A proposed framework to generate climate forcing for simulations of future permafrost thaw

Context

There is a need for transient predictions of permafrost development in the context of climate change. As permafrost observations are temporally and spatially sparse, we need to rely on modelled permafrost time series extending in-situ observations to serve as validation data driving transient predictions of future permafrost thaw.
The challenge here is to **downscale** climate model data to a site scale and apply the climate forcing to an impact model that respects **variability in surface and sub-surface properties**.

Research questions

- How can we compare and select models that best represent the **climate** in our target area?
- How can the comparison and selection process be updated when permafrost variables are prioritized over the representation of climate variables?
- Based on the **impact model performance**, which climate forcing data is best suited for driving permafrost models?

Approach

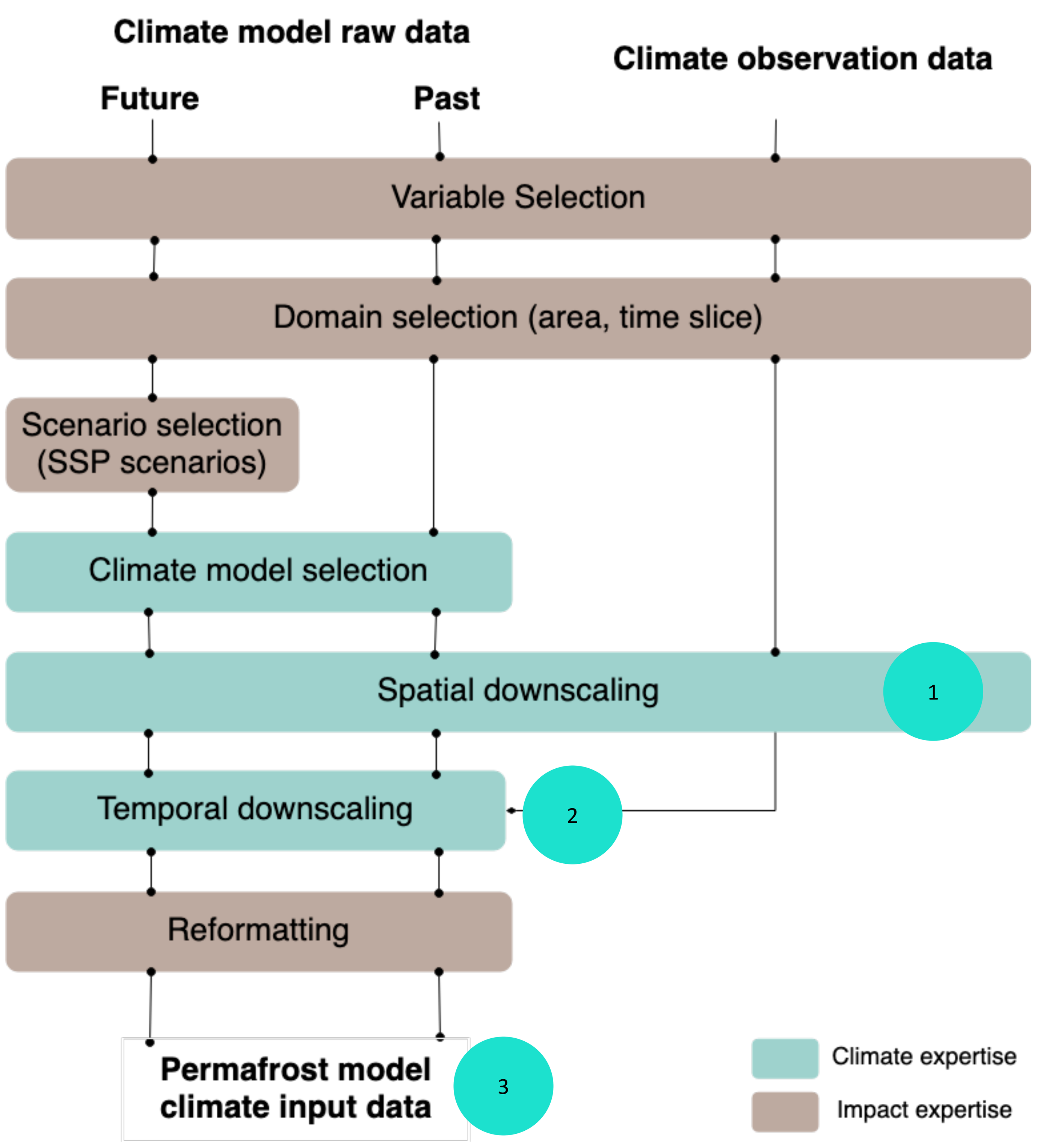

Figure 1: Climate data processing chain.

