Can the Last Glacial Maximum constrain climate sensitivity?

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[1] We investigate the relationship between the Last Glacial Maximum (LGM) and climate sensitivity across the PMIP2 multi-model ensemble of GCMs, and find a correlation between tropical temperature and climate sensitivity which is statistically significant and physically plausible. We use this relationship, together with the LGM temperature reconstruction of Annan and Hargreaves (2012), to generate estimates for the equilibrium climate sensitivity. We estimate the equilibrium climate sensitivity to be about 2.5°C with a high probability of being under 4°C, though these results are subject to several important caveats. The forthcoming PMIP3/CMIP5 models were not considered in this analysis, as very few LGM simulations are currently available from these models. We propose that these models will provide a useful validation of the correlation presented here. **Citation:** Hargreaves, J. C., J. D. Annan, M. Yoshimori, and A. Abe-Ouchi (2012), Can the Last Glacial Maximum constrain climate sensitivity?, *Geophys. Res. Lett.*, *39*, L24702, doi:10.1029/2012GL053872.

1. Introduction

[2] The Last Glacial Maximum (LGM, 19–23 ka before present) is often considered to be one of the most promising paleoclimate intervals for estimating the climate's response to radiative forcing. This is commonly summarised through the equilibrium climate sensitivity (i.e., the global mean temperature response under a sustained doubling of the atmospheric CO_2 concentration). The radiative forcing during the LGM was large and is reasonably well-known [*Jansen et al.*, 2007], and the large amount of proxy data available allows us to constrain the temperature change both regionally and globally [*Annan and Hargreaves*, 2012]. The LGM has been used previously to estimate climate sensitivity, often with ensembles in which parameters are varied in a single climate model [e.g., *Annan et al.*, 2005; *Schneider von Deimling et al.*, 2006a; *Holden et al.*, 2009; *Schmittner et al.*, 2011]. Best estimates from these analyses range from 2.3°C [*Schmittner et al.*, 2011] to 3.6°C [*Holden et al.*, 2009], with 90% uncertainty ranges reaching from about 1°C to 5°C. While some differences between these results can be attributed to different interpretations of the proxy data, recent work [*Yokohata et al.*, 2010; *Yoshimori et al.*, 2011; *Klocke et al.*, 2011] has also shown that single model ensembles generally do not span the range of responses that are covered by structurally different models. Moreover, these single model ensemble experiments are

generally performed with models of low resolution and/or complexity, due to computational limitations. Thus, the robustness of these results could be questionable. In this paper we investigate the multi-model ensemble which contributed to the Paleoclimate Modelling Intercomparison Project (PMIP2) [*Braconnot et al.*, 2007] and the World Climate Research Programme's Coupled Model Intercomparison Project phase 3 (CMIP3) [*Meehl et al.*, 2007]. Our rationale is that the wider range of uncertainty which emerges from structural rather than merely parametric differences, may provide a more robust and reliable result [*Annan and Hargreaves*, 2010; *Yokohata et al.*, 2011; *Hargreaves et al.*, 2011].

[3] In a previous analysis, *Crucifix* [2006] found no relationship between LGM and $2 \times CO_2$ climates across a small ensemble of these models. However, *Hargreaves et al.* [2007] and *Hargreaves and Annan* [2009] found that, within a single model ensemble, the correlation between climate sensitivity and temperature change at the LGM was much stronger if attention was focussed on the LGM temperature change in the tropics, rather than globally. This is a physically plausible result, since, during the LGM interval, the greenhouse gas forcing is relatively more important in the tropics than at higher latitudes where there are also major changes in ice sheets, and where biases in sea ice extent can also lead to large variation in temperature anomalies [*Hargreaves and Annan*, 2009]. Interestingly, among the mainly negative results of *Crucifix* [2006], there was some hint of a correlation between the LGM tropical temperature change and the warming in this region for a doubling of CO_2 in his Figure 2c. However, with only 4 models contributing to this analysis, the correlation would have to have been 0.9 or greater to be significant at the 5% level under a one-tailed test, and this threshold was not reached.

