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How do carbon cycle uncertainties affect IPCC temperature projections?

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Abstract

Carbon cycle uncertainties associated with the Intergovernmental Panel on Climate Change temperature-change projections were treated differently between the Fourth and Fifth Assessment Reports as the latter focused on concentration- rather than emission-driven experiments. Carbon cycle feedbacks then relate to the emissions consistent with a particular concentration. A valuable alternative is to include all uncertainties in a single step from emissions to temperatures. We use a simple climate model with an observationally constrained parameter distribution to explore the carbon cycle and temperature-change projections, simulating the emission-driven Representative Concentration Pathways. The resulting range of uncertainty is a somewhat wider and asymmetric *likely* range (biased high).

Keywords: **carbon cycle uncertainties; temperature-change projections; simple climate model**

1. Introduction

The latest global-mean surface temperature-change (ΔGMST) projections from the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report Working Group I (AR5 WGI; IPCC, 2013a) are based on the Representative Concentration Pathways (RCPs; Moss *et al.,* 2010). The results span a *likely* range of 0.3–4.8 °C in 2081–2100 (relative to 1986–2005) across the four RCPs, where *likely* is an assessment with a greater than 66% probability (Stocker *et al.,* 2013). The spread in the temperature-change projections stems from the set of greenhouse-gas emission trajectories used in the analysis together with model uncertainties connected to each set of emissions. The emission trajectories span a broad range of uncertainties in the future growth of anthropogenic greenhouse gases (GHGs) and the underlying socio-economic drivers (population growth, economic growth, energy intensity etc.). Model uncertainty arises from simulations of physically plausible responses by the Earth's climate system to increasing GHG emissions.

The two main differences between ΔGMST projections in the Fourth (IPCC, 2007) and Fifth Assessment Reports (IPCC, 2013a) are the changeover from the Special Report on Emission Scenarios (SRES; Nakicenovic *et al.,* 2000) to the RCPs and the different presentation of carbon cycle uncertainties in the AR5 results. Most of the AR5 projections were concentration-based rather than emission-based results and so it is difficult to assess how large the spread in uncertainty would have been if emission-driven scenarios were used and the carbon cycle uncertainties also accounted for. Based on previous studies (Huntingford *et al.,* 2009; Bodman *et al.,* 2013; Booth *et al.,* 2013), we would expect the carbon cycle feedbacks to lead to a wider range of future feedbacks, and therefore, uncertainties in ΔGMST projections than that due to climate sensitivity alone. This is partly because the majority of complex climate models are atmosphere–ocean general circulation models (AOGCMs) and not Earth system models (ESMs), so do not include the carbon cycle. They therefore need to be supplied with CO_2 concentrations (Hibbard *et al.,* 2007). Accordingly, by applying atmospheric CO_2 inputs, the Coupled Model Intercomparison Phase 5 (CMIP5) experiments were designed to allow AOGCMs to participate (Friedlingstein *et al.,* 2014).

These CO_2 inputs include a best estimate for carbon cycle feedbacks established using the simplified climate model MAGICC (Wigley and Raper, 2001; Meinshausen *et al.,* 2011a). The carbon cycle parameter settings used for this purpose were based on the Bern-CC model in order to preserve consistency between CMIP3 and CMIP5 (Meinshausen *et al.,* 2011b) and not observationally constrained parameters as in this study (refer Section 2). Note that the Bern-CC model has a below average carbon cycle feedback (Friedlingstein *et al.,* 2006), which may contribute toward underestimating the temperature response.

