Reduced uncertainty in temperature projections using carbon cycle and climate observations

Roger Bodman^{1,2}, Peter Rayner¹ & David Karoly¹

¹*The University of Melbourne, Melbourne, Australia.*

²*Victoria University, Melbourne, Australia.*

The future behaviour of the carbon cycle is a major contributor to uncertainty in temperature projections for the 21st century. Using a simplified climate model, we show that, for a given emission scenario, it is the second most important contributor to this uncertainty after climate sensitivity, followed by aerosol impacts. Historical measurements of carbon dioxide concentrations have been used along with global temperature observations to help reduce this uncertainty. This results in an increased probability of exceeding a 2°C global-mean temperature increase by 2100 while reducing the probability of surpassing a 6°C threshold for non-mitigation scenarios such as the SRES A1B and A1FI scenarios¹, as compared to IPCC projections. Climate sensitivity, the response of the carbon cycle and aerosol effects remain highly uncertain but historical observations of temperature and carbon dioxide imply a trade-off between them so that temperature projections are more certain than they would be considering each factor in isolation. As well as pointing out the promise from the formal use of observational constraints in climate projection, this also highlights the need for an holistic view of uncertainty.

20 Introduction

21 The last decade has seen a great deal of research into quantifying the uncertainty of climate
22 projections as a guide to sensible adaptation and mitigation activity. The two most common
23 techniques have been multi-model ensembles (such as the CMIP3, Third Coupled Model In-
24 tercomparison Project² and C4MIP, Coupled Carbon Cycle Climate Model Intercomparison
25 Project³) and perturbed physics experiments⁴. These experiments have allowed us to isolate
26 those factors responsible for the spread of model ensembles. They have identified factors con-
27 tributing to the overall climate sensitivity and uncertainty in the radiative response to aerosol
28 changes, as well as the response of the carbon cycle, including some assessment of the feed-
29 backs between climate change and carbon fluxes.

30 More recently, observations have been used to provide direct constraints on model behaviour^{5,6}.
31 Computational complexity has largely precluded the use of full Earth system models (ESMs)
32 and restricted the facets of model behaviour that can be constrained. Full ESMs generally ex-
33 plore fewer model parameters or use statistical emulation to expand their sample size. Most
34 critically, the carbon cycle behaviour remains largely untreated (with a rare exception⁷), despite
35 the sensitivity of global-mean temperature change projections to carbon cycle processes⁸. In-
36 stead, typically, simple models have been calibrated against the coupled carbon cycle/climate
37 models of Friedlingstein *et al.*³ for which only limited formal calibration is possible and which
38 do not address parametric uncertainty.

39 Here we apply historical observations to address the scientific uncertainty of the climate
40 system. Our general method has been to identify those model parameters most responsible for

uncertainty in global–mean temperature changes, and then to constrain them with historical observations. The model used was MAGICC version 6.3 (Model for the Assessment of Greenhouse Gas Induced Climate Change), a reduced complexity Earth System Model⁹, whose climate system parameters have previously been estimated using historical observations⁶. More recently, the climate system and carbon cycle parameters have been calibrated against both CMIP3 and C4MIP models⁹.

MAGICC has been involved in recent studies of temperature change projections using SRES and RCP scenarios^{10,11}. However, as noted in Rogelj *et al.*¹¹, calibration with just the C4MIP models neglects structural and methodological uncertainties and is therefore unlikely to represent the range of carbon cycle uncertainties. Here, for the first time, observations have been used to directly constrain the model’s carbon cycle parameters. We then generate probability distributions for global–mean temperature change that reflect uncertainties for the combined climate system and carbon cycle, taking into account a comprehensive range of model and observational uncertainties.

Contribution to uncertainty

We see that, before using observations to improve prediction, the climate sensitivity, carbon cycle response and aerosol impacts are the three leading contributors to uncertainty (in that order). This was determined by a linear analysis of the uncertainty contributions to the simulated temperature change in 2100 from the model’s primary parameters. Prior probability distributions for the model’s parameters were estimated based on previous calibration exercises^{6,9} and earlier studies¹², although larger uncertainties were used for the carbon cycle parameters (see

Methods and Supplementary Information for further details).

