Uncertainty in non-CO_2 greenhouse gas mitigation: Make-or-break for global climate policy feasibility

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Abstract

Despite its projected crucial role in stringent, future global climate policy, non-CO_2 greenhouse gas (NCGG) mitigation remains a large uncertain factor that has received relatively little scientific attention. A revision of the estimated mitigation potential could have massive implications for the feasibility of global climate policy to reach the Paris Agreement climate goals. Here, we provide a systematic bottom-up estimate of the total uncertainty in NCGG mitigation, by developing "optimistic, default and pessimistic" long-term non-CO_2 marginal abatement cost (MAC) curves. The global 1.5-degree climate target is found to be out of reach under pessimistic MAC assumptions, as is the 2-degree target under high emission assumptions. MAC uncertainty translates into a large projected range in (all in a 2-degree scenario) relative NCGG reduction (40–58%), carbon budget (± 120 Gt CO_2) and policy costs (± 16%). Partly, the MAC uncertainty signifies a gap that could be bridged by human efforts, but largely it indicates uncertainty in technical limitations.

Introduction

Roughly one-third of present-day global warming can be attributed to non-CO_2 greenhouse gases (NCGGs), such as methane (CH_4), nitrous oxide (N_2O) and fluorinated greenhouse gases (HFCs, PFCs, SF_6 and NF_3) [4]. Correspondingly, reaching ambitious climate targets also requires deep reductions of these gases [5, 6]. Reducing NCGG emissions as part of a mitigation strategy can have substantial benefits, including 1) cost reductions [1,7,11-16], 2) rapid impacts on temperature (given the short lifetimes of some NCGGs [8], and, 3) substantial health benefits, as several gases are also air pollutants [17]. Nevertheless, most attention in climate policy analysis has been paid to CO_2, given its large share in overall emissions [18].

Global climate change mitigation research relies heavily on integrated assessment models (IAMs)[20]. For projected NCGG mitigation, these IAM models almost universally use NCGG marginal abatement cost (MAC) curves. These are region- and source-specific datasets used in climate policy research and scenario development to estimate emission reduction potentials and costs. Comprehensive sets of long-term MAC curves are rarely produced, and many models use relatively old information [19, 21]. Moreover, IAMs typically use only "one" middle-of-the-road estimate. Therefore, the inherently high uncertainty and possible large consequences for climate policy are largely unknown or at least hidden in most climate change mitigation scenarios.

This study aims to understand the uncertainty in the mitigation potential of emissions from all major NCGG emission sources and the implications for climate policy feasibility, strategies and costs. For this, we develop "optimistic", "pessimistic", and default NCGG MAC curves based on the most recent literature, representing the uncertainty range in relative emissions reductions. We subsequently assess the implications of the MAC curve uncertainty in meeting the objectives of the Paris Agreement using the IMAGE 3.2 integrated assessment model [2, 3]. By varying assumptions on human activities, this setup also allows an assessment of the impact of human activities on overall uncertainty, next to the implications from technical uncertainty represented by the MACs.

The MACs represent all major emitting sectors: agriculture, industry, waste and fossil fuel production. (see methods and supplement S1). They have been developed using the method by ref. [1] but complemented with uncertainty ranges and the inclusion of an additional approx. 120 recent studies on mitigation measures. The MAC uncertainty analysis is performed with the most detail for the agricultural sources since 1) these are hardest to abate (and thus most relevant in stringent climate scenarios) [21], 2) mitigation potentials are most uncertain, and 3) can be based on the fully bottom-up approach by [1], with quantitative estimates for all underlying parameters. The agricultural MACs are built-up from quantitative components, representing 1) reductions when measures can be applied, 2) technical applicability, 3) non-technical implementation barriers, 4) technological progress, 5) correction for overlap between measures and 6) costs (See Methods and supplement S2). For each component, uncertainty ranges have been estimated, where possible, based on the most recent literature. In a Monte Carlo (MC) simulation, these input parameters have been varied to determine the lower and upper bounds of the overall relative reduction potential per emissions source. For all non-agricultural sources, uncertainty has been estimated by deriving source-specific maximum reduction potentials from literature and expert insights from the GAINS research group [22, 23] (see Methods and supplement S6). A full MC analysis is not possible for these sources, since most values of the underlying parameters are unknown, as the short-term MAC data is based on external databases. However, reduction potentials for non-agriculture sources are generally higher than for agriculture sources, implying lower uncertainty and lower residual emissions in stringent climate scenarios [21]. All MAC curves are available for further research (including model-based analysis). See supplement “Data_MAC_CH4N2O”.

