Globally resolved surface temperatures since the Last Glacial Maximum

Climate changes across the past 24,000 years provide key insights into Earth system responses to external forcing. Climate model simulations\(^1\)\(^2\) and proxy data\(^3\)\(^4\) have independently allowed for study of this crucial interval; however, they have at times yielded disparate conclusions. Here, we leverage both types of information using paleoclimate data assimilation\(^9\)\(^10\) to produce the first proxy-constrained, full-field reanalysis of surface temperature change spanning the Last Glacial Maximum to present at 200-year resolution. We demonstrate that temperature variability across the past 24 thousand years was linked to two primary climatic mechanisms: radiative forcing from ice sheets and greenhouse gases; and a superposition of changes in the ocean overturning circulation and seasonal insolation. In contrast with previous proxy-based reconstructions\(^5\)\(^6\) our results show that global mean temperature has slightly but steadily warmed, by \(-0.5\,^\circ\text{C}\), since the early Holocene (around 9 thousand years ago). When compared with recent temperature changes\(^7\), our reanalysis indicates that both the rate and magnitude of modern warming are unusual relative to the changes of the past 24 thousand years.

The interval of time spanning the Last Glacial Maximum (LGM; 21–18 thousand years ago, ka) to the preindustrial era represents the most recent large-scale reorganization of the climate system, over which the Earth rapidly transitioned out of a cold, glaciated state with vast Northern Hemisphere ice sheets into a warm interglacial. Constraining the evolution of global surface temperatures during this critical time period provides an excellent opportunity to better understand the mechanisms of large-scale climate change, including Earth system interactions and responses to various forcings (for example, greenhouse gases, albedo/ice-sheet and orbital changes).

A number of prior studies have sought to characterize the global surface temperature evolution from the LGM to present\(^1\)\(^2\)\(^3\)\(^4\)\(^5\)\(^6\)\(^7\)\(^8\)\(^9\)\(^10\)\(^11\). Of particular note, Shakun et al.\(^3\) and Marcott et al.\(^6\) established a global mean surface temperature (GMST) estimate spanning the deglacial and Holocene periods using ~80 marine and terrestrial temperature proxies (hereafter, the Shakun–Marcott curve; SMC). However, subsequent comparisons of SMC to other global temperature reconstructions and transient LGM-to-present model simulations revealed discrepancies surrounding the timing, magnitude, and rapidity of deglacial warming and of millennial-scale cooling events\(^3\)\(^4\). One of the most prominent differences between SMC and climate model simulations is the direction of global temperature change across the Holocene. Whereas SMC shows a cooling trend, modelling results indicate there should be a warming, a phenomenon termed the Holocene temperature conundrum\(^8\). More recent work has sought to reconcile these differences by using either independent\(^12\)\(^13\) or additional\(^14\)\(^15\) proxies, and by correcting for possible proxy seasonal biases\(^3\)\(^4\)\(^12\). Nonetheless, all of these approaches have a fundamental limitation in that none provide a dynamically constrained full-field view of climate evolution since the LGM. Conversely, although climate models provide a self-consistent and spatially complete representation of the climate system, they are known to have biases due to inaccurate representation of climate processes\(^10\)\(^14\)\(^16\). Moreover, the fidelity of paleoclimate simulations of the LGM and Holocene depends on the accurate knowledge of paleoclimate boundary conditions, which are known with varying levels of certainty and may not be independent from proxies\(^3\)\(^15\)\(^16\).

The Last Glacial Maximum reanalysis

Here, we revisit the evolution of global temperatures from the LGM to present using an offline paleoclimate data assimilation approach that formally combines proxy and independent model information\(^9\)\(^10\)\(^17\). The resulting ‘Last Glacial Maximum reanalysis’ (LGMR) product offers the first proxy-constrained, dynamically consistent and spatiotemporally complete view of climate change for the past 24 kyr. The LGMR enables us to diagnose the major modes of climate variability, refine our understanding of global temperature changes across the Holocene, and compare current anthropogenic global warming with the rate and magnitude of change seen in the recent geological record.

Following ref.\(^10\), we focus on assimilating geochemical proxies for sea surface temperature (SST) with established Bayesian proxy forward models\(^19\)\(^20\). To ensure that the proxy data have sufficient temporal resolution and length to inform our reconstruction, we required that records be at least 4,000 years long, have a median time resolution of 1,000 years or less, and contain a radiocarbon-based
The diversity, size and spatial coverage of our proxy compilation offers new insight into LGM-to-present climate evolution on its own. However, transient offline data assimilation further leverages the full-field dynamical insights available from climate models to bypass issues related to heterogeneous proxy spatial distribution. The model ‘prior’ for the assimilation consists of 50-year average states from 17 LGM-to-present time-slice experiments conducted with the isotope-enabled Community Earth System Model version 1 (CESM1; Extended Data Table 1 and Methods; refs. 10,22). We reconstruct climate at 200-year intervals, adhering to the resolution limitations of the majority (>90%) of our proxy data. For a given time interval, we estimate proxy values from the model prior at the locations where geochemical measurements exist using our Bayesian forward models, which take into account seasonal growth preferences on a per-species basis for δ¹⁸O and Mg/Ca (refs. 20,21) and seasonal production for TEX⁺⁶ (refs. 37,38) although some SST records that met these criteria were excluded due to complications related to proxy interpretation and (or) their latitudinal distribution. The diversity, size and spatial coverage of our proxy compilation ensures that it is based on priors from a single model (iCESM), which are inevitably biased by model deficiencies, resolution and uncertainties in boundary conditions. However, we can objectively test the veracity of the LGMR by comparing the simulated fields with the observations and the proxy data. We also sampled age uncertainty to ensure that this source of error was propagated into our assimilated fields. As in proxy-only analyses (3,4,6,11), this results in some temporal smoothing of our LGMR ensemble mean but does not impact the fidelity of millennial-scale trends or features (Methods).

The LGMR highlights the exceptional and spatially heterogeneous nature of deglacial climate change (Fig. 2). Reconstructed GMST reveals a distinct three-part sequence across the past 24 kyr. From 24–17 ka, the Earth is in a ubiquitously cold glacial state. The thermal imprints of the North American and Eurasian ice sheets are near their maximum extent, with terrestrial cooling relative to the preindustrial below −20 °C across the glaciated high northern (>45°N) and southern (>45°S) latitudes (Fig. 2). At 16.9 ka (median; 95% confidence interval CI) = 18.5–16.0 ka; Supplementary Information), global-scale deglaciation (the second stage) abruptly begins. Deglacial global warming shows a familiar two-step rise that is punctuated by the millennial-scale Bølling–Allerød (14.8–12.8 ka) to Younger Dryas (12.8–11.7 ka) events. Following the Younger Dryas cooling event, the Earth enters its final transition towards the present interglacial. In the third part of the GMST sequence, early Holocene (11 ka onward) warming stabilizes by 9.5 ka (11.2–8.7 ka) and is followed by a small (~0.5°C) but significant (>99%) probability from 9.5–0 ka) global warming until preindustrial times. A vestigial cold imprint over northeastern North America is all that remains of the once-great Northern Hemisphere ice sheets at 9 ka as mild, albeit widespread, high-latitude warming ensues; Antarctica shows a notable east-west thermal dipole next to a relatively warm Southern Ocean; whereas mild cooling persists across much of the tropics (Fig. 2).