The uncertainty contributions for the A1FI emission scenario show that about 63% of the uncertainty stems from the climate system parameters, with over 90% of this due to the climate sensitivity parameter (Table 1), while just three additional parameters account for much of the remainder (ocean vertical diffusivity, land ocean warming ratio and the land ocean heat exchange coefficient). The carbon cycle accounts for around 30% of the uncertainty in temperature change in 2100, most of which is captured by six parameters: two temperature feedback parameters for respiration and net primary productivity (NPP), plus the CO₂ fertilisation factor, the fraction of NPP to plant and plant to detritus, plus an ocean carbon cycle impulse response scaling factor. A single parameter was used for the aerosol forcing uncertainty, the fossil fuel derived sulfate aerosol forcing in 2005, with the indirect or cloud albedo effect scaled from the total direct effect. This set of eleven parameters accounts for 96% of the model's parametric uncertainty.

[Table 1]

Constraining with observations

The Monte Carlo Metropolis–Hastings algorithm (MCMH) was applied to constrain the eleven model parameters identified above using 20th–century observations. These included global–mean temperature change, land minus ocean and hemispheric temperature differences¹³, time series for ocean heat content changes¹⁴, and a 1960–2008 ocean vertical temperature change profile¹⁵. Observations for the carbon cycle employed atmospheric CO₂ concentrations from

82 Mauna Loa¹⁶.

83 Details of the resulting posterior distributions for the parameters are provided in Supple-
84 mentary Table S1 and Figure S1. Note that individual distributions are not independent, so
85 that, for example, the distribution for climate sensitivity is not a stand-alone result since the
86 observational constraints introduce sizeable correlations between some of the parameters (pa-
87 rameter correlations are included in Supplementary Table S2). For example, a strong aerosol
88 effect (which reduces temperature changes) requires a higher climate sensitivity to match the
89 observed temperature changes, as found in other studies¹⁷.

90 We repeated the linear uncertainty analysis with the posterior covariance to determine
91 which parameters and combinations are most responsible for the improved knowledge of pro-
92 jected temperature change (Supplementary Figure S3). About 60% of the reduction in tem-
93 perature standard deviation comes from uncertainty reduction in individual parameters with
94 the other 40% arising from parameter covariance. The largest single contribution comes from
95 the climate sensitivity. There is also a large contribution from combinations of carbon cycle
96 parameters even though the individual parameters are not well-constrained. Studies that do
97 not consider these covariances are likely to overestimate uncertainty in temperature change
98 projections.

99 To assess the benefit of constraining the model's parameters using the carbon cycle ob-
100 servations, we compared three ensembles of predicted temperature change for 2100 under the
101 SRES A1FI scenario. Ensembles were generated by constraining model parameters with differ-
102 ent combinations of constraints. The 'Combined' ensemble used both climate and carbon cycle

observations, the ‘Without’ case used no carbon cycle observations, and the ‘Hybrid’ case used the prior C4MIP distribution for carbon cycle parameters and the ‘Combined’ ensemble for all others. All cases were constrained by 20th-century temperature data.

The results (Table 2) reveal the benefit of including carbon cycle observations in the MCMH algorithm, where the effect is to limit the spread in the right-hand side of the probability distribution, reducing the likelihood of very high CO₂ concentration and temperature changes by 2100.

[Table 2]

Probabilistic temperature projections

The observationally constrained posterior parameter distribution was applied to the SRES A1FI, A1B and A2 emission scenarios. Details for temperature change and CO₂ concentrations in 2100 are provided for the prior and posterior distributions, with and without the carbon cycle temperature feedbacks (Table 3), while the global-mean temperature change results are illustrated in Figure 1.

