How do carbon cycle uncertainties affect IPCC temperature projections?

Roger W. Bodman,1* Peter J. Rayner2 and Roger N. Jones1
1Victoria Institute of Strategic Economic Studies, Victoria University, Melbourne, Australia
2School of Earth Sciences, The University of Melbourne, Melbourne, Australia

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-driven 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 CO2 concentrations (Hibbard et al., 2007). Accordingly, by applying atmospheric CO2 inputs, the Coupled Model Intercomparison Phase 5 (CMIP5) experiments were designed to allow AOGCMs to participate (Friedlingstein et al., 2014).

These CO2 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
Carbon cycle uncertainties affect IPCC temperature 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 CO2 between different sinks, temperature feedbacks related to plant and soil respiration and CO2 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).

| Scenario IPCC AR5 | Mean | Likely range |
|-------------------|------|--------------|
| 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      |

| Scenario MAGICC CC-off | Median | 67% range |
|------------------------|--------|-----------|
| 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   |

| Scenario 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   |

aCMIP5 likely range is a 5–95% model range calculated from the ensemble of projections and assessed as likely (IPCC, 2013a, 2013b).
bWhere 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 CO2 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 CO2 fertilisation effect and oceanic CO2 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 CO2 concentrations which could then be modeled by the AOGCMs.

Table 2 shows that the our MAGICC CC-on median CO2 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 CO2 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 CO2 fertilization effect and carbon uptake across the land and ocean sinks (which is the reason for the uncertainty range in the MAGICC CC-off CO2 concentration results, Table 2), whereas the concentrations for the
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
The CO₂ concentration ranges differ from our results, with most of the CMIP5 ESMs having higher estimates. The emission-driven average CO₂ concentration at 2100 was 985 ± 97 ppm, whereas the MAGICC CC-on median was 916 ppm. However, most of the ESMs overestimate the historical CO₂ concentrations (Friedlingstein et al., 2014) and therefore may be overestimating CO₂ 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 CO₂ 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 CO₂ concentrations were not considered in the concentration-driven CMIP5 simulations (IPCC, 2013a: SPM.20). 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.

Acknowledgements

We gratefully thank Malte Meinshausen and Jens Kattge for supplying the MAGICC and MCMH code, respectively. We also thank the anonymous reviewers for their helpful comments. We acknowledge the World Climate Research Programmes Working Group on Coupled Modeling, which is responsible for CMIP and thanks to Scott Power and Greg Kociuba, Australian Bureau of Meteorology, for extracting and summarizing the RCP ΔGMST change projections from the CMIP5 archive. RB is funded by a Victoria University Postdoctoral Research Fellowship. PR is in receipt of an Australian Professorial Fellowship (DP1096309).

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.

References

Armour KC, Bitz CM, Roe GH. 2013. Time–varying climate sensitivity from regional feedbacks. Journal of Climate 26: 4518–4534, doi: 10.1175/JCLI-D-12-00544.1.

Bodman RW, Karoly DJ, Rayner PJ. 2013. Uncertainty in temperature projections reduced using carbon cycle and climate observations. Nature Climate Change 3: 725–729, doi: 10.1038/NCLIMATE1903.

Booth BBB, Bernie D, McNeall D, Hawkins E, Caesar J, Boulton C, Friedlingstein P, Sexton DMH. 2013. Scenario and modelling uncertainty in global mean temperature change derived from emission-driven global climate models. Earth System Dynamics 4: 95–108, doi: 10.5194/esd-4-95-2013.

Collins M, Knutti R, Arblaster J, Dufresne J-L, Fichefet T, Friedlingstein P, Gao X, Gutowski WJ, Johns T, Knirrer G, Shongwe M, Tebaldi C,
Weaver AJ, Wehner M. (2013). Long–term climate change: projections, commitments and irreversibility. Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, London and New York, NY: Cambridge University Press.

Friedlingstein P, Cox P, Betts R, Bopp L, von Bloh W, Brovkin V, Cadule P, Doney S, Eby M, Fung I, Bala G, John J, Jones C, Joos F, Kato T, Kawamiya M, Knorr W, Lindsay K, Matthews HD, Raddatz T, Rayner P, Reich C, Roeckner E, Schnitzler K-G, Schnur R, Strassmann K, Weaver AJ, Yoshikawa C, Zeng G. 2006. Climate–carbon cycle feedback analysis: results from the C4MIP model intercomparison. Journal of Climate 19: 3337–3353.

Friedlingstein P, Meinshausen M, Arora VK, Jones CD, Anav A, Liddicoat SK, Knutti R. 2014. Uncertainties in CMIP5 climate projections due to carbon cycle feedbacks. Journal of Climate 27: 511–526, doi: 10.1175/JCLI-D-12-00579.1.

Hibbard KA, Meehl GA, Cox PM, Friedlingstein P. 2007. A strategy for climate change stabilization experiments. Eos 88: 217–219.

Huntingford C, Lowe JA, Booth BB, Jones CD, Harris GR, Gohar LK, Meir P. 2009. Contributions of carbon cycle uncertainty due to carbon cycle feedbacks. Teclis 61B: 355–360, doi: 10.1111/j.1600-0889.2009.00414.x.

