Supplementary Material to “Climate Sensitivity Estimated From Temperature Reconstructions of the Last Glacial Maximum” by Schmittner et al.

Contents:

1. Climate Model, Radiative Forcing and Ensemble Generation
2. Temperature Reconstructions
3. Snowball Earth
4. Simulated Temperature Changes and Residuals
5. Statistical Analysis
6. Sensitivity Tests
7. Vegetation Simulation

1. Climate Model, Radiative Forcing and Ensemble Generation

The UVic Earth System Climate Model (version 2.8 with parameters as described in detail in [Schmittner et al., 2008]) includes a three-dimensional ocean general circulation model, a dynamic-thermodynamic sea ice model, a simple one-layer energy-moisture balance model of the atmosphere as well as land-surface and dynamic terrestrial vegetation components. Since vegetation is allowed to respond dynamically to changes in climate and CO$_2$ concentrations, it is treated as an internal interactive feedback, rather than as part of the prescribed forcing as in previous studies without interactive vegetation.

In order to generate model versions with different climate sensitivities we have changed a parameter in the formulation of outgoing planetary longwave radiation at the top-of-the-
atmosphere $Q_{PLW}$ in the atmospheric Energy-Moisture Balance Model (EMBM) of the UVic model version 2.8 [Weaver et al., 2001; Schmittner et al., 2008]. The UVic model uses a polynomial formulation by Thompson and Warren (1982):

$$Q_{PLW} = c_{00} + c_{01}r + c_{02}r^2 + (c_{10} + c_{11}r + c_{12}r^2)T_a + (c_{20} + c_{21}r + c_{22}r^2)T_a^2 + (c_{30} + c_{31}r + c_{32}r^2)T_a^3$$

(S1)

that depends on surface air temperature $T_a$ and surface relative humidity $r$. In order to keep global preindustrial surface air temperature constant we varied the slope of this curve with respect to $T_a$ by changing $c_{10}$ and $c_{00}$ simultaneously (Figure S1). Equation S1 implicitly includes the effects of the water vapor and lapse-rate feedbacks as well as cloud feedbacks on infrared radiation. The larger the slope $c_{10}$ the larger the response of $Q_{PLW}$ will be to a given change in temperature. Since this is a negative feedback, the climate sensitivity is smaller the larger the slope $c_{10}$. We have created an ensemble of 26 different model versions by varying $c_{10}$ from 1.7 to 18.1 Wm$^{-2}$K$^{-1}$. The standard model uses $c_{10} = 2.6$ Wm$^{-2}$K$^{-1}$. Present-day observations do not provide firm constraints on these parameters as illustrated in Figure S1, although very small and very large values can probably be excluded. However, we have retained models with extreme values in order to gauge the constraints imposed by LGM data only, without considering constraints from present day observations.

We carried out three types of simulations with each ensemble member: a pre-industrial control run, a double CO$_2$ run (to determine $ECS_{2xC}$) and four LGM experiments. The LGM experiments consider uncertainty in dust forcing, wind stress and initial conditions (different initial states of the Atlantic Meridional Overturning Circulation AMOC). All simulations were integrated for 2000 years. The average of the last 500 years were used for the analysis.
Our standard model simulations of the Last Glacial Maximum (LGM) include radiative forcing from larger continental ice sheets ($\Delta F_{sfc} = -2.2 \text{ W/m}^2$) [Peltier, 2004], lower greenhouse gas concentrations ($\text{CO}_2$, $\text{CH}_4$, $\text{N}_2\text{O}$) ($\Delta F_{GHG} = \Delta F_{\text{CO}_2} + \Delta F_{\text{CH}_4} + \Delta F_{\text{N}_2\text{O}} = -2.8 \text{ W/m}^2$) [Flückiger et al., 1999; Ramaswamy et al., 2001; EPICA et al., 2004], changes in the seasonal distribution of insolation (annually averaged $\Delta F_{\text{ins}} = 0 \text{ W/m}^2$), and higher atmospheric dust levels (Figure S2; $\Delta F_{\text{dust}} = -0.9 \text{ W/m}^2$) [Mahowald et al., 2006b]. The total radiative forcing in the standard model $\Delta F_{\text{LGM}} = \Delta F_{sfc} + \Delta F_{\text{GHG}} + \Delta F_{\text{dust}} = -5.9 \text{ W/m}^2$ is similar to previous estimates [Hansen et al., 1984], but less than another recent study [Kohler et al., 2010] who estimated $\Delta F_{\text{LGM}} = -9.5 \text{ W/m}^2$, partly because of higher assumed dust $\Delta F_{\text{dust}} = -1.9 \text{ W/m}^2$ and ice sheet $\Delta F_{sfc} = -3.2 \text{ W/m}^2$ forcing by [Kohler et al., 2010] and because [Kohler et al., 2010] prescribe surface albedo changed from changes in vegetation $\Delta F_{\text{veg}} = -1.1 \text{ W/m}^2$, which is considered an internal feedback in our study.