Offline data assimilation products are strongly dependent on the covariance structure of the model prior (16). A limitation of the LGMR is that it is based on priors from a single model (iCESM), which are inevitably biased by model deficiencies, resolution and uncertainties in boundary conditions. However, we can objectively test the veracity of the LGMR, including its spatial representation, using two independent methods of statistical validation. First, we use our posterior LGMR fields to reconstruct withheld proxy time series (for example, ref. 39).
Across the ensemble, the majority of records are skilfully reconstructed (Methods) with no obvious signs of regional biasing (Extended Data Fig. 2). Second, following ref. 20, we compare posterior δ¹⁸O of precipitation (δ¹⁸O_p) to independent ice core- and speleothem-derived δ¹⁸O_p time series (Extended Data Table 2). On a global scale, we find notable improvement in the posterior comparison of δ¹⁸O_p over the modelled state, with a ~30% reduction of error and a large increase in variance explained (Extended Data Fig. 3). LGMR recovers 65–90% of the ice core δ¹⁸O_p variance (n = 13 records; Extended Data Table 2), including divergent Holocene trends in east versus west Antarctica δ¹⁸O_p (Extended Data Fig. 4). Both tests suggest that our posterior assimilation is robust, but the close correspondence between LGMR δ¹⁸O_p and ice core proxy records in particular emphasizes that the LGMR is producing a realistic climate state.

**Drivers of global temperature change**

To gain further insight into the drivers of global surface temperature change during the past 24 ka, we decompose our LGMR temperature fields into spatiotemporal modes of variability using empirical orthogonal function (EOF) analysis (Supplementary Information). As expected, the first spatial mode, EOF1, exhibits positive loading across the globe and explains the majority (>90%) of the surface temperature covariance during the past 24 ka (Fig. 3a). This mode is clearly associated with de-glaciation, with the strongest amplitude concentrated atop the North American and Fennoscandian ice sheets. The uniform nature of EOF1 implies an association with changes in greenhouse gas (GHG) radiative forcing and ice sheet albedo. Given the monotonic nature of the associated principal component time series, PC1, GHG forcing24 can explain 92% of the EOF1 variance (Fig. 3b). However, there are notable differences between the two time series: during the early to mid-Holocene, GHG radiative forcing increases at around 12 ka and then gradually decreases, while PC1 steadily increases. This implies GHG forcing alone is not sufficient for explaining the leading mode of global temperature variability.

Modelling experiments indicate that the magnitude of ice sheet albedo forcing is comparable to (if not greater than) GHG forcing across the deglacial transition20,21. By considering GHG and ice sheet forcing together, we account for 98% of the variance in PC1 as well as the observed warming during the Holocene (Fig. 3c). The inclusion of ice sheet albedo forcing also explains the strong EOF1 loading atop North America and Fennoscandia (Fig. 3a). Although other radiative forcings, such as vegetation and dust, probably also impacted LGM-to-present temperature change20 our EOF results imply that these were of lesser importance in terms of their global footprint, particularly during deglaciation.

The second mode of global temperature variability, EOF2, explains only 3.5% of the variance. However, it is distinct from its neighbouring tailing modes and physically interpretable (Supplementary Information). This mode is a hemispheric dipole, with strong positive loading across the Southern Ocean and negative loading spanning much of the Northern Hemisphere would not cause mean annual cooling; this conflicts with conventional Milankovitch orbital theory20. In addition, spatial correlation analyses of either orbital series with surface temperatures indicate that the strongest coupling occurs in the Southern Hemisphere (Extended Data Fig. 5b). The strong loading of EOF2 in the...
Southern Ocean in particular could point towards a feedback with regional sea ice; a longer summer (and shorter winter) would increase the extent of summertime sea ice retreat while decreasing its growth during wintertime, resulting in an increase in mean annual insolation exceeds 250 W m−2 following ref. 27).

The residual component of PC2 closely follows ($R^2 = 0.80$) 231Pa/230Th proxy records of AMOC from the Bermuda Rise30–31 (Fig. 3c). Prior studies have also identified this ‘bipolar seesaw’ mode32,33, which represents the millennial-scale events that occurred during the last deglaciation (Heinrich event 1, the Bølling–Allerød, and the Younger Dryas). Correlation analysis shows that Northern Hemisphere surface temperatures in LGMR are strongly related to AMOC changes (Extended Data Fig. 5c). A decrease in Atlantic heat transport would also lead to compensating warmth in the Southern Hemisphere, similar to the loading pattern of EOF2. However, the particularly strong loading found across the Indian and Pacific Ocean sectors of the Southern Ocean does not match the classic fingerprint of the oceanic bipolar seesaw34. Similarly, the strong loading in the eastern North Pacific is not typical of a modelled response to an AMOC slowdown35,36. It does, however, reflect the underlying proxy records from this region, which show a strong response of SST to North Atlantic climate variability37. Columbia River megaflood meltwater forcing may have contributed to the severe cooling observed in deglacial SST records from the Gulf of Alaska38; however, step-wise deglacial cooling might also be explained by dynamic changes in the subpolar gyre boundary39.

Comparison to proxy-only insights

LGMR GMST shows several notable differences when compared to the proxy-only SMC reconstruction. Focusing first on pre-Holocene differences, the LGMR has a more abrupt onset of deglaciation at ~17 ka, and a more muted Bølling–Allerød–Younger Dryas transition (Fig. 4a). The LGMR also indicates nearly twice as much glacial cooling, but this can be explained by the fact that the SMC is based mostly on SST proxies and was not scaled to infer GMST; we scale it here for comparison (Fig. 4a). To diagnose the origin of the other differences, we generated a proxy-only GMST reconstruction from our SST compilation (Methods). Although our compilation has many more proxy SST records (and no terrestrial records), it is strongly correlated with SMC ($R^2 = 0.98$).

