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Analysis of uncertainties in the estimates of nitrous oxide and methane emissions in the UK's greenhouse gas inventory for agriculture

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HIGHLIGHTS

- We calculated the uncertainty in the estimated emissions of N_2O and CH_4 from UK agriculture.
- IPCC Emission factors EF_1 and EF_5 contributed most to the uncertainty in N_2O emissions.
- Enteric fermentation emission factors contributed most to the uncertainty in CH_4 emissions.
- We note the importance of incorporating variables into calculations at the correct scale.

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ABSTRACT

The UK's greenhouse gas inventory for agriculture uses a model based on the IPCC Tier 1 and Tier 2 methods to estimate the emissions of methane and nitrous oxide from agriculture. The inventory calculations are disaggregated at country level (England, Wales, Scotland and Northern Ireland). Before now, no detailed assessment of the uncertainties in the estimates of emissions had been done. We used Monte Carlo simulation to do such an analysis. We collated information on the uncertainties of each of the model inputs. The uncertainties propagate through the model and result in uncertainties in the estimated emissions. Using a sensitivity analysis, we found that in England and Scotland the uncertainty in the emission factor for emissions from N inputs (EF_1) affected uncertainty the most, but that in Wales and Northern Ireland, the emission factor for N leaching and runoff (EF_5) had greater influence. We showed that if the uncertainty in any one of these emission factors is reduced by 50%, the uncertainty in emissions of nitrous oxide reduces by 10%. The uncertainty in the estimate for the emissions of methane emission factors for enteric fermentation in cows and sheep most affected the uncertainty in methane emissions. When inventories are disaggregated (as that for the UK is) correlation between separate instances of each emission factor will affect the uncertainty in emissions. As more countries move towards inventory models with disaggregation, it is important that the IPCC give firm guidance on this topic.

1. Introduction

It is widely accepted that anthropogenic actions are affecting the global climate system in a negative way, and that greenhouse gas concentrations in the atmosphere should be stabilized to levels that will prevent negative impacts on the climate system (UNFCCC, 1992). The first quantitative targets for the reduction of greenhouse gas emissions produced by industrialized countries (known as Annex I countries) were made in the Kyoto protocol. In order to monitor progress on this, all Annex I countries are required to report annual emissions and sinks of greenhouse gases from various sectors. To ensure that the calculation of emissions from each sector and

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reporting is done to a consistent standard a series of guidelines have been produced by the IPCC (IPCC, 1996; Penman et al., 2000; Eggleston et al., 2006). These guidelines set out the methods that should be used to calculate emissions. There are three 'Tiers' of complexity in the calculations. Tier 1 calculations use a basic model, whereby readily-available national or international statistics (known as activity data) are combined with IPCC default emission factors to estimate emissions. The Tier 2 calculations generally disaggregate the activity data and use various emission factors that reflect regional and temporal differences. Tier 3 methods use more complex models and highly disaggregated activity data sources.

Within the model framework the parameters (which include emission factors) and variables (the activity data) may be regarded as inputs to the model. Similarly the calculated emissions may be regarded as the model outputs.

Estimates of emissions are uncertain. This is for a number of reasons. Firstly, the model inputs are themselves uncertain. Activity data are typically estimated from sample surveys and these estimates will be uncertain unless the whole population is surveyed accurately. The model parameters are estimated from experiments and there are errors associated with these derivations. Uncertainties in estimated emissions are also attributed to errors in the conceptualization of the model framework, for example a model may over simplify a process by omitting certain factors. These errors are less straightforward to quantify and are not included in the quantification of the uncertainty in estimates of emissions (see Eggleston et al., 2006). All Annex I countries are obliged, as far as possible, to quantify the uncertainties in their estimates of emissions by determining how uncertainties in the model inputs propagate through the model. This is important because it enables the analyst to assess how reliable estimates are and to evaluate statistically whether reductions in emissions are significant.