Ice sheets are prescribed as fixed differences in the surface elevation in the model (not interactive). This affects surface air temperatures according to a fixed lapse rate (5K/km), which leads to a changed albedo because of accumulating snow cover. (Albedo is not prescribed.) Forcing due to surface albedo changes associated with the increased land area covered with ice sheets was estimated by performing an additional simulation with pre-industrial boundary conditions but added LGM ice sheets. The difference in shortwave fluxes at the top of the atmosphere between this experiment and the pre-industrial control run gives the forcing due to surface albedo changes resulting in the value of $\Delta F_{sfc} = -2.2 \text{ W/m}^2$ reported above. Northern hemisphere ice sheets contribute $-1.8 \text{ W/m}^2$, southern hemisphere ice sheets $-0.3 \text{ W/m}^2$ and changes in non-ice sheet covered areas $-0.1 \text{ W/m}^2$. This estimate, which includes the effects of
changes in snow cover, is within the range (−1.9 to −2.9 W/m²) of previous studies [Hewitt and Mitchell, 1997; Broccoli, 2000; Taylor et al., 2007] but smaller than the −3.2 W/m² by [Kohler et al., 2010]. We do not consider the effect of surface albedo changes caused by differences in land-sea distribution away from ice sheets associated with exposed continental shelves. This effect has been estimated to be small (−0.4 W/m²) [Broccoli, 2000]. Including this forcing, which is 7% of the total, could decrease our estimate of ECS₂xC slightly (by up to 0.2 K).

For dust we use two-dimensional maps (Figure S2) of longwave and shortwave radiative forcing for the LGM and pre-industrial climate as simulated by the interactive dust model of [Mahowald et al., 2006b], which uses the Community Atmospheric Model, as described in [Mahowald et al., 2006a]. The dust model results were tuned for the LGM to best match available deposition observations, and matched these observations for the current climate, especially in the annual mean. The shortwave and longwave impacts of desert dust were included, as described in [Yoshioka et al., 2007]. We assumed the best available optical values for the desert dust particles [Yoshioka et al., 2007], but these are uncertain [Sokolik and Toon, 1999], and there are large differences in the results if different optical values are used [Perlwitz et al., 2001].

2. Temperature Reconstructions

We have combined recent syntheses of global sea surface temperatures (SSTs) from the Multiproxy Approach for the Reconstruction of the Glacial Ocean (MARGO) project [Waelbroeck et al., 2009] and surface air temperatures (SAT) over land based on pollen distributions [Bartlein et al., 2010], with additional data (see subsection 2.1 below) from ice
sheets, land and ocean [Shakun et al., in review].

2.1. Shakun et al. (submitted) LGM temperature dataset

This dataset consists of 54 proxy temperature records spanning some or the entire LGM interval (19-23 ka) that are not included in the MARGO (2009) or Bartlein et al. (2011) datasets. The records are based on various proxies from ocean, land, and ice, including alkenones (n=21), foraminiferal Mg/Ca (n=18), foraminiferal assemblages (n=4), TEX$_{86}$ (n=4), MBT/CBT (n=2), and ice cores (n=5). LGM temperature anomalies and errors were calculated following the methods used by MARGO (2009). One difference, however, is that many of these records (n=34) are high-resolution time series that extend to the late Holocene. Therefore, LGM anomalies for these records were calculated as the difference between the 19-23 ka and 0-2 ka means. This approach only assumes that the proxies accurately record the magnitude of LGM-Late Holocene temperature change, rather than absolute LGM temperatures. For the remaining 20 records, LGM anomalies were calculated from modern mean annual temperature at 10 m water depth using the World Ocean Atlas 98 dataset, as done by MARGO (2009). Twenty-six of the ocean records come from locations where the MARGO 5°x5° LGM temperature anomaly grid already contains values. Therefore, these MARGO grid points were updated with these new records, and errors were propagated following MARGO’s (2009) methods.

