



# Mountain glacier evolution since the last interglacial

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**Abstract.** Mountain glacier evolution since the last interglacial remains poorly constrained, with limited spatial and temporal coverage. Conventional modelling approaches typically target major climatic events, operate at coarse spatial resolution over limited spatial domains, or employ simplified representations of ice dynamics. Here, we address these limitations by applying the Instructed Glacier Model (IGM), to reconstruct, for the first time, mountain glacier evolution since  $\sim 130$  ka at 500 m resolution across nine mountain ranges in North America, South America, Eurasia, and Africa. We perform 707 parameter-calibration simulations by varying paleoclimate and ice-dynamic parameters, and validate model performance by assessing glacier extent and ice thickness. The model outputs are evaluated using a spatial frequency map approach, which identifies a set of acceptable model results rather than a single best-fit simulation. As a result, we identify areas of robust agreement and those sensitive to parameter choices, providing a systematic way to visualise spatial uncertainty and glacier–climate–topography interactions. Together, our framework is a scalable foundation for next-generation, uncertainty-aware reconstructions turning glacier modelling at orbital-timescales into a reproducible, expandable workflow that can be deployed across mountain ranges worldwide. All data are publicly available at <https://archive.sigma2.no/dataset/evolution-of-mountain-glaciers-since-the-last-interglacial> (Barndon et al., 2026b) and the animations at <https://av.tib.eu/series/2022> (Barndon et al., 2026a).

## 1 Introduction

Most major mountain ranges around the world are known to have been glaciated during the Late Pleistocene (Thackray et al., 2008; Hughes and Gibbard, 2018; Ehlers et al., 2011; Lima et al., 2026). However, glacial evolution for many mountain ranges is unknown through large parts of the Last Glacial Cycle ( $\sim 120$  to  $\sim 11.7$  ka) and the Holocene ( $\sim 11.7$  ka to today). Although numerous paleoglacier reconstructions have been conducted using geomorphic (e.g., Clapperton, 1983; Osmaston, 2004; Gillespie and Zehfuss, 2004; Gobejishvili et al., 2011; Groos et al., 2021; Delmas et al., 2022) and numerical models (e.g., Kessler et al., 2006; Kull et al., 2008; Stansell et al., 2022; Doughty et al., 2023), these studies have often reconstructed steady-state conditions or performed transient simulations centred around major climatic events such as the Last Glacial Maximum (LGM; 26.5–19 ka) and the Younger Dryas (12.9–11.7 ka).



While some mountain ranges have been the focus of transient simulations of glacier evolution beyond the LGM (e.g., Becker et al., 2017; Seguinot et al., 2018; Yan et al., 2021, 2023; Juvet et al., 2023), these simulations are generally performed at spatial resolutions coarser than the kilometre scale. Valley glaciers can often be narrower than 1 km, and individual valley glaciers are therefore not resolved in simulations at such resolutions. Transient simulations through glacial-interglacial cycles can be performed at sub-kilometre spatial resolutions (e.g., Sternai et al., 2013; Kaufmann and Romanov, 2012), but typically at the cost of limiting the modelled area to small catchments and adopting simplified ice-dynamic formulations. Therefore, glacier evolution simulations have so far remained constrained by a trade-off between simulation duration, spatial resolution, spatial coverage, and ice-dynamic complexity. This trade-off is due to the computational costs and runtime demands of conventional numerical modelling approaches, such as the Parallel Ice Sheet Model (PISM, (e.g., Seguinot et al., 2018; Juvet and Cordonnier, 2023)), and Plummer-Phillips-type models (e.g., Doughty et al., 2023; Leonard et al., 2014)). These conventional models are consequently unsuitable for simulating entire mountain ranges at finer spatial resolution over full glacial-interglacial cycles.

Computational limitations, however, are now being overcome by the state-of-the-art Instructed Glacier Model (IGM; Juvet et al. 2022; Leger et al. 2025), a glacier modelling framework in which ice-flow dynamics are emulated using physics-informed deep learning. Whereas conventional glacier models rely on central processing unit (CPU) based solvers that numerically compute ice-flow physics at every time step, machine learning models can bypass these computationally expensive approaches, replacing them with rapid neural network inference that accelerates simulations by orders of magnitude.

Previous IGM-based studies reported reductions in glacier simulation runtime of one to three orders of magnitude relative to conventional CPU-based modelling approaches (Juvet et al., 2022; Juvet and Cordonnier, 2023; Cook et al., 2023; Leger et al., 2025). IGM has thereby overcome not only the computational bottlenecks of millennial-scale transient, high-resolution glacier modelling, but also facilitates more extensive model parameterisation and sensitivity testing. The latter are essential for studying glacier evolution in regions with complex topography and limited empirical evidence, where a range of plausible glacier–climate scenarios must be explored to quantify uncertainty and assess model robustness.

Despite the advances in glacier evolution models, challenges have remained in model calibration (climate and parametrisation) and model-data comparison (i.e., model evaluation), including:

1. Limited temporal resolution and sparse spatial coverage of proxy records for paleoclimate reconstructions;
2. Simplified or poorly constrained parametrisations of processes in glacier models (e.g., basal sliding, ice rheology, surface mass balance);
3. Limited availability and sparse spatial distribution of well-dated, geomorphic evidence data for comparison with model outputs;
4. Lack of standardised model-data comparison workflows and performance metrics in paleo-glacier modelling studies.

In this study, we applied IGM in a suite of diverse mountain ranges worldwide and developed a workflow including the compilation of paleoclimate reconstructions, tests of parametrisations, and several model-data comparison approaches. To estimate regional climate changes, we compiled 102 paleo-records from a range of different paleo-proxies, including glacier recon-





structions, glacier ice cores, and pollen records. We further calibrated the regional climate by performing ensemble parameter variation across a minimum of 27 full glacier simulations in each region. The ensemble calibration was made possible by IGM's computational efficiency, allowing us to explore a range of paleoclimate and model parametrisations in each simulation domain. Finally, we applied an evaluation framework that moves beyond a single best-fit simulation by focusing on a set of best-performing simulations. This is achieved by comparing simulation outputs against geomorphic glacier reconstructions and by evaluating the spatial likelihood of glacier presence across the ensembles of plausible model outputs.

As a result, we present three-dimensional higher-order transient glacier simulations covering 130 ka to present at 500 x 500 m spatial resolution in nine mountain ranges in four continents, and across the tropics and mid-latitudes (Fig. 1). We also modelled several data-sparse mountain regions for the first time. Such simulations are essential not only for estimating mountain glacier responses to climate changes, but also for interdisciplinary alpine research, including studies of sediment flux, lake development, and the timing and pathways of vegetation dynamics (Sternai et al., 2013; Kaufmann and Romanov, 2012; Flantua et al., 2019; Hurtado and Gallen, 2025). Such reconstructions are also increasingly used to bound mountain barriers, corridors, and high-altitude refugia in archaeological and anthropological studies, informing hypotheses about where and when people could move, settle, and adapt under glacial climates (Li et al., 2019; Bortolini et al., 2021).

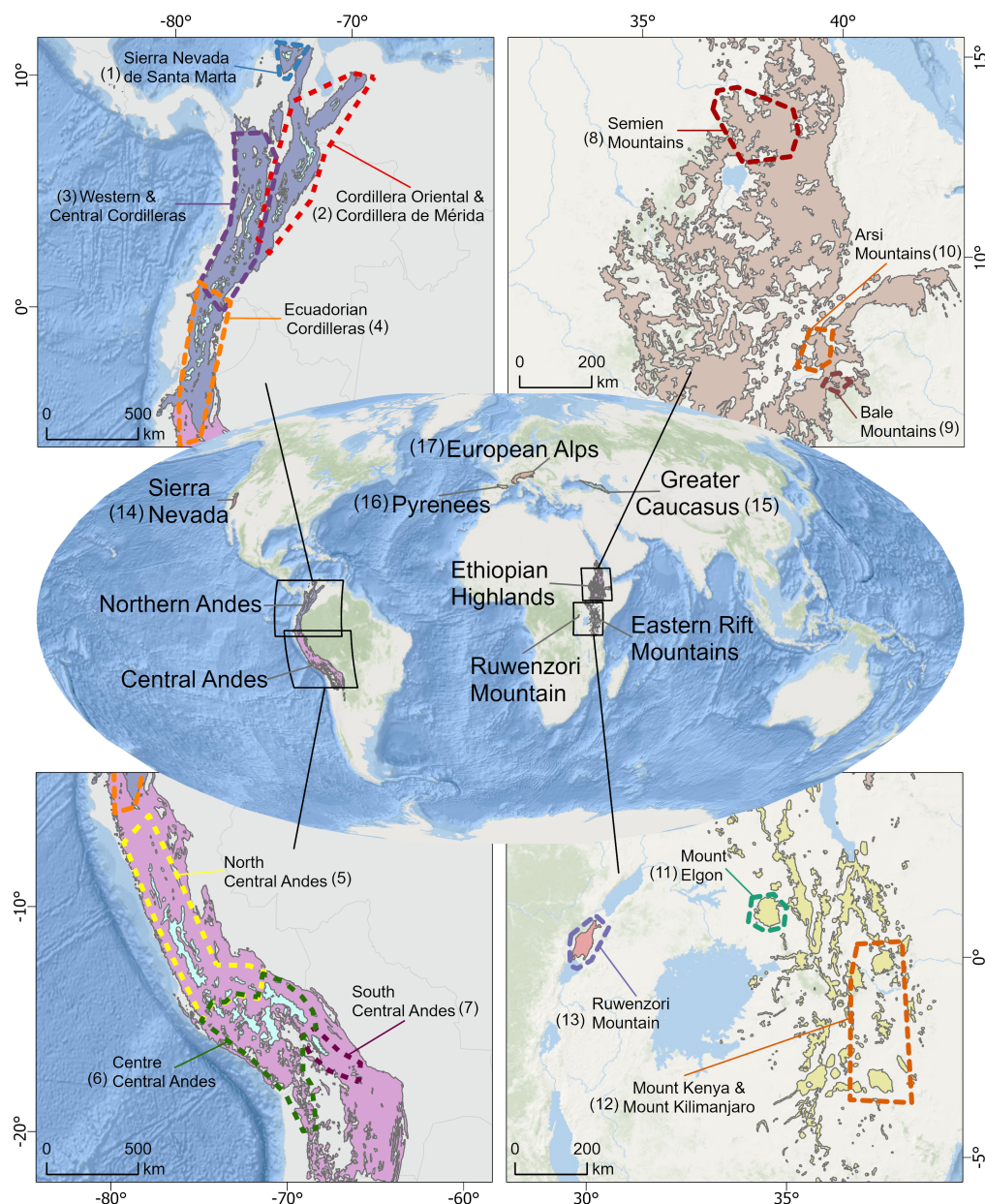
## 2 Methods

We first describe the selection process for the mountain ranges in Sect. 2.1 and outline the IGM setup in Sect. 2.2 and 2.3. Ice flow parameters, modules and related physical relationships are detailed in Sect. 2.3, before moving to the paleoclimate forcing in Sect. 2.4. The surface mass balance formulation is explained in Sect. 2.5, followed by the simulation ensembles and corresponding parameter calibration in Sect. 2.6. The methods conclude with the model-data comparison workflow in Sect. 2.7 and how we evaluate model performance in Sect. 2.8.

### 2.1 Selected mountain ranges

We selected the mountain ranges (Fig. 1) based on two primary criteria: (1) their geographic distribution across tropical and mid-latitude regions, and different continents; and (2) the availability of geomorphic glacier reconstructions for model-data comparison, informed by the new GLACIMONTIS geodatabase (Lima et al., 2025, 2026). The latter provides geomorphic glacier reconstructions across global mountain regions (see Sect. 2.7.1). We also required (3) fully terrestrial glaciers (not marine-terminating), as ice–ocean interactions are not yet developed for IGM; and (4) independency from the major ice sheets, since modelling entire ice sheets is beyond the scope of the present study. This last criterion excludes, for example, the Scandinavian mountains and Canadian Rockies and Coast Mountains.

Although the selection criteria yield numerous eligible glaciated regions across the continents, comprehensive modelling of all potential areas is outside the scope of this study. The objective is therefore not global glacier modelling, but the simulation of glacial evolution across a diverse selection of mountain ranges spanning multiple continents and climatic regimes. Conse-



**Figure 1. Selected mountain ranges and simulation domains for glacier evolution modelling.** The selected mountain ranges are shown in the background in coloured polygons. The simulation domains are shown by polygons with coloured dashed lines. Mountain ranges and simulation domains are the same for Sierra Nevada (USA), European Alps, and Greater Caucasus. See overview in Table 1. Simulation domains range from  $\sim 8,000$  to  $300,000 \text{ km}^2$ . Mountain ranges are derived from Snethlage et al. (2021, 2022) at different hierarchical levels 3-5. Basemap is powered by Environmental Systems Research Institute (ESRI), General Bathymetric Chart of the Oceans (GEBCO), Garmin, NaturalVue in ArcGIS Pro 3.2.2 (2023).



quently, nine mountain ranges were selected to encompass a broad range of climatic and topographic settings, enabling the assessment of the broader applicability of IGM under varying environmental conditions.

As climatic forcing and ice-dynamic parameters can vary within a given mountain range, and modelling large domains requires substantial memory resources, we divided the mountain ranges into seventeen simulation domains (Fig. 1). For the Northern Andes, these are: (1) Sierra Nevada de Santa Marta, (2) Eastern Cordillera & Cordillera de Mérida, (3) Western & Central Cordilleras, and (4) Ecuadorian Cordilleras. The Central Andes are split in (5) North Central Andes, (6) Centre Central Andes, and (7) South Central Andes. The Ethiopian Highlands are divided into: (8) Semien Mountains, (9) Bale Mountains, and (10) Arsi Mountains. The Eastern Rift Mountains are divided into: (11) Mount Elgon, (12) Mount Kenya and Mount Kilimanjaro. The remaining domains are stand-alone: (13) Ruwenzori Mountains, (14) Sierra Nevada (USA), (15) Greater Caucasus, (16) Pyrenees and (17) European Alps.

## 2.2 Model setup

To define a bed elevation for each of the seventeen simulation domains, we derived the ice-free present-day elevation by subtracting present-day ice thickness (Farinotti et al., 2019) from the GEBCO global terrain model (GEBCO Bathymetric Compilation Group, 2025). As the global ice thickness distribution dataset is originally at 25 m resolution (15 arc-second), we used bilinear resampling to match the 500 m resolution of the global terrain model.

Every simulation was modelled at a spatial resolution of 500 x 500 m and with 10 layers of vertical resolution. The ice thickness and ice flow components of the model were recalculated at least once every year, while the climate parameters and surface mass balance (SMB) were calculated once per year. Finally, each simulation was initialised with a 10 kyr spin-up period starting from the ice-free present-day bed topography. The spin-up period was performed to initiate a stable, glaciated state before entering the period of interest (130 ka), rather than starting the simulation from zero ice. To achieve this, the 10 kyr spin-up period was forced with constant climate parameters, where temperature and precipitation was equal to the model year ~130 ka. As the IGM simulations reached a steady state in this constant climate relatively quickly, with some locations stabilising in under 3 kyr, the 10 kyr spin-up period was sufficient for our model. For the resulting dataset, ice thickness, ice flow components, climate parameters and the SMB were saved at 100-yr frequency.

## 2.3 The Instructed Glacier Model

IGM is a glacier evolution model that speeds up simulations by approximating ice-flow equations using a physics-informed deep learning emulator (Jouvet and Cordonnier, 2023). Its computational efficiency arises from two key features. First, IGM leverages GPU parallelization throughout its entire framework via the TensorFlow Python library. Second, IGM replaces the computationally intensive ice-flow solver with a physics-informed convolutional neural network that is trained initially and periodically re-trained during simulations. This emulator minimises the demands associated with solving three-dimensional higher-order (Blatter-Pattyn) ice-flow physics. Further methodological details are found in the original publications (Jouvet and Cordonnier, 2023; Leger et al., 2025).



The Blatter-Pattyn stress-balance model (Blatter, 1995) includes horizontal shear and longitudinal stresses, as well as vertical shear stresses. Although it retains simplifying assumptions relative to Full Stokes solutions, such as hydrostatic vertical normal stress, it provides a physically consistent representation of glacier flow in complex mountain terrains. This results in smoother velocity fields, improved behaviour near ice margins, and more realistic dynamic responses. By comparison, the Shallow Ice Approximation (SIA) includes only vertical shear stresses. The SIA assumptions are often violated in mountain glacier settings, which are characterised by steep slopes, strong stress gradients, lateral drag, and complex topography over short distances.

The emulator is pre-trained on a variety of glacier settings, and continues frequent retraining to a novel flow-regime during simulation (Leger et al., 2025). In our model, the retraining frequency was set to every 7th time step where each time step is variable but maximum one year (See Supplementary Table S5 (Excel) for default parameter values for all simulation experiments). Physical laws and relationships inform the training of the emulator. For example, Glen’s flow law (Glen, 1955; Nye, 1953) and the Blatter-Pattyn approximation to the Stokes equations (Blatter, 1995; Pattyn, 2003) are used to compute stresses and strain rates. At the lower boundary, sliding and basal shear stress are computed with a power-law (Weertman-type) friction law (Weertman, 1957).

