

Reply to Referee comments on egusphere-2025-6393: „Unravelling the tree cover dynamics over the last 20,000 years on the Northern Hemisphere” by Anne Dallmeyer et al.

Reviewer 2:

Summary: Dallmeyer et al. attempt to unravel the climate drivers of Northern Hemisphere tree cover dynamics over the last 20,000 years using the pollen-based REVEALS reconstruction, a transient MPI-ESM simulation, and a statistical emulator with bias-corrected climate forcing. I commend the authors on the addressing several complex scientific topics, from proxy-model agreement to climate drivers of vegetation dynamics to dynamic vegetation modeled processes, as well as using several independent linear and non-linear statistical measures. They have several interesting findings, including the ability of MPI-ESM to capture broad trends in tree cover and water- vs energy-limited conditions over the last deglaciation and Holocene, but substantial regional data-model mismatches that cannot be resolved with bias correction of climate information, and the dominance of summer temperature as a climate driver in simulated high-latitude forests. Overall, I feel that the scope of the paper may be too large and therefore is difficult to follow as a reader, but with some clarifications and improvements it will be appropriate for the *Climate of the Past*. I explain some minor and major comments in more detail below.

We thank the reviewer for the positive assessment of our study and for the constructive and helpful comments. We greatly appreciate the time and effort invested in evaluating our work.

Our detailed responses to the reviewer’s comments are provided below. For clarity, the reviewer’s comments are shown in black, and our responses are given in blue. We have carefully considered all suggestions and have revised the manuscript accordingly to improve its clarity and quality.

We agree that the manuscript covers several interconnected topics. To improve readability, we revised parts of the manuscript to clarify the structure of the Results and Discussion section. In particular, we added a short introductory paragraph at the beginning of the Results and Discussion section to explicitly outline its structure and the guiding research questions, thereby better guiding the reader through the different analyses. We believe these revisions improve the clarity and logical flow of the manuscript while maintaining its overall scope. We have added:

LL227: “We structure our analysis around a sequence of interconnected questions that progressively link model evaluation with process understanding. We begin by comparing simulated and reconstructed tree cover dynamics from the Last Glacial Maximum to the present (Sect. 3.1), establishing the overall level of agreement between MPI-ESM and REVEALS. Building on this, we quantify and characterize the spatio-temporal differences between both datasets (Sect. 3.2), thereby identifying where and when discrepancies occur.

In a next step, we investigate the underlying mechanisms by analysing the main drivers of tree cover change (Sect. 3.3). This process-based perspective is further refined by explicitly contrasting regions with high and low model–data agreement to assess which factors constrain tree cover dynamics in the model (Sect. 3.4). Finally, we address the question whether a bias-corrected climate can reduce the identified model–data differences (Sect. 3.5), thereby assessing the influence of systematic climate biases on simulated tree cover dynamics.”

Minor Comments:

Line 163: grid should be capitalized → done

Line 233 and Figure 8: The panels are not labeled with letters but are referenced in the text (Fig. 8d)

A: We added panel labels to the figure.

Major Comments:

R: This study has a high number of acromyns and shortened words (e.g., BiasCorr_Variance, F_CO2, r-group-1) that make it very difficult to know what exactly is being discussed. I recommend lengthening and clarifying the group names to make them more self-explanatory so that readers do not need to study the main text and/or figure captions before looking at each plot. Two examples of this: (1) Table 1: why not use the “Group” as “group_name” so that the meaning of the groups is more clear in the text? Naming a group “Positive Correlation Group” rather than “r_group 1” would be easier to understand. (2) Figure C1: why do you use 1, 2, and 3 as x-axis labels rather than writing out Positive, None, Negative Correlations? This adds an unnecessary layer of complexity to an already complex paper.

A: Thank you for this helpful comment. We agree that the original naming (e.g., “r_group 1” and numeric axis labels) was not sufficiently intuitive and could make interpretation more difficult for the reader.

In response, we have revised the group names throughout the manuscript and now use more descriptive terms (e.g., “positive-correlation-group,” “high-MAE-group”, ...) in both the text and tables. We have also clarified and standardized abbreviations such as F_+ and R_- in the main text to improve readability.

At the same time, we have retained abbreviated labels within the figures themselves to avoid overcrowding and maintain visual clarity. We believe this provides a good balance between readability in the manuscript and clarity in the graphical presentation.