The climate data processing chain (Fig. 1) describes all the steps needed to prepare climate model data for application to permafrost models at a local scale. These steps address challenges concerning resolution of climate model data when using it to simulate smaller-scale impacts. Impact model expertise is needed to select forcing variables for driving models. When evaluating the climate data that is forcing the permafrost model, it is also important to examine the errors in certain variables that have a larger influence on impact model performance than others.

1 *Spatial resolution of climate model data*

CHALLENGE: Global climate models have a resolution of one degree (about 100 km). However, the climate can vary largely over these distances, impacting heat fluxes into the ground.

APPROACH: De-biasing of climate model data using topographically downscaled reanalysis as reference data. The de-biasing methods applied also consider inter-variable dependencies

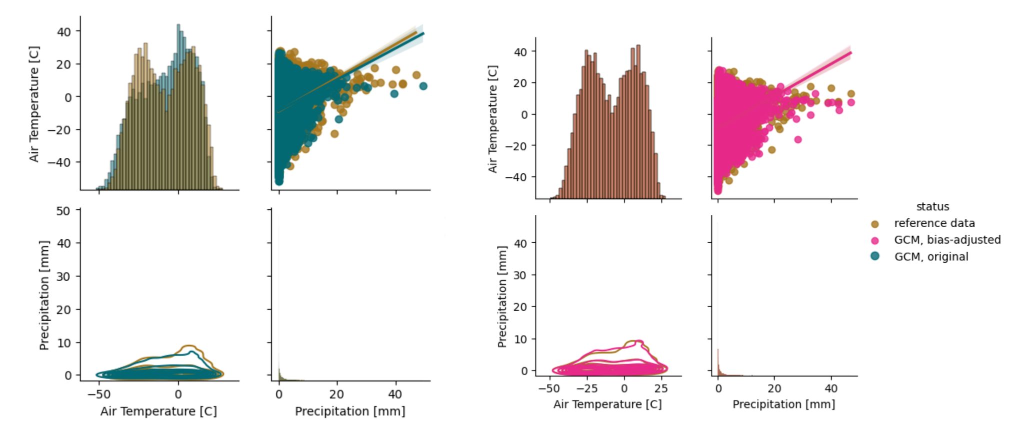

Figure 3: Comparing de-biased climate model data and original climate model data in terms of distribution and inter-variable dependency on the example of temperature and precipitation.

2 *Temporal resolution of climate model data*

CHALLENGE: Climate models often provide outputs only at a daily temporal resolution. Most permafrost models use sub-daily climate forcing data.

APPROACH: Using a technique called temporal disaggregation, we can derive sub-daily dynamics for each variable from reference data corresponding to the “most similar meteorological day” at that time of year. These dynamics are then applied to the de-biased daily climate model data.

