

NON-ANALOGUES IN PALEOECOLOGICAL RECONSTRUCTION: MODEL BEHAVIOUR AND IMPLICATIONS

Simon Goring¹, J Sakari Salonen², Miska Luoto², Jack Williams^{1,3}

Abstract—Fossil pollen is a widespread proxy for past vegetation that is used for paleoclimatic reconstruction, but the limits of its utility are not well known. Newer methods for climate reconstruction (CR) using machine learning techniques may improve the abilities of CR techniques, but little is known about model accuracy under conditions of non-analogue vegetation known to have occurred in the past. Here we generate non-analogue pollen assemblages by excluding close neighbors from calibration datasets, testing the ability of five CR techniques using pollen, including two machine learning techniques, to accurately reconstruct climate under non-analogue conditions.

I. MOTIVATION

Pollen assemblages are widely used for paleoclimatic reconstruction during the Holocene, but this method is also applied to much earlier pollen assemblages [1], [2] where the presence of non-analogue vegetation may bias results in unforeseen ways. Non-analogue pollen assemblages arise from non-analogue vegetation communities that may be the result of sets of climate variables that no longer co-exist, ecological conditions resulting from differing rates and directions of species migration, release from herbivores, or as a result of changes in human land use.

Predicting climate from pollen in non-analogue space is likely to increase the uncertainty of models, possibly introduce systematic bias in predictions, and increase the variability of predictions across a time-series from a single site. However, high-quality terrestrial proxies for climate are important for understanding past climate change, and can act as a constraint on models of past climate change derived

from GCMs in regions where little proxy data is available. Thus, understanding the behaviour of climate reconstruction (CR) methods using pollen from non-analogue vegetation is an important step in improving our understanding of past climate.

Although we cannot know the values for temperature or precipitation in the past with certainty, non-analogue assemblages do exist in a modern context, and we can construct false non-analogues using a modified *h*-block sampling procedure (*sensu* [3]) that examines analogue distance rather than geographical distance. By undertaking this research we hope to provide a better understanding of the limitations and strengths of various commonly used CR methods under non-analogue conditions in the past.

II. METHOD

The pollen dataset was obtained from the North American Modern Pollen Database east of 100°W [4]. Five CR methods were used to reconstruct mean daily July temperature (T_{jul}) from the modern pollen data: the modern analogue technique (MAT [5]), weighted averaging (WA [6]), weighted averaging partial least squares (WAPLS [7]), boosted regression trees (BRT [8]) and random forests (RF [9]). Each model has been used previously in the pollen literature, and has unique strengths and weaknesses.

For each CR method and each sample site we reconstruct T_{jul} using pollen samples further than an analogue distance, $d_{ana} = \{0, 0.01, \dots, 1\}$. The calibration dataset was bootstrapped 30 times, based on prior simulations, sampling with replacement and T_{jul} for the focal sample was predicted, to obtain a variance parameter, a mean prediction, bias estimate, root mean squared error of prediction and a sample size estimate. Simulations were run on an Amazon AWS EC2 server as a parallel process across 30 cores.

Corresponding author: S Goring, University of Wisconsin, Madison WI goring@wisc.edu ¹ Department of Geography, University of Wisconsin-Madison, Madison, WI, USA ²Department of Geosciences and Geography, University of Helsinki, Helsinki, Finland ³ Center for Climatic Research, University of Wisconsin-Madison, Madison, WI

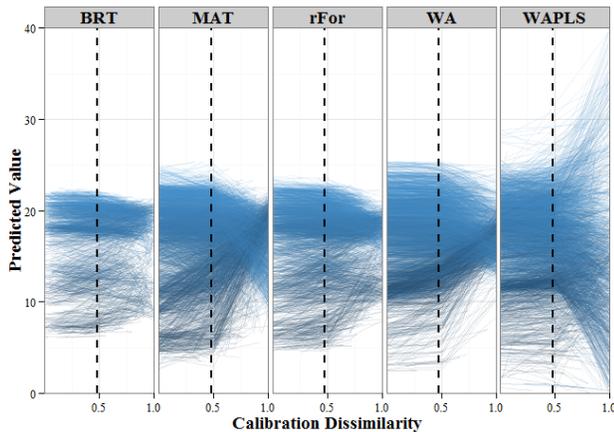


Fig. 1. Predicted July temperature using each of five pollen-based reconstruction methods at increasing analogue exclusion distances. The leftmost predictions represent prediction using the complete dataset. Coloring indicates initial temperatures, with darker colours representing cooler temperatures. Most methods show reversion to the mean, while WAPLS shows strong divergence at higher analogue exclusion distances.