R: A video animation of the forest cover through time would be incredibly powerful and helpful for following the description of results, a great example of this is Shafer et al. (2021)

A: This is a valuable suggestion. We now provide a video illustrating vegetation changes in the supplementary material of the paper. In addition, we refer here to another video showing the biome distribution based on the simulation used in this study alongside reconstructions (<https://hdl.handle.net/21.11116/0000-000B-2420-8>).

R: Lines 327-329: How did you determine this list of climate drivers to consider? I am wondering why other variables, such as incident solar insolation and mean annual temperature, were not included.

A: The selection of variables is motivated by their known importance for vegetation productivity and bioclimatic thresholds implemented in the model (T_c , T_w). We have not performed a statistically rigorous variable performance but did test other climate drivers such as annual mean temperature, insolation, and growing degree days, but did not find an added value from including other drivers. Including too many drivers, that are partly dependent on each other and those don't provide much independent information, also increases the risk of overfitting and inferring non-

causal ecological relationships. Therefore, we include climate variables that represent the important climatic growth limitations from growing season warmth, winter cold, and moisture availability, in addition to CO₂ for representing plant-physiological CO₂ influences.

We added to the manuscript:

L186: "The selection of these variables is motivated by their known importance for vegetation productivity and the implementation of bioclimatic thresholds for T_w and T_c in JSBACH."

R: Line 453-454: What climate variables/regions changed the most dramatically with bias correction? It would be very useful to see a couple time slice plots where the bias-corrected climate makes a large difference in simulated tree cover. For example, on lines 588-591, you mention that the model is too cold in the northern high-latitudes. This would be helpful to understand your interpretation of impacts of bias correction on simulated tree cover.

A: Thank you for this helpful suggestion. We agree that spatial snapshots of the emulator output and climate forcing would be useful to better illustrate the impact of bias correction.

However, because we apply a delta method, the temporal evolution of anomalies is preserved: the difference between the bias-corrected and simulated T_{warm} and T_{cold} remains constant over time, and precipitation mainly changes in amplitude rather than spatial pattern. We therefore focus on time series of Northern Hemisphere means to represent temporal changes, complemented by maps at selected time slices.

Specifically, we decided to show one climate snapshot at the time of maximum change (~12 ka BP), along with tree cover and its differences for three representative periods. We added the following figures to the Appendix B:

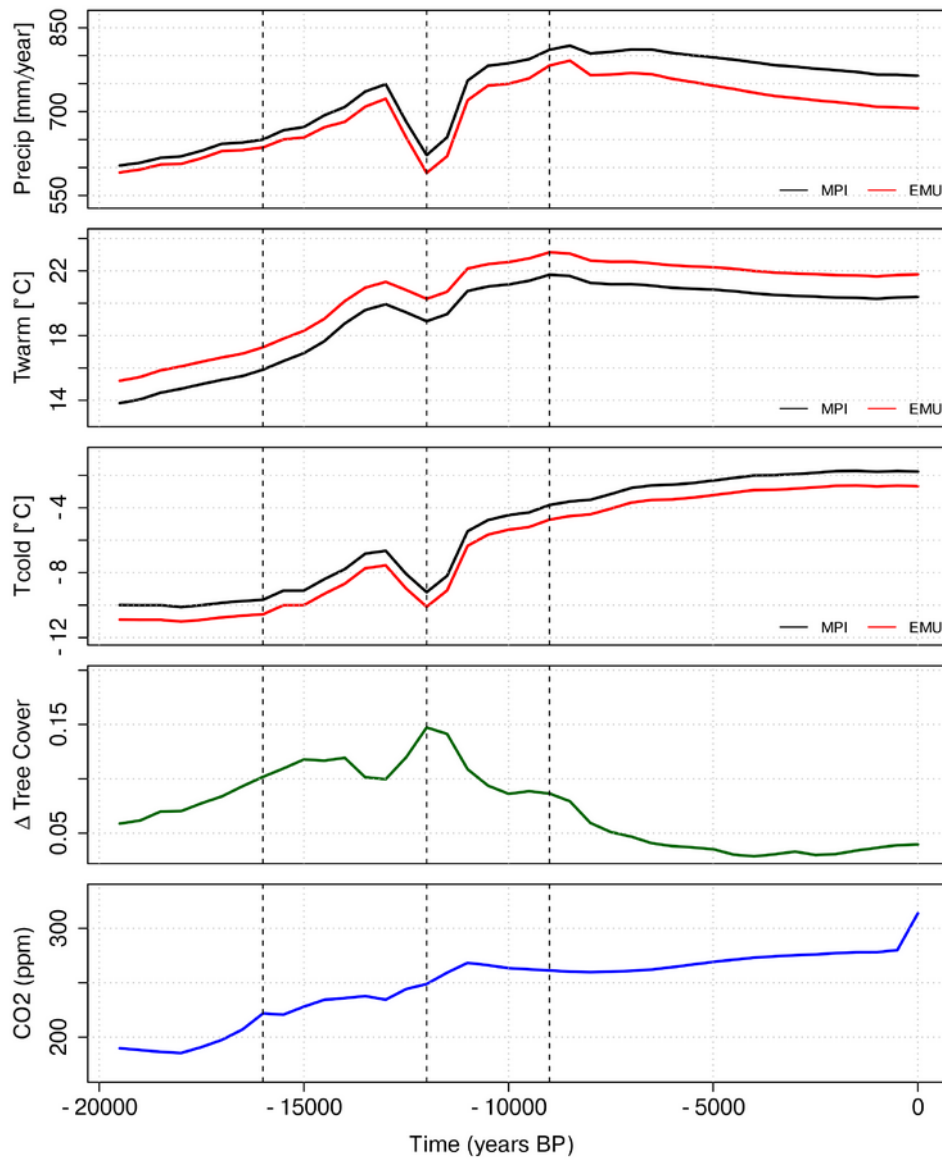


Fig. B1: Time series of Northern Hemisphere mean precipitation (precip), temperature of the warmest (T_{warm}) and coldest month (T_{cold}) for the original (MPI) and bias-corrected (EMU) climate, together with the corresponding difference in mean tree cover between the bias-corrected emulation and the original simulation. Shown is also the global atmospheric CO₂ concentration that is used as predictor in the emulation. The dotted lines mark the three time-slices for which maps of tree cover are provided in Fig. B2

