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

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

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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-CO₂ 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 CO₂ emissions and their uncertainties stemming from estimates of fuel carbon content, net calorific value and oxidation fraction. Our historical reconstructions of fossil-fuel CO₂ emissions are consistent with other inventories in terms of average and range. The uncertainties sum up to a ±15% relative uncertainty in cumulative CO₂ emissions by 2300. Uncertainties in the emissions of non-CO₂ 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 CO₂ emission and on non-CO₂ 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 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 CO₂ 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, Andrés 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.
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\textsubscript{2} emissions

When calculated from energy-based fuel extraction data (superscript\textsubscript{ene}), CO\textsubscript{2} emissions in kgC yr\textsuperscript{-1} resulting from the use of a type \textit{f} fuel are given by:

\[ E_{\text{CO}_2}^{\text{f}} = F_{\text{O}_f} C_{\text{f}} e_{\text{f}}^{\text{ene}} \]  \hspace{1cm} (1)

where \( C_{\text{f}} \) is the fuel carbon content in kgC J\textsuperscript{-1} produced, \( F_{\text{O}_f} \) the fraction oxidized of the extracted fuel (unitless) through combustions and uses, and \( e_{\text{f}}^{\text{ene}} \) the amount of fuel extracted in J yr\textsuperscript{-1}. When calculated from mass-based fuel extraction data (superscript\textsubscript{phy}), \( e_{\text{f}}^{\text{phy}} \) is the mass extracted per year:

\[ E_{\text{CO}_2}^{\text{f}} = F_{\text{O}_f} C_{\text{f}} NCV_{\text{f}} e_{\text{f}}^{\text{phy}} \]  \hspace{1cm} (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 fuel, and \( e_{\text{f}}^{\text{phy}} \) is the mass extracted per year:

\[ E_{\text{CO}_2}^{\text{f}} = F_{\text{O}_f} C_{\text{f}} NCV_{\text{f}} e_{\text{f}}^{\text{phy}} \]  \hspace{1cm} (2)
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)).

<table>
<thead>
<tr>
<th>Oxidation fractions</th>
<th>100% oxidation</th>
<th>CDIAC</th>
<th>Lower</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal</td>
<td>1</td>
<td>0.982</td>
<td>0.964</td>
</tr>
<tr>
<td>Oil</td>
<td>1</td>
<td>0.918</td>
<td>0.836</td>
</tr>
<tr>
<td>Gas</td>
<td>1</td>
<td>0.98</td>
<td>0.96</td>
</tr>
</tbody>
</table>

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 CO2 emission over the historical period and for each of the three future extraction scenarios.

2.3. Non-CO2 co-emissions associated with the use of fossil fuels

Non-CO2 species are co-emitted with CO2 during fossil-fuel combustion and use in industrial processes because of non-carbon elements oxidized (e.g. sulfur giving SO2), high temperature combustions oxidizing atmospheric nitrogen (N2O and NOX), or incomplete combustion processes (CH4, CO, BC, OC and VOCs). We also consider ammonia (NH3) emissions which occur through leaks during the production of coke where ammonia is used to reduce nitrogen oxides (NOX) emissions (EEA 2013). Methane (CH4) produced during extraction, venting and flaring is however excluded. These species impact the climate system as greenhouse gases (CO2, CH4, N2O), ozone precursors (CO, NOX, VOCs), aerosols or aerosol precursors (SO2, NH3, NOX, OC, and BC).

In order to link the emissions of co-emitted species with those of CO2, we define co-emission ratios (RF,g) for each fuel f, and species g:

\[ E^{f,g} = R^{f,g} E^{f,CO2} \]  

(3)

where \( E^{f,g} \) is the co-emission of g for the fuel f. Since we derive CO2 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 through which technology each fuel is used. We evaluate global mean ratios (RF,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-CO2 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 CO2 emissions. Under this assumption, if the weighted spread in national co-emission ratios for a species 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 CO2 emissions, and we extract the resulting mean, 2.5th and 97.5th percentiles to define Rℓ,mean, Rℓ,low and Rℓ,high, the difference Rℓ,high minus Rℓ,low over 1970–2012 being the spread in weighted co-emission ratios. We then rescale Rℓ,low / Rℓ,mean and Rℓ,high / Rℓ,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 RF,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 CO2 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 \( \text{SO}_2 \) 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.

