Assessing uncertainty in the cost-effectiveness of agricultural greenhouse gas mitigation

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Abstract

Information on the uncertainty of quantitative results feeding into public decision making is essential for designing robust policies. However, this information is often not available in relation to the economics of greenhouse gas (GHG) mitigation in agriculture. This paper analyses the uncertainty of the mitigation estimates provided by a Marginal Abatement Cost Curve (MACC). The case study is based on the GHG MACC developed for Scottish agricultural soils. The qualitative assessment disentangled the different sources and types of uncertainty in the cost-effectiveness analysis of GHG mitigation options. The quantitative assessment estimated the statistical uncertainty of the results by propagating uncertainty through the model, using three uncertainty scenarios. The results show that the uncertainty in the economically optimal abatement in Scottish agricultural soils is high with the medium and high uncertainty scenarios, with the ratio of the 95% CI to the mean being 0.57-1.01 and 0.98-1.4, respectively, while the low uncertainty scenario resulting in a ratio of the 95% CI to the mean of 0.24-0.68. However, the ranking of the measures are relatively robust with all three uncertainty scenarios, especially in terms of which options have cost-effectiveness below the carbon price threshold.

Keywords: marginal abatement costs curves, uncertainty, greenhouse gases, agriculture, GHG mitigation
JEL code: Q54

Introduction

With the effects of global warming becoming apparent, governments are introducing policies to reduce greenhouse gas (GHG) emissions across their whole economies. These policies, designed to promote climate change mitigation, should be informed by sound scientific evidence on the effectiveness of possible mitigation options. Information about the feasibility, GHG abatement potential and cost of these options are essential for designing mitigation policies. However, estimating this information is inherent with uncertainties. Robust policies, which aim to achieve their environmental, economic and social targets across a range possible futures, have to take into account these uncertainties (Lempert and Schlesinger 2000). Ignoring uncertainty can result in sub-optimal recommendations for policy development and can thus be costly to society.

In agriculture, where the high variability in GHG emissions hugely constraints the implementation of a robust GHG emission quantification (Olander et al. 2013) – which, in turn, is essential in the implementation of market-based instruments – non-market based environmental policies are prominent. These instruments are either based on voluntary uptake with no need for monitoring (e.g. information provision on resource efficiency via advisory services), or require only the monitoring of management practices but not the emissions (e.g. limits on nitrogen fertiliser use). However, for such policies policy makers have to select the set of management options to be supported, and information on uncertainties in the effectiveness and costs of the options is needed for such an exercise.

In certain fields of climate change research integrating uncertainty in the analysis has become the norm, particularly in the physical sciences (like climate modelling), but also to some extent in economic research. Peterson (2006) gives an extensive overview of the economic models on climate change which integrate uncertainty in their assessments. These exercises either target the global economy or the energy system, usually reporting on the uncertainties in GHG emission, damage costs or mitigation costs. Such results are particularly valuable for high level policy decisions, but, being global or regional representations, they are limited in advising policy development at the national level, where information on specific mitigation options, locations and sectors are needed. However, authors discussing the economics of GHG mitigation in agriculture rarely feature uncertainty analysis in their results. Some exceptions include uncertainty analysis of mitigation potential of biogas production in Germany (Meyer-Aurich et al. 2012), and farm level mitigation potential and cost estimates on a UK farm with uncertainty reported on the total emissions and on one mitigation option (Gibbons et al. 2006). This lack of uncertainty analysis in agricultural economic assessments can be partly explained by the difficulties imposed by the heterogeneity of the sector (regarding farming systems, farming practices, climatic and soil conditions and farmers' behaviour) and by the variety of practical implementations of the possible mitigation options, both of which impede the availability of uncertainty information on underlying inputs of economic assessment models.

Information on uncertainty only becomes relevant if it is included in the policy decision making process. There are a range of decision support tools to help communicating uncertainty to policy makers. Uncertainty which can be quantified can be included in the economic assessment, for example, by the propagation of uncertainty (Tol 1999) or by cost-benefit analysis with real options (Maart-Noelck and Musshoff 2013). Other tools, such as robust decision making techniques (Hallegatte et al. 2012; Kann and Weyant 2000; Vermeulen et al. 2013), allow unquantifiable elements of uncertainty to be taken into account. Nevertheless, the complexity in uncertainty analysis often negatively impacts on the knowledge exchange between scientist and policy makers, resulting in limited integration of uncertainty information in the decision making process (Knaggard 2013). A mutual engagement from both scientists and policy makers could help to overcome some of the obstacles in communicating and utilizing uncertainty information (Smith and Stern 2011). Here we make a systematic attempt to analyse the uncertainty in the cost-effectiveness assessment of GHG mitigation in agriculture, with the ultimate aim of providing policy recommendations. The systematic analysis consists of two parts: i) establishing an inventory of the uncertainties which play a role in cost-effectiveness assessment (specifically marginal abatement cost curves, MACCs) in agricultural GHG mitigation, and ii) quantitative uncertainty assessment of the GHG mitigation cost-effectiveness assessment relating to Scottish agricultural soils.

The marginal abatement cost curve analysis is a decision making tool widely used today for assessing GHG mitigation policy. It has been deployed in numerous instances to estimate the optimal level of mitigation effort and to prioritise mitigation actions in terms of their cost-efficiency (i.e. the cost of reducing GHG emission), often feeding into the policy process, for example in the EU, US and UK (Kesicki and Strachan 2011). The MACCs' popularity with policy makers can be partly explained by its high visuality: it is able to convey condensed information in a relatively simple way. However, this power has to be used with caution, as it can increase the risk of overconfidence in the results – especially if uncertainty is not represented, which is often the case. One of the noted shortcomings of most of the MACC analyses by date is the lack of uncertainty analysis (Kesicki and Ekins 2012), which is particularly true for the land use sector. Nevertheless, it is possible to address this shortcoming of the MACC analysis, as we present in this paper.