The similarity of the proxy-only reconstruction and the SMC illuminates at least two shortcomings that are effectively mitigated by our data assimilation approach. First, proxy-specific GMST reconstructions suggest that the gradual deglacial onset is most likely to be linked to the Mg/Ca data, which show early deglacial SST increases relative to $U_{137}$ and $U_{153}$ (Extended Data Fig. 6a and Supplementary Information). Such differences may reflect proxy-specific spatial bias (Fig. 1); data assimilation will mitigate these differences by balancing signals from other nearby proxies. Second, data assimilation allows us to overcome problems associated with spatial aliasing in the proxy distribution. Unlike the enhanced Younger Dryas cooling shown by the proxy-only curves (Fig. 4a), LGMR reveals that Younger Dryas cooling was in fact confined to the Northern Hemisphere (and, specifically, the North Atlantic and North Pacific sectors; Extended Data Fig. 7). Thus, the stronger expression of the Younger Dryas in the proxy-only GMST curves could reflect Northern Hemisphere bias in the proxy distribution during the deglaciation (Fig. 1a).

Holocene global temperature trends

The LGMR provides an updated view of the Holocene temperature conundrum2. All of the proxy-only reconstructions—including SMC, Temp12K and ours—show a cooling trend that begins at ~7 ka BP and continues through the Holocene (Fig. 4b). In contrast, LGMR shows a small (0.25 °C) but significant warming ($P > 0.9$) based on ensemble analysis since 7 ka (Fig. 4b). The Holocene trend in LGMR does not come from the model prior; in fact, the model suggests a warmer mid-Holocene due to a prescribed ‘Green Sahara’ (Methods; Extended Data Table 1). Rather, it is a feature of the assimilation: the early-mid Holocene warming in Mg/Ca

Fig. 3 | Leading modes of LGM-to-present surface temperature variability. a, b, Empirical orthogonal function (EOF) 1 and EOF 2 of surface air temperature during the past 24 kyr. c, Comparison between the associated principal component time series and climatic drivers. From top: PC1 (red) versus greenhouse gas (GHG) radiative forcing35, albedo radiative forcing (derived following ref. 34), and combined GHG and albedo radiative forcing; PC2 (blue); the ‘residual’ component of the regression of 65°S summer duration (the number of days where mean-annual insolation exceeds 250 W m−2 following ref. 27).
(and, to a lesser extent, U37K' and δ18Oc) that underlies the conundrum is nearly eliminated after assimilating each proxy type into iCESM (Extended Data Fig. 6). Such consistency implies that a warming trend through the Holocene is a robust solution. This solution is generally similar to the temperature evolution simulated by TraCE-21k (Fig. 4b) indicating that the Holocene conundrum is effectively resolved by data assimilation.

Most likely, this is related to how data assimilation weights the proxies to compute a global average. Data assimilation weights proxies based on their uncertainties and the model-proxy covariance structure and uses this information to update the surface air temperature field. In contrast, proxy-only reconstructions rely on simple latitudinal binning and weighting. This renders the latter approach particularly sensitive to latitudinal bands with sparse proxy coverage or outliers. Sensitivity tests (Supplementary Information) suggest that limited number of proxies in the Southern Ocean latitude band (45–60°S) can account for about half of the early Holocene warmth in our proxy-only GMST curve (Extended Data Fig. 6b). This implies the Holocene conundrum may be, in part, an artifact of poor spatial averaging. More broadly, given that proxies are unevenly distributed, proxy-only reconstructions do not represent a true global average. In contrast, LGMR-based GMST is based on a spatially complete field, and thus is truly a global mean air temperature. This is a clear strength of the LGMR over existing reconstructions.

Proxy seasonal bias may also play a role2,8. The LGMR uses proxy forward models that account for seasonal plankton growth19–21 and allow δ18Oc and Mg/Ca seasonality to change through time. Our proxy-only curves use inversions of the same models but require that seasonality be temporally fixed. Thus, the proxy-only reconstructions could be more affected by seasonal bias. However, analyses exploring the impact of seasonally biased records, as well as the ‘dynamic’ seasonality in LGMR, indicate that seasonality has a minimal influence on the Holocene GMST trajectory in both proxy-only reconstructions and data assimilation (Extended Data Fig. 6a–c and Supplementary Information). Within the confines of our forward modelling assumptions, seasonal bias is a less prominent contributor to the conundrum than spatial weighting.

Finally, the LGMR allows us to directly assess 20th and 21st century warming from the broader vantage point of the past 24 kyr. When
juxtaposed alongside the last millennium reanalysis (also a paleoclimate data assimilation product) and observational HadCRUT5 (Fig. 2), we find that 2010–2019 mean GMST exceeds the upper bound (>99.9th percentile) of decadal-estimated values from the LGM by a considerable margin: >0.5 °C, or +1.5 °C above mean Holocene GMST. These findings differ from those of Marcott et al. 4, who suggested that early 21st century temperatures (2000–2009) had not yet exceeded early Holocene values and reflect increased confidence over ref. 7, who find that 2010–2019 warming is at the ~80% CI of mid-Holocene centennial-scale values. Similarly, we find the HadCRUT5-observed rate of 20th to 21st century warming (0.96 °C per century) registers near the upper bound of LGM deglacial warming rates (that is, >99th percentile; Fig. 5). A similar conclusion is reached when comparing HadCRUT5 warming rates to the monthly resolved TraCE-21k simulation scaled to match the largest magnitude of deglacial warming shown by the LGM (Fig. 5 and Supplementary Information) 2. The LGM underscores the dramatic nature of anthropogenic warming, whose magnitude and rate appear unusual in the context of the past 24 kyr.

Online content
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Methods

Proxy compilation and screening

We collated a globally dispersed set of 573 SST proxy records spanning the past 24 kyr. Following ref. 10, we focus on geochemical proxies for SST including alkenone U37K′ (146 records), the TetraEther Index of 86 carbons (TEX86; 28 records), the elemental ratio of Mg to Ca in planktic foraminifera (Mg/Ca; 129 records), and the oxygen isotopic composition of planktic foraminifera (δ18O; 270 records). As in ref. 10, we limit our analyses to these proxies because we have already developed Bayesian forward models for each of them18–21 that we can use in our paleoclimate data assimilation scheme (see the ‘Paleoclimate data assimilation’ section below). These data tend to cluster along coasts where sedimentation rates are high, and in regions where sampling efforts have historical focused (for example, the Atlantic sector and Northern Hemisphere). By comparison, data coverage across ocean interiors—in particular, the Pacific and (to a lesser extent) Southern Oceans—is sparse. For consistency, we recalibrated all age models using the Marine13 radiocarbon calibration curve39 with the BACON age model program40 and local estimates of deviations from the global marine radiocarbon reservoir age (ΔR). This procedure also allowed us to generate ensembles (n = 1,000) of possible age models for each record that were used to propagate dating uncertainties into our data assimilation product (see sections ‘Paleoclimate data assimilation’ and ‘Proxy-only global mean temperature below’).