Scenario analysis. The MAC curves have been used as an input to IMAGE in conjunction with Shared Socio-economic Pathway (SSP) based scenario assumptions [34]. The scenarios are described in Table 1. The core set to assess the implications of the MAC uncertainty is based on SSP2, a scenario with middle-of-the-road socio-economic and technological development assumptions. The scenarios are set to reach a 1.5- and 2-degrees Celsius target in 2100 (represented by 2.0 W/m^2 and 2.6 W/m^2 radiative forcing targets) under optimistic, default and pessimistic NCGG MAC assumptions (i.e., with high (H), medium (M) and low (L) reduction potentials, respectively). The mitigation scenario implications are compared to a no climate policy baseline (Base). Pre-2100 temperature overshoots are allowed.

In addition, the analysis includes two additional SSP scenarios (in a 2-degree case) to assess the additional uncertainty due to human activities: SSP1 and SSP3, with low and high GHG-emitting activities, respectively (see methods for underlying scenario assumptions). SSP1 is combined with optimistic MAC assumptions (H) and SSP3 with pessimistic assumptions (L) to represent the extremes in NCGG emissions. The goal of the scenario analysis is to analyze the effect of MAC uncertainty and uncertainty in human NCGG emitting activities on:

- Feasibility of scenarios

- NCGG emission reductions (total and source-specific)
- Climate policy costs
- Remaining global carbon budgets, i.e., the need for CO_2 mitigation

The scenarios used to assess uncertainty in GHG-emitting activities (2H_SSP1 and 2L_SSP3) have only been used for the feasibility and carbon budget calculations. Policy costs and NCGG reduction are not directly comparable due to different cost and baseline emission assumptions.

Table 1: Scenario setup

Scenario	NCGG MAC reduction potential	Human GHG-emitting activities	Radiative forcing target 2100 (W/m^2)
Base	n.a.	Medium (SSP2)	n.a. *
2H	High / Optimistic	Medium (SSP2)	2.6
2M	Medium	Medium (SSP2)	2.6
2L	Low / Pessimistic	Medium (SSP2)	2.6
1.5H	High / Optimistic	Medium (SSP2)	2.0
1.5M	Medium	Medium (SSP2)	2.0
1.5L **	Low / Pessimistic	Medium (SSP2)	2.0
2H_SSP1	High / Optimistic	Low (SSP1)	2.6
2L_SSP3 **	Low / Pessimistic	High (SSP3)	2.6

* No target set. Default SSP2 baseline settings lead to a forcing level of 6.0 – 6.2 W/m^2

** Infeasible scenarios (see Results)

Results

Literature study agricultural measures. The goal of the literature study has been to include recent case studies on agricultural measures to the former dataset [1] by collecting information on reduction efficiencies (RE), technical applicability (TA) and costs. RE represents the relative emission reduction when a measure is applied. TA represents the share of the baseline emissions where a measure can be applied. Table 2 gives an overview of the included measures and associated RE values (supplement S4 includes a table with all emission sources and a description of the measures and assumptions for all emission sources). Several agricultural sources included in [1] have been excluded here because they are implicitly part of other measures or conflict with them (CH_4 enteric fermentation: Improved milk production, extended productive life and for N_2O fertilizer: fertilizer free zone, sub-optimal fertilizer application). The following additional measures have been included in this study: for CH_4 enteric fermentation: Seaweed asparagopsis taxiformis as a feed supplement (optimistic case only); for CH_4 manure: solid-liquid separation; for N_2O fertilizer: Biochar (optimistic case only), no-tillage, irrigation practices, and for N_2O manure: Anaerobic digestion and manure acidification.

Table 2: Included agricultural reduction measures, associated reduction efficiencies (when fully applied) and underlying literature

	Measures	Range in reduction efficiencies (%)	References reduction efficiencies
CH_4 - Enteric fermentation	Addition of nitrate to the feed	21-42	[36-43]
	Genetic selection and breeding	8-31	[44-48]
	Adding tannins as a food supplement	10-32	[49-53]
	Grain processing	10-38	[51, 54-56]
	Improved health monitoring and illness prevention	4-20	[47, 57-59]
	Seaweed (Asparagopsis taxiformis)	12-99.5	[60-65]
CH4 - Rice production	Rice straw mitigation	26.5-61	[66-71]
	Direct seeding	16.6-47	[66, 70, 72-74]
	Replacing urea with ammonium sulphate	14.18-42	[66, 70, 75, 76]
	Addition of phosphogypsum	28-86	[66, 70, 77-80]
	Alternate flooding and drainage	18.8-79	[37, 50, 54, 55, 65, 66, 68-80][81-88]
CH_4 - Manure	Manure acidification	61-98	[51, 69, 89-93]
	Anaerobic digestion	25-75	[66, 94-96]
	Solid-liquid separation	46-81	[94, 95]
	Manure storage: duration	38-76	[97]
	Housing systems and beddings	4-96	[36, 51, 98-102]
	Manure storage covering	0-90	[36, 51, 91, 103]
N_2O - Fertilizer	Nitrification inhibitors	17-60	[30, 36, 104-114]
	Improved land manure application	5-50	[111, 115-119]
	Irrigation practices	15-67	[120-123]
	Biochar	14-38	[124-127]
	Spreader maintenance	22-42	[15, 66, 128, 129]
	Improved agronomy practices	14-54	[119, 130-135]
	No-tillage	25-48	[136-140]
N_2O- Manure	Reduced dietary protein	0-52	[51, 141-145]
	Decreased manure storage time	35-35	[51]
	Manure storage covering	30-75	[36, 51]
	Improved animal housing systems and bedding	9-88	[36, 98, 100, 101]
	Anaerobic digestion	34-75	[96, 146, 147]
	Acidification	0-96	[148-153]