The CMIP5 concentration-driven projections do not directly allow for carbon cycle feedbacks, although the RCP concentrations include an implicit carbon cycle feedback based on the Bern-CC model (Meinshausen *et al.,* 2011b). However, this means that the uncertainties associated with temperature feedbacks and other physical processes that affect atmospheric

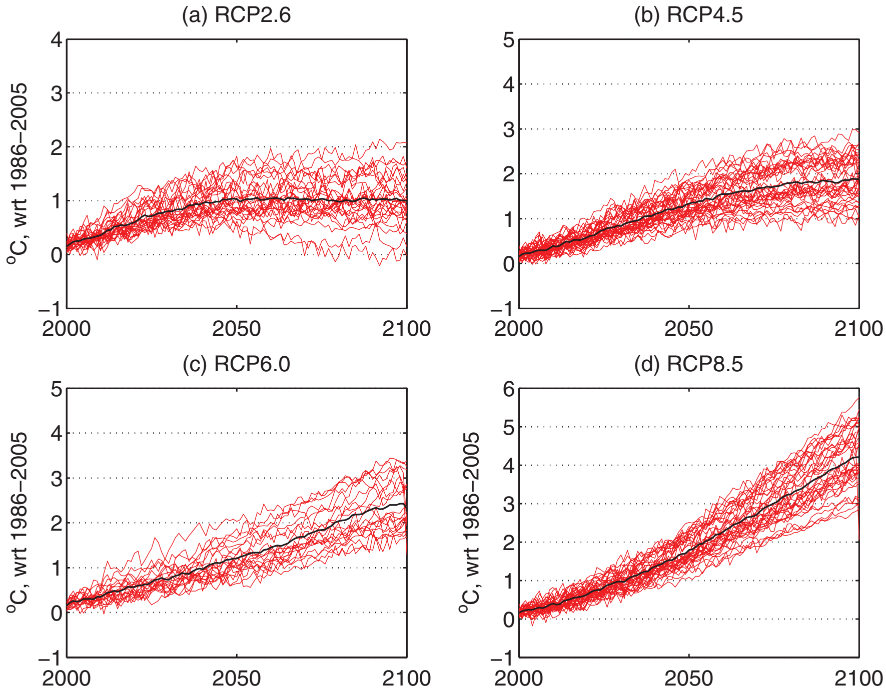

Figure 1. RCP CMIP5 ensembles for ΔGMST (relative to 1986–2005) for the four RCPs (concentration-driven experiments). Red lines are a single realization for each model, black line the ensemble mean: (a) RCP2.6, 27 models, (b) RCP4.5, 37 models, (c) RCP6.0, 20 models and (d) RCP8.5, 36 models (Source: Greg Kociuba, Australian Bureau of Meteorology).

CO_2 concentrations were not explored in the CMIP5 concentration-driven projections.

The global-mean surface air temperature anomalies derived from CMIP5 are illustrated here in Figure 1. This is the data used to calculate the likely range for the AR5 projections for each of the RCPs shown in Table 1. The calculation for the 5–95% interval is set around the mean and based on the standard deviation from the sample of models in the multi-model ensemble, assuming a normal distribution (Collins *et al.,* 2013). These 'ensembles of opportunity' do not necessarily represent the full range of potential model uncertainty, as there remain issues of model independence, limited validation and so forth (for a more detailed discussion refer Tebaldi and Knutti, 2007).

In this article, we explore how carbon cycle uncertainties affect the AR5 temperature-change projections had they been emissions-driven rather than concentration-driven experiments. The carbon cycle uncertainties referred to here include the partitioning of CO_2 between different sinks, temperature feedbacks related to plant and soil respiration and CO_2 solubility in the ocean. They do not include those associated with tipping points such as permafrost melting or extensive vegetation changes. We tested these differences using CMIP5 (Taylor *et al.,* 2012) ensembles and our implementation of the reduced complexity upwelling-diffusion energy-balance model MAGICC that explores parameter uncertainties in the carbon cycle (Wigley and Raper, 2001; Meinshausen *et al.,* 2011a; Bodman *et al.,* 2013). Parameter uncertainties are constrained by the use of observations with a Bayesian data assimilation process.

Table 1. Estimates of ΔGMST change for the RCP scenarios as per the AR5 CMIP5 results (IPCC, 2013a, 2013b) and our MAGICC simulations for two emissions-driven cases, one with carbon cycle temperature feedbacks off (MAGICC CC-off) and one with them on (MAGICC CC-on).