Some screening of our proxy compilation was necessary to remove low-resolution, short and adversely situated proxy records. Generally speaking, we removed records whose median age resolution was less than 1,000 years or were less than 4,000 years long (Extended Data Fig. 1). However, the former constraint was relaxed for records situated in or near the Southern Ocean, where data coverage is sparse, so as to retain as many time series as possible from this undersampled region. To remove anomalous influences of sea ice on our proxy estimates (in particular, the influence of sea ice on the δ18O of seawater46) we removed records situated at locations where preindustrial mean annual SSTs were less than 0 °C (a value assumed to roughly approximate the perennial sea ice edge), as estimated from the World Ocean Atlas 201341. This resulted in 4 δ18O records being removed from locations each north of 80°N. Following ref. 19, we also omitted all U37K′ records situated north of 70°N or within the modern Arctic sea ice zone, due to known biases in the alkenone temperature proxy that are likely to arise from lipid contributions from Isocrysalidales species living in sea ice45. We also removed two western Atlantic sites, OCE326-GGC26 (43°29′N, 54°52′W) and OCE326-GGC30 (43°53′N, 62°48′W; ref. 41). While these U37K′ records have been featured in prior mean global Holocene temperature reconstructions6, they show an extremely large (up to 10 °C) cooling over the Holocene that most likely reflects a shift in the Gulf Stream/Labrador Current boundary61. This poses a problem for our data assimilation technique, because CESM1.2 does not put this sharp boundary in the same place as observations. Assimilation of these sites thus has a tendency to cause a large regional bias in SSTs. Although similar issues arising in part from coarse model resolution probably affect other frontal regions, no sufficient cause was found to warrant the removal of any additional records. All told, our selection criteria resulted in the removal of 34 records.

Proxy only global mean temperature reconstruction

To provide a point of comparison for our data assimilation results, we generated a reconstruction of global mean temperature change using only the proxy data, broadly following the methodology of ref. 41. This was done by first estimating a ‘reference’ preindustrial proxy value for each site and then appending each value at the top of its respective N × 1 proxy record. This produced an (N + 1) × 1 vector of proxy values for each site i, where the +1 denotes the appended preindustrial reference value. For sites with value(s) overlapping the preindustrial (that is, 0–4 kyr BP; see ref. 10), the preindustrial reference was computed as the 0–4 kyr mean proxy value. For sites without preindustrial overlap, reference proxy values were estimated by using the nearest core-top value18–21. As in ref. 44, if no core-top locations existed within a threshold 300 km radius, an observational preindustrial SST estimate was taken from the HadISST product17 and forward modelled to a proxy estimate. All (N + 1) × 1 vectors were then calibrated to SSTs using the Bayesian inverse models18–21. For the δ18O and TEX86 models18,20 we used prior standard deviation values of 10 °C, while for the Mg/Ca models18,21 we used values of 5 °C and 6 °C, respectively. All prior standard deviation values are conservative, and only minimally impact the posterior. The Mg/Ca model, BAYMAG, also requires constraints on salinity, pH and bottom water calcite saturation (Ω). The BAYMAG package includes functions to estimate past changes in salinity and pH. Briefly, following refs. 21,46, these functions scale the global sea level18 to an inferred LGM global change of 1.1 psu, then add this to the modern mean annual value of surface salinity for each site, as estimated from the World Ocean Atlas 201341. Similarly, to estimate changes in pH, BAYMAG scales the ice core CO2 record44 to an inferred global increase of 0.13 pH units during the LGM, and then adds this curve to the modern mean annual value of surface pH estimated from the Global Ocean Data Analysis Project version 2 (GLODAPv218). Following ref. 21, Ω is estimated at each record’s bathymetric depth using the GLODAPv2 product and assumed to be constant through time. The δ18O model, BAYFOX, requires constraints on the time-evolution of δ18O of seawater (δ18Osw). For this, we first scaled the benthic stack of ref. 52 to an estimated change in global δ18Osw (arising from changes in global ice volume of +1% at the LGM (18 ka) relative to the preindustrial following ref. 56). This scaled curve was then added to the modern mean annual δ18Osw value18 and interpolated in time for each site.

The posterior SST estimates produced by the Bayesian inverse models are a matrix of dimension (N + 1) × M, where M contains 1,000 possible SST histories and core-top reference values for each time entry N + 1 of each i site. These matrices were sorted from least to greatest along dimension M, which preserves the ‘shape’ of the time series, after which a normally distributed analytical certainty of N × M matrix of SST anomalies.

To produce a GMST anomaly curve, SST anomaly values and associated ages were randomly drawn from our ensemble of M posterior values and our ensemble of 1,000 age models, respectively, and then sorted into contiguous 200-year bins spanning back to 24 ka. If more than one data point per record occurred in a given 200-year bin, those SST data points were averaged, to ensure that higher-resolution records did not bias the GMST. Following refs. 41,46, the data within each time bin were binned by latitude, with the bin size randomly selected between 2.5 and 20, and then global average SST (GSST) was computed as the latitudinally weighted zonal average between 60°S and 60°N. Following refs. 41,46, GSST was then scaled by a value randomly chosen between 1.5 and 2.3 to transform the values to GMST. This Monte Carlo process was repeated 10,000 times, to propagate errors arising from the SST estimation, age modelling, latitudinal weighting, and GSST to GMST scaling.

Climate model simulations

The climate model priors are drawn from newly developed and pre-existing climate simulations with the water isotope-enabled Community Earth System Model, versions 1.2 and 1.3 (ICESM1.2 and
**Paleoclimate data assimilation**

The data assimilation method incorporates an offline ensemble square root Kalman filter approach, following the methodology of ref. 10 using the data assimilation MATLAB code package DASH version 3.6.1 (source code available at https://github.com/jonKing93/DASH). We refer the reader to this previous work for a full mathematical description. Briefly, the method combines a set of prior climate states from our model simulations \(X_{\text{prior}}\) with new information from the proxy observations (the ‘innovation’, \(Y_{\text{obs}} - Y_{\text{est}}\)) to compute a ‘posterior’ matrix of assimilated past climate states, \(X_{\text{post}}\). The posterior mean and deviations from the mean are each computed separately (see refs. 10, 73); the Kalman filter mean ‘update’ equation is:

\[
X_{\text{post}} = X_{\text{prior}} + K(Y_{\text{obs}} - Y_{\text{est}}). 
\]

(1)

\(X_{\text{prior}}\) is an \(N \times M\) matrix of prior climate states from CESM, where dimension \(N\) contains the model grid point data for SST and SSS (both at monthly and mean-annual resolution), and mean-annual surface air temperature (SAT), \(\delta^{18}O_{\text{sw}}\), precipitation amount-weighted \(\delta^{18}O\) (\(\delta^{18}O_{\text{p}}\)), and mean-annual precipitation rate collapsed into a concatenated vertical ‘state vector’, and dimension \(M\) represents the number of state vector ensemble members; the overbar in all cases denotes averaging across the ensemble dimension (producing, in this case, a vectorized ensemble ‘mean’ update).

