_4	N_2O	F
NL	Tg CO_2 eq.	220	182	17	18	2	217	180	17	18	2
	Level (%)	100	83	8	8	1	100	83	8	8	1
	Uncertainty (2σ)%	4.1	2.1	15.1	42.0	28.1	3.9	1.5	15.1	42.0	28.1
UK	Tg CO_2 eq.	650	556	41	40	13					
	Level 950	100	86	6	6	2					
	Uncertainty (2σ)%	14	2.4	13	226	17.9					
Flanders	Tg CO_2 eq.	92	76	7	9						
	Level (%)	100	83	7	10						
	Uncertainty (95% interval)	−3.95;+4.97	±2.75	−14.6;+17.2	−28.9;+44.6						
Finland	Tg CO_2 eq.	86	73	5	7	1	63	50	5	7	1
	Level (%)	100	86	6	8	1	100	80	8	11	1
	Uncertainty (95% interval)	−14;+15	±15	±20	−40;+10	−10;+20	−4;+8	±2	±20	−40;+10	−10;+20
Norway	Tg CO_2 eq.						63	48	6	6	3
	Level (%)						100	76	10	10	5
	Uncertainty (2σ)%						17	4	20	170	
Austria	Tg CO_2 eq.	78	60	8	9		80	68	10	2	
	Level (%)	100	77	11	12		100	85	12	3	
	Uncertainty (2σ)%	10.5[a]	4.7[a]	47.5[a]	69.4[a]		3.8[b]	1.0[b]	28.5[b]	23.9[b]	

[a] : Including random and systematic uncertainties.
[b] : Includes only random uncertainties.

Total CO_2 emission in the Netherlands increases slightly for the triangular and uniform variants compared to the base case. The uncertainty in this category, which is responsible for more than 80 % of the total GHG emissions, increases slightly from 2.06 % (base case) to 2.13% (triangular) and 2.25 % (uniform). At this level of aggregation, the effect of the scenario is still visible, but it is very small. We also examined the effect in the largest sub-sector that uses natural gas in the Netherlands: Public Electricity and Heat Production (1A1a). This sub-sector is responsible for more than 10% of the total Dutch GHG emissions. We found that changing the PDF of natural gas to a triangular and a uniform distribution increased the mean of the emissions only slightly (0.7%). The influence of changing the shape of the PDF on the uncertainties is however visible. The uncertainty was 1.12 % in the base case. It increased to 1.76 % (triangular) and 2.34 % (uniform). The impact on the relative trend of the CO_2 emission in this sub-sector is minor (5.5 % base case and 5.6 % for both the triangular and uniform variants).

4.3.2. *Sensitivity to assumed correlation coefficients*

The partial correlations used in the base case are not exactly known and only reflect our understanding of the direction and importance of the dependencies. Therefore it is necessary to assess the influence of the partial correlation values in the final outcome. In order to do this, we assess two cases: one in which the partial correlation coefficients are systematically increased (correlations of 0.5 in the base case are changed to 0.75; correlation factors of 0.75 are changed to 0.9) and one in which correlation factors of 0.5 are systematically lowered to 0.1. The results show that neither the mean nor the uncertainties of CO_2, N_2O, CH_4 and F emissions and the total GHG emissions change significantly in any of the two cases (<0.5%). However, uncertainties in the trends show a slight change as a result of the increasing correlations (first case). For instance, uncertainty in the trend for the total CO_2 emissions changes from 1.64 to 1.54% while uncertainty in the trend for the total GHG emissions changes from 4.53 to 3.93%. For our second case, uncertainty in the trend of the total GHG emission increases from 4.53% (base case) to 4.75% while uncertainty in the trend of the total CO_2 emissions increases from 1.64% in the base case to 1.77%.