[4] The PMIP2 project is now finished and the ensemble complete. Thus, with more models available, it is possible to re-examine this issue in more detail. Here we explore the correlations in this ensemble between temperature change at the LGM both globally and locally, with equilibrium climate sensitivity. We find a strong relationship between equilibrium climate sensitivity and LGM temperature change in the tropics. Combined with a new estimate of LGM temperature change [*Annan and Hargreaves*, 2012], we use two different approaches to generate estimates of climate sensitivity. Our results are consistent with previous estimates, and we propose that the forthcoming PMIP3/CMIP5 models (not included in this analysis, as few LGM simulations from these models are currently available) will provide an interesting test of the hypothesis.

2. Analysis of the PMIP2 Models

[5] We use the outputs of 7 models which participated in the PMIP2 project [*Braconnot et al.*, 2007]. The models are listed in Table 1 along with some key output statistics. The PMIP2 models were predominantly state of the art atmosphere-ocean

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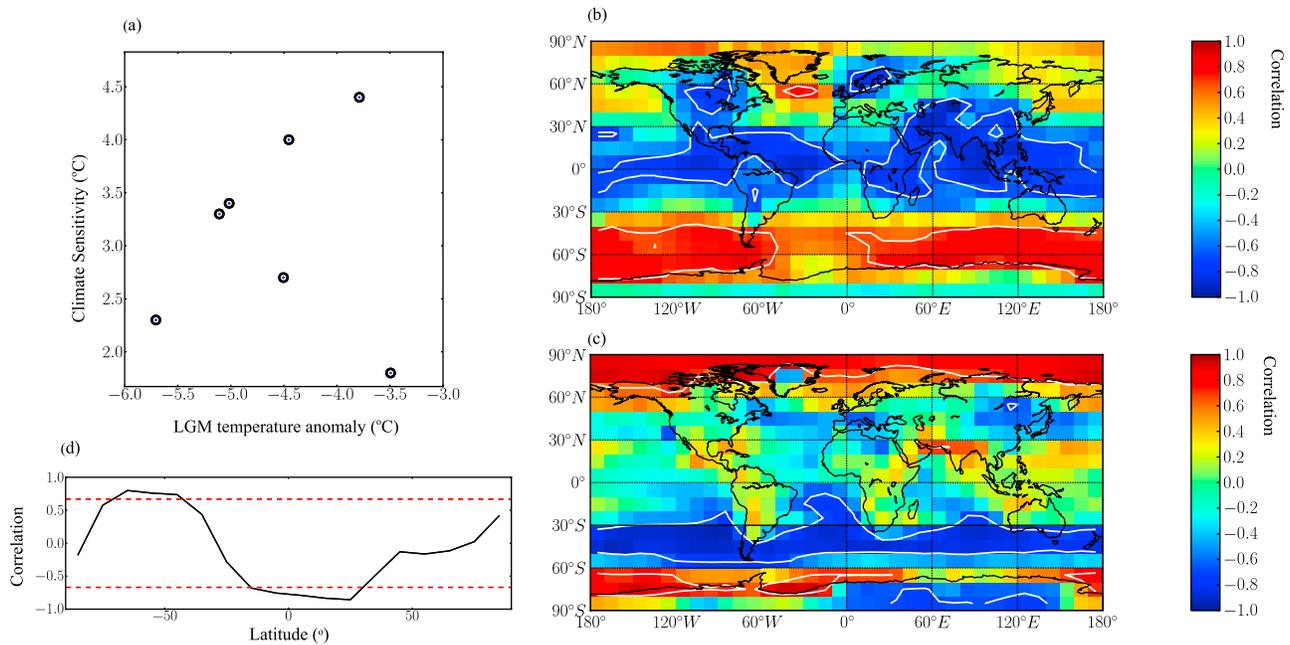
Figure 1. Relationships in the PMIP2 ensemble between climate sensitivity and (a) global average of LGM temperature change (no correlation), (b) local LGM temperature change, contour indicating region with significant correlation, (c) local pre-industrial control climate, (d) zonally averaged LGM temperature change, with dotted line indicating threshold for 95% significance using a one-sided t-test.