[Table 3]

[Figure 1]

The median, mode and likely ranges for temperature change in 2090–2099 were com-

pared to the IPCC AR4 best estimate and likely range results for these three scenarios and illustrated by the uncertainty bars in Figure 1 (numerical details are set out in Supplementary Table S4). The MAGICC mode temperature changes at 2090–2099 are almost the same as the AR4 best estimates for the A1B and A1FI scenarios, while the likely ranges are reduced at both extremes. This increases the probability of exceeding a 2°C global–mean temperature increase by 2100 and reduces the probability of surpassing a 6°C threshold. The differences arise from the observational constraints imposed by the MCMH calibration process, with the interaction of the individual asymmetric parameter distributions, the interplay of the uncertainties from both the carbon cycle and aerosol radiative forcing, and the amount of sulfur dioxide emissions in the individual scenarios. The central estimate and upper bound for the A2 scenario are noticeably cooler than the AR4 estimates as a result of the higher aerosol cooling.

Projections based on the prior and posterior distributions with and without the carbon cycle temperature feedbacks (Table 3) show how the uncertainty ranges are reduced, although the central estimates reveal little change. The impact of the carbon cycle temperature feedbacks are also evident, with increases in CO₂ concentrations demonstrating a net positive feedback effect. The likely ranges are also wider with the temperature feedbacks on, indicating how emissions driven temperature change projections are affected by both the carbon cycle feedbacks and the uncertainties in those feedbacks. Concentration driven projections will underestimate the amount of temperature change unless this issue is allowed for.

Probability of exceeding 2°C

The posterior parameter distributions also allow an assessment of the probability of exceeding selected temperature targets. For example, for the 2°C target associated with dangerous climate change^{18,19}, Figure 2 plots the three SRES scenarios for (a) global-mean temperature change and (b) land only surface temperature changes, relative to pre-industrial (rather than relative to 1980–1999 as in the previous figures and tables).

[Figure 2]

The A1B scenario shows a slightly increased probability of exceeding 2°C as compared to A1FI at the start of the 21st-century because of higher initial CO₂ emissions. The A1FI scenario has a greater than 50% chance of exceeding 2°C by around 2045, although over the land surface this 50% is exceeded a decade earlier, around 2035. By the end of this century, the probability of exceeding 2°C global-mean temperature change is more than 95%, whilst the probability over land is close to 100% for all three scenarios.

Limitations in this work stem from inadequacies in the model and our estimation process. MAGICC is a simplified ESM which lacks certain processes capable of increasing the uncertainty (e.g., water and nutrient cycles and liberation of carbon in permafrost). It also removes the state dependence of other processes such as ocean diffusivity or surface albedo. Finally, a single model cannot explicitly consider structural uncertainty²⁰ although it can be included in the observational uncertainty²¹.

The treatment of prior PDFs in Bayesian calibration always requires care^{20,22}. The main results of this paper are, however, based on reasonable assumptions or are insensitive to the choice of prior. The extra information available from carbon cycle observations does depend on the prior since, if there is little prior uncertainty, there is little to add. We agree with Rogelj *et al.*¹¹ that C4MIP ranges underestimate total uncertainty and expanded them accordingly. The impact of uncertainty covariance on temperature projections depends only weakly on the magnitude of the posterior uncertainty itself. The specification of data uncertainty is also beset with difficulty. Here we have used only decadal averaged data consistent with the capabilities of MAGICC and have included observation error correlations to deal with potential persistent errors.

The experiments presented here were based on selected SRES emission scenarios for the purposes of comparison to previous studies. However, emission scenarios need to be reassessed to allow for revised expectations in global economic growth, energy intensity, per capita consumption and demography. In addition, it would be useful to provide probabilistic temperature change projections using the RCPs (Representative Concentration Pathways), perhaps following Rogelj *et al.*¹¹.

Methods

Sensitivity analysis. MAGICC was run with a nominally standard set of initial parameter values (10 climate, one combined aerosol and 18 carbon cycle parameters) and A1FI emissions to establish a reference temperature change, then re-run for each parameter in turn, with the parameter value changed by 1% of its standard deviation. The difference in the year 2100

181 temperature change results then provides an uncertainty measurement of the model outputs for
 182 each of the input parameters (the Jacobian of the model $\mathbf{J}$)²³. The variance of each parameter
 183 provides the content for the covariance matrix $\mathbf{C}(v)$. To first order, the uncertainty of the
 184 temperature projection $\mathbf{U}$ is given by:

$$\mathbf{U} = \mathbf{J}\mathbf{C}(v)\mathbf{J}^T \quad (1)$$

185 where the superscript represents the transpose of the matrix $\mathbf{J}$.

