Earth's Future

Supporting Information for

Sea Level and Socioeconomic Uncertainty Drives High-End Coastal Adaptation Costs

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Contents of this file

Text S1 to S6
Figures S1 to S11
Table S1 to S2
Introduction

This Supporting Information includes some additional guidance for those who would like to use the MimiCIAM implementation of the Coastal Impact and Adaptation Model (CIAM), initial validation against the previous version of CIAM, descriptions of the main damage functions within CIAM, a supplemental experiment to examine sensitivity to the chosen storm surge exposure data set, and some tables and figures to support and expand on the results presented in the main text. The additional user guidance is meant to help distinguish between the various software components of our work. Specific details for replication of these results and running new cases with the MimiCIAM model are given in the code repositories online and linked in Text S1 below.

The Dataset files that we provide include all of the raw or processed data (in CSV form) that is necessary in order to reproduce the figures shown in the main text and the Supporting Information figures. The Monte Carlo sampling procedure is necessarily random, so if the code is re-run from scratch then the exact quantiles may differ slightly from those presented in the main text. However, Figure S8 suggests that they will not differ substantially.

Text S1. Guidance for users of MimiCIAM

Three repositories hold the bulk of support for this paper, starting with Mimi.jl, which provides the framework and baseline support for the implementation of the CIAM model (Diaz, 2016) in the second repository, MimiCIAM.jl. Both Mimi and MimiCIAM are available as packages that are imported in the third repository, which is specific to this project. The third repository detailed below leverages MimiCIAM.jl to perform the work and experiments for this paper, and provides support for replication and exploration of our results. The following is a brief overview of the purpose and contents of each of these repositories. More detailed user information may be found within the individual repositories linked below.

Mimi.jl (https://www.mimiframework.org): The Mimi project is a Julia package that provides a component model for integrated assessment models. Much of the work aligns with the aforementioned National Academies of Sciences (National Academies of Sciences & Medicine, 2017) recommendation for a flexible, modular, uniform computational platform for integrated assessment models.

MimiCIAM.jl (https://github.com/raddleverse/MimiCIAM.jl): MimiCIAM is a Julia package leveraging the Mimi.jl framework to produce a Julia implementation of the CIAM model adapted from Diaz (2016). The README for this repository contains details on running the default version of the model, looking at the results, and some of the options for modifying the parameterization and underlying data such as the local mean sea level rise projections as discussed next. Details on other inputs are available upon request if the information in the README does not answer further questions.
CIAM input data for projections of local mean sea levels are provided as a comma-separated value (CSV) file. Each column corresponds to a CIAM coastal segment and has a column header (first row) containing the name of that segment. Each row corresponds to the local annual mean sea-level change relative to the start of the model simulation period, for each model time step. An input argument gives the CIAM user the option to provide a list of segments that is a subset of the full set of 12,148 coastal segments, and run CIAM with only this subset. The model codes that accompany this work include a file that provides the latitude and longitude coordinates for each coastal segment, a script that runs CIAM for a given subset of segments (if provided), and writes CSV model output files to save the costs and optimal adaptation decisions for each segment for each time step.

**CIAM_uncertainty_propagation** ([https://github.com/raddleverse/CIAM_uncertainty_propagation](https://github.com/raddleverse/CIAM_uncertainty_propagation)): This repository holds the scripts for this paper, which rely heavily on the infrastructure in the two preceding repositories, MimiCIAM.jl and Mimi.jl. These scripts allow for replication of paper results, including two primary types of experiments: (1) the baseline MimiCIAM simulations and (2) the Monte Carlo Ensembles. The README for this repository contains details on running these on a local machine, and/or running analysis through provided notebooks. Details are available upon request if the information in the README does not answer further questions.