GCMs, with one being an intermediate-complexity model with simplified atmosphere. For most models, their climate sensitivities were presented in Table 8.2 of *Randall et al.* [2007], with the value for ECBILT being taken from *Goosse et al.* [2005]. Due to the ongoing nature of model development, these sensitivity values may not precisely correspond to the sensitivities of the models used in the PMIP2 LGM simulations, which introduces some additional uncertainty into our results. However, we expect this to be a relatively minor factor in our analysis. We were unable to obtain a climate sensitivity estimate for the CNRM model, so it is not included in this analysis. Some modelling centres also contributed "AOV" model variants to the PMIP2 database, which included an interactive vegetation component. The climate sensitivities of these model variants may be slightly different from the standard "AO" version, but were not provided. Therefore, we do not include these simulations here.

[6] Model outputs for the LGM were calculated as 100y averages to minimise the effect of internal variability. The PMIP2 experimental protocol for the LGM accounts for the largest and best-quantified forcings during that interval, which include reduced greenhouse gas concentrations, minor changes in orbital parameters, and extensive increases in northern hemisphere ice sheets. The experimental design and main results are described more fully by *Braconnot et al.* [2007]. Despite some limitations in the forcing protocol [*Schneider von Deimling et al.*, 2006b], the model outputs appear to generally provide a reasonable representation of the Last Glacial Maximum [*Hargreaves et al.*, 2011]. The global averages of the annual mean temperature anomaly fields simulated by these models at the LGM range from 3.5 to 5.7°C colder than present.

[7] As *Crucifix* [2006] found for a subset of these models, there is no correlation between the equilibrium climate sensitivities and global LGM temperature anomalies ΔTL_G

(Figure 1a). However, previous work has shown that the correlation of sensitivity with LGM temperature anomaly varies regionally [*Hargreaves et al.*, 2007; *Hargreaves and Annan*, 2009]. We therefore interpolated the model data to a 10 degree grid and calculated the correlation between the temperature change at each grid box, and the (global) climate sensitivity. Regional changes in future climate are left for future study. The results are presented in Figure 1b. There is a large scale spatially coherent pattern, with a strong negative correlation over much of the tropical region, and also a region of strong positive correlation in the Southern Ocean. With the LGM temperature anomaly defined here as LGM minus present day, the physically plausible sign for these correlations is negative, under the expectation that similar processes are contributing substantially to both past and future climate changes. A large proportion (27%) of the globe exceeds the 95% confidence threshold for a one-sided test of negative correlation (which for 7 models, is given by r = 0.67). We checked by bootstrapping to see whether such a large area of high correlation was likely to appear by chance. The sensitivities were randomly assigned to the models, and the correlation maps calculated as before. In repeated resampling, the highly negatively correlated area exceeded 27% in only 2% of cases, and we conclude that the existence of such a large, highly-correlated area is highly significant at the 97.5% level.

[8] The positive correlation observed over the Southern Ocean is rather counterintuitive, as it implies that the models which cool least strongly here under the negative LGM forcing are the ones which also show the strongest warming globally for an increase in CO_2. Further investigation of the model results (Figure 1c) reveals that a large part of the Southern Ocean region also exhibits a very strong correlation between the climate sensitivity and the modelled pre-industrial climate state itself. *Trenberth and Fasullo* [2010] also found that there was a strong relationship between

