Uncertainty in projected climate change arising from uncertain fossil-fuel emission factors

Environmental Research Letters

OPEN ACCESS

RECEIVED
27 October 2017

REVISED
2 February 2018

ACCEPTED FOR PUBLICATION
1 March 2018

PUBLISHED
29 March 2018

LETTER

Uncertainty in projected climate change arising from uncertain fossil-fuel emission factors

Y Quilcaille[1,2,6], T Gasser[3], P Ciais[1], F Lecocq[2], G Janssens-Maenhout[4] and S Mohr[5]

1 Laboratoire des Sciences du Climat et de l'Environnement, LSCE/IPSL, Université Paris Saclay, CEA—CNRS—UVSQ, 91191 Gif-sur-Yvette, France
2 Centre International de Recherche sur l'Environnement et le Développement (CIRED), CNRS—PontsParisTech—EHESS—AgroParisTech—CIRAD, 94736 Nogent-sur-Marne, France
3 International Institute for Applied Systems Analysis (IIASA), 2361 Laxenburg, Austria
4 European Commission, Joint Research Centre, 21027 Ispra, Italy
5 Institute for Sustainable Futures, University of Technology Sydney, UTS Building 10, 235 Jones St., Ultimo, NSW 2007, Australia
6 Author to whom any correspondence should be addressed.

E-mail: quilcail@centre-cired.fr

Keywords: emissions, climate, fossil fuels, uncertainty, Earth system modelling

Supplementary material for this article is available online

Abstract

Emission inventories are widely used by the climate community, but their uncertainties are rarely accounted for. In this study, we evaluate the uncertainty in projected climate change induced by uncertainties in fossil-fuel emissions, accounting for non-CO_2 species co-emitted with the combustion of fossil-fuels and their use in industrial processes. Using consistent historical reconstructions and three contrasted future projections of fossil-fuel extraction from Mohr *et al* we calculate CO_2 emissions and their uncertainties stemming from estimates of fuel carbon content, net calorific value and oxidation fraction. Our historical reconstructions of fossil-fuel CO_2 emissions are consistent with other inventories in terms of average and range. The uncertainties sum up to a ±15% relative uncertainty in cumulative CO_2 emissions by 2300. Uncertainties in the emissions of non-CO_2 species associated with the use of fossil fuels are estimated using co-emission ratios varying with time. Using these inputs, we use the compact Earth system model OSCAR v2.2 and a Monte Carlo setup, in order to attribute the uncertainty in projected global surface temperature change (ΔT) to three sources of uncertainty, namely on the Earth system's response, on fossil-fuel CO_2 emission and on non-CO_2 co-emissions. Under the three future fuel extraction scenarios, we simulate the median ΔT to be 1.9, 2.7 or 4.0 °C in 2300, with an associated 90% confidence interval of about 65%, 52% and 42%. We show that virtually all of the total uncertainty is attributable to the uncertainty in the future Earth system's response to the anthropogenic perturbation. We conclude that the uncertainty in emission estimates can be neglected for global temperature projections in the face of the large uncertainty in the Earth system response to the forcing of emissions. We show that this result does not hold for all variables of the climate system, such as the atmospheric partial pressure of CO_2 and the radiative forcing of tropospheric ozone, that have an emissions-induced uncertainty representing more than 40% of the uncertainty in the Earth system's response.

1. Introduction

Sources of uncertainty in climate change projections are numerous (Cox and Stephenson 2007, Hawkins and Sutton 2009, Allen *et al* 2000), ranging from the future evolution of anthropogenic drivers of climate change like future greenhouse gas and aerosol emissions, to the modeling of the Earth system's response. Scenarios based on contrasted socio-economic storylines and an ensemble of integrated assessment models (Moss *et al* 2010, O'Neill *et al* 2014) are used to explore the uncertainty in future human activities. For such a given emission scenario, the uncertainty in climate change is estimated by using different Earth system models (Flato *et al* 2013) to translate emissions into changes in concentrations, radiative forcing and climate. However, the extent in which the uncertainty in emissions affects climate change projections is not well known.

Fossil fuel use is the largest anthropogenic driver of the climate system. The burning of fossil fuels emits carbon dioxide (CO_2) to the atmosphere, and the fraction of CO_2 remaining airborne is the largest anthropogenic forcing of climate change. Other climate forcing agents such as carbon monoxide (CO), sulfur dioxide (SO_2) or nitrogen oxides (NO_x) are also co-emitted with the burning of fossil fuels, their use as feedstock in various industrial processes. During their extraction, fugitive emissions occur,in particular methane (CH_4) (Kirschke *et al* 2013, EEA 2013). The amount of each species emitted by these three activities related to fossil fuels is estimated via emission inventories, which combine activity data such as the mass of fuel used or the energy obtained from these fuels, with emission factors related to the carbon content of fuels and to technologies that produces co-emitted species (EEA 2013).

Because of the various methodologies and input data they use, different emission inventories show differences in their estimates of fossil CO_2 emissions (e.g. Olivier 2002, Marland *et al* 2009, Andres *et al* 2012). At a national scale, the major sources of uncertainties in inventories may be emission factors (Zhao *et al* 2011), although this remains unsure at a global scale. The *2006 IPCC Guidelines for National GHG Inventories* (IPCC 2006) recommend to use a mean carbon content for lignite of 101 $kgCO_2/GJ$ with a range from 91 to 115 $kgCO_2/GJ$ (95% confidence interval); hence a 10% uncertainty in the CO_2 emissions from lignite. For co-emitted non-CO_2 species, the uncertainty is much larger because their emissions depend not only on the composition of each fuel (in carbon, sulfur, nitrogen) but also on technologies that determine the fuel-use efficiency in different sectors, on the presence, enforcement of use, and efficiency of emission control devices (e.g. stack desulfurization) and on operating conditions (EEA 2013, IPCC 2006, Granier *et al* 2011). For instance, according to the *EMEP/EEA Air Pollutant Emission Inventory Guidebook 2013* (EEA 2013), the emission factor of CO for the burning of brown coal to produce electricity and heat is 8.7 gCO/GJ, but the associated 95% confidence interval ranges from 6.7 to 60.5 gCO/GJ. This means that a given amount of energy produced by the combustion of brown coal comes with a −20 to +600% uncertainty on CO emissions. Albeit CO has a minor contribution on climate change compared to other compounds such as CO_2, its impact on air quality is stronger (Crippa *et al* 2016).

In this study, we investigate how uncertainty in emission factors for CO_2 and non-CO_2 emissions associated with the combustion of fossil-fuels and their use in industrial processes affects climate change projections. First, we calculate ranges of uncertainty in CO_2 and non-CO_2 fossil-fuel co-emissions for historical and for three contrasted future scenarios of fossil fuel extraction. Second, we translate this uncertainty into a range of radiative forcing and climate change using the OSCAR v2.2 Earth system model, using a Monte-Carlo approach. Finally, we analyze the variance of the system and compare the uncertainty from emission factors to the one on the temperature response to emissions through Earth system processes.

2. Methods

An overview of our method is described in figure 1. Extraction scenarios (section 2.1) are combined with carbon contents, net calorific values and fractions of oxidations (section 2.2) to produce fossil-fuel CO_2 projections. To evaluate the fossil-fuel co-emissions, we calculate co-emission ratios, which are factors linking the fossil-fuel CO_2 emissions to the non-CO_2 emissions associated with fossil fuels (section 2.3). We complete these projections with non-fossil-fuel emissions and other anthropogenic drivers (section 2.4). Finally, the reduced-form Earth system model OSCAR is used with these drivers through a Monte-Carlo setup (section 2.5) to evaluate all required uncertainties. 5% and 95% quantiles are calculated to obtain the confidence intervals, whereas variances are used to calculate each contribution to the total variance.

2.1. Extraction scenarios

We take the historical reconstruction of fossil-fuel extraction (1750–2012) and three future extraction scenarios (up to 2300) made by Mohr *et al* (2015). Country-scale data is aggregated to the global scale for eight types of coal, five types of oil and five types of gas. Peat extraction, flaring and cement production are not included. The three future extraction scenarios were produced with the GeRS-DeMo model (Mohr and Evans 2010). Additionally, since conversion factors are provided by Mohr *et al* (2015), historical reconstruction and scenarios can be expressed both in energy values and in mass of extracted fuels. The future abundance in fossil fuels remains uncertain (Ward *et al* (2012), but this uncertainty is not included here. We use only three future scenarios, differing by their assumptions regarding ultimately recoverable resources, with a 'Low', 'Best Guess' (called 'Medium' hereafter) and 'High' case. For comparison, the Low scenario is between RCP2.6 and RCP4.5, the Medium close to RCP4.5 and the High near to RCP6.0 (Van Vuuren *et al* 2011). These scenarios include no climate policy or transition to non-fossil energy sources (unlike RCPs Clarke *et al* 2014) or SSPs (Riahi *et al* 2017), but this is not a limitation for our study since we focus on the climate change uncertainty induced by uncertain emission factors and for this purpose, we just need fossil-fuel scenarios comparable to those showed by the IPCC.

