

Review of “PeatClim v1.0: A climate-driven machine-learning model for predicting potential paleo-peatland distribution and its key climate controls”

General Comments

The manuscript by Chen et al. describes the development and assessment of PeatClim v1.0, a machine learning-based model for the prediction of potential peatland distribution. Because the method predicts areas where climatic conditions would permit peatland development, in the absence of inhibiting non-climatic factors, it can be applied in deep time settings where the latter constraints may prove difficult or impossible to estimate.

The manuscript justifies the value of the method proposed, and clearly articulates the process of model development and evaluation. Overall, the manuscript provides an intriguing and novel empirically-based alternative to current methods for estimating the prevalence of peatlands in deep time. My main comments, presented below, concern (1) the possibility of optimistic bias in the reported True Skill Statistic (TSS), resulting from the structure of the cross-validation procedure, and (2) a more extensive discussion of model behavior in the preindustrial climate simulation.

Specific Comments

Assessing the importance of spatial autocorrelation

As the authors acknowledge (lines 429-430), the purely random assignment of spatially autocorrelated data to calibration or validation partitions during cross-validation tends to inflate performance metrics (Telford and Birks, 2005, 2009; Bahn and McGill, 2013; Ploton et al., 2020; Wang et al., 2023). The highly non-uniform distribution of peatland presences (Figure 1) may make this a particularly thorny issue for the present data, as any given grid cell scoring a peatland presence in a validation partition will surely have several physically adjacent cells also scoring a presence in the calibration partition. This structure may permit PeatClim to exhibit greater predictive skill during cross-validation than it would when extended to other contexts, such as the deep time settings envisioned by the authors (lines 17-19). If left unaddressed, this issue could present a major challenge to the generalized usage of PeatClim. Previous studies have established that the magnitude of optimistic bias can be large (e.g. Ploton et al., 2020, their Figure 4; Roberts et al., 2017, their Figure B1.1), but the current manuscript makes no attempt to evaluate whether it poses a serious hazard here.

I encourage the authors to explore methods that assess the potential significance of this issue. One of several possibilities would be an additional cross-validation experiment that employs a blocked or buffered structure to prevent grid cells in close proximity from being

split between calibration and validation (see methods and discussion in Roberts et al., 2017). This experiment would also test the authors' proposal that non-climatic constraints on peat development, imperceptible to PeatClim, explain why the model predicts peatlands across a far greater geographic area than supported by the PEATMAP and Peat-DBase data (e.g. lines 396-401, Figure S8). I find this explanation plausible, but it rests upon an understanding that the TSS values from cross-validation accurately reflect the model's generalized predictive abilities. Optimistic bias in cross-validation, arising from spatial autocorrelation of the data, would support the alternative explanation that the model predicts peatland development with lesser skill than the reported TSS values suggest.

Because this autocorrelation-based explanation and non-climatic controls on peatland development are both consistent with the tendency of PeatClim to predict vast areas of potential peatland, a test that distinguishes between the two would significantly enhance the manuscript. This test would be particularly relevant for researchers who may consider applying PeatClim in future work, as it would provide greater confidence that the model's performance on modern data resembles that expected in deep time settings, where the correctness of predictions is ultimately unverifiable.

Further discussion of PI simulation

In order to compare HTLTPeatland behavior across WorldClim and non-WorldClim climate data, the authors present peatland predictions under a simulated preindustrial climate from the HadCM3BL atmosphere-ocean coupled general circulation model. Because the authors explicitly envision PeatClim as a tool "for quantitatively investigating peatland evolution in the geological past using palaeoclimate model outputs" (line 434), I view this comparison as an important aspect of the study. However, the comparison itself receives relatively little discussion (lines 406-412), with interpretations limited to only the final two sentences (lines 410-412).

Space permitting, I encourage the authors to expand this text to more comprehensively discuss (1) reasons for differences between HTLTPeatland outputs on the WorldClim and HadCM3BL climate data, and (2) best practices for future applications of PeatClim in pre-Quaternary settings. Because particular interactions between PeatClim and HadCM3BL may prove significant to interpreting peatland reconstructions in these more ancient settings, further guidance by the authors on this subject would facilitate use of the method for this purpose.

Miscellaneous

Lines 64-65: The empirical structure of PeatClim also requires uniformitarian assumptions, though it remains possible that these assumptions are weaker than those the authors point out for these models. Additional text directly comparing the plausibility of these assumptions would strengthen the manuscript.

Lines 67-69: This summary of the Lottes and Ziegler (1994) heuristics in this sentence is imprecise. The peat prediction map of Lottes and Ziegler (1994, their Figure 6) anticipates peat formation to occur in areas with a high “percentage of months during which the precipitation was 40 mm and above during the months that that temperature was 10 °C and above”. By comparison, the current phrasing in the manuscript (“requiring monthly precipitation greater than 40 mm and temperatures above 10 °C”) leaves the link between precipitation and temperature somewhat ambiguous.

Line 70-71: As expressed in the comment above, the reliance of PeatClim on modern peatland-climate relationships introduces uniformitarian assumptions to the method (e.g. that no forms of dataset shift [Moreno-Torres et al., 2012] have occurred between the training domain of the present and the application domain of the past). If peatland-climate relationships have indeed shifted over geologic time, as the authors here propose, we should not necessarily expect PeatClim to be robust to those changes. I suggest further discussion of the methodological assumptions required by PeatClim.

Lines 139-145: I recommend that any exploration of the spatial autocorrelation issue carried out for the global peatland dataset also be applied to the LTPeatland and HTPeatland subsets. It seems very plausible that stratifying the peatlands by temperature would also strengthen any autocorrelative effect relative to the global dataset.

Lines 167-206: Given the structure of these cross-validation procedures, it appears that the same data were used to select optimal pseudo-absence hyperparameter values and assess model performance. Strictly speaking, such a structure may bias that performance assessment, whereas nested cross-validation would permit hyperparameter optimization and performance evaluation to occur on separate data. Still, it remains possible that this tweak wouldn't make a material difference to the selection of an algorithm or pseudo-absence hyperparameters (see Wainer and Cawley, 2021).

Technical Comments

Line 93: Change “undertake” to “undertaken”.

Line 94: Change “could be found from” to “can be found in”.

Line 106: Change “Worldclim” to “WorldClim”.

Line 133: Change “constrains” to “constraints”.

Lines 292-293: Remove “the” from “the northeastern Eurasia”.

Line 425: Replace “are formed” with “have been formed”.

Lines 425-426: Modify to “... different time periods, and some...”.

References

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