Last Glacial Maximum pattern effects reduce climate sensitivity estimates

Vincent T. Cooper¹*, Kyle C. Armour¹,2, Gregory J. Hakim³, Jessica E. Tierney⁵, Matthew B. Osman⁴, Cristian Proistosescu⁵, Yue Dong⁶, Natalie J. Burls⁷, Timothy Andrews⁸, Daniel E. Amrhein⁹, Jiang Zhu⁹, Wenhao Dong¹⁰,¹¹, Yi Ming¹², Philip Chmielewicz⁵†

Here, we show that the Last Glacial Maximum (LGM) provides a stronger constraint on equilibrium climate sensitivity (ECS), the global warming from increasing greenhouse gases, after accounting for temperature patterns. Feedbacks governing ECS depend on spatial patterns of surface temperature (“pattern effects”); hence, using the LGM to constrain future warming requires quantifying how temperature patterns produce different feedbacks during LGM cooling versus modern-day warming. Combining data assimilation reconstructions with atmospheric models, we show that the climate is more sensitive to LGM forcing because ice sheets amplify extratropical cooling where feedbacks are destabilizing. Accounting for LGM pattern effects yields a median modern-day ECS of 2.4°C, 66% range 1.7°C to 3.5°C (1.4° to 5.0°C, 5 to 95%), from LGM evidence alone. Combining the LGM with other lines of evidence, the best estimate becomes 2.9°C, 66% range 2.4° to 3.5°C (2.1° to 4.1°C, 5 to 95%), substantially narrowing uncertainty compared to recent assessments.

INTRODUCTION

Equilibrium climate sensitivity (ECS) is the steady-state response of global mean near-surface air temperature to a doubling of atmospheric CO₂ from preindustrial levels. ECS is a focus of climate policy and projections because it governs Earth’s long-term response to anthropogenic greenhouse gas changes (1, 2). Recently, the World Climate Research Programme’s 2020 climate sensitivity assessment, hereafter “WCRP20” (1), updated the 66% “likely” range for ECS to 2.6° to 3.9°C (2.3° to 4.7°C, 5 to 95%) with a central estimate of 3.1°C, which informed the “likely” range of 2.5° to 4.0°C (2.0° to 5.0°C, “very likely”) and central estimate of 3°C in the Intergovernmental Panel on Climate Change’s Sixth Assessment Report (“IPCC AR6”) (2). This narrowing of uncertainty compared to previous assessments was achieved by quantitatively combining evidence from process understanding of climate feedbacks, observations over the historical record (1870 to present), and paleoclimate reconstructions of past cold and warm periods. Of these lines of evidence, paleoclimate data from the Last Glacial Maximum (LGM), approximately 21,000 years ago, provide a leading constraint on the upper bound of ECS (1–3).

Using paleoclimate data to constrain modern-day ECS requires accounting for how climate feedbacks change across different climate states (1, 2, 4–9). The standard assumption is that colder climates are less sensitive (i.e., have more-negative feedbacks) than warmer states (1, 2, 5–9). However, the simple assumption that feedbacks change with global mean temperature does not account for how feedbacks depend on changing spatial patterns of sea-surface temperature (SST), a phenomenon known as the SST “pattern effect” (10–15).

A robust understanding of the SST pattern effect has been developed in the context of recent warming. Over the past century, SSTs have warmed more in the tropical west Pacific and less in the east Pacific and Southern Ocean (12, 16, 17). SST changes in tropical regions of deep convection (e.g., the west Pacific) produce strongly negative (stabilizing) feedbacks, whereas SST changes in regions with reflective low clouds (e.g., the east Pacific) or sea ice produce relatively positive (destabilizing) feedbacks (11–15, 18). This transient pattern of SST trends is expected to reverse in the future as the tropical east Pacific and Southern Ocean eventually warm at higher rates, producing more-positive feedbacks and a more-sensitive climate at equilibrium (15, 19, 20). Accounting for this transient pattern effect causes the historical record to become a weak constraint on high values of ECS (1, 2, 16, 17, 21), leaving the LGM as a leading constraint on the ECS upper bound (1).

However, pattern effects have not been accounted for in LGM evidence for modern-day ECS (1–3, 5, 22). If the spatial pattern of SST change in equilibrium at the LGM differs from the pattern of future warming, then the climate feedbacks governing climate sensitivity will differ as well. Continental ice sheets are responsible for approximately half of the total LGM forcing (3, 23, 24) and drive distinct climate responses from changes in topography, albedo, and sea level (23, 25–30), suggesting that patterns of SST change at the LGM may differ substantially from those in response to a modern-day doubling of CO₂. Previous work acknowledged this possibility (1, 2) but did not account for LGM pattern effects because no quantification had yet been made. A key question is, would accounting for LGM pattern effects strengthen or weaken constraints on modern-day ECS?

Here, we quantify the LGM pattern effect and its uncertainty by leveraging two recent advances. First, with the advent of paleoclimate data assimilation (31), spatially complete reconstructions of SST and sea ice now exist for the LGM (3, 32–34), including estimated uncertainties. Second, recent progress in quantifying pattern effects...
Dependence of modern-day ECS on pattern effects

ECS and climate feedbacks are connected through the standard model of global mean energy balance:

\[ \Delta N = \lambda \Delta T + \Delta F \]  

(1)

where \( N \) is the top-of-atmosphere radiative imbalance; \( \lambda \) is the net climate feedback (negative for stable climates); \( T \) is the near-surface air temperature; and \( F \) is the “effective” radiative forcing, i.e., the change in net downward radiative flux after atmospheric adjustments to imposed perturbations but excluding radiative responses to changing surface temperature \((\Delta T)\). Differences \((\Delta)\) are relative to an equilibrium reference state, e.g., the preindustrial period. When the forcing is a CO\(_2\) doubling (2xCO\(_2\)) of preindustrial values, and the climate system reaches equilibrium \((\Delta N = 0)\), the resulting \(\Delta T\) is referred to as the ECS

\[ \text{ECS} = -\Delta F_{2x}/\lambda_{2x} \]  

(2)

where \(\Delta F_{2x}\) is the effective radiative forcing (ERF), and \(\lambda_{2x}\) is the net feedback for 2xCO\(_2\). More-negative values of \(\lambda_{2x}\) indicate a less-sensitive climate (lower ECS).