We are concerned with emissions of nitrous oxide (N_2O) and methane (CH_4) from the agricultural sector. In the UK, this sector contributes substantially to the total emissions of CH_4 and N_2O. Baggott et al. (2007) estimated that, in the UK, approximately 60% of N_2O emissions and 40% of CH_4 emissions were due to agriculture. Brown et al. (2012) compiled the greenhouse gas inventory from agriculture for 1990 to 2010 using the IPCC guidelines published in 2000 (Penman et al., 2000). They did not do a detailed assessment of the uncertainty. We set out to quantify the uncertainty in the emissions of N_2O and CH_4 from agricultural in the UK for the year 2010 and the baseline year (1990), and the uncertainty in the trend between these two years. We considered each of the four countries that make up the UK (England, Wales, Scotland and Northern Ireland) separately. There are several methods that can be used to quantify how the uncertainties in the model inputs propagate through to the model output, i.e. the emissions (see Heuvelink, 1998). We chose to use Monte Carlo simulation because it is straightforward to use, can account for dependencies between inputs, and is arguably more flexible than other methods. This method has been used by other groups estimating emissions from agriculture (Monni et al., 2007; Karimi-Zindashty et al., 2012) and is recommended by the IPCC for inventories that contain large uncertainties (Eggleston et al., 2006). In Monte Carlo simulation model inputs are treated as random variables and are described by a probability density function (PDF). The mean of the PDF describes the expected value of the input and the variance reflects the uncertainty. A value for each input is pseudo-randomly sampled from the PDFs and the model is run to produce an output value. This process is repeated many times (typically thousands of times) resulting in a set of output values which form an empirical distribution that describes the uncertainty. Statistics such as the mean, variance and 95% confidence intervals can be derived from this distribution.

There may be correlations in the errors of two or more inputs. For activity data, these correlations may occur if two or more variables are estimated from the same data source. If variables are estimated using independent sources of data then there will be no correlation in the errors. Similarly, two or more emission factors obtained from the same sets of experiments may have correlated errors. The measure of correlation is typically estimated as part of the statistical procedure used to estimate these parameters (see Milne et al., 2011a). These correlations are accounted for by describing the inputs with multivariate distributions.

As well as quantifying the uncertainty in the emissions (as stated above), our objective was to identify the model inputs that contributed most to the uncertainty of the estimated emissions so that we could target these for improvement in future inventories. To improve both the precision in the estimates of emissions and to reduce the uncertainty in the estimates of emissions, more Tier 2 and Tier 3 calculations are needed in the inventory. These calculations require activity data at a scale of resolution finer than countrywide (for example, statistics on crop areas for the various soil-climatic regions), and new emission factors that match these scales of resolution. These inputs can be time consuming and expensive to derive, and that is why we wanted to identify the inputs that had the most effect on the uncertainty in the total emissions. We undertook a sensitivity analysis to do this. Once we had identified the inputs that influenced uncertainty the most, we explored the effect of reducing their uncertainty by reducing the standard deviation of the PDFs that we used to describe them by 50% in turn.

2. Method

The current greenhouse gas inventory for agriculture in the UK uses the methods from the IPCC guidelines published in 2000 (Penman et al., 2000; Brown et al., 2012). The calculations of CH_4 from enteric fermentation in dairy and beef cows, and the calculations of CH_4 from manure management use Tier 2 methods. All other calculations used Tier 1 methods. Almost all of the activity data and emission factors have some uncertainty associated with them. We used Monte Carlo simulation to quantify how the uncertainties in the model inputs propagate through the model. We used @Risk software (Palisade, 2010) to run our Monte Carlo simulation. Some initial testing showed that running the Monte Carlo simulation for 300,000 iterations gave acceptable convergence. We assessed the convergence of the simulation by considering the stability of the 95% percentile. We chose a convergence tolerance of 1% on the 95% percentile.

In order to do our Monte Carlo simulation, we sought PDFs to describe the uncertainties in the model inputs. This is detailed below.

2.1. Uncertainty in the activity data

2.1.1. Synthetic fertilizer use

To estimate the amount of fertilizer applied to each crop in each country, the fertilizer rates for each crop were multiplied by the respective crop areas. The expected values and standard errors for these variables were calculated using national survey data (Defra, 2010a,b; DARDNI, 2010). Where the standard errors were small compared to the mean (less than 25%) we assumed the uncertainty was normally distributed, otherwise we assumed a lognormal distribution. This is because when standard errors become larger, there is a greater chance of sampling negative values for the variables (which would not make sense).

2.1.2. Nitrogen applied as sewage sludge

This variable was calculated by multiplying the amount of sewage applied to the land (t year^{-1}) by the expected amount of