2.2 Mg/Ca salinity bias

Recent research suggests that foraminiferal Mg/Ca may be sensitive to salinity [Mathien-Blard and Bassinot, 2009; Arbuszewski et al., 2010]. If so, correcting Mg/Ca records for the ~1 psu increase in global ocean salinity at the LGM would decrease reconstructed SSTs. The magnitude of this temperature correction would vary with the absolute value of the salinity and
SST at the core site due to the nonlinear relationships between salinity and “excess Mg/Ca”, and Mg/Ca and SST. For example, [Mathien-Blard and Bassinot, 2009] estimate an additional 1°C LGM cooling for a western tropical Pacific record, while [Arbuszewski et al., 2010] calculate an additional 1.8°C cooling for a Caribbean record. Since none of the Mg/Ca records used in our study have been corrected for this salinity effect, taking it into account would increase reconstructed LGM cooling and thus our estimate of climate sensitivity. Nonetheless, we estimate that the impact on our results would be minor. In particular, Mg/Ca accounts for only 9% (66 of 742) of the individual SST reconstructions used here, and only 5% of the global (ocean and land) temperature reconstructions. Assuming a typical temperature correction of -1°C for the Mg/Ca records due to this salinity effect and averaging that through to the LGM global cooling estimate would increase it on the order of ~0.05°C (i.e., 5% of 1°C). This is well within the error of our 3.6 ± 1°C LGM cooling estimate and would have little effect on the likely range of climate sensitivity we report.

3. Snowball Earth

Figure S4 shows the transition to a completely ice covered Earth for a high climate sensitivity model (ECS$_{2xCO_2}$ = 8.2 K).

4. Simulated Temperature Changes and Residuals

Figure S5 shows the zonally averaged temperature changes from the best fitting model (ECS$_{2xCO_2}$=2.4 K), Figure S6 shows the spatial distribution of the residuals (model minus reconstructions). The correlation coefficient for the 2D temperature changes is 0.53 and the root
mean squared error is 2.3 K.

5. Statistical Analysis

For the purpose of model-data comparison the reconstructions were mapped from their original grids (5×5° grid for the SSTs and Shakun et al. data and 2×2° grid for the pollen data) onto the model grid (1.8×3.6°) and 0.32 K was added to the modeled SST everywhere in order to account for the 120 m lower sea level at the LGM. The value of ΔSST_{SL}=0.32 K was determined from an additional model simulation in which sea level was explicitly lowered and a constant global mean lapse rate of 5 K km^{-1} was used to calculate surface air temperatures. The analysis uses modeled SSTs over the oceans and SATs over land.

The differences ρ = M − O between model M and observations O are called residuals in the following. M and O represent temperature differences between the LGM and the LH. Residuals are a function of latitude $x$ and longitude $y$ and are calculated using only those model grid points where paleo data are available. We decompose the residuals

\[ \rho = [\rho] + \rho^* \]  
(S2)

into a zonal average (one-dimensional, 1D)

\[ [\rho] = \frac{\sum \rho_i a_i}{\sum a_i}, \]  
(S3)

and the (two-dimensional, 2D) deviation from the zonal mean

\[ \rho^* \]  
(S4)
\[ \rho^* = [\rho] - \rho(x, y). \] 

(S5)

Corresponding independent 1D and 2D likelihoods are calculated for \([\rho]\), and \(\rho^*\), using error estimates \(\sigma([\rho])\), and \(\sigma(\rho^*) = \sigma(\rho)\), respectively. Assuming Gaussian statistics the total likelihood that observations \(O\) could have resulted from model \(M\) is calculated by multiplying the, by construction independent, likelihoods

\[
L(O \mid M) = \exp \left( -\frac{\sum_{i,j} \frac{\rho_{i,j}^2}{\sigma_{i,j}^2}}{2 \sum_{i,j} a_{i,j}} \right) = L_{1D}L_{2D} = \exp \left( -\frac{\sum_{j} \frac{[\rho]_j^2}{\sigma_j^2([\rho])}}{2 \sum_{j} a_j} \right) \exp \left( -\frac{\sum_{i,j} \frac{\rho_{i,j}^*^2}{\sigma_{i,j}^2}}{2 \sum_{i,j} a_{i,j}} \right), \quad (S6)
\]

where the summation integrates over longitude (index \(i\)) and latitude (index \(j\)). The probability \(P\) that \(M\) is consistent with \(O\) follows from Bayes’ theorem

\[
P(M \mid O) = \frac{L(O \mid M)P(M)}{P(O)}, \quad (S7)
\]

where \(P(M)\) is the prior probability and

\[
P(O) = \int L(O \mid M)dM \quad (S8)
\]

is a normalization constant.