ΔGMST, °C at 2081–2100 relative to 1986–2005		
Scenario IPCC AR5	**Mean**	**Likely range[a]**
RCP2.6	1.0	0.3–1.7
RCP4.5	1.8	1.1–2.6
RCP6.0	2.2	1.4–3.1
RCP8.5	3.7	2.6–4.8
MAGICC CC-off	**Median**	**67% range[b]**
RCP2.6	0.7	0.2–1.3
RCP4.5	1.8	1.1–2.6
RCP6.0	2.4	1.6–3.4
RCP8.5	3.7	2.5–4.9
MAGICC CC-on	**Median**	**67% range**
RCP2.6	0.9	0.4–1.8
RCP4.5	2.1	1.2–3.2
RCP6.0	2.7	1.7–3.9
RCP8.5	4.0	2.7–5.5

[a]CMIP5 *likely range* is a 5–95% model range calculated from the ensemble of projections and assessed as *likely* (IPCC, 2013a, 2013b).
[b]Where the 67% interval is just that.

2. Method

To explore the effect of including carbon cycle uncertainties on ΔGMST change projections, we applied our version of the MAGICC version 6 model that samples plausible ranges of key parameters based on historical data (Bodman *et al.,* 2013). MAGICC is a simple climate model that has been developed and maintained for nearly 30 years (Wigley and Raper, 1987; Wigley and Raper, 2001; Meinshausen *et al.,* 2009; Meinshausen *et al.,* 2011a). It is an energy-balance model with an upwelling-diffusive ocean for the climate in conjunction with land and ocean carbon cycle components. Although substantially less complex than fully coupled three-dimensional ESMs, it has been shown to perform well in terms of emulating complex models, such as those used for CMIP3 (Meinshausen *et al.,* 2011c). In addition to calibrating MAGICC's parameters for emulating complex models, its climate parameters have been calibrated against historical observations using Monte Carlo-based Bayesian statistical techniques that run the model thousands of time, testing the model's results to arrive at probability distributions for the main parameters rather than single point estimates (Meinshausen *et al.,* 2009; Rogelj *et al.,* 2011; Rogelj *et al.,* 2012). The latter research work calibrated MAGICC's carbon cycle parameter against the C4MIP models (Friedlingstein *et al.,* 2006); whereas, here, we use a method that includes observed CO_2 concentrations (1960–2010) to estimate the key carbon cycle parameters, along with other observations to constrain key climate parameters (Bodman *et al.,* 2013). Results from complex models were not used in this process, although they do help in guiding the selection of parameter prior distributions. This calibration technique results in a posterior parameter distribution that can then be used to run MAGICC, iterating through the parameter sets to generate temperature-change results for a given greenhouse-gas concentration pathway or emission trajectory.

One important difference between the use of MAGICC to estimate ΔGMST and the process used in AR5 is that here, MAGICC uses emissions as inputs, whereas CMIP5 used concentrations selected to emulate a specific set of emissions for which the carbon cycle feedbacks were tuned to the C4MIP Bern-CC carbon cycle model (Meinshausen *et al.,* 2011b). We generated ΔGMST distributions for the four emissions-driven RCPs using the aforementioned parameter distribution for two cases, with and without the carbon cycle temperature feedbacks. The case with the carbon cycle temperature feedbacks off means that the CO_2 fertilsation effect and oceanic CO_2 uptake contribute to the temperature-change uncertainty while the carbon cycle temperature feedbacks do not (they are simply not applied as adjusting factors in the calculation of ΔGMST). The case with carbon cycle feedbacks on tested the fuller range of uncertainty.

3. Results

We calculated a set of emissions-driven RCP projections to compare with the concentration-driven AR5 results, using parameter uncertainties constrained by the 20th century observations. The second part of Table 1 presents our results. One set is with the carbon cycle temperature feedbacks switched off (MAGICC CC-off), then a set with the carbon cycle temperature feedbacks on (MAGICC CC-on). These results use the same reference periods as the AR5, with shaded time series plots given in Figure 2.

Using the emissions associated with each RCP and no carbon cycle temperature feedbacks, we obtain results similar to the AR5 mean and breadth across the *likely range* with our 67% confidence interval. This similarity suggests that the MAGICC uncertainty range is comparable with the uncertainty range given for the complex models even though they are not equivalent. We are using parameter uncertainty combined with historical constraints, whereas the AR5 uses a climate model ensemble.