Next to collecting data on RE values (Table 2), the literature study also contributed to updating the default assumptions for the components TA [154, 155] and costs [57, 66, 67, 17, 119, 156-163]. Supplement S5 provides an overview of all input values to the Monte Carlo analysis.

Optimistic / default / pessimistic MAC curves. The “optimistic”, default and “pessimistic” MAC curves have been developed for all major NCGG sources for 26 world regions and the 2020-2100 period (See supplement “Data_MAC_CH4N2O”). Figure 1 shows the MAC curves for the five agricultural sources (example: Western Europe). See supplement S8 for an overview of the non-agricultural MACs (CH_4 and N_2O). As the approach and part of the data were similar to those used in Harmsen et al., 2019 [1], it is relevant to compare the maximum reduction potentials (MRPs) of the MACs in both studies (see also supplement S7 with an MRP comparison for all sources in 2050 and 2100). For the agricultural sources, the Harmsen et al., 2019 [1] default estimate is generally found between this study’s default and optimistic value, i.e., that this study’s default reduction potential is generally somewhat lower. N_2O emissions from manure form an exception with a slightly higher MRP due to newly included measures. This is mainly the result of the Monte Carlo approach used in this study, where lower implementation and technical applicability values are included in the solution space. For CH_4 rice, recent studies also indicate a lower reduction efficiency. Further, this study assumes a higher overlap between CH_4 manure measures.

Climate targets are out of reach under pessimistic assumptions. Of the scenarios described in Table 1, both 1.5L and 2L_SSP3 have proven to be infeasible. This implies that under pessimistic NCGG mitigation assumptions, the 1.5-degree climate target cannot be reached, despite maximum climate policy efforts. Further, the combination of high GHG-emitting activities (SSP3-based) and a low NCGG mitigation potential would even keep the 2-degree climate target out of reach. Figure 2 shows the results from the scenario exercise. Optimistic NCGG assumptions (indicated in light green) correspond with high NCGG reductions, lower policy costs and higher carbon budgets, with opposite relations under pessimistic assumptions (indicated in orange).

Range in NCGG reduction. Unsurprisingly, MAC uncertainly results in considerable ranges in projected NCGG reductions (panel a). This is indicated by the range under the same (SSP2) baseline assumptions, with (in relative difference with a no climate policy baseline in CO_2 equivalents) 40% to 58% in the 2-degree case and 54%-65% in the 1.5-degree case. Net NCGG reductions only provide an overall indication because of the policy-dependent choice of GWP metric (here: AR4 GPW_{100}) to convert NCGG emissions to CO_2 equivalents. Supplement S9 gives the source-specific relative and absolute reductions. Methane mitigation is the main contributor to total NCGG reduction (in 2100: 45-51%), followed by HFCs (31-38%), N_2O (13-17%) and small contributions of SF_6 (1.7%) and PFCs (0.5%). In all mitigation scenarios, total F-gases are reduced by more than 90% in 2100, leaving most of the uncertainty with CH_4 and N_2O.[1] An average 57% of total CH_4 reductions is realized in fossil energy. However, the scenario differences are largely defined by differences in projected agriculture emissions. This is also the case for N_2O where 90% of the emissions are produced in agriculture. The optimistic MAC scenarios favor early-century NCGG mitigation, due to its lower-cost, high mitigation potential. While this does not result in notable climatic differences in the 2-degree scenarios, the optimistic 1.5-degree scenario is found to have a 0.04-0.05 degree C lower mid-century peak temperature than the default 1.5 case (not shown).

Climate policy costs. Global climate policy costs (Figure 2, panel b) strongly depend on the availability of NCGG mitigation options. When low-cost options are exhausted, climate targets can only be met by “moving up the MAC curve”. This is indicated by the 32% difference in cost between the pessimistic and optimistic 2-degree scenarios and a 59% difference between the default and optimistic 1.5-degree scenarios, where nearly all options need to be applied. Although the absolute policy costs are highly uncertain (here, estimated at roughly 1% - 1.5% of global GDP), the relative scenario differences give a more robust indication of the large implications of NCGG MAC uncertainty.