4.3.3. *Use of IPCC default values*

In this scenario, the IPCC default uncertainty values are used instead of the Dutch specific values[7]. Our results show that the uncertainty of the total CO_2 emissions for 1990 increased from 2.21 to 3.64%, while the uncertainty for 2004 increased from 2.06 to 3.64%. The major cause for the change is the increase in the uncertainty of the CO_2 emission factor for some of the major categories of the Stationary Combustion sector to 7% (for gases and solids in the base case the uncertainty in the emission factors were

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[7] The IPCC values are taken from the '2006 IPCC Guidelines for National GHG Inventories'. In the sub-sectors where no IPCC default uncertainty values are available, the uncertainty values are not changed. If the IPCC guidelines mention a range of uncertainty values, a medium (average) value was chosen for the uncertainty. If the IPCC guidelines mention uncertainties for TIER 1, TIER 2 or TIER 3 analyses, the uncertainty value for the TIER 2 analysis are taken.

between 1 and 2%). This holds, for example, for natural gas and solid fuel use for the sub-sector public electricity and heat production, and natural gas use for manufacturing industries and construction and for residential use. Together, these categories account for more than half of the total carbon emissions in the Netherlands. For 1990, the uncertainty of the total CH_4 emissions increased from 18.6% for the base case to 19.1% in this scenario. For 2004, the uncertainty decreased from 15.1 to 14.5%. The decrease in 2004 is mainly caused by the decrease uncertainty value applied to the CH_4 emissions from Enteric Fermentation and Manure Management. While the IPCC default uncertainty for the activity data for both sectors is slightly higher than the uncertainty in the Dutch Tier 1 analysis, the uncertainty for the emission factor is much lower than the one used in the Dutch NIR. For instance, for Manure Management the uncertainty value used for the emission factor in our base case is 100%, while the IPCC default value is 20% for a Tier 2 analysis.

The uncertainty in the total N_2O emissions in 1990 decreased from 47% in the base case to 27% in this scenario. The uncertainty in the total N_2O emissions for 2004 decreased from 42 to 25%. The explanation to the decrease can be found in the data used for the three sectors that account for the majority of the N_2O-emissions (Nitric acid production, Direct N_2O emissions from agricultural soils and Indirect N_2O emissions from nitrogen used in agriculture). For nitric acid production the uncertainty for activity data is decreased from 10 (base case) to 2% for this scenario, while the emission factor uncertainty is decreased from 50 (base case) to 20%. Therefore the uncertainty in the emission resulting from using IPCC default values decreases from 51 to 20%. The uncertainty of the implied emission factors for several categories, within the Direct N_2O emissions from agricultural soils, changes from 60% with a normal distribution (base case) to a triangular distribution from −70 to +200% (IPCC default). The mean increases, because of the asymmetrical distribution and therefore the uncertainty in the emission decreases from 65 to 41% for 2004. The uncertainty of the emission factor for the indirect N_2O emissions goes from 200% with a log normal distribution to a triangular distribution from −90 to +200%. The uncertainty of the emission for 2004 decreased from 180 to 85%. Since N_2O uncertainties have a high contribution to the total uncertainty in the Netherlands (see Section 3.2), using IPCC defaults values for N_2O emissions reduce also the level of uncertainty of the total Dutch GHG emissions. For 1990 the uncertainly would decrease from 5.39% (base case) to 4.79% in this scenario. For 2004 the uncertainly would decrease from 4.05 to 3.98%.

5. Conclusions

In this article we have assessed to what extent a Monte Carlo analysis of the uncertainties in the Dutch NIR has added value compared to a Tier 1 analysis and we compared the Netherlands uncertainty assumptions to those made in Tier 2 studies in other European countries. The main conclusions of this study can be summarized as follows:

- The resulting uncertainties of the Monte Carlo analysis for the total emissions and for each type of GHG are in the same order of magnitude as those obtained by the Tier 1 analysis, although a somewhat higher trend uncertainty was found.
- Accounting for correlations is important, and for the Netherlands inventory it has a larger impact on the uncertainty in the trend than on the uncertainty in the total GHG emission.
- In the Tier 1 analysis as presented in the Dutch NIR, the calculated uncertainties for the total emissions of the different GHG are increased with a correction factor based on expert judgment to account for uncertainties not captured in the Tier 1 (see values in brackets in Table 2). The argumentation for this correction factor has been that Tier 1 does not account for correlations and asymmetrical distributions and that there are gaps in knowledge which increase the uncertainty in the calculated emission figures. The present Monte Carlo analysis has shown that accounting for correlations and asymmetrical distribution functions does not necessarily lead to a significant increase in uncertainty in total GHG emissions.
- Uncertainty assumptions in the Netherlands are well in the range of European studies.
- The resulting uncertainty in total Dutch GHG emissions is in the lower range compared to other European countries. This can be explained by the fact that the Netherlands has a higher share of CO_2 emissions (relative to emissions of non-CO_2 GHGs) compared to most other countries. Since CO_2 emissions factors are relatively well understood and monitored, their uncertainty is quite low and hence the significance of emissions with larger uncertainties (e.g. CH_4 and N_2O) is in the Netherlands smaller than in other countries. Furthermore, some countries (e.g. Norway and the United Kingdom) report very large uncertainty in the total N_2O emissions (respectively 170 and 226%). These high values influence significantly their uncertainty in the total GHG emissions.
- A ranking of uncertain inputs of the emission model according to their contribution to variance reveals that the main contributors to overall uncertainty are related to N_2O emissions from agricultural soils (especially indirect N_2O emissions), the N_2O implied emission factors of Nitric Acid Production, CH_4 from managed solid waste disposal on land, and the implied emission factor of CH_4 from manure management from cattle. These results are well in agreement with the top sources contributing most to total annual uncertainty reported in the NIR 2006. The added value of the Monte Carlo analysis is that while the NIR can only rank the contributing sources in terms of the combined uncertainty, by performing a Monte Carlo analysis it is possible to distinguish whether the most important contributing sources to total uncertainty are found in the activity data or the emission factor of the different sectors. Monte Carlo, hence, provides a more detailed picture that can be used in a later stage to define specific areas where further research can help to decrease uncertainties in the total emissions.

- The diagnostic diagram that plots parameter regression sensitivity against parameter pedigree reveals that for the uncertainty in total GHG emission improvements in our knowledge of the emission factors for the IPCC categories 4D3 (indirect N_2O emissions from agricultural soils), 4D1 (direct N_2O emissions from agricultural soils), 2G (indirect N_2O from combustion and industrial processes) and 4B1 (Emissions from manure management: cattle) might be given the highest priority. Inspection of the pedigree analysis shows that the main problem in the knowledge base of these categories is in validation and empirical basis. For the trend uncertainty the ranking does not alter substantially from the one provided by the pedigree analysis.
- Despite decreasing the uncertainty in the categories named above, the Dutch Tier 1 assessment could be improved to emulate the Tier 2 results by adjusting the Tier 1 uncertainty inputs for sector 6A (landfills); adjusting the Tier 1 uncertainty of activity data for 1A4a (commercials) and by reconsidering the Tier 1 uncertainty inputs for 4D (indirect N_2O emissions from agricultural sources) and discuss with other European countries the reasons for the differences in uncertainty assumptions across countries for this category.
- For future years, as long as the emission model does not change substantially and the share of CO_2 and non-CO_2 gases is not substantially different from 2004, it seems justified to use Tier 1 as main method for uncertainty analysis in the NIR. However, because of ongoing emission reduction efforts and changes over time in the fuel mix as well as in the shares of non-CO_2 greenhouse gases, we recommend repeating the Monte Carlo analysis regularly (every 4 years) as part of the QA/QC procedures.

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Appendix. Supplementary data

Supplementary data associated with this article can be found in the online version, at doi:10.1016/j.atmosenv.2008.07.059.

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