With carbon cycle temperature feedbacks included, the median, lower and upper bounds for ΔGMST all increase, the upper bound most of all. For example, for RCP8.5, the AR5 projections span 2.6–4.8 °C and the MAGICC results with the carbon cycle temperature feedbacks off span a similar range of 2.5–4.9 °C. Including carbon cycle temperature feedbacks increases the range to 2.7–5.5 °C, mostly at the upper bound. The emission-driven CC-on results produce a more asymmetric distribution biased to higher temperature increases, implying higher levels of risk if the uncertainties stemming from the carbon cycle are included.

The lower temperature-change results in the AR5 projections may be partly due to the choice of carbon cycle settings used to generate the RCP concentrations for the CMIP5 simulations (MAGICC with carbon cycle parameters based on the Bern-CC model). If the RCP concentrations were based on a median of the C4MIP models or the observationally constrained parameter set of Bodman *et al.* (2013) then the range of temperature-change outcomes would be expected to shift upwards. This could potentially be explored further using the C4MIP or Bodman *et al.* (2013) distributions, deriving upper and lower bounds for the CO_2 concentrations which could then be modeled by the AOGCMs.

Table 2 shows that the our MAGICC CC-on median CO_2 concentration values at 2100 correspond closely to the RCP-specified amounts with very small differences of 2–4 ppm for RCP2.6, RCP4.5 and RCP6.0, while RCP8.5 differs by 20 ppm or 2%. The CO_2 concentration amounts and likely uncertainty ranges are greater for the CC-on cases as compared with CC-off (Table 2). The CC-off runs have lower median values than those specified for the RCP concentration-driven runs as these are derived from MAGICC with feedbacks turned on (refer also Meinshausen *et al.,* 2011b). The MAGICC CC-off runs still have carbon cycle uncertainty stemming from the parameterisation of the CO_2 fertilization effect and carbon uptake across the land and ocean sinks (which is the reason for the uncertainty range in the MAGICC CC-off CO_2 concentration results, Table 2), whereas the concentrations for the

