

1 Supplementary information: Notes on computational resources

Note S1. We ran IGM using both a local desktop machine with a NVIDIA GeForce RTX 5080 GPU (16GiB), and the high-performance computing system Saga, provided by Norwegian *supercomputer* infrastructure Sigma2. Smaller simulation domains (e.g. Ruwenzori, Mount Kenya, and Sierra Nevada de Santa Marta) could be modelled entirely using the local GPU. Processing runtime for these domains varied from 2.98 hours for the Bale Mountains (Ethiopian Highlands) to 101.73 hours for the Eastern Cordillera and Mérida Cordillera (Northern Andes). Averaged processing time per simulation domain can be seen in Table S3. The remaining domains were modelled using Saga. Saga has 16 nodes with GPU's that are used in parallel: 8 nodes with the NVIDIA P100 (16 GiB RAM) GPU and 8 nodes with NVIDIA A100 (80 GiB RAM). The NVIDIA P100 model is sufficiently powerful to run IGM at 500 m spatial resolution, allowing multiple simulations in parallel on the same node. Only the European Alps could not be modelled with the P100 GPU, as the extent of the simulation domain and the exceptionally large amount of ice build-up required more than 16 GiB of RAM. Thus, the European Alps were modelled using the A100 GPU.

2 Supplementary tables

Table S1. Regional scaling factor (RSF) statistics for each mountain range. RSF median is equal to "Initial f_{regional} " in Table 1. Sorted by number of available temperature proxy sources n .

Mountain range	n	Mean ΔT	Median ΔT	IQR ΔT	SD ΔT	Min ΔT	Max ΔT	EPICA ΔT	RSF median	RSF mean	RSF IQR
Central Andes	27	-5.881	-6.000	1.800	1.648	-10.000	-3.000	-9.475	0.633	0.621	-0.190
Eastern Rift Mountains	22	-4.318	-4.200	2.238	1.601	-6.950	-0.400	-9.475	0.443	0.456	-0.236
European Alps+Pyrenees	19	-10.100	-11.300	3.800	2.877	-14.500	-3.450	-9.475	1.193	1.066	-0.401
Ruwenzori Mountain	18	-4.110	-4.500	2.625	1.990	-6.500	-0.233	-9.475	0.475	0.434	-0.277
Ethiopian Highlands	9	-5.022	-5.300	1.800	1.525	-7.000	-3.000	-9.475	0.559	0.530	-0.190
Northern Andes	8	-7.250	-7.250	0.625	0.655	-8.000	-6.000	-9.475	0.765	0.765	-0.066
Greater Caucasus	3	-7.792	-7.500	0.438	0.505	-8.375	-7.500	-9.475	0.792	0.822	-0.046
Sierra Nevada (USA)	3	-6.283	-5.750	0.950	1.056	-7.500	-5.600	-9.475	0.607	0.663	-0.100

Note: n = proxy count; ΔT values in $^{\circ}\text{C}$; IQR = interquartile range; SD = standard deviation; EPICA ΔT = EPICA temperature anomaly (19000–26000 ka); RSF = regional scaling factor.

Table S2. Computation time with simulation area comparison. Computation time is calculated by the mean of all experiments of an ensemble. LGM ice extent and volume refer to the modelled value of the best fit simulation. Centre Central Andes and the European Alps simulations were performed on the A100 GPU, and therefore cannot be directly compared to the other simulations for performance. Table sorted by mean computation time.

	Simulation domain	Mean comp. time (h)	LGM extent (km^2)	LGM volume (km^3)	Bounding box (km^2)
(2)	Eastern Cordillera & Mérida	101.73	19,769.50	3,125.62	232,779.49
(5)	North Central Andes	75.79	34,897.12	10,897.12	247,976.15
(6)	Centre Central Andes	75.67 (A100)	50,624.75	5,235.90	243,600.5
(3)	Western and Central Cordilleras	50.77	7,867.75	1,461.40	191,260.44
(15)	Greater Caucasus	32.52	11,038.5	664.92	135,757.55
(17)	European Alps	31.27 (A100)	122,774.75	57,956.20	291,188.87
(7)	South Central Andes	22.91	4,181.25	701.93	40,521.20
(4)	Ecuadorian Cordilleras	17.18	9,031.0	1,411.85	139,539.26
(1)	Sierra Nevada de Santa Marta	15.55	14,662.50	2,782.77	21,312.37
(14)	Sierra Nevada (USA)	15.53	8,079.00	1,241.33	87,010.71
(13)	Ruwenzori Mountain	5.26	375.00	28.25	9,409.68
(12)	Mount Kenya & Mount Kilimanjaro	5.01	419.75	28.26	67,646.30
(8)	Semien Mountains	4.85	35.75	2.57	33,483.82
(16)	Pyrenees	4.67	9,276.25	1,646.92	55,846.43
(11)	Mount Elgon	4.04	116.0	10.24	8,304.51
(10)	Arsi Mountains	3.10	104.0	15.30	186,699.27
(9)	Bale Mountains	2.98	365.75	70.44	2,442.39

Table S3. The area of each sensitivity category of the frequency maps per simulation domain. Each area of the frequency maps are given a name according to their reflecting parameter-calibration sensitivity. High (0–25%), Moderate (25–75%), and Low (75–100%) show both the area of the frequency map, and the glaciated areas sensitivity to parameter change. The percentage for each area compared to the total area of the frequency map is also listed.

Location		Parameter-calibration sensitivity	Area (km ²)	Area (%)
(1)	Sierra Nevada de Santa Marta	High	107.00	7.14
		Moderate	139.00	9.28
		Low	1252.25	83.58
(2)	Eastern Cordillera & Mérida Cordillera	High	1288.50	5.83
		Moderate	1840.50	8.32
		Low	18981.00	85.85
(3)	Western & Central Cordillera	High	720.25	7.85
		Moderate	1350.50	14.71
		Low	7108.00	77.44
(4)	Ecuadorian Cordilleras	High	1596.75	14.10
		Moderate	987.25	8.72
		Low	8744.00	77.19
(5)	North Central Andes	High	2066.25	4.78
		Moderate	2767.75	6.41
		Low	38351.50	88.81
(6)	Centre Central Andes	High	2707.50	4.49
		Moderate	4286.00	7.11
		Low	53272.25	88.40
(7)	South Central Andes	High	262.25	5.44
		Moderate	423.50	8.78
		Low	4137.50	85.78
(8)	Semien Mountains	High	14.00	23.05
		Moderate	12.50	20.58
		Low	34.25	56.38
(9)	Bale Mountains	High	19.50	4.75
		Moderate	35.50	8.65
		Low	355.50	86.60
(10)	Arsi Mountains	High	9.00	6.77
		Moderate	27.25	20.49
		Low	96.75	72.74
(11)	Mount Elgon	High	20.50	12.93
		Moderate	30.50	19.24
		Low	107.50	67.82
(12)	Mount Kenya & Mount Kilimanjaro	High	63.75	14.30
		Moderate	41.50	9.31
		Low	340.50	76.39
(13)	Ruwenzori Mountain	High	19.50	4.89
		Moderate	31.00	7.77
		Low	348.25	87.34
(14)	Sierra Nevada (USA)	High	2836.25	11.93
		Moderate	6203.50	26.08
		Low	14742.25	61.99
(15)	Greater Caucasus	High	12976.50	13.33
		Moderate	16361.00	16.80
		Low	68044.50	69.87
(16)	Pyrenees	High	626.75	4.72
		Moderate	1460.50	10.99
		Low	11200.50	84.29
(17)	European Alps	High	8215.50	3.86
		Moderate	14909.25	7.00
		Low	189883.50	89.14

Table S4. Default IGM parameter values set for all simulation experiments.

IGM parameter name	Description	System component	Value	Unit
clim_update_freq	Frequency at which the climate is updated using glacial index	Input climate	100.0	yr
smb_accpdd_update_freq	Update the Surface Mass Balance (SMB) each x years	Surface mass balance	1.0	yr
smb_accpdd_thr_temp_snow	Threshold temperature for solid precipitation	Surface mass balance	0.0	°C
smb_accpdd_thr_temp_rain	Threshold temperature for liquid precipitation	Surface mass balance	2.0	°C
smb_accpdd_shift_hydro_year	This serves to start Oct 1. the acc/melt computation	Surface mass balance	0.75	yr
smb_accpdd_ice_density	Density of ice for conversion of SMB into ice equivalent	Surface mass balance	910.0	kg m ⁻³
smb_accpdd_wat_density	Density of water	Surface mass balance	1000.0	kg m ⁻³
iflo_regu_weertman	Regularization parameter for Weertman's sliding law	Basal sliding	10 ⁻¹⁰	n/a
iflo_exp_glen	Glen's flow law exponent	Ice flow	3.0	n/a
iflo_exp_weertman	Weertman's law exponent	Basal sliding	4.0	n/a
iflo_gravity_cst	Acceleration due to gravity of a free falling object	Ice flow	9.81	m s ⁻²
iflo_ice_density	Density of ice	Ice flow	910.0	kg m ⁻³
iflo_Nz	Number of grid points for the vertical discretization	Ice flow	10.0	n/a
iflo_vert_spacing	Discretization density to get more points towards bed than surface	Ice flow	4.0	n/a
iflo_thr_ice_thk	Threshold ice thickness for computing strain rate	Ice flow	0.1	m
iflo_dim_arrhenius	Dimension of the arrhenius factor (horizontal 2D or 3D)	Ice flow	3.0	n/a
iflo_retrain_emulator_freq	Frequency at which the emulator is retrained, 0 means never	Neural network	7.0	time steps
iflo_retrain_emulator_lr	Learning rate for the retraining of the emulator	Neural network	10 ⁻⁵	n/a
iflo_retrain_emulator_nbit	Number of iterations at each time step for retraining the emulator	Neural network	1.0	iterations
iflo_force_max_velbar	Artificially upper-bound of ice velocities	Ice flow	3000.0	m yr ⁻¹
iflo_network	The type of network, it can be cnn or unet	Neural network	"cnn"	n/a
iflo_nb_layers	Number of layers in the Convolutional Neural Network (CNN)	Neural network	16.0	n/a
iflo_nb_out_filter	Number of output filters in the CNN	Neural network	32.0	n/a
iflo_conv_ker_size	Size of the convolution kernel	Neural network	3.0	n/a
iflo_min_sr	Minimum strain rate	Ice flow	10 ⁻⁵	yr ⁻¹
iflo_max_sr	Maximum strain rate	Ice flow	1.0	yr ⁻¹
time_start	Simulation start	Time	-140000.0	a
time_end	Simulation end	Time	2000.0	a
time_save	Save output variable frequency	Time	100.0	yr
time_cfl	CFL number for the stability of the mass conservation scheme	Time	0.3	...
time_step_max	Maximum time step allowed, used only with slow ice	Time	10.0	yr
thk_slope_type	Slope limiter for the ice thickness equation (godunov or superbee)	Ice flow	"superbee"	n/a
vflo_method	Method to retrieve vertical velocities (kinematic, incompressibility)	Ice flow	"incompressibility"	n/a
enth_till_friction_angle_phi_min	Minimum till friction angle in bed-elevation dependent scheme	Yield stress	15.0	°
enth_till_friction_angle_phi_max	Maximum till friction angle in bed-elevation dependent scheme	Yield stress	50.0	°
enth_drain_rate	Water draining rate	Yield stress	0.001	mm yr ⁻¹
enth_till_wat_max	Maximum water till tickness	Yield stress	2.0	m
enth_tau_min	Lower caping bound for yield stress	Yield stress	10000.0	Pa
enth_tau_max	Upper caping bound for yield stress	Yield stress	10000000000.0	Pa
avalanche_update_freq	Update frequency of the avalanche module	Avalanche	5.0	yr
avalanche_angleOfRepose	Angle of repose. For bed slopes above this, ice "avalanches"	Avalanche	45.0	°

