Evidence for higher Earth-system sensitivity from long-term carbon-cycle observations

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Key Points:
1. Fusing multiple deep-time paleo carbon dioxide (CO2) proxy data sets with a long-term carbon-cycle model tightens the estimated range of Earth-system sensitivity from 1.6-7.6 °C to 3.8-6.6 °C (5-95% range) and raises the median from 3.8 °C to 5.1 °C per doubling of CO2.
2. We use a mixture model and Bayesian calibration to improve the match between modeling results and CO2 proxy data throughout the Cenozoic.
3. A global sensitivity analysis identifies research into reducing the uncertainties associated with chemical weathering as a promising pathway to further constrain Earth-system sensitivity.

Projections of future temperature are critical for developing sound strategies to address climate risks, but depend on deeply uncertain Earth system properties, including the Earth-system sensitivity (ESS). The ESS is the long-term (e.g., millennial-scale and longer) global warming resulting from a doubling of atmospheric carbon dioxide (CO2) levels, relative to pre-industrial conditions. Long-term carbon cycle models provide a common approach to estimate ESS, but previous efforts either lack a formal data assimilation framework, or focus on paleo periods with the most available data. Here, we improve on ESS estimates by using a Bayesian approach to fuse deep-time paleoclimate data with a long-term carbon cycle model. Our updated ESS estimate of 5.1 °C (3.8–6.6 °C; 5-95% range) shows a higher and narrower range than previous assessments, implying increased long-term future temperatures and risks. Our sensitivity analysis reveals that chemical and plant-assisted weathering parameters interact strongly with ESS in affecting the simulated atmospheric CO2. Research into improving the understanding about these weathering processes hence provides potentially powerful avenues for further constraining this fundamental and policy-relevant Earth-system property.

Understanding the relationship between global temperatures and changes in atmospheric carbon dioxide (CO2) concentration has been a quest for more than a century1. The current deep uncertainty surrounding this sensitivity poses considerable challenges for the design of climate change policies2. Of particular interest is the equilibrium response of global mean temperature to a doubling of CO2 relative to pre-industrial conditions, termed the “climate sensitivity”3. The climate sensitivity is critical for mapping projections of CO2 forcing to global temperature, and is based on “fast” feedback responses to changes in radiative forcing. These fast feedbacks include, for example, changes in water vapor, lapse rate, cloud
cover and snow/sea-ice albedo\textsuperscript{4}. Even with detailed constraints from the instrumental period, climate sensitivity estimates based on the historic record alone are still subject to considerable uncertainties\textsuperscript{5-8}.

Consideration of longer-term responses offers a glimpse into the deep-time paleoclimate evolution of ESS and can inform estimates of the related, longer-term equilibrium response, termed “Earth-system sensitivity” (ESS). The ESS can include slower responses such as changes in vegetation cover, land-ice or carbon burial rates, for example\textsuperscript{4}. Indeed, a growing body of evidence suggests large fluctuations in CO\textsubscript{2} and temperature during the last 420 Myrs, which would allow for improved quantification of climate sensitivity and insight into factors affecting the climate response across a wide range of climate states, including both icehouse and greenhouse conditions (Fig. 1 and Supplementary Table 1)\textsuperscript{9-15}.

Previous work has estimated climate sensitivity over geological timescales using varying combinations of long-term carbon-cycle models and temperature and CO\textsubscript{2} proxy data (Fig. 1). Using a geochemical model and CO\textsubscript{2} proxies (indirect measurements of CO\textsubscript{2} concentrations) from the last 420 million years, ref. 16 concluded that climate sensitivity falls between 1.6 and 5.5 °C (95% confidence), well within the range of the fast-feedback climate sensitivity from other studies using climate data from the last millennium\textsuperscript{7,8,17}. Many studies suggest that ESS larger than 1.5 °C is a general feature of the Phanerozoic\textsuperscript{9,10,13,18}. Previous work also showed that climate sensitivity during glacial periods may be double that of non-glacial periods, with best estimates around 6 to 8 °C\textsuperscript{11,15}. Recently, ref. 19 suggested that Early Cenozoic climate was primarily driven by changing CO\textsubscript{2}, and estimated a climate sensitivity of 2.1 to 4.6 °C using temperature and CO\textsubscript{2} proxies from the Early Eocene Climate Optimum (ca. 51 to 53 Myr).

\textbf{Figure 1. Summary of Earth-system sensitivity and associated uncertainties from previous and this study.} Category 1: ESS derived from long-term carbon cycle models are shown as colored boxes [yellow box (ref. 20); grey boxes (ref. 11); and red boxes (this work)]; Category 2: ESS derived from temperature and CO\textsubscript{2} proxies [blue squares (ref. 10); orange triangles (ref. 4); filled red circles (ref. 19), green diamond (ref. 21); green box (ref. 22); magenta horizontal bar (ref. 23); purple square (ref. 24); hollow red circle (pre-PETM) (ref. 25); and hollow blue circle (PETM) (ref. 25)]. The vertical error bars represent the 68% probability range, except for ref. 19 which shows 66% probability range.
There are still large uncertainties surrounding ESS estimates, despite the wealth of paleoclimate proxy data for temperatures and CO$_2$ concentrations (Fig. 1). These previous studies report different kinds of Earth-system climate sensitivities, so it is important to distinguish between various “flavors” of climate sensitivity, depending on which factors are considered (for example, forcings independent of CO$_2$ versus feedbacks related to the CO$_2$ forcing). The GEOCARBSULFvole long-term carbon and sulfur cycle model and its previous incarnations has been used widely in previous studies. GEOCARBSULFvole includes a version of ESS where the only independent radiative forcings are CO$_2$, solar evolution and changing geography ($\Delta T(2x)_{[CO2, geog, solar]}$, in the notation of ref. 4).

In long-term carbon-cycle models, many uncertainties stem from uncertainties surrounding CO$_2$ proxy data and carbon-cycle model parameters. Specifically, the errors in proxy CO$_2$ data are often asymmetric, and many model parameters have a complex relationship among them, and their effects on modeled CO$_2$ concentrations. Previous assessments do not fully account for these model parameter interactions, or neglect the asymmetric error structure. This raises the question of how these assumptions affect estimates of ESS. Additionally, reducing uncertainty in ESS can help to inform strategies to manage future climate risks. This raises the related question of which research has the highest promise to constrain ESS, given this common model framework. Here, we address these questions by: (i) considering interactions among model parameters, (ii) implementing a formal parameter calibration approach and (iii) performing a detailed sensitivity analysis for the model parameters, to assess where to focus future efforts to constrain key uncertainties.

