An impact-centric framework for preparing and selecting climate model data for permafrost studies

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Introduction

Predictions of permafrost variables can complement observations as information source for climate-sensitive decisions. These rely on climate model data. Their utility is limited by coarse resolution, biases, and uncertainties. However, improvements in climate data, e.g., by correcting biases, do not always lead to better permafrost predictions.

Research questions

(1) How do bias correction algorithms affect statistical properties in both climate data and ground thermal regimes?
(2) Do the best-matched atmospheric time series result in the best permafrost simulations?

Bias correction

Bias correction matches distributions of climate variables. Quantile mapping aligns each distribution individually while multi-variate algorithms also correct for inter-variable dependencies.

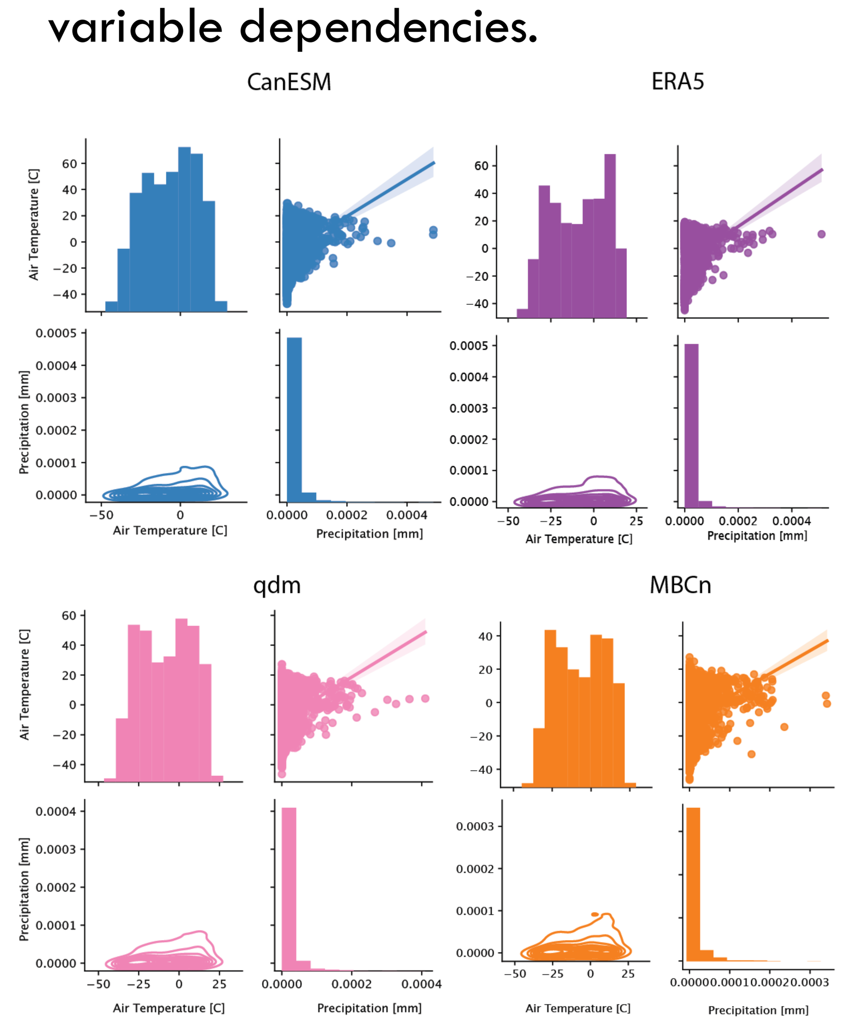

Figure 1: Marginal distributions of temperature and precipitation (diagonal elements) and inter-variable dependencies (non-diagonal elements), for original model (CanESM), reference data (ERA5), quantile-mapping-corrected (qdm) and multi-variate-corrected (MBCn).

Bias-correction preserves trends from the climate model and uses different algorithms to align distributions from the reference data.

The choice of bias-correction algorithm matters.