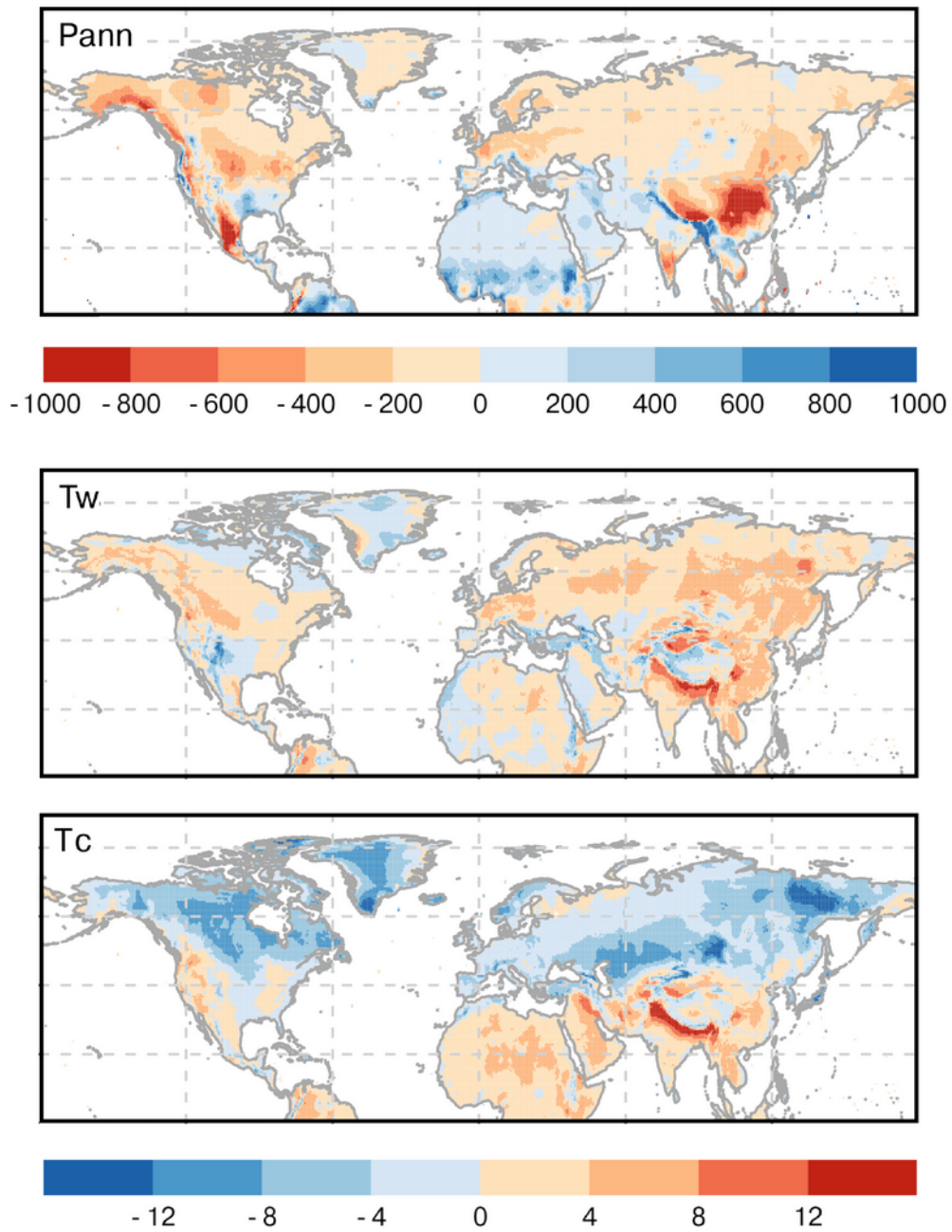


Fig. B2: Difference in annual mean precipitation (Pann) [mm/year] and in the temperature of the warmest (Tw) and coldest (Tc) month [K] at 12,000 years BP between the bias-corrected and the original simulation. The difference was calculated after remapping the simulation onto a 0.5° grid.

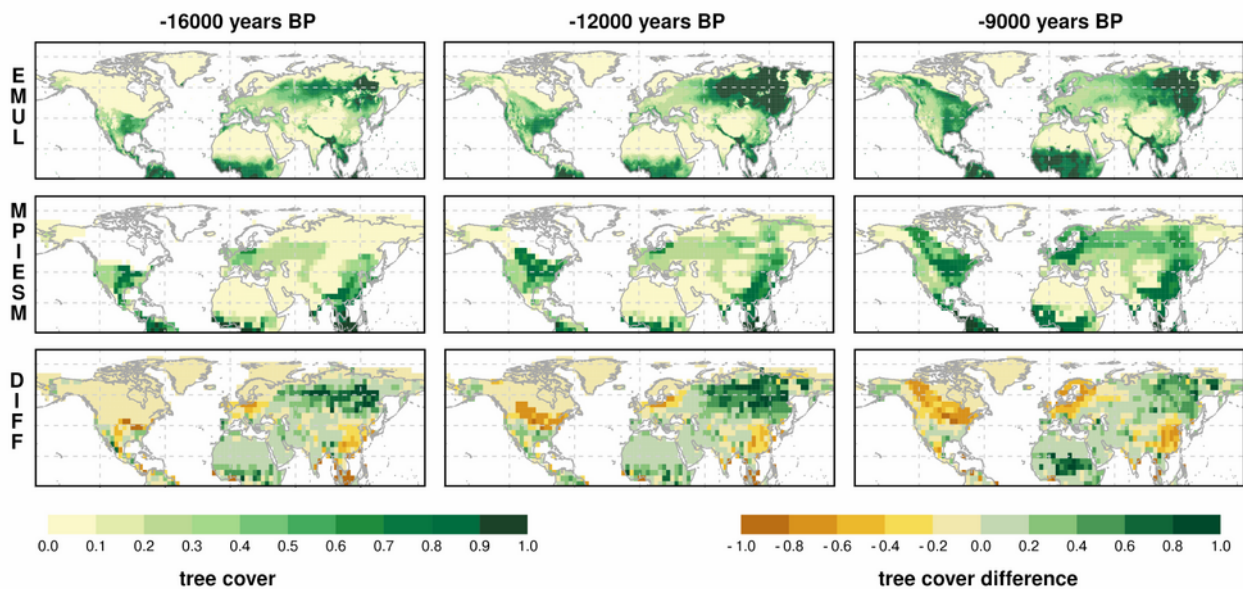


Fig. B3: Tree cover fraction at different time steps according to the emulation with bias-corrected climate and the MPI-ESM simulation. The bottom panel also shows the difference between the two; for this, the emulation has been remapped to a T31 grid.