The paper is structured as follows. The sources of uncertainties in the cost-effectiveness assessment are explored in the next section. The data and methods of the quantitative uncertainty assessment are presented in Section 3, while the results are introduced in Section 4. Section 5 discusses the importance of the different sources of uncertainty in the economic assessment, examines the quantitative results and provides recommendations for policy makers and for future research.

Sources of uncertainty in the economic assessment of agricultural GHG mitigation

Uncertainty around the level, efficiency and costs of future GHG mitigation activities is embedded in the complex feedback loop existing between the economy and the environment, with each step having layers of uncertainty attached to it. Figure 1 provides a schema of this loop, featuring the importance of GHG mitigation and policy. Looking at the sources of uncertainty we see that our representations about the processes happening in the environment (GHG concentration, weather, systems impact) are dominated by biogeochemical uncertainties. Modelling the activities in the economy and the effects on society bears the additional uncertainties around technological solutions, economical processes, human behaviour and politics.

Figure 1. Sources of uncertainty in the climate change feedback loop (based on Smith and Stern (2011))

In the case of agriculture and land use natural processes have a major influence on activities and emissions, and therefore play a key role in determining the effectiveness of mitigation options. Modelling the choice of land use activities, types of crops, number of livestock, and, equally importantly, the farm management activities are hindered by biogeochemical uncertainties. For example, the variability in weather conditions makes the biophysical processes and therefore the nitrous-oxide (N_2O) emissions variable, resulting in uncertainty in their estimates. At the same time the variable weather also has an impact on farmers' decision making about the timing and amount of nitrogen fertiliser used, which in turn affects the emissions and ultimately the effectiveness of the mitigation options applied. The economic and policy environment is also a big driver of decisions on agricultural activities, therefore economical and political uncertainties prevail in our representations. For instance, the future evolution of energy and agricultural commodity prices together with renewable policies will have an important impact both on the land area used for human food and animal feed production and on the financial costs and benefits of mitigation technologies. An important addition to the list of uncertainties is the behavioural aspect of the main decision makers (farmers and other land managers), which, also in dependence on the policy environment, defines the diffusion of mitigation technologies and thus has a direct effect on total abatement.

Some of these uncertainties can be quantified and included into numeric models – we refer to this as statistical uncertainty (some authors use different terms, like imprecision, Knightian risk, conditional probability). Statistical uncertainty can be expressed via probabilities, for example the 100-year global warming potential of methane is estimated to be in the range of 19.3-31.5 with a 90% confidence, with a mean of 25.0 (Reisinger et al. 2010). In the agricultural context statistics about current and historic cropping and livestock activities, input and output prices, experimental data of gaseous emissions and carbon sequestration all have statistical uncertainties, even though this information is not always reported. Besides the uncertainties of experimental data models, as imperfect tools representing the reality, also have their own uncertainties which can be quantified if compared with observed data. An example can be a farm economic model looking at the changes in the farm profit: its results can be compared with existing data on farm profits and the error in the results can be quantified.

On the other hand, there exist uncertainties which cannot be quantified statistically. This deep uncertainty (also called ambiguity or Knightian uncertainty) can arise for many reasons, and becomes more prominent with models of complex systems predicting future scenarios. If the model's predictions are too far in the future, or the phenomenon cannot be simulated realistically, we face deep uncertainty (Hallegatte et al. 2012; Smith and Stern 2011).

Value uncertainty occurs when a value depends on personal judgement, like the discount rate chosen to reconcile the needs of future and current generations, or the value of human life (Kann and Weyant 2000). However, value uncertainty can be quantitatively modelled with scenarios, though the results of scenarios cannot be aggregated.

The qualitative and quantitative assessment in this paper explores the uncertainty in the MACC analysis of the cropland- and grassland-related GHG mitigation options in Scotland. MACC analyses are models which build on data obtained often both from biophysical and economic models and from expert opinions. By the nature of the outputs of the MACC models, they can be neither calibrated nor validated – this is, in itself, is a deep uncertainty in the MACC analyses. Though the uncertainty of the MACC models themselves cannot be assessed against observations, uncertainty information can still be obtained about the results of the MACC analysis by looking at the statistical and deep uncertainties of the inputs. The statistical uncertainty of the inputs – if information exists on them – then can be propagated through the MACC model.

The main uncertainties in the economic assessment of agricultural GHG mitigation are described in Table 1. Deep uncertainties prevail in all of the model inputs. Value uncertainties exist regarding the global warming potential (GWP) metric and the discount rate. As for the latter, both private and social discount rates can be used when building scenarios, relevant to private decision making and public decision making, respectively. Deep uncertainties also arise from the underlying modelling processes. This is partly a result of predictions about the future of our complex ecological-economic system which will exist under a climate we do not have observations about, and partly stems from the lack of uncertainty information from the underlying modelling exercises. Uncertainties can, at least in theory, be quantified wherever data are collected about current natural, economic or behavioural phenomena, such as energy prices, current uptake of low-carbon technologies by farmers or enteric methane emissions from cattle. However, given the variability in these phenomena, modelling is often needed to generate input for the cost-efficiency assessments – adding deep uncertainty to every input of the MACC models. If neither direct data nor modelling results are available as inputs, assessments often rely on expert knowledge, where the quantification of uncertainties is even more difficult, and therefore often ignored, aggravating the deep uncertainties in the assessment.