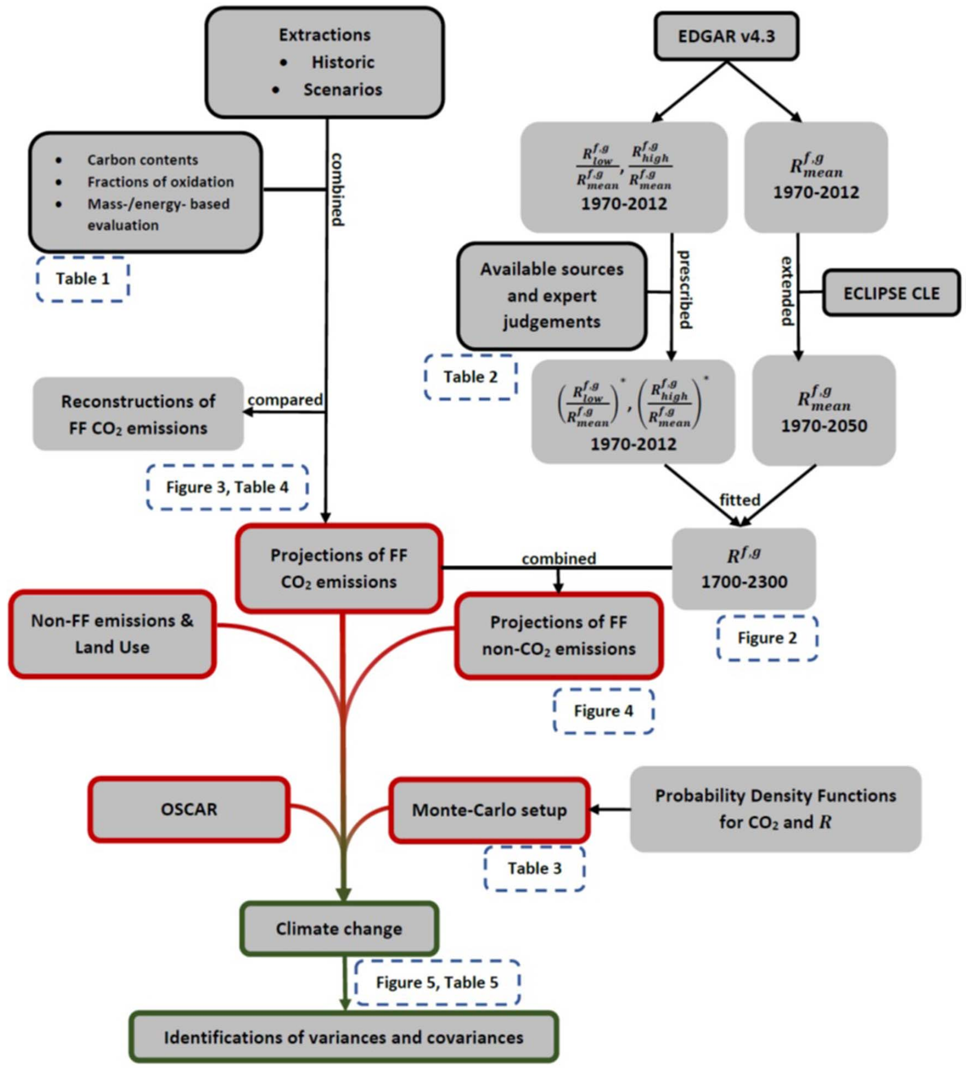

Figure 1. Overview of the method used in this study. For different parts, we give references to the relevant tables and figures. 'FF' stands here for fossil-fuel, and *R* corresponds to co-emission ratios.

The Mohr *et al* scenarios have the advantage of documenting fuel extraction of various fuel types (allowing us to address uncertainty on carbon contents) and to be fully consistent regarding the different fuel types between the historical and future periods.

2.2. CO_2 emissions

When calculated from energy-based fuel extraction data (superscript$^{\mathrm{ene}}$), CO_2 emissions in $\mathrm{kgC\,yr^{-1}}$ resulting from the use of a type *f* fuel are given by:

$$E_f^{CO_2} = FO_f C_f e_f^{\mathrm{ene}} \tag{1}$$

where C_f is the fuel carbon content in $\mathrm{kgC\,J^{-1}}$ produced, FO_f the fraction oxidized of the extracted fuel (unitless) through combustions and uses, and e_f^{ene} the amount of fuel extracted in $\mathrm{J\,yr^{-1}}$. When calculated from mass-based fuel extraction data (superscript$^{\mathrm{phy}}$), e_f^{ene} is adapted using NCV_f, the net calorific value of the fuel in J per unit mass of extracted fuel, and e_f^{phy} is the mass extracted per year:

$$E_f^{CO_2} = FO_f C_f \mathrm{NCV}_f e_f^{\mathrm{phy}} \tag{2}$$

To account for uncertain carbon contents or uncertain net calorific values—depending whether equation (1) or (2) is used—we use four different data sources to obtain six different values: Mohr *et al* (2015), CDIAC (Boden *et al* 1995, IPCC 1996), the IPCC (2006) average, and its lower and upper bounds of the 95% confidence interval (detailed values in appendix 1 available at stacks.iop.org/ERL/13/044017/mmedia). The use of equation (1) or (2) is motivated by the differences observed in the sets of NCV and the associated uncertainties. The resulting different emission factors cause these two approaches not to be equivalent.

Regarding the uncertainty on oxidation fractions, we use the CDIAC values (Marland and Rotty 1984) to produce three sets of oxidation fractions as shown in table 1. These values are also applied globally. Note that we do not use the oxidation fractions from other

Table 1. Sets of oxidation fractions used. The lower case is built to be symmetrical to the 100% oxidation case with respect to the central CDIAC values (Marland and Rotty (1984)).

Oxidation fractions	100% oxidation	CDIAC	Lower
Coal	1	0.982	0.964
Oil	1	0.918	0.836
Gas	1	0.98	0.96

data sources, either because they are not explicitly reported, or because they are based on a different definition. Here, the oxidation fraction defined as the fraction of the fuel oxidized during combustion in energy uses and during non-energy uses (Marland and Rotty 1984). We do not use the confidence intervals from (Marland and Rotty 1984) because the Tier 1 default oxidation fractions of IPCC (2006) lies out of this interval, they are all equal 100%. However, the intervals that we define at a global scale may still be underestimated, Liu *et al* (2015) shows for the case of China a 92% oxidation rate.

The combination of the four carbon contents (one being a distribution), three oxidation fractions and two sources of fuel extraction data (energy-based or mass-based) provides us with a distribution of fossil-fuel CO_2 emission over the historical period and for each of the three future extraction scenarios.

2.3. Non-CO_2 co-emissions associated with the use of fossil fuels

Non-CO_2 species are co-emitted with CO_2 during fossil-fuel combustion and use in industrial processes because of non-carbon elements oxidized (e.g. sulfur giving SO_2), high temperature combustions oxidizing atmospheric nitrogen (N_2O and NO_X), or incomplete combustion processes (CH_4, CO, BC, OC and VOCs). We also consider ammonia (NH_3) emissions which occur through leaks during the production of coke where ammonia is used to reduce nitrogen oxides (NO_X) emissions (EEA 2013). Methane (CH_4) produced during extraction, venting and flaring is however excluded. These species impact the climate system as greenhouse gases (CO_2, CH_4, N_2O), ozone precursors (CO, NO_X, VOCs), aerosols or aerosol precursors (SO_2, NH_3, NO_X, OC, and BC).

In order to link the emissions of co-emitted species with those of CO_2, we define co-emission ratios ($R^{f,g}$) for each fuel *f*, and species *g*:

$$E^{f,g} = R^{f,g} E^{f,CO_2} \qquad (3)$$

where $E^{f,g}$ is the co-emission of *g* for the fuel *f*. Since we derive CO_2 emissions from extraction and not consumption data (Davis *et al* 2011), we have to use global and not regional co-emission ratios because we do not know where and though which technology each fuel is used. We evaluate global mean ratios ($R^{f,g}_{\mathrm{mean}}$) for each co-emitted compound and for coal, oil and gas, using the EDGARv4.3.2 database (Olivier *et al* 2015) over 1970–2012 The matching of fuels is described in figure 2.1 of the appendix. These ratios are extended to 2050 using the Current Legislation (CLE) scenario of ECLIPSEv5.0 (Stohl *et al* 2015). This scenario is consistent with the absence of climate policies in our extraction scenarios (Mohr *et al* 2015). To back-cast these global ratios over the whole period (1750–2300), two different rules are created. The first rule is a constant extension of the average of the ratios over 1970–1975 to 1700–1970; and of that over 2007–2012 to 2012–2300 (Constant rule). For the second rule we fit an S-shaped function over the 1970–2012 data from EDGARv4.3.2 and using the evolution to 2050 from ECLIPSEv5.0 as an additional constraint (Sigmoid rule). These two rules are shown in figure 2.