We used IGM’s default values for the input parameters in the ice flow modules (Appendix Table A1). For climate forcing and surface mass balance (SMB) calculations, custom modules were required to adapt to the input parameters of the paleoclimate forcing. To shorten computation cost and calibration time, modules for enthalpy and isostatic adjustment were not included (see more in Sect. 4.4). Our model therefore assumed isothermal glaciers in all locations and throughout simulation time spans.

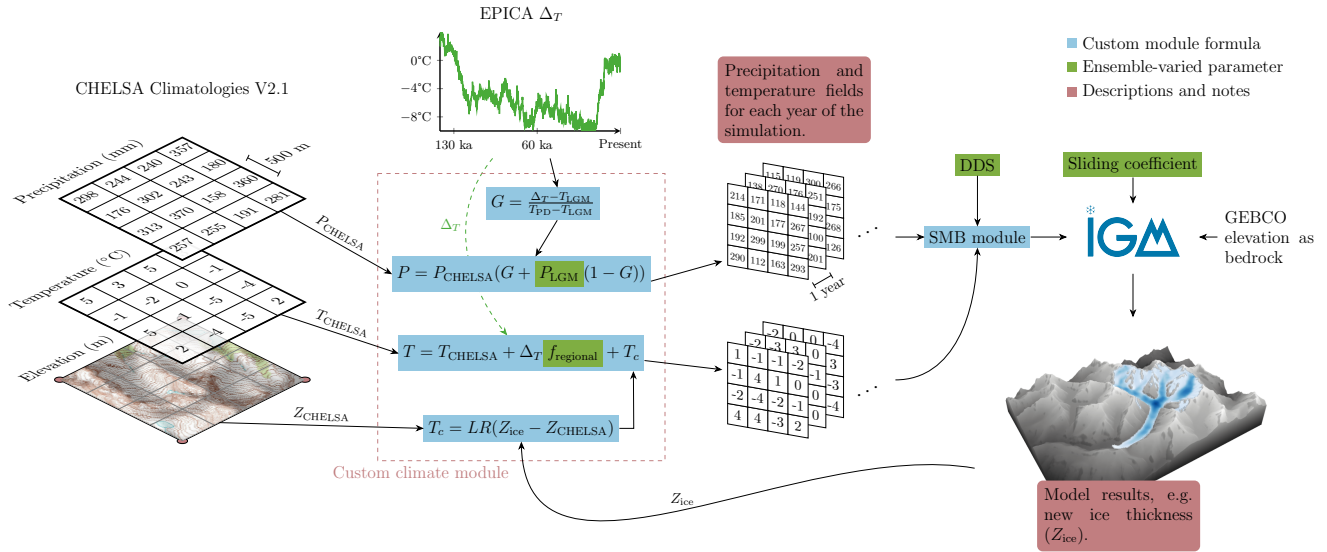
The glacier model simulations were run either locally on an NVIDIA GeForce RTX 5080 GPU or externally on Sigma2 using several NVIDIA P100 GPUs and NVIDIA A100 GPUs. Sigma2 is a high-performance computing system that provides multiple nodes with two GPU types, as part of the Norwegian *supercomputer* infrastructure. See Supplementary information Note S1 for more details on computational resources (GPU and HPC usage).

## 2.4 Paleoclimate forcing

To create regionally optimised simulations, we tailored the input parameters to the specific climatic settings of each simulation domain. The following sections outline how this was performed for temperature (Sections 2.4.1, 2.4.2, and 2.4.3) and precipitation (Sect. 2.4.4). Figure 2 gives an overview of how these parts interact and form the workflow developed for this study.

### 2.4.1 Temperature

To represent temperature forcing through time, we imposed a time-varying temperature anomaly on a present-day climatology. We used monthly mean near-surface air temperature from CHELSA V2.1 (Karger et al., 2017, 2025) as the modern reference ( $T_{\text{CHELSA}}$ ), which provides 1 km resolution climatologies for 1981–2010. CHELSA is based on downscaled ERA-Interim reanalysis (Karger et al., 2017). We further downscaled CHELSA to 500 m using bilinear interpolation to match the glacier model grid.



**Figure 2. Methodology workflow for the paleoglacier modelling framework.** The ensemble-varied parameters are shown in green boxes, namely degree-day scaling (DDS), LGM precipitation adjustment factor ( $P_{LGM}$ ), sliding coefficient, and regional temperature scaling ( $f_{regional}$ ). Equations related to the custom python modules for IGM are shown in blue. Lapse rate ( $LR$ ) is the average lapse rate within the bounding box of the simulation domain. Note that the CHELSA elevation ( $Z_{CHELSA}$ ) is only used for the calculations of the temperature lapse rate and correction, while the GEBCO elevation without the present-day ice surface is used as the actual bedrock elevation in simulations. Values are plausible but for illustration only.

We estimated the temporal evolution of temperature anomalies using the EPICA Dome C ice-core record (Jouzel et al., 2007). Polar temperature changes are amplified relative to global-mean temperature changes (and the amplification differs between Antarctica and the Arctic), so polar anomalies cannot be applied directly as regional mountain temperature changes (Masson-Delmotte et al., 2006; Hansen et al., 2013; Xie et al., 2022). We therefore scaled the EPICA temperature anomaly with a regional factor, following approaches used in paleoglacier modelling (e.g., Seguinot et al., 2018). For each grid cell ( $x, y$ ) and time step  $t$ , regional temperature is defined as:

$$T(x, y, t) = T_{CHELSA} + \Delta T_{EPICA} \cdot f_{regional} \quad (1)$$

where  $\Delta T_{EPICA}(t)$  is the EPICA Dome C temperature anomaly and  $f_{regional}$  scales this anomaly to a domain-representative regional magnitude.





## 160 2.4.2 Regional scaling factor

We estimated  $f_{\text{regional}}$  using independent constraints on LGM cooling for each simulation domain. First, we calculated the mean EPICA anomaly for the LGM interval (26.5–19 ka) (Jouzel et al., 2007; Clark et al., 2009), yielding  $\Delta T_{\text{EPICA,LGM}} = -9.5^\circ\text{C}$ . This Antarctic anomaly does not represent regional LGM cooling in mountain environments because local circulation, lapse-rate structure, and orographic effects modulate temperature changes.

165 For each mountain range, we compiled published estimates of LGM temperature change ( $\Delta T_{\text{regional,LGM}}$ ) from proxy-based and model-based reconstructions (82 studies; bibliography in Supplementary Table S5), broadly following the synthesis approach of Becker et al. (2016). We then defined the regional scaling factor as:

$$f_{\text{regional}} = \Delta T_{\text{regional,LGM}} / \Delta T_{\text{EPICA,LGM}}. \quad (2)$$

Because reconstruction density is uneven across ranges, we only derived a range-specific  $\Delta T_{\text{regional,LGM}}$  when at least a  
 170 minimum sample size of 10 reconstructions was available. This criterion reduced sensitivity to individual records and improved representativeness. For ranges with fewer reconstructions, we adopted a global scaling factor of 0.5 (Hansen et al., 2013). Compiled  $\Delta T_{\text{regional,LGM}}$  values were averaged to obtain a representative  $f_{\text{regional}}$  for each simulation domain (Table 1). These values were subsequently adjusted in some ranges (see Section 2.6.1).

## 2.4.3 Temperature lapse rate and correction

175 To account for the vertical temperature change as ice thickness varies during simulations, we adjusted the CHELSA surface temperatures using a regional lapse rate. The lapse rate is the vertical temperature gradient in the atmosphere, calculated here using linear regression of  $T$  against  $z$  in individual windows of 3x3 pixels, then averaged over all windows in the region. Before averaging, the calculated lapse rates were cleaned following Tukey’s method (1977) of using 1.5 times the interquartile range as a threshold for outliers. This resulted in a unique lapse rate for each domain, which was held constant throughout each  
 180 simulation. Present-day temperature data were obtained from CHELSA-BIOCLIM+ (Bioclimatic factor 01; Mean annual temperature) (Brun et al., 2022) and the same ice-free present-day topography used in the glacier modelling (GEBCO Bathymetric Compilation Group, 2025). The difference in the range of the averaged lapse rate values for each mountain range between ice-free and ice-covered topography was negligible.

To find the temperature correction ( $T_c$ ) as surface elevation changes in time through a simulation, the lapse rate was multi-  
 185 plied by the difference between the modelled ice elevation and the CHELSA elevation ( $z_{\text{CHELSA}}$ ) at each time step:

$$T_c = \text{LR}(z_{\text{ice}} - z_{\text{CHELSA}}) \quad (3)$$

where  $z_{\text{ice}}$  is the upper ice surface elevation at runtime.  $T_c$  was then added to the temperature  $T(x, y, t)$  from Eq. 1.

## 2.4.4 Precipitation

To simulate regional differences in precipitation variations over time, we adjusted the CHELSA present-day climate data (V2.1  
 190 dataset (Karger et al., 2017, 2025)) with precipitation anomalies. Anomalies were calculated with a glacial index method (e.g.,



**Table 1. Overview of regional scaling factors per mountain range.** Initial  $f_{\text{regional}}$  is either the value calculated from the LGM paleotemperature reconstruction studies (i.e., our literature review), or the global mean (0.5). Calibrated  $f_{\text{regional}}$  refers to the actual value used in the simulation ensembles, in some cases adjusted after test simulations (see Section 2.6). Temperature difference is the LGM temperature (here the minimum EPICA temperature, at roughly 24 ka:  $-9.5^{\circ}\text{C}$ ) difference to present day, after applying the calibrated  $f_{\text{regional}}$ . See Fig. 1 for the mountain ranges and simulation domains, and Regional Scaling Factor statistics in Supplementary Table S1.

| Mountain region              | # Proxy records | Initial $f_{\text{regional}}$ | Simulation domain                             | Adjusted $f_{\text{regional}}$ | LGM temperature depression ( $^{\circ}\text{C}$ ) |
|------------------------------|-----------------|-------------------------------|-----------------------------------------------|--------------------------------|---------------------------------------------------|
| Central Andes                | 27              | 0.50                          | (5) North Central Andes                       | 0.35                           | 3.70                                              |
|                              |                 |                               | (6) Centre Central Andes                      | 0.35                           | 3.70                                              |
|                              |                 |                               | (7) South Central Andes                       | 0.35                           | 3.70                                              |
| Eastern Rift Mountains       | 22              | 0.44                          | (11) Mount Elgon                              | 0.65                           | 6.88                                              |
|                              |                 |                               | (12) Mount Kenya & Mount Kilimanjaro          | 0.44                           | 4.65                                              |
| European Alps & the Pyrenees | 19              | 1.19                          | (17) European Alps                            | 0.90                           | 9.52                                              |
|                              |                 |                               | (16) The Pyrenees                             | 1.10                           | 11.64                                             |
| Ruwenzori Mountains          | 18              | 0.47                          | (13) Ruwenzori Mountains                      | 0.50                           | 5.29                                              |
| Ethiopian Highlands          | 9               | 0.50                          | (8) Semien mountains                          | 0.65                           | 6.88                                              |
|                              |                 |                               | (9) Bale Mountains                            | 0.45                           | 4.76                                              |
|                              |                 |                               | (10) Arsi Mountains                           | 0.60                           | 6.35                                              |
| Northern Andes               | 8               | 0.50                          | (1) Sierra Nevada de Santa Marta              | 0.50                           | 5.29                                              |
|                              |                 |                               | (2) Eastern Cordillera & Cordillera de Mérida | 0.74                           | 7.83                                              |
|                              |                 |                               | (3) Western & Central Cordillera              | 0.65                           | 6.88                                              |
|                              |                 |                               | (4) Ecuadorian Cordilleras                    | 0.50                           | 5.29                                              |
| Greater Caucasus             | 3               | 0.50                          | (15) Greater Caucasus                         | 0.50                           | 5.29                                              |
| Sierra Nevada (USA)          | 3               | 0.50                          | (14) Sierra Nevada (USA)                      | 0.50                           | 5.29                                              |





Jouvet et al., 2023; Leger et al., 2025; Castillo-Llarena et al., 2024; Kaufmann and Romanov, 2012) based on the EPICA Dome C temperature record.

First, the EPICA Dome C record was rescaled to yield a glacial index  $G(t)$  with  $G(t=0)=1$  at the model present-day (2000 CE) and  $G(t=LGM)=0$  at the LGM:

$$195 \quad G(t) = \frac{\Delta T_{EPICA}(t) - \Delta T_{LGM}}{\Delta T_{PD} - \Delta T_{LGM}} \quad (4)$$

where  $\Delta T_{LGM}$  is the EPICA  $\Delta T$  at LGM ( $-10.6^\circ\text{C}$ ) and  $\Delta T_{PD}$  is the EPICA  $\Delta T$  at present-day ( $0^\circ\text{C}$  by definition).

Next, we applied a precipitation factor that is tailored for each simulation domain to control the magnitude of precipitation reduction or enhancement at LGM. Precipitation is then calculated as:

$$P = P_{chelsa}(G + P_{LGM}(1 - G)) \quad (5)$$

200 where  $P$  is the model precipitation ( $\text{kg m}^2 \text{a}^{-1}$ ),  $P_{chelsa}$  is the observed monthly mean precipitation ( $\text{kg m}^2 \text{a}^{-1}$ ) from the CHELSA dataset,  $G$  is the glacial index, and  $P_{LGM}$  is the precipitation factor that represents the relative change in precipitation at the time of the coldest EPICA  $\Delta T$ .

## 2.5 Surface Mass Balance

We used a positive degree-day (PDD) model to calculate the SMB, adapted from Leger et al. (2025). In a PDD model, ac-  
 205 cumulation occurs when precipitation falls as snow, typically when the temperature is below  $0^\circ\text{C}$ , and ablation occurs when temperatures are higher than  $0^\circ\text{C}$ . Here, we applied a linear snow-rain precipitation transition from  $0^\circ\text{C}$  to  $2^\circ\text{C}$ . Precipitation is all snow when the temperature is below  $0^\circ\text{C}$  and all rain when the temperature is higher than  $2^\circ\text{C}$ .

PDD was calculated following Calov and Greve (2005) and Hock (2003), where our temperature input (Sect. 2.4.1) is corrected by the lapse rate (Sect. 2.4.3), and precipitation is normalised by a glacial index time series (2.4.4). Additionally, we  
 210 apply melt factors for snow and ice, which vary according to a common degree-day scaling (DDS) in the parameter calibration (Sect. 2.6), and a fixed refreeze factor of 60%. Snow redistribution from steep valley walls onto the glacier by avalanches is handled by IGM's avalanche module.

## 2.6 Calibration of parameter values

### 2.6.1 Test simulations

215 Before starting the simulation ensemble covering 130 ka to present, we first performed test simulations on a shorter time-span around the LGM (35 to 20 ka) at a coarser resolution of 1000 m. These were used to identify a plausible range of parameter values, and helped constrain the parameter ranges tested in the full simulation ensemble. The parameters varied in these test simulations were the regional scaling factor ( $f_{\text{regional}}$ ), the precipitation factor ( $P_{LGM}$ ), degree-day scaling (DDS), and the sliding coefficient. As these coarse resolution tests are computationally cost-effective, a larger range of values could be checked before  
 220 deciding on plausible ranges for the full simulation ensemble.



Model outputs from the test simulations were scored against empirical data following the same procedure applied to the full simulation ensemble (see Sect. 2.7), excluding the model-data comparison steps relating to the present-day. Following the evaluation of the test simulations, we assessed the performance of each tested parameter value. The best performing values for each parameter were retained and used for the full simulation ensemble. For  $f_{\text{regional}}$ , only one value was selected. For precipitation, DDS and sliding coefficient, three values were selected for each.

## 2.6.2 Simulation ensemble

For a given mountain region, the simulation ensemble is a set of simulations at 500 m spatial resolution, that span the full 130 ka plus the 10 kyr spin-up. Across the seventeen simulation domains, individual simulation runtime ranged from  $\sim 2.98$  hours (Bale Mountains) to  $\sim 101.73$  hours (Eastern Cordillera & Cordillera de Mérida; Supplementary Table S2). Each simulation ensemble comprised a minimum of 27 simulations, in which each simulation was assigned a unique combination of parameter values. The three ensemble-varied parameters were precipitation factor, DDS and the sliding coefficient (Table 2), and three values were tested for each parameter. The regional scaling factor was not varied in the full simulation ensemble. In cases where these ensemble simulations yielded low model-data comparison scores (i.e., substantial deviations in ice extent and volume relative to the empirical datasets), the entire workflow was repeated using new parameter values for the test simulations. In these cases, the simulation ensemble was expanded from 27 simulations up to, in one case, 108 unique simulations.