Table 1. An inventory of uncertainties in the economic assessment of agricultural GHG mitigation

Model inputs	Source of uncertainty	System	Type of uncertainty
Global warming potential (GWP) of GHGs	Variability of the atmospheric processes	Biogeochemical	Statistical

Model inputs	Source of uncertainty	System	Type of uncertainty
	Modelling future atmospheric processes	Biogeochemical	Statistical and deep
	Choice of GWP metric	Economic	Value
Agricultural activity levels (e.g. 0.9 M ha permanent grassland)	Historic agricultural activity, prices and other economic variables	Economic	Statistical
	Modelling future changes in farming activities as a function of demographic and economic changes	Economic and political	Statistical and deep
GHG abatement achievable by the mitigation options (e.g. 0.1 t CO_2e/ha/year) AND Biophysical interactions between the mitigation options (e.g. 10% reduction in the GHG abatement of option A if applied together with option B)	Variability of the weather and in the soil processes involved in N_2O emissions	Biogeochemical	Statistical
	Modelling future soil processes	Biogeochemical	Statistical and deep
	Modelling how farmers will actually implement the mitigation options	Behavioural	Statistical and deep
	Modelling future changes in the abatement efficacy of the mitigation options	Technological	Statistical and deep
Applicability of the mitigation options (e.g. % of land area)	Weather and soil types	Biogeochemical	Statistical
	Current and future type of farming systems (e.g. organic)	Economic	Statistical and deep
Likely additional uptake of the mitigation options by farmers (e.g. 45% of land area)	Current farm management practices	Economic	Statistical
	Variability in farmers' behaviour	Behavioural	Statistical
	Modelling farmers' future behaviour	Behavioural	Statistical and deep
	Modelling future changes in the economy and farming	Economic and political	Statistical and deep
Annualised net cost of the mitigation options (e.g. £1.40 /ha/year)	Historic prices and other economic variables	Economic	Statistical
	Modelling future changes in prices and farming practices	Economic, technological	Statistical and deep
	Modelling future farm finances	Economic	Statistical and deep
	Choice of discount rate	Economic	Value

A quantitative assessment of the statistical uncertainty of the cost-effectiveness of mitigation options are presented in the next two sections via a case study of the Scottish agricultural MACC. MACCs represent the marginal cost of emission reduction (i.e. the cost of each additional unit of abatement). The level of the economically optimal abatement is where the MACC intercepts the marginal damage cost curve, which measures the marginal cost of GHG emissions to the society (i.e. the cost arising from having each additional unit of GHG in the atmosphere). Uncertainty in the MACC and in the marginal damage cost curve result in uncertainty in the economic optimum (Figure 2). A MACC which is assessing alternative technologies as mitigation options is likely to have additional uncertainties both in the abatement potential and cost of each option and also in the ranking of the mitigation options. Thus the uncertainty information becomes highly relevant when a MACC is used in the policy process where the aim is to stimulate the uptake of selected mitigation options.

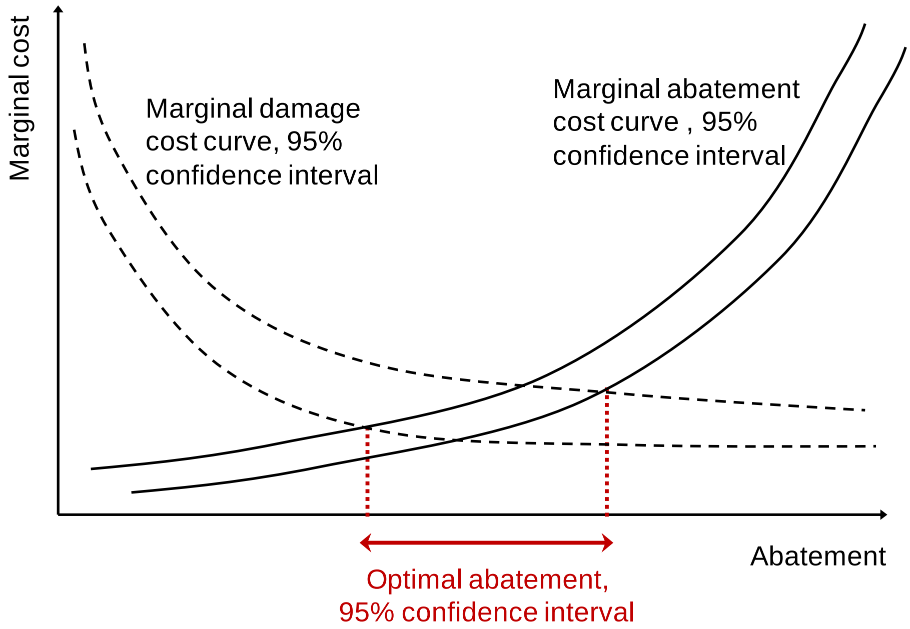


Figure 2. Effect of uncertainty on the optimal abatement level (based on Smith and Stern (2011))