Here, we aim to quantify the difference in feedbacks \((\Delta \lambda)\) operating in the modern climate under 2xCO\(_2\) \((\lambda_{2x})\) and at the LGM \((\lambda_{LGM})\)

\[ \Delta \lambda = \lambda_{2x} - \lambda_{LGM} \]  

(3)

Following recent research on pattern effects in the historical record \((1, 16, 17)\), we estimate \(\lambda_{2x}\) and \(\lambda_{LGM}\) using AGCM simulations with SST and sea-ice concentration (SIC) prescribed as surface boundary conditions. We further evaluate the contributions to \(\Delta \lambda\) from pattern effects and global mean temperature changes between the LGM and 2xCO\(_2\).

To infer the modern-day ECS from LGM evidence, Eqs. 2 and 3 can be combined \((1, 16)\) to yield

\[ \text{ECS} = \frac{-\Delta F_{2x}}{\lambda_{LGM} + \Delta \lambda} \]  

(4)

where \(\lambda_{LGM}^*\) is the estimate of the unadjusted LGM feedback (determined using Eq. 1 applied to that state), which we take from previous assessments \((1–3)\), and \(\Delta \lambda\) is estimated from our AGCM simulations. The value of \(\Delta \lambda\) depends on spatial patterns of LGM SST and SIC anomalies, for which we use state-of-the-art reconstructions \((3, 32–34)\) based on data assimilation.

RESULTS

Using data assimilation reconstructions to quantify pattern effects

Similar to Bayesian statistics, paleoclimate data assimilation \((31)\) begins with a “prior” estimate of the climate state from model ensembles. Proxy data provide indirect climate observations that update the prior, balancing relative error in the prior and the observations. This results in a “posterior” state estimate, constrained by observations and accounting for uncertainty in priors and data. Since the posterior is sensitive to priors \((35, 36)\), proxies, and methods, we sample this uncertainty by using multiple reconstructions.

Figure 1 shows the four SST reconstructions (Materials and Methods) we use to quantify the LGM pattern effect. All four reconstructions have a prominent common feature: amplified extratropical cooling in both the North Pacific and North Atlantic Oceans. While the LGM reconstructions differ in other regions that are important for climate feedbacks, e.g., the tropical Pacific \((11–15)\) and Southern

![Fig. 1. Patterns of SST anomalies from data assimilation at the LGM compared to modern-day doubling of CO\(_2\) (2xCO\(_2\)). LGM reconstructions include (A) LGMR (32), (B) Amrhein (34), (C) IgmdA (3), (D) Annan (33), and (E) shows the mean of the four LGM patterns. (F) Pattern of the multimodel mean from near-equilibrium 2xCO\(_2\) simulations in LongRunMIP (39), initialized from preindustrial control. To show SST patterns, local SST anomalies are divided by absolute values of global mean SST anomalies. All panels show annual means. LGM reconstructions are infilled to modern coastlines (Materials and Methods).]
Ocean (19, 37, 38), their robust agreement in the northern extratropics proves to be essential for the LGM pattern effect. The zonally consistent maximum near 40°N in SST anomalies at the LGM is in strong contrast to the near-equilibrium response to modern-day 2xCO₂ (Fig. 1F and fig. S1) as simulated by climate models in LongRunMIP (Materials and Methods) (39), suggesting the potential for feedbacks to differ between LGM and 2xCO₂ climates. Using data-constrained patterns to quantify how LGM feedbacks compare to feedbacks in 2xCO₂ is an advance over past comparisons (all based on models), which have produced conflicting results (text S1) (22, 23, 40–44). While our method overcomes the problem of unconstrained SST patterns from coupled atmosphere-ocean simulations of the LGM, we still rely on AGCMs to estimate feedbacks and their uncertainties.

We calculate net feedbacks using AGCMs with prescribed SST and SIC. We first conduct AGCM simulations with a “baseline” pattern representing the preindustrial climate, for which we use SST and SIC in the Late Holocene (mean of 0 to 4000 years ago) from the LGM Reanalysis (LGMR) (32). We then perform AGCM simulations with SST and SIC (Materials and Methods) from 2xCO₂ in LongRunMIP (39) and the four LGM reconstructions (3, 32–34) (SST in Fig. 1; SIC in fig. S2). Last, we calculate global mean ΔN and ΔT in each 2xCO₂ and LGM simulation relative to the baseline, which yields net feedbacks as λ = ΔN/ΔT using Eq. 1. All forcings are held constant (ΔF = 0) at modern-day levels across our AGCM simulations; therefore, all changes in simulated top-of-atmosphere radiation and feedbacks can be attributed solely to SST/SIC differences (Materials and Methods).

We find that λ₂x is more negative (stabilizing) than λₐGM, indicating that the climate system is more sensitive to LGM forcing than to 2xCO₂ (Fig. 2). We use the LGMR pattern (Fig. 1A) in five AGCMs (CAM4, CAM5, CAM6, GFDL-AM4, and HadGEM3-GC3.1-LL) to evaluate uncertainty from atmospheric model physics, and we use all four LGM reconstructions (Fig. 1, A to D) in CAM4 and CAM5 to evaluate uncertainty from LGM patterns. This approach is supported by the result that AGCMs tend to reproduce observed relationships between SSTs and top-of-atmosphere radiation when observed SST patterns are prescribed (45, 46). The LGM pattern effect, Δλ in Eq. 3, is negative across all five AGCMs and all four LGM reconstructions. The five AGCMs produce a mean Δλ = −0.40 Wm⁻² K⁻¹ (Fig. 2B; detailed results in tables S1 and S2). We also evaluate uncertainty in the 2xCO₂ pattern but find that this is of secondary importance (Materials and Methods; figs. S3 and S4). Our main result is that the climate is more sensitive to LGM forcing than it is to modern-day 2xCO₂ forcing (Δλ < 0), implying lower estimates of modern-day ECS by Eq. 4, and this finding is robust despite uncertainties in atmospheric physics and LGM reconstructions.