Previous work using GEOCARBSULFvole

GEOCARBSULFvole is a long-term carbon and sulfur cycle model that simulates atmospheric concentrations of CO$_2$ and O$_2$ based on mass and isotopic balance over the last 540 million years. While other long-term carbon-cycle model choices are available, we employ the GEOCARBSULFvole model here due to its extensive use as an inverse modeling tool for constraining ESS and other geophysical uncertainties using CO$_2$ proxy data. The model structure assumes that the atmosphere and ocean is a single system where rivers and volcanic degassing deliver input to the atmosphere-ocean system, and the ocean loses material in the form of carbonate, organic matter, gypsum and pyrite. The shape of the modeled CO$_2$ curve is well-characterized, with high values (> 1000 ppm) between 540 and 400 Myr and around 250 Myr, compatible with the lower solar luminosity in the early Phanerozoic.

Our adopted GEOCARBSULFvole model (henceforth, “GEOCARB”) has 69 input parameters (including both constant and time-variable parameters; see Supplementary Tables 2-3). GEOCARB assumes a single ESS parameter ($\Delta T(2x)$) for the last 420 Myrs of non-glacial periods, and includes a parameter (GLAC) to amplify the ESS during the late Paleozoic (330-260 Ma) and late Cenozoic (34-0 Ma) glacial periods. During glacial periods, the effective ESS is then $\Delta T(2x)^{(g)} = GLAC \times \Delta T(2x)$. Thus, uncertainty in ESS reflects both imperfect knowledge of ESS (within our modeling framework) and real variation in ESS over time. Previous work to constrain the uncertainty in the model parameters relies on several important assumptions. The prior distribution centers are held fixed in their Monte Carlo resampling strategy and only the widths are adjusted; if a parameter sample leads to model failure, then the input range is considered unlikely and rejected. Model failure can result from unphysical carbon or sulfur fluxes, or from unphysical O$_2$ or CO$_2$ concentrations, within the GEOCARB simulation. This resampling approach risks missing key parameter interactions, and propagating biases in the centers of parameters’ distributions.

Here, we expand on previous work by improving the uncertainty characterization of both proxy CO$_2$ and associated model parameters. First, we use Markov chain Monte Carlo sampling to account for parametric observational uncertainties and asymmetric observational uncertainties for about 420 Myr of
CO₂ proxy data (see Methods). This improves on previous ESS estimates by updating the centers of all parameters’ distributions and implementing a formal mixture model likelihood function\(^\text{12}\), and accounts for the asymmetric proxy data uncertainties. Second, we quantify the influence on model output of all model parameters and their interactions with one another in a sensitivity analysis. This allows us to highlight key parameter interactions and thereby identify promising areas for continued improvement in our understanding of ESS.

**Results**

**Inference for Earth-system sensitivity**

We use a Bayesian calibration approach\(^3\) to update the parameters’ prior distributions\(^\text{12}\) and sample from the posterior distribution of the 69 GEOCARB parameters. The essence of this calibration method is to iteratively sample model parameters, and “steer” the sampling toward values of parameters (including ESS) that yield simulations that agree well with the CO₂ proxy data, within the uncertainties in the model and data. We find a posterior ensemble median ESS (the parameter \(\Delta T(2x)\) in GEOCARB) of 5.1 °C per doubling of CO₂ (5-95% credible range of 3.9-6.7 °C; Fig. 2). Our ESS estimates agree well with a recent estimated 5-95% range of 3.7-7.5 °C\(^2\). Both studies used formal Bayesian calibration approaches, as opposed to simple Monte Carlo methods, which may contribute to our higher ESS estimates (see Supplementary Figure 2). While our ESS estimates are higher than previous GEOCARB work\(^\text{11,16}\), we also tighten constraint on the high-risk upper tail of the distribution: we find 14% probability associated with ESS above 6 °C, similar to 16% in ref. 11, but find only 2% probability of ESS above 7 °C, in contrast to 8% from ref. 11 (“PR2011” in Fig. 2).

![Figure 2. Posterior probability density for Earth-system sensitivity parameter (\(\Delta T(2x)\), solid line), relative to the prior density (dotted line) and ref. 11 (PR2011, dashed line). At bottom, the points provide median estimates from each study and whiskers denote the 5-95% uncertainty ranges.](attachment:image.png)

The fact that the ESS estimate of ref. 20 is higher than other studies, including this one, can be attributed largely to the selection of a single constant ESS value (see Supplementary Figures 2 and 3). Our posterior estimates for the glacial scaling factor, GLAC, are centered at 2.1 (ensemble median; 5-95% range: 1.5-2.8), which is consistent with the central value of 2 used in previous work\(^\text{11}\).
Owing to our higher estimates of \( \Delta T(2x) \) and correlated uncertainties with GLAC, our estimated distribution for the net glacial period ESS is centered at 11 °C (5-95% range of 7.2-16.1 °C). This range is higher and wider than the range of 6-8 °C from a previous GEOCARB analysis\(^{11}\), although still within the uncertainty ranges for that and other glacial period ESS assessments\(^{10}\). Our results thus reconcile the distribution of ESS between estimates that place more probability weight below 2.5 °C\(^{4,11,16}\) and the high-end estimates of ref. 20, whose posterior ESS estimates are a mix of the glacial and non-glacial ESS estimates presented here.

**Constraint of paleo-CO\(_2\) evolution**

We find that the CO\(_2\) proxy records, after accounting for widely asymmetric uncertainties, provide a tighter constraint on the evolution of paleoclimate CO\(_2\) as compared to ref. 12 (Fig. 3). The tighter constraint is due primarily to the implementation of the formal calibration approach and use of a mixture model likelihood as opposed to the assumption of a single unimodal log-normal likelihood in each time window (see Methods and Supplemental Figure 1).

![Figure 3. Probabilistic model hindcast, best estimates and proxy observational data points (circle markers) and CO\(_2\) proxy amount and age uncertainty ranges (whiskers). The blue shaded region denotes the 95% credible range from this work and the blue solid line denotes the maximum posterior score simulation from this work (i.e., best estimate; solid blue line). For comparison, the red shaded region denotes the 95% range from ref. 12 (their Fig. 2a), and the red dashed line is the ensemble median from that work.