Carbon budgets. Under equal climate targets, cumulative CO_2 emissions need to compensate for differences in NCGG emissions, which can be expressed in an allowable global CO_2 budget for the remainder of the century (Figure 2, panel C).[2] MAC uncertainty alone translates into a 240 Gt CO_2 range in the carbon budget under 2-degree conditions. Lower (SSP1-based) GHG-emitting activities can increase this value by a projected 38 Gt. No feasible low-enough carbon budget (i.e., level of CO_2 mitigation) can be found under the high-emitting, low mitigation conditions in 2L_SSP3. MAC uncertainty is projected to result in a (partial) 73 Gt range in the carbon budget in the 1.5-degree case. The carbon budget estimates from this study’s bottom-up uncertainty analysis are relatively consistent with top-down analyses of large scenario ensembles. As part of the IPCC’s 1.5 degree Special Report and more recent 6th Assessment Report, It has been estimated that uncertainty in future NCGG emissions could affect the global carbon budget by ±250 Gt CO_2 or ±220 Gt CO_2, respectively [222, 223]. Here, we find a slightly smaller range in a 2-degree case only and with a single model. The large disadvantage of the top-down approach is the difficulty in distinguishing between factors underlying the range. These could also simply be the exclusion of emission categories in models or a simplified representation of NCGG emissions, next to assumptions on activities and mitigation options. Regardless, both the top-down and bottom-up estimates portray NCGGs as a huge uncertain factor, considering the remaining CO_2 budgets of roughly 1000 Gt and 400 Gt in a 2-degree and 1.5-degree case, respectively.

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[1] The gas-specific uncertainty is also reflected by differences in the climatic influence of individual gases. The projected (MAGICC6.3-based) difference in high vs. low radiative forcing in a 2-degree case in 2100 is for (in W/m^2): CH_4: 0.08, N_2O: 0.05, F-gases: 0.02.

[2] The average carbon budgets presented here are lower than in AR6 (1150 and 500 GtCO2, in a 2- and 1.5 degree scenario [222]) due to more conservative definitions of the climate targets, reflected in lower forcing targets.

Discussion

This study shows the crucial role that NCGG mitigation needs to fulfill in future stringent climate change mitigation scenarios. It also makes clear that uncertainty in future NCGG mitigation implies that we cannot be confident about the feasibility of stringent climate goals. More NCGG mitigation measure deployment, case studies and research can help in three ways in this respect: 1) It maximizes learning and thus reduction potentials, while lowering costs 2) It stimulates early action, limiting short-term climate change and avoiding limitations in longer-term upscaling, and 3) It helps understand the limitations of NCGG mitigation, leading to more accurate and effective policy strategies.

The MAC curves exclude natural emission sources that can be influenced by human influence, most importantly, wetlands. The human-induced GHG emission fluxes (notably from CH_4 and CO_2) from wetlands are highly uncertain and could either be net positive or negative [224]. This study also excludes uncertainties in NCGG atmospheric chemistry and climate effects. For all non-included factors, we assumed default values, implying that the uncertainty range is larger in both positive and negative directions, making it likely that NCGG uncertainty has even larger implications for climate policy feasibility.

Note that the MAC curves solely specify relative reductions at different price levels. They are agnostic about the likelihood of climate ambitions, which are almost certainly regionally constrained (e.g., lack of finance or ceilings on food prices), represented by the carbon price. These constraints can be estimated exogenously or specified in IAM-based scenario studies. The information in the MACs only represents climate policy implications. Mitigation measures might not be desirable when including non-climate socio-economic aspects (e.g., NCGG pricing leading to higher food prices or negative environmental implications of intensive agriculture).

The MAC curves should only be used as an uncertainty benchmark and explicitly not as a representation of high, default and low ambition levels. It would be misleading to present the optimistic or pessimistic MACs as realistic options that depend on policy choices. To a large degree, the MAC mitigation uncertainty indicates uncertainty in technical limitations, which cannot be influenced by human efforts, whereas the “human ambition element” should be represented by the carbon price. However, it can be argued that highly uncertain, “soft” MAC components such as the implementation potential (representing the level of social barriers) or R&D efforts behind technological progress could allow for some minor additional gain at high ambition levels.

Online Methods

The method section is structured in four parts: 1) A description of the system boundaries and the coverage of global NCGG emissions, 2) An approach to construct the MACs (provided in more detail in supplement S2), 3) The development of the “optimistic, default and pessimistic” MACs and 4) A description of the scenario analysis.

System boundaries

The MAC curves and scenario assessment in this study are based on the emission source categories of the IMAGE 3.2 model [2, 3], representing all anthropogenic NCGGs. The MAC curves in this study cover 92% of the present-day NCGG emissions and 96% of the projected emissions in 2100 (see supplement S1). The MAC curves represent potential emission reductions under CO_2 equivalent prices up to 4000 \$(2005)/tCeq (or 1446 \$(2020)/tCO_2eq.), the maximum price that is applied in the IMAGE IAM framework. Emissions and emission reductions are calculated for the 26 global IMAGE regions (see supplement S3). Regional differences in present-day emission intensities and activities are fully represented in the scenario assessment. Regional emissions in the base year (2015 to 2020, depending on the source) are calibrated with data from several detailed databases covering different emissions sources; CEDS [24], GAINS [23], EDGAR 4.2.3 [25], [26].