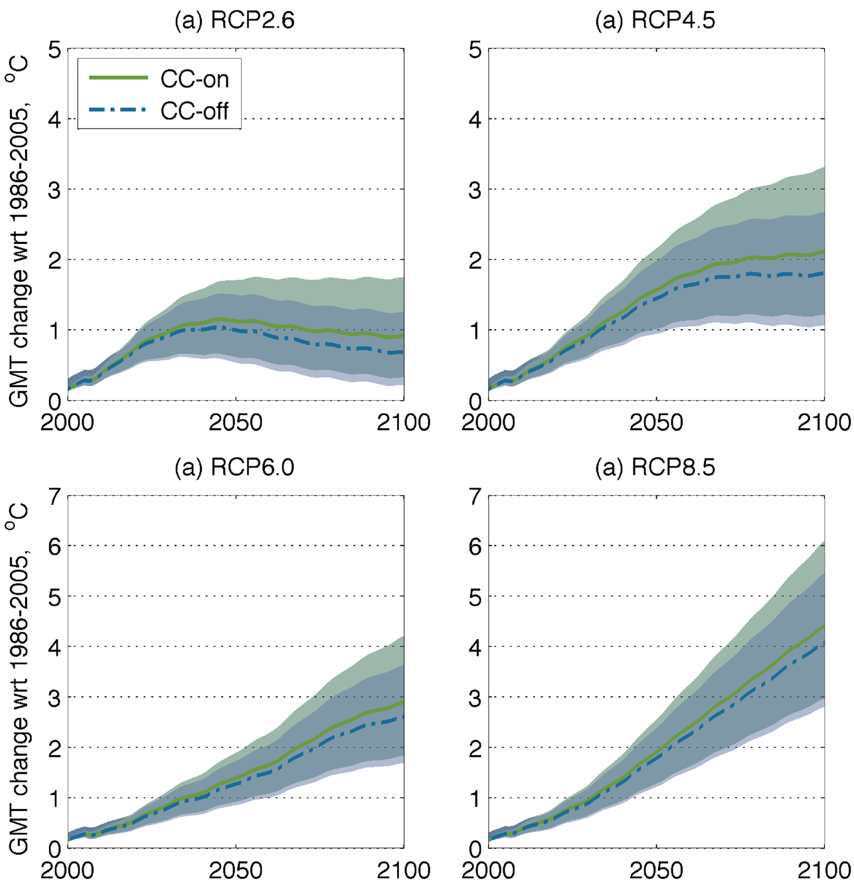

Figure 2. Plume plots for ΔGMT change projections 2000–2100, °C relative to 1986–2005. MAGICC results with carbon cycle temperature feedbacks on (CC-on) and switched off (CC-off) (a) RCP2.6, (b) RCP4.5, (c) RCP6.0 and (d) RCP8.5. Shaded regions indicate the 67% confidence interval for CC-on (green) and CC-off (blue), with median results as solid green and dashed blue lines, respectively.

CMIP5 RCP concentration-driven runs have a single pathway.

4. Discussion

We have tested the effect of allowing for carbon cycle uncertainties by deriving probabilistic ΔGMST projections using a simple ESM with a historically constrained parameter distribution. This increases the range of uncertainty as compared with concentration-driven RCP scenarios, with an asymmetric distribution for the uncertainty ranges that is biased toward higher values. The *likely range* of temperature change is also warmer [except for RCP2.6, where the MAGICC CC-on results are only slightly different to the AR5 multi-model ensemble (MME)].

The increased asymmetry is largely a result of the stronger carbon cycle temperature feedbacks being more evident in the higher forcing scenarios with greater ΔGMST (Table 1). The associated MAGICC carbon cycle parameters are only weakly constrained by the calibration process and remain a significant source of uncertainty in the forward projections.

Our MAGICC results are consistent with other studies that have examined the emission-driven RCP8.5 scenario, the only experiment in the CMIP5 protocol that includes both concentration- and emission- driven simulations (Friedlingstein *et al.,* 2014; Shao *et al.,* 2014). This is achieved with our Bayesian historical calibration method for the key climate and carbon cycle parameters – not through calibrating the simple model to emulate the complex models. Note that uncertainties in the IPCC AR5 and those presented here are not equivalent. The AR5 uncertainty range is estimated from the spread of results from an ensemble of complex climate models and assessed as *likely* by expert judgment. We utilize a joint parameter distribution derived from calibration against historical data with a single simple climate model. The likely range is then the 67% range confidence interval obtained from the spread in model results.

For the CMIP5 emission-driven RCP8.5 temperature-change results, Friedlingstein *et al.* (2014) reported a temperature range of 2.5–5.6 °C, with a MME mean of 3.9 ± 0.9 °C (1σ). Converting this to a *likely* uncertainty range, with ±1.64 times the standard deviation of the MME mean (Collins *et al.,* 2013), yields a range of 2.4–5.4 °C. This is similar to the MAGICC CC-on results reported here (Table 1; median 4.0 °C, *likely* range 2.7–5.5 °C). Likewise, for their concentration-driven RCP8.5 results, MME mean 3.7

Table 2. CO_2 concentrations at 2100 for the CMIP5 RCP pathways and our MAGICC simulations for two emissions-driven cases, one with carbon cycle temperature feedbacks off (MAGICC CC-off) and one with them on (MAGICC CC-on).

CO_2 concentrations at 2100 (ppm)		
Scenario	**CO_2 concentration**	
RCP2.6	421	
RCP4.5	538	
RCP6.0	670	
RCP8.5	936	
MAGICC CC-off	**Median**	**67% range**[a]
RCP2.6	393	372–421
RCP4.5	490	449–540
RCP6.0	611	553–678
RCP8.5	831	739–933
MAGICC CC-on	**Median**	**67% range**
RCP2.6	419	389–475
RCP4.5	536	475–643
RCP6.0	666	583–798
RCP8.5	916	775–1129

[a]Where the 67% interval is just that.