The \(P \times 1\) vector \(Y_{\text{obs}}\) consists of \(P\) globally dispersed \(\delta^{18}O_{\text{C}}, \text{Mg/Ca}, U_{\text{U}^{137}},\) and \(\text{TEX}_{\text{es}}\) proxy observations. The \(P \times M\) matrix \(Y_{\text{est}}\) contains the corresponding set of \(P\) proxy estimates, generated from the model output from each \(M\) state using our Bayesian forward models. For details concerning the Bayesian models, the readers are referred to the original publications 11–21. In brief, the forward model for \(\delta^{18}O\) requires monthly SST and mean annual \(\delta^{18}O_{\text{sw}}\). These \(\delta^{18}O\) values are computed on a species- and growing season-specific basis 22 that allows us to explicitly account for foraminiferal seasonal preferences in our forward model proxy estimates. Both the \(U_{\text{U}^{137}}\) and \(\text{TEX}_{\text{es}}\) models require only SST as inputs, with the former requiring monthly SST due to the seasonal response of \(U_{\text{U}^{137}}\) production in the North Pacific, the North Atlantic and the Mediterranean 23, and the latter only mean annual SST 15. Finally, the forward model for Mg/Ca requires both monthly SST and SSS to compute species-specific growing season Mg/Ca values, in addition to sea surface pH, bottom water calcite saturation state (\(\Omega\)), and the laboratory cleaning method. The latter is provided in the original publications, and SST and SSS are drawn from CESM output. For \(pH\) and \(\Omega\), we follow the same procedure as the proxy-only reconstruction (described above).

The innovation \((Y_{\text{obs}} - Y_{\text{est}})\) represents the new information from the observations not already provided by the prior estimates. As shown in equation (1), these values are weighted by the \(N \times P\) matrix \(K\), the Kalman gain, which takes the general form:

\[
K = \text{cov}(X_{\text{prior}}, Y_{\text{est}}) \times \left[\text{cov}(Y_{\text{est}}, Y_{\text{est}}) + R\right]^{-1} 
\]

(2)

where ‘\(\text{cov}\)’ denotes the covariance expectation (approximated by an ensemble mean, with the ensemble mean removed). The \(P \times P\) matrix \(R\) prescribes the error covariance associated with each proxy observation. Thus, the Kalman gain weights the innovation by the covariance of the forward-modelled proxy estimates with the prior climate states and the uncertainties of the prior-estimated proxy ensemble and the proxy observations. In our case, \(R\) is diagonal, that is, the errors are presumed to be independent. \(R\) is user-defined, but ideally based on an estimate of true proxy uncertainties. Following ref. 10, in which the impact of different values of \(R\) on the posterior were systematically tested, we use the error values output from our Bayesian forward models scaled by \(1/5\), but further refine this by specifying a slightly different scaling factor for each proxy type. To determine these proxy-specific
for each record, we performed jack-knife (leave one record out) and ‘only-one record’ assimilation experiments (no $R$ scalings applied) to assess the ability of any particular record to predict all others when that record was either removed, or solely retained, respectively. From these experiments, we then ranked each record by validating the only-one and all-but-one reconstructions against the non-assimilated proxies. This allowed assessment for the percent of tests for which this proxy resulted in ‘improvement’ (as denoted by the ratio of the posterior to prior squared error of all predicted, independent proxies, where a ratio less than unity indicates improvement). Using these rankings for each proxy type, we then weighted each proxy-specific scaling factor by the improvement factor, and subsequently weighted these rankings by total record count to maintain an average $R$ scaling of 1/5 across all available proxy records. The specific scaling factors that we calculated were $r_{LGM} = 3.13^{-1}$, $r_{east} = 1.36^{-1}$, $r_{max} = 2.86^{-1}$ and $r_{min} = 7.27^{-1}$, indicating $^{18}O$ to be the most reliable (and numerous) proxy type.

Following refs. 10,17, we applied covariance localization to the assimilation to limit spurious relationships between proxies and far-field regions. Validation testing suggested that a 24,000 km localization radius provided optimal posterior results for our dataset (see the ‘Internal and external validation testing’ section below). This differs from ref. 10, which used a narrower 12,000 km localization. The improvement we find using broader localization is likely to relate to the fact that fewer proxies are assimilated here per time step than in ref. 10.

For computing our full 24 ky LGM product, we calculated $Y_{post}$ at 200-year increments using the following approach. First, we selected 80% of our proxy records at random for inclusion in our assimilation, with the remaining 20% of records withheld for statistical validation (see the ‘Internal and external validation testing’ section below). For each record, we randomly prescribed an age scale by drawing from the 1,000 viable posterior BACON-derived age models. Second, for each 200-year interval, $Y_{obs}$ was compiled as all of the available proxy data points whose ages are within the bounds of the current reconstruction age interval. When multiple data points from a single record occurred within a given 200-year age interval, these values were averaged. We then randomly selected $M = 60$ state vector ensembles from the iCESM output using a transient ‘evolving prior’ approach (see below) and used the Bayesian forward models to produce the matrix $Y_{est}$. $Y_{est}$ was then computed from $Y_{obs}$ and $Y_{est}$ (equation (1)) with $R$ in the Kalman gain (equation (2)) scaled to the appropriate proxy type. Finally, this process was repeated for a total 500 times for each time interval, to create a 500-member LGM-to-present ensemble of posterior states. This Monte Carlo procedure ensures that proxy, age-model and model prior uncertainties are included in the assimilated product. Since the proxy age-model uncertainties in particular can be on the order of centuries (interquartile range of 320–770 years across all data points), this sampling procedure has the effect of smoothing the posterior ensemble mean time series on sub-millennial timescales, as in prior proxy-only analyses3,4,6.

Assimilating the LGM-to-present climate evolution at 200-year intervals directly reflects our underlying proxy data compilation. ~96% of the proxy records have a median resolution that is higher than 200 years (Extended Data Fig. 1). However, if all >60,000 compiled data points are considered together, >90% of the paleoclimate data have sample resolutions of ≤200 years. While ideally, the amount of time represented by the model prior would also equal 200 years, this would have considerably limited the number of model priors available (a maximum of 58 prior states across our all iCESM time-slice simulations, and as few as four priors for a given interval; Extended Data Table 1).

To increase the number of iCESM priors available for assimilating our marine proxies while still roughly adhering to our reconstruction interval, we instead used 50-year average priors, following ref. 10. Prior experimentation by ref. 10 showed only marginal differences in LGM and preindustrial posteriors once time-averaging of our iCESM prior fields exceed interannual time periods, justifying this choice.