DISCUSSION

Physical mechanisms driving LGM pattern effects

For comparison with our feedbacks in AGCMs driven by LGM reconstructions, we examine previously published results (23) from AGCMs coupled to mixed-layer “slab” oceans (Fig. 2), which allow SST changes in response to imposed forcings but exclude changes in ocean dynamics (47). These mixed-layer model versions of CESM1-CAM5 (23), CESM2-CAM6 (48), and CESM2-PaleoCalib (49) (using a modified CAM6), which differ from our AGCM experiments by including forcings from ice sheets and greenhouse gases, also produce Δλ < 0. Although disagreements in simulated SST patterns compared to proxy data suggest that free-running coupled models cannot reliably estimate the value of Δλ, the coupled models point to mechanisms driving Δλ that are consistent with the reconstructions and our AGCM simulations. In this section, we begin by reviewing simulations in coupled models that demonstrate the physical mechanisms linking patterns of forcing, SST response, and climate feedbacks.

First, we compare zonal mean patterns of ERF and SST changes from CESM1-CAM5 simulations (23) under three forcing scenarios: 2xCO₂ forcing, LGM forcing (ice sheets and greenhouse gases), and

Downloaded from https://www.science.org at Natl Ctr Atmospheric Res on May 14, 2024
LGM ice-sheet forcing alone (including coastline changes). The local-
ized ice-sheet forcing causes the amplified SST response in the north-
ern extratropics at the LGM compared to 2xCO\textsubscript{2} (Fig. 3, A to C). Explan-
ing the Northern Hemisphere’s response to LGM ice sheets has
been a focus of previous studies, which found that amplified SST
cooling in the northern extratropics is associated with changes in
atmospheric stationary waves, driven by changes in ice-sheet al-
bedo and topography (23, 29, 30, 50). Differences in SST responses
between LGM and 2xCO\textsubscript{2} persist at quasi-equilibrium in a fully coupled
(atmosphere-ocean GCM) version of CESM1-CAM5 (Fig. 3C and
fig. S5). Comparing the fully coupled model’s response (Fig. 3C)
with the data assimilation patterns (Fig. 3D) that we use to
quantify pattern effects supports the finding that LGM ice sheets
amplify SST cooling in the northern extratropics (23, 29, 30), but this
cooling pattern is more pronounced in proxy reconstructions.
The amplified cooling of extratropical SST, driven by ice-sheet forcing,
causes the LGM feedback to be less stabilizing than the feedback
induced by CO\textsubscript{2} forcing alone.

Decomposing $\lambda$ from our AGCM simulations into component
feedbacks (fig. S6), including results from direct model output and
from radiative kernels (Materials and Methods), shows that short-
wave cloud feedbacks are responsible for much of the negative value
of $\Delta \lambda$ and for much of the spread across AGCMs. The combined feed-
back from changes in lapse rate and water vapor also contributes to
negative values of $\Delta \lambda$. While shortwave clear-sky feedbacks from sea
ice and snow are also more positive for the LGM, cloud masking
strongly damps the impact of those LGM feedbacks. Accounting for
cloud masking (51, 52), feedbacks from surface albedo are more posi-
tive in 2xCO\textsubscript{2}, i.e., contribute a positive $\Delta \lambda$, offsetting the negative
total $\Delta \lambda$. Overall, our results align with the previous studies focused
on the historical record that emphasize cloud and lapse-rate feed-
backs in pattern effects (11, 13, 15, 20).

Spatial distributions of feedbacks (fig. S7) clarify the connection
between ice-sheet forcing, SST response, and cloud feedbacks. Where
the SST cooling from LGM ice sheets is amplified in the North Pacific
and North Atlantic, positive shortwave cloud feedbacks are promi-
\\ntent because of increases in reflective low clouds (11–15, 18, 30).
\n\nCompared to 2xCO\textsubscript{2} simulations, LGM reconstructions have rela-
\tively small SST anomalies in tropical ascent regions (fig. S1) where
feedbacks are most negative (11–14, 18, 37). However, tropical pat-
tterns at the LGM differ across reconstructions, adding to the uncer-
tainty in the LGM pattern effect. Despite these differences in the
tropics, all four reconstructions produce a negative pattern effect due
to the robust amplification of cooling in the northern extratropics.
The role of the northern extratropics illustrates that pattern effects
are not always dominated by the tropical Pacific, distinguishing the
LGM pattern effect from the well-studied pattern effect of the his-
torical period. In summary, the LGM SST pattern produces a less-
negative global climate feedback compared to the 2xCO\textsubscript{2} SST pattern
and $\Delta \lambda < 0$.

Separating pattern effects from temperature dependence
of feedbacks
While our explanation for feedback differences between LGM and
2xCO\textsubscript{2} forcing focuses on SST pattern differences, we also estimate
how $\Delta \lambda$ is affected by global mean temperature within our AGCM
simulations. Our main AGCM simulations (Fig. 2), which determine
our estimate of total $\Delta \lambda$, include not only the impact of SST patterns
on feedbacks (pattern effects) but also differences in feedbacks
caused by other asymmetries between LGM cooling and modern-
day warming under 2xCO\textsubscript{2} forcing (temperature dependence). We
\n\nconsider that
\n\n$$\Delta \lambda \approx \Delta \lambda_{\text{Pattern Only}} + \Delta \lambda_T$$

(5)

where $\Delta \lambda_{\text{Pattern Only}}$ is the feedback change due to different patterns
of SST anomalies and $\Delta \lambda_T$ is the feedback change due to different global
mean temperatures ($T$). Recent community assessments (1, 2) assume
that warmer climates are more sensitive ($\Delta \lambda_T > 0$) (5–9, 41), which is
at odds with the total $\Delta \lambda < 0$ we find for the LGM in AGCMs and
coupled models (Fig. 2).

To separate pattern effects from temperature dependence, we per-
form additional “pattern-only” simulations in CAM4, CAM5, and
CAM6 using the LGMR and 2xCO\textsubscript{2} patterns. For these simulations, we
\n\nmultiply local SST anomalies by constant scaling factors to yield
\n\nglobal mean $\Delta \text{SST} = -0.5$ K with constant baseline SIC (Materials and
\n\nMethods). SST scaling preserves spatial patterns of anomalies but
forces global mean $\Delta T$ to be small and equal across simulations, i.e.,
\n\n$\Delta \lambda_T \approx 0$ in the pattern-only simulations. We then repeat the feedback
calculations, computing $\Delta \lambda_{\text{PatternOnly}}$ as in Eq. 3. We estimate the temperature dependence $\Delta \lambda_T$ as the residual difference between the main and pattern-only AGCM simulations, rearranging Eq. 5 to $\Delta \lambda_T \approx \Delta \lambda - \Delta \lambda_{\text{PatternOnly}}$ (Materials and Methods). We note that ice-albedo contributions to $\Delta \lambda$ could arise from SST patterns or temperature dependence, but our partitioning of $\Delta \lambda$ treats sea ice as part of $\Delta \lambda_T$.