Data and Methods

This paper revisits data used to derive the GHG MACC developed for UK agriculture (Moran et al. 2011), restricting the analysis to Scottish soils. Moran et al. (2011) estimated the cost and abatement potential of options applicable in the UK agriculture, and calculated the ratio of these to attain the cost-effectiveness of the options (£ tCO_2e^{-1}) for the years 2012, 2017 and 2022, considering interactions between the options. Future predictions included changes in agricultural activities and prices, but not changes in the climate. Four uptake scenarios were modelled, reflecting different assumptions about the future policy environment: low feasible potential (LFP), central feasible potential (CFP), high feasible potential (HFP) and maximum technical potential (MTP), assuming uptake rates of 7-18%, 45%, 85-92% and 100% respectively – see (Moran et al. 2008) for a detailed description. To reflect Scottish environmental circumstances and farming practices, the input data on abatement rates and applicability have been updated (Eory et al. 2013). In the current exercise we focused on the following options which relate to cropland (including temporary grasslands):

- Using biological fixation to provide nitrogen inputs
- Reducing N nitrogen fertiliser
- Improving land drainage
- Avoiding nitrogen application in excess
- Using manure nitrogen to its full extent
- Introducing of new species (including legumes)
- Improving the timing of mineral nitrogen application
- Improving the timing of slurry and poultry manure application
- Using controlled release fertilisers
- Using nitrification inhibitors

- Adopting systems less reliant on inputs
- Adopting plant varieties with improved N-use efficiency
- Separating slurry applications from fertiliser applications by several days
- Using reduced tillage and no-till techniques
- Using composts, straw-based manures in preference to slurry

As information on the statistical uncertainty of the inputs was not available we conducted an uncertainty assessment rather than an uncertainty analysis - in other words, we assessed the impact of uncertainty on the results, rather than trying to quantify the level of uncertainty within the results (since the latter – an uncertainty analysis – would rely on existing quantitative information regarding the uncertainty of the inputs, commonly in the form of density functions, PDFs).
Given the scarcity of quantitative knowledge regarding the level of input uncertainty, three uncertainty scenarios were created for each input variable (“wide”, “medium” and “narrow” scenarios), which are respectively based on assuming that levels of uncertainty are high, medium or low. PDFs were assigned to the distribution of each of the input variables under each of these three scenarios: the nature of the uncertainty assessment means that the parameterisation of these PDFs is based on the authors’ judgment. Three different parametric models for assigning PDFs were considered in each case: the censored normal, truncated normal and triangular distributions. These three distributions were considered in order to investigate the effect of the shape of the PDF, and these specific distributions were chosen because they all allow natural limits of the values of variables (i.e. the fact that uptake rates must lie between 0 and 1) to be dealt with in a particular way. The three models each describe the PDF in terms of two parameters - the mode (the value associated with the highest probability) and the uncertainty range (the range that includes 95% of probability, or, for the triangular distribution, 100% of probability). The mode is taken to be the value of the each parameter that was originally used in the MACC, and the uncertainty range is specified separately for each variable and uncertainty scenario (Table 2) – for some variables (e.g. net cost) the uncertainty range is assumed to be a multiple of the mode, whilst for others (e.g. uptake) it is assumed to have a value that is unrelated to the mode.
The three parametric distributions differ in terms of their shape: in the triangular distribution the probability is a linear function of distance from the mode, whilst the censored normal and truncated normal distribution both assume that the distribution of probabilities can be represented by a normal distribution between the natural limits of the variable: these two distributions differ solely in whether they assume that there is non-zero probability of obtaining values that lie exactly at the natural limits (the censored normal allows this, the truncated normal does not), and the two distributions are equivalent to each other – and equivalent to the usual normal distribution – for those variables that have no natural limits (e.g. cost, and, for some mitigation options, abatement rate).

Table 2. Characteristics of the three PDFs assigned to the inputs of the MACC model

Uncertainty source	Description and unit	Natural limits of values of the variable	Uncertainty range		
			Wide PDF	Medium PDF	Narrow PDF
N_2O GWP	100 year GWP [kg CO_2e (kg N_2O)$^{-1}$]	(0, ∞)	Mode * 0.6	Mode * 0.4	Mode * 0.2
Activity levels	Areas of land under different type of crops (four crop categories) [ha]	(0, ∞)	Mode * 0.6	Mode * 0.4	Mode * 0.2

Uncertainty source	Description and unit	Natural limits of values of the variable	Uncertainty range		
			Wide PDF	Medium PDF	Narrow PDF
Applicability	Biophysical feasibility of applying an option on a land category [-]	(0, 1)	1.0	0.6	0.2
Uptake	Level of implementation of a option by farmers across Scotland, on land areas where the option is applicable [-]	(0, 1)	1.0	0.6	0.2
Interaction factors	Factor assigned to each possible pairs of options, describing the synergies and trade-offs in the GHG effectiveness of the options [-]	(0, ∞)	1.0	0.6	0.2
Abatement rate	GHG effectiveness of the options [t CO_2e ha^{-1} year^{-1}]	(0, ∞) (-∞, ∞)	Mode * 4	Mode * 2	Mode
Net cost	Difference between the gross margin of the farm with and without the option applied, calculated with a profit maximising farm model [£ ha^{-1} year^{-1}]	(-∞, ∞)	Mode * 4	Mode * 2	Mode