Assimilating Earth’s transient climate evolution between two fundamentally different glacial versus interglacial states presents a unique obstacle for offline paleoclimate data assimilation (which has largely focused on reconstructing the climate evolution of the Common Era17, a relatively stable background climate state). In terms of Bayesian inference, the challenge is adequately assigning a collection of iCESM priors at each LGM-to-present reconstruction interval that reflects a reasonable prior belief in their viability. For example, a time interval in the late Holocene should not include glacial prior states that contain a Laurentide ice sheet, as the latter induces fundamental changes in spatial covariance that are not realistic for a deglaciated climate state. Conversely, deglacial prior states might include a range of possible Laurentide configurations.

To address this issue, we developed an ‘evolving prior’ approach. For each 200-year interval, we defined a normal probability density function (PDF) with a 1σ range of 4,000 years and a maximum cut-off range of 3σ (±12,000 years). The PDF is truncated to the range of our target time interval (24–0 ka), such that for the tail ends of the reconstruction interval, the PDF ends up being half-normal. We then sampled 60 prior ages from this PDF and rounded them to 0, 3, 6, 9, 12, 14, 16, 18 or 21 ka, the discrete time-slice intervals at which iCESM simulations are available (Extended Data Table 1). For each randomly drawn and rounded age, a model prior was selected (with replacement) from its corresponding iCESM time-slice simulation.

The 1σ range of 4,000 years was chosen to balance the need to include adequate variability in the prior while still excluding model priors that are not physically justified (that is, the inclusion of LGM priors when assimilating mid-late Holocene climatic states, and vice-versa). Similar to ref. 10, rank histogram analysis of our withheld validation proxies10 suggested minimal mean bias of our model priors using this 1σ length scale, but an apparent lack of structural variance (as suggested by a U-shaped rank histogram; see Extended Data Fig. 2 of ref. 10). While increasing the length scale to include a broader range of priors would increase prior variance, validation testing indicated that the 4,000-year length scale was near-optimal, and also resulted in substantial improvement over an ‘agnostic’ prior sampling scheme (for example, one that assigns equal probability of including a prior from any given iCESM timeslice; see the ‘Internal and external validation testing’ section below). We note that the variance in our model prior is fundamentally restricted by the use of a sole model (iCESM). Further work is needed to test the sensitivity of the LGMR reconstruction to the use of different isotope-enabled model priors (once available).

Internal and external validation testing

Statistical validation and tuning of our LGMR product was conducted in two ways, referred hereafter as ‘internal’ and ‘external’ validation. The first approach (‘internal’ validation) involves withholding 20% of the marine proxy per iteration (see the ‘Paleoclimate data assimilation’ section above), and then using the posterior SST, SSS and $^{18}O_{pm}$ fields to forward model these withheld proxy records. These predicted proxy records were then compared with the actual proxy records using standard skill diagnostics: the coefficient of efficiency (CE; a value between 0 and 1, where a value >0 is conventionally taken to represent skill over climatology), the squared Pearson product moment coefficient ($R^2$), and the root mean square error of prediction (RMSEP). The computation of multiple posterior ensembles (that is, $N = 500$), each with 20% withholding, implies each proxy record was randomly withheld and internally validated on average 100 times. These tests yield, on average, CE values that are greater than 0 with no obvious signs of systematic spatial biasing, indicative of skill in our posterior assimilation above our evolving iCESM prior fields. On a global basis all posterior-predicted proxies exhibit a strong correspondence to observed values with $R^2 > 0.95$ and slopes within 5% of their respective 1:1 lines (Extended Data Fig. 2), indicating a lack of systematic bias in the LGMR oceanic climatologies.
Following ref. 10, we also use independent ice core and speleothem records of δ^18O, to externally validate the LGMR. In this more stringent analysis, we compare posterior δ^18O to published ice core δ^18O (which is taken as a direct indicator of precipitation-weighted mean-annual δ^18O_{pr} given that post-depositional processes such as isotopic diffusion10 and sublimation19 do not typically impact ice core record integrity across centennial and longer time scales) and speleothem δ^18O, which is first converted to δ^18O via the methodology of ref. 17 (see also ref. 10). For the speleothem data, we used the SISAL version 1b database10. Records were included in our compilation solely on the basis that they span at least 18 kyr: that is, at least three-quarters of the LGMR reconstruction interval, ensuring overlap with the deglacial period (around 17–9 ka; Fig. 2). Record-specific details are provided in Extended Data Table 2. Following ref. 10, we focus on δ^18O deviations (Δδ^18O), which we generate by differencing all δ^18O values at each time slice interval relative to the 0 ka baseline. This approach is premised on the expectation that δ^18O deviations should be adequately captured by LGMR10 despite known mean δ^18O biases in iCESM22. We then compare both prior and posterior Δδ^18O, with observed Δδ^18O, at the iCESM timeslice intervals (3, 6, 9, 12, 14, 16, 18 and 21 ka) using our statistical diagnostics of covariance and prediction error (R^2 and RMSEP). Positive ΔR^2 (that is, a stronger relationship with observed values in LGMR versus the prior) and negative ΔRMSEP (that is, reduced prediction error in LGMR versus the prior) imply improvement in our LGMR posterior relative to the iCESM priors. Overall, this external validation test indicates that LGMR substantially improves over the prior, with a nearly 30% error reduction (RMSEP_{prior} = 2.60%, RMSEP_{posterior} = 1.92%) and approaching two times greater variance explained in our posterior-predicted values relative to the prior (R^2_{prior} = 0.37; R^2_{posterior} = 0.62). Although much of the improvement is driven by ice core δ^18O estimates (Extended Data Figs. 3 and 4), offsets with speleothem δ^18O observations are also strongly reduced in LGMR relative to iCESM. The comparably poor temporal covariance shown by global speleothem δ^18O values relative to ice cores (Extended Data Fig. 4; Extended Data Table 2) may reflect local-scale influences on speleothem δ^18O records, such as groundwater storage, mixing, recharge and residence time variations; sub-grid-scale topographic and (or) precipitation influences; and uncertainties arising from indirectly inferring δ^18O_{pr} from δ^18O_{calcite} or δ^18O_{dissolution} measurements52. In addition, the iCESM prior range of δ^18O across the LGM to present in the tropics is considerably smaller than in the high latitudes (for example, Extended Data Fig. 4), which might restrict the posterior solutions for the speleothems (see ref. 42).