3 Supplementary figures

The figures included here consist of both frequency maps and confusion-matrix overviews. Each domain is plotted as the frequency of simulated LGM ice extent of the top-ranked 8 simulations from the ensemble. The reconstructed LGM ice extent of the empirical dataset GLACIMONTIS (Lima et al., 2026) is plotted as a black outline over the frequency map. Time-evolving ice extent, ice volume, modelled temperature and mean monthly precipitation is also included next to the map.

S1	European Alps	6
S2	Arsi Mountains	7
S3	Bale Mountains	8
S4	Greater Caucasus	9
S5	Centre Central Andes	10
S6	Eastern Cordillera & Cordillera de Mérida	11
S7	Ecuadorian Cordilleras	12
S8	Mount Kenya & Mount Kilimanjaro	13
S9	Mount Elgon	14
S10	North Central Andes	15
S11	Sierra Nevada de Santa Marta	16
S12	Semien Mountains	17
S13	Western & Central Cordillera	18
S14	Validation Northern Andes	19
S15	Validation Central Andes	20
S16	Validation European Alps and North Central Andes	21
S17	Validation Caucasus and Mount Kenya & Mount Kilimanjaro	22
S18	Validation Ethiopian Highlands and Mount Elgon	23

S1 European Alps

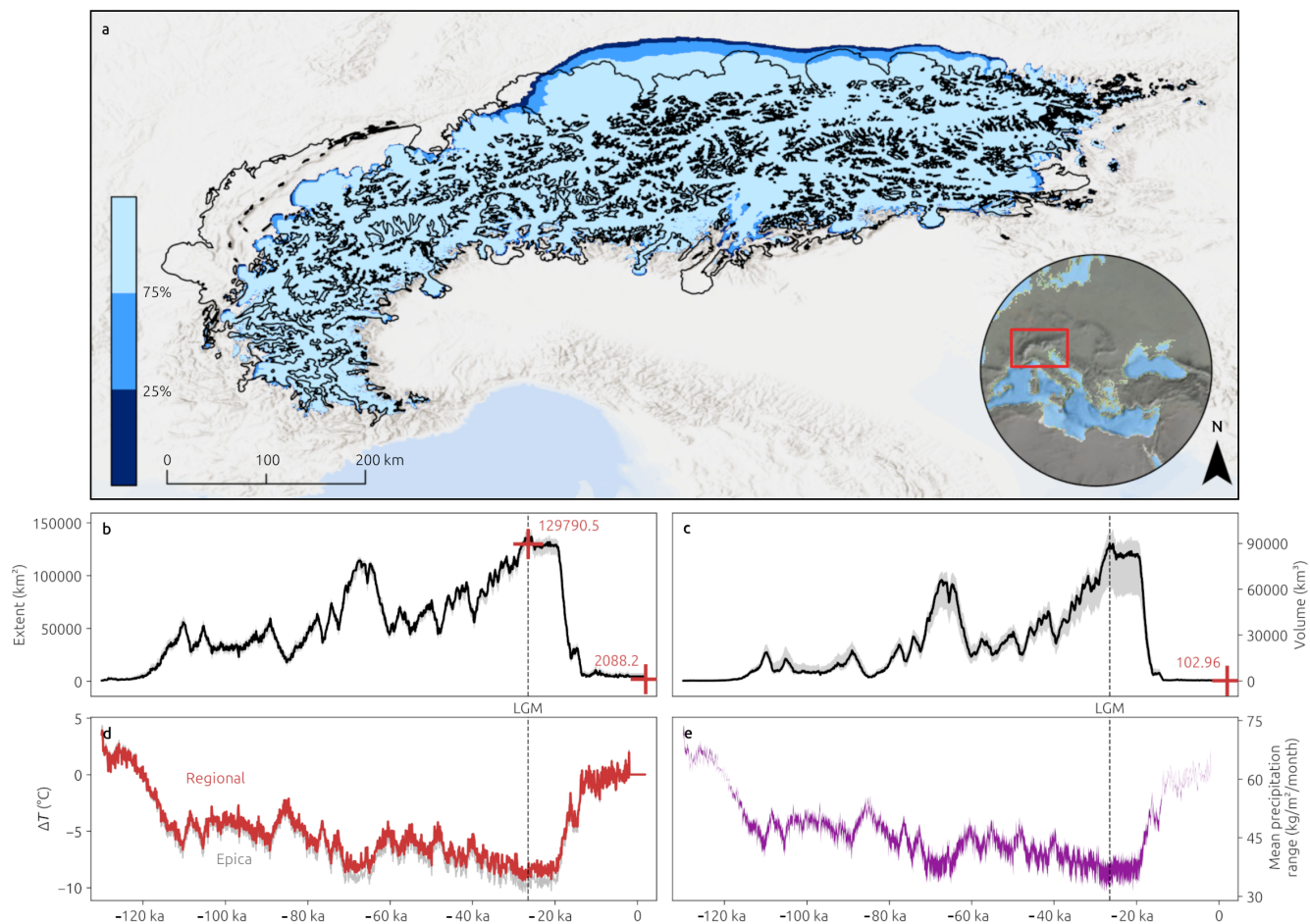


Figure S1. Frequency of simulated LGM ice extent of the European Alps using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 0.4 and 0.5 respectively.

S2 Arsi Mountains

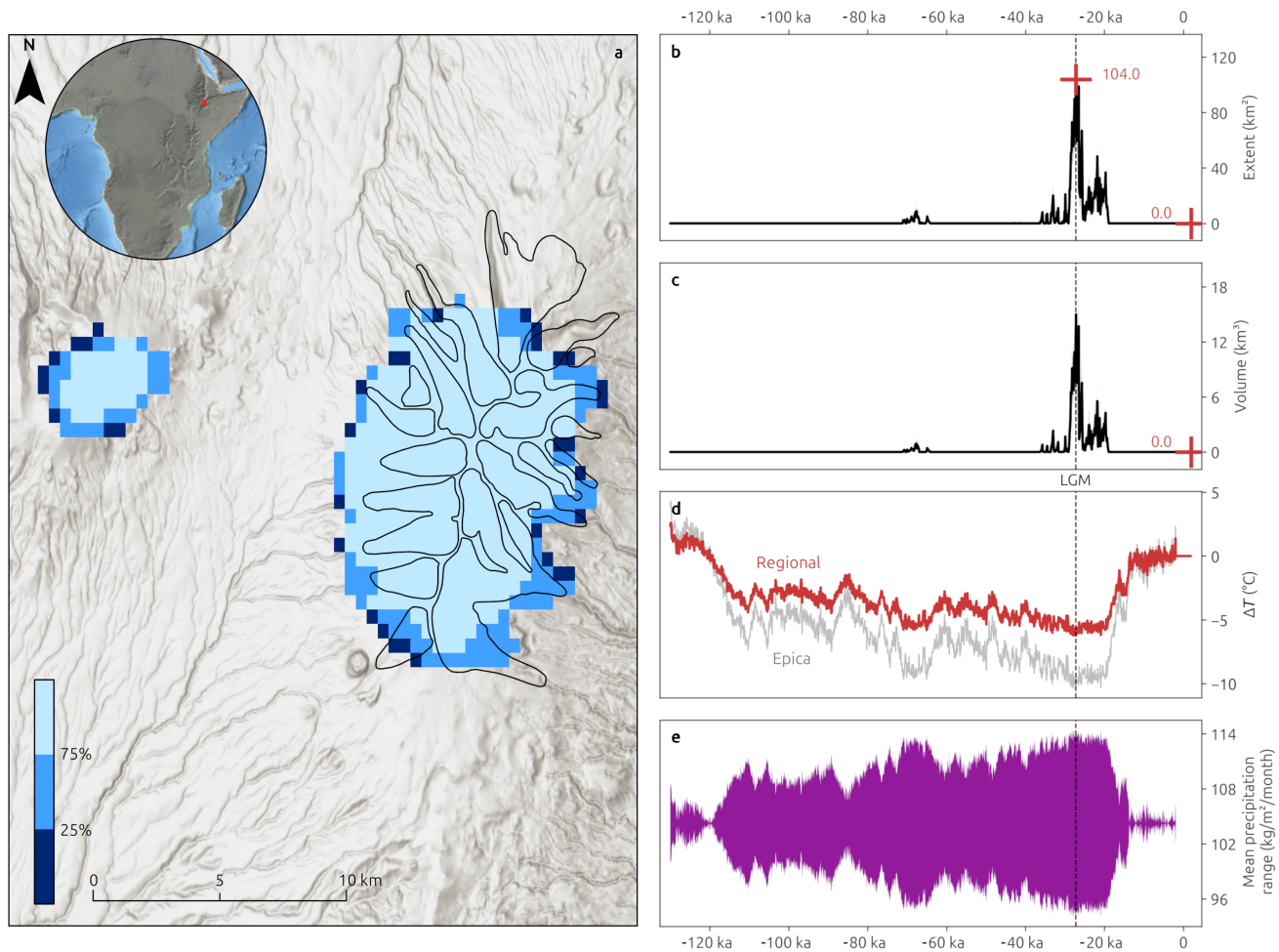


Figure S2. Frequency of simulated LGM ice extent of the Arsi Mountains using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 0.9 and 1.1 respectively.