During the Mesozoic and Cenozoic Eras, our simulations improve the low bias found in previous work using GEOCARB\(^{11,12}\) (see Supplementary Figure 1). We attribute this to two primary factors. First, we consider uncertainty in all 69 of the GEOCARB geophysical parameters, and include a new parameter to account for uncertainty in model structure and representation of the geophysical processes it seeks to capture\(^{35}\). Second, we assimilate an expanded data set\(^{28}\), which has more proxy data in the 500-2,000 ppmv CO\(_2\) range relative to these previous GEOCARB analyses\(^{11,12}\). Throughout the past 200 Myr, the modeled uncertainty range in CO\(_2\) concentration (shaded envelope in Fig. 3) is narrower than the uncertainties in CO\(_2\) proxy data. This apparent model overconfidence is also a feature characteristic of previous GEOCARB analyses (see Supplementary Figure 1). This could potentially point to a key process
modulating paleoclimate atmospheric CO₂ being missing from the model, or to disjoint high-probability regions of the parameter-space, but further investigation is outside the scope of this work.

**Model uncertainties influencing ESS uncertainties**

Uncertainty in our estimates of ESS stem from uncertainty in paleo proxy data, but also from uncertainty in the modeled CO₂ time series. We conduct a global sensitivity analysis by decomposing the variance in the modeled CO₂ time series into variance contributions attributable to each of the 69 GEOCARB model parameters (first-order sensitivities), and interactions among the parameters (second- and higher-order sensitivities). We also estimate total parameter sensitivity for each parameter, which is the proportion of model output variability attributable to a parameter and all of its interactions with other parameters. These sensitivities offer unique insight into which processes most strongly control the evolution of paleoclimate CO₂. Some previous analyses using GEOCARB have focused on model sensitivity to a few select parameters (FERT, LIFE, GYM, ACT, GLAC and ∆T(2x)), but were silent on the sensitivity to many others, including the assumed time series of isotopic forcing.

We use a scaled sum-of-squared-errors as a simple measure of the sensitivity of the modeled CO₂ to changes in the model inputs (see Methods). We define as “sensitive” any parameter whose lower 90% confidence bound for total model sensitivity is more than 1% of the model output variance.

We identify 25 parameters to which the GEOCARB model is sensitive (Fig. 4). A complete listing of the sensitive parameters is provided in Supplementary Table 4. The first-order sensitivity to ∆T(2x) is the largest single contributor to total variance in model output (12%), followed by GYM (8%; the rate of chemical weathering by gymnosperms, relative to angiosperms) and ACT (5%; the activation energy for dissolution of calcium and magnesium silicate rocks on land).

![Figure 4. Sensitivity of modeled CO₂ time series to changes in input parameters, by decomposing the variance in the modeled CO₂ time series using the Nash-Sutcliffe efficiency (see Supplemental Information). Light gray nodes represent first-order sensitivity indices; dark gray nodes represent total sensitivity indices; light gray bars represent second-order sensitivity indices for the interaction between the parameter pair. Larger nodes/bars denote higher model sensitivities to those inputs.](image-url)
First- and second-order sensitivities among plant-assisted weathering parameters account for 13% of the total model output variance, and chemical weathering parameters account for another 10%. We find second-order sensitivities between $\Delta T(2x)$ and GYM, and between GYM and ACT, of 3% and 1.5% of total model output variance, respectively (Fig. 4). Taken together with the work of ref. 12, which found a similar result but also included the chemical weathering parameter LIFE, these sensitive interaction terms highlight improvements in the representation of weathering processes as a potential avenue to improve estimates of ESS. Specifically, better constraint of weathering processes has potential to yield improved constraint on key weathering parameters (i.e., GYM and/or ACT), which will, in turn, better constrain ESS.

We find that GEOCARB is sensitive to the time series input parameters for weathering fluxes ($f_{Aw_{\_A}}$, the fraction of land area that undergoes chemical weathering) and seafloor spreading and degassing ($f_{SR}$ and $f_C$, the rates of seafloor spreading and effect of CO$_2$ degassing, relative to present, respectively) (Fig. 4). The first- and second-order effects of uncertainty in all 12 time series parameters accounts for about 9% of the total model output variance.

**Discussion and implications**

We update previous estimates of ESS using the GEOCARBSULFvolc model$^{11,16}$ by including a larger CO$_2$ proxy data record$^{28}$, implementing an improved likelihood function and formal data-model fusion approach$^{37}$ and conducting a global sensitivity analysis to examine the parameter controls on simulated CO$_2$ concentrations. We find a tighter and higher range of credible ESS estimates than previous work$^{11}$. This change can be explained by our improved calibration approach and improved seafloor spreading time series$^{38}$ (see Supplementary Figure 1). These results constitute a substantial step forward in characterizing the Earth-system temperature response to changes in atmospheric CO$_2$ concentrations, and determining where to invest future research to constrain this relationship.

Our analysis advances the field in several important aspects, but there remain caveats that point to fruitful research directions. While our results have improved on the low-CO$_2$ bias found throughout the Mesozoic Era characteristic of previous GEOCARB analyses$^{11,12}$, a low bias persists. Our use of a mixture-model likelihood function reveals multimodality in the CO$_2$ proxy record as a driving force behind this low bias and the associated apparent model overconfidence in that time period (see Supplementary Figures 1 and 4). This points to possible competing physical processes governing CO$_2$ evolution during the Cenozoic that our model does not adequately capture, or to regions of the parameter-space that are inaccessible to our calibration approach.

Through a global sensitivity analysis, we find that chemical and plant-based weathering mechanisms are tied strongly to ESS in their control of CO$_2$ evolution. The identified sensitivities to weathering processes and paleo-temperature time series reflect the tight link between variation in ESS and variation in temperature, which leads to changes in weathering rates. These results indicate the value of improved knowledge of weathering processes as an avenue to further constrain ESS, thereby improving our understanding of the relationship between atmospheric CO$_2$ concentrations and changes in Earth’s climate.