We add the following text to the Appendix B (LL760): „Time series of Northern Hemisphere mean precipitation, warm- and cold month temperature for both the original and bias-corrected climate, together with the corresponding difference in mean tree cover between the bias-corrected emulation and the original simulation are shown in Fig. B1 in the Appendix B. In addition, spatial maps of the climate variables at the time of maximum change (~12 ka BP), as well as maps of emulated tree cover, simulated tree cover, and their difference for three representative time slices, are provided in Fig B2 and B3 in the Appendix B.“

And to Section 3.5 (LL511): “The bias-corrected climate and examples of the resulting tree cover emulation in comparison with the original simulation is provided in Fig. B1-B3 in the Appendix B. “

R: Lines 582-583: I’m not entirely convinced that the tree cover response is too sensitive to CO₂-level. This implies that tree cover is responding very strongly to the physiological impacts of CO₂ concentrations, which should play some role, but I am not sure that you have included all of the potential climate predictors that capture the indirect, temperature-related effects of CO₂. You have included two temperature-related predictors, Tw and Tc. Do these strongly correlate with CO₂ level, or does mean annual temperature more closely vary with CO₂ level? Can you clarify the implications of “the sensitivity of the tree cover response to CO₂-changes seem to be too strong in this model version” on the way that photosynthesis/stomatal conductance is represented in MPI-ESM and JSBACH?

A: We agree that the strong tree cover response to CO₂ does not necessarily imply an unrealistically strong direct physiological effect alone. In MPI-ESM, vegetation responds to CO₂ through coupled physiological processes and indirect climate feedbacks, and the signal emerges across multiple intermediate scales between leaf-level photosynthesis in JSBACH and biome-scale vegetation

dynamics. However, we think that the temperature-related effects of CO₂ are mostly accounted for by the included temperature predictors (Tw and Tc). We additionally tested annual mean temperature in the GAM and correlation analyses, and it didn't provide any added value compared to including Tw and Tc.

The strong CO₂ sensitivity is consistent with CMIP6 analyses (e.g., Arora et al., 2020), which show that MPI-ESM exhibits a relatively high CO₂ fertilisation effect compared to the multi-model mean. Furthermore, Kleinen et al. (2023) suggest that the high CO₂ sensitivity in MPI-ESM may contribute to model–data mismatches in methane levels since the last deglaciation.

Structural aspects of the photosynthesis formulation may contribute to the high sensitivity. The current JSBACH implementation has a comparatively weak temperature constraint relative to other models. As shown by Rogers et al. (2017), leaf-level productivity increases substantially from preindustrial to elevated CO₂ levels (e.g., 380 to 550 ppm), indicating a strong physiological CO₂ response already at canopy scale.

In addition, limited water stress representation and the absence of nutrient limitations may further enhance the simulated CO₂ fertilisation effect.

To support our statement in the revised version, we now point to previous studies that have documented the high CO₂ sensitivity in MPI-ESM and related JSBACH configurations.

We have added in the revised manuscript (LL506): „This high sensitivity to CO₂ in MPI-ESM has also been observed in other studies (Arora et al., 2020; Kleinen et al., 2023a; Rogers et al., 2017).

R: Section 3.3: The emulator approach to disentangle the importance of different climate drivers is very interesting. In Figure 7, you visualize the most important climate driver in each grid cell, but I'm wondering how often there is a mixture of variables that have substantial importance (e.g., let's say in N America, P and Tw are always the highest correlations so in many grid cells that are light blue or orange there is only a small difference their relative importance and which one is "most important") and that information is missing from this figure. Would it be possible to add this information by modifying the shade of the colors? For example, if P is the most important predictor in one grid cell and far outcompetes other predictors, it is light blue, but if it is only slightly more important than other predictors, it is closer to white.

Thank you for this helpful suggestion. We agree that Figure 7, in its current form, does not convey how strongly the leading predictor outcompetes the other variables, and therefore may obscure regions where multiple drivers have similar importance. To address this, we will revise the figure by marking the grid cells with black dots where the difference in correlation coefficients between the leading predictor and the second most important predictor exceeds 0.1, which corresponds to the median of all differences. This will help highlight regions with significant differences more clearly.