Using LGM Tropical temperature as a constraint on climate sensitivity
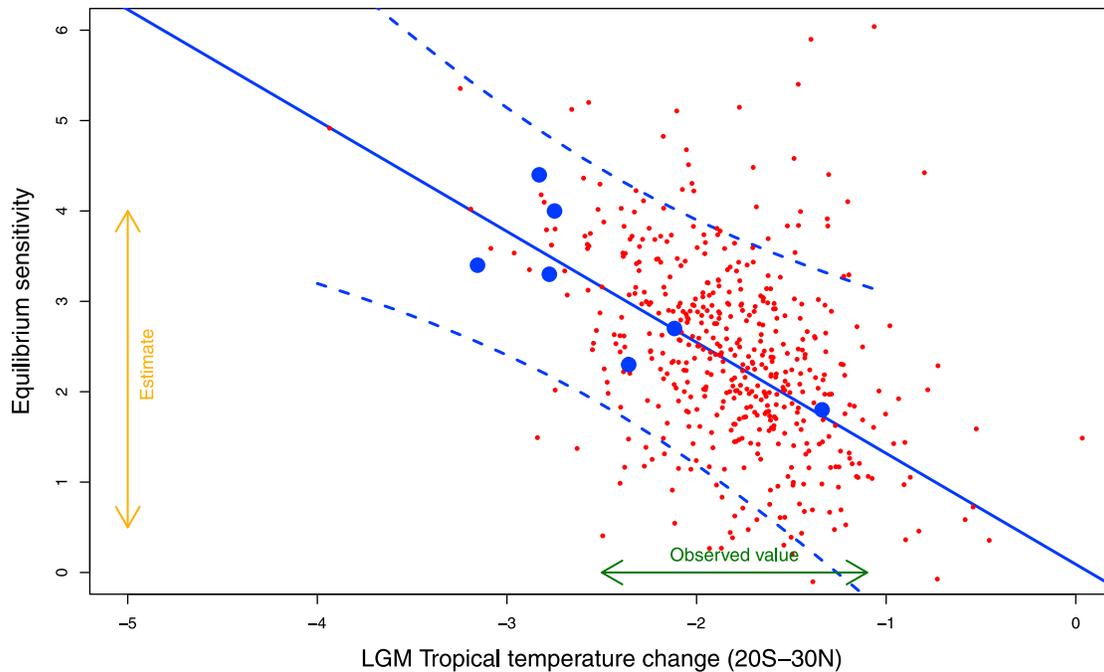

Figure 2. Climate sensitivity estimated from the correlation between LGM tropical (20°S–30°N) temperature change and climate sensitivity. Blue dots: PMIP2 models. Blue lines: predictive range from regression. Red dots: sample from predictive distribution for climate system.

climate sensitivity and the energy balance in the southern hemisphere, and *Haynes et al.* [2011] identified large biases in the cloud cover as playing a significant role in this. However, the region with high positive correlation in Figure 1b only covers 12% of the globe, and under the same bootstrapping analysis as above, the existence of such an area with high correlation only reaches the 75% significance level. Thus, it is important to recognise that it may simply be an artefact of the small sample size. If this correlation was found to persist with a larger ensemble, it would certainly merit further investigation.

[9] Averaging over latitudinal bands, the correlation structure shows a strong correlation in the tropics (Figure 1d). Therefore, we focus our analysis on the area from 20°S–30°N where the zonally-averaged correlation exceeds the 95% significance threshold, and the direct influence of Southern Ocean biases is minimal. While it could be argued that this area was selected in part due to the post-hoc observation of the high correlation (which of course formally invalidates the significance test) it must be noted that the tropical region was previously identified by *Hargreaves et al.* [2007] and *Hargreaves and Annan* [2009] (using results from a single model ensemble) as a place where useful results might be obtained. Using the standard tropical area 30°S–30°N, the correlation is slightly lower at −0.75, but this still exceeds the 90% confidence threshold for a one-sided test.

3. Estimation of Climate Sensitivity

[10] In principle, the existence of such a relationship between past and future climate change should enable us to predict the latter using observations of the former. We now present results using two somewhat different approaches to this.

[11] The observational analysis is drawn from *Annan and Hargreaves* [2012], who combined a large recent collection of proxy data together with the PMIP2 model database to generate a new spatial field of LGM temperature change through a multiple linear regression approach. It should be noted that, although the model outputs were already used in this analysis, *a priori* unknown scaling factors were applied to the model output fields, and thus we do not consider that the results are in any way biased towards the model values. In fact the reconstruction agrees closely with the mean of the data points, and shows rather less cooling than most of the GCMs simulate, especially over the tropical region. The reconstruction has an area-averaged cooling of $1.8 \pm 0.7°C$ (5–95% CI) over the region 20°S–30°N. This estimate is heavily dependent on the MARGO data set [*MARGO Project Members*, 2009] and thus is subject to any unrecognised biases or uncertainties in that data set. A cooler LGM reconstruction