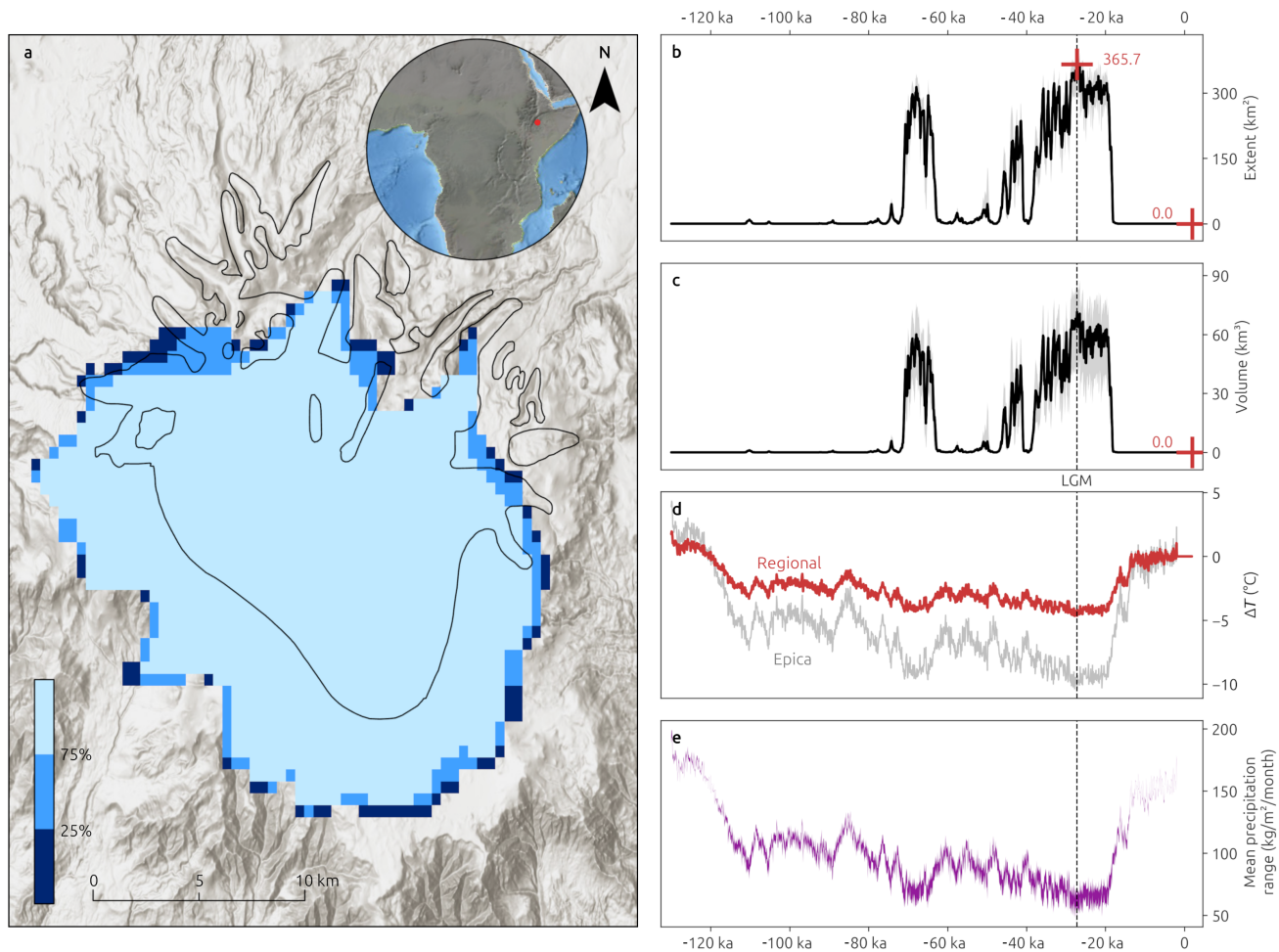


Figure S3. Frequency of simulated LGM ice extent of the Bale Mountains using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 0.3 and 0.5 respectively.

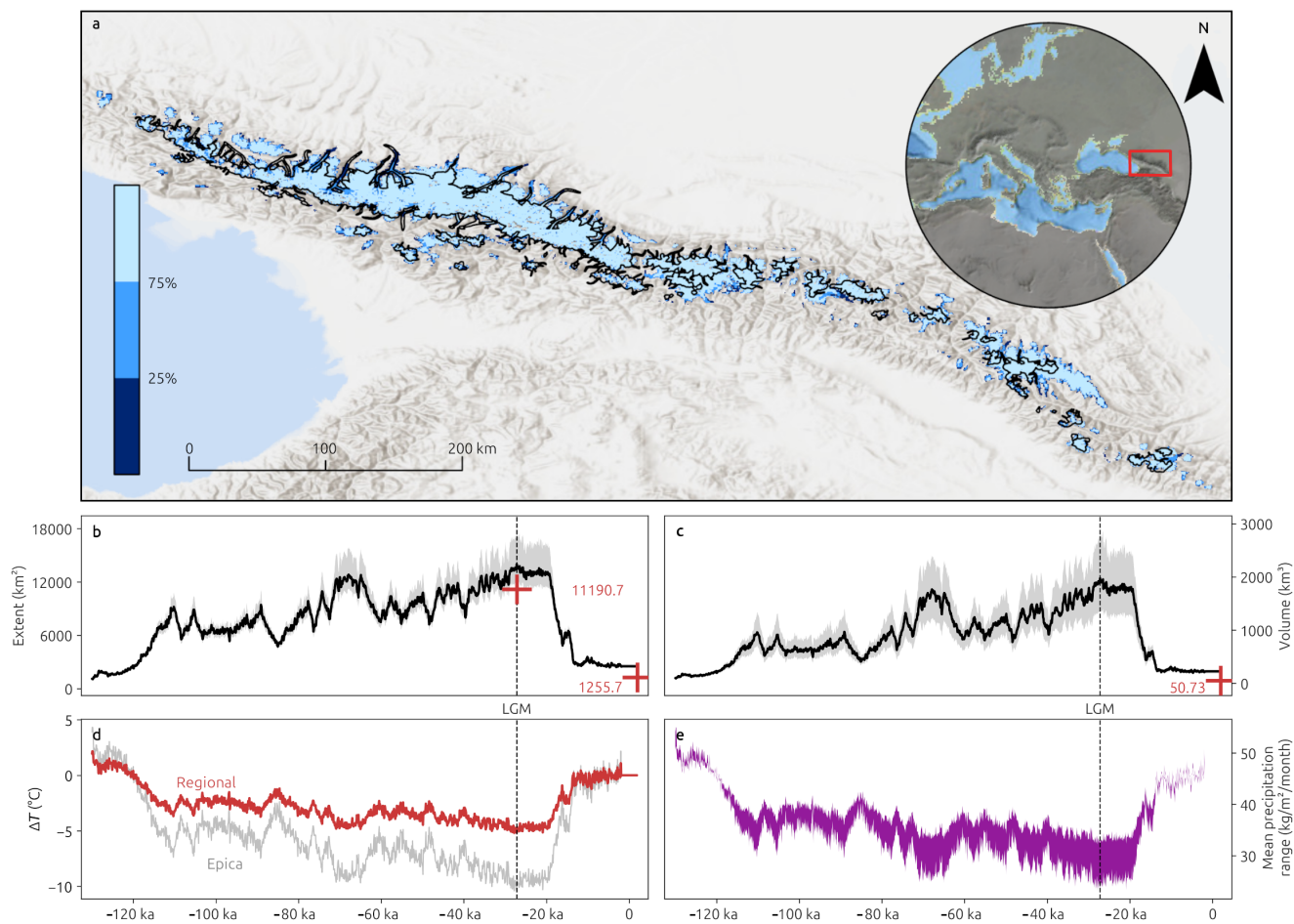


Figure S4. Frequency of simulated LGM ice extent of the Greater Caucasus using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 0.3 and 0.7 respectively.

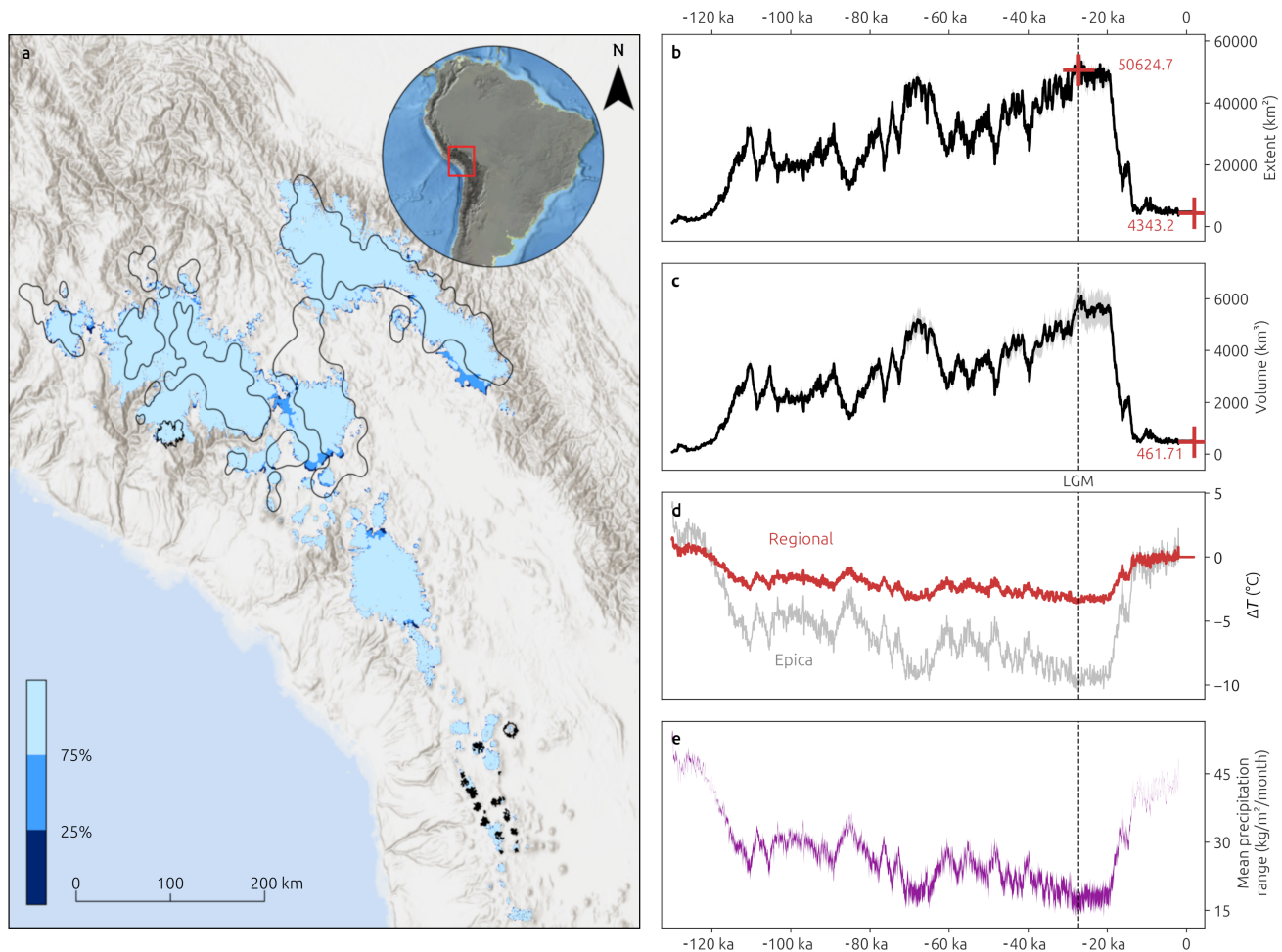


Figure S5. Frequency of simulated LGM ice extent of the Centre Central Andes using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 0.3 and 0.4 respectively.