Activity levels and the global warming potential of N_2O were assumed to have the lowest uncertainty under all uncertainty scenarios - the former based on the fact that annual farming statistics in Scotland are estimated with high certainty, and the latter based on the confidence range of GWPs reported by the IPCC (2007). Applicability, uptake and interaction factor (IF) values were based on expert judgement in the original exercise, therefore higher uncertainty were assigned to them than to GWP and activity levels. Applicability and uptake can be of any value between 0 and 1, while IFs are mostly between 0 and 1, with some values – representing synergies, like between ‘Improving land drainage’ and ‘Using nitrification inhibitors’ – falling between 1 and 1.1. As their uncertainty is assumed not to be proportional to their value, their uncertainty was expressed in absolute terms. Net costs, which were outputs from a farm level financial model with no information on their uncertainty were assigned with relatively high uncertainties. Abatement rates, whose values were based on expert judgement, are similarly assigned fairly high levels of uncertainty. However, the abatement rates of seven mitigation options were assumed to be non-negative, whilst for the other eight mitigation options is was assumed that their value might become negative, i.e. with some probability they might be increasing, rather than reducing, GHG emissions. These eight options were: ‘Improving land drainage’, ‘Introduction new species (including legumes)’, ‘Improving the timing of mineral nitrogen application’, ‘Improving the timing of slurry and poultry manure application’, ‘Adopting plant varieties with improved N-use efficiency’, ‘Separating slurry applications from fertiliser applications by several days’, ‘Using reduced tillage and no-till techniques’, ‘Using composts, straw-based manures in preference to slurry’.
Statistical uncertainty of the inputs was propagated through the model via Monte Carlo analysis. The Monte Carlo analysis for each combination of year, uptake scenario, uncertainty scenario, parametric model and uncertainty source simply involved simulating 1000 sets of input values using the relevant input PDFs, and then running each set of simulated inputs through the MACC calculations in order to produce a PDF for the MACC

outputs. The key outputs were the ranking of each measure and the economically optimal abatement potential. The latter corresponds to the cumulative abatement potential of all of the options of the MACC which have a cost-effectiveness value (CE) below the marginal damage cost curve, hereby approximated by the shadow price of carbon (SPC), with a value of £29 $(CO_2e\ t)^{-1}$ (Price et al. 2007). Monte Carlo simulations were run for all 3 * 4 * 3 * 3 * 8 = 864 combinations of year (2012, 2017, 2022), uptake scenario (LFP, CFP, HFP and MTP), uncertainty scenario (narrow, medium, wide), parametric model (censored normal, truncated normal, triangular) and uncertainty source (N_2O GWP, activity level, applicability, uptake, interaction factors, abatement rate, net cost, or all seven sources combined). When running Monte Carlo simulations for all seven sources combined the uncertainties associated with the different sources were assumed to be independent, in the absence of any quantitative information on possible dependence between them. This can result in a potentially minor overestimation of the uncertainties of the outputs.

Results

Uncertainty of the economically optimal GHG abatement

The level of economically optimal GHG abatement is one of the key quantities that summarises the MACC. We quantify uncertainty within this by looking at the ratio of the width of the 95% confidence interval to the mean.

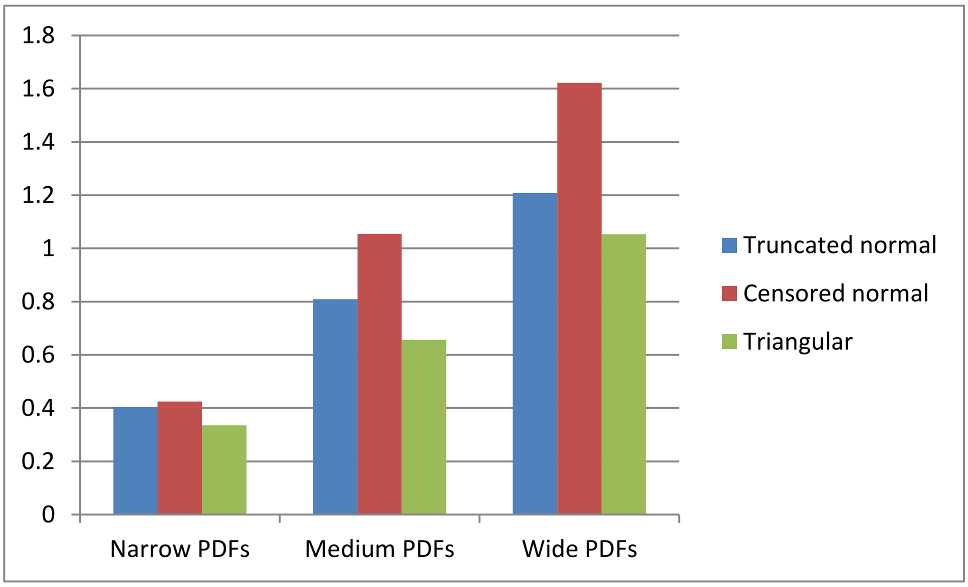
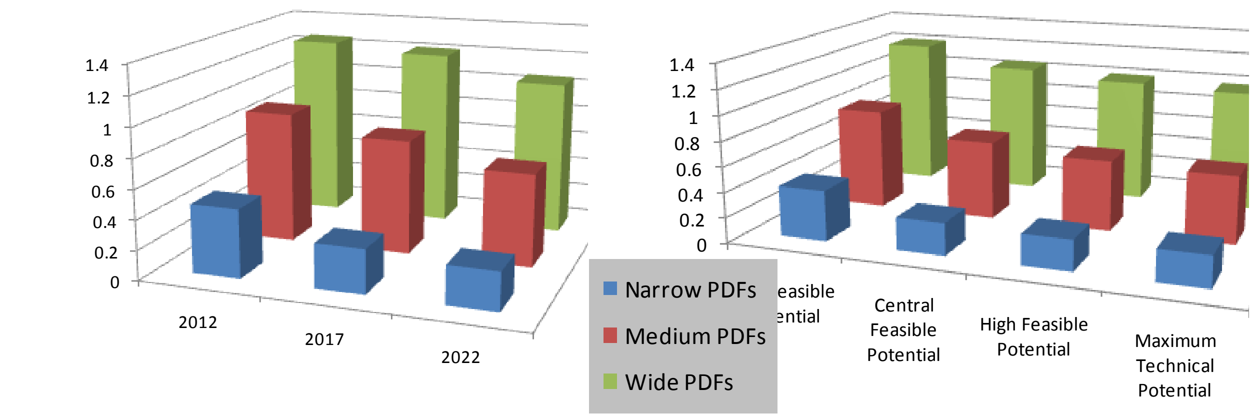