Table 1. Climate Models Used in This Study[a]

Name	S	ΔTL_G	ΔTL_T	ΔTL_{NT}
CCSM	2.7	−4.50	−2.16	−2.11
ECBILT	1.8	−3.49	−1.37	−1.34
ECHAM	3.4	−5.02	−3.18	−3.16
FGOALS	2.3	−5.71	−2.42	−2.36
HadCM3	3.3	−5.11	−2.73	−2.78
IPSL	4.4	−3.79	−2.73	−2.83
MIROC	4.0	−4.45	−2.70	−2.75

[a]S, ΔTL_G, ΔTL_T and ΔTL_{NT} indicate the equilibrium climate sensitivity, global average of surface air temperature at the LGM, average of tropical (30°S–30°N) surface air temperature at the LGM and average of northern tropical (20°S–30°N) surface air temperature at the LGM respectively (all in °C).

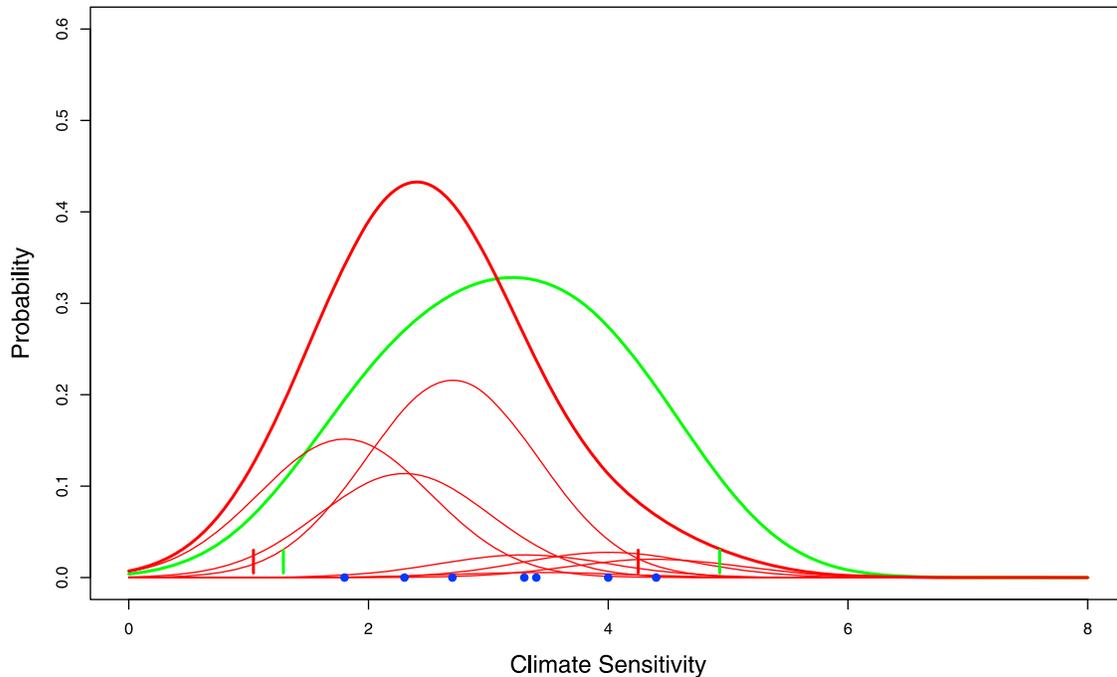**Climate sensitivity estimated through weighting of the PMIP models**

Figure 3. Bayesian approach to estimating climate sensitivity. Green curve shows prior, thick red curve is posterior and vertical bars show 5–95% range. Blue dots show model values and thin red curves indicate weighted contribution of each model to the posterior.

would naturally result in higher estimated sensitivities, in the following calculations.