**Methods**

We use the parameter central estimates and uncertainty ranges given by ref. 11. There are 69 parameters in total: 56 constant parameters and 12 time series parameters native to the model, and we have added a statistical parameter $\sigma$ to represent the expected mismatch between the GEOCARB model and CO$_2$ proxy data, capturing the notion that no model is perfect. The constant parameters are assigned Gaussian prior distributions, with the exception of Earth-system sensitivity ($\Delta T(2x)$) and white noise parameter ($\sigma$), which
are assigned log-normal priors. The time series parameters take distinct values at each of the 58 model time steps. Following previous work, we assume the model and forcing time series parameters are in steady state between model time steps. Each time series is assigned one parameter representing the cumulative density function quantile at which the parameter time series will be modulated relative to the central estimate from previous work. These time series parameters are assigned as priors beta distributions with both shape parameters = 5, which gives a symmetric distribution centered at 0.5 and 5-95% range of 0.25 to 0.75. This choice encourages sampling closer to the centers of fitted distributions from previous work, as well as to combat the accumulation of measure on the edges of the large (69) dimensional parameter-space. We update the time series for seafloor spreading rate (ISR) to match the more recent work of ref. 38, and evaluate the sensitivity of our results to this improvement in a set of supplemental experiments (see Supplementary Figure 1). In our adopted GEOCARB model, we have fixed an error that was noted in previous GEOCARB versions wherein the forcing time series for the fraction of land area that undergoes chemical weathering relative to present (the parameter fAw_fA) was previously not normalized to 1 relative to the final model timestep (which roughly represents present-day conditions).

Using the CO₂ proxy data set as in ref. 28, containing 1,215 proxy data points, we fit skew-normal distributions to each data point, given their uncertainty ranges, using a differential evolutionary optimization algorithm. We discard two data points with unphysical negative CO₂ concentration values, leaving 1,213 data points for analysis. We fit a skew-normal mixture model to estimate the joint likelihood within 10-Myr windows (to match the model time-step). Weights for the mixture model components are computed following ref. 11. We discard as unrealistic any simulations outside of the 0-50,000 ppmv CO₂ range.

We use a robust adaptive Markov chain Monte Carlo approach to sample from the posterior distributions of the model parameters, given the fitted likelihood surface and the parameters’ prior distributions. We use a preliminary Markov chain of 1.5x10⁷ iterations to converge to samples from the parameters’ stationary distribution and estimate the number of iterates required to obtain the desired sample sizes for analysis. Then, we use the final parameter state and proposal covariance from this preliminary chain to initialize five parallel Markov chains of 1.5x10⁶ iterations each. We use the Gelman and Rubin potential scale reduction factor to assess convergence and examine the autocorrelation function to thin the five chains, each of 1.5x10⁶ iterates, to a final pooled sample of 6,443 simulations for analysis. Experiments adjusting the final sample size confirmed our results are insensitive to changes in sample size (see Supplementary Figure 6).

We draw parameter samples from their prior distributions to use as nodes for the sensitivity analysis. As a preliminary filter for physically plausible simulations, we apply a precalibration. Simulations pass the precalibration test if they satisfy two simple constraints:

1) 0 ppmv < CO₂ < 50,000 ppmv at all times
2) 280 ppmv < present-day CO₂ < 400 ppmv.

Note that the effect of the present-day CO₂ pre-calibration constraint is to effectively fix an upper bound on the variance in this model output of interest for the Sobol’ analysis. After pre-calibration, we use two independent samples of 21,902 parameter sets as nodes for the sensitivity analysis.

The model output selected as a sensitivity measure is the Nash-Sutcliffe efficiency:

\[
NS = 1 - \frac{\sum_{t=1}^{T} \sum_{k=1}^{n_t} (y_{t,k} - \bar{y})^2}{\sum_{t=1}^{T} \sum_{k=1}^{n_t} (\bar{y}_{t,k} - \bar{y})^2},
\]
where $\eta_t$ is the modeled CO$_2$ at timestep $t$; there are $T$ timesteps total; there are $n_t$ data points falling between timesteps $t$ and $t+1$; $y_k$ is the $k$th data point during the timestep $t$; and $\bar{y}$ is the mean of all data points. The essence of the Sobol’ global sensitivity analysis is to decompose variance in the model output ($NS$) as components attributable to variance in model parameters, and interactions among parameters. We diagnose convergence of the sensitivity indices when the widest 90% confidence interval width is less than 10% of the highest total sensitivity index$^{43}$. We consider parameters as significant (i.e., the model is sensitive to these parameters) if their lower 90% confidence bound is greater than 1% of the total variability in model output.

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**Author contributions**

All authors contributed to the study design, T.E.W. carried out the experiments, T.E.W. and Y.C. wrote the first draft of the manuscript, and all authors contributed to the final version of the manuscript.

**Data and Code availability**

All model codes, analysis codes, data and results used for analysis are freely available from https://github.com/tonyewong/GEOCARB-calibration and are distributed under the GNU general public license.

**Conflicting interests**

The authors are not aware of conflicting interests.
Supplementary Information

Accompanying Evidence for higher Earth-system sensitivity from long-term carbon-cycle observations, by Tony E. Wong, Ying Cui, Dana L. Royer and Klaus Keller

1 Model calibration

1.1 Model and data
We use the GEOCARBSULFvolc (“GEOCARB”) model as in Royer et al. (2014) and use the CO₂ proxy records as in ref. 2, which contain paleosols ($n=521$), stomata ($n=263$), boron ($n=224$), alkenones ($n=193$) and liverworts ($n=14$), for a total of 1,215 data records. We remove two data points with unphysical negative CO₂ values, leaving 1,213 for analysis.

In our series of supplemental experiments, we perform several calibrations using the data set employed by ref. 3. This data set contains 635 CO₂ proxy records. To evaluate the sensitivity of the model output to input forcing time series, we also perform calibrations using two alternative updated seafloor spreading rate time series (the parameter fSR). One time series is derived from Lenton et al. (2018), and the other is from Domeier and Torsvik (2019). It has been noted in the literature that previous versions of the GEOCARB model contained an error wherein the forcing time series for the fraction of land area that undergoes chemical weathering relative to present (the parameter fAw_fA) was not normalized so the fraction in the final model timestep was 1 (which roughly represents present-day conditions). We have fixed this error in our adopted GEOCARB version.

1.2 Likelihood function
First, we use a differential evolutionary algorithm to fit skew-normal distributions to each of the 1,213 proxy data points in the analysis data set. Then, within each 10 Myr time slice, we compute mixture model weights for all data points within that time slice. The cross-section of the likelihood surface for that time step is then the skew-normal mixture model defined by those weights and the fitted skew-normal distributions for each data point. This procedure has the benefits of retaining the asymmetric error structure of the individual skew-normal uncertainty distributions for each data point, while simultaneously being much more computationally efficient than assuming an independent joint likelihood function for all 1,213 data points. This assumes independence between time steps, as do other similar works. We do not employ the age uncertainties in the data set because not every data point has an associated age uncertainty, and for clarity of comparison among the supplemental experiments using the data set of ref. 3.