To estimate the uncertainty in the co-emission ratios, we use an approach combining different elements. Relative uncertainty in global non-CO_2 emission is taken from the literature whenever possible, and we made assumptions for the remaining species for which we did not find literature data, as shown in table 2. We assume that the relative uncertainty in co-emission ratios is correlated to the inter-country spread in national co-emission ratios, weighted by national CO_2 emissions. Under this assumption, if the weighted spread in national co-emission ratios for a specie increases two-fold over a period, the uncertainty in the global co-emission ratios increases two-fold as well. The weighting by emissions is used to give less importance to countries that have less industrial activity. To do so, we extract from EDGARv4.3.2 the co-emission ratios for 113 world regions (most of them being individual countries) (Narayanan and Walmsley (2008)), we weight each region's ratios by its CO_2 emissions, and we extract the resulting mean, 2.5th and 97.5th percentiles to define $R^{f,g}_{\mathrm{mean}}$, $R^{f,g}_{\mathrm{low}}$ and $R^{f,g}_{\mathrm{high}}$, the difference $R^{f,g}_{\mathrm{high}}$ minus $R^{f,g}_{\mathrm{low}}$ over 1970–2012 being the spread in weighted co-emission ratios. We then rescale $R^{f,g}_{\mathrm{low}}/R^{f,g}_{\mathrm{mean}}$ and $R^{f,g}_{\mathrm{high}}/R^{f,g}_{\mathrm{mean}}$ using the values and the period of time or year shown in table 2. Finally, we apply the Constant or Sigmoid extension rules as for $R^{f,g}_{\mathrm{mean}}$ to obtain the future uncertainties in the co-emission ratio of each species.

2.4 Non fossil-fuel emissions and other drivers

Past and future emissions from other sources than fossil-fuel (hereafter 'background' emissions) are prescribed as follows. For the historical period, we take CO_2 emissions caused by cement production and flaring from CDIAC (Boden *et al* 2013), and for other species we take existing inventories (EDGAR 4.2 JRC 2011) and ACCMIP (Lamarque *et al* 2010) of which we remove the fossil-fuel related sectors. For 2011–2100, we take emissions from the non-fossil-fuel sectors of the RCP6.0 (Meinshausen *et al* 2011). After 2100, we assume constant emissions at their levels of 2100. Note that the sectors associated with fossil-fuels in ACCMIP/RCP are slightly different from the sectors that we use. For instance, energy sector in ACCMIP/RCP include both fossil-fuels energies and

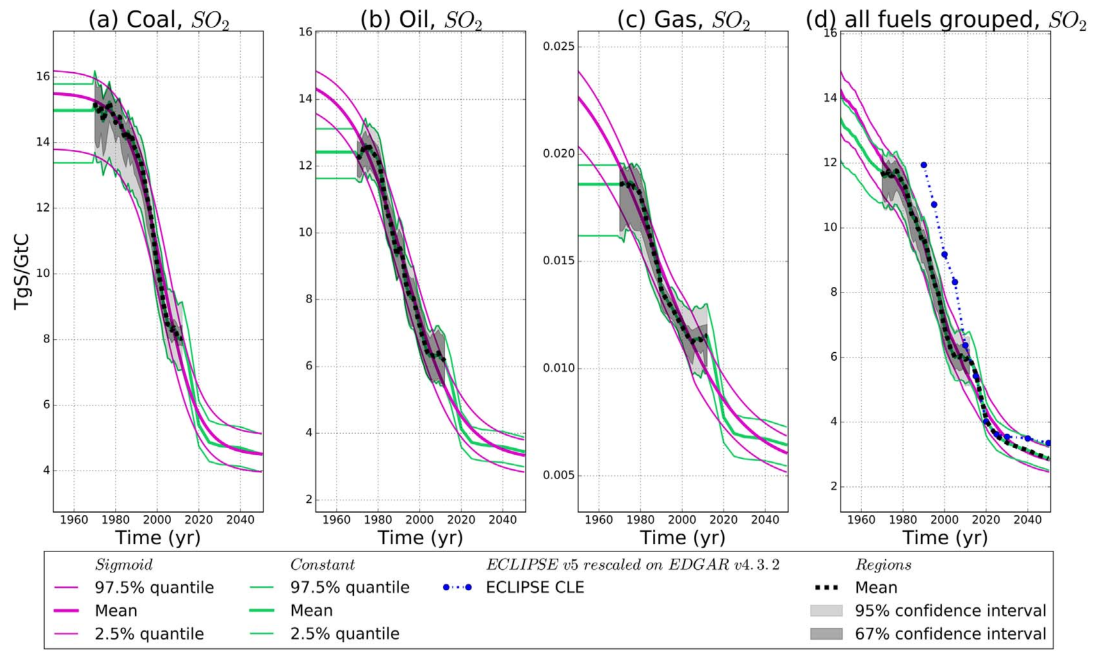

Figure 2. Co-emission ratios for SO_2 emitted when using coal (*a*), oil (*b*) and gas (*c*). The central black dotted line shows the global ratio taken from the EDGAR v4.3.2 dataset (Olivier *et al* (2015)). The histogram of co-emission ratios for GTAP regions (Narayanan and Walmsley (2008)) is represented, with its confidence intervals (shaded areas). Colored lines show the two extrapolation: Sigmoid (pink) and Constant (green).

Table 2. Relative uncertainty and period of time or date of rescaling used for co-emission ratios.

Compound	Relative uncertainty	Year(s) of application	Source
SO_2	±12%	2000–2010	Smith *et al* 2011 [27]
BC	−32% to +118%	1996	Bond *et al* 2004 [28]
OC	−42% to +97%	1996	Bond *et al* 2004 [28]
NOx	±30%	2003–2013	Janssens-Maenhout *et al* 2015 [29]
CO	±20%	2003–2013	Janssens-Maenhout *et al* 2015 [29]
CH_4	±10%	1990–2010	IPCC 2006 [12]
N_2O	±10%	1990–2010	IPCC 2006 [12]
VOC	±20%	2003–2013	Assumed same as CO
NH_3	±10%	1990–2010	Assumed same as N_2O

biomass energies, whereas we excluded the latter in our analysis. Because of these discrepancies, the non-fossil fuels emissions of these datasets added to our fossil-fuel emissions sum up to a slightly different total of the ones of the inventories. However, this inconsistency has no impact on our results, since we focus on the uncertainty caused by emissions from fossil-fuel alone.

Land-use and land-cover change data come from the LUH1.1 dataset (Hurtt *et al* 2011) for 1750–2100. After 2100, land-cover is assumed constant, while harvest and shifting cultivations keep their 2100 levels.

2.5. Climate change projections

We use the compact Earth system model OSCAR v2.2 (Gasser *et al* 2017a, Arneth *et al* 2017, Gasser *et al* 2017b) to simulate climate change given uncertain fossil-fuel emissions and co-emissions. This model includes all the relevant components of the Earth system: the oceanic and terrestrial carbon cycles, the tropospheric and stratospheric chemistries of non-CO_2 greenhouse gases and ozone, and the direct and indirect climate effects of aerosols (Gasser *et al* 2017a). For each Earth system process it features, OSCAR v2.2 is calibrated on more complex models to emulate their own range of sensitivity.

To estimate the uncertainty in projected climate change, a probabilistic Monte Carlo framework is used. The Monte Carlo ensemble is made of 1000 elements drawn by taking randomly: Earth system-related parameters (66 parameters of OSCAR v2.2, see table 3 of Gasser *et al* 2017a); the method through which fossil-fuel CO_2 emissions are calculated, energy-based or mass-based extractions (two options), carbon contents or net calorific values (four options since here we use the IPCC-2006 data [12] as a distribution), oxidation fractions (three options); and non-CO_2 species co-emission ratios (27 distributions from since we have nine species times three fuels).

When we have several distinct options, e.g. for the parameters of OSCAR or the choice of energy-based or mass-based fuel extraction data, each option is given the same probability. For variables related to CO_2 emissions and co-emission ratios, we fit a distribution over these probabilities and then draw a random

Table 3. Categories of simulations to attribute the uncertainty in projected climate change to Earth system response, CO_2 emissions and non-CO_2 species co-emissions. For each element of the Monte Carlo ensemble, the eight simulations of each line of the table are generated and used for the attribution to the variances and covariances.