± 0.7 °C, the equivalent *likely* range is 2.6–4.9 °C, very close to our MAGICC CC-off median 3.7 °C, *likely* range 2.5–4.9 °C.

The CO_2 concentration ranges differ from our results, with most of the CMIP5 ESMs having higher estimates. The emission-driven average CO_2 concentration at 2100 was 985 ± 97 ppm, whereas the MAGICC CC-on median was 916 ppm. However, most of the ESMs overestimate the historical CO_2 concentrations (Friedlingstein *et al.,* 2014) and therefore may be overestimating CO_2 concentrations by 2100. The carbon cycle is not the only factor affecting the temperature outcomes, with other forcing components such as aerosols being important contributors.

The HadCM3C ESM has been run using a perturbed parameter approach to sample projected temperature-change uncertainties for emission-driven RCP2.6 and 8.5 scenarios (Booth *et al.,* 2013). A similar conclusion to ours was reached, but the different model structures between their ESM and the SCM used in this study suggest further areas for investigation. They do however suggest using historical constraints on carbon cycle uncertainties, which we have done. The study by Booth *et al.* (2013) has a wider range of temperature results across their full Earth system ensemble than we find, although this is reduced when they subsample the ensemble to exclude climate sensitivities above the CMIP5 range. For example, their RCP8.5 10th–90th percentile range for the full ensemble is 4.2–8.1 °C, but 4.2–6.8 °C when subsampled. The corresponding MAGICC CC-on range is 3.0–6.5 °C when set to the matching reference periods (see also Table S1, Supporting Information).

Differences in the Booth *et al.* (2013) ESM results arise from their ensemble having many members with climate sensitivity over 3 °C (refer Figure 3(e) in Booth *et al.,* 2013) as well as members with stronger carbon cycle feedbacks. Some of the ensemble members also have CO_2 concentration results that diverge from present-day observations. The HadCM3C model was not explicitly calibrated against historical data, and therefore, the sampled parameter space is not constrained in the same way as our SCM.

The similarities between our MAGICC ΔGMST projections and those of Friedlingstein *et al.* (2014) and Booth *et al.* (2013) for the fewer emission-driven scenarios that have been modeled suggest that the MAGICC setup and calibration technique used here is able to generate meaningful results, albeit with its own limitations (noted below), just as the complex models have their own issues.

The role of the carbon cycle is clearly understood by the authors of the IPCC's AR5 WGI Chapter 12, who explain that uncertainties in carbon cycle feedbacks are addressed in a different way to the AR4 because temperature projections are based on the concentration-driven RCPs (Collins *et al.,* 2013). Instead of uncertainty stemming from the causal sequence emissions to concentrations to radiative forcing to temperature change, concentrations are fixed for each RCP and then the uncertainty moves to either side in the causal chain (Hibbard *et al.,* 2007). Therefore, the ΔGMST projections in the AR5 presented in the WGI Summary for Policymakers Table SPM.2 (IPCC, 2013b; IPCC, 2014), may underestimate the likelihood of reaching higher temperatures given current knowledge. Temperature uncertainties stemming from the carbon cycle are related to cumulative emissions in, for example Figure SPM.10 (IPCC, 2013b; IPCC, 2014). If the uncertainties for the whole causal chain are to be included, the uncertainties prior to obtaining concentrations then need to be added in later. What we have done is to present a range of uncertainty for ΔGMST across the four emission-driven RCPs following the more intuitive and physically natural causal chain. These different ways of presenting temperature-change projections have implications for climate policy makers and climate risk management, especially if temperature or related positive feedbacks have a marked effect on the carbon cycle.