186 The results, that is, the relative contributions to uncertainty from the primary model parameters
 187 for the A1FI emission scenario, are provided in Table 1 (the sensitivity of these results
 188 to the emissions pathway, initial parameter values and second-order effects is discussed in the
 189 Supplementary Information).

190 **Monte Carlo Metropolis–Hastings algorithm.** Our implementation of the Monte Carlo Metropolis–
 191 Hastings (MCMH) algorithm compares model results from each iteration to a combined set of
 192 historical climate and carbon cycle observations, applying a decision rule to accept or reject
 193 each parameter set. The posterior parameter distribution is based on the Bayesian formulation:

$$f(\mathbf{p}) = \eta L(\mathbf{p})\rho(\mathbf{p}), \quad (2)$$

194 where $L(\mathbf{p})$ is the likelihood function, $\rho(\mathbf{p})$ is the prior probability density for the vector
 195 of parameters, and η is a normalisation constant (refer Knorr and Kattge²⁴, Mosegaard and
 196 Sambridge²⁵, along with the Supplementary Information, for full details).

197 A set of 11 parameters was selected for the MCMH processing on the basis of the un-
 198 certainty analysis explained above. Prior parameter distributions were established based on

previous studies and existing model calibrations^{6,9}. Gaussian uncertainties were assumed for both prior parameters and the observations. Our method included boundary values that result in truncated normal distributions for the model parameters, with boundaries selected to restrict the parameter space to physically realistic settings. All of the data, except the ocean temperature change profile, were organised into decadal averages to smooth out natural variability, since MAGICC does not simulate this feature of the climate system. Measurement uncertainties were obtained from the respective data sets in addition to a component for the natural variability to derive an overall observational standard deviation; these formed the diagonal elements of the error covariance matrix.

We analysed the error residuals from an initial run and found that they were well represented by a correlation time-scale of 30 years. The MCMH algorithm was then re-run, using these correlations. It was executed 50,000 times to obtain 37,926 accepted parameter sets, where the relatively high acceptance rate reflects the quality of the estimated priors. The resulting posterior distribution can then be used in conjunction with a given emission scenario to produce probabilistic global-mean temperature change projections.

References

1. Nakicenovic, N. & Swart, R. *IPCC Special Report on Emissions Scenarios* (Cambridge University Press, Cambridge, UK, 2000).
2. Meehl, G. *et al.* The WCRP CMIP3 multi-model dataset: A new era in climate change research. *Bull. Am. Meteorol. Soc.* **88**, 1383–1394 (2007).
3. Friedlingstein, P. *et al.* Climate–carbon cycle feedback analysis: results from the C4MIP

model intercomparison. *Journal of Climate* **19**, 3337–3353 (2006).

4. Collins, M. *et al.* Climate model errors, feedbacks and forcings: a comparison of perturbed physics and multi-model ensembles. *Climate Dynamics* **36**, 1737–1766 (2011).

5. Forest, C. E., Stone, P. H. & Sokolov, A. P. Constraining climate model parameters from observed 20th century changes. *Tellus* **60A**, 911–920 (2008).

6. Meinshausen, M. *et al.* Greenhouse-gas emission targets for limiting global warming to 2°C. *Nature* **458**, 1158–1162 (2009).

7. Ricciuto, D. M., Davis, K. J. & Keller, K. A Bayesian calibration of a simple carbon cycle model: The role of observations in estimating and reducing uncertainty. *Global Biogeochemical Cycles* **22**, GB2030 (2008).

8. Booth, B. B. B. *et al.* High sensitivity of future global warming to land carbon cycle processes. *Environmental Research Letters* **7** (2012).

9. Meinshausen, M., Raper, S. C. B. & Wigley, T. M. L. 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 (2011).

10. Meinshausen, M. *et al.* The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. *Climatic Change* **109**, 213–241 (2011).

11. Rogelj, J., Meinshausen, M. & Knutti, R. Global warming under old and new scenarios using IPCC climate sensitivity range estimates. *Nature Climate Change* **2**, 248–253 (2012).