Construction of the MAC curves

The MACs are built up from individual source-specific measures and assumptions on long-term developments (See supplement S2 for a more detailed description). The relative reduction potential (*RP*) (in %) of each mitigation measure in year *t* and region *r* is determined by Eq. 1. The maximum reduction potential (*MRP*) (in %) is the maximum relative abatement compared to baseline source emissions when all source-specific measures are implemented (Eq. 2).

$$RP_{(t,r)} = RE * TA_{(r)} * OVcorr_{(t,r)} * IP_{(t)} \qquad (1)$$

$$MRP_{(t,r)} = (RP_{1\,(t,r)} + RP_{2\,(t,r)} + RP_{3\,(t,r)} \ldots + RPx_{(t,r)}) * TP_{(t)} - Bcorr_{(t,r)} \qquad (2)$$

With (all in %): *TA:* Technical applicability, this is the part of the baseline that can technically be covered by the measure. This is often 100% but can be lower, e.g., if only a sub-process is targeted or if regional climatic circumstances are unsuitable. *RE:* Reduction efficiency, i.e., the relative reduction in case a measure can be applied, generally based on multiple case studies. *IP:* Implementation potential represents (the lack of) non-technical barriers. This is assumed to increase in time due to improved technology diffusion and policy acceptance. *OVcorr:* Correction for overlap between measures that target the same emissions. If a subsequent measure is applied, it has a diminished benefit due to lower remaining emissions. Note that this correction increases with time as IP increases (based on [27], see S2). *TP:* Technological progress, increase of the reduction potential with time as a result of new or improved technologies. This is the only factor that is larger than 100% (see S2). *Bcorr:* Correction for regional emission reductions that already occur in the baseline scenario, e.g., due to zero or negative cost measures, such as the use of fugitive CH_4 emissions as an energy source, or non-climate policy reductions, such as from air quality measures.

Marginal costs

The combination of measures with the highest estimated maximum reduction potential is used to construct MAC curves. It is assumed that the least costly measures are implemented first. When multiple measures are used, mitigation costs increase due to diminishing returns when measures overlap, with for any measure x:

$$\text{Cost new}_x = \text{Cost old}_x * 1/\text{OVcorr}_x \qquad (3)$$

Regional differences

Regional differences in mitigation potential are included if these are known. These differences are reflected in the parameters: technical applicability, reduction efficiency, and costs. Partly, these are due to socio-economic circumstances (e.g., different present-day emission intensities and different levels of advancements in farming techniques) that can have short-term implications on mitigation potentials. However, in the case of similar biophysical circumstances across regions, we assume convergence in mitigation potentials (i.e., in minimum emission intensities) in the long term and at maximum carbon prices. Where differences in mitigation potentials are known to be caused by biophysical differences, such as regional temperature, precipitation, geography, etc., this has been taken into account in the form of quantitative constraints of the components underlying the MACs. In this study, we differentiated between regions with high, medium and low technical applicability for enteric fermentation and CH_4 manure (see supplement S5), based on the GAINS model global CH_4 mitigation potentials for livestock in 2030 and 2050 [22]. Regional differences in reduction efficiency are incorporated in the measure ‘anaerobic digestion’, which has different known impacts in warm and cold environments. Regional differences in costs are incorporated based on region-specific cost assessments (see tables S5.2 and S5.3).

Emission categories

The MACs for the agricultural emission sources *(CH_4 from rice production, CH_4 from enteric fermentation in ruminants, CH_4 and N_2O from manure, and N_2O from fertilizer)* have been constructed fully bottom-up, using the described methodology, as was also used in [1]. Here, we have updated the agricultural MAC curves by including (mostly) reduction efficiency data from ±120 recent studies. For the Monte Carlo analysis, ranges have been defined for all underlying MAC components (see section 2.3).

All non-agricultural sources are directly based on [1], with only a few, minor modifications to the default values for the maximum reduction potentials (MRPs). For the development of the pessimistic and optimistic MACs, MRP ranges have been varied, based on literature (see supplement S6). Waste and industry MACs *(*CH_4 *from landfills/solid waste,* CH_4 *from sewage and wastewater,* N_2O *from adipic and nitric acid production,* N_2O *from transport, and* N_2O *from domestic sewage),* are based on data up to 2030 [28-30] but have added assumptions on the technological progress up to 2100, largely based on current best practices [1]. Fossil energy MACs *(*CH_4 *from coal, oil and gas production)* are based on a dataset from the GAINS model [23, 31] with added long-term (MRP) assumptions on including promising technologies that are currently not in use on a large scale. The default F-gas MACs (*HFCs, PFCs and* SF_6) are directly used from [1], including recent calibrations by [26] and [32].