The AR5 affirms that there is no fundamental difference between the behavior of the CMIP5 ensemble in comparison with the CMIP3. Instead, the differences are largely due to the scenarios, choice of reference periods and treatment of uncertainty. With respect to the main differences between the AR4 and AR5 ΔGMST projections, the change over from the SRES emission scenarios in the AR4 to the RCP concentration pathways in the AR5, meant that the effect of carbon cycle uncertainties on atmospheric CO_2 concentrations were not considered in the concentration-driven CMIP5 simulations (IPCC, 2013a: SPM, p20). This implies that the AR4 results were based on emission-driven modeling, while the AR5 results were based on concentration-driven modeling; this is not the case. In practice, both the CMIP3 and CMIP5 results that were used to inform the SRES and RCP projections respectively were concentration-driven. Global-mean surface temperature-change (ΔGMST) projections in the AR4 were based on multi-model ensemble results using the SRES scenarios and the CMIP3 archive. The SRES emission scenarios were converted to concentrations using either the MAGICC or Bern-CC reduced complexity ESMs (Collins *et al.,* 2013), effectively producing concentration pathways akin to the RCPs. Carbon cycle uncertainties were then added afterwards, with the upper and lower bounds of the MME mean extended by +60% and −40% using expert judgment informed by the less complex models. As the AR4 explains 'The AOGCMs cannot sample the full range of possible warming, in particular because they do not include uncertainties in the carbon cycle' (IPCC, 2007). The range derived from the AR4 MME has 'additional uncertainty estimates obtained from published probabilistic methods using different types of models and observational constraints: the MAGICC SCM and the BERN2.5CC coupled climate-carbon cycle EMIC tuned to different climate sensitivities and carbon cycle settings, and the C4MIP coupled climate-carbon cycle models' (Meehl *et al.,* 2007).

These details are re-confirmed in the AR5 (Collins *et al.,* 2013), where the limitation of using a constant fractional uncertainty is noted, particularly for a scenario such as RCP2.6. The AR5 WGI ΔGMST projections were derived similar to the AR4, from multi-model ensembles drawn from the CMIP5 concentration-driven experiments. The likely uncertainty range was then assessed as ±1.64 times the standard deviation of the MME, i.e. as a 5–95% confidence interval (Collins *et al.,* 2013). This approach was used to indicate the spread in model results but is not a formal measurement for the uncertainty. A check on our results (Table 1) found that the +60% and −40% calculation does not adequately characterize the AR5 *likely* range, especially for the very low- and very high-emission scenarios.

The different quantification of key climatic variables between one report to the next and its traceability in assessing risk is an important issue. These differences may lead to risks being either under- or over-estimated, as well as changing their significance for policymakers. All known contributions to uncertainty should be quantified where possible or at least identified. Assessments, especially Summaries for Policymakers, need to address the issue of traceability between assessments otherwise policymakers will not have a clear guide to changing climate risks.

As preparations for the next round of climate model intercomparisons (CMIP6) are being made and thoughts turn toward a Sixth Assessment Report, the choice of model experiments and long-term climate change projections should include a review of how model uncertainties are being managed and presented. No matter how models are driven, forwards and backwards compatibility that can fully capture uncertainty should be a goal of such assessments. Emission-driven scenarios can then be part of the core experimental protocols allowing results to be presented across a range of different model types, ESMs operating at different resolutions, intermediate complexity models and simple climate models.

As a single model, MAGICC cannot explicitly consider structural uncertainty (Knutti *et al.,* 2008). Furthermore, constraining its parameters using historical data does not necessarily form a reliable basis for future projections as one or more of those parameters may be state dependent. This is probably the case for climate sensitivity (Armour *et al.,* 2013) and the future behavior of the carbon cycle, particularly as the temperature feedback effects are only poorly constrained by historical data. As a simplified ESM, MAGICC also lacks certain processes that could increase uncertainty (such as water and nutrient cycles, the release of carbon from permafrost and albedo changes due to ice cover and vegetation, as well as changes in ocean ventilation and stratification and changes on the ocean's biological carbon cycle). Nevertheless, it is a valuable tool for evaluating and comparing emission scenarios.

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Supporting information

The following supporting information is available:

Table S1. Comparison of global-mean surface temperature change (ΔGMST) between MAGICC and HadCM3C simulations (Booth *et al.*, 2013) for emission-driven RCP8.5 and RCP2.6 pathways. The temperature changes are set relative to pre-industrial and based on 5-year averages at the end of the century.

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