III. EVALUATION

Most predictive methods are stable until the non-analogue threshold is met. Beyond this threshold the number of available samples declines rapidly and performance drops substantially, indicating high sensitivity to the sample neighborhood for each of these methods.

MAT, RF and BRT models are generally similar in their behaviour. MAT’s behavior is dependent on finding close neighbors, as such, the likelihood of having poor fit increases substantially as close analogues are excluded. This is manifested in the apparent ‘flip’ in predictions (Fig. 1), where warm samples are predicted to be cold and *vice versa* at high analogue distances due to the absence of climatically (and ecologically) similar samples in the multivariate sample space. WA captures the T_{jul} gradient most accurately within the analogue space (Fig. 1), up until the 95%ile threshold where predictions rapidly converge to the dataset mean for T_{jul} .

BRT and RF seem most robust of the methods within non-analogue space, but interestingly predictions are the most constrained along the T_{jul} gradient. This implies that these methods are likely to underestimate the length of climatic gradients if used for regional-scale reconstructions, which may result in higher apparent sensitivity to climatic changes when compared to paleoecological data. However, BRT and RF appear much more robust as the analogue distance increases, simulating a move into no analogue space

(Fig 1). These methods display none of the characteristic ‘flipping’ of MAT or WA (Fig. 1). BRT and RF predictions also fail to show the complete divergence of predictions shown by WAPLS.

These results appear to support the utility of WA with monotone deshrinking for predictions within analogue space, while machine learning techniques (BRT and RF) perform better in non-analogue space. This indicates a hybrid model is likely appropriate for continental-scale reconstruction, and that greater emphasis on analogue distance is necessary within pollen-based environmental reconstruction in general.

ACKNOWLEDGMENTS

SJG was supported by NSF EF-1241868, and an Amazon AWS in Education Grant. JSS was supported by the Academy of Finland (project no. 278692) and a Finnish Cultural Foundation grant.

REFERENCES

- [1] P. Bartlein, S. Harrison, S. Brewer, S. Connor, B. Davis, K. Gajewski, J. Guiot, T. Harrison-Prentice, A. Henderson, O. Peyron, *et al.*, “Pollen-based continental climate reconstructions at 6 and 21 ka: a global synthesis,” *Climate Dynamics*, vol. 37, no. 3-4, pp. 775–802, 2011.
- [2] P. E. Tarasov, T. Nakagawa, D. Demske, H. Österle, Y. Igarashi, J. Kitagawa, L. Mokhova, V. Bazarova, M. Okuda, K. Gotanda, *et al.*, “Progress in the reconstruction of Quaternary climate dynamics in the Northwest Pacific: A new modern analogue reference dataset and its application to the 430-kyr pollen record from Lake Biwa,” *Earth-Science Reviews*, vol. 108, no. 1, pp. 64–79, 2011.
- [3] R. Telford and H. Birks, “Evaluation of transfer functions in spatially structured environments,” *Quaternary Science Reviews*, vol. 28, no. 13, pp. 1309–1316, 2009.
- [4] J. Whitmore, K. Gajewski, M. Sawada, J. Williams, B. Shuman, P. Bartlein, T. Minckley, A. Viau, T. Webb, S. Shafer, *et al.*, “Modern pollen data from North America and Greenland for multi-scale paleoenvironmental applications,” *Quaternary Science Reviews*, vol. 24, no. 16, pp. 1828–1848, 2005.
- [5] J. Overpeck, T. Webb, and I. Prentice, “Quantitative interpretation of fossil pollen spectra: dissimilarity coefficients and the method of modern analogs,” *Quaternary Research*, vol. 23, no. 1, pp. 87–108, 1985.
- [6] C. J. ter Braak and S. Juggins, “Weighted averaging partial least squares regression (WA-PLS): an improved method for reconstructing environmental variables from species assemblages,” *Hydrobiologia*, vol. 269, no. 1, pp. 485–502, 1993.
- [7] C. J. ter Braak and H. van Dame, “Inferring pH from diatoms: a comparison of old and new calibration methods,” *Hydrobiologia*, vol. 178, no. 3, pp. 209–223, 1989.
- [8] G. De’ath, “Boosted trees for ecological modeling and prediction,” *Ecology*, vol. 88, no. 1, pp. 243–251, 2007.
- [9] L. Breiman, “Random forests,” *Machine learning*, vol. 45, no. 1, pp. 5–32, 2001.