Experiment	Earth system	CO_2 emissions	Co-emissions rations	Decomposition
EXP_0	default	median	median	Only median
EXP_1	default	median	*varying*	Variance from non-CO_2 emissions
EXP_2	default	*varying*	median	Variance from CO_2 emissions
EXP_3	default	*varying*	*varying*	CO_2 emissions and non-CO_2 emissions
EXP_4	*varying*	median	median	Variance from Earch system
EXP_5	*varying*	median	*varying*	Earch system and non-CO_2 emissions
EXP_6	*varying*	*varying*	median	CO_2 emissions and Earth system
EXP_7	*varying*	*varying*	*varying*	All variances and co-variances

value from this distribution. According to IPCC (2006), we use lognormal distributions for CO_2 emissions, whereas lognormal or gamma distributions are used for co-emission ratios, depending on the quality of the fit. We assume the same drawn point in the distribution for all years, therefore we assume a 100% correlation of the uncertainty through time.

For each element of the ensemble, we produce eight categories of simulations with OSCAR v2.2 in which the Earth system parameters, the parameters of fossil-fuel CO_2 emissions, and those of co-emitted species emissions are either the drawn value or kept constant (see table 3). The results of these simulations are used to analyze the uncertainty in projected climate change by attributing the variance of global temperature change to each one of the three sources of uncertainty, on the Earth system response, on CO_2 emissions, and on non-CO_2 co-emissions (their ratios to CO_2 emissions). We point out however that the default configuration of OSCAR is used as a proxy of what would be a hypothetical (non-existing) 'median' configuration. The small difference between these two causes a residual in the attribution of the variance—which we will show is negligible.

3. Results

3.1. CO_2 emissions

In figure 3 (left part) we compare the reconstructed trajectories of historical CO_2 emissions from fossil-fuel combustion and use in industrial processes (36 trajectories from varied emission parameters as in section 2.2) with those from the EDGAR v4.3.2 (Olivier *et al* (2015)) and CDIAC (Boden *et al* (2017)) inventories. These inventories do not use the same fuel extraction data than ours from Mohr *et al* but their emission factors or oxidation fractions may coincide with some of our 36 estimates.

Over 1970–2008, the mean of our reconstructions (black) is 8% higher than EDGAR v4.3.2 (blue) and 5% higher than CDIAC (red). Before 1970, this relative difference with CDIAC decreases and the mean of our reconstructions is 10% lower than the CDIAC inventory in 1900 (not shown). This difference stabilizes to 5% in the period 1750–1800 Comparing our reconstructions of CO_2 emissions to EDGAR emissions point to stronger differences concerning non-conventional fuels. Still, part of the difference is likely explained by the different extraction datasets used. However, a detailed comparison is not possible, because the extractions per fuel type and region used by CDIAC and EDGAR are not provided.

In table 4, we compare the range of reconstructed CO_2 emissions with other widely used inventories for the years 2005 and 2010. When considering only energy-based estimates, our range of historical emissions is representative of the dispersion in the inventories. When considering the mass-based method however, this range is doubled. It shows that net calorific values are a key source of uncertainty in our calculations.

Figure 3 (right part) shows the future trajectories of fossil-fuel CO_2 emissions based on the Mohr *et al* (2015) extraction scenarios. High quality coals and conventional oil and gas are consumed first. After 2100, the extractions of the different fuels are mostly decreasing. As exceptions, the extractions of lignite, coal bed methane, shale gas, tight gas, hydrates and kerogen oil tend to decrease only after 2150. For all scenarios, the relative range of uncertainty in emission tends to increase after 2010, up to a 24% uncertainty in the High scenario, 36% in the Medium, and 21% in the Low. This increase in uncertainty in the future is caused by an increase in the share of non-conventional fuels being consumed in the future, these fuels having more uncertain carbon contents and net calorific values. For instance, in the Low scenario, the share of total emissions of natural bitumen increases to 40% around 2110, and the share of extra heavy oils increases to 20% around 2090, because of the increasing scarcity in conventional oil. In the Medium and High scenarios, resources in kerogen oil are enough that its emissions reach 100% in 2280 and 57% in 2248, respectively. For today's estimates, these non-conventional fuels have limited consequences because of their low level of consumption, but this will likely change in the future.

3.2. Non-CO_2 emissions

Non-CO_2 co-emissions trajectories are presented in figure 4 for the scenario Medium. The sectoral inconsistency mentioned in section 2.4 requires a rescale of those emissions to be comparable to most existing inventories. Emissions are rescaled only in this figure

Table 4. Total CO_2 fossil-fuel emissions. We show the 95% uncertainty ranges of our reconstructions over the historical period, compared to five inventories in 2005 and 2010 (EDGAR 4.3 (Olivier *et al* (2015)), IEA (IEA), CDIAC (Boden *et al* (2017)), EIA (EIA) and BP (BP)), depending on the use of energy- or mass-based reconstructions. We also show the ranges obtained in our three scenarios of extraction at the time of peak emission, of peak uncertainty, and cumulated over 2000–2300.

	2005	2010	Scenario	Peak of emissions	Maximum of uncertainty	Cumulated on 2000–2300
EDGAR4.3, IEA, CDIAC, EIA and BP	7.34–8.26: ±6%	8.14–9.13: ±6%	High	2049: ±12%	2248: ±24%	±15%
Energy-based reconstructions	7.23–8.30: ±7%	8.37–9.62: ±7%	Medium	2021: ±13%	2281: ±36%	±15%
Mass-based reconstructions	7.23–9.39: ±13%	8.37–10.32: ±10%	Low	2018: ±13%	2095: ±21%	±13%

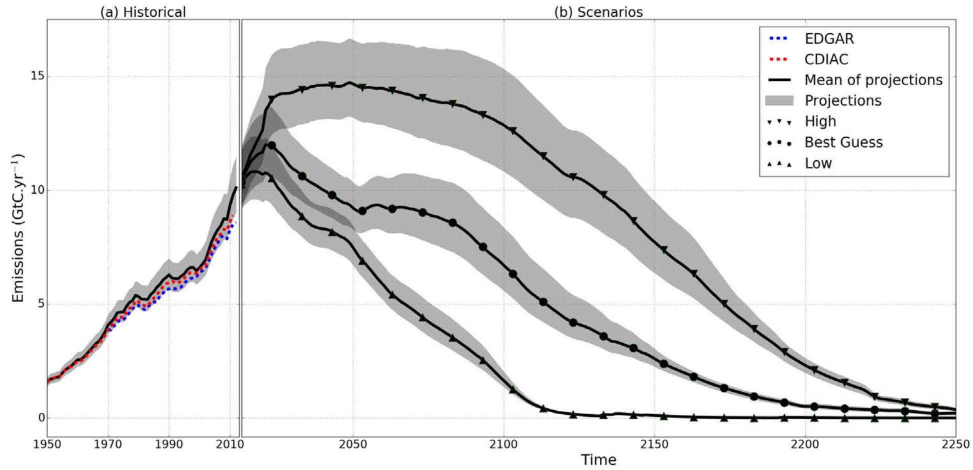

Figure 3. Total CO_2 emissions from fossil-fuel, for the historical period and the three extraction scenarios of Mohr *et al* (2015). We compare the median value of our reconstruction (black) to the inventories from CDIAC (red) and EDGAR 4.3 (blue) over the historical period. The uncertainty (gray shaded area) corresponds to the ensemble of the 36 trajectories of CO_2 emissions obtained by varying the method of inventory (energy-based or mass-based), the oxidation fractions, and the carbon contents or net calorific values (see section 2.2).

using the average over 1970–2000 of EDGAR v4.3.2 emissions following our sectoral definition and that of the ACCMIP, RCP and ECLIPSEv5.0 datasets (Lamarque *et al* 2010, Meinshausen *et al* 2011, Stohl *et al* 2015). Note that we do not compare our non-CO_2 emissions to EDGAR v4.3.2 itself, to avoid obvious matching. Fugitive emissions are included in the fossil-fuel sector of other inventories but not in ours: this means that the rescaling factor for the methane is too large to be meaningful. For this reason, methane is not compared in this figure.