As part of our set of supplemental experiments, we perform calibrations using a unimodal likelihood function structure, as in ref. 3, as opposed to the skew-normal mixture model used in the experiments presented in the main text. We also perform an experiment using normal kernels for the mixture model likelihood function to evaluate the impacts of the observational error asymmetry.

1.3 Parameter calibration approach
We use a robust adaptive Markov chain Monte Carlo (MCMC) statistical calibration approach to draw samples from the joint posterior distribution of the model parameters. The posterior distribution of model parameters $x$, conditioned on the data $y$, is given by Bayes’ theorem as proportional to the likelihood function and the prior distribution:

$$
\pi(x|y) \propto L(y|x) \pi(x).
$$
We take the likelihood function \( L(y \mid x) \) to be a joint skew-normal distribution, over the calibrated model parameters and 1,213 data points (or 635 data points for the supplemental experiments using the data set of ref. 3). We use the same prior distributions for model parameters as in previous work\(^1\). We run a preliminary “warm-up” Markov chain for \( 1.5 \times 10^7 \) iterations to converge to samples from the parameters’ posterior distribution (the Markov chain stationary distribution). Then, we run five parallel Markov chains for 110,000 iterations for the experiments using only the six parameters from ref. 3, or for \( 1.5 \times 10^6 \) iterations for the experiments using all 68 GEOCARB parameters; all experiments use the additional white noise uncertainty parameter. These Markov chains are all initialized from the final state of the long warm-up chain.

We diagnose convergence using a threshold of 1.1 for the Gelman and Rubin potential scale reduction factor\(^11\). We compute the autocorrelation function for each chain and determine the lag at which the autocorrelation is maintained less than 0.05 for each of the model parameters in that chain. We thin each of the parallel Markov chains using their respective lags and pool the thinned samples to yield a final ensemble for analysis. We repeat this process for each of the supplemental experiments. In the experiments using all 69 GEOCARB parameters, some of the parallel Markov chains become stuck in local posterior modes for brief periods. In these instances, we either trim the part of the chain where it becomes stuck (if it is near the beginning or end of the chain) or we discard the chain entirely.

### 1.4 Impacts of error asymmetry

When we repeat the calibration as described in the main text but fit normal distributions to each data point instead of skew-normal distributions, the resulting distribution for Earth-system sensitivity (ESS, \( \Delta T(2x) \)) is biased slightly high relative to the results of the main text (Fig. S1), with a median of 5.2 °C (relative to 5.1 °C in the main text), and a 5-95% range of 3.9-6.8 °C (main text: 4.4-6.0 °C). We hypothesize that this accounts in part for the fact that the ESS estimate of ref. 9 is higher and wider than other recent works (Fig. S1). The larger part of the difference in estimates is attributable to the use of a single ESS for both glacial and non-glacial periods (Supplementary Figure 3) and to the use of a formal model calibration approach (Supplementary Figures 1 and 2).

### 2 Global sensitivity analysis

#### 2.1 Sobol’ method

Sobol’ method for global sensitivity analysis is based on decomposition of the variance in the output from a large ensemble of model simulations, and attributing this variance to variance in the model input parameters\(^12\). Sobol’ method enables the calculation of the sensitivity of model output to each parameter and every order of interaction among the parameters. For example, second-order sensitivities are how the variance in model output is affected by two particular parameters and the interactions between them.

Total variance in the model sensitivity output of interest \( m \) can be decomposed as

\[
V[m] = \sum_{i=1}^{p} V_i + \sum_{i<j} V_{ij} + \sum_{i<j<k} V_{ijk} + \ldots + V_{123\ldots p},
\]

where \( V[m] \) represents the total variance in the model output of interest, \( V_i \) represents the first-order contribution from parameter \( x_i \) to the variance, \( V_{ij} \) represents the second-order contribution of interactions between parameters \( x_i \) and \( x_j \) to the variance, and so on; \( V_{123\ldots p} \) represents the variance in model output due to interactions among all of the parameters.

The first-order sensitivity index for a parameter \( x_i \) is the ratio of the variance contribution from first-order effects of the parameter \( x_i \) on the model output metric, to the total variance in output:
The second-order sensitivity index for a parameter pair \((x_i, x_j)\) is defined analogously to the first-order indices, and computed as:

\[
S_{ij} = \frac{V_{ij}}{V} - S_i - S_j.
\]

The total sensitivity index for a parameter \(x_i\) is one minus the ratio of the total variance in model output with parameter \(x_i\) removed from the analysis, to the original total variance,

\[
T_i = 1 - \frac{V_{-i}}{V},
\]

where the subscript \(-i\) denotes that parameter \(x_i\) has been removed from the analysis.

We approximate the sensitivity indices by using Monte Carlo integration. In this set-up, an ensemble of quasi-random samples covering the parameter-space is needed, totaling \(2N\) simulations. This ensemble is divided into two equal-sized, independent samples, which we denote \(A\) and \(B\). Each of the sub-ensembles \(A\) and \(B\) is of size \(N\).

The simulations of sub-ensemble \(A\) are used to calculate the mean and total variance in model output as:

\[
m_0 = \frac{1}{N} \sum_{j=1}^{N} m(x_j),
\]

\[
V[m] = \frac{1}{N} \sum_{j=1}^{N} m^2(x_j) - m_0^2.
\]

Then, the variance contributions for a parameter \(x_i\) are estimated using the samples from sub-ensemble \(B\) as

\[
V_i = \frac{1}{N} \sum_{j=1}^{N} m(x^A_j) m(x^B_{-ij}, x^A_{ij}) - m_0^2
\]

and

\[
V_{-i} = \frac{1}{N} \sum_{j=1}^{N} m(x^A_j) m(x^A_{-ij}, x^B_{ij}) - m_0^2.
\]

In these equations, \(m(x^A_j)\) refers to the model output when run with the \(j\)-th set of parameters from sub-ensemble \(A\), and (for example) \(m(x^A_{-ij}, x^A_{ij})\) refers to the model output when run with the \(j\)-th set of parameters from sub-ensemble \(A\), but parameter \(x_i\) is replaced by its value from the \(j\)-th set of parameters from sub-ensemble \(B\).