**Table 2.** Summary of ensemble-varying parameters and parameters that are constant within a domain, but may differ between domains. The 'Min' and 'Max' columns represent the range of tested parameter values across all domains. The 'Ensemble-constant parameters' section lists parameters that were not varied in an ensemble for one domain, but could still vary between domains.

| Ensemble-varying parameters  | Symbol                | Description                                                        | Min  | Max  | Unit                             |
|------------------------------|-----------------------|--------------------------------------------------------------------|------|------|----------------------------------|
| Precipitation factor at LGM  | $P_{\text{LGM}}$      | Glacial index method precipitation at LGM compared to present day. | 0.1  | 2.1  |                                  |
| Sliding Coefficient          |                       | Coefficient in the friction law.                                   | 0.01 | 0.45 | $\text{MPa yr}^m \text{ m}^{-m}$ |
| Degree-day scaling           | DDS                   | A scaling factor to adjust the melt rate factors of ice and snow.  | 0.8  | 4.5  |                                  |
| Ensemble-constant parameters |                       |                                                                    |      |      |                                  |
| Regional scaling factor      | $f_{\text{regional}}$ | Adjustment applied to the EPICA temperature.                       | 0.2  | 1.1  |                                  |
| Lapse rate (regional mean)   | $LR$                  | Vertical temperature gradient                                      | -6.6 | -4.4 | $\text{K km}^{-1}$               |

## 2.7 Model-data comparison

Model performance was evaluated by comparison with known present-day glacier extents and reconstructed LGM glacier extents (Sect. 2.7.2) acquired from empirical datasets. Estimated present-day ice volume was also compared to the modelled ice volume (Sect. 2.7.3), and these metrics were combined to rank and score the simulations in each ensemble.



## 240 2.7.1 Empirical datasets

To evaluate our simulated LGM outputs, we used the new GLACIMONTIS geodatabase (Lima et al., 2025, 2026) as the empirical dataset. GLACIMONTIS integrates geomorphic-based reconstructions of maximum recorded areal extents of mountain glaciers during marine isotope stages (MIS) 3–2 (i.e., during the local LGM spanning 57–14 ka), compiled from 209 studies across 271 mountain ranges worldwide. For the model-data comparison purposes, we used the "filtered reconstructions" layer, which is a combination of different published geomorphological reconstructions of the ice extents during the local LGM. Reconstructions contributing to domains used in this study are listed in Table 3.

To ensure comparability with GLACIMONTIS, we extracted the maximum total ice extent during 57–14 ka from each full simulation. In the case of the Ruwenzori Mountains, geomorphic-based reconstructions of LGM glacier extent were not available. Instead, previous studies evaluated model performance using present-day glacier extent (Doughty et al., 2020, 2023) or through visual comparison with geomorphic features such as the Mubuku Valley moraine (Kaufmann and Romanov, 2012; Doughty et al., 2023). Consequently, we performed a model–model comparison against the simulations of Doughty et al. (2023) who developed a high-resolution model specifically tailored to the Ruwenzori Mountains, building upon earlier work by Doughty et al. (2020). Although our approach was perhaps not ideal, it followed recommendations by Zekollari et al. (2022), who suggested that, in the absence of robust geomorphic constraints, glacier dynamics and evolution can be evaluated against outputs from more complex or higher-resolution models. To ensure comparability with GLACIMONTIS, we extracted the maximum total ice extent during 57–14 ka from each full simulation. In the case of the Ruwenzori Mountains, geomorphic-based reconstructions of LGM glacier extent were not available. Instead, previous studies evaluated model performance using present-day glacier extent (Doughty et al., 2020, 2023) or through visual comparison with geomorphic features such as the Mubuku Valley moraine (Kaufmann and Romanov, 2012; Doughty et al., 2023). Consequently, we performed a model–model comparison against the glacier simulations of Doughty et al. (2023) who developed a 2D SIA flow model of high-resolution (100m) model specifically tailored to the Ruwenzori Mountains, building upon earlier work by Doughty et al. (2020). Although our approach was perhaps not ideal, it followed recommendations by Zekollari et al. (2022), who suggested that, in the absence of robust geomorphic constraints, glacier dynamics and evolution can be evaluated against outputs from more complex or higher-resolution models.

Because our paleoclimate forcing is spatially uniform within each simulation domain (i.e., EPICA DOME C-derived temperature anomalies were scaled by a fixed regional factor  $f_{\text{regional}}$ , and domain-wide precipitation factor  $P_{\text{LGM}}$ ), within-domain asynchrony in local maxima is expected to be limited. Consistent with this, a supplementary test using the pixel-wise maximum ice extent across 35–18 ka (i.e., time independent maximum ice extent) produced only minor, localised differences, with no clear improvement or degradation to assessed model performance.

For the present-day empirical dataset, we used the Randolph Glacier Inventory (RGI) 7.0 (RGI Consortium, 2023) and the (Farinotti et al., 2019) global dataset of estimated glacier ice thickness. The RGI 7.0 is a global inventory of contemporary glacier outlines derived from multiple data sources with a nominal inventory date centred around the year 2000, which we refer hereafter as 'modelled present-day'. We extracted the simulated glacier outlines of the present-day to validate against the RGI



**Table 3. Geomorphic-based glacier reconstructions used for model-data comparison at the LGM as compiled in the GLACIMONTIS geodatabase (Lima et al. 2025; 2026) with exception of Ruwenzori Mountains.**

| Mountain range         | Source                                                                                                                                                                                                                                                                                                                          |
|------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Northern Andes         | Clapperton, 1983; Stansell et al., 2007; Frenierre et al., 2011; IDEAM, 2012                                                                                                                                                                                                                                                    |
| Central Andes          | Clapperton, 1983; Klein et al., 1999; Ammann et al., 2001; Ramage et al., 2005;<br>Kull et al., 2011; Heine, 2011; Bromley et al., 2009; Emmer et al., 2021; Lee et al., 2022;<br>Mark and Seltzer, 2022; Gallardo et al., 2024                                                                                                 |
| Ethiopian Highlands    | Umer et al., 2004; Gross et al., 2021                                                                                                                                                                                                                                                                                           |
| Eastern Rift Mountains | Osmaston, 2004                                                                                                                                                                                                                                                                                                                  |
| Ruwenzori Mountains    | NA                                                                                                                                                                                                                                                                                                                              |
| Sierra Nevada          | Gillespie and Zehfuss, 2004; Walter, 2022                                                                                                                                                                                                                                                                                       |
| Greater Caucasus       | Gobejishvili et al., 2011                                                                                                                                                                                                                                                                                                       |
| Pyrenees               | Delmas et al., 2022                                                                                                                                                                                                                                                                                                             |
| European Alps          | Buoncristiani and Campy, 2004; Schlüchter, 2004; Bini et al., 2004; Castiglioni, 2004;<br>Carraro and Giardino, 2004; Van Husen, 2004; Fiebig et al., 2004; Bavec and Verbič, 2004;<br>Burkhalter and Bini, 2009; Ferk et al., 2017; Schuster et al., 2020; Serra et al., 2022;<br>Kamleitner et al., 2022; Rettig et al., 2023 |

7.0 dataset. The same approach was applied to the present-day glacier volume, which is based on the Farinotti et al. (2019) consensus estimate of ice thickness of all glaciers on Earth derived from RGI 6.0 (RGI Consortium, 2017). This practice is consistent with other glacier-modelling studies that validate present-day glacier area and volume against RGI and RGI-derived benchmark datasets (e.g., Yan et al., 2018; Wijngaard et al., 2019; Yang et al., 2025; Bonsoms et al., 2025).

### 2.7.2 Model-data comparison: glacier ice extent

We used a confusion matrix approach to compare the simulated area extent outputs of each ensemble simulation at the LGM and present-day against the empirical datasets. Before model-data comparison, ice thickness lower than 5 m was removed from the model output. Although a confusion matrix approach is not yet commonly applied for assessing model performance (e.g., Depolli et al., 2024), it is often applied in the validation of spatial products (e.g., Robbins et al., 2024; Li et al., 2025).

To quantify spatial agreement (i.e., ice-cover fit and mismatch) between the simulated and empirical glacier extents, we classified our outputs into glacier presence, absence, overestimation and underestimation (Fig. 3). Further, confusion matrix-based scores were calculated as follows to summarise spatial model-data agreement within a simulation domain at the modelled LGM and present-day:

$$\text{Confusion matrix score} = \frac{\text{CP} + \text{CA}}{\text{CP} + \text{CA} + \text{U} + \text{O}} \quad (6)$$

where CP is correct presence (i.e., both the model output and the empirical data indicate glacier presence), CA is correct absence (i.e., both the model output and the empirical data indicate glacier absence), U is underestimation (i.e., the empirical



290 data indicate ice presence but the model output does not), and O is overestimation (i.e., the model output indicates glacier presence but the empirical data do not).

The correct absence category strongly influenced the confusion matrix score as it was calculated over the entire bounding box of a simulation domain. Although relative ranking of ensemble simulations was preserved, the influence of the large bounding boxes artificially inflated the scores, often approaching 100% agreement across all simulations in the ensemble.

295 As an alternative, we developed the Critical Success Index (CSI), which excluded the correct absence from the calculation and, therefore, yielded more interpretable measures of model–data agreement:

$$\text{Critical Success Index (CSI)} = \frac{CP}{CP + U + O} \quad (7)$$

Both confusion matrix and CSI were used in the final analysis of the ensembles (see Sect. 2.7.4.) For comparison purposes and to establish a baseline of what could be considered an acceptable CSI, our model-data comparison methodology was applied to  
 300 previously published numerical glacier simulations of LGM mountain glaciers. We selected three simulated regions of varying size and location: the European Alps (Jouvet et al., 2023), Nevado de Chani in Southern Andes (Mey et al., 2020), and the Himalayas (Yan et al., 2018). These simulations served only as a general indicator of performance when compared with the CSI of the simulated glaciers during the testing and pre-calibration phases of this study.

### 2.7.3 Model-data comparison: ice volume

305 The present-day modelled simulated ice volume was compared to the empirical dataset (Farinotti et al., 2019). To assess the model-data agreement for each simulation, we calculated the absolute difference in total ice volume ( $V_{\text{diff}}$ ) between the model outputs and the empirical dataset as:

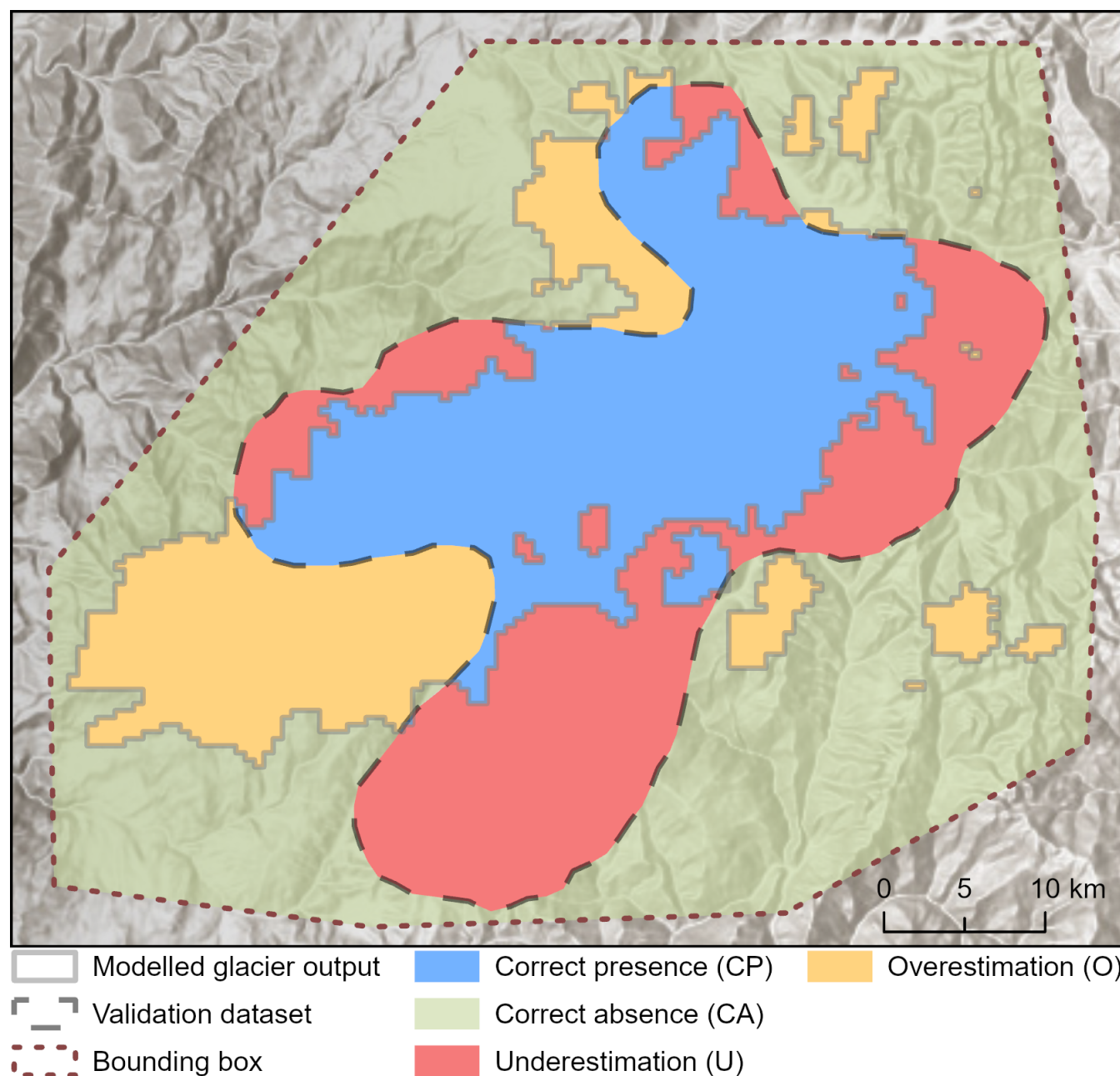
$$V_{\text{diff}} = |V_{\text{model}} - V_{\text{empirical}}| \quad (8)$$

### 2.7.4 Model-data comparison ranking

310 To assess model-data agreement of the simulation ensembles and to rank the individual simulations, we combined the three model-data comparison approaches (confusion matrix, critical success index, and volume difference). First, simulations were scored using both a confusion matrix and a critical success index for both the LGM and the present-day. This yielded four ranked (i.e., ordered) lists of simulations. Then, the volume difference at present-day was calculated, producing a fifth ranked list. The volume difference was only calculated for the present-day, since empirical data for volume at the LGM do not exist  
 315 for most of our study areas. The five ranked lists were then equally weighted to find the average rank for each simulation. For each simulation  $n$  within an ensemble, the average rank  $R_n$  is calculated as:

$$R_n = \frac{r_1 + r_2 + r_3 + r_4 + r_5}{5} \quad (9)$$

where  $r_1$  is the rank of the confusion matrix score at the LGM,  $r_2$  is the rank of the confusion matrix score at the modelled present-day,  $r_3$  is the CSI at the LGM,  $r_4$  is the rank of the CSI at the modelled present-day, and  $r_5$  is the rank associated with



**Figure 3. Spatial application of the confusion matrix to validate a simulated area in the Ecuadorian Cordilleras (Northern Andes).** In this schematic example, correct presence (CP), correct absence (CA), underestimation (U) and overestimation (O) are mapped by comparing the glacier simulated area to the geomorphic reconstructed glacier of Clapperton (1983), acquired from the GLACIMONTIS geodatabase (Lima et al., 2025, 2026)





the volume comparison for the present-day. The value of  $R_n$  is only used to order the list of simulations in a new final ranked list; this way each simulation number  $n$  was assigned a rank (1–27, or higher) where rank 1 is the best fit simulation. The final averaged lists for parameter ranges for each domain are given in Table A2.

## 2.8 Simulation evaluation and ice-cover frequency

Multiple parameter and forcing combinations can produce similarly plausible glacier configurations. Therefore, our model evaluation yielded a set rather than a single best-fit simulation. To define an optimised subset for each domain, we retained the eight top-performing simulations from each ensemble of typically 27+ simulations. Within this optimised subset, ice cover frequency at a given grid cell is the proportion of those eight members that simulate ice presence at that grid cell. We then calculated the 25th, 50th, and 75th percentiles to visualise the interquartile range (IQR) of glacier extent and sensitivity to choice of model setup, thus distinguishing areas of robust agreement ( $\geq 75\%$ ) from areas where glacier presence occurred only under specific combinations of climate and ice-dynamic parameters ( $\leq 25\%$ ). The intermediate range ( $>25\%$ – $<75\%$ ) indicates regions where glacier presence was inconsistent across acceptable model setups.