As our CO_2 emission reconstruction lies in the range of other inventories (table 4), and as our co-emission ratios are based on EDGAR v4.3.2 (figure 2), with literature data to constrain the ranges of the ratios (table 3), we observe in figure 4 that our historical reconstructions of non-CO_2 emissions are also comparable to existing inventories such as Smith *et al* (2011), but also Stern (2006) and Cofala *et al* (2007). This is especially true in the case of SO_2 which is an important species because of its strong climate cooling effect. Around the years 2000 and 2010, our emissions of OC and BC follow values close to those of EDGARv4.3.2 per construction, and these are also comparable to Novakov *et al* (2003) (which also use BC/CO_2 ratios), Ito and Penner (2005) and Junker and Liousse *et al* (2006). For BC, our estimate lies close to the ECLIPSEv5.0 present-day assessment (Stohl *et al* 2015) and that of Bond *et al* (2004). For OC, however, the difference is larger, especially in 2000, but each estimate remains within the uncertainty range of one another. For other species—that is CO, NO_x, VOCs, N_2O and NH_3—our estimates are also comparable to the ACCMIP (Lamarque *et al* 2010) and EDGAR v4.2 datasets (JRC 2011).

For the future projections, this Medium scenario is somewhat close to RCP4.5 in terms of extracted fossil fuels, but our co-emission ratios reach those of ECLIPSEv5.0 CLE in 2050–by construction. The policy and technological assumptions underlying the RCPs and the CLE scenario of ECLIPSEv5.0 are different from our projections based on CO_2 emissions and a plausible evolution of co-emitted ratios, so that there is no reason for our non-CO_2 emissions future curves to match exactly the RCP ones. Still, our projections remain relatively consistent with the RCPs for all species, with the notable exception of NH_3 (figure 4). This difference is caused by the lower correlation of NH_3 emissions with CO_2 emissions. NH_3 emissions are especially caused by the use of catalysis to reduce NO_x emissions, and this advocate for the use of ratios of NH_3 emissions over NO_x emissions. However,

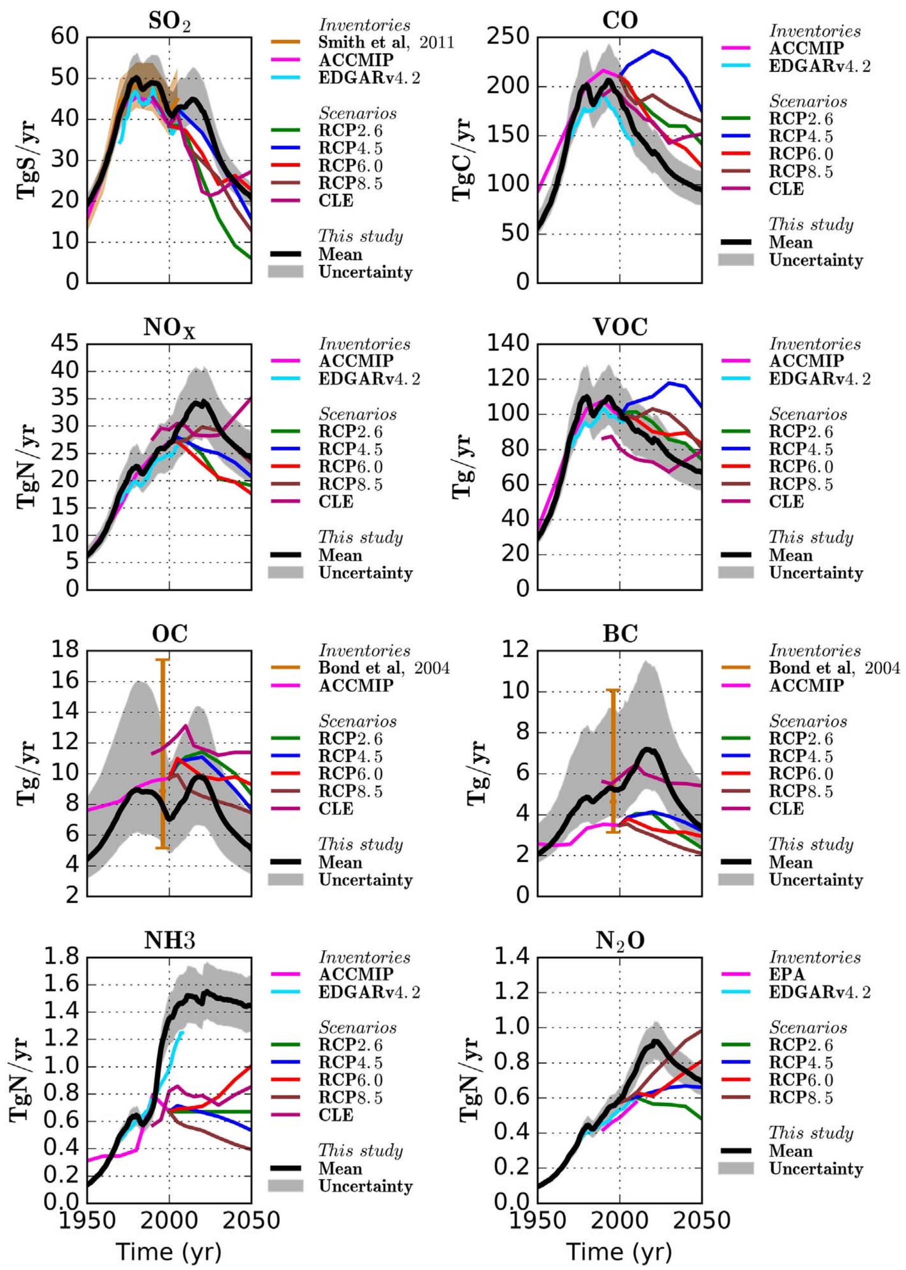

Figure 4. Fossil-fuel emissions for the scenario of extraction 'Medium'. The black plain line is the median of trajectories, and in shaded gray is the 95% confidence interval evaluated from all trajectories. For comparison are represented the co-emissions associated with fossil-fuel sectors from ACCMIP (Lamarque *et al* (2010)), EDGAR 4.2 (JRC 2011), EPA (EPA), the RCP (Meinshausen *et al* (2011)) and the scenario CLE of ECLIPSEv5.0 (Stohl *et al* (2015)). The 90% confidence interval from Smith *et al* (2011) for total SO_2 emissions has been transformed into a 95% confidence interval assuming normal distribution. The 95% intervals from Bond *et al* (2004) for fossil-fuel BC and OC emissions are also represented. The sectoral inconsistency (e.g. biomass energy not included in our analysis) mentioned in section 2.4 requires for the comparison a rescale. Only in this figure, our emissions are multiplied by the emissions of EDGAR v4.3.2 for the sectors matching ACCMIP and RCP sectors, and divided by the emissions of EDGAR v4.3.2 for the sectors corresponding to our analysis.

when combining the ratio for NH_3 emissions over NO_x to the co-emissions ratio for NO_x, this fades the stronger correlation between NH_3 and NO_x, which is a flaw of the approach through co-emission ratios.

3.3. Climate change projections

The upper panel of the figure 5 shows global surface temperature change with respect to the average of 1986–2005 (ΔT) simulated with OSCAR v2.2 and for the three future scenarios. In the Low, Medium and High scenarios, respectively, the 90% uncertainty range of ΔT in 2100 due to uncertain Earth system parameters only are 1.1 °C–2.6 °C, 1.5 °C–3.0 °C and 1.9 °C–3.6 °C, with median values of 1.8 °C, 2.2 °C and 2.7 °C. With the uncertainty from fossil-fuel CO_2 and non-CO_2 emission parameters only, these ranges are 1.8 °C–2.0 °C, 2.1 °C–2.4 °C and 2.6 °C–2.9 °C around 2100, which is about 6 times smaller than the Earth system uncertainty. When both the Earth system parameters and the emission parameters vary, the total uncertainty range remains very close to the case with varying Earth system parameters only. This