The model output selected as a sensitivity measure is the Nash-Sutcliffe efficiency:

\[
NS = 1 - \frac{\sum_{t=1}^{T} \sum_{k=1}^{n_t} (\eta_t - y_{t,k})^2}{\sum_{t=1}^{T} \sum_{k=1}^{n_t} (y_{t,k} - \bar{y})^2},
\]

where \(\eta_t\) is the modeled CO\(_2\) at timestep \(t\); there are \(T\) timesteps total; there are \(n_t\) data points falling between timesteps \(t\) and \(t+1\); \(y_{t,k}\) is the \(k\)-th data point during the timestep \(t\); and \(\bar{y}\) is the mean of all data points. We diagnose convergence of the sensitivity indices when the widest 90% confidence interval width
is less than 10% of the highest total sensitivity index\(^{14}\). We consider parameters as significant if the lower 90% confidence bound is greater than 1% of the total variability in model output.

### 2.2 Precalibration

Through preliminary experiments, we found that sampling the sub-ensembles \(A\) and \(B\) directly from the prior distributions leads to unstable results. We hypothesize that this is attributed to the relatively high-dimensional parameter-space \((p=69)\) and presumed independence of the prior distributions. As the number of dimensions increases, an increasing proportion of the hyper-volume is located near the surface - i.e., in the tails of the prior probability distribution. This “concentration of measure” leads to an increasing number of simulations sampled from the outskirts of what prior knowledge regarding the model parameters suggests is plausible. In other words, a random sample from the joint prior distribution in high dimension is quite likely to originate from the tails. These less likely parameter samples, in turn, lead to large variability in model output, which yields overestimates of parameter sensitivity indices. We tackle this challenge by using a precalibration that removes from the ensemble any parameter sets that result in physically implausible CO\(_2\) simulations\(^{15}\). The two precalibration constraints are:

1) \(0 \text{ ppmv} < \text{CO}_2 < 50,000 \text{ ppmv}\) at all times, and  
2) \(280 \text{ ppmv} < \text{present-day CO}_2 < 400 \text{ ppmv}\).

In order to obtain the sub-ensembles \(A\) and \(B\) for the Sobol’ sensitivity analysis, we first draw parameters from the prior distributions specified by previous studies\(^1\), and apply a precalibration as specified in the main text Methods. We begin the precalibration procedure with a total of 2,200,000 Latin hypercube samples, and 43,805 parameter sets pass the precalibration windows. This leads to precalibrated sub-ensembles \(A\) and \(B\) of 21,902 simulations each for the Sobol’ analysis. These sub-ensembles serve as nodes for the Monte Carlo integration of the Sobol’ method. Some simulations within the Sobol’ analysis lead to model failure when the parameters from the two sub-ensembles are shuffled together (see Sec. 2.1). In these cases, the simulations are discarded. The low rate of success in the Monte Carlo precalibration (about 2%) is a result of the complex relationship among a large number of parameters, and the simulated CO\(_2\) time series.
3 Figures and Tables

| Age (Myr) | Paleoclimate sensitivity (*°C/2x CO₂*) | Upper uncertainty | Lower uncertainty | Time period | Reference |
|-----------|----------------------------------------|-------------------|------------------|-------------|-----------|
| 3.3       | 7.1                                    | 1                 | 1                | Middle Pliocene | Pagani et al. (2010) |
| 3.3       | 8.7                                    | 1.3               | 1.3              | Middle Pliocene | Pagani et al. (2010) |
| 4.2       | 9.6                                    | 1.4               | 1.4              | Early Pliocene  | Pagani et al. (2010) |
| 34        | 6.4                                    | 3.3               | 2.0              | Eocene-Oligocene | Rohling et al. (2012) |
| 36        | 6.7                                    | 1.0               | 1.8              | Late Eocene    | Rohling et al. (2012) |
| 40        | 3.5                                    | 1.1               | 1.1              | Middle Eocene Climate Optimum | Bijl et al. (2010) |
| 56        | 3.7 to 6.7                             | n/a               | n/a              | PETM          | Rohling et al. (2012) |
| 0 – 40, 260 – 340 | 6-8                             | n/a               | n/a              | Glacial Periods | Park and Royer (2011) |
| 0-420     | 3.8                                    | 2.2               | 1.5              | Phanerozoic    | Park and Royer (2011) |
| 0-420     | 2.8                                    | 3.4               | 1.3              | Phanerozoic    | Royer et al. (2007) |
| 36.9      | 3.3                                    | 0.3 (66% confidence) | 1.2 (66% confidence) | Late Eocene   | Anagnostou et al. (2016) |
| 53.2      | 3.8                                    | 0.8 (66% confidence) | 1.2 (66% confidence) | Early Eocene  | Anagnostou et al. (2016) |
| 0-100     | 5.6                                    | 1.3               | 1.2              | Since 100 million years ago | Krissansen-Totton and Catling (2017) |
| 32-58     | 3.5-8.9 (68% probability)              |                   |                  | Eocene        | Cramwinckel et al. (2018) |
| 201-233   | 3.82                                  | n/a               | n/a              | Late Triassic | Knobbe and Schaller (2017) |
| 3.025 - 3.264 | 5.01                           | n/a               | n/a              | Middle-Pliocene | Haywood et al. (2013) |
| 55.8      | 3.3 to 5.6                             | n/a               | n/a              | Pre-PETM      | Shaffer et al. (2016) |
| 55.8      | 3.7 to 6.5                             | n/a               | n/a              | PETM          | Shaffer et al. (2016) |

**Supplementary Table 1.** Paleo constraint on climate sensitivity and its uncertainty estimates.
| Parameter name | Description |
|----------------|-------------|
| Sr             | $^{87}$Sr/$^{86}$Sr isotopic ratio of shallow marine carbonate |
| d13C           | $\delta^{13}$C isotopic ratio of shallow marine carbonate |
| d34S           | $\delta^{34}$S isotope ratio of calcium sulfate |
| fR             | Effect of continental relief on chemical weathering relative to present |
| fL             | Fraction of land area covered by carbonates relative to present |
| fA             | Land area relative to present |
| fD             | Global river runoff relative to present (excluding changing CO$_2$, solar luminosity) |
| fAw_fA         | Fraction of land area that undergoes chemical weathering relative to present |
| RT             | Response of temperature change on fD |
| GEOG           | Change in land surface temperature relative to present, assuming present CO$_2$ and solar luminosity |
| fSR            | Seafloor spreading rate relative to present (proxy for CO$_2$ degassing) |
| fC             | Effect of carbonate content of subducting oceanic crust on CO$_2$ degassing rate relative to present |