12. Bodman, R. W. *Estimating uncertainties in future global warming using a simple climate model*. Ph.D. thesis, The University of Melbourne (2011).

- 242 13. Brohan, P., Kennedy, J. J., Harris, I., Tett, S. F. B. & Jones, P. D. Uncertainty estimates in
243 regional and global observed temperature changes: A new data set from 1850. *Journal of*
244 *Geophysical Research* **111**, D12106 (2006).
- 245 14. Domingues, C. M. *et al.* Improved estimates of upper-ocean warming and multi-decadal
246 sea-level rise. *Nature* **453**, 1090–1093 (2008).
- 247 15. Wijffels, S. E. *Vertical ocean temperature change profile, 1960–2008 (personal communi-*
248 *cation)*. CSIRO Wealth from Oceans Flagship, Hobart, Tasmania, Australia (2010).
- 249 16. Masarie, K. A. & Tans, P. P. Extension and integration of atmospheric carbon dioxide data
250 into a globally consistent measurement record. *Journal of Geophysical Research* **100**,
251 11,593–11,610 (1995). URL withupdatesat[http://www.esrl.noaa.gov/](http://www.esrl.noaa.gov/gmd/ccgg/trends/global.html)
252 [gmd/ccgg/trends/global.html](http://www.esrl.noaa.gov/gmd/ccgg/trends/global.html).
- 253 17. Tanaka, K. & Raddatz, T. Correlation between climate sensitivity and aerosol forcing and
254 its implication for the “climate trap”. *Climatic Change* **109**, 815–825 (2011).
- 255 18. Hansen, J. E. A slippery slope: How much global warming constitutes “dangerous anthro-
256 pogenic interference”. *Climatic Change* **68**, 269–279 (2005).
- 257 19. Schneider, S. H. & Lane, J. An overview of ‘dangerous’ climate change. In Schellnhuber,
258 H. J., Cramer, W., Nakicenovic, N., Wigley, T. M. L. & Yohe, G. (eds.) *Avoiding Dangerous*
259 *Climate Change*, chap. 2 (Cambridge University Press, 2006).
- 260 20. Knutti, R. *et al.* A review of uncertainties in global temperature projections over the
261 twenty-first century. *Journal of Climate* **21**, 2651–2662 (2008).

21. Tarantola, A. *Inverse Problem Theory and Methods for Model Parameter Estimation* (Society for Industrial and Applied Mathematics, 2005).
22. Frame, D. J. *et al.* Constraining climate forecasts: the role of prior assumptions. *Geophysical Research Letters* **32**, L09702 (2005).
23. Rayner, P. J., Koffi, E., Scholze, M., Kaminski, T. & Dufresne, J.-L. Constraining predictions of the carbon cycle using data. *Philosophical Transactions of the Royal Society* **369**, 1955–1966 (2011).
24. Knorr, W. & Kattge, J. Inversion of terrestrial ecosystem model parameter values against eddy covariance measurements by Monte Carlo sampling. *Global Change Biology* **11**, 1333–1351 (2005).
25. Mosegaard, K. & Sambridge, M. Monte Carlo analysis of inverse problems. *Inverse Problems* **18**, R29–R54 (2002).

Acknowledgments We gratefully thank Malte Meinshausen and Jens Kattge for supplying the MAG-ICC and MCMH code respectively. This research was supported by the Australian Research Council through the Discovery Projects funding scheme (project number FF0668679) and an ARC Professorial Fellowship (DP1096309).

Author contributions R.B, P.R. and D.K designed the research. R.B. carried out the analysis, with P.R. adding the linear uncertainty analysis of the posterior covariance. R.B. wrote the paper. All authors discussed the results and edited the manuscript.

Additional information Supplementary Information accompanies this paper on www.nature.com/natureclimatechange. Reprints and permissions information is available online at www.nature.com.

283 com/reprints. Correspondence and requests for materials should be addressed to R.B. (email:
284 roger.bodman@vu.edu.au). Results are archived at [http://hdl.handle.net/102.100.100/](http://hdl.handle.net/102.100.100/9790)
285 9790.

286 **Competing financial interests** The authors declare that they have no competing financial interests.