IPCC. 2007. Climate Change 2007: The Physical Science Basis. Contribution of Working Group I of the Fourth Assessment Report, Cambridge, London: Cambridge University Press.

IPCC. 2013a. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I of the Fifth Assessment Report Cambridge University Press.

IPCC. 2013b. Summary for policymakers. Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM. Climate Change 2013: The Physical Science Basis. Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, London and New York, NY: Cambridge University Press.

IPCC. 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Geneva, Switzerland: IPCC.

Knutti R, Allen MR, Friedlingstein P, Gregory JM, Hegerl GC, Meehl G, Meinshausen M, Murphy JM, Plattner G-K, Raper SCB, Stocker TF, Stott PA, Teng H, Wigley TML. 2008. A review of uncertainties in global temperature projections over the twenty-first century. Journal of Climate 21: 2651–2662, doi: 10.1175/2007JCLI2119.1.

Meehl GA, Stocker TF, Collins W, Friedlingstein P, Gaye A, Gregory JM, Kitoh A, Knutti R, Murphy J, Noda A, Raper SCB, Watterson I, Weaver A, Zhao Z-C. 2007. Global climate projections. Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averett KB, Tignor M, Miller HL. Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press: Cambridge, London and New York, NY.

Meinshausen M, Meinshausen N, Hare W, Raper SCB, Frieler K, Knutti R, Frame DJ, Allen MR. 2009. Greenhouse-gas emission targets for limiting global warming to 2°C. Nature 458: 1158–1162, doi: 10.1038/nature08017.

Meinshausen M, Raper SCB, Wigley TML. 2011a. Emulating coupled atmosphere–ocean and carbon cycle models with a simpler model, MAGICC6 – part 1: model description and calibration. Atmospheric Chemistry and Physics 11: 1417–1456, doi: 10.5194/acp-11-1417-2011.

Meinshausen M, Smith SJ, Calvin K, Daniel JS, Kainuma M, Lamarque J-F, Matsumoto K, Montzka S, Raper SCB, Riahi K, Thomson A, Velders GJM, van Vuuren D. 2011b. The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. Climatic Change 109: 213–241, doi: 10.1007/s10584-011-0156-z.

Meinshausen M, Wigley TML, Raper SCB. 2011c. Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – part 2: applications. Atmospheric Chemistry and Physics 11: 1457–1471, doi: 10.5194/acp-11-1457-2011.

Moss RH, Edmonds JA, Hibbard K, Manning M, Rose SK, van Vuuren DP, Carter TR, Emori S, Kainuma M, Kram T, Meehl GA, Mitchell JFB, Nakicenovic N, Riahi K, Smith MJ, Stouffer RJ, Thomson AM, Weyant JP, Wilbanks TJ. 2010. The next generation of scenarios for climate change research and assessment. Nature 463: 747–756, doi: 10.1038/nature08823.

Nakicenovic N, Davidson O, Davis G, Grubbler A, Kram T, La Rovere EL, Metz B, Moreira T, Pepper W, Pitcher H, Sankovski A, Shahka P, Swart R, Watson R, Dadi Z. (2000). IPCC Special Report on Emissions Scenarios, Cambridge, London: Cambridge University Press.

Rogelj J, Hare W, Lowe J, van Vuuren DP, Riahi K, Matthews B, Hanaoka T, Jiang K, Meinshausen M. 2011. Emission pathways consistent with a 2 °C global temperature limit. Nature Climate Change 1: 413–417, doi: 10.1038/nclimate1258.

Rogelj J, Meinshausen M, Knutti R. 2012. Global warming under old and new scenarios using IPCC climate sensitivity range estimates. Nature Climate Change 2: 248–253, doi: 10.1038/nclimate1385.

Shao P, Zeng X, Zeng X. 2014. Differences in carbon cycle and temperature projections from emission- and concentration-driven earth system model simulations. Earth System Dynamics Discussions 5: 991–1012, doi: 10.5194/esdd-5-991-2014.

Stocker TF, Qin D, Plattner G-K, Alexander LV, Allen SK, Bindoff NL, B focusing the Next Generation of Scenarios for Climate Change Research and Assessment (NGSSC). Earth System Dynamics 9: 843–892, doi: 10.5194/esd-9-843-2018.

Taylor KE, Stouffer RJ, Meehl GA. 2012. An Overview of CMIP5 and the Experiment Design. Bulletin of the American Meteorological Society 93: 485–498, doi: 10.1175/BAMS-D-11-00094.1.

Tebaldi C, Knutti R. 2007. The use of the multi-model ensemble in probabilistic climate projections. Philosophical Transactions of the Royal Society 365: 2053–2075, doi: 10.1098/rsta.2007.2076.

Wigley TML, Raper SCB. 1987. Thermal expansion of sea level at high and low latitudes and its role in the greenhouse effect. Nature 330: 127–131.

Wigley TML, Raper SCB. 2001. Interpretation of high projections for global–mean warming. Science 293: 451–454, doi: 10.1126/science.1061604.