**Supplementary Table 2.** Time-varying model parameter names and descriptions.
### Supplementary Table 3. Constant model parameter names and descriptions.

| Parameter name | Description |
|----------------|-------------|
| ACT | Activation energy for dissolution of calcium and magnesium silicate rocks on land |
| ACTcarb | Activation energy for dissolution of carbonates on land |
| VNV | Rate of chemical weathering in volcanic silicate rocks relative to non-volcanic silicate rocks |
| NV | Rate of chemical weathering in non-volcanic silicate rocks |
| exp_NV | Exponent relating physical erosion to the mean $^{87}$Sr/$^{86}$Sr isotopic ratio of non-volcanic silicate rocks |
| LIFE | Rate of chemical weathering in a minimally-vegetated world relative to present (angiosperm-dominated) |
| GYM | Rate of chemical weathering by gymnosperms relative to angiosperms |
| FERT | Exponent for fraction of vegetation whose growth is stimulated by elevated CO$_2$ |
| exp_fnBb | Exponent for effect of climate on silicate/carbonate weathering in absence of vascular plants relative to present |
| deltaT2X ($\Delta T(2x)$) | Earth-system sensitivity; increase in temperature from doubling CO$_2$ |
| GLAC | Factor by which deltaT2X changes during glacial periods |
| J | Coefficient for stable carbon isotopic fractionation between shallow-marine carbonate and organic matter |
| n | Exponent for stable sulfur isotopic fractionation between shallow-marine CaSO$_4$ sulfur and pyrite sulfur |
| Ws | Effect on temperature from linear increase in solar luminosity over time |
| exp_fd | Exponent that scales the dilution of dissolved HCO$_3^-$ with river runoff ($fd$) |
| Fwpa_0 | Sulfate flux from oxidative weathering of old pyrite at present |
| Fwsa_0 | Sulfate flux from weathering of CaSO$_4$ at present |
| Fwga_0 | Carbon flux from weathering of old sedimentary organic matter at present |
| Fwca_0 | Carbon flux from weathering of old calcium and magnesium carbonates at present |
| Fmg_0 | Carbon degassing flux from volcanism, metamorphism and diagenesis of organic matter at present |
| Fmc_0 | Carbon degassing flux from volcanism, metamorphism and diagenesis of carbonates at present |
| Fmp_0 | Carbon degassing flux from volcanism, metamorphism and diagenesis of pyrite at present |
| Fms_0 | Carbon degassing flux from volcanism, metamorphism and diagenesis of CaSO$_4$ sulfur at present |
| Fwsi_0 | Weathering flux for all calcium and magnesium silicates at present |
| Xvolc_0 | Fraction of total calcium and magnesium silicate weathering derived from volcanic rocks at present |
| CAPd13C_0 | Stable carbon isotopic fractionation between shallow marine carbonate and organic matter at present |
| CAPd34S_0 | Stable sulfur isotopic fractionation between shallow marine CaSO$_4$ sulfur and pyrite sulfur |
| oxygen_570 | Mass of atmospheric O$_2$ at 570 Mya |
| Gy_570 | Mass of young crustal organic carbon at 570 Mya |
| Cy_570 | Mass of young crustal carbonate carbon at 570 Mya |
| Ca_570 | Mass of old crustal carbonate carbon at 570 Mya |
| Ssy_570 | Mass of young CaSO$_4$ sulfur at 570 Mya |
| Spy_570 | Mass of young pyrite sulfur at 570 Mya |
| dlsy_570 | $\delta^{34}$S isotope ratio of young CaSO$_4$ at 570 Mya |
| dlcy_570 | $\delta^{13}$C isotope ratio of young carbonate carbon at 570 Mya |
| dlp_570 | $\delta^{34}$S isotope ratio of young pyrite sulfur at 570 Mya |
| dly_570 | $\delta^{13}$C isotope ratio of old pyrite sulfur at 570 Mya |
| dlq_570 | $\delta^{34}$S isotope ratio of old organic matter at 570 Mya |
| Rcy_570 | $\delta^{34}$Sr/$^{86}$Sr ratio of young carbonates undergoing weathering at 570 Mya |
| Rca_570 | $\delta^{34}$Sr/$^{86}$Sr ratio of old carbonates undergoing weathering at 570 Mya |
| Rv_570 | $\delta^{34}$Sr/$^{86}$Sr ratio of sub-aerial and submarine volcanic rocks at 570 Mya |
| Rg_570 | $\delta^{34}$Sr/$^{86}$Sr ratio of non-volcanic silicates at 570 Mya |
| Fob | Calcium and magnesium flux between basalt and seawater |
| COC | Mass of carbon in the ocean |
| Ga | Mass of old crustal organic carbon |
| Ssa | Mass of old CaSO$_4$ sulfur |
| Spa | Mass of old pyrite sulfur |
| ST | Mass of sulfur in the oceans and interacting rocks (undergoing weathering, burial, etc.) |
| dst | $\delta^{34}$S of ST |
| CT | Mass of carbon in the oceans and interacting rocks |
| dct | $\delta^{13}$C of CT |
| kwpy | Rate constant expressing mass dependence for young pyrite sulfur |
| kwsy | Rate constant expressing mass dependence for young CaSO$_4$ sulfur |
| kwgy | Rate constant expressing mass dependence for young organic matter weathering |
| kwc | Rate constant expressing mass dependence for young carbonate weathering |
| stdev | Additional modeling uncertainty parameter |
| Parameter name | Description |
|----------------|-------------|
| ACT            | Activation energy for dissolution of calcium and magnesium silicate rocks on land |
| VNV            | Rate of chemical weathering in volcanic silicate rocks relative to non-volcanic silicate rocks |
| e<sup>NV</sup> | Exponent relating physical erosion to the mean $^{87}$Sr/$^{86}$Sr isotopic ratio of non-volcanic silicate rocks |
| NV             | Coefficient relating physical erosion to the mean $^{87}$Sr/$^{86}$Sr isotopic ratio of non-volcanic silicate rocks |
| GYM            | Rate of chemical weathering by gymnosperms relative to angiosperms |
| FERT           | Exponent for fraction of vegetation whose growth is stimulated by elevated CO<sub>2</sub> |
| $\Delta T(2x)$ | Earth-system sensitivity; increase in temperature from doubling CO<sub>2</sub> |
| Ws             | Effect on temperature from linear increase in solar luminosity over time |
| e<sup>ID</sup> | Exponent that scales the dilution of dissolved HCO<sub>3</sub> with river runoff (fD) |
| Fmc<sub>0</sub> | Carbon degassing flux from volcanism, metamorphism and diagенesis of carbonates at present |
| Fwsi<sub>0</sub> | Weathering flux for all calcium and magnesium silicates at present |
| Xvolc<sub>0</sub> | Fraction of total calcium and magnesium silicate weathering derived from volcanic rocks at present |
| RV<sub>570</sub> | $^{87}$Sr/$^{86}$Sr ratio of sub-aerial and submarine volcanic rocks at 570 Mya |
| RG<sub>570</sub> | $^{87}$Sr/$^{86}$Sr ratio of non-volcanic silicates at 570 Mya |
| Fob            | Calcium and magnesium flux between basalt and seawater |
| kwcy           | Rate constant expressing mass dependence for young carbonate weathering |
| Sr             | $^{87}$Sr/$^{86}$Sr isotopic ratio of shallow marine carbonate (time-series) |
| fR             | Effect of continental relief on chemical weathering, relative today (time-series) |
| fA             | Land area, relative to present (time-series) |
| fD             | Global river runoff relative to present (excluding changing CO<sub>2</sub>, solar luminosity) (time-series) |
| fAw fA         | Fraction of land area that undergoes chemical weathering relative to today (time-series) |
| RT             | Response of temperature change on fD (time-series) |
| GEOG           | Change in land surface temperature relative to present, assuming present CO<sub>2</sub> and solar luminosity (time-series) |
| fSR            | Seafloor spreading rate relative to present (time-series) |
| fC             | Effect of carbonate content of subducting oceanic crust on CO<sub>2</sub> degassing rate relative to present (time-series) |