The magnitude and sign of $\Delta \lambda_T$ is found to be model dependent, in agreement with recent multimodel assessments (22, 53), but $\Delta \lambda_T$ appears to be positive and directionally consistent with standard assumptions (1, 2) for feedback temperature dependence. However, $\Delta \lambda_{\text{PatternOnly}}$ is negative and larger than $\Delta \lambda_T$ such that total $\Delta \lambda < 0$ in each AGCM (fig. S8 and table S3). These results suggest that total $\Delta \lambda$ for the LGM is mostly attributable to SST pattern effects, and $\Delta \lambda_T$ plays a smaller role over this range of climates. Recent assessments (1, 2) considered $\Delta \lambda_T$ for the LGM but did not account for the larger, opposing term, $\Delta \lambda_{\text{PatternOnly}}$. The substantial LGM pattern effect found here motivates revising the LGM evidence for modern-day ECS.

Climate sensitivity accounting for LGM pattern effects

Constraining modern-day ECS with paleoclimate evidence requires accounting for how forcings and feedbacks differ in paleoclimates relative to the modern-day $2xCO_2$ scenario (1, 2, 5). LGM inferences of ECS begin with applying Eq. 1 to the LGM in equilibrium, estimating the unadjusted LGM feedback as $\lambda^*_{\text{LGM}} = \frac{\Sigma \Delta F}{\Delta \sigma}$. ERFs ($\Delta F$) include not only CO$_2$ but also ice sheets (including sea level) and, depending on the timescale chosen for ECS (1–3, 5), five additional changes that have distinct impacts at the LGM: vegetation, dust, N$_2$O, and CH$_4$ (Materials and Methods). $\lambda^*_{\text{LGM}}$ must then be adjusted for differences in feedbacks (Δλ) relative to those operating in modern-day $2xCO_2$, following Eq. 4.

Our results suggest that the LGM feedback is more positive than the $2xCO_2$ feedback because of the LGM ice-sheet forcing and resulting SST pattern. Failing to account for this difference in feedbacks would lead to the inference of higher values of modern-day ECS from the LGM, e.g., (54). Some past studies using fully coupled models have considered these feedback differences indirectly by applying an “efficacy” adjustment (55) to the LGM forcings. The efficacy framework has led to disparate results for multiple reasons: changes in how forcing is quantified (22, 44, 57), and the behavior of intermediate-complexity models with simplified cloud feedbacks (42, 43). Because efficacy is equivalent to the ratio of feedbacks $\lambda_{\text{LGM}}/\lambda_{\text{LGM}}$ (58, 59), our results could be framed as a median LGM-forcing efficacy of 1.7 (Materials and Methods; tables S1 and S2), consistent with recent studies that find LGM-forcing efficacy greater than 1 using ERF and fully coupled models (23, 48, 49). However, the pattern effect framework we use replaces the need for forcing efficacy (text S1) (59), aligns with modern AGCM methods of quantifying feedbacks (60) and ERF (61), and incorporates data from the latest reconstructions of the LGM.

To demonstrate the impact of LGM pattern effects, we follow methods in WCRP20 (1) and focus on the 150-year timescale of climate sensitivity (S) applicable to modern warming (Materials and Methods) (1, 2). We use WCRP20 because that assessment uniquely allows updates of individual parameters and quantitatively combines lines of evidence, but our results would have the same directional impact on other assessments (2, 3). We use forcing values from WCRP20 to estimate the unadjusted LGM feedback, $\lambda^*_{\text{LGM}}$ in Eq. 4. However, given emerging evidence (2, 3, 32, 62, 63) after WCRP20, we report results using a global temperature anomaly for the LGM of $\Delta T_{\text{LGM}} = -6 \pm 1 K$ in addition to WCRP20’s value of $-5 \pm 1 K$. We implement our key finding by revising the LGM $\Delta \lambda$ to now include LGM pattern effects. We assign a normal distribution to $\Delta \lambda_0$, $N(\mu = -0.37, \sigma = 0.23) \text{ Wm}^{-2} \text{ K}^{-1}$, reflecting spread across AGCMs and SST reconstructions (Materials and Methods). Our assessment of $\Delta \lambda$ and its uncertainty relies on AGCMs to estimate feedbacks from prescribed SST/SIC patterns. We include additional uncertainty tests in figs. S4 and S9, demonstrating that our general conclusions hold if the assumed $\sigma$ for $\Delta \lambda$ is doubled.

Accounting for the LGM pattern effect reduces climate sensitivity inferred from the LGM evidence (Fig. 4). With $\Delta T_{\text{LGM}} \approx -6 \text{ K}$, maximum likelihood for $S$ from the LGM evidence alone becomes 2.0 K (change of $-1.3 \text{ K}$). Assuming a prior that is uniform in $S$ from 0 to 20 K (Materials and Methods) for the LGM evidence alone (table S4), we find a posterior median for modern-day ECS of 2.4 K, 66% “likely” range 1.7 to 3.5 K (1.4 to 5.0 K, 5 to 95%). Combining the updated LGM evidence with existing likelihoods for the other lines of evidence (process understanding, historical record, and Pliocene) yields revised Bayesian probability distributions for the two priors in WCRP20: uniform in $\lambda$ (WCRP20’s “Baseline”) and uniform in $S$ (a robustness test).

The impact of the LGM pattern effect on the combined evidence is most pronounced on the upper bound of $S$, which has been notoriously difficult to constrain (64). Assuming that $\Delta T_{\text{LGM}} \approx -6 \pm 1 \text{ K}$, the median and 66% range from combining lines of evidence for $S$ becomes 2.9 K (2.4 to 3.5 K) with a uniform-$\lambda$ prior or 3.1 K (2.6 to 3.9 K) with a uniform-$S$ prior. Corresponding 5 to 95% ranges are 2.1 to 4.1 K with uniform-$\lambda$ and 2.3 to 4.7 K with uniform-$S$. Accounting for pattern effects in $\Delta \lambda$ for the LGM thus reduces the central estimate of modern-day ECS by approximately 0.5 K and reduces the 66% range’s upper bound by 0.6 and 0.9 K for the uniform-$\lambda$ and uniform-$S$ priors, respectively, indicating substantially stronger constraints than WCRP20 (1) even after allowing for more glacial cooling. While the qualitative assessment in IPCC AR6 (2) cannot be quantitatively updated, these results suggest stronger constraints on modern-day ECS than assessed there, as well.