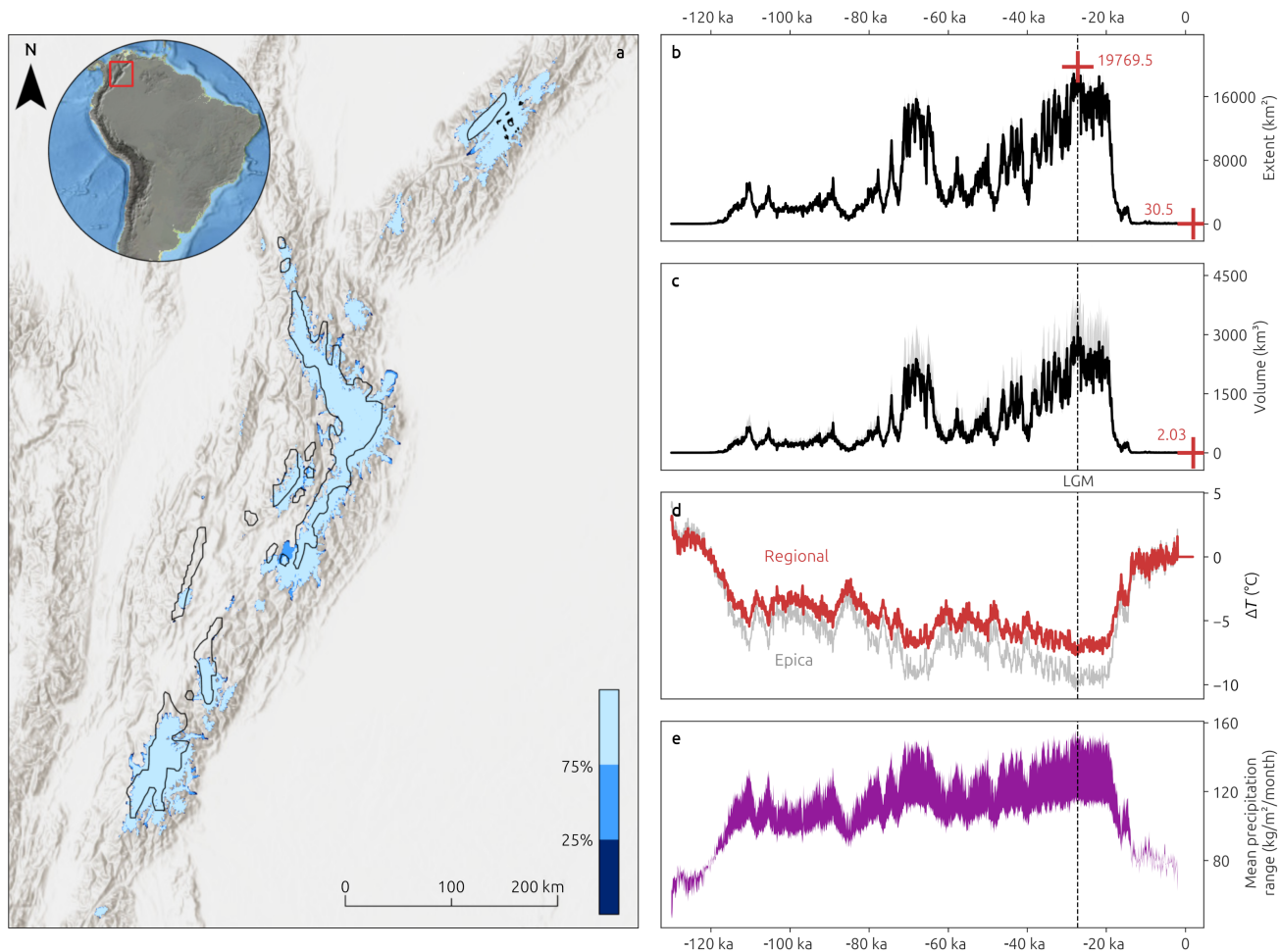


Figure S6. Frequency of simulated LGM ice extent of the Eastern Cordillera & Cordillera de Mérida using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 1.5 and 2.5 respectively.

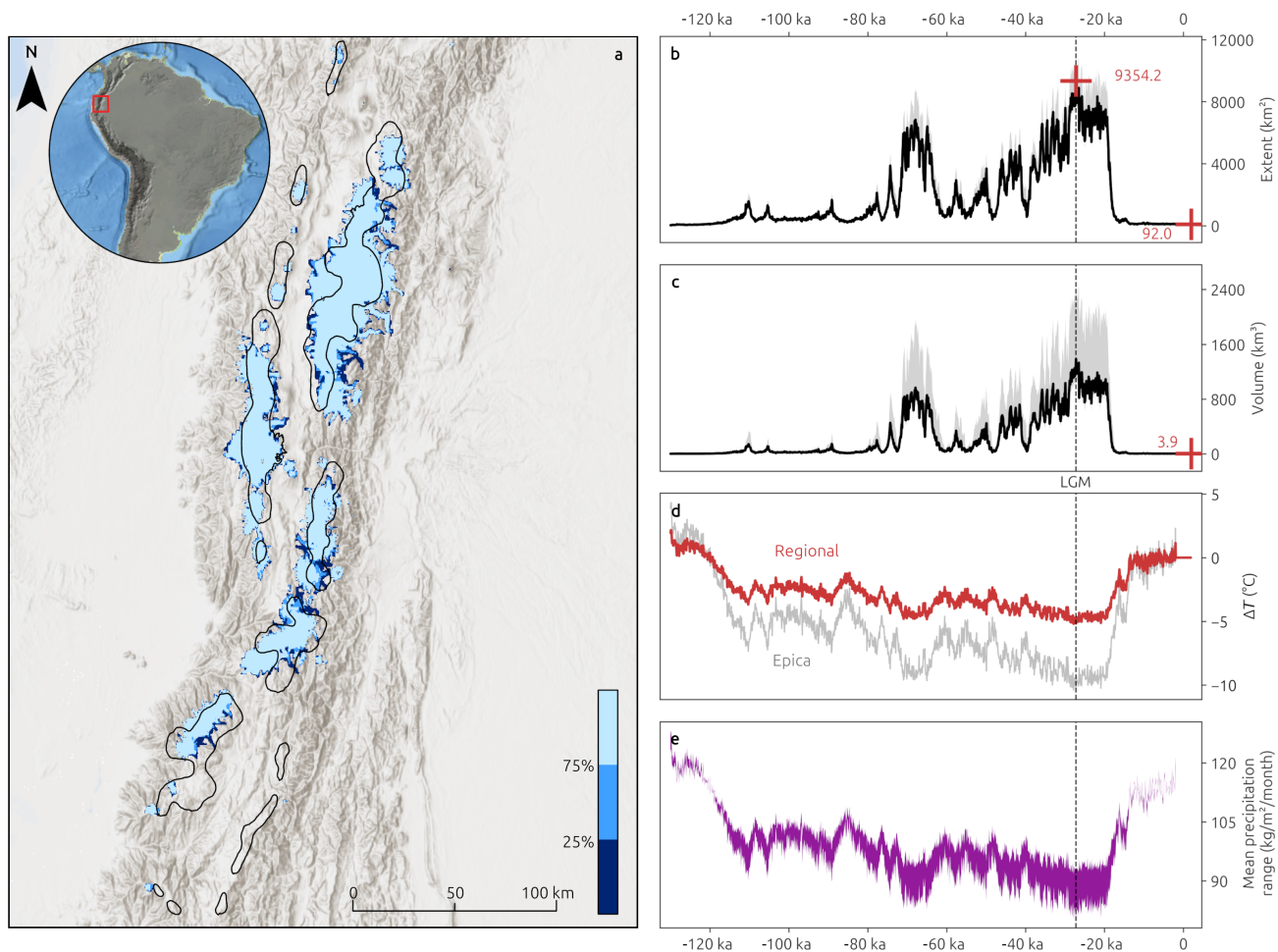


Figure S7. Frequency of simulated LGM ice extent of the Ecuadorian Cordilleras using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 0.7 and 1.0 respectively.