MAC uncertainty range

Agriculture: Monte Carlo analysis

The uncertainty analysis for agricultural sources is based on a Monte Carlo (MC) analysis where the underlying parameters have been randomly varied and subsequently run 1000 times. The outcome of the MC analysis is a range in relative reductions at all carbon eq. prices between zero and 4000$/tC. The pessimistic, default and optimistic MACs are based on the 5th, 50th and 95th percentile in reductions for each carbon price, respectively.

Each MAC component value within a range is given equal weight (i.e., uniform distribution) (see supplement S5 for the input values, assumptions and motivation). The minimum and maximum for the reduction efficiency (RE) component are based on case studies found in the literature. For each measure, the highest and lowest outliers were excluded to prevent the distribution from being skewed. The minimum and maximum of the distributions of the other MAC components are based on a delta value (all in ±%points, since uncertainty is expected to be equally large at high and low values, except for costs, which is given in US$ and where absolute uncertainty is expected to be proportional to values) around the default component value (unless new information was available, this was based on ref. [1]. The default delta values are (in ±%points): TA(40), OVcorr(30), IP(30), TP(10) (note, this applies to the “diff” term, explained in S1) and (in ±%): Cost(80). The cost delta value is large because of particularly large uncertainty. The values of all components can never be lower than 0 and higher than 100%. Where found relevant, based on existing literature, the sampling was constrained by technical limits (e.g., a TA value is never allowed to be higher than 70% if it is known that 30% of the baseline emissions cannot be reduced by a certain measure).

Non-agricultural sources: range in maximum reduction potentials

The optimistic, default and pessimistic MACs for the non-agricultural sources have been developed by varying the maximum reduction potentials (MRPs) in 2050 and 2100 and scaling them in intermediate years. A full MC analysis is not possible for these sources, since most values of the underlying parameters are unknown, as the short-term MAC data is based on external databases. However, reduction potentials are generally higher, implying lower uncertainty and lower residual emissions in stringent climate scenarios [21]. The default MACs are largely equal to those developed by [1], with some small modifications (see supplement S6 for the quantitative assumptions by source). Where known, estimates of current technical reduction potentials (based on projections by GAINS and US-EPA [12, 22, 33]) were used as a minimum value for the pessimistic MACs.

Scenario analysis

The MAC curves have been used as an input to IMAGE 3.2 [2, 3] in conjunction with Shared Socio-economic Pathway (SSP) based scenario assumptions [34]. The scenarios are described in Table 1. The core set to assess the implications of the MAC uncertainty is based on SSP2, a scenario with middle-of-the-road socio-economic and technological development assumptions. In these scenarios, a 1.5- and 2-degrees Celsius target should be reached in 2100 (represented by 2.0 W/m^2 and 2.6 W/m^2 radiative forcing targets), under optimistic, default and pessimistic NCGG MAC assumptions (i.e., with low (L), medium (M) and high (H) reduction potentials, respectively). The mitigation scenario implications are compared to a no climate policy baseline (Base). Pre-2100 temperature overshoots are allowed.

In addition, the analysis includes two additional SSP narratives (in a 2-degree case) to assess the additional uncertainty due to human activities: SSP1 and SSP3, with low and high GHG-emitting activities, respectively. The underlying scenario assumptions for SSP1 and SSP3 are described in [35] with included updates [3]. SSP1 is combined with optimistic MAC assumptions (H) and SSP3 with pessimistic assumptions (L) to represent the extremes in NCGG emissions. The goal of the scenario analysis is to analyze the effect of MAC uncertainty and uncertainty in human NCGG emitting activities on:

- Feasibility of scenarios
- NCGG emission reductions (total and source-specific)
- Climate policy costs
- Remaining global carbon budgets, i.e., the need for CO_2 mitigation

The scenarios used to assess uncertainty in GHG-emitting activities (2H_SSP1 and 2L_SSP3) have been used for the feasibility and carbon budget calculations only. Policy costs and NCGG reduction are not directly comparable due to different cost and baseline emission assumptions.

Table 1: Scenario setup

Scenario	NCGG MAC reduction potential	Human GHG-emitting activities	Radiative forcing target 2100 (W/m^2)
Base	n.a.	Medium (SSP2)	n.a. *
2H	High / Optimistic	Medium (SSP2)	2.6
2M	Medium	Medium (SSP2)	2.6
2L	Low / Pessimistic	Medium (SSP2)	2.6
1.5H	High / Optimistic	Medium (SSP2)	2.0
1.5M	Medium	Medium (SSP2)	2.0
1.5L **	Low / Pessimistic	Medium (SSP2)	2.0
2H_SSP1	High / Optimistic	Low (SSP1)	2.6
2L_SSP3 **	Low / Pessimistic	High (SSP3)	2.6

* No target set. Default SSP2 baseline settings lead to a forcing level of 6.0 – 6.2 W/m^2

** Infeasible scenarios (see Results)

Declarations

Acknowledgements

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Data availability

The optimistic, default and pessimistic CH_4 and N_2O MAC curves are made available as supplement “Data_MAC_CH4N2O”.