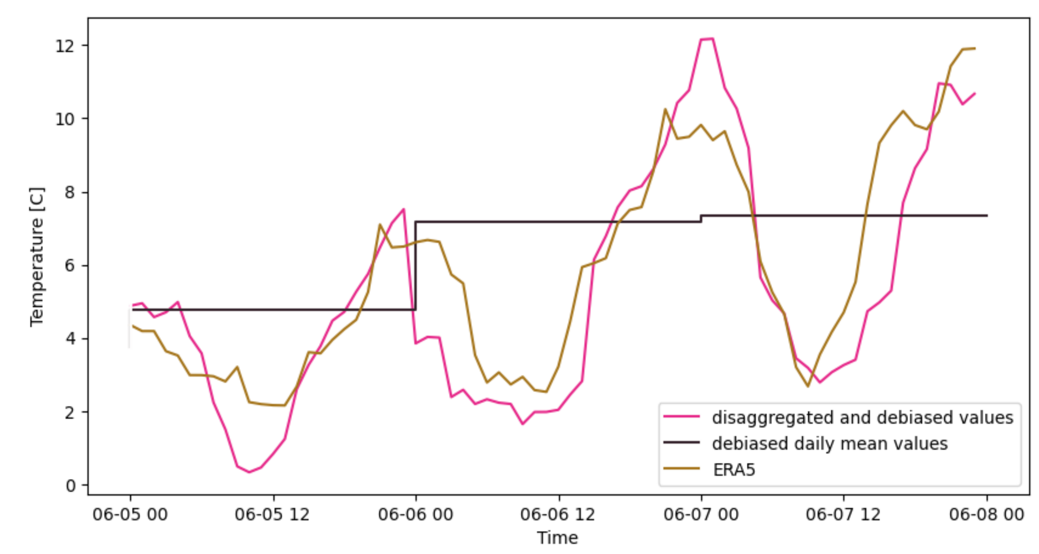

Figure 4: Disaggregated and de-biased climate model data, with ERA5 hourly values for reference.

3 *Comparison metrics*

CHALLENGE: Climate models simulate long-term trends and statistical properties of climate variables, while weather data capture short-term and variable conditions. Therefore, alternative comparison metrics are essential to bridge this gap and assess a model's performance accurately.

APPROACH: Applying comparison metrics which measure statistical distribution of variables, such as correlation factors and energy distance, help evaluate how well climate models reproduce statistical characteristics and long-term trends observed in climate data, even if they may not precisely match individual weather events.

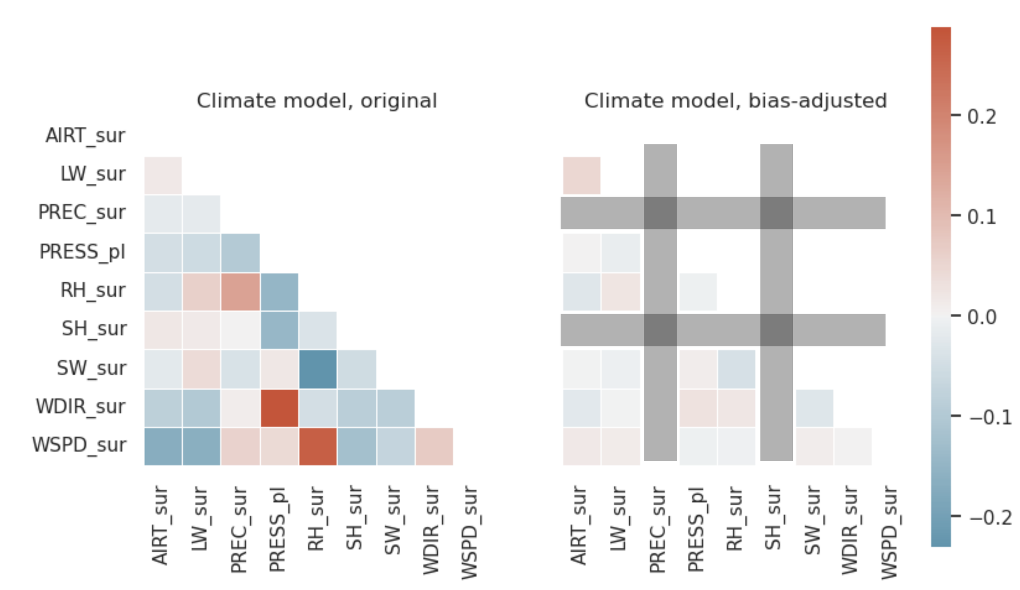

Figure 5: Difference between correlation coefficients of climate model data and ERA5 reference data. Measure of representation of inter-variable dependencies

Added value of this simulation framework

Running permafrost simulation ensembles with pre-processed climate forcing data allows for

- Representation of **transient** permafrost change
- **Propagation of uncertainties** related to driving climate, when using multiple climate models and scenarios
- Spatial and temporal **portability** (due to spatial downscaling)

Next steps

- Extending climate forcing and permafrost trends to future climate scenarios
- Examining impact of each individual variable on impact model output, per terrain type
- Approximating confidence associated with modelling results
- Supporting the understanding of thaw-induced hazards through the provision of modelling results

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