Figure 3. The ratio of the width of the 95% CI to the mean of the economically optimal GHG abatement for the different PDF shapes: truncated normal, censored normal and triangular, for the three uncertainty scenarios (narrow, medium and wide PDFs), all for the central feasible potential uptake scenario, in year 2022, for all uncertainty sources combined

In Figure 3 we compare the levels of uncertainty associated with different uncertainty scenarios and parametric models for all seven uncertainty sources combined, for the uptake scenario CFP and year 2022. The uncertainty in the wide scenario is, unsurprisingly, higher than that in the medium scenario, and this is, in turn, higher than that in the narrow scenario. The censored normal produces higher estimates of uncertainty than the other two parametric models because it is the only model to allow a non-zero probability that the true value will be equal to the natural limit of the variable (e.g. 0 or 1, for uptake rate). The estimated levels of

uncertainty for the truncated normal and triangular model are more similar, but uncertainty is generally lowest for the triangular model.
When propagating the uncertainties of all the inputs across the three uncertainty scenarios, four uptake scenarios and three years (truncated normal PDFs), the ratio of the 95% CI to the mean of the economically optimal GHG abatement ranged from 0.24 to 1.40, the lowest uncertainty existing for the high feasible potential in 2022 with narrow PDFs, and the highest uncertainty existing for the low feasible potential in 2012, with wide PDFs. In general, the uncertainty of this output metric decreases with the increasing level of uptake as we move from scenario LFP to scenario MTP, and also as the results are projected further in the future (Figure 4) – both findings can mainly be explained by the assumption of a linearly increasing level of uptake through time.



a) b)

Figure 4. The ratio of the width of the 95% CI to the mean of the economically optimal GHG abatement (truncated normal distributions, for all uncertainty sources combined). a) Central feasible potential uptake scenario, for three different years and three different uncertainty scenario, b) Year 2022, for four different uptake scenario and three different uncertainty scenario

The contribution of the uncertainty in each input category to the uncertainty of the economically optimal abatement was examined by propagating the uncertainty of one input category at a time, for all the three years, four uptake scenarios and three PDF assumptions – see an example on Figure 5. The uncertainty in abatement rate was the most important contributor in most of the cases, apart from the scenarios with low uptake rates – as is the case for the year 2012 and for the uptake scenario LFP – where the uncertainty of the uptake inputs is the most important driver. The uncertainty in the abatement rate is exacerbated by the interaction factors, which reduce (or increase) the abatement rate of the options without affecting the costs.

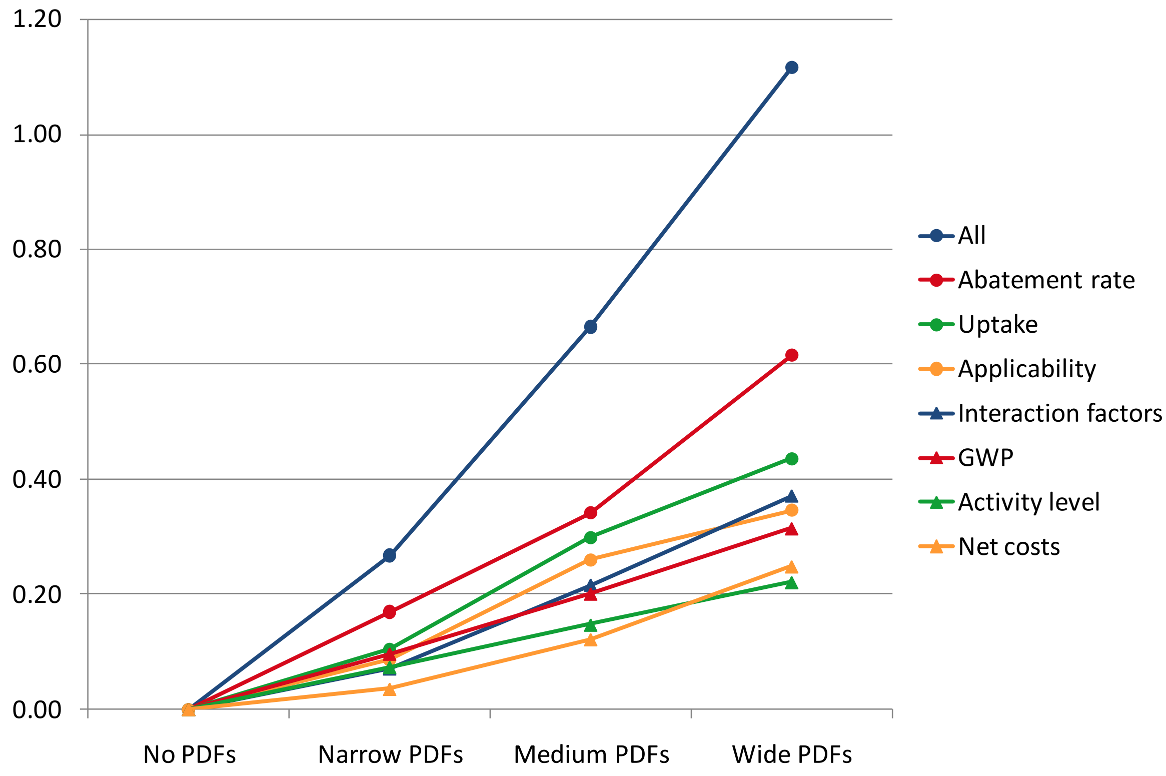


Figure 5. The ratio of the width of the 95% CI to the mean of the economically optimal GHG abatement (truncated normal distributions, 2022 central feasible potential) as propagating the uncertainty of individual groups of inputs and all the inputs.