## 2.9 Benchmark model-data comparison

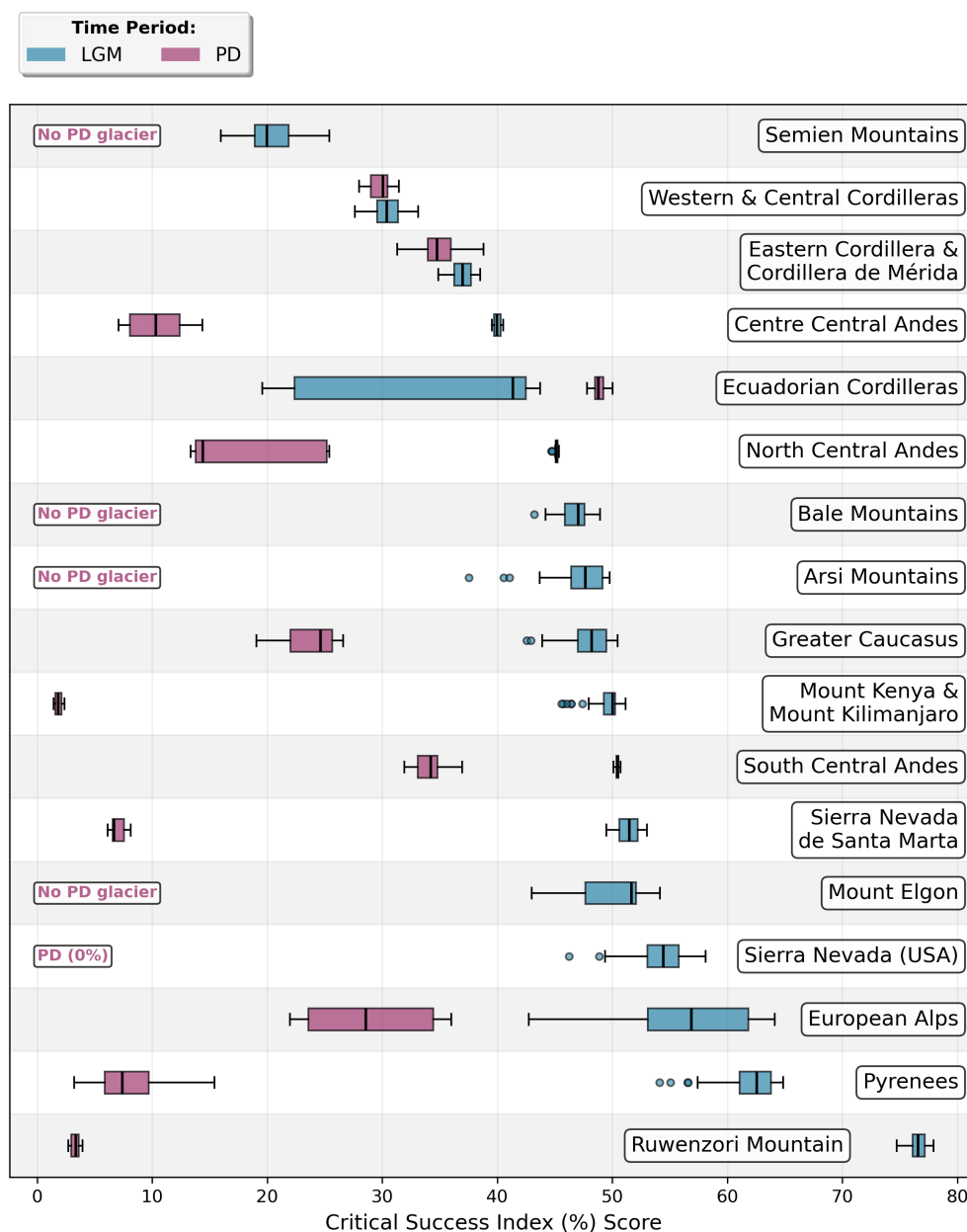
We applied CSI as a reference for comparing model performance of our work to other models. The three benchmark regions were: European Alps, Nevado de Chani in Southern Andes (Mey et al., 2020), and the Himalayas (Yan et al., 2018).

# 3 Results

## 3.1 Critical Success Index (CSI) at the LGM and present-day

Our assessment for model-data agreement in glacier ice extent (i.e., CSI) varied substantially among domains (spatial variability) and between timesteps, i.e. the LGM and present-day (temporal variability). The variability of ensemble scores can be seen in Figure 4, where the CSI is plotted from all 27+ simulations of each ensemble. Present-day CSIs were generally lower than LGM scores in almost all regions where present-day glaciers exist, with the exception of the Ecuadorian Cordilleras and the top-ranked simulations in the Eastern Cordillera & Cordillera de Mérida (Fig. 4). Mean simulation accuracy, quantified by the CSI, was 48% for the LGM and 21% for the present-day (PD) across all domains. Glacier size alone did not explain performance: both small-glacier domains (e.g., Ruwenzori Mountains and Semien Mountains) and large-glacier domains (e.g., European Alps and the Central Andes) included high- and low-scoring simulations. In domains without present-day glaciers (Semien Mountains, Bale Mountains, Arsi Mountains and Mount Elgon), CSI were 100% when glacier absence was correctly simulated.

The highest LGM CSI was obtained in the Ruwenzori Mountains (77%), whereas the lowest was obtained in the Semien Mountains (25%). Nine domains achieved LGM CSI above 50% (i.e., strong model-data agreement), and three domains scored



**Figure 4. Critical Success Index (CSI) for the Last Glacial Maximum (LGM; blue) and present-day (PD; pink), indicating overlap (in ice extent) between the simulation ensemble and the empirical data.** Box plot shows median as a line, interquartile range as boxes, and min–max scores as whiskers for the full set of simulations (27+ simulations) within each ensemble. Some domains have no present-day glaciers and therefore receive a score of 100% when the ensemble correctly simulates glacier absence; these cases are labelled 'No PD glacier'. In contrast, Sierra Nevada (USA) has small present-day glaciers that were not simulated by the ensemble, yielding a CSI of 0%. Simulation domains are vertically ordered by median LGM score.



below 40% (i.e., weak model-data agreement). Another five domains achieved CSI below 50% but above 40%, yielding moderate model-data agreement.

In our benchmark model-data comparison, we applied CSI as a reference for comparing model performance of our work to other models. The CSI for the three benchmark regions were: 72% for the European Alps (Jouvet et al., 2023), 35% for Nevado de Chani in Southern Andes (Mey et al., 2020), and 43% for the Himalayas (Yan et al., 2018). The overall average LGM CSI of simulations in our study (48%) was consistent with benchmark model-data comparison (Yan et al., 2018) and (Mey et al., 2020)), but was lower than benchmark results reported for the European Alps ((Jouvet and Cordonnier, 2023)).

Among domains with present-day glaciers, CSI remained below 50%. Ensemble score variability was higher than at the LGM in the Pyrenees, South Central Andes, Greater Caucasus, North Central Andes, Centre Central Andes, and Eastern Cordillera & Cordillera de Mérida. In contrast, in the Ruwenzori Mountains, Ecuadorian Cordilleras, and Western & Central Cordilleras, the LGM showed higher ensemble score variability.

The best-fit simulation for each domain (i.e., defined as the single simulation with the highest combined performance across LGM and PD; see Table 4) showed a different distribution of CSI than the full ensemble. Although fifteen best-fit simulations still achieved LGM CSI above 40%, only six exceeded 50%, compared to nine domains exceeding LGM CSI of 50% when considering all simulations in the ensembles. In several domains, the simulation that best matched the LGM did not coincide with the simulation that best matched the present day. For example, in the Pyrenees the best-ensemble PD CSI was ~15%, whereas the best-fit simulation selected across both time steps yielded a PD CSI of 8% (Table 4).



**Table 4. Overview of CSI for simulation ensembles for each domain, with the number of completed individual simulations, and the best-ranked simulation results in percentage for the two time steps; Last Glacial Maximum (LGM) and present-day (PD). The percentages of overestimation ( $O$ ), underestimation ( $U$ ) and correct presence ( $CP$ ) are calculated relative to the sum of the three categories, e.g., overestimation =  $O/(O + U + CP)$ . Correct absence ( $CA$ ) is calculated relative to the total ( $O + U + CP + CA$ ). Each score is taken from the overall highest-ranked simulation of the ensemble, considering all model-data comparison methods for both LGM and PD. This means, for example, that there could be individual ensemble simulations with a higher LGM score than shown here.**

|      | Domain                                       | Simulation<br>(#) | Time<br>step | CSI<br>(%) | Confusion<br>Matrix (%) | Over-<br>estimation<br>(%) | Under-<br>estimation<br>(%) | Correct<br>presence<br>(%) | Correct absence<br>( $\frac{CA}{O+U+CP+CA}$ ) |
|------|----------------------------------------------|-------------------|--------------|------------|-------------------------|----------------------------|-----------------------------|----------------------------|-----------------------------------------------|
| (1)  | Sierra Nevada<br>de Santa Marta              | 27                | LGM          | 49.48      | 95.20                   | 11.08                      | 39.44                       | 49.48                      | 90.50                                         |
|      |                                              |                   | PD           | 8.13       | 99.28                   | 90.50                      | 0.35                        | 8.13                       | 99.22                                         |
| (2)  | Eastern Cordillera &<br>Cordillera de Mérida | 27                | LGM          | 37.96      | 93.82                   | 47.30                      | 14.74                       | 37.96                      | 90.04                                         |
|      |                                              |                   | PD           | 38.11      | 99.99                   | 41.02                      | 20.88                       | 38.11                      | 99.98                                         |
| (3)  | Western &<br>Central Cordilleras             | 27                | LGM          | 29.29      | 94.50                   | 23.65                      | 47.06                       | 29.29                      | 92.23                                         |
|      |                                              |                   | PD           | 31.44      | 99.99                   | 27.19                      | 41.37                       | 31.44                      | 99.98                                         |
| (4)  | Ecuadorian<br>Cordilleras                    | 27                | LGM          | 41.82      | 94.11                   | 24.48                      | 33.70                       | 41.82                      | 89.89                                         |
|      |                                              |                   | PD           | 49.35      | 99.95                   | 15.72                      | 34.93                       | 49.35                      | 99.90                                         |
| (5)  | North Central<br>Andes                       | 27                | LGM          | 45.27      | 89.06                   | 30.59                      | 24.14                       | 45.27                      | 80.02                                         |
|      |                                              |                   | PD           | 25.22      | 99.55                   | 37.80                      | 36.98                       | 25.22                      | 99.41                                         |
| (6)  | Centre Central<br>Andes                      | 36                | LGM          | 40.45      | 84.37                   | 38.66                      | 20.89                       | 40.45                      | 73.76                                         |
|      |                                              |                   | PD           | 14.36      | 98.39                   | 80.54                      | 5.10                        | 14.36                      | 98.12                                         |
| (7)  | South Central<br>Andes                       | 27                | LGM          | 50.55      | 93.33                   | 25.94                      | 23.50                       | 50.56                      | 86.52                                         |
|      |                                              |                   | PD           | 36.95      | 98.92                   | 52.34                      | 10.71                       | 36.95                      | 98.29                                         |
| (8)  | Semien<br>Mountains                          | 27                | LGM          | 24.75      | 99.89                   | 49.70                      | 25.54                       | 24.76                      | 99.86                                         |
|      |                                              |                   | PD           | 100.00     | 100.00                  | 0.00                       | 0.00                        | 0.00                       | 100.00                                        |
| (9)  | Bale<br>Mountains                            | 45                | LGM          | 48.94      | 91.17                   | 37.68                      | 13.38                       | 48.94                      | 82.71                                         |
|      |                                              |                   | PD           | 100.00     | 100.00                  | 0.00                       | 0.00                        | 100.00                     | 100.00                                        |
| (10) | Arsi<br>Mountains                            | 27                | LGM          | 49.10      | 90.15                   | 31.29                      | 19.60                       | 49.10                      | 80.65                                         |
|      |                                              |                   | PD           | 100.00     | 100.00                  | 0.00                       | 0.00                        | 100.00                     | 100.00                                        |
| (11) | Mount Elgon                                  | 27                | LGM          | 46.81      | 98.93                   | 22.77                      | 30.42                       | 46.81                      | 97.99                                         |
|      |                                              |                   | PD           | 100.00     | 100.00                  | 0.00                       | 0.00                        | 0.00                       | 100.00                                        |
| (12) | Mount Kenya &<br>Mount Kilimanjaro           | 108               | LGM          | 50.51      | 96.57                   | 42.05                      | 9.84                        | 48.11                      | 91.84                                         |
|      |                                              |                   | PD           | 1.66       | 99.77                   | 97.44                      | 0.49                        | 2.07                       | 99.81                                         |
| (13) | Ruwenzori<br>Mountain                        | 54                | LGM          | 77.03      | 98.96                   | 11.21                      | 11.77                       | 77.03                      | 95.48                                         |
|      |                                              |                   | PD           | 3.71       | 99.70                   | 96.15                      | 0.14                        | 3.71                       | 99.69                                         |
| (14) | Sierra Nevada<br>(USA)                       | 27                | LGM          | 56.59      | 90.29                   | 19.34                      | 24.07                       | 56.59                      | 77.64                                         |
|      |                                              |                   | PD           | 0.00       | 99.96                   | 0.00                       | 100.00                      | 0.00                       | 99.96                                         |



Table 4 continued

|      | Location            | Simulation<br>(#) | Time step | CSI<br>(%) | Confusion<br>Matrix (%) | Over-<br>estimation<br>(%) | Under-<br>estimation<br>(%) | Correct<br>presence<br>(%) | Correct absence<br>$(\frac{CA}{O+U+CP+CA})$ |
|------|---------------------|-------------------|-----------|------------|-------------------------|----------------------------|-----------------------------|----------------------------|---------------------------------------------|
| (15) | Greater<br>Caucasus | 60                | LGM       | 48.88      | 94.20                   | 28.87                      | 22.25                       | 48.88                      | 88.64                                       |
|      |                     |                   | PD        | 26.61      | 98.48                   | 57.15                      | 16.24                       | 26.61                      | 97.92                                       |
| (16) | Pyrenees            | 81                | LGM       | 64.83      | 93.28                   | 22.16                      | 13.01                       | 64.83                      | 80.90                                       |
|      |                     |                   | PD        | 8.16       | 99.99                   | 18.97                      | 72.86                       | 8.16                       | 99.99                                       |
| (17) | European Alps       | 53                | LGM       | 64.12      | 80.10                   | 20.26                      | 15.62                       | 64.12                      | 44.29                                       |
|      |                     |                   | PD        | 30.10      | 98.58                   | 64.83                      | 5.06                        | 30.10                      | 97.97                                       |

Ice overestimation was predominant in most present-day glacier simulations, except in Sierra Nevada (USA), the Western and Central Cordilleras, and the Pyrenees. At the LGM, patterns were more balanced: some domains showed higher underestimation (e.g., Sierra Nevada de Santa Marta, Ecuadorian Cordilleras, Sierra Nevada (USA), Western and Central Cordilleras), others showed higher overestimation (e.g., Pyrenees, European Alps, Greater Caucasus, Arsi Mountains), while many domains showed moderate contributions from both (e.g., Ruwenzori Mountains, Sierra Nevada (USA), South Central Andes).

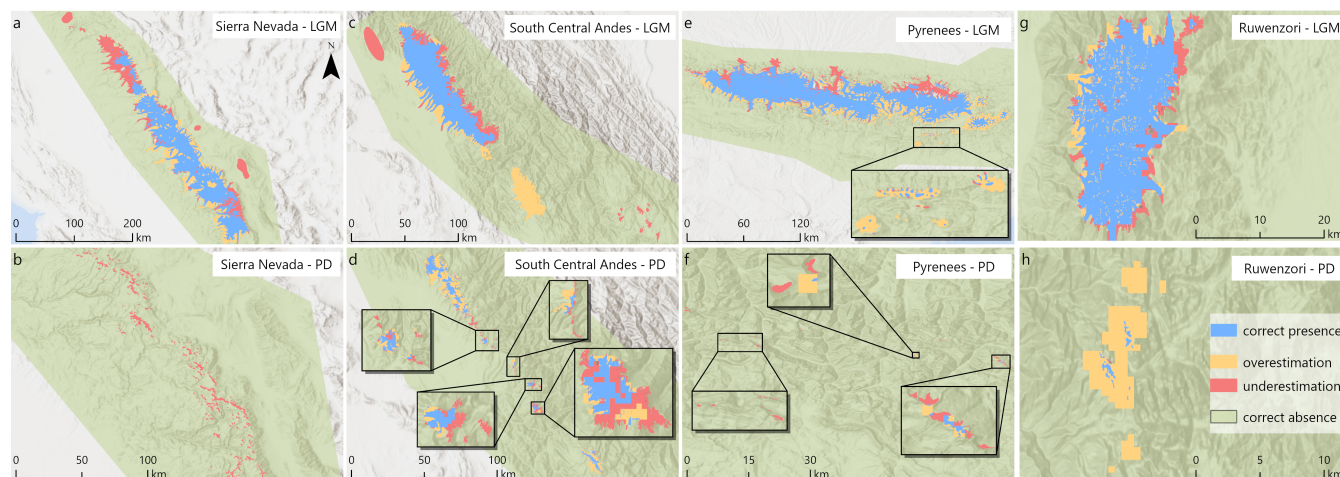
3.2 Spatial patterns of over- and underestimation in glacier ice extent at the LGM and present-day

Given the large number of study areas, we focused here on four representative domains (one per continent) to present model performance and transient glacier evolution: the Pyrenees, the Ruwenzori Mountains, the South Central Andes, and the Sierra Nevada (USA). These domains differed in climatic forcing, topographic setting, glacier geometry, and data availability. As CSI reflects the spatial overlap between modelled and empirical ice extent at each time step, to diagnose why a given simulation achieved a low or high CSI, we decomposed model-data agreement into overestimation, underestimation, correct presence, and correct absence (Fig. 5). Results from the other simulation domains are shown in Supplementary Figures S14 – S18.

In the Sierra Nevada (USA), even though correct presence accounted for 56% of the empirical data ice extent (10,942 km<sup>2</sup>) at the LGM, we also observed substantial underestimation at both the LGM and the present-day (Fig. 5a–b), corresponding to 24% (~4,628 km<sup>2</sup>) and 100% (~35 km<sup>2</sup>), respectively. At the LGM, over- and underestimation showed strong spatial pattern: most overestimation (19%, ~3,735 km<sup>2</sup>) occurred in the southern ice field, while underestimation was concentrated in the northern ice field and in scattered ice caps.