Table 1: Relative contributions to scientific uncertainty from MAGICC's primary climate–carbon cycle parameters towards global–mean temperature change in 2100 with A1FI emissions. Parameter groups: 4 climate system, 1 combined aerosol and 6 carbon cycle parameters that account for 96% of the uncertainty from a total of 29 selected parameters.

Parameter name	uncertainty contribution %
climate sensitivity ΔT_{2x}	58.4%
ocean vertical diffusivity K	2.0%
land ocean warming ratio R_{lo}	1.7%
land ocean heat coefficient κ_{lo}	0.6%
sulfate aerosol forcing in 2005 AF_{sox}	4.7%
CO ₂ fertilisation factor β_s	8.4%
temperature feedback factor, respiration σ_R	8.0%
temperature feedback factor, NPP σ_{NPP}	7.4%
carbon flux partition, NPP to plant g_P	2.5%
ocean cc impulse response scale factor O_r	2.2%
carbon flux partition, plant to detritus q_H	0.1%

Table 2: SRES A1FI CO₂ concentrations and global–mean temperature change results at 2100 relative to 1980–1999 for the ‘Combined’, ‘Without’ (i.e., without carbon cycle observations), and ‘Hybrid’ cases.

	‘Combined’	‘Without’	‘Hybrid’
CO ₂ concentration, ppm			
median	943	1070	1037
mode	907	958	960
likely range	803–1140	851–1408	807–1399
Temperature change, °C (relative to 1980–1999)			
median	4.2	4.5	4.5
mode	4.1	4.1	4.4
likely range	2.9–5.7	3.1–6.2	3.0–6.5

Table 3: CO₂ concentrations and global-mean temperature change in 2100 relative to 1980–1999 for three SRES emission scenarios, A1B, A1FI and A2, with results for the prior and posterior parameter distributions, with and without the carbon cycle temperature feedbacks (without temperature feedbacks corresponds to setting the four temperature feedback factors for respiration σ_R , net primary productivity (NPP) σ_{NPP} , detritus σ_Q and soil σ_U , to zero.)

Carbon cycle temperature feedbacks:	Prior dist'n		Post. dist'n	
	On	Off	On	Off
A1B emission scenario				
	CO ₂ concentration, ppm			
median	752	659	704	641
mode	663	646	673	622
likely range	595–1050	571–761	612–846	576–717
	Temperature change, °C relative to 1980–1999			
median	3.6	3.2	3.1	2.8
mode	2.7	3.1	2.9	2.8
likely range	1.9–5.8	1.8–4.6	2.1–4.4	1.9–3.9
A1FI emission scenario				
	CO ₂ concentration, ppm			
median	1010	882	943	856
mode	914	869	907	831
likely range	781–1383	752–1020	803–1140	760–962
	Temperature change, °C relative to 1980–1999			
median	4.7	4.2	4.2	3.9
mode	4.2	4.0	4.1	3.9
likely range	2.6–7.0	2.5–5.9	2.9–5.7	2.7–5.2
A2 emission scenario				
	CO ₂ concentration, ppm			
median	844	779	811	759
mode	786	768	792	738
likely range	691–1062	673–895	716–928	681–847
	Temperature change, °C relative to 1980–1999			
median	3.3	3.0	3.1	2.8
mode	3.0	2.8	3.0	2.8
likely range	1.9–4.8	1.8–4.2	2.2–4.0	2.0–3.7

Figure 1 Time series of global–mean temperature change for selected SRES marker scenarios: (a) A1B, (b) A1FI and (c) A2, as anomalies with respect to 1990 (1980–1999 mean) based on the posterior parameter distributions. Black line: median, shaded regions 66% (dark), 95% (medium) and 99% (light) confidence intervals. The uncertainty ranges at the sides are the IPCC likely range and best estimate (grey column) for 2090-2099 and our corresponding results (blue column); the black bars are the respective best estimate and mode (refer Supplementary Information Table S3 for numerical details).

Figure 2 Probability of exceeding 2°C global–mean temperature change relative to pre-industrial for A1FI (black line), A1B (blue line) and A2 (pale blue line) emission scenarios: (a) global–mean and (b) land–surface temperature change.