[12] For our first estimate of climate sensitivity, we directly project the observed range forward using the regression relation, as in *Boé et al.* [2009]. Since there is substantial uncertainty in the predictand (i.e., the tropical mean temperature change at the LGM), we first generate an ensemble of samples to represent our uncertainty in this value, each one of which is then used to generate an estimate of sensitivity through the predictive distribution of the regression (red dots, Figure 2). Through this process, we obtain an ensemble of sensitivity values which has a mean of 2.3°C and a 90% range of 0.5–4.0°C. This result is consistent with most previous estimates of climate sensitivity, but a little lower than many and the upper bound in particular is rather tight.

[13] An alternative approach is to apply a Bayesian weighting to the models in the style of a Bayesian Model Averaging approach [*Hoeting et al.*, 1999]. For our prior, we start by assigning equal weight to each model. Due to the very small sample, we need to use a substantial kernel bandwidth of 0.7°C to generate a density estimate, giving a prior with a median of 3.1°C and a 5–95% range of 1.3–4.9°C (green curve, Figure 3). It is clear that this prior is already quite strongly constrained compared to many climate sensitivity estimates using modern data. When we update the weights using the likelihood function arising from the observational estimate, the posterior is shifted towards slightly lower values, with 5–95% range of 1.0–4.2°C and a median of 2.5°C. Clearly both approaches give very similar results, with the marginally higher values from the Bayesian method being attributable to the fact that the models (and thus the prior) have somewhat stronger LGM responses

than the observational estimate. With such a small ensemble, the results are rather sensitive to the presence or absence of individual models. Thus we present this result arising from the PMIP2 ensemble primarily as a hypothesis to be tested by future ensembles. In particular, the PMIP3 ensemble which will develop over the next few years should include at least twice as many models, and therefore can be expected to give more robust results.

[14] The PMIP2 experimental protocol for the LGM omits forcing due to atmospheric dust [*Claquin et al.*, 2003] and vegetation changes [*Crucifix and Hewitt*, 2005], but while these are poorly constrained, they are likely to be net cooling influences. The modelling experiments of *Schneider von Deimling et al.* [2006a] estimate the effect of dust to be a cooling of about 0.3–0.9°C as the climate sensitivity varies from 1.5 to 4.5°C, which amounts to around 15% of the total simulated cooling in those experiments. We can attempt to account for this (at least approximately) by increasing the modelled tropical cooling results of the PMIP2 models by a factor of 1/0.85. When we do this, the median Bayesian posterior estimate is reduced to 2.0°C with a 5–95% range of 0.2–4.0°C, and the regression-based estimate falls to 2.0°C with a range of 0.8–3.6°C. However, it must be noted that this dust correction is rather simplistic, being based on a single energy balance model, and more complex models may show a broader range of behaviour. The effect of vegetation changes might also be of a similar magnitude [*Crucifix and Hewitt*, 2005], but a quantitative estimate of this seems rather speculative at this time. Thus, we retain the original results with the caveat that they are likely biased high due to this effect. Work to better evaluate the full range of forcings

could help to refine these estimates and should be a priority for future research.

4. Conclusion

[15] We have found evidence in the PMIP2 ensemble of a relationship between LGM cooling in the tropics, and equilibrium climate sensitivity. Based on this result, we estimate climate sensitivity to be around 2.5°C with a high probability of lying below 4°C. While our analysis could be suspected of a data snooping (or multiple comparison) bias, since we focus on the region where we find the highest correlation, the tropics were previously identified as a promising area to test [*Hargreaves et al.*, 2007], and the correlation is also physically plausible due to the nature of the radiative forcings. One puzzling result is the appearance of a counterintuitive correlation between sensitivity and the LGM cooling in the southern ocean, which may be related to the poor representation of clouds in this area. Our estimate of climate sensitivity is comparable to previous LGM-based estimates, though we expect our results to have been biased high due to limitations of the experimental protocol in the PMIP2 experiments. We propose that the forthcoming PMIP3/CMIP5 ensemble may prove to be an interesting test of this correlation, which may also help to refine our estimate though the expected increase in sample size to more than 15 models. However, the limitations of the experimental protocol (particularly the radiative forcings) are a cause for concern and hinder the interpretation of these model simulations.

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