Uncertainty in the ranking of the mitigation options

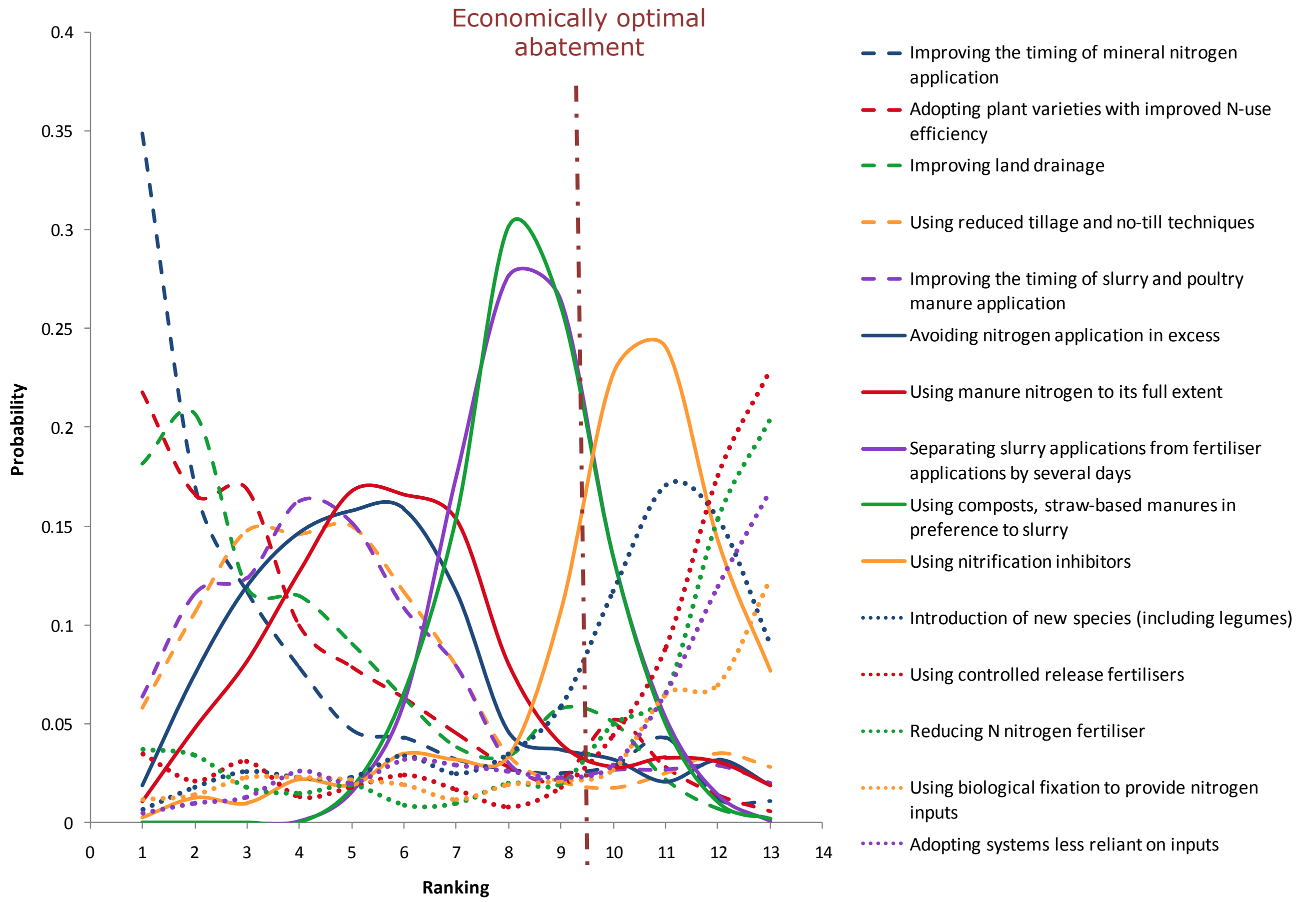


Figure 6. The ratio of the width of the 95% CI to the mean of the economically optimal GHG abatement (truncated normal distributions, for all uncertainty sources combined), 2022, central feasible potential, wide PDFs

The input uncertainty results in uncertainty in the ranking of the mitigation options due to the uncertainty in their cost-effectiveness and in the interaction factors. Figure 6 reveals that this uncertainty can be relatively high in the ranking of some options if wide PDFs are propagated through the model. For example the ranking of 'Improving land drainage' has a wide, trimodal distribution, and though being ranked as the third best option (out of nine options with a CE below the SPC) it still has an 8% uncertainty of its cost-effectiveness being higher than the shadow price of carbon. The options with cost-effectiveness closest to 0 are the least uncertain in terms of ranking, which can be partly explained by the PDFs assigned to the net costs and the abatement rate, both of which are proportional to the mode. However, in spite of the uncertainty in the individual ranking of the options, the set of options which are estimated to be cost-effective are relatively stable, having only a few options crossing the SPC threshold form either side.