Error estimates \(\sigma^2 = \sigma_M^2 + \sigma_O^2\) include model errors \(\sigma_M\) and errors in the observations. The decomposition (S6) exploits the reduction of random errors (the standard error of the mean decreases with \(N^{-0.5}\), where \(N\) is the number of observations), due to zonal averaging. Errors were estimated by closely following the approach taken by MARGO [Waelbroeck et al., 2009].

The LGM temperature reconstructions come with published error estimates shown in Fig. S3. These are the errors used for the 2D likelihood \(\sigma(\rho^*) = \sigma(\rho) = \sigma(x,y) = \sigma_{i,j}\).
Errors for the zonal mean

\[ \sigma([\rho]) = \sqrt{\sigma_o^2([O]) + \left(1 - \frac{A_D}{A}\right)\sigma_{VAR}^2} \]  

(S9)

contain contributions from the standard error of the weighted zonal mean observations

\[ \sigma_o([O]) = \sqrt{\sum_i (a_i \sigma_i)^2 \over \sum_i a_i}, \]  

(S10)

and from incomplete data coverage. \(A_D\) denotes the zonally integrated area of grid boxes containing observations, \(A\) is the surface area of all grid boxes and \(\sigma_{VAR}\) is the standard deviation of the residuals at each latitude band calculated from the best fitting model (ECS2xC=2.4 K) and therefore includes the model error. The dark shading in Fig. (3) shows that \(\sigma([\rho])\) is smaller than the zonal mean of \(\sigma(\rho)\) at most latitudes, particularly in the tropics. It is dominated by the second term in the root in eq. (S9), which varies from around 1 K² in the tropics to between 4 and 24 K² at mid- to high latitudes in the northern hemisphere, whereas the first term is negligible (<0.06 K²). The fraction of surface area not covered by observations (1-\(A_D/A\)) varies from around 0.5 in the tropics to 0.8 and higher at high latitudes (not shown). Doubling the data coverage would decrease \(\sigma([\rho])\) by about 30%, which would sharpen the 1D PDF (Fig. 3) considerably decreasing the upper most likely limit from 4.2 K to about 3.7 K.

6. Sensitivity Tests

6.1 Dust Forcing

In order to account for the uncertainty in dust forcing we have estimated the surface temperature
response to dust forcing using a subset of 11 models with different ECS and performed an
additional LGM experiment for each of those models without dust radiative forcing. Assuming a
linear response to dust forcing, we first interpolated between these simulations to fill in the
additional ECS values for which no experiments had been performed, and then we
interpolated/extrapolated the surface temperature response to 0×Dust, 0.5×Dust, 1×Dust,
1.5×Dust, and 2×Dust.

The resulting marginal likelihood is shown in Figure S7 (top panel). Using a uniform
prior results in maximum likelihoods for models without dust forcing and ECS_{2×C}=2.5 K. This
indicates that considering dust forcing does not improve the agreement of the model with the
temperature reconstructions. However, models with up to about 1.5× the standard dust forcing
and 2.1 K < ECS_{2×C} < 2.6 K result in very similar likelihoods of > 0.18. The location of the
ECS_{2×C} at the maximum likelihood depends slightly on the dust forcing, varying from 2.5 K for
0×Dust to 2.3 K to 2×Dust, as does the median, which decreases from 2.7 K (0×Dust) to 2.4 K
(2×Dust). Probabilities for high climate sensitivities are reduced stronger if dust forcing is
considered: likely (83% cumulative probability) and very likely (95% cumulative probability)
levels decrease from 4.0 K and 4.9 K to 3.5 K and 4.3 K, respectively.