Permafrost metrics under consideration
MAGST – Mean annual ground surface temperature
ALT – Active-layer thickness
TDD – Thaw-depth duration

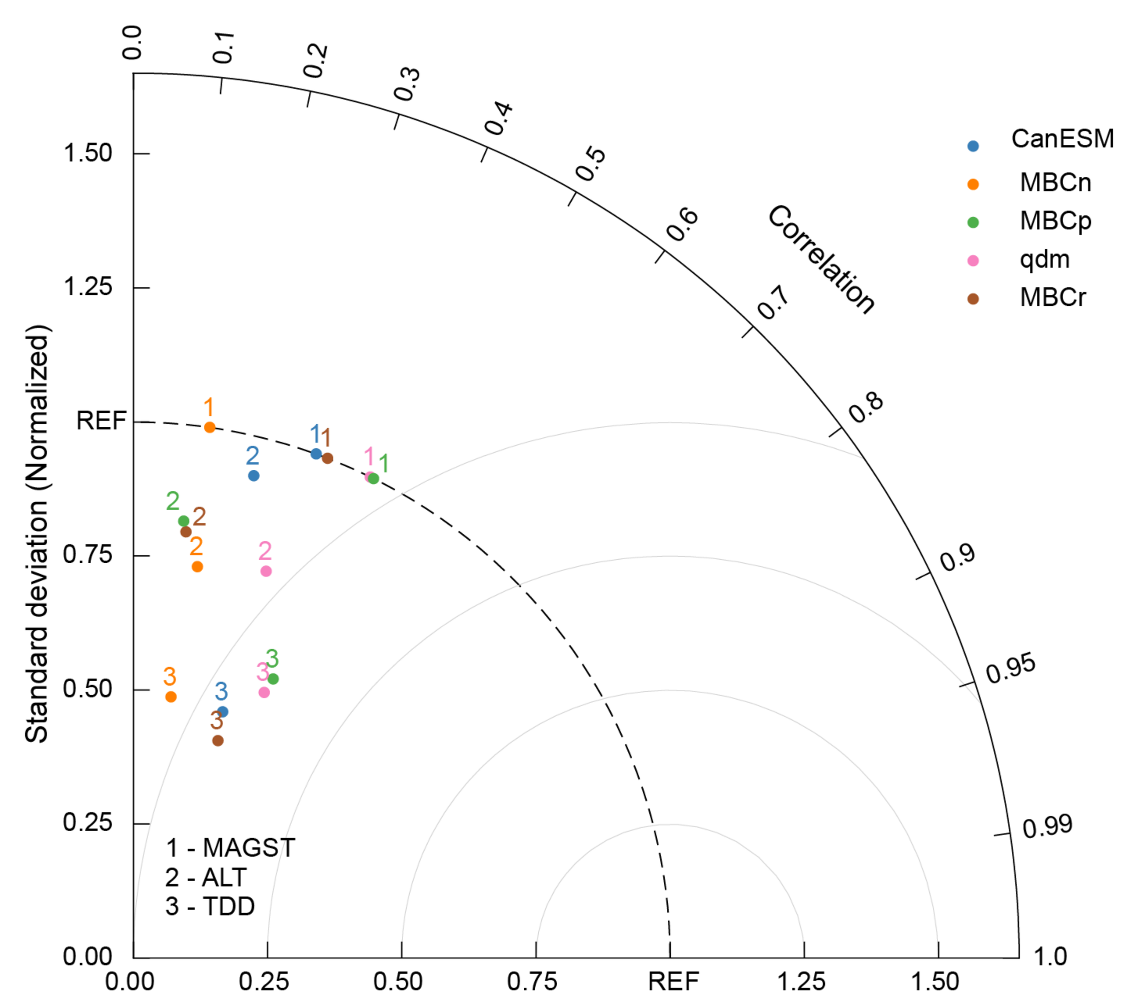

Figure 3: Taylor Diagrams summarize how closely each simulated permafrost metric matches observations. The points nearest REF align best with the reference data.