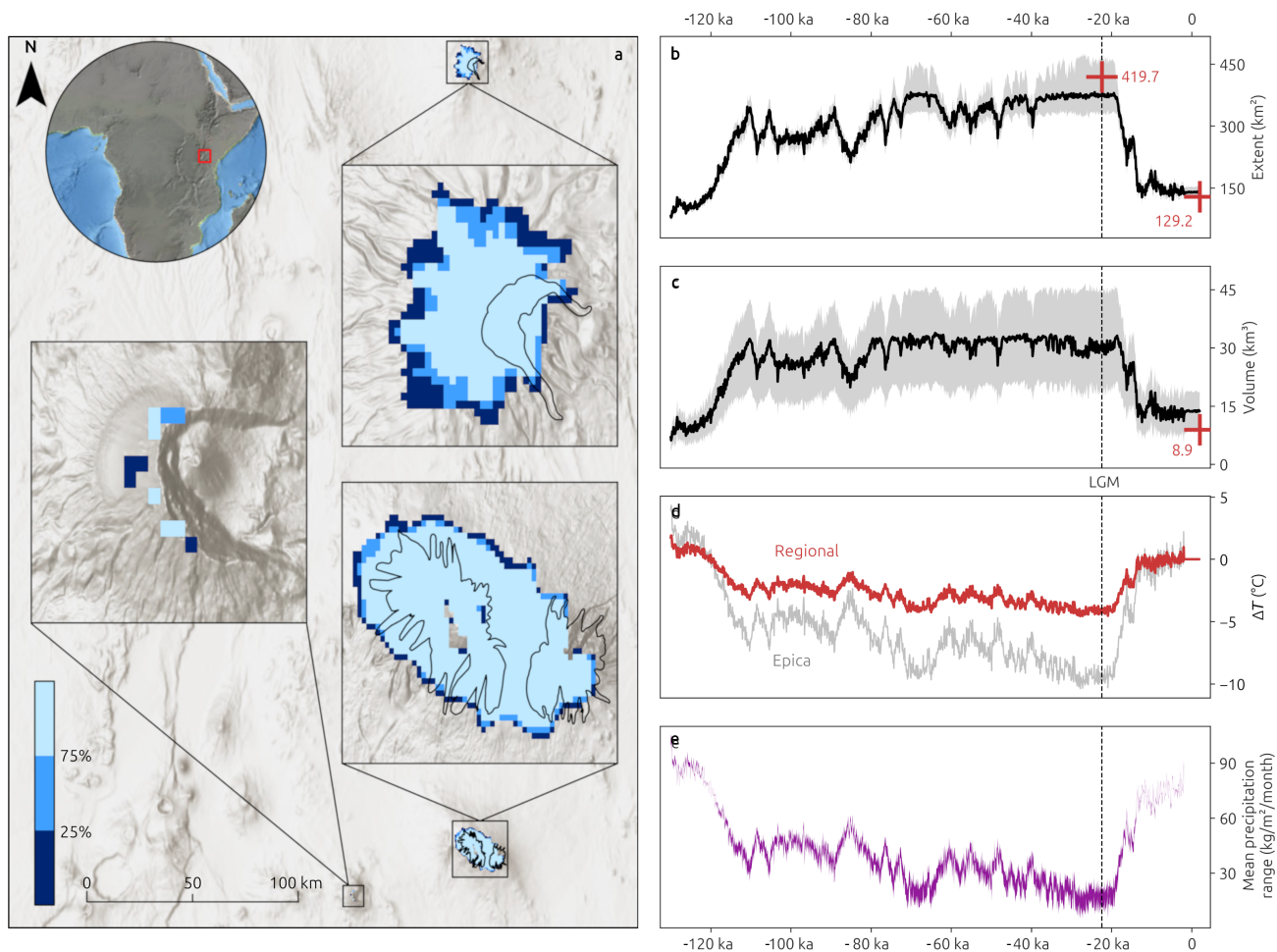


Figure S8. Frequency of simulated LGM ice extent of the Mount Kenya & Mount Kilimanjaro using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 0.05 and 0.2 respectively.

S9 Mount Elgon

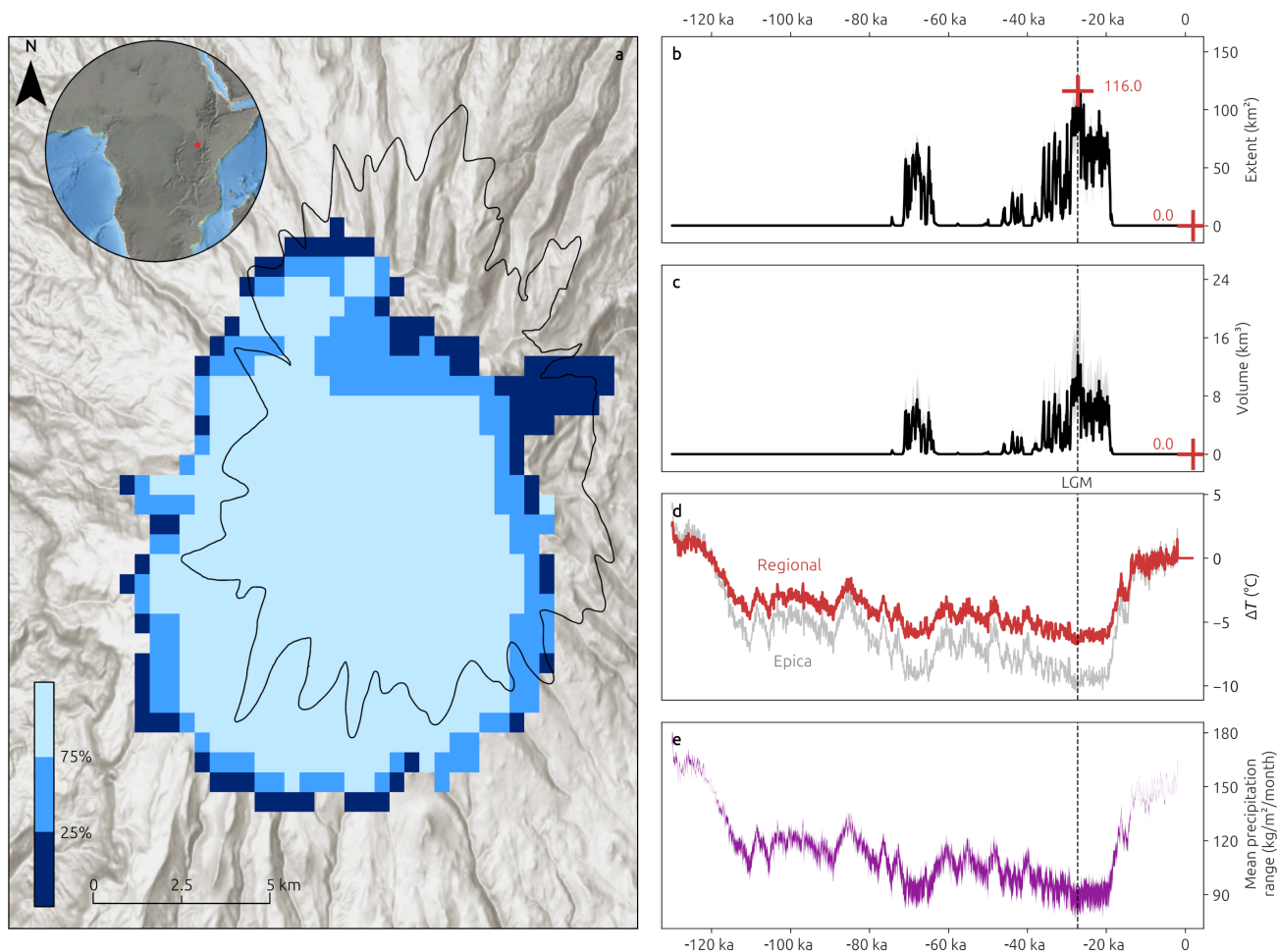


Figure S9. Frequency of simulated LGM ice extent of the Mount Elgon using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 0.5 and 0.75 respectively.

S10 North Central Andes

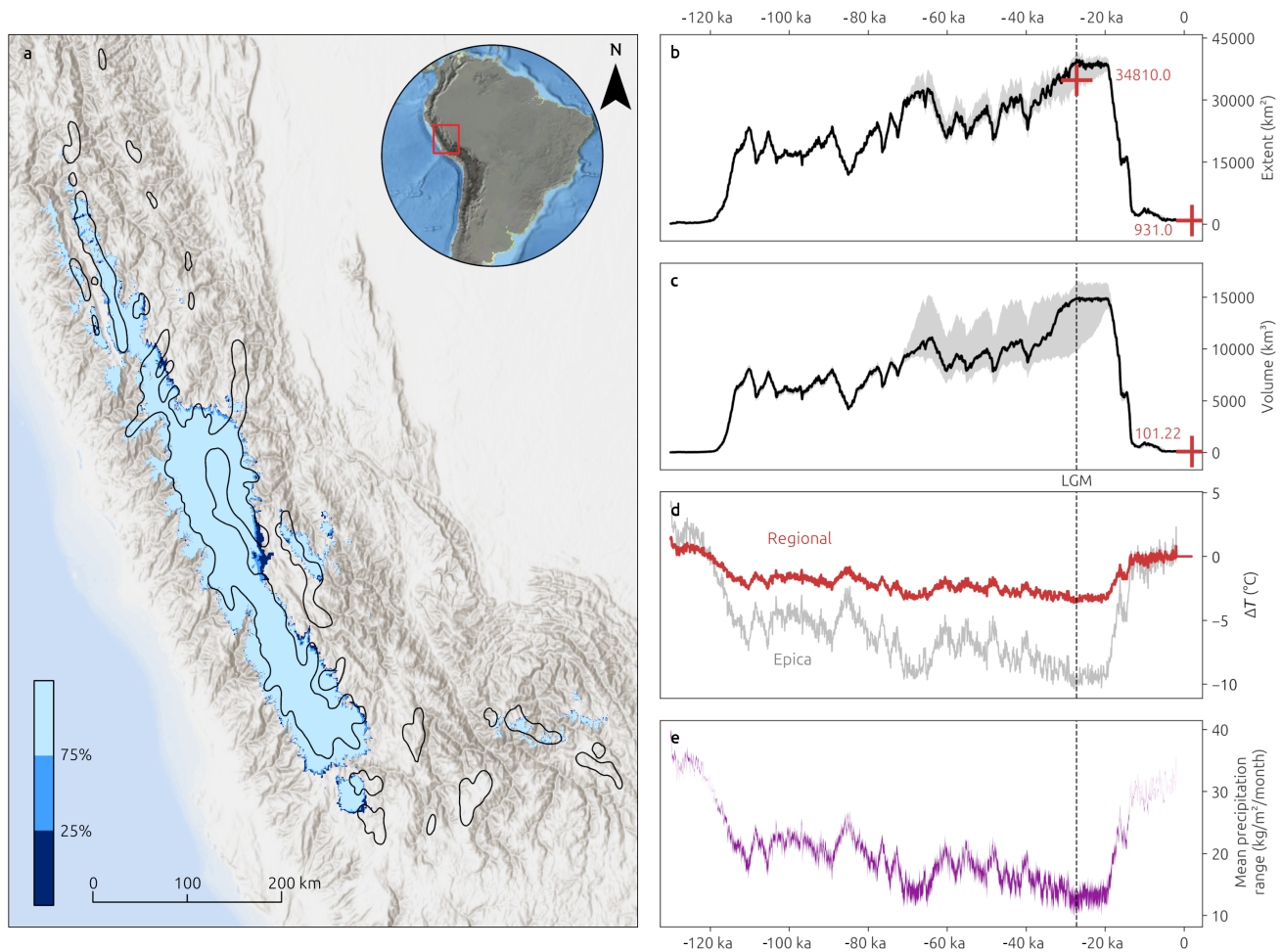


Figure S10. Frequency of simulated LGM ice extent of the North Central Andes using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 0.3 and 0.4 respectively.