The use of a uniform prior for dust forcing neglects existing knowledge about glacial dust
levels. In order to consider this knowledge, we include a Gaussian prior with a standard
deviation of 0.5× and a mean 1× the standard dust forcing. This choice is based on a 20% error
of present day dust radiative forcing due to uncertainties in optical properties [Mahowald et al.,
2010] and a 30% error due to uncertainties in LGM dust levels [Mahowald et al., 2006a;
Mahowald et al., 2006b]. The marginal likelihood using this prior is shown as contour lines in
the top panel of Fig. S7. Integration over this marginal likelihood results in the PDFs shown in Figure 3. We note that the effect of this prior on the PDFs is minimal. Using a uniform prior results in almost unchanged PDFs (not shown).

6.2 Wind Stress Forcing

The UVic model uses prescribed wind stress at the sea surface in order to force the ocean and sea ice model components. In the standard model we use present day wind stress. In order to account for changes in winds at the LGM we applied an anomaly (LGM minus LH) calculated from the coupled ocean-atmosphere general circulation model GENMOM [Alder et al., 2011]. Monthly mean anomalies were added to the seasonal climatology of the wind stress fields.

The resulting marginal likelihood shown in the center panel of Fig. S7 shows that the maximum likelihood decreases as the GENMOM wind stress anomaly is added. This indicates that adding the GENMOM wind stress anomaly leads to less agreement of the models with the LGM temperature reconstructions. The reasons for this perhaps surprising model behavior are not clear. It could be that GENMOM and the UVic model are incompatible. The Atlantic Meridional Overturning Circulation is significantly stronger in models with GENMOM wind stress forcing. For models with ECS$_{2xCO_2}$ = 2.5 K the AMOC is stronger in the LGM run than in the LH run, a result that is probably inconsistent with deep ocean carbon isotope and other paleodata. This response could be a reason for the reduced likelihoods. Further analysis is beyond the scope of this paper and left to future studies.

Correlation coefficients are lower and RMS errors higher for models with GENMOM wind stress forcing. The decrease in maximum likelihood is more pronounced than for the dust
forcing. For these reasons we do not consider wind stress anomalies in the calculation of the PDF in Fig. 3.

Note that wind stress forcing does not systematically affect the location of the maximum likelihood or the width of the distribution, suggesting that it has a minimal influence on the resulting PDFs.

6.3 Sea Level SST Correction

The correction of $\Delta SST_{SL}=0.3$ K added to the simulated SST in order to account for the lower sea level during the LGM was estimated by one additional model simulation as described in section 5. The value of 0.3 K is only half of what one would expect from a simple application of a constant lapse rate of 6 K/km. Uncertain model parameters, such as the application of a reduction of the lapse rate in the calculation of outgoing longwave radiation over topography (this parameter is called $rfactor$ in the UVic model version 2.8 source code) may be the reason for this deviation and suggest that the model derived value may be quite uncertain. We address this uncertainty by varying $\Delta SST_{SL}$ from 0 to 0.6.

The resulting marginal likelihoods shown in Figure S8 show higher maximum likelihoods at the highest $\Delta SST_{SL}$. However, we believe such high values are unrealistic because they would exceed the observed lapse rate. We think that other model deficiencies are the reason for the underestimated land sea difference as discussed in the main text. High values for $\Delta SST_{SL}$ compensate for these other model deficiencies leading to higher marginal likelihoods. Assuming a Gaussian prior for $\Delta SST_{SL}$ centered around 0.3 with a one-sigma of 0.15 results in a posterior PDF very similar to the one shown in Fig. 3.
6.4 Other Uncertainties

Our study does not provide a complete uncertainty assessment. We have taken into account a number of known important uncertainties such as dust forcing. Others, however, are not included, for example uncertainties in the reconstruction of the ice sheets. Also our model ensemble does not scan the full parameter space. E.g. changes in shortwave radiation due to clouds are not taken into account.

7. Vegetation Simulation

Our simulations include the influence of climate and atmospheric CO$_2$ concentrations on the vegetation distribution. Figure S8 shows that the largest changes in simulated vegetation occur at northern hemisphere high latitudes. The simulated dramatic reduction of the boreal/temperate forest in the northern hemisphere extra-tropics from $1.8 \times 10^{-7}$ km$^2$ to $0.4 \times 10^{-7}$ km$^2$ is consistent with pollen reconstructions and previous offline vegetation modeling [Harrison and Prentice, 2003]. The extent of tropical forest decreases in the model from $2.7 \times 10^{-7}$ km$^2$ to $2.4 \times 10^{-7}$ km$^2$ is qualitatively consistent with, but quantitatively much less, than simulated by [Harrison and Prentice, 2003] who find reductions of $(1.1 \pm 0.3) \times 10^{-7}$ km$^2$. Globally the area covered by C$_3$ grass decreases by 10% (from $4.0 \times 10^{-7}$ km$^2$ to $3.6 \times 10^{-7}$ km$^2$) whereas C$_4$ grass coverage increases by 20% (from $1.1 \times 10^{-7}$ km$^2$ to $1.3 \times 10^{-7}$ km$^2$) consistent with the competitive advantage of C$_4$ photosynthesis under low CO$_2$. 