In the Pyrenees, underestimation was concentrated on the northern slopes (13%, ~1,388 km<sup>2</sup>) at the LGM, whereas overestimation was concentrated on the southern slopes (~2,363 km<sup>2</sup>; Fig. 5e). In addition, scattered valley glaciers and small ice caps were dominated by overestimation, in contrast to the Sierra Nevada (USA). Present-day glaciers in the Pyrenees (Fig. 5f) covered only ~3 km<sup>2</sup>, and most of this area was underestimated (~2 km<sup>2</sup>), similar to the Sierra Nevada (USA).

The South Central Andes and the Ruwenzori Mountains showed broadly similar error partitioning, but with a west–east asymmetry. In the South Central Andes at the LGM, correct presence accounted for 51% (~2,763 km<sup>2</sup>; Fig. 5c). Underesti-



**Figure 5. Spatial representation of the confusion matrix results (glacier overestimation, underestimation, correct presence and correct absence) of the best-fit simulation for the simulation domains of Sierra Nevada (USA), South Central Andes, Pyrenees and Ruwenzori Mountains at the Last Glacial Maximum (LGM, panels a,c,e,g) and present-day (PD, panels b,d,f,h).** The top row showcases the confusion matrix at the LGM, while the bottom row showcases the confusion matrix at the present-day. For the Sierra Nevada (USA) at the present-day (b) the glacier size is exaggerated by an outline with 1 pt width for visualisation purposes.

mation dominated on the eastern slopes and in isolated ice caps and valley glaciers (24%, 1,284 km<sup>2</sup>), whereas overestimation dominated on the western slopes (26%, 1,410 km<sup>2</sup>). We observe a large LGM glacier (757 km<sup>2</sup>) simulated in an area that has glaciers in the present-day empirical dataset (Fig. 5d), but has not been reconstructed according to the GLACIMONTIS geodatabase (Lima et al., 2025, 2026), very likely suggesting a false absence of glaciers in the geodatabase. At the present-day, overestimation dominated (53%, 365 km<sup>2</sup>), with some exceptions of underestimation in smaller, fragmented glacier areas.

In the Ruwenzori Mountains (Fig. 5g–h), overestimation was concentrated on the western slopes (11%, 47 km<sup>2</sup>), whereas underestimation was concentrated on the eastern slopes (12%, 50 km<sup>2</sup>), with a correctly simulated total glacier area of ~327 km<sup>2</sup> (77%) at the LGM. At the present-day, overestimation was dominant (96%, 28 km<sup>2</sup>).

### 3.3 Transient glacier evolution and parameter sensitivity

The magnitude and rate of glacier response to climate variability differed among mountain ranges. Several relatively warm phases occurred since the Last Interglacial and were generally associated with reduced glacier extent and volume prior to 80 ka and after 18 ka. See *Video Supplement* for animations of the glacier evolution for all mountain ranges Barndon et al. (2026a).

In the Semien Mountains, Mount Elgon, Greater Caucasus, and Sierra Nevada (USA), 30% of the modelled glaciated area was sensitive to parameter choices (i.e., ice cover frequency was below 75% in the top-ranked eight simulations). Meanwhile, in the Bale Mountains, Ruwenzori Mountains, European Alps, the Pyrenees, Centre Central Andes, Eastern Cordillera & Cordillera de Mérida, North Central Andes, Sierra Nevada de Santa Marta and South Central Andes, less than 20% of the modelled domain was sensitive to parameter choices. Below, we focus on four example domains (Sierra Nevada (USA), South





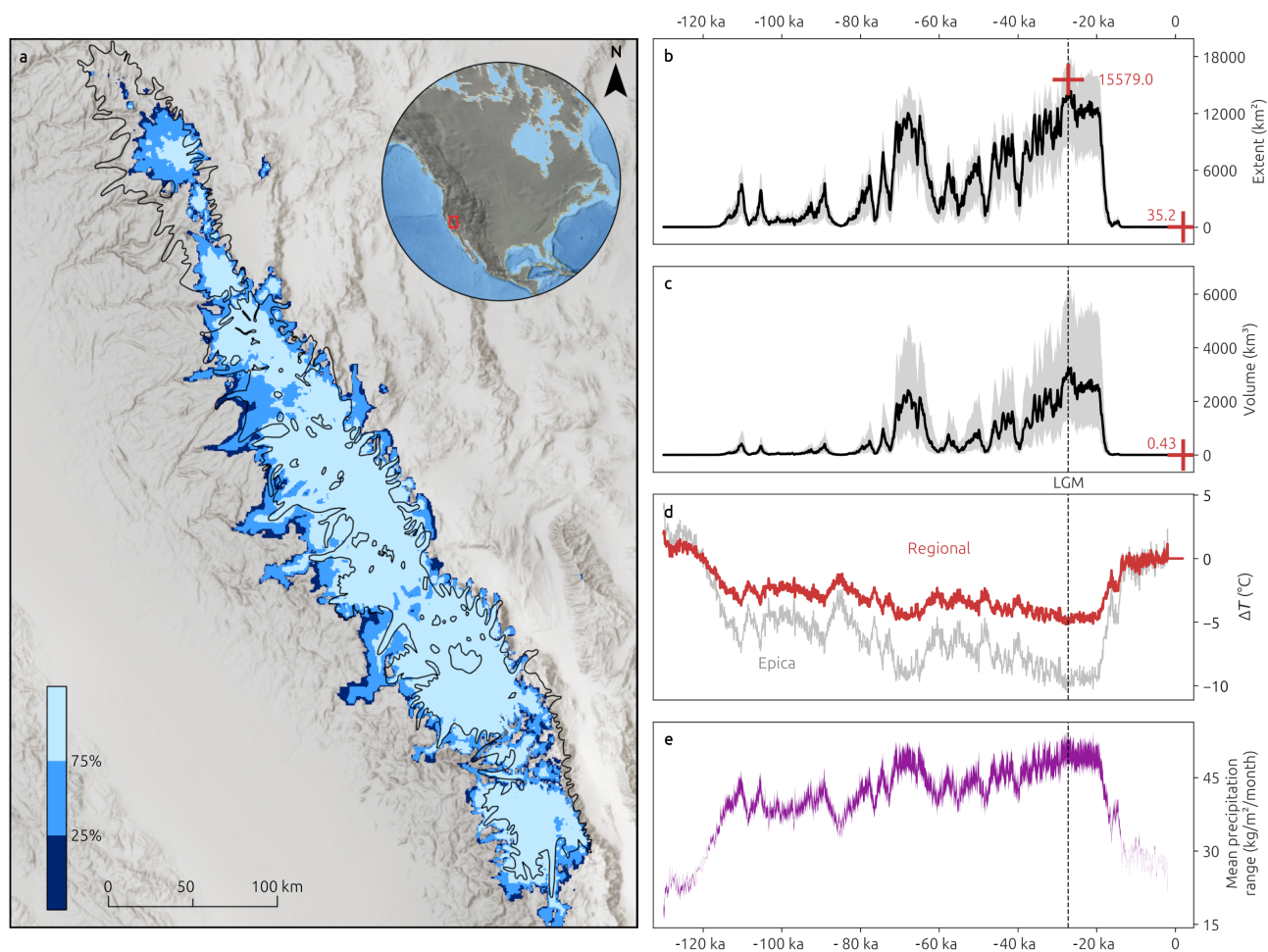
Central Andes, Pyrenees and Ruwenzori Mountains) while the full parameter-calibration sensitivity for all domains is found in Supplementary Table S3.

410 The Sierra Nevada (USA) was among the most parameter-sensitive domains, with both extent and volume varying markedly across the ensemble (Fig. 6b–c). It was also highly responsive to climate variability, with glacier extent and volume reaching very low levels at 108, 103, 97, 85, and 16 ka. Only 62% ( $\sim 14,742 \text{ km}^2$ ) of glacier extent was robust to parameter calibration (light blue; Fig. 6a). Parameter-sensitive glacier extent comprised  $9,039 \text{ km}^2$ , including  $2,836 \text{ km}^2$  (12%) that was highly sensitive to parameter choices, and  $11,906 \text{ km}^2$  (26%) that showed moderate sensitivity to parameter choice (Fig. 6a).  
 415 Parameter-calibration sensitivity was stronger on the western than on the eastern side. The southernmost area exhibited comparatively lower parameter sensitivity on both the western and eastern slopes. In this simulation domain, parameter sensitivity played a key role in accurately simulating not valley-glacier extent, but not the ice-field configuration.

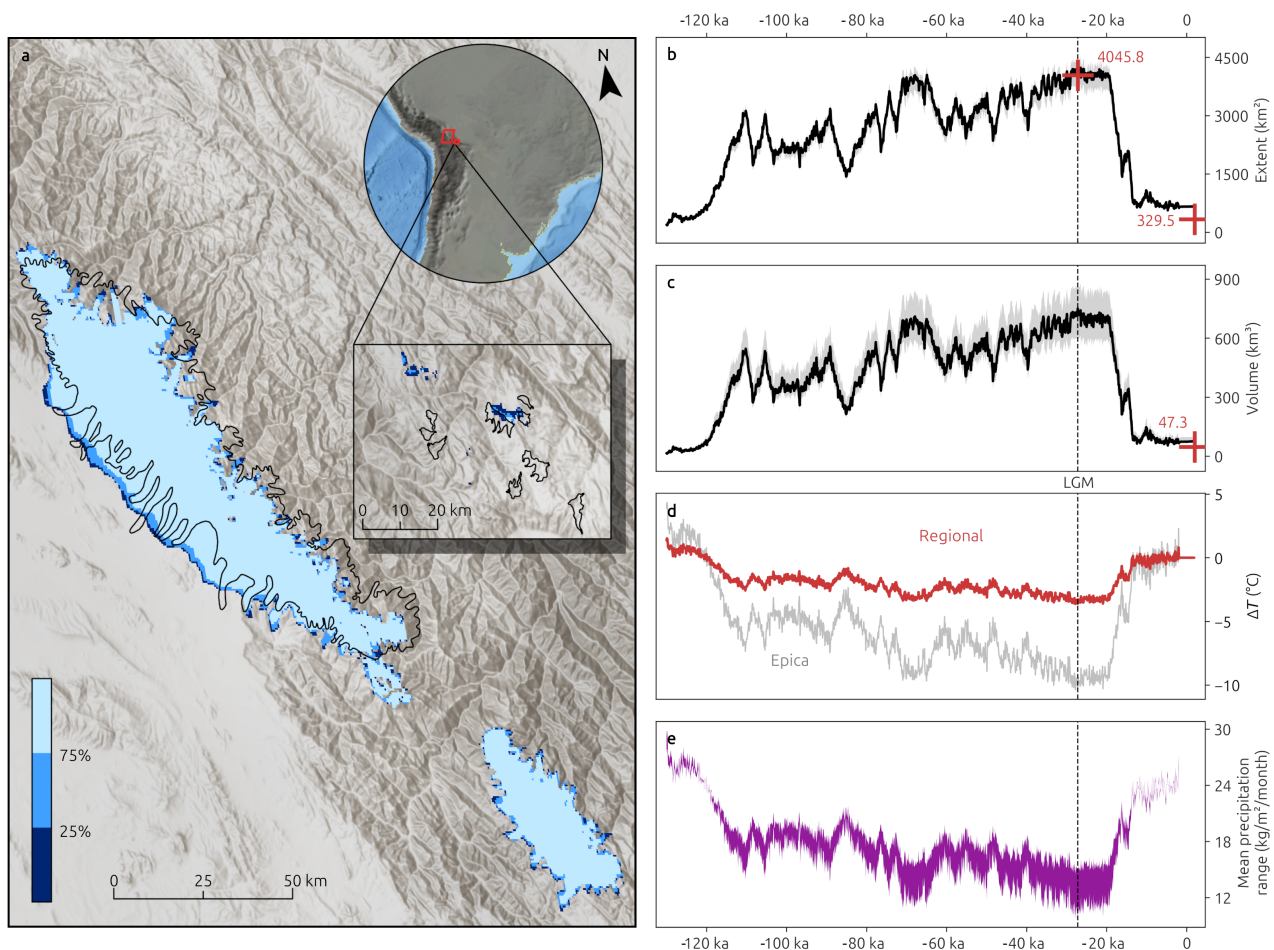
The South Central Andes showed limited variation in simulated glacier extent across the ensemble, with 86% ( $685 \text{ km}^2$ ; light blue) of its total area being represented in at least 75% of the eight highest-ranking simulations. Parameter-calibration  
 420 sensitivity is more pronounced in the west and in the small scattered valley glaciers (Fig. 7a), represented by a small area of moderate parameter-calibration sensitivity (blue;  $419 \text{ km}^2$  and 9% of total glaciated area), and even smaller area of high parameter-calibration sensitivity (dark blue;  $262 \text{ km}^2$  and 6% of total glaciated area). In this domain, there was no clear influence of parameter-calibration on modelling valley glaciers from the larger ice fields. Moreover, glaciation persisted since the last interglacial. Even though the regional temperature remained relatively stable, there were several minor melting events,  
 425 but the glacier extent prior to the Holocene did not reach the present-day extent.

In the Pyrenees, glacier extent showed moderate parameter sensitivity even though areas of low parameter-calibration sensitivity accounted for 84% (light blue,  $11,201 \text{ km}^2$ ) of total glaciated area (Fig. 8a). In contrast, most of the parameter-driven variability influenced the shape, extent and spatial distribution of valley glaciers (i.e., valley-glacier geometry; blue and dark blue; 16% of total glaciated area). Thus, no clear spatial pattern in parameter sensitivity was observed. Moreover, parameter-  
 430 calibration sensitivity in glacier extent appeared to be pronounced around the LGM (Fig. 8b), while the ice volume showed parameter-calibration sensitivity beyond the LGM, e.g. in MIS 4 (Fig. 8c). The interstadials are less sensitive to parameter choices with respect to both ice extent and volume. During the Last Glacial Cycle, our models suggest that the Pyrenees experienced near-complete deglaciation at least four times (roughly at 108 ka, 97 ka, 85 ka, and 16 ka), reaching extents and volumes comparable to present-day conditions. Present-day extents have remained similar since 13 ka. LGM conditions were  
 435 sustained for a short interval of 3 kyr, before the start of deglaciation.

Finally, in the Ruwenzori Mountains, glacier extent varied little in the top-ranked simulations. A total of 88% ( $348 \text{ km}^2$ ) of the total glaciated area had low sensitivity to parameter-calibration (light blue; Fig. 9a), and only 22% ( $50 \text{ km}^2$ ) of the total glaciated area was highly sensitive to parameter-calibration (blue and dark blue). Although the ice extent was highly insensitive to parameter-calibration (Fig. 9b), ice volume showed higher sensitivity (Fig. 9c), not only during stadials, but also  
 440 during interstadials. Since the Last Interglacial, the Ruwenzori Mountains simulations remained persistently glaciated, with relatively muted interstadial reductions that did not approach present-day ice-free conditions. The LGM ice conditions were prolonged, with relatively stable ice conditions for  $\sim 10 \text{ kyr}$ .

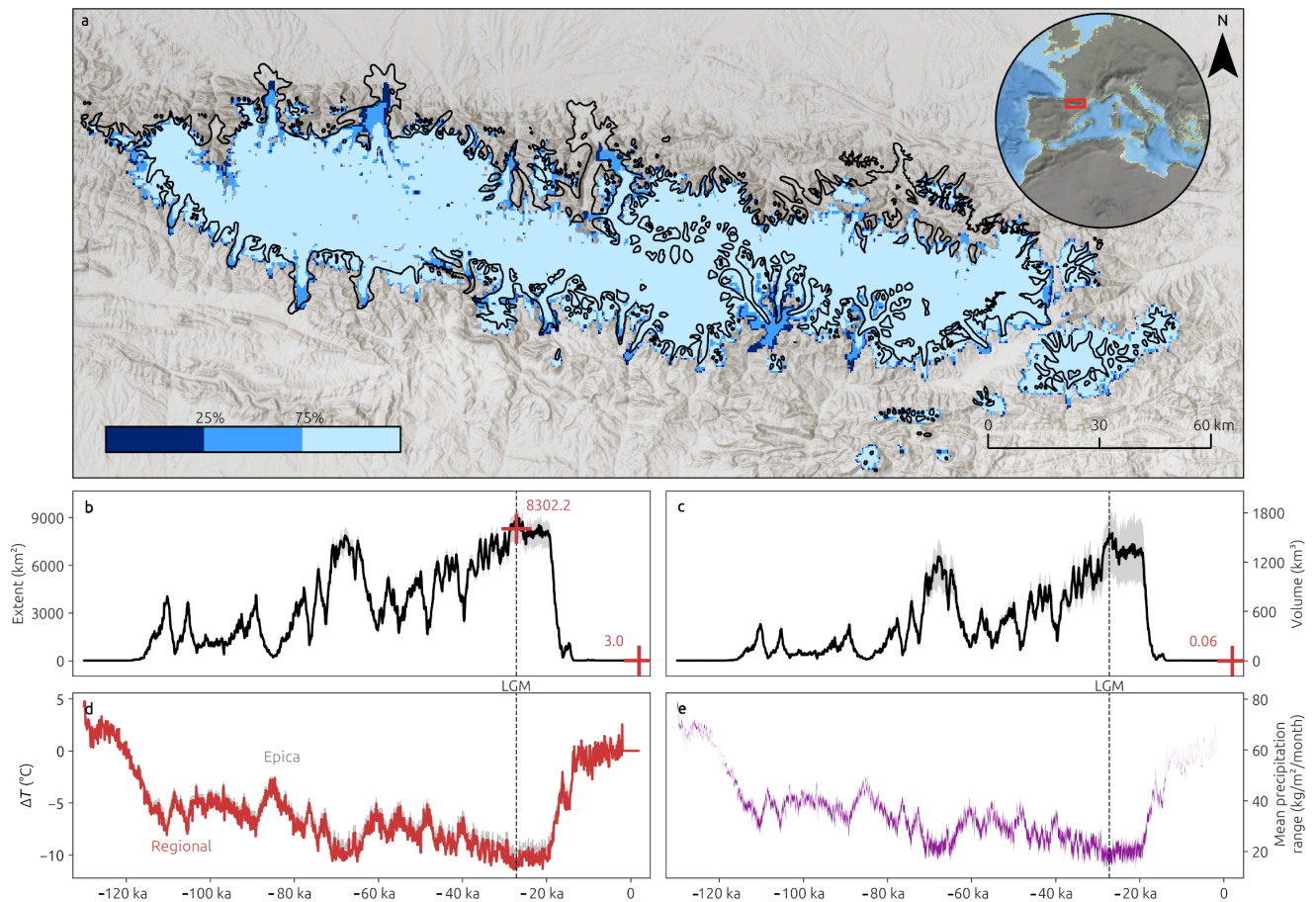


**Figure 6. Simulated LGM extent frequency of the Sierra Nevada (USA) mountain range using the top-ranked eight simulations from the ensemble.** Panel a shows the frequency map of simulated extents and the empirical glacier extent (GLACIMONTIS: Lima et al. (2025, 2026)) as a black line. Of the 8 best ranked simulations, the coloured ranges indicates the ice extent that cover  $> 0$  to  $\leq 25\%$  (2 simulations),  $> 25$  to  $< 75\%$  (exclusive, 4 simulations),  $\geq 75$  to  $100\%$  (2 simulations). Panels b–e show simulation and climate parameters for the full simulation period (130 ka to present-day). In panel b and c the median extent and volume are shown as black lines, while the range based on the rest of the top-ranked eight simulations is shown in grey. The red crosses display the empirical data points used for comparison. In panel d "Regional" temperature is from Eq. 1 and the EPICA curve is the original temperature ( $\Delta T_{\text{EPICA}}$ ). In panel e, the mean precipitation within the simulation domain is shown as a range (solid purple) based on the minimum and maximum precipitation adjustment parameters ( $P_{\text{LGM}}$ ) in the ensemble, here 1.8 and 2.1, respectively.