Accounting for LGM pattern effects—enabled by recent advances in LGM SST reconstruction using paleoclimate data assimilation and in quantifying pattern effects using atmospheric models—provides a tighter upper bound on modern-day ECS. While each line of evidence will surely evolve as scientific understanding improves, the results presented here demonstrate that pattern effects must be accounted for when inferring modern-day climate sensitivity from paleoclimate periods that are substantially affected by non-CO$_2$ forcing.

MATERIALS AND METHODS

Data assimilation reconstructions of the LGM

We use four LGM reconstructions to quantify the LGM pattern effect, sampling uncertainty across data assimilation methods and model priors (35, 36). Osman et al. (32) produced the time-dependent “LGMAR” spanning the past 24,000 years; the SST and SIC fields that represent the LGM in their reanalysis are time means spanning 19,000 to 23,000 years ago. Tierney et al. (3) produced the state estimate “LgmDA” dataset. Both the LGMR and LgmDA use priors from isotope-enabled simulations in iCESM1.2 and iCESM1.3.
assimilation of seasonal and annual SST proxies in an ensemble Kalman filter; there are differences in the proxy databases and methods between the two reconstructions. Annan et al. (33) also used an ensemble Kalman filter but with a multimodel prior, including 19 ensemble members from a wide array of climate models spanning PMIP2 (launched in 2002) to PMIP4 (launched in 2017); they assimilated annual SST proxies and land-temperature proxies; they also applied an adjustment to the prior ensemble to center the prior around available proxy data. Amrhein et al. (34) fit the MITgcm ocean model to seasonal and annual SST proxies (65) using least squares with Lagrange multipliers by adjusting prior atmospheric fields from a CCSM4 LGM simulation (66). While these approaches use a diversity of DA methods, versions of CESM1-CAM5 form the prior for two of the reconstructions (3, 32), and the prior covariances could be biased by model errors. Moreover, archived proxy data are geographically inhomogeneous with strong preferences for the NH and tropics; additional data could lead to greater SST agreement across reconstructions outside of the NH.

Simulations with AGCMs

SST/SIC boundary conditions for the LGM, Late Holocene baseline, and 2xCO₂ are prepared to maintain constant forcing, i.e., ΔF = 0 in Eq. 1, across simulations. Topography is held constant, i.e., the LGM ice sheets are not present in AGCM simulations because their impact is already included as a forcing, and we are isolating feedbacks from changing SST/SIC. For the LGM and Late Holocene datasets, we adjust for differences relative to modern coastlines using kriging and extrapolation in polar regions. Details of sea-level adjustments are provided in text S3.

The 2xCO₂ SST/SIC is the multimodel mean of 200 years from the end of six 2xCO₂ simulations, initialized from preindustrial control states, in LongRunMIP (39): CESM1.0.4 (years 2300 to 2500), CNRM-CM6-1 (years 550 to 750), HadCM3L (years 500 to 700), MPI-ESM-1.2 (years 800 to 1000), GFDL-ESM2M (years 4300 to 4500), and MIROC3.2 (years 1803 to 2003). These simulations are near equilibrium but only represent an estimate of the true equilibrium SST response to 2xCO₂.

The Late Holocene, defined as the climatological mean of 0 to 4000 years ago in the LGMR (32), is used as the baseline SST/SIC for all feedback calculations. This baseline represents a long-term mean of the preindustrial climate, constrained by assimilation of proxy data. After adjusting for modern sea level, the four LGM boundary conditions and the 2xCO₂ boundary condition for SST are prepared by adding the SST anomalies from each of the four reconstructions to the Late Holocene baseline SST. Because of nonlinear behavior of sea ice, the LGM and 2xCO₂ boundary conditions for SIC are not added to the baseline as anomalies but rather are used directly (fig. S2).

We run simulations with the Late Holocene baseline, 2xCO₂, and LGMR in each of five AGCMs. We run simulations with all four of the LGM reconstructions (LGMR, LgmDA, Amrhein, and Annan) in CAM4 and CAM5, sampling the spread in LGM feedbacks from different reconstructions in two AGCMs that have distinct relationships linking SST patterns to radiative feedbacks based on their respective Green’s functions (12, 18). Spin-up/analysis period/climatological forcing for each AGCM is as follows: 5 years/25 years/2000 for CESM1.2.2.1-CAM4 (67), CESM1.2.2.1-CAM5 (68), and CESM2.1-CAM6 (69) at 1.9° × 2.5° latitude-by-longitude resolution; 5 years/25 years/2014 for HadGEM3-GC3.1-LL (70) at N96, 135-km resolution; and 1 year/30 years/2001 for GFDL-AM4 (71) at C96, ~100-km resolution. Parent coupled models of the AGCMs considered here sample a wide range of climate sensitivities, from 2.95 to 5.54 K, and the AGCMs span a wide range of pattern effects in the historical record, from 0.38 to 0.84 Wm⁻² K⁻¹ (17).

To compute λ, we take global means over the analysis periods for net top-of-atmosphere radiative imbalance (N) and near-surface air temperature (T). Differences are taken relative to the
Late Holocene baseline, yielding effective feedbacks (72) as $\lambda = \Delta N / \Delta T$ for LGM and 2xCO₂ simulations, given that $\Delta F = 0$ in Eq. 1 by design.