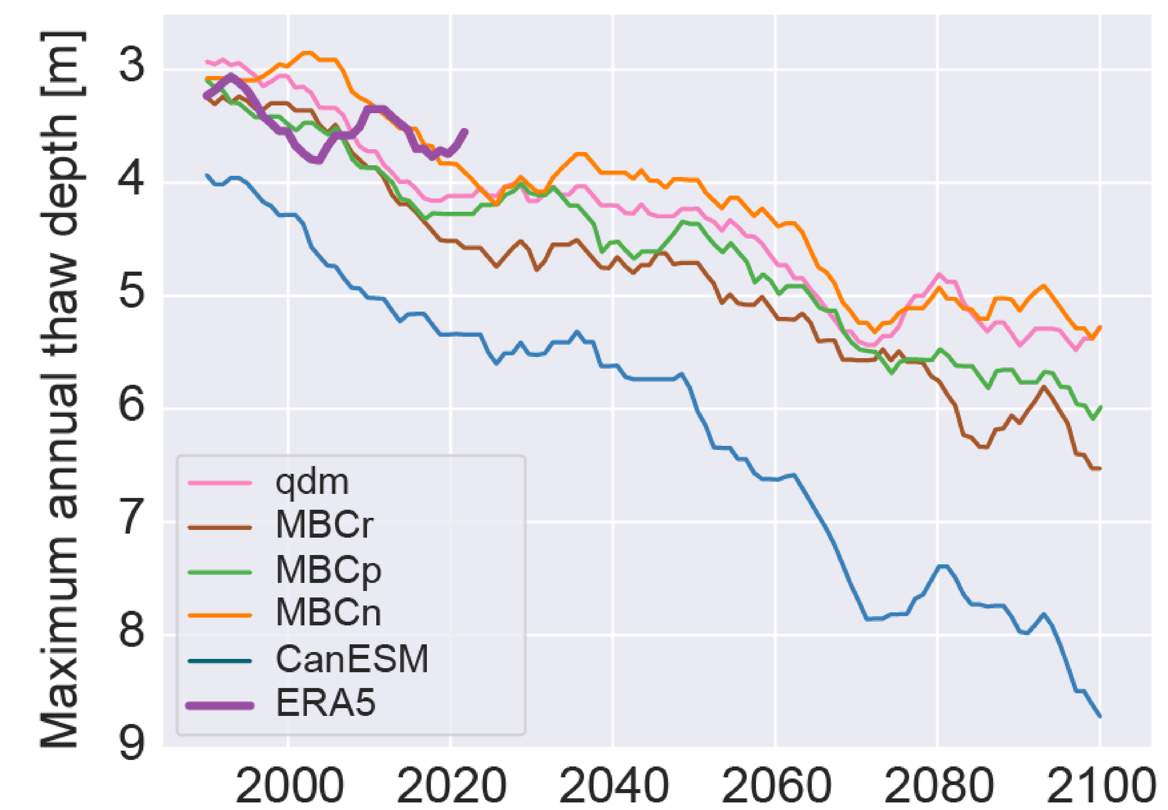

Figure 2: Time series of simulated maximum annual thaw depth with ERA5 as reference dataset.

Depending on the permafrost metric under consideration, the best-performing driving climate dataset varies.

	Climate (Energy distance)	MAGST (MBE [%])	ALT (MBE [%])	TDD (MBE [%])
CanESM	1.0857	-22.20	46.73	29.36
MBCn	0.00886	-1.07	13.20	12.75
MBCp	0.0092	-0.11	10.49	9.08
qdm	0.0093	-0.76	5.95	9.56
MBCr	0.0094	-9.54	17.17	14.95

Table 1: Example table of performance measures for original climate model data and bias correction algorithms. Best-performing driving data are marked in orange.