**Supplementary Table 4.** Descriptions of the 25 sensitive parameters.
**Supplementary Figure 1.** Estimated 95% credible ranges (blue shaded region and solid line) for CO$_2$ hindcast and maximum likelihood ensemble members from the series of calibration experiments modifying the calibration data set used (either Park and Royer (2011) \textsuperscript{3} (“PR2011”) or Foster et al. (2017) \textsuperscript{2} (“F2017”)), the parameters considered in the calibration (either the six parameters matching Park and Royer (2011) (“PR2011”) or all of the parameters (“all”)), the seafloor spreading rate time series used (matching Park and Royer (2011) (“PR2011”), matching Lenton et al. (2018) \textsuperscript{4} (“L2018”) or Domeier and Torsvik (2019) \textsuperscript{5} (“DT2019”)), whether the likelihood function employed is unimodal (“unimodal”, matching that of Park and Royer (2011)) or a mixture model (“mixture”, matching the main text), and whether the uncertainties for each CO$_2$ proxy data point are assumed to be distributed normally (matching Krissansen-Totton and Catling (2017) \textsuperscript{9}), skew-normally (matching the main text), or log-normally (matching Park and Royer (2011)). For comparison, the 95% range from the hindcast of Royer et al. (2014) \textsuperscript{1} is also plotted (red shaded region and dashed line). The data set employed for the calibration (either Park and Royer (2011) or Foster et al. (2017)) is plotted as scatter points. Panel (i) corresponds to the results presented in the main text.

| Data   | Parameters | tSR      | Likelihood | Uncertainties |
|--------|------------|----------|------------|---------------|
| F2017  | all        | DT2019   | mixture    | normal        |
| F2017  | all        | DT2019   | mixture    | skew-normal   |
| F2017  | all        | DT2019   | unimodal   | skew-normal   |
| PR2011 | all        | DT2019   | mixture    | skew-normal   |
| F2017  | PR2011     | DT2019   | mixture    | skew-normal   |
| F2017  | PR2011     | DT2019   | unimodal   | skew-normal   |
| PR2011 | PR2011     | DT2019   | mixture    | skew-normal   |
| PR2011 | PR2011     | PR2011   | unimodal   | skew-normal   |
| PR2011 | PR2011     | PR2011   | unimodal   | log-normal    |

**Supplementary Figure 2.** Estimated 5-95% credible ranges and medians for Earth-system sensitivity from the series of calibration experiments modifying the calibration data set used (either Park and Royer (2011) \textsuperscript{3} (“PR2011”) or Foster et al. (2017) \textsuperscript{2} (“F2017”)), the parameters considered in the calibration (either the six parameters matching Park and Royer (2011) (“PR2011”) or all of the parameters (“all”)), the seafloor spreading rate time series used (matching Park and Royer (2011) (“PR2011”), matching Lenton et al. (2018) \textsuperscript{4} (“L2018”) or Domeier and Torsvik (2019) \textsuperscript{5} (“DT2019”)), whether the likelihood function employed is unimodal (“unimodal”, matching that of Park and Royer (2011)) or a mixture model (“mixture”, matching the main text), and whether the uncertainties for each CO$_2$ proxy data point are assumed to be distributed normally (matching Krissansen-Totton and Catling (2017) \textsuperscript{9}), skew-normally (matching the main text), or log-normally (matching Park and Royer (2011)). The bottom row corresponds to the results of Park and Royer (2011), and the second row corresponds to the results presented in the main text.
Supplementary Figure 3. Results for Earth-system sensitivity (ESS) from main text (solid blue line and filled circle), the corresponding glacial period ESS (orange dot-dashed line and open circle), the ESS distribution assuming normally-distributed uncertainties for the proxy CO$_2$ data (green dashed line and open triangle), and the 5-95% range for ESS reported by ref. 9 (black range and filled triangle).
Supplementary Figure 4. Time slice of the mixture model likelihood surface at ages 240 Myr (a) and 50 Myr (b).
Supplementary Figure 5. Fitted likelihood surface (red shaded region denotes 95% credible range, solid dashed line denotes the median), proxy data points (x markers) and model ensemble (blue shaded region denotes the 95% credible range and the solid line denotes the maximum likelihood ensemble member).

Supplementary Figure 6. Estimated 5-95% credible ranges (dashed lines) and medians for Earth-system sensitivity from the experiments presented in the main text for sample sizes ranging from 250 to 6,250 in increments of 250.
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