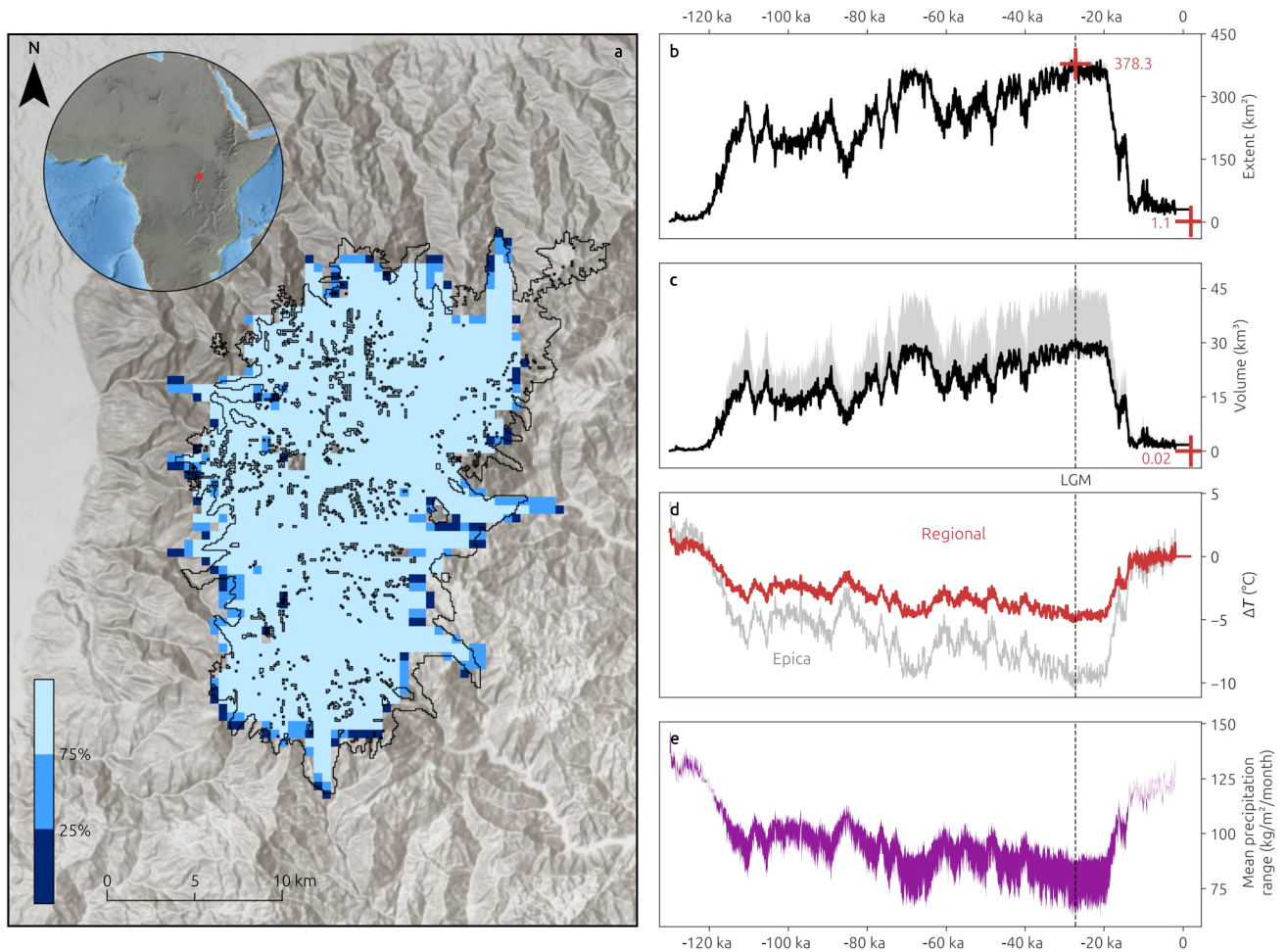


**Figure 7. Frequency of simulated LGM ice extent of the South Central Andes using the top-ranked eight simulations from the ensemble.** Panel **a** shows the frequency map of simulated extents and the empirical glacier extent (GLACIMONTIS: Lima et al. (2025, 2026)) as a black line. Of the eight best ranked simulations, the coloured ranges indicates the ice extent that cover  $> 0$  to  $\leq 25\%$  (2 simulations),  $> 25$  to  $< 75\%$  (4 simulations),  $\geq 75$  to  $100\%$  (2 simulations). Panels **b–e** show simulation and climate parameters for the full simulation period (130 ka to present-day). In panel **b** and **c** the median extent and volume are shown as black lines, while the range based on the rest of the top-ranked eight simulations is shown in grey. The red crosses display the empirical data points used for comparison. In panel **d** "Regional" temperature is from Eq. 1 and the EPICA curve is the original temperature ( $\Delta T_{\text{EPICA}}$ ). In panel **e**, the mean precipitation within the simulation domain is shown as a range (solid purple) based on the minimum and maximum precipitation adjustment parameters ( $P_{\text{LGM}}$ ) in the ensemble, here 0.4 and 0.6, respectively.





**Figure 8. Frequency of simulated LGM ice extent of the Pyrenees mountain range using the top-ranked eight simulations from the ensemble.** Panel **a** shows the frequency map of simulated extents and the empirical glacier extent (GLACIMONTIS: Lima et al. (2025, 2026)) as a black line. Of the eight best ranked simulations, the coloured ranges indicate the ice extent that cover  $> 0$  to  $\leq 25\%$  (2 simulations),  $> 25$  to  $< 75\%$  (4 simulations),  $\geq 75$  to  $100\%$  (2 simulations). Panels **b–e** show simulation and climate parameters for the full simulation period (130 ka to present-day). In panel **b** and **c** the median extent and volume are shown as a black lines, while the range based on the rest of the top-ranked eight simulations is shown in grey. The red crosses display the empirical data points used for comparison. In panel **d** "Regional" temperature is  $T$  from Eq. 1, while the EPICA curve is the original temperature ( $\Delta T_{\text{EPICA}}$ ). In panel **e**, the mean precipitation within the simulation domain is shown as a range (solid purple) based on the minimum and maximum precipitation adjustment parameter ( $P_{\text{LGM}}$ ) in the ensemble, here 1.8 and 2.1, respectively.



**Figure 9. Frequency of simulated LGM ice extent of the Ruwenzori Mountains using the top-ranked eight simulations from the ensemble.** Panel **a** shows the frequency map of simulated extents and the empirical glacier extent (GLACIMONTIS: Lima et al. (2025, 2026)) as a black line. Of the eight best ranked simulations, the coloured ranges indicate the ice extent that covers  $> 0$  to  $\leq 25\%$  (2 simulations),  $> 25$  to  $< 75\%$  (4 simulations),  $\geq 75$  to  $100\%$  (2 simulations). Panels **b–e** show simulation and climate parameters for the full simulation period (130 ka to present-day). In panel **b** and **c** the median extent and volume are shown as a black lines, while the range based on the rest of the top-ranked eight simulations is shown in grey. The red crosses display the empirical data points used for comparison. In panel **d** "Regional" temperature is  $T$  from Eq. 1 and the EPICA curve is the original temperature ( $\Delta T_{\text{EPICA}}$ ). In panel **e**, the mean precipitation within the simulation domain is shown as a range (solid purple) based on the minimum and maximum precipitation adjustment parameter ( $P_{\text{LGM}}$ ) in the ensemble, here here 0.5 and 0.7, respectively.



## 4 Discussion

In this paper, we focus on IGM performance and model-data comparison approaches, and broader challenges of modelling mountain glaciers across varying ranges and long time scales. Across simulation domains, we found that each mountain range expresses a distinct "glacier fingerprint": a characteristic combination of topographic confinement, glacier geometry, and climatic gradients that governed how glaciers built up, connected, and retreated through time. These fingerprints shaped not only glacier evolution, but also where and when model–data agreement was high or low, and which sources of uncertainty dominated (forcing, parameterisation, resolution, or empirical data constraints). Rather than expecting a single set of modelling choices to perform uniformly across regions, our results highlighted how range-specific spatial structure and climate heterogeneity interacted with model resolution and calibration to produce systematic, interpretable patterns of mismatch.

Here, we first discuss the cross-domain controls on performance, focusing on how glacier configuration (continuous glacier vs fragmented glaciers), glacier size (large vs small ice bodies) and time slice (LGM vs present-day) influenced CSI-based agreement. We then discuss the example domains covered in our Results section (Sect. 4.1) to illustrate how these general patterns manifested in contrasting mountains and to identify which parameters most strongly influenced ensemble variation. Then, we discuss broader challenges of paleoglacier modelling in mountains worldwide over orbital time-scales (Sect. 4.3), and evaluate limitations and practical implications of our IGM parametrisation and selected modules (Sect. 4.4). Lastly, we finally consider what our evaluation framework reveals about uncertainty and transferability across mountain ranges (Sect. 4.5).

### 4.1 Spatial configurations and climate heterogeneity

Model–data agreement varied systematically with both glacier geometry and the scale at which glaciers were resolved. Across domains, CSI was generally lower where glaciers were small and spatially fragmented (e.g., Semien Mountains), whereas domains dominated by more continuous ice fields or larger ice caps tended to yield higher agreement (e.g., European Alps; Ruwenzori Mountains at the LGM). In fragmented settings, many glaciers occupied only one or a few grid cells at 500 m resolution, so even modest positional offsets between modelled and reconstructed margins translated into disproportionately large losses of spatial overlap and therefore low CSI.

A second control is internal climate heterogeneity within large mountain systems, which can limit the transferability of a single forcing and parameter set across an entire range. In extended ranges spanning strong along-mountain gradients (e.g., Central Andes), domain partitioning, expanded parameter ranges, and careful bounding-box design became important modelling decisions: parameter values that improved fit in one sector could generate systematic over- or underestimation elsewhere. Together, these results suggested that robust transient modelling for contrasting mountain ranges is feasible, but that the main determinants of model performance are (i) the match between glacier size and model resolution, (ii) the representativeness of climate forcing across mountains with internal climate gradients, and (iii) the degree to which empirical datasets are available to constrain parameters in each region and period.





Temporal patterns largely reflected these same geometric controls. Agreement was typically higher during the LGM, when glaciers formed more spatially coherent ice fields and occupied more grid cells, than during the present-day, when glaciers are smaller and more fragmented. At the same time, LGM reconstructions exposed stronger sensitivity in the relative expression of valley glaciers versus ice fields and in total ice volume, highlighting that higher spatial agreement did not necessarily imply lower parameter uncertainty.

## 4.2 Regional examples: contrasting controls on model–data agreement

To illustrate how the cross-domain controls identified above manifested in practice, we discuss the set of example simulation domains highlighted in the Results. For each domain, we summarise (i) the dominant spatial mismatch patterns at the LGM and present-day, (ii) the parameters that most strongly controlled ensemble spread, and (iii) whether remaining discrepancies were most consistent with forcing uncertainty, resolution limits, or missing processes.

The LGM simulation ensemble of the Ruwenzori Mountains revealed a close accordance between our simulated dataset and the model by Doughty et al. (2023) with a best-fit CSI of 77% (Fig. 9). This was especially evident when considering the top 25% extent (light blue), which, for example, matched individual valley glacier outlets to the south and west. Due to the small size of the present-day glaciers (Fig. 5h), several rounds of test-simulations were necessary before selecting parameters for the ensemble. The LGM glacier extent was sensitive to temperature and precipitation changes, while the model routinely overestimated the extent at present-day. To find the closest possible match for both LGM and present-day, we had to perform 54 simulations. Even then, the best-fit present-day CSI only reached 3.71%. Model performance for present-day could potentially be improved by increasing the spatial resolution, which is feasible for mountain ranges with smaller glacier extents, as the Ruwenzori Mountains. However, mountains ranges with larger glacier extents, such as the Northern Andes, further domain partitioning and much higher total computation time would still be required even with the application of the IGM.

The Pyrenees (Fig. 8) is another domain with small present-day glaciers (Fig. 5f). However, its present-day CSI reached 8% against 4% in Ruwenzori Mountains even though the first was more sensitive to climate and glacier parameter change at the LGM (Fig. 8a–c). In the Pyrenees, the sliding coefficient varied considerably among top ranked simulations, in comparison with the Ruwenzori Mountains where sliding coefficient was consistent among top ranked simulations. We also observed that our top ranked Pyrenean simulations heavily underestimated valley glacier extents in the northern region despite multiple parameter combinations, while the southern region was mainly correctly estimated or overestimated. This pattern was consistent with the mass balance PDD scheme not accounting for the effect of slope aspect and topographic shielding on melt-factors.

In the Central Andes, consisting of North Central Andes, Centre Central Andes, and South Central Andes (Fig. 1), we obtained intermediate-to-high CSI of ~45% for the LGM. Unlike most other simulation domains, the most important calibration parameters for Central Andes were the sliding parameter and the melt rates (DDS controlling the SMB melt rates, see Table 2). The sliding parameter varied from  $0.27 \text{ MPa yr}^m \text{ m}^{-m}$  in the North Central Andes to  $0.005 \text{ MPa yr}^m \text{ m}^{-m}$  in the Centre Central Andes. During testing, it became apparent that much higher melt rates (DDS of up to 4.5, compared to the 'usual' of ~1.5) yielded better extents for both LGM and the present-day. However, the South Central Andes (Fig. 7) did not follow the same pattern, highlighting the main challenge of modelling such an extended mountain range. At the LGM, glaciated areas



across this domain varied greatly with respect to their optimal climate and ice dynamic parameter values. Due to the regional  
 510 distribution of glacier and climatic differences, we had to adjust the shape of the bounding boxes several times to achieve  
 well-calibrated simulations.

In the Sierra Nevada (USA), the last peak of glaciation was found at  $\sim 14$  ka with a median glacier ice extent of  $\sim 600$  km<sup>2</sup>  
 (Fig. 6b), followed by deglaciation at  $\sim 13$  ka. However, a fully ice-free period from 13 ka to present-day is an underestimation  
 of glacier extent, considering that the Sierra Nevada (USA) still has glaciers at the present. The spatial resolution of the model  
 515 is a possible reason that the simulations missed these present-day glaciers. Present-day glacier extents (0.5 to 1 km<sup>2</sup>) are of  
 similar scale to the model resolution (0.25 km<sup>2</sup>), meaning they covered a small number of grid cells in the simulation. Another  
 reason for the lack of ice could be related to the factors missed from the model: for example topographic shading, snow re-  
 distribution by wind, avalanching (from locally steep slopes not resolved at 500m). Some areas exist with larger glaciers, but  
 these were also underestimated by the simulations (Fig. 5b).

### 520 4.3 Challenges of paleoglacier modelling in mountains

Our models across mountain ranges show that predictive performance is scale-dependent: agreement improves when glacier ge-  
 ometry is well resolved and spatially coherent, but declines where present-day glacier extent is near the grid limit, highlighting  
 resolution, domain design, and parameter sensitivity as important determinants of model–data fit across time.