References


Kohler, P., R. Bintanja, H. Fischer, F. Joos, R. Knutti, G. Lohmann, and V. Masson-Delmotte


Mathien-Blard, E., and F. Bassinot (2009), Salinity bias on the foraminifera Mg/Ca thermometry: Correction procedure and implications for past ocean hydrographic reconstructions, Geochem Geophy Geosy, 10, Q12011, Doi 10.1029/2008gc002353.


Shakun, J. D., P. U. Clark, F. He, Z. Liu, B. Otto-Bliesner, S. A. Marcott, A. C. Mix, A. Schmittner, and E. Bard (in review), CO2 forcing of climate during the last deglaciation.


Figure S1: Outgoing longwave radiation $Q_{PLW}$ at the top-of-the-atmosphere as a function of surface air temperature $T_a$. Colored lines show results of the parameterization by Thompson and Warren (1982) (equation S1) with different slopes and approximately constant $T_a$ at its preindustrial value of 13°C. Colored numbers denote the ECS$_{2xCO2}$ of the different model versions. Symbols show near-surface (2 m) air temperature data from the NCEP reanalysis [Kalnay et al., 1996] and longwave radiation from ERBE satellite measurements [Ramanathan et al., 1989] averaged over 10 degree latitudinal bands.
Figure S2: Annual mean dust forcing (LGM minus pre-industrial) as a function of longitude and latitude used as a perturbation to the fluxes at the top-of-the-atmosphere in the UVic model. Top: shortwave forcing, center: longwave forcing, bottom: total (shortwave plus longwave) forcing. Negative (blue) values denote a cooling influence, positive (red) a warming. From [Mahowald et al., 2022].
Figure S3: Error in the LGM temperature reconstructions [Waelbroeck et al., 2009; Bartlein et al., 2010; Shakun et al., in review].
Figure S4. Snow and ice cover (white) in the LGM experiment with a ECS$_{2xCO_2}$=8.3°C at different times during the integration. Top: 100 model years after the switch to LGM boundary conditions, center: 440 years, and bottom: 460 years.
Figure S5: Zonally averaged surface temperature changes (LGM minus LH) from the best-fitting model (ECS_{2xCO2}=2.4 K). Black: surface temperature (SST over the ocean corrected for sea level lowering by adding 0.3 K, and SAT over land) masked by the grid points that contain reconstructions. Red: unmasked surface temperature (SST over the ocean and SAT over land). Green: unmasked SAT. Blue unmasked SST.
Figure S6: Residuals (difference in temperature change between model and reconstructions) from the best fitting model (ECS$_{2x} = 2.4$ K) as a function of longitude and latitude. Top panel shows residuals everywhere, bottom panel only those grid points where the error is outside the observational error estimates, which accounts for 25% of the global surface area covered by observations.
Figure S7: Sensitivity tests. (a)-(c) Marginal likelihood as a function of dust forcing (a), wind...
stress forcing (b), and SST sea level correction (c) assuming a uniform prior probability (color).

Contour lines in (a) and (c) result from a Gaussian prior probability with a mean of $1 \times$ and a standard deviation of $0.5 \times$ the standard dust forcing (a) and a mean of $0.3 \text{ K}$ and a standard deviation of $0.25 \text{ K}$ (c). In (b) $1 \times$ wind stress forcing corresponds to models with a wind stress anomaly from GENMOM added, $0 \times$ corresponds to no anomaly added. Thick black lines in (a)-(c) show ALL PDFs (right scale) resulting from integrating the marginal likelihood.
Figure S8: Simulation of dominant vegetation type for the present day (top) and the LGM (bottom) in model ECS$_{2xCO_2}$ = 2.6 K. Five different plant functional types are simulated: broadleaf trees (green), needleleaf trees (blue), C$_3$ grass (brown), C$_4$ grass (orange), and shrub (light green) in addition to bare soil (yellow).