To evaluate the impact of uncertainty in the 2xCO₂ pattern, we also consider existing simulations of abrupt-4xCO₂ with 150-year regressions (73) of $\Delta N$ versus $\Delta T$, denoted as $\lambda_{4x(150yr)}$ to estimate $\lambda_{2x}$ (results in figs. S3 and S4 and tables S1 and S2). Results are consistent using either method of estimating $\lambda_{2x}$. To compute $\lambda_{2x}$ using $\lambda_{4x(150yr)}$, we apply a timescale adjustment ($\zeta$) to reconcile feedbacks from equilibrium paleoclimate data with the feedback that applies to 150-year effective sensitivity ($S$), as in WCRP20. We use the central estimate from WCRP20 of $\zeta = 0.06$, and Eq. 3 is modified to $\Delta \lambda = \lambda_{4x(150yr)} / (1 + \zeta) - \lambda_{\text{LGM}}$

To investigate how spread across the ensemble members from the two most recent LGM reconstructions affects our results, we run additional simulations using CAM4 and CAM5 with the quartiles of ensemble members that produce the most negative and most positive $\lambda_{\text{LGM}}$ in the LGMR (32) and Annan (33) reconstructions (error bars in Fig. 2). To determine the SST/SIC boundary conditions for these experiments, ensemble members in each dataset are initially ranked by estimating $\lambda_{\text{LGM}}$ with CAM5 Green’s functions (18) applied to SST anomalies from each ensemble member. CAM4 Green’s functions (12) produce similar rankings. Green’s functions are only used for ranking and discarded thereafter. We group the ensemble members into quartiles based on rank, and the mean SST/SIC (only SST for the Annan reconstruction) is computed across ensemble members in each quartile. Mean SST anomalies representing the first and fourth quartiles, the most and least negative feedbacks, are used in the additional AGCM simulations. Note that CAM5 with the Annan ensemble’s extreme negative $\lambda_{\text{LGM}}$ produces $\Delta \lambda > 0$. In this quartile, most ensemble members have warming at the LGM over substantial portions of the Southern Ocean (fig S10). This suggests that $\Delta \lambda$ could be positive if the Southern Ocean experienced warming at the LGM, which appears unlikely based on SST proxy data (3, 32, 65), reconstructed deep-ocean temperatures (74), and proxy data indicating increased Antarctic sea ice at the LGM (75).

**Pattern-only simulations separating pattern and temperature dependence**

Feedback differences can be attributed to differences in SST patterns and in global mean near-surface air temperature (1) such that $\Delta \lambda \approx \Delta \lambda_{\text{PatternOnly}} + \Delta \lambda_{\text{T}}$. To separate pattern and temperature impacts on $\Delta \lambda$, we conduct additional pattern-only simulations in CAM4, CAM5, and CM6 with the LGMR and 2xCO₂ patterns. For these simulations, we multiply local SST anomalies by constant scale factors, $k$, which are determined for each pattern so that the global mean $\Delta \text{SST}$ is reduced to $-0.5$ K for both simulations. The constant scale factor for a given pattern of anomalies is calculated from the global mean $\Delta \text{SST}$ as $k = -0.5 \text{ K} / \Delta \text{SST}_{\text{Global}}$ and scaled patterns are then created as $\Delta \text{SST}_{\text{Scaled}} = k \Delta \text{SST}$ at each grid cell. We hold SIC constant at the Late Holocene baseline.

SST scaling preserves the spatial pattern of anomalies but forces global mean $\Delta T$ to be small enough that feedback changes due to temperature dependence are negligible ($\Delta \lambda_{\text{T}} \approx 0$). We repeat the feedback calculations, computing $\Delta \lambda_{\text{PatternOnly}} \approx \lambda_{2x,k} - \lambda_{\text{LGM}}$ as in Eq. 3. While there is no existing method that directly isolates temperature dependence in AGCM simulations, the temperature dependence can be approximated as the residual difference between our main and pattern-only simulations, rearranging Eq. 5 to $\Delta \lambda_{\text{T}} \approx \Delta \lambda - \Delta \lambda_{\text{PatternOnly}}$. In this framework, feedback changes due to sea ice are included in temperature dependence.

We use this pattern-scaling method because it aligns with intuition for pattern effects captured by Green’s functions (12, 18). We do not use Green’s functions to calculate the pattern-only feedbacks, but we briefly discuss the Green’s functions framework here to explain the pattern-only AGCM simulations. In the linear framework of Green’s functions

$$\Delta N = \sum_j \frac{\partial N}{\partial \text{SST}_j} \Delta \text{SST}_j + \epsilon_N$$

$$\Delta T = \sum_j \frac{\partial T}{\partial \text{SST}_j} \Delta \text{SST}_j + \epsilon_T$$

where $j$ represents each grid cell, $\Delta \text{SST}_j$ represents the full SST anomaly at grid cell $j$, $\partial N / \partial \text{SST}_j$ represents the global mean top-of-atmosphere radiative response to a unit increase in local SST at grid cell $j$, $\partial T / \partial \text{SST}_j$ similarly represents the response of global mean near-surface air temperature, and $\epsilon$ represents changes that are independent of SST. Because the feedback $\lambda = \Delta N / \Delta T$, constant scale factors, applied as $k \Delta \text{SST}$, appear in the feedback calculation as $\lambda = (k \Delta N) / (k \Delta T)$ if $\epsilon_N = \epsilon_T = 0$ and SST patterns determine $\lambda$. In this case, where SST patterns are the sole control on $\lambda$, scale factors cancel and have no effect on feedbacks or pattern effects. By comparing feedbacks from scaled pattern-only simulations with feedbacks from simulations with full SST anomalies, we quantify feedback changes that cannot be explained by SST patterns, which we attribute to feedback dependence on global mean temperature. For example, temperature dependence could arise from $\partial N / \partial \text{SST}_j$ changing with global mean temperature or from sea ice appearing at lower latitudes as temperature decreases.

**Feedback decomposition using model fields and radiative kernels**

Net $\lambda$ is calculated from changes in top-of-atmosphere radiation ($\Delta N$) divided by changes in global mean temperature ($\Delta T$). $\Delta N$ can be separated into shortwave clear-sky (SWcs), longwave clear-sky (LWcs), and cloud radiative effect (CRE)

$$\Delta N = \Delta N_{\text{SWcs}} + \Delta N_{\text{LWcs}} + \Delta N_{\text{CRE}}$$

Each component of the radiation is available from AGCM output, and dividing all terms by $\Delta T$ yields feedbacks for each component, which sum to the net feedback. The total clear-sky feedback is the sum of shortwave and longwave components. Because CRE is calculated as all-sky radiation (N) minus clear-sky radiation, CRE is affected by changes in noncloud variables.