We used external validation testing to choose both the covariance localization radius and evolving prior ιr range (see the ‘Paleoclimate data assimilation’ section for a description of each). Between the two, our tests show that LGMR is most sensitive to the choice of localization radius. We tested values between 6,000 km and infinite (that is, no localization) and found a relatively broad localization cut-off (24,000 km) is near-optimal (Extended Data Table 3). In contrast, LGMR shows comparatively less sensitivity to choice of the ιr range for sampling iCESM priors, with acceptable external validation scoring for values between ιr = 2,000–6,000 years (Extended Data Table 3). For our final LGMR product we chose a value of ιr = 4,000 years as this was shown to provide near-optimal validation scoring (Extended Data Table 3), while also constituting a reasonable ‘middle ground’ between enabling adequate variance amongst iCESM model priors throughout the past 24 kyr while excluding physically unjustifiable states (see discussion above).

Data availability
All LGMR and associated proxy data are publicly available via the National Oceanic and Atmospheric Administration (NOAA) Paleoclimate Data Archive (https://www.ncdc.noaa.gov/paleo/study/33112). Source data are provided with this paper.

Code availability
The MATLAB code used for the reconstruction (DASH), are publicly available (https://github.com/JonKing93/DASH), as are all accompanying Bayesian proxy forward models (BAYSAR, BAYSPLINE, BAYFOX, and BAYMAG) used in this study (https://github.com/jessstierney). The iCESM1.2 model code is available at https://github.com/NCAR/iCESM1.2.
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Additional information
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Extended Data Fig. 1 | Time resolution and temporal coverage of the SST proxy data compilation. **a**, Histogram of record resolution (denoting the median sample resolution for each record), computed for each proxy type. **b**, Histogram of record length for each proxy type.
Extended Data Fig. 2 | Statistical validation of randomly withheld marine geochemical proxies. **a**, From left: observed versus forward-modelled δ¹⁸O, mean values for each site using the posterior data assimilation estimates. Shown at right are the associated median $R^2$ validation scores (each based on $n = 100$ LGMR ensemble members), computed on a per-site basis (see Methods section "Internal and external validation testing"). **b–d**, As in **a**, but for $U'_37$ (**b**), Mg/Ca (**c**) and TEX₈₆ (**d**), respectively.
Extended Data Fig. 3 | Validation using independent δ¹⁸O ice core and speleothem records. a, 3 ka–preindustrial (PI; 0 ka) posterior Δδ¹⁸O field; overlying markers show the observed 3 ka–PI Δδ¹⁸O values from speleothems and ice cores. Only records spanning at least 18 of the past 24 kyr are shown. ΔR² and ΔRMSEP values denote the change in observed versus posterior assimilated Δδ¹⁸O values relative to the prior (that is, iCESM) estimated values. b–h, As in a, but for values differenced at 6, 9, 12, 14, 16, 18 and 21 ka versus the PI, respectively. i, All observed Δδ¹⁸O versus model prior values; dashed line indicates the 1:1 relationship. j, All observed Δδ¹⁸O versus posterior values, which show a strong improvement in ΔR² and ΔRMSEP over the prior. Note that each scatter point shown in panels i, j corresponds to an external validation site shown in panels a–h.
Extended Data Fig. 4 | Time-comparison of posterior LGMR δ\(^{18}\)O\(_{\text{w}}\) with selected δ\(^{18}\)O\(_{\text{w}}\) ice core and speleothem records. Uncertainty ranges denote the ±1\(\sigma\) level (dark) and 95% confidence range (light) from the LGMR ensemble. Also shown for comparison are the full range (shaded grey) and median iCESM time slice prior values (50-year means) for each site. See also Extended Data Table 2.
Extended Data Fig. 5 | Influences on global surface temperature evolution during the past 24 kyr. a–c, Spatial LGM-to-present correlations between surface air temperature (SAT) and combined greenhouse gas and global albedo radiative forcing13 (a); summer length at 65°S (b); and the $-1 \times ^{231}$Pa/$^{230}$Th AMOC proxy index from Bermuda Rise29–31 (c; shown such that SAT correlations are positive with AMOC strength).
Extended Data Fig. 6 | Proxy-specific GMST reconstructions and comparison of Holocene GMST trends. a, $\delta^{18}$O, $U_{37}^{\prime}$, and Mg/Ca-derived GMST reconstructions, derived using both the proxy-only (PO) and data assimilation (DA) approaches. In a, the shaded regions show the ±1σ range across $n = 50$ ensemble members for the DA-based GMST estimates, and $n = 10,000$ realizations for the PO-based GMST estimates (note uncertainty ranges are not shown for the dotted-dashed curves). b, Sensitivity of the Holocene GMST evolution to the removal of proxies situated in contiguous 15° latitudinal bands, both for the PO and DA approaches. c, Sensitivity of the DA-based Holocene GMST evolution to proxy seasonality (computed by fixing foraminifera growth seasonality to either preindustrial (PI) or LGM monthly SSTs for Mg/Ca and $\delta^{18}$O, or by removing records with seasonal alkenone production for $U_{37}^{\prime}$), and to the ‘pooled’ foraminifera species SST calibrations of refs. 20,21 (see Supplementary Information). All ∆GMST time series denote deviations relative to the past 2 kyr.
Extended Data Fig. 7 | Hemispheric variability during the past 24 kyr.

Ensemble distribution \((n = 500)\) of LGMR-estimated Northern Hemisphere (NH; red) and Southern Hemisphere (SH; blue) mean hemispheric temperatures during the past 24 kyr. Shown at top is the surface temperature spatial difference for the Bølling–Allerød (BA) and Younger Dryas (YD) intervals. Range of hemispheric last deglacial and interglacial onset timings are shown as histograms at bottom. The LGMR is plotted alongside reconstructed decadal hemispheric temperatures from the last millennium reanalysis v2.117 and HadCRUT5 observational product11.
### Extended Data Table 1 | Information on the iCESM simulations used for generating model priors