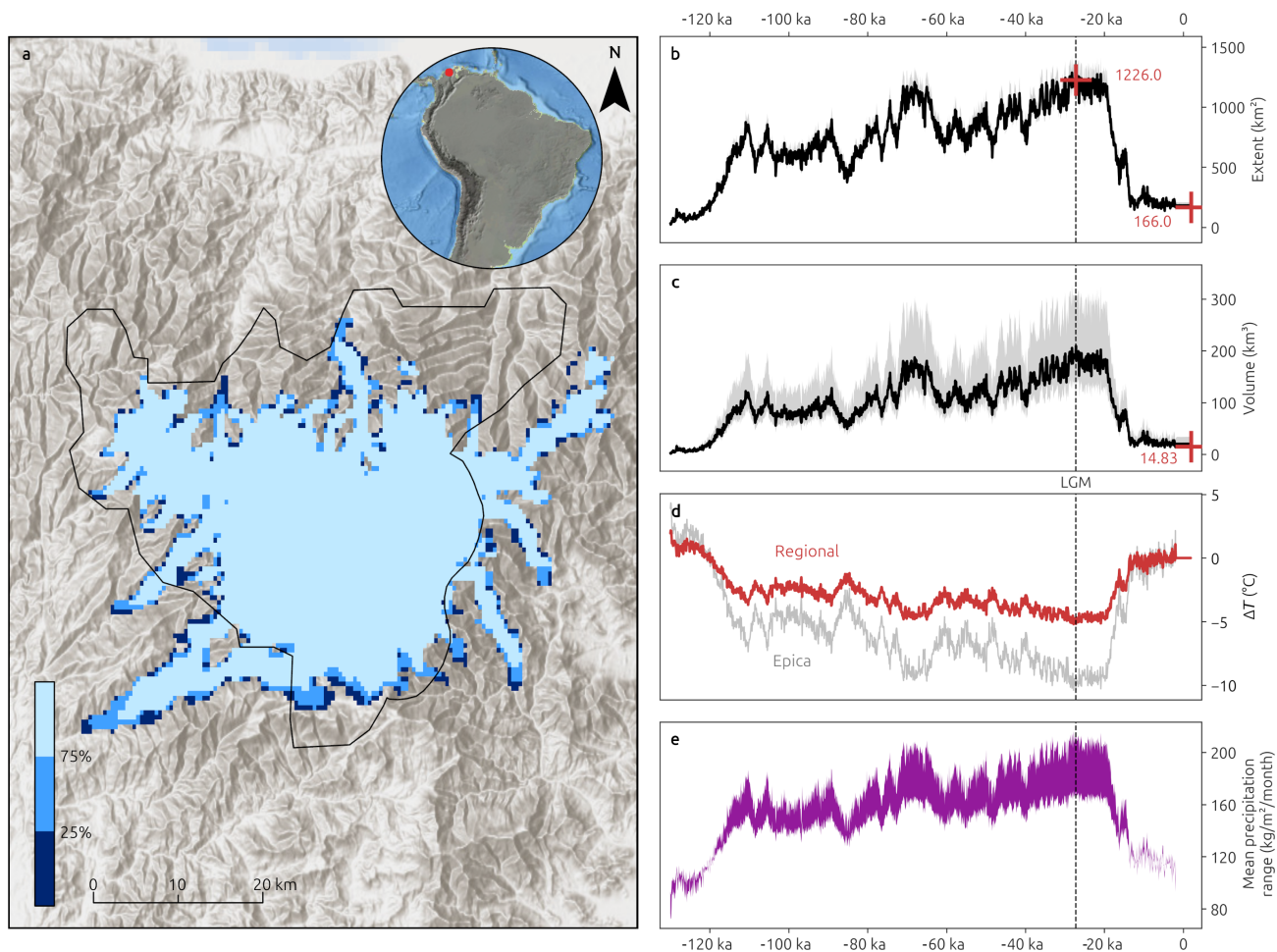


Figure S11. Frequency of simulated LGM ice extent of the Sierra Nevada de Santa Marta using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 1.5 and 1.9 respectively.

S12 Semien Mountains

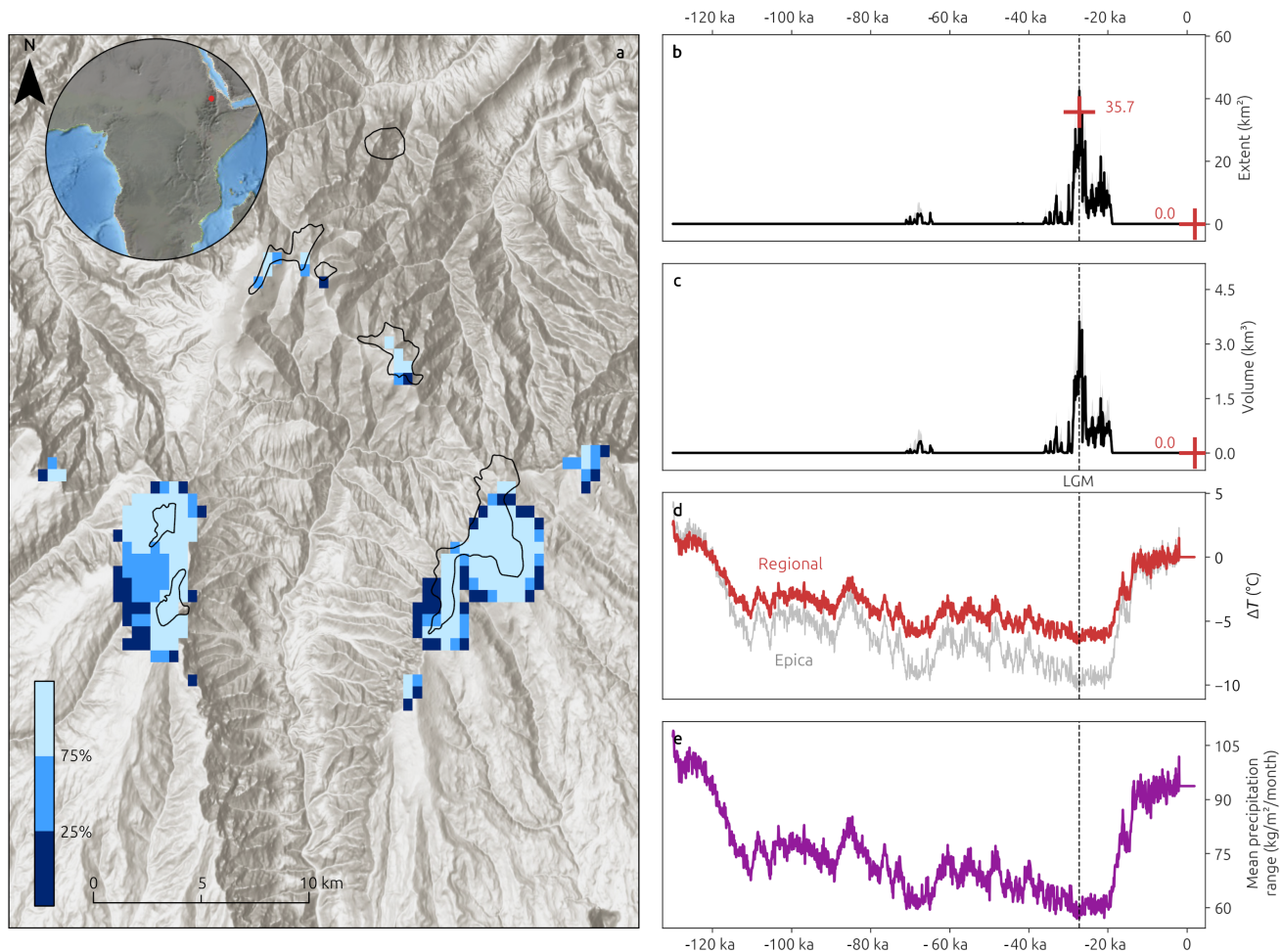


Figure S12. Frequency of simulated LGM ice extent of the Semien Mountains using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 0.6 and 0.8 respectively.

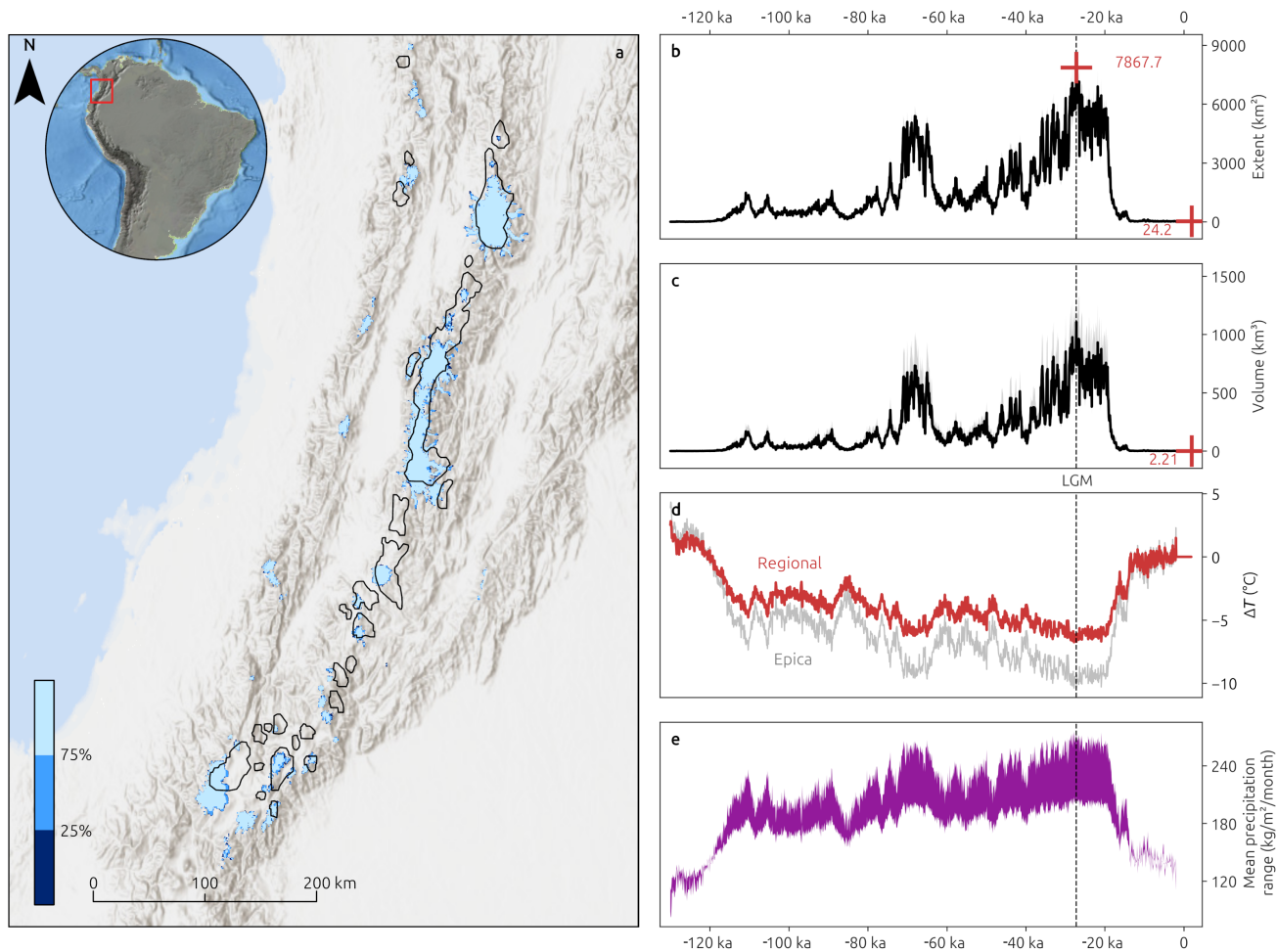


Figure S13. Simulated LGM extent frequency of the Western & Central Cordilleras using the top-ranked 8 simulations from the ensemble. Panel **a** show the frequency of simulated extents and the validation extent outline as a black line. Panels **b–e** show simulation and climate parameters for the full simulation time (130 ka – present-day). In panel **e** the mean precipitation within the bounding box is shown as a range based on the minimum and maximum precipitation adjustment parameter (P_{LGM}) in the ensemble, here 1.5 and 2.0 respectively.