Code availability

We provide a stand-alone, Python-based script that can be used to perform the Monte Carlo analysis to build and analyze the agricultural MACs (supplement Agriculture_MAC_Monte_Carlo_Tool.ipynb).

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Figures

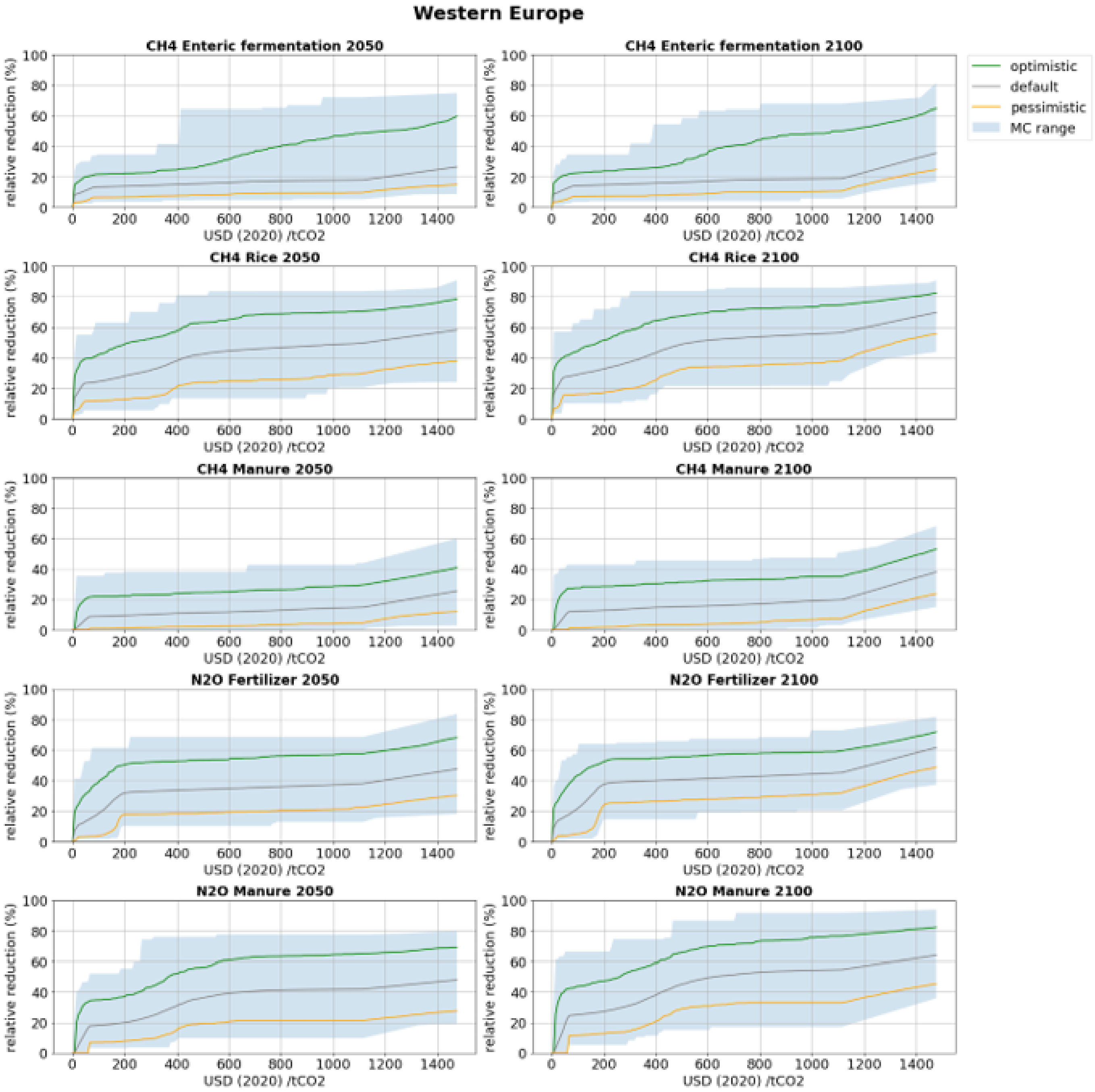

Figure 1

Agricultural MAC curves. Example: Western Europe. Optimistic (green), default (grey) and pessimistic (orange) MACs represent the 5th, 50th and 95% percentile in a 1000 MAC range. The blue-shaded area shows the Monte Carlo range. Left panels: 2050, Right panels: 2100. Relative reduction (Y-axis) is relative to the present-day, global mean emission intensity. CO_2 eq. prices (X-axis) are given in 2020$