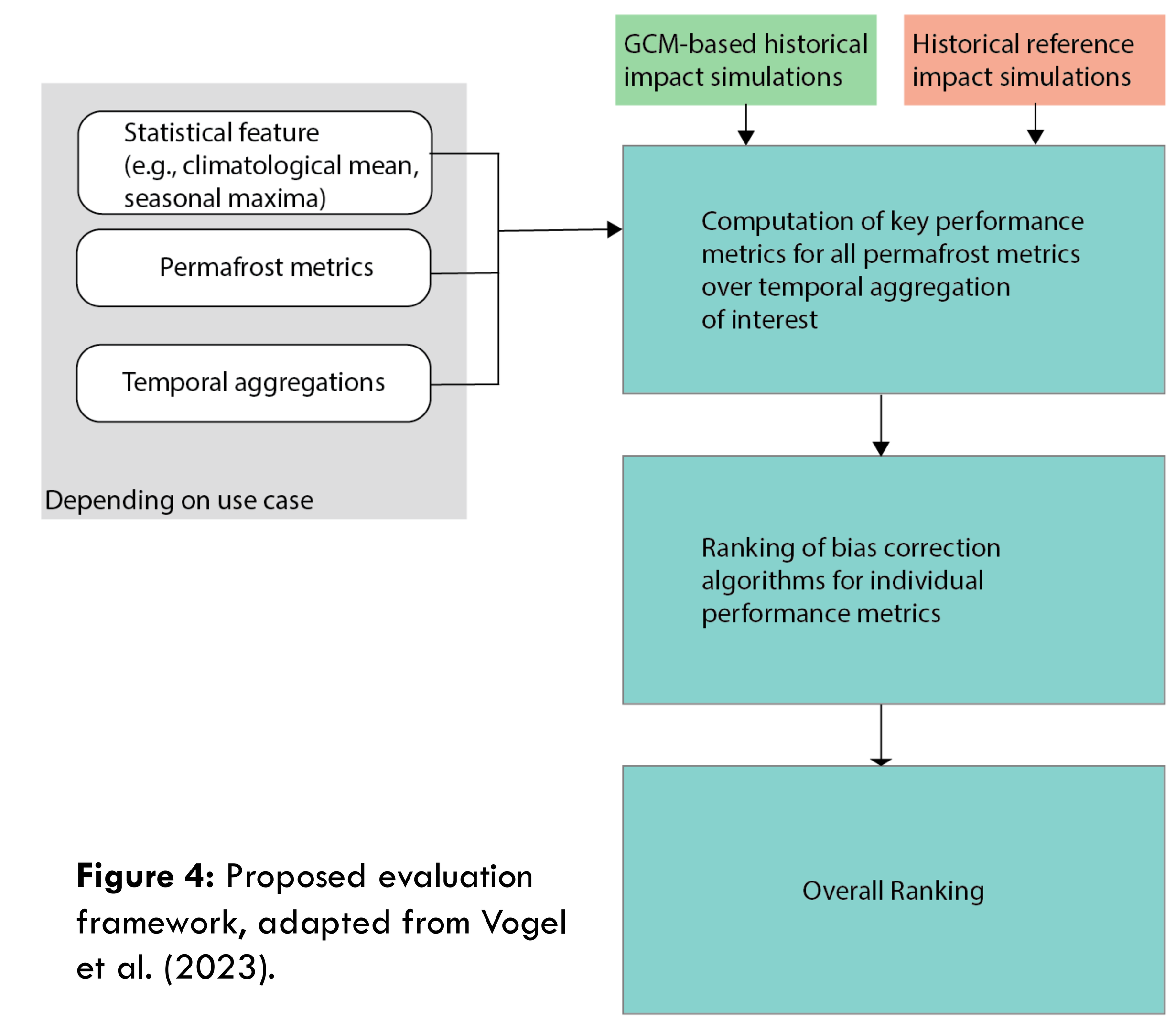

Figure 4: Proposed evaluation framework, adapted from Vogel et al. (2023).

The performance of climate driving data for permafrost predictions needs to be evaluated in its ability to represent permafrost metrics of interest.

We propose a comprehensive evaluation framework (Fig. 4) that can be adapted to use cases and information needs.

Quantifying remaining biases and uncertainties increases trust in climate model output data and permafrost simulations driven by that data.

Next steps

Does the ranking performance vary for different permafrost terrains?

How do biases stemming from climate forcing data compare to other uncertainties in predictions of future permafrost change?

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Literature

Cannon, A.J. Multivariate quantile mapping bias correction: an N-dimensional probability density function transform for climate model simulations of multiple variables. Clim Dyn 50, 31–49 (2018).

Vogel, E. et al. (2023). An evaluation framework for downscaling and bias correction in climate change impact studies. Journal of Hydrology, 622, 129693.

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