S14 Validation Northern Andes

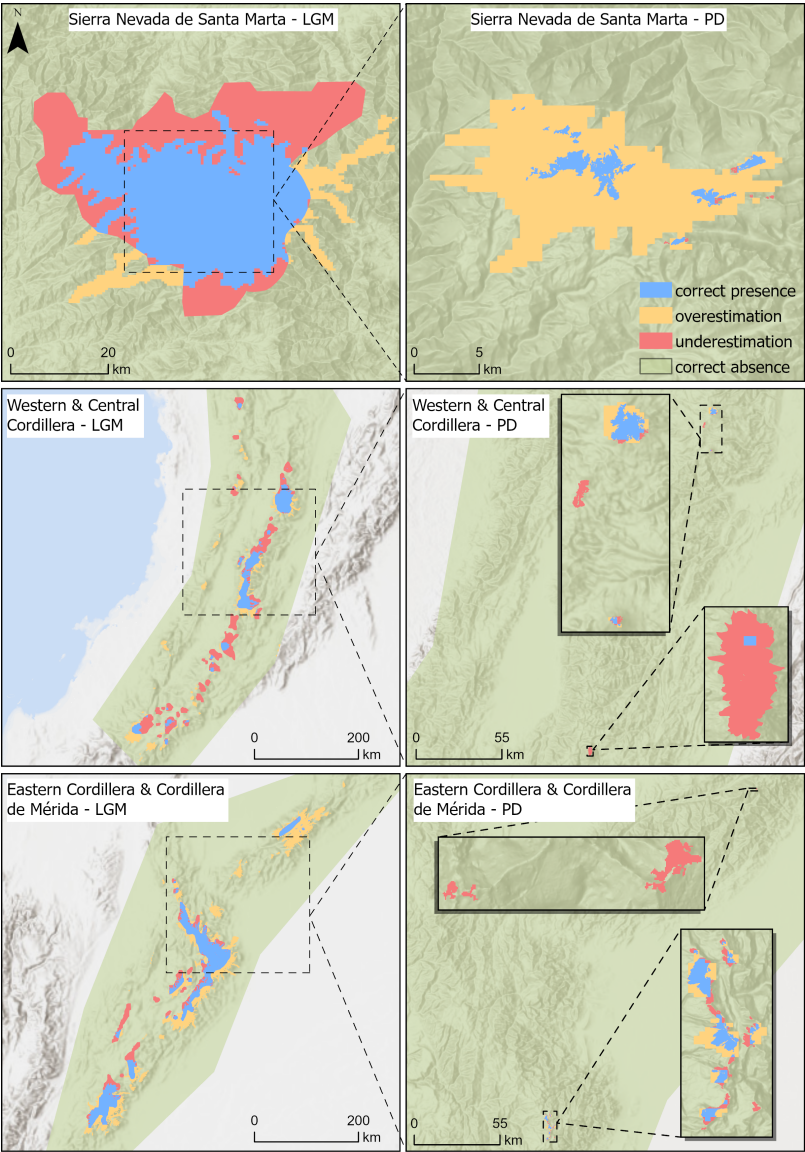


Figure S14. Spatial representation of the confusion matrix results (glacier overestimation, underestimation, correct presence and correct absence) of the best-fit simulation for the simulation domains of Sierra Nevada de Santa Marta, Western & Central Cordillera, and Eastern Cordillera & Cordillera de Mérida.

S15 Validation Central Andes

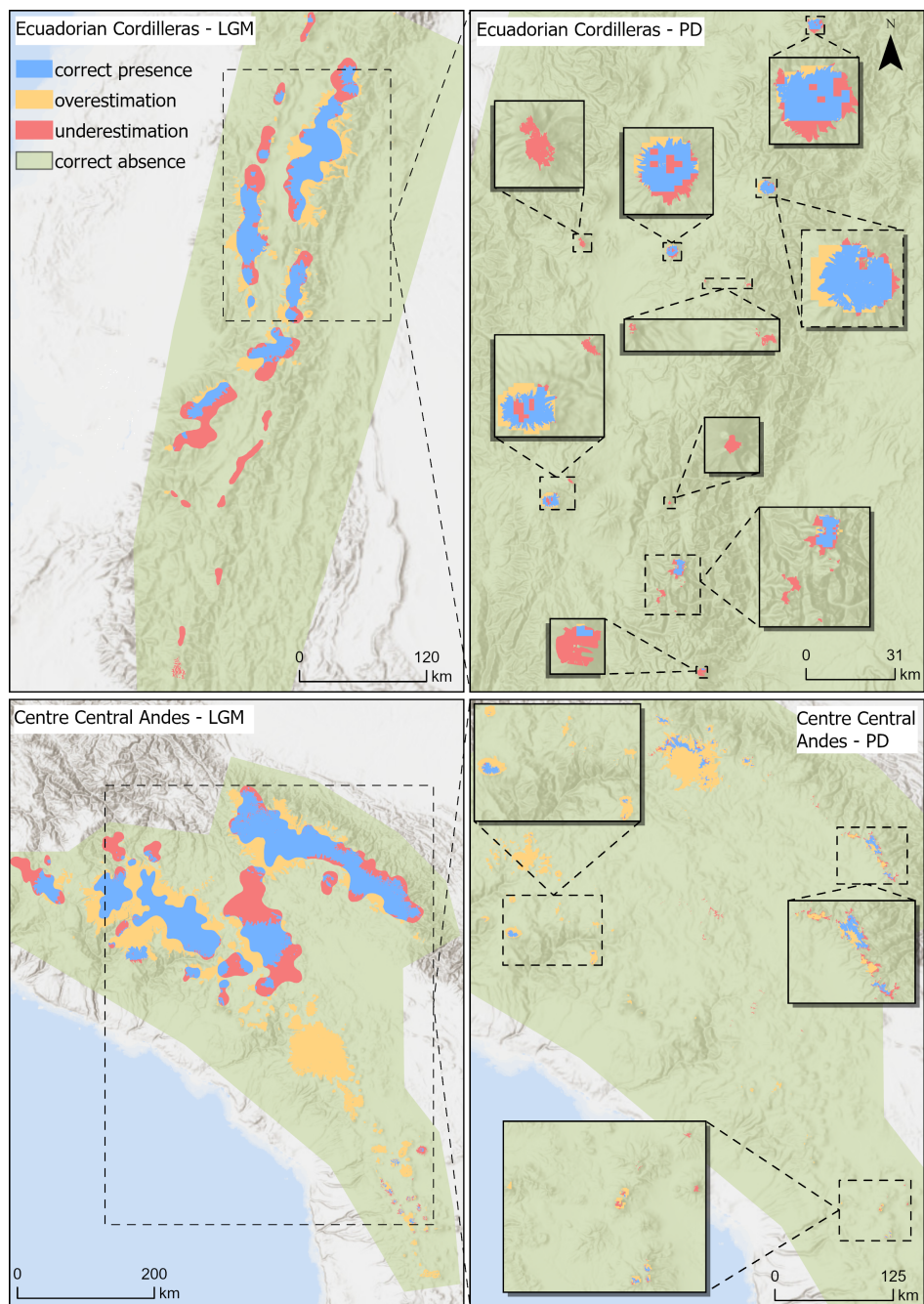


Figure S15. Spatial representation of the confusion matrix results (glacier overestimation, underestimation, correct presence and correct absence) of the best-fit simulation for the simulation domains of Ecuadorian Cordilleras and Centre Central Andes.