With radiative kernels (51, 76), feedbacks can be decomposed into contributions from temperature, moisture, and surface albedo. Cloud feedbacks can be estimated by controlling for changes in noncloud variables, and feedbacks from changing surface albedo can be adjusted to account for overlying cloud cover, which we do here following past studies (51). Radiative kernels are linearized around a specific climate in a specific model, however, and are prone to errors when applied to different climates and models. We use CAM5 kernels (77), convolving them with the monthly mean climatology of anomalies in each AGCM simulation to produce feedbacks in figs. S6 and S7 and zonal means in figs. S12 to S22 (described in text S5).
HadGEM3-GC3.1-LL is not included in kernel analysis due to model output limitations. GFDL-AM4’s 2xCO₂ simulation has error in the kernel-derived clear-sky feedback equal to 15.6% of the actual feedback, exceeding the 15% threshold commonly used as a test of clear-sky linearity (I5, I76); all other simulations have clear-sky feedback errors less than 10%. Residuals shown in fig. S6 are based on total (all-sky) radiation: \( \lambda_{\text{Residual}} = \lambda_{\text{Net}} - \Sigma_\lambda \), where \( \lambda_{\text{Net}} \) is the net feedback from model output and \( \Sigma_\lambda \) is the sum of the each of the following kernel-derived feedbacks: Planck, lapse rate, water vapor, surface albedo, shortwave cloud, and longwave cloud.

### Bayesian estimate of modern-day climate sensitivity

We follow methods (I) and code (I78) provided by WCRP20 for calculating climate sensitivity, but we provide a summary of relevant methods here. ECS is the steady-state change in global mean temperature (I7) from a doubling of CO₂, traditionally with ice sheets and vegetation assumed fixed. When inferring climate sensitivity that is relevant to modern warming from paleoclimate evidence, changes in the paleoclimate radiative budget that are distinct from feedback processes in modern-day 2xCO₂ are treated as forcings; this is typically accomplished by separating “slow” timescale changes as forcings (e.g., ice sheets, LGM). However, given evidence (I2, I32, I62, I63) published after WCRP20 showing LGM cooling centered on \(-6^{\circ}C\) instead of \(-5^{\circ}C\), we report our main results using both assumptions for \( \Delta T_{\text{LGM}} \) (Fig. 4 and fig. S4).

To estimate \( S \), we use a modified version of WCRP20’s energy balance for the LGM

\[
\Delta T_{\text{LGM}} = \frac{-0.57 \Delta F_{\text{2x}} + \Delta F'}{1 + \frac{\lambda_{\text{2x}}}{\lambda_{\text{LGM}}}} - \Delta \lambda
\]

which determines \( \lambda_{\text{2x}} \) and \( S = -\Delta F_{\text{2x}}/\lambda_{\text{2x}} \). We substitute our \( \Delta \lambda \), which includes pattern and temperature dependence. Other than testing a colder \( \Delta T_{\text{LGM}} \), the parameters are unchanged from WCRP20 with the following normal distributions: modern-day forcing from 2xCO₂ \( \Delta F_{\text{2x}} \sim N(4.0, 0.3) \text{ Wm}^{-2} \); total non-CO₂ LGM forcing of \( \Delta F' \sim N(-6.15, 2) \text{ Wm}^{-2} \) (consisting of \(-3.2 \text{ Wm}^{-2} \) from ice sheets, \(-1.1 \text{ Wm}^{-2} \) from vegetation, \(-1.0 \text{ Wm}^{-2} \) from dust aerosols, \(-0.28 \text{ Wm}^{-2} \) from N₂O, and \(-0.57 \text{ Wm}^{-2} \) from CH₄); the timescale transfer parameter from ECS to the 150-year feedback of \( \zeta \sim N(0.06, 0.2) \); and LGM temperature change \( \Delta T_{\text{LGM}} \sim N(-5, 1) \text{ °C} \), or revised \( \Delta T_{\text{LGM}} \sim N(-6, 1) \text{ °C} \). In WCRP20, \( \Delta \lambda = \Delta \lambda_{\text{2x}} = -\alpha \Delta T_{\text{LGM}}/2 \), with \( \alpha = N(0.1, 0.1) \text{ Wm}^{-2} \text{K}^{-2} \).

Quantification of non-CO₂ ERF from ice sheets (including sea level), dust and other aerosols, vegetation, and other greenhouse gases represents substantial uncertainty. As noted in (I23), estimates of the ERF for each component of LGM forcing still need to be constrained, and the uncertainty in radiative effects especially due to dust/aerosols (I79, I80) and vegetation changes may be underestimated in WCRP20. Future paleoclimate research on dust and other aerosols (I81–I83) and vegetation (I84, I85) could improve the estimates used here and in paleoclimate modeling (I86, I87). Recent assessments (I1–I3) discuss how dust and other aerosols, vegetation, and non-CO₂ greenhouse gases also act as feedbacks on fast timescales, and some studies (I3, I54) have calculated a version of climate sensitivity that assumes equivalency in these feedbacks (and in feedbacks from SST patterns) between the LGM and modern-day CO₂, leading to higher values of ECS (I3). In the IPCC AR6 (I2) framework for modern-day ECS, these biogeochemical and non-CO₂ biogeochemical changes are presented as feedbacks (central value of \(-0.01 \text{ Wm}^{-2} \text{K}^{-1} \)). However, AR6 does not address how to account for the LGM’s distinct dust/aerosol and vegetation changes when estimating modern-day ECS from LGM evidence, and this accounting should be a topic of future research.

From the AGCM results in this study, we incorporate pattern effects in \( \Delta \lambda \) of Eq. 6, assigning a revised \( \Delta \lambda \sim N(-0.37, 0.23) \text{ Wm}^{-2} \text{K}^{-1} \). The revised distribution for \( \Delta \lambda \) in our study is based on propagating uncertainty, estimated as spread across AGCMs and LGM reconstructions. To combine uncertainty, we assume that within CAM6, GFDL-AM4, and HadGEM3, the spread in \( \Delta \lambda \) from different LGM reconstructions would be the same as in CAM4 and CAM5. We add the differences in \( \Delta \lambda \) from each pattern in CAM4 and CAM5, where differences are computed relative to \( \Delta \lambda \) using the LGMR pattern, to the results from the remaining three AGCMs. The effect is to treat errors as arising independently in reconstructions and AGCMs. We include \( \lambda_{\text{2x}} \) from extreme quartile simulations using ensemble members from Annan and LGMR as part of the combined sample. There are eight simulations from CAM4 and eight from CAM5 that determine spread from LGM patterns. Note that the spread from LGM patterns is similar between CAM4 and CAM5 (Fig. 2).