#### 4.3.1 Temperature forcing

525 For many mountain regions worldwide, paleoclimate data remain insufficient to (i) provide continuous transient temperature  
 forcing through time and (ii) constrain along-range and cross-range spatial gradients. Long terrestrial records that include  
 quantitative paleotemperature estimates are rare and geographically clustered (see synthesis by Hooghiemstra et al., 2022).  
 Existing compilations of temperature-sensitive proxy data have improved coverage, but many are focused on the LGM-to-  
 Holocene period (e.g., Farrera et al., 1999; Bartlein et al., 2011), leaving large gaps for earlier periods and for many mountain  
 530 systems. This creates a fundamental identifiability problem for transient glacier simulations: multiple forcings can produce  
 similar extents, especially when precipitation is also weakly constrained.

Within these constraints, our approach combining  $\Delta T_{\text{EPICA}}$  with regionally informed scaling factors derived from multiple  
 proxy sources provided a pragmatic way to impose a continuous transient temperature signal while retaining regional flexibil-  
 ity. However, limited proxy coverage also implied that the temperature–precipitation combinations explored during calibration  
 535 could not always be independently anchored to a physically-based "ground truth", increasing reliance on model–data compar-  
 ison by geomorphic constraints. Expanding and harmonising mountain paleoclimate syntheses would therefore be particularly  
 valuable for strengthening mountain reconstructions in different disciplines (e.g., Rentier et al., 2025; Flantua et al., 2019) and  
 narrowing forcing uncertainty (Russo et al., 2024; Lleshi et al., 2025).

Because EPICA provided our common temporal backbone for our temperature forcing, stadials and interstadials occurred  
 540 synchronously across all simulation domains. What differed between mountain ranges was primarily the magnitude of the re-  
 gional response rather than the timing of particular events. As noted above, continuous, spatially coherent paleoclimate recon-



structions remain scarce for the Late Pleistocene, particularly at the spatial resolution required for mountain glacier modelling. Many global reconstructions primarily target the LGM-to-Holocene period (e.g., MARGO Project Members, 2009; Marcott et al., 2013; Kageyama et al., 2021), while other available products are too coarse to capture the topographic heterogeneity that governs mountain temperature and precipitation fields (e.g., Krapp et al., 2021; Rentier et al., 2025). This limitation matters because transient paleoglacier simulations require assumptions not only about the magnitude of climate change through time, but also about how spatial gradients evolve within a mountain system.

In our framework, present-day spatial patterns were provided by the CHELSA climatology, and transient temperature was imposed by scaling the EPICA Dome C anomaly ( $\Delta T_{\text{EPICA}}$ ) using a domain-specific factor ( $f_{\text{regional}}$ ). While this approach captured first-order regional cooling and warming, it implicitly assumed that the spatial structure of temperature (and any imposed precipitation scaling) remained stationary through time. Yet proxy evidence indicates that mountain climate can exhibit pronounced spatial heterogeneity in climate gradients. Thus, a unique “best” forcing for an entire mountain range is unlikely to exist (Riechers et al., 2022). Because proxy coverage is insufficient in many mountain regions to reconstruct the transient evolution of such gradients, we therefore treated forcing as an uncertain boundary condition, and addressed this uncertainty through domain partitioning model-data comparison against geomorphic constraints, rather than relying on a single prescribed forcing realisation.

#### 4.3.2 Domain partitioning

To improve agreement between simplified forcing and true climatic heterogeneity, and thereby improve simulated patterns of glacier thickness and extent, we partitioned mountain ranges into multiple simulation domains where needed. This strategy is particularly important in mountains composed of widely separated high-elevation ranges, where applying one shared forcing would inevitably yield realistic behaviour for some ranges and implausible outcomes for others. For the Eastern Rift Mountains, for instance, modelling Mount Elgon, Mount Kenya and Mount Kilimanjaro as one domain (i.e., with identical forcing and glacier-dynamic settings) would over-simplify their distinct climatic contexts. Similarly, the Northern Andes and the Ethiopian Highlands showed strong internal gradients that were better represented by subdividing the range into smaller, more homogeneous domains (Fig. 1).

At the same time, domain partitioning was not always feasible. Because Pyrenean glaciers were largely interconnected at the LGM, splitting the domain into independent north–south simulations would break the physical coherence of the glacier extent. However, in our simulations, the LGM glacier cover seemed overestimated on the southern side, whereas the northern side was more consistent with the empirical dataset, though with higher rates of underestimation. In this case, we retained a single simulation domain but expanded the range parameter values, allowing the model-data comparison procedure to identify parameter sets that best balance model–data agreement across the connected system. More consistent with preserving a connected ice mass, is the other option to introduce spatially varying climate/SMB perturbations within a single domain (e.g., a north–south or east–west gradient in the PDD melt factor, or catchment-specific precipitation offsets as ensemble parameters), which can address spatial gradients of influence for the glacier modelling without splitting the domain.



575 The target spatial resolution of 500 m imposed hardware constraints for running IGM for our domains. Several early domain delimitations (encompassing larger portions of the mountain ranges) exceeded the memory capacity of the GPUs with <16 GiB RAM, requiring further division of the simulation domains into smaller bounding boxes. Where possible, we placed boundaries between hydrological catchments to minimise the risk of truncating flow pathways and to preserve coherent ice flow structures. This strategy, however, was not always possible: in strongly interconnected systems such as the European Alps, splitting the domain would cut across continuous LGM ice masses and compromise mass conservation and the physical validity of the simulations. For that reason, the European Alps ensemble was run in full as a single domain on the 80 GiB RAM A100 GPUs of the Sigma2/Saga HPC system.

#### 4.4 Model parameters in IGM

To keep the multi-range transient simulations computationally feasible, we applied several deliberate simplifications. First, and most importantly, we excluded fully coupled thermodynamics. At the spatial and temporal scales explored here (i.e., several mountain ranges at 500 m for the last 130 kyr), incorporating thermodynamic evolution would substantially increase runtime and complexity, and it remains secondary to our primary objective: applying and testing IGM for a suite of contrasting mountain ranges and reconstructing transient ice extent since the last interglacial. While thermodynamic state can influence glacier ice extent and flow through its effects on basal conditions and viscosity, explicitly resolving these processes across multiple large domains and long timescales will be kept as an improvement in future follow-up work. We therefore prioritised a workflow that could be tested and applied consistently across mountain regions and would focus computational resources on creating, for the first time, spatially explicit ice-extent reconstructions for mountains across varying latitudes and the full Last Glacial Cycle and Holocene.

Secondly, we omitted isostatic adjustment for a number of different reasons. Bedrock deformation due to isostatic adjustment resulting from the weight of overlying ice can affect surface elevation, and therefore mass balance and glacier extent. However, physically credible isostasy modelling requires additional region-specific parameters that themselves require reference data and calibration. For many mountains, such data are still unavailable. Applying standardised, i.e. default parameters to all mountain ranges, could also add potential noise to simulations if default parameters are not appropriate in specific regions. For most mountain ranges in this study, glacial-interglacial changes in ice volume are considered too small to substantially impact our simulated ice extent. However, for domains with large ice development (notably the European Alps and as medium-sized systems such as the Ecuadorian Cordilleras), neglecting isostatic adjustment could affect reconstructed extents and should be addressed in follow-up work. Here, the isostatic adjustment calculations are further complicated by the necessary division of simulation domains. As the mountain ranges are split and modelled in smaller sections, they are isolated from each other, which could lead to underestimating the isostatic adjustment. For these reasons, we omitted isostasy from this work, while recognising it as a clear priority for future transient paleoglacier reconstructions.



## 4.5 Model-data comparison

Various tools have been developed to quantify the agreement between model outputs and geomorphic and geochronological glacial evidence (e.g., Napieralski et al., 2006; Li et al., 2007, 2008; Ely et al., 2021; Archer et al., 2023), and several quantitative methods have been applied to evaluate the spatial agreement between model and empirical datasets (e.g., Becker et al., 2016; Candaş et al., 2020; Köse et al., 2022; Leger et al., 2025; Lecavalier et al., 2014; Lecavalier and Tarasov, 2025). To date, a standardised model-data comparison framework, often addressed as model validation, has not been widely adopted. This could be mostly due to the availability of empirical data, heterogeneity of topographic characteristics, glacier size and system type, and climate and glaciological regime. Approaches that are suitable for large connected glacier systems in temperate mountains with deep valleys and well-defined glacier flow paths will likely not work for scattered glacier systems in tropical mountains with complex ice dispersal and high-elevation plateaus, as model errors and evaluation metrics behave differently across mountain ranges.

The availability, spatial distribution and quality of geomorphic evidence data plays a key role for the decision on model-data comparison approaches. While some mountain ranges have a very dense evidence of geomorphic features, cosmogenic dates and detailed geomorphological maps, allowing model-data agreement to be evaluated not only by ice extent, but also by ice thickness, glacier flowlines, and timing of deglaciation, other mountain ranges have only sparse and fragmentary evidence from a few proxy records. One possible alternative would be to evaluate model performance against present-day glaciers. However, many mountain ranges investigated in paleoglacier studies are currently ice-free, and the availability, spatial resolution and mapping methodologies of present-day glacier inventories vary considerably among mountain ranges and studies. Lastly, good model-data agreement at a single time step (e.g., present day) does not necessarily indicate that the model accurately reproduces glacier behaviour through time. This is clearly evidenced in our study, where the best performing simulations in the LGM do not necessarily perform best at present-day. Consequently, studies differ in their choice of methodological approaches, metrics and compared targets, and often rely on study-specific judgement to determine acceptable results (Gandy et al., 2024). Thus, we observe that it is unlikely that a single “one-size-fits-all” methodology can be universally effective to assess and quantify model performance.

Rather than attempting to develop a globally standardised model-data comparison framework that performed equally across all mountain ranges or using different approaches for each mountain range, we focused on refining how model outputs were visualised and evaluated. We emphasised parameter-driven variability (i.e., how glaciers are sensitive to parameter values and combinations) in simulated ice cover, rather than selecting a single best-fit reconstruction. Similar, ensemble-based approaches have previously been implemented in ice-sheet modelling studies to evaluate acceptable model behaviour across parameters (e.g., Tarasov and Peltier, 2004; Lecavalier and Tarasov, 2025; Ely et al., 2021; Leger et al., 2024; DeConto and Pollard, 2016). In such studies, subsets of acceptable simulations were used to constrain model behaviour. Meanwhile, mountain glacier modelling has explored parameter-sensitivity through climate sensitivity experiments (e.g., Candaş et al., 2020; Jiang et al., 2022; Köse et al., 2022)). However, these approaches typically evaluate glacier geometry by binary measures (i.e., acceptable





or not acceptable) and through bulk metrics, such as total glacier area, extent, volume or equilibrium-line altitude, rather than  
 640 analysing the spatial consistency of ice cover across ensembles of acceptable simulations.

Across all the different evaluation approaches, geomorphic evidence provides the necessary reference. Accordingly, we used  
 geomorphic-based reconstructed paleoglacier extents as spatial constraints against which simulated ice cover was assessed.  
 While assessing glacier model behaviour through comparison with geomorphic-based reconstructions has been also adopted  
 in several other studies (e.g., Becker et al., 2016; Seguinot et al., 2018; Jouvét et al., 2023; Castillo-Llarena et al., 2024;  
 645 Leger et al., 2025), it is not without limitations. Geomorphic reconstructions inherently reflect incomplete and time-integrated  
 evidence of past glacier extent, and therefore introduce uncertainties that must be considered when interpreting model–data  
 agreement.

Some mountain ranges have a wide variety of geomorphic and geochronological field-based evidence, as in the Pyrenees  
 (Delmas et al., 2022; Calvet et al., 2011), the European Alps (e.g., Bini et al., 2004; Braakhekke et al., 2020; Bini, 2009; Rettig  
 650 et al., 2023), and the Sierra Nevada (USA) (Gillespie and Zehfuss, 2004; Walter, 2022). However, other mountain ranges,  
 especially at lower latitudes, have limited information (e.g., Bale and Arsi Mountains (Groos et al., 2021; Osmaston et al.,  
 2005); Greater Caucasus (Gobejishvili, 2004; Gobejishvili et al., 2011)). For some ranges, the GLACIMONTIS reconstructions  
 are largely schematic (i.e., simplified or conceptual polygons) representations of past glacier geometry. These were likely  
 inferred from limited geomorphic and geochronological evidence, as seen in most of the Northern and Central Andes (IDEAM,  
 655 2012; Clapperton, 1983) and in the Mounts Kenya, Kilimanjaro and Elgon (Osmaston, 2004; Chen et al., 2018), although a  
 limited number of small areas showcase more detailed reconstructions (e.g., Klein et al., 1999; Lee et al., 2022; Kull et al., 2008;  
 Gallardo et al., 2024). The Ruwenzori Mountains lies on the end of this spectrum, where no geomorphic-based reconstruction  
 exists and model-data agreement has been previously assessed based on a single moraine (Doughty et al., 2023).

Model–data evaluation might reflect differences in the availability and quality of geomorphic evidence rather than differences  
 660 in model performance alone. When evaluation is based on limited geomorphic evidence (e.g., individual moraines), model per-  
 formance may be a misrepresentation of the model validity. As a result, a model may appear to perform well if it reproduces  
 glacier presence at a small number of mapped features, even if large parts of the glacier extent are misrepresented. Conversely,  
 disagreement at a single geomorphic indicator may produce a low score even when the overall spatial pattern of glacier ex-  
 tent is broadly consistent with geomorphic interpretation. In cases where simulations showed substantial spatial variability in  
 665 overestimated, underestimated, or correctly reproduced glaciers (as observed in our results, see Fig. 5), the use of fragmented  
 geomorphic evidence for model-data comparison may introduce additional bias. However, we argue that geomorphic-based  
 glacier reconstructions and individual geomorphic evidence are invaluable baseline information that should be considered with  
 care for broad-scale glacier modelling, and validation and evaluation processes, and discussed on a case-by-case basis.

To illustrate the above point, we observed large "overestimated" LGM glacier areas in the South Central Andes (Fig. 5c) and  
 670 Centre Central Andes (Supplementary Fig. S5) where geomorphic-based reconstructions were not available or only schematic  
 (Ehlers et al., 2011; Lima et al., 2026). However, present-day glaciers do exist (Fig. 5d, Supplementary Fig. S15). Similar  
 patterns are seen in the Western & Central Cordillera, Eastern Cordillera & Cordillera de Mérida, Mount Kenya & Mount  
 Kilimanjaro, Arsi Mountains, and Greater Caucasus, while not in mountain ranges with a higher availability of geomorphic



evidence (e.g., European Alps, Pyrenees). It is likely that these modelled glaciers are not overestimations, but rather areas lack-  
675 ing research. At the same time, where geomorphic-based reconstructions existed, our simulations correctly modelled glaciers  
(i.e., no large "underestimated" LGM glacier areas) though perhaps not with the correct extent. This highlights an added value  
of our paleo-glacier modelling, which is to identify possible spatial gaps in empirical glacio-geomorphological data and guide  
future fieldwork.

Our CSI approach for evaluation metric allows simulations to be systematically compared within an ensemble, providing  
680 a consistent basis for ranking simulations across different time steps and error types (e.g., overestimation and underestima-  
tion). Rather than determining a single "best-fit" scenario, this approach shifts the objective from identifying the most likely  
glacier configuration to evaluating model behaviour. As a result, it helped us reveal which parameter combinations consistently  
improved spatial agreement and which produced systematic mismatches. This ensemble-based perspective is particularly valu-  
able in paleoglacier modelling, where multiple simulations may produce comparable levels of agreement despite representing  
685 different glacier configurations.

## 5 Conclusions

Our study provides, for the first time, a suite of transient simulations that reconstructs mountain glacier evolution across multi-  
ple mountain ranges from the last interglacial to the present. We demonstrate that high-resolution, orbital-timescale mountain  
glacier modelling is now tractable at global scale. By leveraging GPU efficiency within the Instructed Glacier Model (IGM)  
690 (Jouvet et al., 2022; Jouvet and Cordonnier, 2023), we bridge the gap between physically-grounded ice dynamics and the  
computational demands of 130 kyr transient simulation ensembles across nine mountain ranges (seventeen simulation do-  
mains) in North America, South America, Europe and Africa. Importantly, we target several mountain ranges, particularly in  
the tropics, where research has been limited. With our framework, we discuss several long-standing challenges regarding: (i)  
uncertainty in initialisation and forcing, (ii) poorly constrained paleoclimate parameters, (iii) poorly constrained ice-dynamic  
695 parametrisations, (iv) unevenly distributed empirical data, and (v) the lack of standardised, reproducible evaluation methods.

For much of the period since the Last Interglacial, geomorphological and geochronological evidence of glacier fluctuations is  
sparse, discontinuous, or overprinted by later advances — often dominated by LGM signals — limiting empirical reconstruc-  
tions beyond a few key time slices. Our results therefore address a major spatial–temporal gap by offering continuous estimates  
of glacier extent and geometry through time. These reconstructions can guide targeted field campaigns by highlighting likely  
700 ice-margin positions and data gaps. In addition, they provide a transferable boundary condition for interdisciplinary moun-  
tain research, including studies of paleovegetation dynamics, human migration and habitat accessibility, transient paleoclimate  
modelling that requires evolving topography, and landscape evolution questions spanning sediment flux, fluvial networks, and  
lake and coastal development.