S16 Validation European Alps and North Central Andes

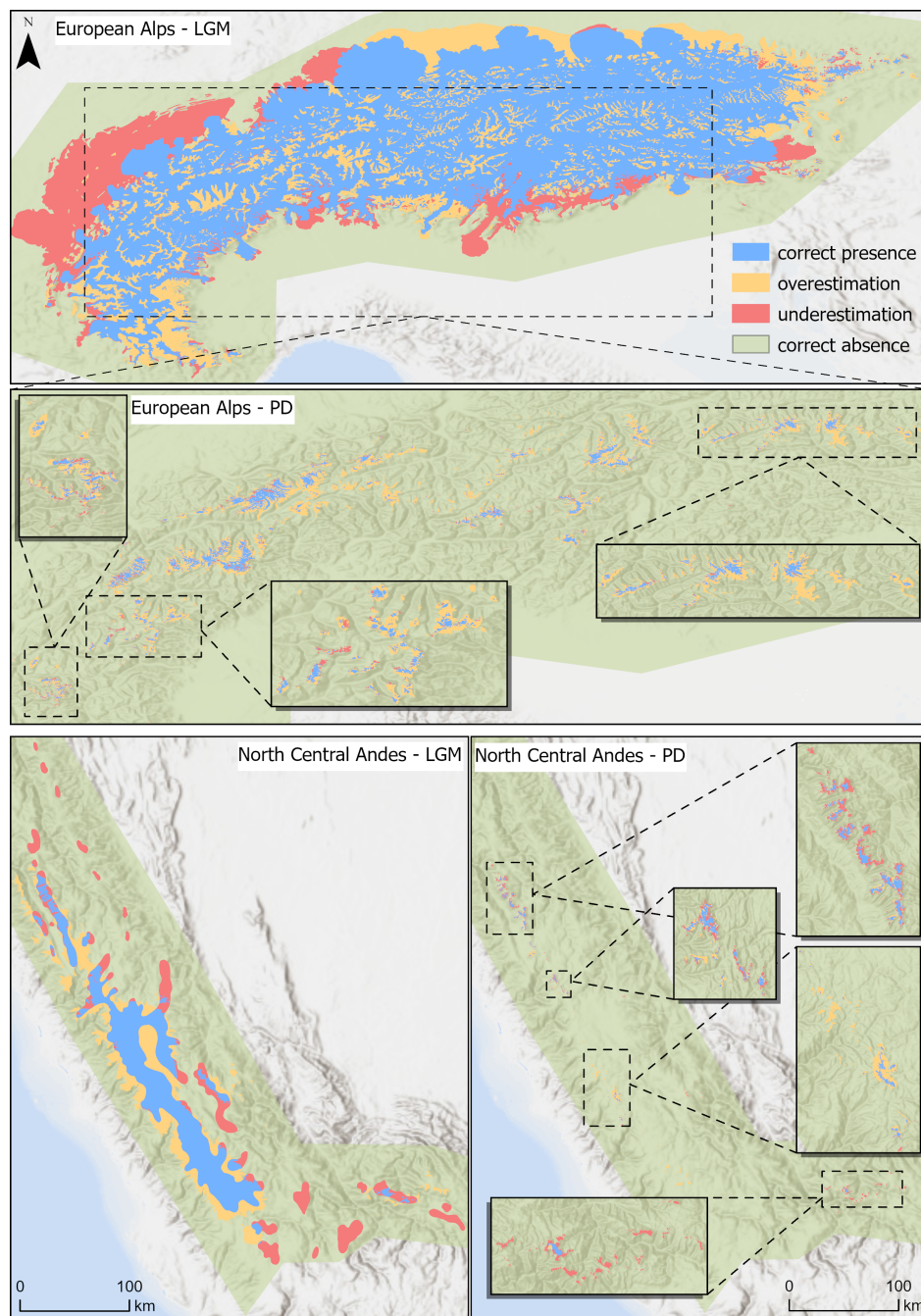


Figure S16. Spatial representation of the confusion matrix results (glacier overestimation, underestimation, correct presence and correct absence) of the best-fit simulation for the simulation domains of European Alps, and North Central Andes.

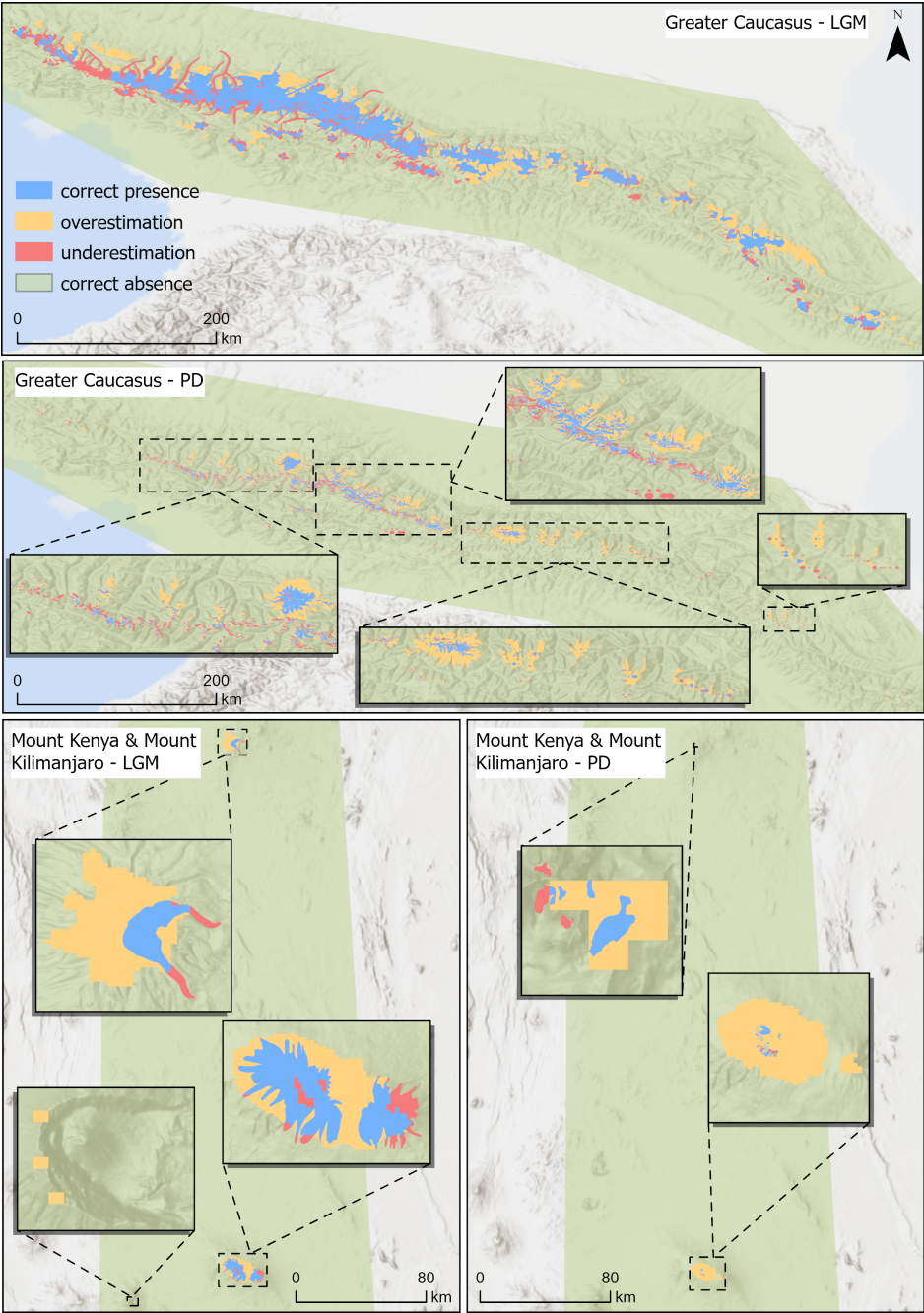


Figure S17. Spatial representation of the confusion matrix results (glacier overestimation, underestimation, correct presence and correct absence) of the best-fit simulation for the simulation domains of Greater Caucasus and Mount Kenya & Mount Kilimanjaro.

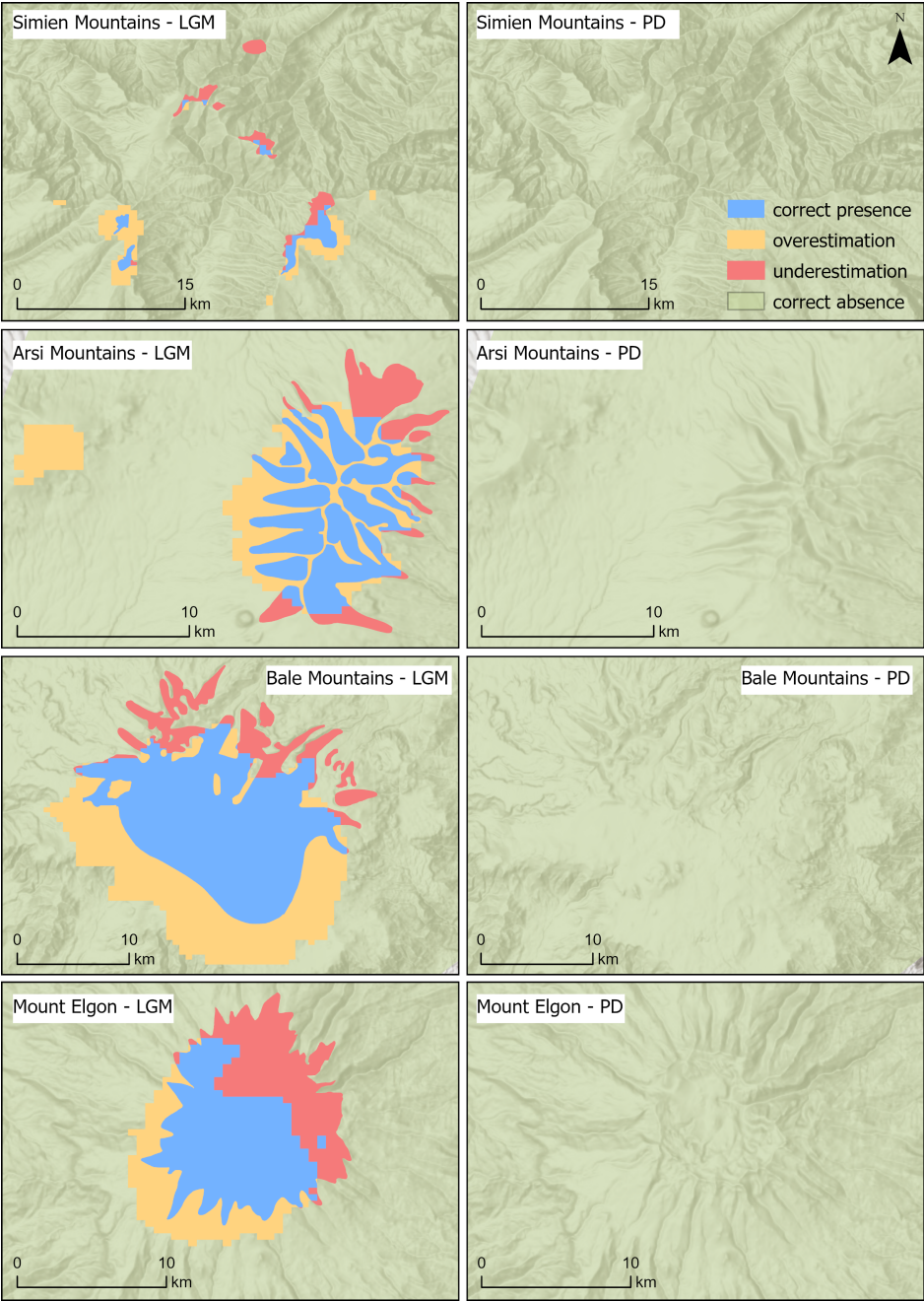


Figure S18. Spatial representation of the confusion matrix results (glacier overestimation, underestimation, correct presence and correct absence) of the best-fit simulation for the simulation domains of Semien Mountains, Arsi Mountains, Bale Mountains and Mount Elgon.

References

Lima, A. C., Dulfer, H. E., Hughes, A. L. C., Margold, M., Barr, I., Laabs, B. J. C., and Flantua, S. G. A.: Mountain glacier extents at the Last Glacial Maximum, Nature Scientific Data, <https://doi.org/10.1038/s41597-026-06841-z>, 2026.