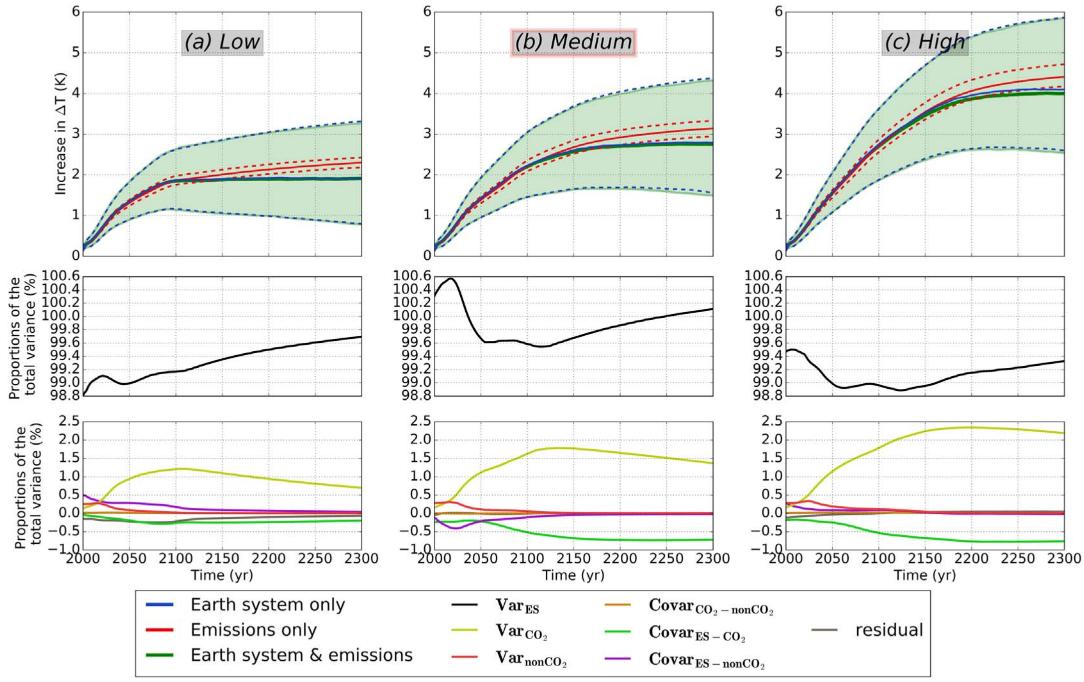

Figure 5. Upper panel: global surface temperature changes (in K) with respect to the average of 1986–2005 for the three extraction scenarios in the upper panels. The median and the 90% uncertainty range are shown for three experiments: with Earth system parameters varying (blue intervals), CO_2 and non-CO_2 emission parameters varying (red intervals), and both varying at the same time (green plain line and shaded area). In the middle and lower panels, the variances and covariances identified are represented in terms of proportion of the total variance.

shows that the total uncertainty on ΔT is largely dominated by the Earth system uncertainty, despite an uncertainty of about 15% in cumulative CO_2 emission estimates (figure 3), and uncertainties of up to a factor 2 for some non-CO_2 emissions (figure 4). This can be explained by the logarithmic relation of radiative forcing associated with CO_2 with the atmospheric concentration of CO_2 (Myhre *et al* 1998). These results, summarized in table 5, also holds for the years 2200 and 2300. Besides, the ΔT obtained from the Low scenario are very close to the results for RCP4.5 from ESM (Knutti and Sedláček 2012, Collins *et al* 2013), the Medium scenario to RCP6.0 and the High scenario somewhat between RCP6.0 and RCP8.5. Knowing the correspondence of the three scenarios of extraction with the ones of RCP (figure 11 of Van Vuuren *et al* 2011), and taking into account that the emissions from non-fossil fuels are prescribed here by RCP6.0, these projections in ΔT are consistent with the projections of RCP. The fact that the uncertainty in global mean temperature is dominated by the uncertainty in the Earth system's response is consistent with Prather *et al* (2009) and Sokolov *et al* (2009).

In figure 5, using our 8 factorial simulations we attribute the variance of temperature change with all sources of uncertainty varying (green in figure 5) to variances and co-variances specific to uncertainties in the Earth system, fossil-fuel CO_2 emissions and non-CO_2 co-emissions. It is confirmed that the Earth system uncertainty largely dominates, since its attributed variance stays around 100% of the total variance in the three scenarios.

The variance attributed to fossil-fuel CO_2 emissions peaks below 1.5%, 2% and 2.5% of the total variance in the Low, Medium and High scenarios, respectively; thus being quite negligible. The later CO_2 fossil-fuel emissions are peaking; the later the proportion of their associated variance peaks. Conversely, the co-variance attributed to the coupling of fossil-fuel CO_2 emissions and the Earth system does not peak at all. It increases (in absolute value) in all three scenarios to reach respectively −0.2%, −0.7% and −0.8% by 2300. This negative co-variance reduces even further the importance of accounting for the uncertainty in fossil-fuel CO_2 emission estimates at the same time as that in the Earth system's response. The dampening effect of the carbon cycle, that removes roughly half of yearly anthropogenic emissions from the atmosphere (Le Quéré *et al* (2016)), explains this negative sign of the covariance between fossil-fuel CO_2 emission uncertainty and Earth system uncertainty.

The variance attributed to non-CO_2 emissions present a similar profile in all three scenarios. It peaks at about 0.3% of the total variance, around 2025—a time at which it becomes less in magnitude than the variance attributed to fossil-fuel CO_2 emissions. The shorter lifetimes for most of the non- CO_2 species explains this decrease with time. The co-variance attributed to the coupling of non-CO_2 emissions and the Earth system is the only one that appears to be scenario-dependent. In the Low and High scenarios, it decreases with time,

Table 5. Median and 90% ranges for the increase in global temperature with respect to the average of 1986–2005 (°C), for the three scenarios of extractions and for the simulations with variations of the parameters relative to the emissions, or to the Earth system, or both. The relative uncertainties are given in parentheses. For comparison, the mean and ranges in 2100 of the RCP are given (based on a Gaussian assumption, by multiplying the multi-model standard deviation by 1.64).

Scenarios	Simulations	2100	2200	2300
Scenario 'Low'	Emissions (EXP_3	1.9±0.1 (±6%)	2.1±0.1 (±6%)	2.3±0.1 (±5%)
	Earch system (EXP_4)	1.9±0.7 (±39%)	1.9±1.0 (±54%)	1.9±1.3 (±66%)
	Emissions and Earch system (EXP_7)	1.8±0.8 (±41%)	1.9±1.0 (±54%)	1.9±1.2 (±65%)
Scenario 'Medium'	Emissions (EXP_3)	2.2±0.1 (±6%)	2.9±0.2 (±6%)	3.1±0.2 (±6%)
	Earth system (EXP_4)	2.2±0.8 (±36%)	2.7±1.2 (±43%)	2.8±1.4 (±51%)
	Emissions and Earth system (EXP_7)	2.2±0.8 (±36%)	2.7±1.2 (±43%)	2.7±1.4 (±52%)
Scenario 'High'	Emissions (EXP_3)	2.7±0.2 (±6%)	4.1±0.2 (±6%)	4.4±0.3 (±6%)
	Earth system (EXP_4)	2.7±0.9 (±32%)	4.0±1.4 (±35%)	4.1±1.6 (±40%)
	Emissions and Earth system (EXP_7)	2.7±0.9 (±33%)	3.9±1.4 (±36%)	4.0±1.7 (±42%)
RCP2.6		0.9±0.7 (±73%)		
RCP4.5		1.9±0.7 (±38%)		
RCP6.0		2.3±0.8 (±34%)		
RCP8.5		4.0±1.2 (±30%)		

starting with a positive value in 2000 of 0.5% and 0.3%, respectively, of the total variance. In the Medium scenario, it is negative and peaks at about –0.4%. These various behaviors show the complex interplay between all the non-CO_2 species, their timing of emission, and the Earth system's response and various couplings and feedbacks.

The co-variance attributed to the coupling of CO_2 and non-CO_2 emissions remains negligible (<0.1%) throughout all three scenarios. The residual term remains also negligible, except in the Low scenario. Because this scenario has less CO_2 emissions, it indicates that the default configuration of OSCAR differs more from a hypothetical median configuration for processes related to non-CO_2 species than for the carbon cycle.

4. Discussion

A sensitivity analysis has been performed to evaluate the rule of the extension rule used to extrapolate the co-emission ratios (section 2.3), the background of non-fossil emissions and land-use change (section 2.4) and the number of runs in the Monte-Carlo ensemble (appendix section 3). This analysis emphasizes our conclusions concerning the relative importance of the Earth system's response and the emissions.

We use a global approach to estimate CO_2 emissions and non-CO_2 co-emissions trajectories based on global 'emission factors', and this can be deemed a caveat of our study. The use of national data, both for CO_2 and co-emissions, would certainly provide more accurate estimates (Andres *et al* (2012)). However, in the dataset we use, the national data is expressed in terms of extraction, whereas the actual driver of emission in a country is fossil-fuel consumption (Davis *et al* (2011). Going from the former to the latter requires trade data which is not available over distant periods in the past, nor is it for the future. Although datasets of national fossil-fuel consumption do exist, they are not openly available (Speirs *et al* 2015). Similarly, we use global instead of national NCVs, carbon contents, and co-emission ratios, whereas these factors vary greatly among countries. Using national values for these factors would be possible, but it implies having a bottom-up approach based on fuel consumption data, for which fuels, emitting technologies and operating conditions should be distinguished, especially for non-CO_2 co-emissions (Peng *et al* 2016). In this case, evaluating the resulting uncertainty would require a tremendous effort, in order to produce data that is not provided even by well-established inventories.