Critically, we translated ensemble uncertainty into a transparent, spatially-explicit evaluation product. Rather than selecting  
705 a single "best" simulation, we evaluated model outputs using different metrics (including the CSI) together with extent and  
volume constraints, and summarised results as frequency maps of glacier presence across the set of acceptable simulations.



This allowed us to distinguish areas where glacier occurrence is robust from areas that are parameter-sensitive or weakly constrained by empirical data, thereby formalising model outputs as an interpretable map rather than an implicit caveat. This matters because transient glacier histories are increasingly used as boundary conditions across mountain research – from atmosphere–cryosphere coupling to ecological and geomorphic applications – and confidence in those boundary conditions requires reproducible, quantitative model–data testing that accommodates the uneven coverage and uncertainty of geomorphic reconstructions.

IGM — and, more broadly, physics-informed machine learning coupled with GPU computing — marks a fundamental step change for glacier modelling by making physically grounded, high-resolution ensembles feasible at scale. Beyond reproducing realistic ice geometries and 130 kyr transient evolution across diverse mountain settings at 500 m resolution, our framework provides diagnostic insight into where and why performance degrades, highlighting domains that require finer grids, improved forcing constraints, or tighter regional calibration. This combination of modular domain definition, regional tuning of simulations within ensembles and efficient execution on either local GPUs or HPC allows our framework to be scaled to any mountain range globally.

## 6 Code and data availability

The complete set of scripts with a description of the workflow can be found at <https://github.com/Mountains-in-Motion/paleo-instructed-glacier-model>. All results are published as a dataset on NIRD Research Data Archive (NIRD RDA; <https://archive.sigma2.no/dataset/evolution-of-mountain-glaciers-since-the-last-interglacial>. (Barndon et al., 2026b)) The dataset contains every simulation result from each simulation ensemble (mountain region). It also contains the transient median extent shape (.shp) files for each location, based on the best-ranked 8 and 16 simulations separately. Each simulation includes the IGM logfiles, run statistics (.csv), ice thickness for each time step (.tiff), and glacier evolution data (NetCDF). The NetCDF file contains ice thickness, flow components and spatial climate variables for each time step.

*Video supplement.* Animations of transient mountain glacier extent since the last interglacial for each mountain range are available at <https://av.tib.eu/series/2022> (Barndon et al., 2026a). The animations show the temporal evolution of the median glacier extent derived from the top-ranked eight simulations in each ensemble, providing a representative reconstruction of glacier dynamics while reducing sensitivity to individual parameter choices.

## Appendix A

Tables detailing the simulation calibration ensemble values and model-data comparison result.



**Table A1. Default IGM input parameters used in all simulations, sorted by their model component.** For a full list of parameter values, see Supplement Table S1.

| Name                               | Model Component      | Value               | Unit                                                     |
|------------------------------------|----------------------|---------------------|----------------------------------------------------------|
| Ice density                        | Ice deformation      | 910                 | $\text{kg m}^{-3}$                                       |
| Gravitational acceleration         | Ice deformation      | 9.81                | $\text{m s}^{-2}$                                        |
| Arrhenius factor                   | Ice deformation      | 78.0                | $\text{MPa}^{-n} \text{yr}^{-1}$                         |
| Enhancement factor                 | Ice deformation      | 1                   | –                                                        |
| Glen’s flow law exponent           | Ice deformation      | 3                   | –                                                        |
| Regularisation parameter (Glen)    | Ice deformation      | $1 \times 10^{-5}$  | –                                                        |
| Number of vertical layers          | Ice deformation      | 10                  | –                                                        |
| Vertical spacing (denser near bed) | Ice deformation      | graded              | –                                                        |
| Weertman’s sliding law exponent    | Basal sliding        | 3                   | –                                                        |
| Regularisation parameter (sliding) | Basal sliding        | $1 \times 10^{-10}$ | –                                                        |
| Degree-day factor snow             | Surface mass balance | 1.387               | $\text{m yr}^{-1} \text{K}^{-1}$                         |
| Degree-day factor ice              | Surface mass balance | 2.701               | $\text{m yr}^{-1} \text{K}^{-1}$                         |
| Solid precipitation threshold      | Surface mass balance | 0.0                 | $^{\circ}\text{C}$                                       |
| Liquid precipitation threshold     | Surface mass balance | 2.0                 | $^{\circ}\text{C}$                                       |
| Refreezing factor                  | Surface mass balance | 0.6                 | –                                                        |
| Density of water                   | Surface mass balance | 1000                | $\text{kg m}^{-3}$                                       |
| Density of ice                     | Surface mass balance | 910                 | $\text{kg m}^{-3}$                                       |
| Maximum accumulation rate          | Surface mass balance | 6                   | $\text{m yr}^{-1}$                                       |
| Hydrological year shift            | Surface mass balance | 0.75                | –                                                        |
| Degree-day factor snow             | Surface mass balance | 1.387               | $\text{m yr}^{-1} \text{K}^{-1}$ (meters ice equivalent) |
| Degree-day factor ice              | Surface mass balance | 2.701               | $\text{m yr}^{-1} \text{K}^{-1}$ (meters ice equivalent) |
| Avalanche update frequency         | Avalanche module     | 1                   | yr                                                       |
| Angle of repose                    | Avalanche module     | 30                  | $^{\circ}$                                               |
| Stop redistribution thickness      | Avalanche module     | 0.02                | m                                                        |



**Table A2.** Key varied parameters and parameter values for the top 5 ranked simulations for each simulation domain. Minimum and maximum values used across the ensemble are listed for each parameter. The  $f_{\text{regional}}$  parameter is the regionally adjusted polar amplification factor (i.e., the factor applied to the  $\Delta_T$  Epica temperature). The  $P_{\text{LGM}}$  parameter is the precipitation factor at the Last Glacial Maximum (LGM) compared to the present. Degree-day scaling (DDS) is applied to the degree-day melt factors for ice and snow.

| Location                                     | Varied Parameter      | Rank 1 | Rank 2 | Rank 3 | Rank 4 | Rank 5 | Min    | Max    |
|----------------------------------------------|-----------------------|--------|--------|--------|--------|--------|--------|--------|
| Sierra Nevada<br>de Santa Marta              | $f_{\text{regional}}$ | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    |
|                                              | $P_{\text{LGM}}$      | 1.5    | 1.7    | 1.9    | 1.5    | 1.9    | 1.5    | 1.9    |
|                                              | Sliding Coefficient   | 0.0225 | 0.0225 | 0.0225 | 0.0225 | 0.09   | 0.0225 | 0.0900 |
|                                              | DDS                   | 1.3    | 1.3    | 1.3    | 1.2    | 1.3    | 1.1    | 1.3    |
| Eastern Cordillera &<br>Cordillera de Mérida | $f_{\text{regional}}$ | 0.74   | 0.74   | 0.74   | 0.74   | 0.74   | 0.74   | 0.74   |
|                                              | $P_{\text{LGM}}$      | 1.75   | 1.5    | 1.5    | 2      | 1.75   | 1.5    | 2.0    |
|                                              | Sliding Coefficient   | 0.0225 | 0.0225 | 0.0225 | 0.0225 | 0.0225 | 0.0225 | 0.0900 |
|                                              | DDS                   | 1.3    | 1.3    | 1.2    | 1.3    | 1.2    | 1.1    | 1.3    |
| Western<br>and Central<br>Cordillera         | $f_{\text{regional}}$ | 0.65   | 0.65   | 0.65   | 0.65   | 0.65   | 0.65   | 0.65   |
|                                              | $P_{\text{LGM}}$      | 1.5    | 1.5    | 1.75   | 1.5    | 2.0    | 1.5    | 2.0    |
|                                              | Sliding Coefficient   | 0.045  | 0.0225 | 0.0225 | 0.0225 | 0.0225 | 0.0225 | 0.0900 |
|                                              | DDS                   | 1.5    | 1.5    | 1.5    | 1.4    | 1.4    | 1.2    | 1.5    |
| Ecuadorian<br>Cordilleras                    | $f_{\text{regional}}$ | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    |
|                                              | $P_{\text{LGM}}$      | 0.8    | 0.7    | 0.7    | 0.8    | 0.7    | 0.1    | 0.8    |
|                                              | Sliding Coefficient   | 0.0225 | 0.0225 | 0.0450 | 0.0200 | 0.0225 | 0.0200 | 0.0450 |
|                                              | DDS                   | 1.4    | 1.4    | 1.4    | 1.2    | 1.3    | 1.2    | 1.4    |
| North Central<br>Andes                       | $f_{\text{regional}}$ | 0.35   | 0.35   | 0.35   | 0.35   | 0.35   | 0.35   | 0.35   |
|                                              | $P_{\text{LGM}}$      | 0.3    | 0.3    | 0.4    | 0.3    | 0.35   | 0.3    | 0.4    |
|                                              | Sliding Coefficient   | 0.27   | 0.18   | 0.27   | 0.09   | 0.27   | 0.09   | 0.27   |
|                                              | DDS                   | 4.0    | 4.0    | 4.0    | 4.0    | 4.0    | 3.0    | 4.0    |
| Centre Central<br>Andes                      | $f_{\text{regional}}$ | 0.35   | 0.35   | 0.35   | 0.35   | 0.35   | 0.35   | 0.35   |
|                                              | $P_{\text{LGM}}$      | 0.3    | 0.35   | 0.3    | 0.4    | 0.35   | 0.3    | 0.4    |
|                                              | Sliding Coefficient   | 0.005  | 0.005  | 0.005  | 0.005  | 0.005  | 0.005  | 0.225  |
|                                              | DDS                   | 4.5    | 4.5    | 4.0    | 4.5    | 4.0    | 3.5    | 4.5    |
| South Central<br>Andes                       | $f_{\text{regional}}$ | 0.35   | 0.35   | 0.35   | 0.35   | 0.35   | 0.35   | 0.35   |
|                                              | $P_{\text{LGM}}$      | 0.5    | 0.5    | 0.4    | 0.4    | 0.6    | 0.4    | 0.6    |
|                                              | Sliding Coefficient   | 0.045  | 0.045  | 0.045  | 0.045  | 0.045  | 0.045  | 0.18   |
|                                              | DDS                   | 1.5    | 1.4    | 1.5    | 1.4    | 1.5    | 1.3    | 1.5    |





**Table A2.** Continued.

| Location                           | Varied Parameter      | Rank 1 | Rank 2 | Rank 3 | Rank 4 | Rank 5 | Min    | Max    |
|------------------------------------|-----------------------|--------|--------|--------|--------|--------|--------|--------|
| Semien<br>Mountains                | $f_{\text{regional}}$ | 0.65   | 0.65   | 0.65   | 0.65   | 0.65   | 0.65   | 0.65   |
|                                    | $P_{\text{LGM}}$      | 0.6    | 0.6    | 0.6    | 0.6    | 0.6    | 0.6    | 0.8    |
|                                    | Sliding Coefficient   | 0.0450 | 0.0450 | 0.0900 | 0.0450 | 0.0900 | 0.0450 | 0.1350 |
|                                    | DDS                   | 1.3    | 1.2    | 1.3    | 1.1    | 1.2    | 1.1    | 1.3    |
| Arsi<br>Mountains                  | $f_{\text{regional}}$ | 0.6    | 0.6    | 0.6    | 0.6    | 0.6    | 0.6    | 0.6    |
|                                    | $P_{\text{LGM}}$      | 1.0    | 1.0    | 1.1    | 0.9    | 0.9    | 0.9    | 1.1    |
|                                    | Sliding Coefficient   | 0.0900 | 0.0900 | 0.0450 | 0.0900 | 0.0450 | 0.0225 | 0.0900 |
|                                    | DDS                   | 1.4    | 1.3    | 1.4    | 1.3    | 1.3    | 1.1    | 1.4    |
| Bale<br>Mountains                  | $f_{\text{regional}}$ | 0.45   | 0.45   | 0.45   | 0.45   | 0.45   | 0.45   | 0.45   |
|                                    | $P_{\text{LGM}}$      | 0.3    | 0.3    | 0.3    | 0.3    | 0.3    | 0.3    | 0.5    |
|                                    | Sliding Coefficient   | 0.0450 | 0.0450 | 0.090  | 0.090  | 0.045  | 0.0225 | 0.0900 |
|                                    | DDS                   | 1.4    | 1.5    | 1.5    | 1.4    | 1.3    | 1.3    | 1.5    |
| Mount Elgon                        | $f_{\text{regional}}$ | 0.65   | 0.65   | 0.65   | 0.65   | 0.65   | 0.65   | 0.65   |
|                                    | $P_{\text{LGM}}$      | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.9    |
|                                    | Sliding Coefficient   | 0.0250 | 0.0900 | 0.0900 | 0.0450 | 0.0250 | 0.0250 | 0.0900 |
|                                    | DDS                   | 1.2    | 1.2    | 1.3    | 1.2    | 1.3    | 1.2    | 1.5    |
| Mount Kenya &<br>Mount Kilimanjaro | $f_{\text{regional}}$ | 0.2    | 0.2    | 0.2    | 0.2    | 0.2    | 0.2    | 0.2    |
|                                    | $P_{\text{LGM}}$      | 0.3    | 0.3    | 0.5    | 0.3    | 0.4    | 0.3    | 0.5    |
|                                    | Sliding Coefficient   | 0.4500 | 0.0900 | 0.0150 | 0.1800 | 0.0150 | 0.0100 | 0.4500 |
|                                    | DDS                   | 1.4    | 1.4    | 1.4    | 1.3    | 1.4    | 1.3    | 1.5    |
| Greater<br>Caucasus                | $f_{\text{regional}}$ | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    |
|                                    | $P_{\text{LGM}}$      | 0.5    | 0.5    | 0.6    | 0.5    | 0.5    | 0.3    | 0.7    |
|                                    | Sliding Coefficient   | 0.0450 | 0.0900 | 0.0900 | 0.0450 | 0.0250 | 0.0200 | 0.1800 |
|                                    | DDS                   | 1.2    | 1.2    | 1.3    | 1.2    | 1.4    | 1.2    | 1.7    |
| Sierra Nevada (USA)                | $f_{\text{regional}}$ | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    |
|                                    | $P_{\text{LGM}}$      | 1.8    | 1.8    | 1.8    | 2.0    | 2.0    | 1.8    | 2.1    |
|                                    | Sliding Coefficient   | 0.0225 | 0.0450 | 0.0225 | 0.0225 | 0.0225 | 0.0225 | 0.0900 |
|                                    | DDS                   | 0.8    | 0.8    | 0.9    | 0.8    | 0.9    | 0.8    | 1.0    |
| European Alps                      | $f_{\text{regional}}$ | 0.9    | 0.9    | 0.9    | 0.9    | 0.9    | 0.9    | 0.9    |
|                                    | $P_{\text{LGM}}$      | 0.6    | 0.5    | 0.6    | 0.5    | 0.5    | 0.4    | 0.6    |
|                                    | Sliding Coefficient   | 0.0225 | 0.0900 | 0.0450 | 0.0225 | 0.4500 | 0.0225 | 0.4500 |
|                                    | DDS                   | 1.4    | 1.6    | 1.8    | 1.2    | 1.6    | 1.2    | 1.9    |

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**Table A2.** Continued.

| Location              | Varied Parameter      | Rank 1 | Rank 2 | Rank 3 | Rank 4 | Rank 5 | Min    | Max    |
|-----------------------|-----------------------|--------|--------|--------|--------|--------|--------|--------|
| Pyrenees              | $f_{\text{regional}}$ | 1.1    | 1.1    | 1.1    | 1.1    | 1.1    | 1.1    | 1.1    |
|                       | $P_{\text{LGM}}$      | 0.3    | 0.3    | 0.3    | 0.2    | 0.3    | 0.2    | 0.4    |
|                       | Sliding Coefficient   | 0.450  | 0.090  | 0.4500 | 0.1800 | 0.0900 | 0.0225 | 0.4500 |
|                       | DDS                   | 1.4    | 1.4    | 1.3    | 1.2    | 1.3    | 0.9    | 1.5    |
| Ruwenzori<br>Mountain | $f_{\text{regional}}$ | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    |
|                       | $P_{\text{LGM}}$      | 0.5    | 0.6    | 0.5    | 0.7    | 0.5    | 0.5    | 0.7    |
|                       | Sliding Coefficient   | 0.0225 | 0.0225 | 0.0225 | 0.0225 | 0.0225 | 0.0225 | 0.0900 |
|                       | DDS                   | 1.4    | 1.5    | 1.5    | 1.5    | 1.3    | 1.3    | 1.5    |

*Author contributions.* S.B. ran the glacier simulations. A.C.L. synthesised climate scenarios for glacier simulations, contributed to model setup and simulation improvements, and result analysis. D.C. contributed to model setup and result analysis. A.T.W. designed the initial workflow for running IGM with paleoclimate data and contributed with setting up the local GPU and on Sigma2. T.L. contributed with model setup and the design of the simulation ensemble. R.P.P. contributed to setting up the local GPU and on Sigma2. E.S.R. calculated the original spatial lapse rates and the regional scaling factor values based on regional climate proxies. S.G.A.F. led the project and conceptualization, supervised the methodological development and result analyses, and obtained the funding. S.B., A.C.L., and S.G.A.F. led the writing; all authors contributed to different versions of the manuscript.

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