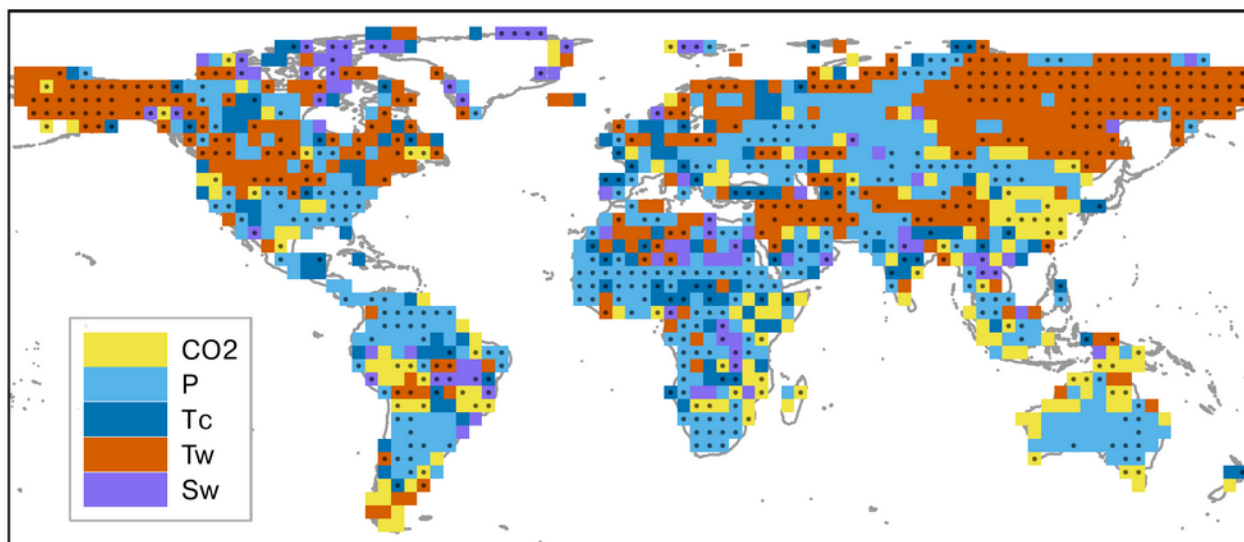


Figure 7: Spatial distribution of the most influential climatic variables determining vegetation dynamics across different regions of the world. Each grid cell is color-coded according to the dominant driver of vegetation change in the emulations, which is here based on the emulation with single variable forcing that show the highest Pearson correlation to the simulated tree cover. The variables considered are atmospheric CO₂ concentration (yellow), annual precipitation (P, light blue), temperature of the coldest month (T_c, dark blue), temperature of the warmest month (T_w, orange) and annual mean soil moisture (Sw, purple). Grid cells marked with black dots indicate regions where the difference in correlation coefficients between the leading predictor and the second most influential predictor exceeds 0.1 (the median difference), highlighting areas with a comparatively strong dominance of a single driver.

References

Arora, V. K., Katavouta, A., Williams, R. G., Jones, C. D., Brovkin, V., Friedlingstein, P., Schwinger, J., Bopp, L., Boucher, O., Cadule, P., Chamberlain, M. A., Christian, J. R., Delire, C., Fisher, R. A., Hajima, T., Ilyina, T., Joetzjer, E., Kawamiya, M., Koven, C. D., Krasting, J. P., Law, R. M., Lawrence, D. M., Lenton, A., Lindsay, K., Pongratz, J., Raddatz, T., Séférian, R., Tachiiri, K., Tjiputra, J. F., Wiltshire, A., Wu, T., and Ziehn, T.: Carbon–concentration and carbon–climate feedbacks in CMIP6 models and their comparison to CMIP5 models, *Biogeosciences*, 17, 4173–4222, <https://doi.org/10.5194/bg-17-4173-2020>, 2020.

Kleinen, T., Gromov, S., Steil, B., and Brovkin, V.: Atmospheric methane since the last glacial maximum was driven by wetland sources, *Climate of the Past*, 19, 1081–1099, <https://doi.org/10.5194/cp-19-1081-2023>, 2023.

Rogers, A., Medlyn, B. E., Dukes, J. S., Bonan, G., von Caemmerer, S., Dietze, M. C., Kattge, J., Leakey, A. D. B., Mercado, L. M., Niinemets, Ü., Prentice, I. C., Serbin, S. P., Sitch, S., Way, D. A., and Zaehle, S.: A roadmap for improving the representation of photosynthesis in Earth system models, *New Phytologist*, 213, 22–42, <https://doi.org/10.1111/nph.14283>, 2017.