| Age (ka) | Model description | Number of priors | Greenhouse gas (CO₂, CH₄, N₂O) | Global δ¹⁸Osw | GMST range (°C) | Citation |
|----------|-------------------|------------------|-------------------------------|--------------|----------------|----------|
| 0        | iCESM1.2: PI      | 16               | 285 / 792 / 276               | 0.05         | 14.03–14.25    | 61       |
| 0        | iCESM1.2: PI      | 10               | 285 / 792 / 276               | 0.05         | 13.22–13.33    | 61       |
| 0        | iCESM1.3: PI      | 10               | 285 / 792 / 276               | 0.05         | 13.68–13.84    | 61       |
| 0        | iCESM1.2 Last Millennium Member #2: 850-1850 CE | 20 | Transient | 0.05 | 12.96–13.26 | 62 |
| 0        | iCESM1.2 Last Millennium Member #3: 850-1850 CE | 20 | Transient | 0.05 | 12.98–13.27 | 62 |
| 3        | iCESM1.2: 3 ka    | 16               | 275 / 580 / 270               | 0.05         | 13.99–14.14    | 10       |
| 6        | iCESM1.2: 6 ka w/ Sahara & 50–90% greened | 16 | 264 / 597 / 262 | 0.05 | 14.14–14.62 | This study |
| 6        | iCESM1.2: 6 ka w/ Sahara greened | 16 | 264 / 597 / 262 | 0.05 | 14.03–14.19 | This study |
| 9        | iCESM1.2: 9 ka w/ Sahara greened | 16 | 260 / 659 / 255 | 0.34 | 13.87–14.09 | This study |
| 12       | iCESM1.2: 12 ka   | 16               | 253 / 478 / 236               | 0.59         | 12.61–12.76    | This study |
| 12       | iCESM1.2: 12 ka w/ freshwater over N. Atl. | 4 | 253 / 478 / 236 | 0.59 | 10.79–11.77 | This study |
| 14       | iCESM1.2: 14 ka   | 16               | 238 / 637 / 255               | 0.73         | 10.05–10.32    | This study |
| 16       | iCESM1.2: 16 ka   | 16               | 224 / 452 / 199               | 0.90         | 9.27–9.45      | This study |
| 16       | iCESM1.2: 16 ka w/ freshwater over N. Atl. | 4 | 224 / 452 / 199 | 0.90 | 7.63–8.45 | This study |
| 18       | iCESM1.2: 18 ka   | 16               | 190 / 370 / 245               | 1.02         | 8.00–8.13      | 10       |
| 21       | iCESM1.2: 21 ka   | 16               | 190 / 375 / 200               | 1.05         | 7.41–7.87      | 10       |
| 21       | iCESM1.3: 21 ka   | 18               | 190 / 375 / 200               | 1.05         | 6.40–7.37      | 61       |

Greenhouse gas concentrations are in ppm for CO₂ and ppb for CH₄ and N₂O. Global mean seawater δ¹⁸O (δ¹⁸O_sw) is in ‰ relative to the Vienna Standard Mean Ocean Water (VSMOW). See Methods for details of the implementation of vegetation and freshwater forcing in related simulations.
Extended Data Table 2 | Geographical and site identification information for ice core and speleothem δ¹⁸O records used for LGMR external validation

| Proxy class | Site name          | Lat. (°N) | Lon. (°E) | R²  | CE | Citation |
|-------------|--------------------|-----------|-----------|-----|----|----------|
| Ice core    | Byrd               | -80.02    | -119.53   | 0.82| -0.71| 73       |
| Ice core    | EDC                | -75.10    | 123.35    | 0.89| 0.49|          |
| Ice core    | EDEMIL             | -75.00    | 0.07      | 0.86| 0.78|          |
| Ice core    | Fuji               | -77.32    | 38.70     | 0.83| 0.66|          |
| Ice core    | Siple              | -81.65    | -149.00   | 0.88| 0.64|          |
| Ice core    | TALDICE            | -72.82    | 159.18    | 0.89| 0.76|          |
| Ice core    | Taylor             | -77.78    | 158.72    | 0.65| -0.65| 84       |
| Ice core    | Vostok             | -78.46    | 108.84    | 0.88| 0.85|          |
| Ice core    | WAIS               | -79.47    | -112.00   | 0.87| 0.22|          |
| Ice core    | Renland            | 71.27     | -26.73    | 0.74| 0.20|          |
| Ice core    | GISP2              | 72.60     | -38.50    | 0.65| 0.05|          |
| Ice core    | GRIP               | 72.58     | -37.63    | 0.58| -0.21| 89       |
| Ice core    | NGRIP              | 75.10     | -42.33    | 0.71| 0.55|          |
| Speleothem  | Cold Air cave      | -24.00    | 29.18     | 0.08| -14.58| 91       |
| Speleothem  | Jaragualé cave     | -21.08    | -56.58    | 0.27| -1.93|         |
| Speleothem  | Jeila cave         | 33.95     | 35.65     | 0.01| -15.69|         |
| Speleothem  | Mawmluh cave       | 25.26     | 91.88     | 0.42| -4.47|         |
| Speleothem  | Liang Luar cave    | -8.53     | 120.43    | 0.06| -5.19|         |
| Speleothem  | Bukit Assam cave   | 4.03      | 114.80    | 0.04| -5.23|         |
| Speleothem  | Xisbalong cave     | 24.20     | 103.36    | 0.20| -3.55|         |
| Speleothem  | Selulair cave      | 41.42     | 31.93     | 0.04| -1.88|         |
| Speleothem  | Botuverá           | -27.22    | -49.16    | 0.10| -7.88|         |
| Speleothem  | Gurung-buda cave   | 4.03      | 114.80    | 0.02| -2.66|         |
| Speleothem  | Nettlebed cave     | -41.25    | 172.63    | 0.27| -4.11|         |
| Speleothem  | Sooreg cave        | 31.76     | 35.02     | 0.17| -5.45|         |
| Speleothem  | EL Condor cave     | -5.93     | -77.30    | 0.02| -0.42|         |

Data from refs. 79-102.
## Extended Data Table 3 | External validation statistics associated with different choices of covariance localization and the 1σ ‘length-scale’ range of the evolving prior sampling

| Localization (km) | 6,000 | 9,000 | 12,000 | 15,000 | 18,000 | 21,000 | 24,000 | ∞  |
|-------------------|-------|-------|--------|--------|--------|--------|--------|    |
| Δ$R^2$ (%)        | 0.09  | 0.19  | 0.23   | 0.24   | 0.24   | 0.25   | 0.25   | 0.16|
| ΔRMSEP (%)        | -0.54 | -0.59 | -0.63  | -0.63  | -0.64  | -0.72  | -0.73  | -0.34|
| Length scale (yr) | 2,000 | 3,000 | 4,000  | 5,000  | 6,000  | ∞      |        |    |
| Δ$R^2$ (%)        | 0.23  | 0.24  | 0.25   | 0.24   | 0.23   | 0.18   |        |    |
| ΔRMSEP (%)        | -0.63 | -0.62 | -0.64  | -0.65  | -0.69  | -0.58  |        |    |

$\Delta R^2$ and $\Delta$RMSEP values denote the change in observed versus posterior assimilated $\Delta \delta^{18}O_p$ values relative to the prior iCESM estimated values; larger $\Delta R^2$ and smaller $\Delta$RMSEP thus denote greater improvement in the assimilated posterior relative to iCESM (see Extended Data Fig. 2i, j for plotted LGMR values). For localization testing, listed $\Delta R^2$ and $\Delta$RMSEP values represent the median across all (n=6) length-scale tests; for length-scale testing, listed $\Delta R^2$ and $\Delta$RMSEP values represent the median across all (n=8) localization tests.