<table>
<thead>
<tr>
<th>Compound</th>
<th>Relative uncertainty</th>
<th>Year(s) of application</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \text{SO}_2 )</td>
<td>±12%</td>
<td>2000–2010</td>
<td>Smith et al 2011 [27]</td>
</tr>
<tr>
<td>BC</td>
<td>−32% to +118%</td>
<td>1996</td>
<td>Bond et al 2004 [28]</td>
</tr>
<tr>
<td>OC</td>
<td>−42% to +97%</td>
<td>1996</td>
<td>Bond et al 2004 [28]</td>
</tr>
<tr>
<td>NOx</td>
<td>±30%</td>
<td>2003–2013</td>
<td>Janssens-Maenhout et al 2015 [29]</td>
</tr>
<tr>
<td>CO</td>
<td>±20%</td>
<td>2003–2013</td>
<td>Janssens-Maenhout et al 2015 [29]</td>
</tr>
<tr>
<td>( \text{CH}_4 )</td>
<td>±10%</td>
<td>1990–2010</td>
<td>IPCC 2006 [12]</td>
</tr>
<tr>
<td>( \text{N}_2\text{O} )</td>
<td>±10%</td>
<td>1990–2010</td>
<td>IPCC 2006 [12]</td>
</tr>
<tr>
<td>VOC</td>
<td>±20%</td>
<td>2003–2013</td>
<td>Assumed same as CO</td>
</tr>
<tr>
<td>( \text{NH}_3 )</td>
<td>±10%</td>
<td>1990–2010</td>
<td>Assumed same as ( \text{N}_2\text{O} )</td>
</tr>
</tbody>
</table>

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-\( \text{CO}_2 \) 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 \( \text{CO}_2 \) 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-\( \text{CO}_2 \) 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 \( \text{CO}_2 \) emissions and co-emission ratios, we fit a distribution over these probabilities and then draw a random
value from this distribution. According to IPCC (2006), we use lognormal distributions for CO₂ 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 CO₂ 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 CO₂ emissions, and on non-CO₂ co-emissions (their ratios to CO₂ 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. CO₂ emissions

In figure 3 (left part) we compare the reconstructed trajectories of historical CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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-CO₂ emissions

Non-CO₂ 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\textsubscript{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.

<table>
<thead>
<tr>
<th>2005</th>
<th>2010</th>
<th>Scenario</th>
<th>Peak of emissions</th>
<th>Maximum of uncertainty</th>
<th>Cumulated on 2000–2300</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy-based reconstructions</td>
<td>7.23–8.30: ±7%</td>
<td>8.37–9.62: ±7%</td>
<td>Medium</td>
<td>2021: ±13%</td>
<td>2281: ±36%</td>
</tr>
</tbody>
</table>

Figure 3. Total CO\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{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 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.

Figure 3. Total CO\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{2} ratios), Ito and Penner (2005) and Junker and Liouise 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\textsubscript{x}, VOCs, N\textsubscript{2}O and NH\textsubscript{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\textsubscript{2} emissions and a plausible evolution of co-emitted ratios, so that there is no reason for our non-CO\textsubscript{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\textsubscript{3} (figure 4). This difference is caused by the lower correlation of NH\textsubscript{3} emissions with CO\textsubscript{2} emissions. NH\textsubscript{3} emissions are especially caused by the use of catalysis to reduce NO\textsubscript{x} emissions, and this advocate for the use of ratios of NH\textsubscript{3} emissions over NO\textsubscript{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 ($\Delta T$) simulated with OSCAR v2.2 and for the three future scenarios. In the Low, Medium and High scenarios, respectively, the 90% uncertainty range of $\Delta T$ 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\textsubscript{2} and non-CO\textsubscript{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\textsubscript{2} emission estimates (figure 3), and uncertainties of up to a factor 2 for some non-CO\textsubscript{2} emissions (figure 4). This can be explained by the logarithmic relation of radiative forcing associated with CO\textsubscript{2} with the atmospheric concentration of CO\textsubscript{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\textsubscript{2} emissions and non-CO\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{2} emission uncertainty and Earth system uncertainty.