With the combined sample, we perform bootstrap resampling (described in text S4) with 10⁶ iterations and a sample size of 19 (equal to the number of actual AGCM simulations). The mean over all iterations is \( \bar{\Delta} = -0.37 (95\% \text{ range: } -0.47 \text{ to } -0.26) \text{ Wm}^{-2} \text{K}^{-1} \), and mean standard deviation (SD) is 0.23 (95% range: 0.15 to 0.31) \text{ Wm}^{-2} \text{K}^{-1} \), which informs our assigned \( \mu \) and \( \sigma \), respectively. In fig. S4, we include an uncertainty test by doubling \( \sigma \) to 0.46 \text{ Wm}^{-2} \text{K}^{-1} \). Using the same bootstrap method, we calculate forcing efficacy (I55) for the LGM, which is equivalent to the ratio of feedbacks \( \lambda_{\text{2x}}/\lambda_{\text{LGM}} \), to have a median value of 1.7 (95% range: 1.5 to 2.0), mean value of 2.1 (95% range: 1.6 to 2.6), and sample SD of 1.1 (95% range: 0.6 to 1.4). Efficacy is strongly affected by division of small values of \( \lambda_{\text{LGM}} \); hence, CAM6 becomes an outlier in the efficacy calculation. We report the median in the main text to reduce the outlier impact.

Calculations for LGM likelihoods and Bayesian probability density functions (PDFs) for \( S \) follow the Monte Carlo methods in WCRP20 (I1, I78). Likelihoods are independent of the prior, but combining the likelihoods with a prior is required to create posterior PDFs that combine lines of evidence. We show results for both priors in WCRP20: the Uniform\((-10, 10) \text{ Wm}^{-2} \text{K}^{-1} \) prior on \( \lambda \) (their Baseline) and the Uniform\((0, 20) \text{ °C} \) prior on \( S \) (robustness test, using a prior that is more conservative regarding the possibility of high climate sensitivity).

### Supplementary Materials

This PDF file includes:
- Supplementary Text
- Figs. S1 to S22
- Tables S1 to S4
- References

### References and Notes


99. A. Yamamoto, A. Abe-Ouchi, M. Shimogawa, W. A. Müller, C. C. W. Nam, N. Notz, S. S. Nyawira, Y. Yamanaka, Global deep ocean oxygenation by enhanced ventilation in the Southern Ocean through a national defense Science and engineering Graduate (ndSeG) Fellowship and high-performance computing support from Cheyenne (doi:10.5065/D6XR99HJ). doi:10.5065/D6XR99HJ provided by the Computational and Information Systems laboratory at the National Science Foundation (nSF). The Community Earth System Model (CESM) project is supported primarily by the NSF. This material is based on work supported by the NSF National Center for Atmospheric Research, which is a major facility sponsored by the NSF under Cooperative Agreement No. 1852977. V.T.C. thanks C. Bitz, D. Hartmann, A. Donohoe, D. Battisti, and anonymous reviewers for thoughtful discussions and comments.

Funding: This work was supported by the following: National Defense Science and Engineering Graduate (NDSEG) Fellowship, US Department of Defense (V.T.C.); National Science Foundation award OCE-2002276 (V.T.C., K.C.A., and G.J.H.); National Oceanic and Atmospheric Administration MAPM Program award NA200AR431039 (K.C.A. and C.P.); Alfred P. Sloan Research Fellowship grant FG-2020-13568 (K.C.A.); a Calvin Professorship in Oceanography (K.C.A.); National Science Foundation award OCE-2003398 (J.E.T. and M.B.O.); National Science Foundation award OCE-2002385 (C.P. and P.C.); National Science Foundation award OCE-2002448 (N.J.B.); National Science Foundation award AGS-1844380 (N.J.B.); National Oceanic and Atmospheric Administration, Climate & Global Change Postdoctoral Fellowship Program, administered by UCAR's Cooperative Programs for the Advancement of Earth System Science (CPAeSS) under award NA210AR4310383 (Y.D.); Met Office Hadley Centre Climate Programme funded by Business, Energy and Industrial Strategy (T.A.); and the European Union's Horizon 2020 Research and Innovation Programme under grant agreement 780289 (T.A.). Author contributions: V.T.C. performed the analysis, designed the simulations, wrote the original draft, and ran the simulations in CAM5 and CAM4. K.C.A. initiated the study with support from G.J.H., C.P., J.E.T., and N.J.B. K.C.A. and G.J.H. supervised the research. G.J.H., J.E.T., M.B.O., and D.E.A. contributed expertise on data assimilation and LGM reconstructions. Y.D., N.J.B., T.A., C.P., J.J., and Y.M. contributed to analysis and interpreting results. T.A. ran AGCM simulations in HadGEM3-GC3-1-LL, W.D. in GFDL-AM4, and P.C. in CAM6. J.D. provided coupled simulations in CESM. All authors contributed to editing the paper. Competing interests: The authors declare that they have no competing interests. Data and materials availability: All data needed to evaluate the conclusions in the paper are present in the paper and/or the Supplementary Materials. SST/SIC boundary conditions and AGCM results are available at github.com/vtcooper/cooper_et al_2024_LGMPatterns or on Zenodo at doi.org/10.5281/zenodo.10651822. LongRunMIP is available at longrunmip.org. LGM3 (32) at doi.org/10.25921/njqd-h0g8, LgmDA (J2) v2.1 at doi.org/10.5281/zenodo.5171432, Amrhein (34) at doi.org/10.5281/zenodo.8110710, and Amman (33) at doi.org/10.5194/cp-18-1883-2022. Previous studies’ coupled model outputs are hosted at doi.org/10.5281/zenodo.3948405 (CESM1-CAMS) (23), doi.org/10.5281/zenodo.4075596 (CESM2-CAM6) (48), and doi.org/10.5065/bd7-wt42 (CESM2-PaleoCalib) (49). Code from WCRP20 to calculate climate sensitivity is available at doi.org/10.5281/zenodo.3945276 (78). CAMS radiative kernels are available through doi.org/10.5281/zenodo.3359041 (77).

Submitted 19 September 2023
Accepted 13 March 2024
Published 17 April 2024

10.1126/sciadv.9461