Discussion and conclusion

The work presented in this paper made an attempt to systematically assess the uncertainties in the GHG abatement potential of agriculture by a case study that involved producing MACC analysis of crops and soil related mitigation options in Scotland. A qualitative analysis disentangled the different sources of uncertainties in the model, identifying statistical, deep and value uncertainties, and a quantitative uncertainty assessment examined the statistical uncertainties of the model.

The qualitative assessment revealed the numerous sources of uncertainty in the economic assessment of agricultural GHG mitigation. These complex assessment exercises incorporate many aspects of uncertainty - from modelling the biophysical processes through to economic, political and behavioural aspects. Deep uncertainties are present in connection to every input variable, and information on the statistical uncertainties is often restricted. Part of the underlying data is easily accessible (like statistics on current activity levels), at least in countries where statistical data are commonly collected on agricultural activities, but even for those data uncertainty information is not commonly reported. There is a vast literature on the potential abatement achievable with the mitigation options, and more and more meta-analysis are available – however, the usually not very rigorous uncertainty reporting practices mean that uncertainty information on abatement rates is hardly available. MACCs, being an *ex ante* assessment, inputs from other modelling exercises are often used – where the uncertainty reporting is usually also scarce. This lack of information necessitated the use of an uncertainty assessment rather than an uncertainty analysis, but useful recommendations still can be drawn from such an exercise.

The uncertainty in the economically optimal abatement becomes high in the medium and wide uncertainty scenarios, with the ratio of the 95% CI to the mean being 0.57-1.01 and 0.98-1.4, respectively, while assuming low uncertainty in the inputs results in much lower uncertainty of this output metric (the ratio of the 95% CI to the mean is 0.24-0.68 across the scenarios). However, the ranking of the measures are relatively robust, especially in terms of which options have cost-effectiveness below the carbon price threshold. These results imply that although there is a high level of uncertainty regarding abatement potential estimates, we have higher certainty in which mitigation options should, at least from the perspective of cost-effectiveness, be implemented on farms. This finding corresponds to Gibbons et al. (Gibbons et al. 2006), who found that the total emissions from the farms are very uncertain, but the relative effects of mitigation options (expressed as a proportion of total farm emissions) had a lower degree of uncertainty.

Looking at the contribution of uncertainties in the input variables to the uncertainty in economically optimal abatement potential, abatement rate and uptake rate are the most important input variables. At the same time these two, along with three more input variables (applicability rate, net costs and interaction factors) have the largest degree of input uncertainty. Inputs which both have high uncertainty and contribute highly to the output uncertainty are the key factors to be addressed if we are to reduce uncertainty in the outputs (Heijungs 1996) – in the case of our assessment these key factors are uptake rate and abatement rate (Figure 7).

Figure 7. Uncertainty assessment of the input variables

There are opportunities to reduce the uncertainty in agricultural GHG mitigation, although when considering these opportunities the effort needed to reduce the uncertainties must be weighed against the benefits gained from more robust predictions. First of all, the data gaps in the uncertainties of the inputs are very large – both for the biophysical and the socio-economic inputs. Improving scientific reporting practice to include quantified data about the statistical uncertainty in underlying research would be one of the most efficient ways to reduce uncertainty. Ongoing research on the biophysical aspects of the mitigation options is constantly providing new data on the abatement rate and at some extent about interaction factors – again, these results are most useful if accompanied by uncertainty estimates. Similar improvements are needed in the economic analyses to reduce uncertainties in cost estimates and also to improve the robustness of future changes in agriculture and land use. Uncertainty in uptake rate can be improved through a better understanding of behavioural processes and of the effects of policy instruments on farmers' choices. Applicability rates are ultimately based on agronomic experts' opinion – formal elicitation of uncertainty in this case is also possible, although resource intensive. Overall, it is likely that the uncertainties in biophysical and economic modelling will become more explicit in the future, reducing the extent of uncertainty in integrated modelling. However, improving our knowledge about the uncertainty in applicability rates and uptake rates requires even more effort. Nevertheless, emphasis should be put on supporting ongoing research about abatement rates and about farmers' behaviour, as the key factors driving the uncertainty of the economically optimal abatement.

MACCs, like other integrative assessment tools, accumulate uncertainties. Input data might include statistics, meta-analysis of field experiments, results from biophysical and financial models, results from expert elicitation exercises, or assumptions based on the judgment of the researchers. These inputs all have their underlying uncertainties, partly quantifiable statistical uncertainties, partly unquantifiable deep uncertainties. However, assessing the importance of these uncertainties – along with what extent to which they can be reduced – is an important step in informing the development of more robust policies. As a general guideline, all economic assessment results should include the following points in order to make useful policy contributions (Kann and Weyant 2000; Smith and Stern 2011):

- Probability-weighted values ('implied probabilities') of the outputs,
- Information on where the model results provide reliable information (i.e. what are the boundaries of the model's relevance),
- Key inputs driving the uncertainty of the outputs and
- The extent of unquantifiable uncertainty.

As a recommendation for policy makers it can be concluded form the current case study that the uncertainty in the economically optimal GHG abatement rate on Scottish soils is high, and to reduce it the focus should be on research effort looking at the potential mitigation efficacy of the mitigation options and at the likeliness of farmers implementing these options in the future. Nevertheless, the ranking of the options is more robust, and the cost-efficiency of the mitigation options is not likely to cross the shadow price of carbon, which is the threshold for economic efficiency.

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