The variance attributed to non-CO\textsubscript{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\textsubscript{2} emissions. The shorter lifetimes for most of the non-CO\textsubscript{2} species explains this decrease with time. The co-variance attributed to the coupling of non-CO\textsubscript{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,
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\textsubscript{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\textsubscript{2} and non-CO\textsubscript{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\textsubscript{2} emissions, it indicates that the default configuration of OSCAR differs more from a hypothetical median configuration for processes related to non-CO\textsubscript{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\textsubscript{2} emissions and non-CO\textsubscript{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\textsubscript{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\textsubscript{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\textsubscript{2} and non-CO\textsubscript{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\textsubscript{2} co-emissions, but this actually strengthens our conclusion regarding the negligibility of this source of uncertainty.

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### 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).

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Simulations</th>
<th>2100</th>
<th>2200</th>
<th>2300</th>
</tr>
</thead>
<tbody>
<tr>
<td>'Low'</td>
<td>Emissions (EXP\textsubscript{1})</td>
<td>1.9±0.1 (±6%)</td>
<td>2.1±0.1 (±6%)</td>
<td>2.3±0.1 (±5%)</td>
</tr>
<tr>
<td></td>
<td>Earth system (EXP\textsubscript{2})</td>
<td>1.9±0.7 (±39%)</td>
<td>1.9±1.0 (±54%)</td>
<td>1.9±1.3 (±56%)</td>
</tr>
<tr>
<td></td>
<td>Emissions and Earth system (EXP\textsubscript{3})</td>
<td>1.8±0.8 (±41%)</td>
<td>1.9±1.0 (±54%)</td>
<td>1.9±1.2 (±65%)</td>
</tr>
<tr>
<td>'Medium'</td>
<td>Emissions (EXP\textsubscript{1})</td>
<td>2.2±0.1 (±6%)</td>
<td>2.9±0.2 (±6%)</td>
<td>3.1±0.2 (±6%)</td>
</tr>
<tr>
<td></td>
<td>Earth system (EXP\textsubscript{2})</td>
<td>2.2±0.8 (±36%)</td>
<td>2.7±1.2 (±43%)</td>
<td>2.8±1.4 (±51%)</td>
</tr>
<tr>
<td></td>
<td>Emissions and Earth system (EXP\textsubscript{3})</td>
<td>2.2±0.8 (±36%)</td>
<td>2.7±1.2 (±43%)</td>
<td>2.7±1.4 (±52%)</td>
</tr>
<tr>
<td>'High'</td>
<td>Emissions (EXP\textsubscript{1})</td>
<td>2.7±0.2 (±6%)</td>
<td>4.1±0.2 (±6%)</td>
<td>4.4±0.3 (±6%)</td>
</tr>
<tr>
<td></td>
<td>Earth system (EXP\textsubscript{2})</td>
<td>2.7±0.9 (±32%)</td>
<td>4.0±1.4 (±35%)</td>
<td>4.1±1.6 (±40%)</td>
</tr>
<tr>
<td></td>
<td>Emissions and Earth system (EXP\textsubscript{3})</td>
<td>2.7±0.9 (±33%)</td>
<td>3.9±1.4 (±36%)</td>
<td>4.0±1.7 (±42%)</td>
</tr>
<tr>
<td>RCP2.6</td>
<td>0.9±0.1 (±73%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP4.5</td>
<td>1.9±0.7 (±38%)</td>
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<tr>
<td>RCP6.0</td>
<td>2.3±0.8 (±54%)</td>
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<tr>
<td>RCP8.5</td>
<td>4.0±1.2 (±30%)</td>
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<td></td>
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</table>
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$_2$ perturbations, we conclude that the emission-induced uncertainty in 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 transparency and improvement of activity data and emission factors.

The different contributions to the total variance of the global surface temperature $\Delta T$ 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 $\pm 11\%$. 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 sub-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 calorific 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)).

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