As explained in section 2.4, our produced emissions associated with fossil-fuel uses are included in broader sectors of the inventories. Energy uses of fossil-fuels are included in the energy sectors that often includes fossil sources and non-fossil sources. For this reason, the sum of our produced fossil-fuel emissions and the selection of non-fossil-fuels emissions from inventories are not strictly equal to the historical total emissions. This implies that our simulation over the historical period remains a scenario, and is no reconstruction of the historical climate change. However, the differences of our emissions to the inventories are close enough to extend our results to the historic period, and then to our scenarios.

Our approach allows us to combine the uncertainty in key parameters (energy or mass-based inventory method; carbon contents; fractions of oxidations; co-emissions) in an efficient manner without the need of making assumptions as to e.g. future use of emitting technologies. As we have shown that our calculated CO_2 and non-CO_2 global emission trajectories and uncertainties are comparable to existing bottom-up data, we argue that our approach is good enough given the purpose of our investigation on the impact of uncertainty in fossil fuel emission estimates on projected climate change. Our study might overestimate the uncertainty in future non-CO_2 co-emissions, but this actually strengthens our conclusion regarding the negligibility of this source of uncertainty.

We choose to present only the uncertainty analysis for the global surface temperature as referred to in the UNFCCC. For the Earth's surface temperature, the total radiative forcing and total annual precipitation change, three global Earth system variables, which integrate the effect of various anthropogenic perturbations, we conclude that the emission-induced uncertainty is negligible. Not the uncertainty of CO_2 emissions, but the Earth system's response variance contribute almost 100% to the change in global precipitation in 2100 with respect to the average for 1986–2005 (appendix, figure 4.6).

However, for others variables such as the atmospheric CO_2 concentration and the radiative forcing of CH_4, of ozone, of aerosols and of black carbon, the emission-induced uncertainty appears less negligible. In the High scenario, the atmospheric concentration of CO_2 in 2100 with respect to the average of 1986–2005 reaches 352 ppm, with a range of 321–390 ppm (appendix, figure 4.1). This is about 42% of total uncertainty, which we attribute at 92% to the Earth system's response in terms of variances. The uncertainty in CO_2 emissions contributes with 8% to the total variance of atmospheric CO_2. The same relative importance of the uncertainty in CO_2 emissions is observed for surface ocean pH. The change of the radiative forcing of tropospheric ozone in 2100 with respect to the average of 1986–2005 shows as well an uncertainty less negligible. In the High scenario, it reaches 0.08 W m^{-2}, with a range of 0.05–0.14 W m^{-2} (appendix, figure 4.3). The range induced by uncertain emissions represents 43% of the range obtained with variations of all the parameters, emissions and Earth system. The range induced by the uncertain Earth system's modelling reaches 86% of the range obtained with variations of all parameters. Radiative forcing of tropospheric ozone can be related to some extent to air quality issues (Crippa *et al* (2016), West *et al* (2013)). As shown in Saikawa *et al* (2017), uncertain emissions hamper air quality assessments. This calls for transparence and improvment of activity data and emission factors.

The different contributions to the total variance of the global surface temperature ΔT show partially compensating effects between all the species and components of the Earth system. Even though we can conclude that the uncertainty of anthropogenic fossil fuel emissions does not have a significant impact on the global temperature change, this is not the case for the impacts on atmospheric CO_2, ocean acidification or air quality.

5. Conclusions

We produced a distribution of historical CO_2 emissions from fossil-fuels with a relative uncertainty range of ±11%. Using broad fuel categories increase the uncertainty, because it masks the change in composition of its fuels (e.g. hard coal, composed of anthracite, bituminous and subi-bituminous coals). Besides, the first resources depleted are conventional oil and gas and coals of good quality, leaving fossil fuels with stronger uncertainties on their carbon contents and net caloric values. Thus the uncertainty on fossil-fuel emissions is likely to increase with time. We have also produced three distributions of emission scenarios whose uncertainty reaches 15% in 2300 for cumulative emissions, and which have been complemented with non-CO_2 co-emission scenarios calculated using top-down estimates of co-emission ratios.

With the compact Earth system model OSCAR and a Monte Carlo setup, we have projected the global temperature change induced by these scenarios. Non-fossil-fuels emissions are provided by inventories on a slightly different sectoral basis, which does not hamper our conclusions. The relative uncertainty in these projections ranges from 42%–65%, and we have shown that the largest share is caused by the uncertainty in the Earth system representation. The uncertainty of anthropogenic emissions from fossil fuel represents only 6% of the variance of the system.

Our study shows that the global median temperature change induced by a given fossil fuel scenario is determined mainly by the uncertainty in the representation of the Earth system's physical processes, and only for an insignificant part by the uncertainty in the estimate of fossil fuel emissions. However, the uncertainty of the fossil fuel emissions has a significant impact on the total variance for other species-specific Earth system variables, such as the atmospheric concentration of CO_2 and the radiative forcing from tropospheric ozone. We also point out that this result may not apply locally, for variables such as precipitation.

Therefore, it remains important to keep improving the emission factors used in emission inventories. For each existing category of fuel, the carbon content and net calorific value have to be periodically updated, to account for the variation in the mix of the fuels that compose it. Factors about non-conventional fuels need particular attention; and so do non-CO_2 species (Li *et al* (2017), Li *et al* (2016)).

Acknowledgments

We thank Robert Andres for providing us with CDIAC data and information. We also thank Laurent Bopp for his help during the beginning of this study. We thank the reviewers for the constructive comments.

ORCID iDs

Y Quilcaille https://orcid.org/0000-0002-1474-0144

References

BP (www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy/downloads.html) (Accessed: 15 March 2018)

EIA (www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm?tid=90&pid=44&aid=8) (Accessed: 15 March 2018)

IEA (www.iea.org/statistics/topics/co2emissions/) (Accessed: 15 March 2018)

US EPA 2012 National Emissions Inventory (NEI) Air Pollutant Emissions Trends Data, 1970–2012 Average Annual Emissions, All Criteria Pollutants (www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data) (Accessed: 15 March 2018)

Allen M R, Stott P A, Mitchell J F B, Schnur R and Delworth T L 2000 Quantifying the uncertainty in forecasts of anthropogenic climate change *Nature* **407** 617

Andres R J *et al* 2012 A synthesis of carbon dioxide emissions from fossil-fuel combustion *Biogeosciences* **9** 1845–71

Arneth A *et al* 2017 Historical carbon dioxide emissions caused by land-use changes are possibly larger than assumed *Nat. Geosci.* **10** 79–84

Boden T, Marland G and Andres R 1995 Estimates of global, regional and national annual CO_2 emissions from fossil-fuel burning, hydraulic cement production and gas-aring: 1950–1992 *Technical Report*, Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, US Department of Energy, Oak Ridge, Tenn., USA, (NDP-O30/R6):600 (http://cdiac.ess-dive.lbl.gov/epubs/ndp/ndp030/ndp0301.htm)

Boden T, Marland G and Andres R 2013 *Global, Regional, and National Fossil-Fuel CO_2 Emissions* (Oak Ridge, TN: Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, US Department of Energy) (http://cdiac.ess-dive.lbl.gov/trends/emis/overview_2010.html)

Boden T, Marland G and Andres R 2017 *Global, Regional, and National Fossil-Fuel CO_2 Emissions* (Oak Ridge, TN: Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, US Department of Energy) (http://cdiac.ess-dive.lbl.gov/trends/emis/overview_2014.html)

Bond T C, Streets D G, Yarber K F, Nelson S M, Woo J H and Klimont Z 2004 A technology-based global inventory of black and organic carbon emissions from combustion *J. Geophys. Res. D Atmos.* **109** 1–43

Clarke L E *et al* 2014 pp 413–510 Assessing transformation pathways. Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth *Assessment Report* of the Intergovernmental Panel on Climate Change 413–510 (www.ipcc.ch/pdf/assessment-report/ar5/wg3/ipcc_wg3_ar5_chapter6.pdf)

Cofala J, Amann M, Klimont Z, Kupiainen K and Höglund-Isaksson L 2007 Scenarios of global anthropogenic emissions of air pollutants and methane until 2030 *Atmos. Environ.* **41** 8486–99

Collins M *et al* 2013 *Long-term Climate Change: Projections, Commitments and Irreversibility, Book Section 12* (Cambridge: Cambridge University Press) pp 1029–1136 (www.ipcc.ch/pdf/assessment-report/ar5/wg1/WG1AR5_Chapter12_FINAL.pdf)

Cox P and Stephenson D 2007 A Changing Climate for Prediction *Science* **317** 207–8

Crippa M, Janssens-Maenhout G, Dentener F, Guizzardi D, Sindelarova K, Muntean M, Van Dingenen R and Granier C 2016 Forty years of improvements in European air quality: regional policy-industry interactions with global impacts *Atmos. Chem. Phys.* **16** 3825–41