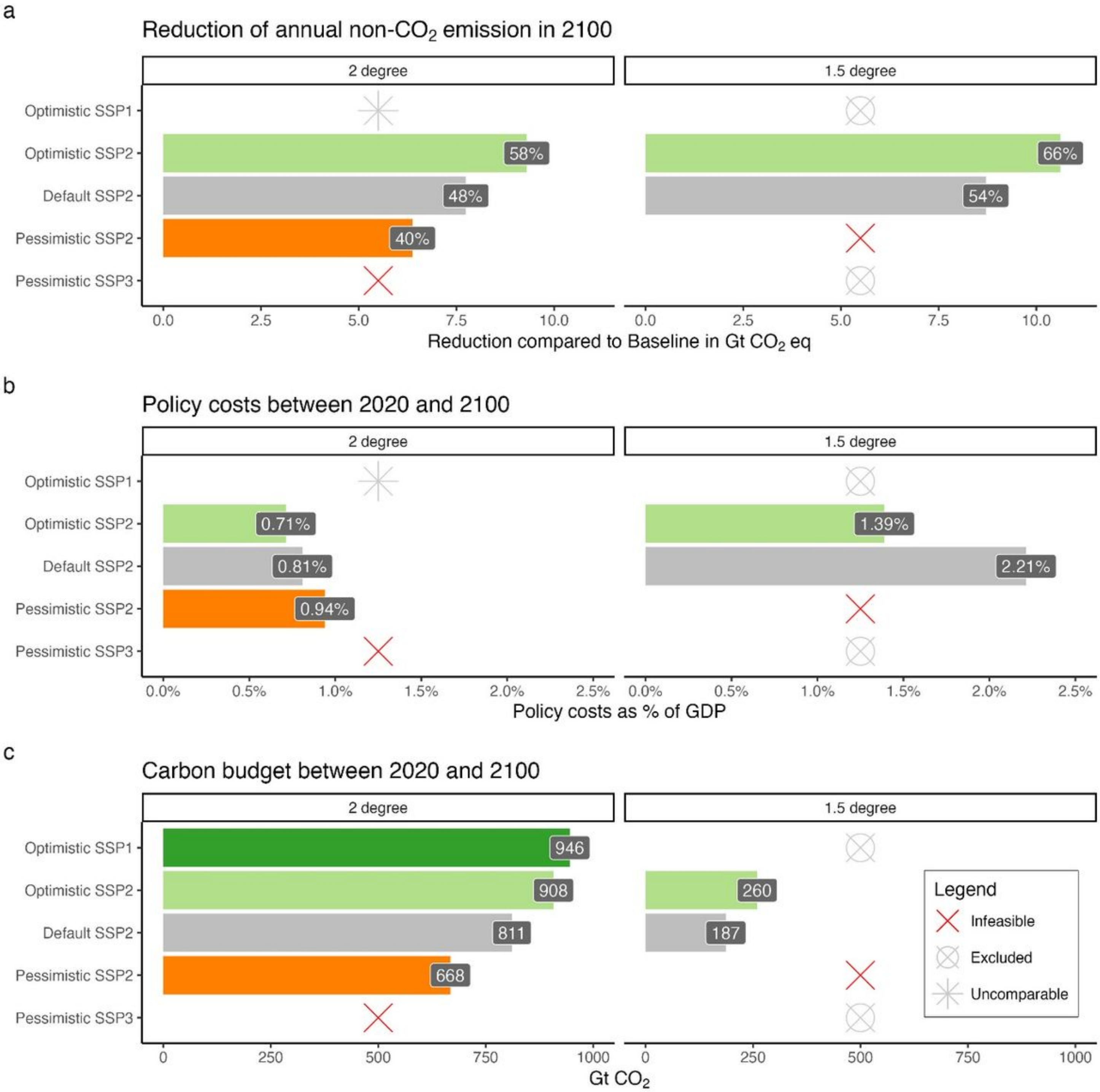

Figure 2

Scenario results. NCGG reduction (a) shows reduced Gt CO_2 equivalents (based on AR4 100-yr GWP) relative to baseline (SSP2) with % reductions in bars. Policy costs (b) represent global, first-order direct expenditures as a percentage of global GDP (PPP), discounted over the 2020-2100 period. Discount rate follows the yearly economic growth, with a Ramsey/Stern function. Carbon budgets (c) represent the net global CO_2 emissions over the 2020 – 2100 period. 2 Degree scenarios: right panels, 1.5-degree scenarios: left panels

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- DataMACCH4N2O.xlsx
- AgricultureMACMonteCarloTool.txt
- SupplementaryInformation.docx