Davis S J, Peters G P and Caldeira K 2011 The supply chain of CO_2 emissions *Proc. Natl Acad. Sci.* **108** 18554–9

EEA 2013 EMEP/EEA air pollutant emission inventory guidebook 2013: Technical guidance to prepare national emission inventories. EEA *Technical Report*, (12/2013):23 (www.eea.europa.eu/publications/emep-eea-guidebook-2013)

Flato G *et al* 2013 *Evaluation of Climate Models, Book Section 9* (Cambridge: Cambridge University Press) pp 741–866 (www.ipcc.ch/pdf/assessment-report/ar5/wg1/WG1AR5_Chapter09_FINAL.pdf)

Gasser T, Ciais P, Boucher O, Quilcaille Y, Tortora M, Bopp L and Hauglustaine D 2017a The compact Earth system model OSCAR v2.2: Description and -rst results *Geosci. Model Dev.* **10** 271–319

Gasser T, Peters G P, Fuglestvedt J S, Collins W J, Shindell D T and Ciais P 2017b Accounting for the climate carbon feedback in emission metric *Earth Syst. Dyn.* **8** 235–53

Granier C *et al* 2011 Evolution of anthropogenic and biomass burning emissions of air pollutants at global and regional scales during the 1980–2010 period *Clim. Change* **109** 163–90

Hawkins E and Sutton R 2009 The potential to narrow uncertainty in regional climate predictions *Bull. Am. Meteorol. Soc.* **90** 1095–107

Hurtt G C *et al* 2011 Harmonization of land-use scenarios for the period 1500–2100: 600 years of global gridded annual land-use transitions, wood harvest, and resulting secondary lands *Clim. Change* **109** 117–61

IPCC 1996 Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories vol. 1–3 *Intergovernmental Panel Climate Change* (Paris: Organisation for Economic Co-operation and Development (OECD) and the International Energy Agency (IEA)) (www.ipcc-nggip.iges.or.jp/public/gl/invs1.html)

IPCC 2006 2006 IPCC Guidelines for National Greenhouse Gas Inventories vol. 1–5 2006 IPCC Guidelines for National Greenhouse Gas Inventories (www.ipcc-nggip.iges.or.jp/public/2006gl/)

Ito A and Penner J E 2005 Historical emissions of carbonaceous aerosols from biomass and fossil fuel burning for the period 1870–2000 *Glob. Biogeochem. Cycles* **19** 1–14

Janssens-Maenhout G *et al* 2015 HTAP-v2.2: A mosaic of regional and global emission grid maps for 2008 and 2010 to study hemispheric transport of air pollution *Atmos. Chem. Phys.* **15** 11411–32

Joint Research Centre 2011 EDGAR4.2: Emission Database for Global Atmospheric Research Global Emissions EDGAR v4.2 (https://doi.org/10.2904/EDGARv4.2)

Junker C and Liousse C 2006 A global emission inventory of carbonaceous aerosol from historic records of fossil fuel and biofuel consumption for the period 1860–1997 *Atmos. Chem. Phys. Discuss.* **6** 4897–927

Kirschke S *et al* 2013 Three decades of global methane sources and sinks *Nat. Geosci.* **6** 813–23

Knutti R and Sedláček J 2012 Robustness and uncertainties in the new CMIP5 climate model projections *Nat. Clim. Change* **3** 369–73

Lamarque J F *et al* 2010 Historical 1850–2000 gridded anthropogenic and biomass burning emissions of reactive gases and aerosols: Methodology and application *Atmos. Chem. Phys.* **10** 7017–39

Le Quéré C *et al* 2016 Global Carbon Budget 2016 *Earth Syst. Sci. Data* **8** 605–49

Li B *et al* 2016 The contribution of China's emissions to global climate forcing *Nature* **531** 357–62

Li M, Klimont Z, Zhang Q, Martin R V, Zheng B, Heyes C, Cofala J and He K 2018 Comparison and evaluation of anthropogenic emissions of SO_2 and NOx over China *Atmos. Chem. Phys.* 1–28

Liu Z *et al* 2015 Reduced carbon emission estimates from fossil fuel combustion and cement production in China *Nature* **524** 335–8

Marland G, Hamal K and Jonas M 2009 How uncertain are estimates of CO_2 emissions? *J. Ind. Ecol.* **13** 4–7

Marland G and Rotty R M 1984 Carbon dioxide emissions from fossil fuels: a procedure for estimation and results for 1950–1982 *Tellus B* **36** 232–61

Meinshausen M *et al* 2011 The RCP greenhouse gas concentrations and their extensions from 1765 to 2300 *Clim. Change* **109** 213–41

Mohr S and Evans P G M 2010 Projection of world fossil fuel production with supply and demand interactions *Chem. Eng. Depart.* **783** 21–171

Mohr S H, Wang J, Ellem G, Ward J and Giurco D 2015 Projection of world fossil fuels by country *Fuel* **141** 120–35

Moss R H *et al* 2010 The next generation of scenarios for climate change research and assessment *Nature* **463** 747–56

Myhre G, Highwood E J, Shine K P and Stordal F 1998 New estimates of radiative forcing due to well mixed greenhouse gases *Geophys. Res. Lett.* **25** 2715–8

Narayanan B G and Walmsley T L 2008 *Global Trade, Assistance, and Production: The GTAP 7 Data Base, Center for Global Trade Analysis* (Purdue University) (www.eea.europa.eu/publications/emep-eea-guidebook-2013)

Novakov T, Ramanathan V, Hansen J E, Kirchstetter T W, Sato M, Sinton J E and Sathaye J A 2003 Large historical changes of fossil-fuel black carbon aerosols *Geophys. Res. Lett.* **30** 1–4

Olivier J, Muntean M and Peters J 2015 Trends in global CO_2 emissions: 2015 report. PBL Netherlands Environmental Assessment Agency and European Commission's Joint Research Centre (JRC) 1–78 (www.pbl.nl/en/publications/trends-in-global-co2-emissions-2015-report)

Olivier J G J 2002 On the quality of global emission inventories. Approaches, methodologies, input data and uncertainties *Thesis* Utrecht University (https://dspace.library.uu.nl/handle/1874/678)

O'Neill B C, Kriegler E, Riahi K, Ebi K L, Hallegatte S, Carter T R, Mathur R and van Vuuren D P 2014 A new scenario framework for climate change research: the concept of shared socioeconomic pathways *Clim. Change* **122** 387–400

Peng S *et al* 2016 Inventory of anthropogenic methane emissions in mainland China from 1980–2010 *Atmos. Chem. Phys.* **16** 14545–62

Prather M J *et al* 2009 Tracking uncertainties in the causal chain from human activities to climate *Geophys. Res. Lett.* **36** L05707

Riahi K *et al* 2017 The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview *Glob. Environ. Change* **42** 153–68

Saikawa E *et al* 2017 Uncertainties in emissions estimates of greenhouse gases and air pollutants in India and their impacts on regional air quality *Environ. Res. Lett.* **12** 065002

Sokolov A P *et al* 2009 Probabilistic forecast for twenty-first-century climate based on uncertainties in emissions (without policy) and climate parameters *J. Clim.* **22** 5175–204

Smith S J, Van Aardenne J, Klimont Z, Andres R J, Volke A and Delgado Arias S 2011 Anthropogenic sulfur dioxide emissions: 1850–2005 *Atmos. Chem. Phys.* **11** 1101–16

Speirs J, McGlade C and Slade R 2015 Uncertainty in the availability of natural resources: fossil fuels, critical metals and biomass *Energy Policy* **87** 654–64

Stern D I 2006 Reversal of the trend in global anthropogenic sulfur emissions *Glob. Environ. Change* **16** 207–20

Stohl A *et al* 2015 Evaluating the climate and air quality impacts of short-lived pollutants *Atmos. Chem. Phys.* **15** 10529–66

van Vuuren D P *et al* 2011 The representative concentration pathways: an overview *Clim. Change* **109** 5–31

Ward J D, Mohr S H, Myers B R and Nel W P 2012 High estimates of supply constrained emissions scenarios for long-term climate risk assessment *Energy Policy* **51** 598–604

West J J, Smith S J, Silva R A, Naik V, Zhang Y, Adelman Z, Fry M M, Anenberg S, Horowitz L W and Lamarque J-F 2013 Co-benefits of mitigating global greenhouse gas emissions for future air quality and human health *Nat. Clim. Change* **3** 885–9

Zhao Y, Nielsen C P, Lei Y, McElroy M B and Hao J 2011 Quantifying the uncertainties of a bottom-up emission inventory of anthropogenic atmospheric pollutants in China *Atmos. Chem. Phys.* **11** 2295–308