**Text S2. CIAM adaptation strategies and cost estimates**

In the event that a coastal segment in CIAM becomes inundated due to local mean sea-level rise, that segment will retreat reactively (in contrast to planned, or proactive, retreat). For the retreat and protection strategies, segments can choose a defense level from among the 10, 100, 1,000, and 10,000-year (presumed maximum) storm surge return periods. Retreat for the 1-year return period is also an option. These protection levels are calculated for each segment based on generalized extreme value distributions, and reported in the DIVA database (Vafeidis et al., 2008). In light of the biases inherent in any global-scale database of storm surge return levels (Hunter et al., 2017; Muis et al., 2017), we conduct a supplemental experiment (see Supporting Information Text S3) to assess the degree to which our estimated coastal adaptation costs and damages are influenced by use of the DINAS-COAST surge exposure data set within DIVA, following the original CIAM implementation. Also following the original formulation of Diaz (2016), reactive retreat is assumed to cost five times the same level of planned retreat.

In CIAM, costs are decomposed into five categories: wetland loss, retreat/relocation costs, inundation (dryland loss), loss of property and life due to flooding, and construction costs (costs associated with building and maintaining seawall protection). Here, we briefly review the structural assumptions for estimating these costs for an arbitrary time step at an arbitrary coastal segment. For a deeper discussion, the
reader is directed elsewhere in the literature, as these have been discussed at length in other works (e.g., Diaz (2016), Vafeidis et al. (2008), Hinkel and Klein (2009), Hinkel et al. (2014)). This description closely mirrors the Supplementary Material (Sec. 2) of Diaz (2016), which will be of high relevance to interested readers.

**Protection costs** are computed from a linear contribution from coastline length, a quadratic contribution from seawall height, and a location-dependent annual cost to occupy the land and maintain the seawalls. This equation is:

\[ \text{Protection Cost} = l \cdot pc \cdot (H^2 + mcH) + l \cdot lv \cdot 1.7H, \]

where \( l \) is the length of coastline, \( pc \) is a country-specific protection construction cost, \( mc \) is the maintenance cost, \( H \) is the height of the seawall protection, and \( lv \) is the occupied land value. The factor of \( 1.7H \) represents the width of the seawall, stemming from an assumption within CIAM that seawalls have a 60-degree slope on each side. The “seawall” protection is meant to generalize the specific types of protective measures that are appropriate to individual geographies of the coastal segments. Reference costs for this generic protection is computed from a review of average dike and seawall costs (Hillen et al. 2010) and a database of national construction and labor cost indices (World bank International Comparison Program, 2011).

**Retreat costs** include the cost of relocating mobile capital and population. The losses from inundation of the evacuated area are included in the next section. Retreat costs are given by:

\[ \text{Retreat Cost} = \theta_L \sigma_L \text{area} (R - R_o) + (\theta_K + dc)\sigma_K \text{area} (R - R_o), \]

where \( \theta_L \) and \( \theta_K \) are cost coefficients for retreat per unit population and mobile capital (respectively), \( \sigma_L \) and \( \sigma_K \) are densities of population and mobile capital, \( dc \) is a demolition cost for immobile capital. Within CIAM, it is assumed that one-fourth of capital is mobile and that demolition costs for immobile capital are 5% of the capital’s value. As retreat can be proactive or reactive, following Diaz (2016), we assume that reactive retreat costs five times as much as proactive retreat. Segments are also assumed to be capable of relocating capital and population within the segments’ borders, and with full productivity upon relocation.

**Inundation costs** represent the losses of unprotected land that falls below local mean sea level. Inundation costs are computed as:

\[ \text{Inundation Cost} = lv \text{area} + (1 - \delta)\sigma_K \text{area}, \]

where \( \text{area} \) is the area of newly-inundated land and \( \delta \) is a depreciation rate parameter. It is assumed that mobile capital stocks (25% of all capital stocks) are reactively relocated when inundated, but immobile capital stocks (75%) are abandoned. However, if a segment pursues proactive retreat as its adaptation strategy, this foresight can avert significant losses. This is represented by the \( \delta \) depreciation parameter, which is between 0 and 1 (Yohe et al., 1995). Interior land value comes from the Global Trade Analysis Project (Baldos and Hertel, 2012). It is assumed that land values increase with increases in income and population density (Yohe et al., 1999).
Wetland costs account for the impacts of sea-level rise and coastal adaptation decisions on wetlands. Wetland costs are assumed to be quadratically related to the rate of sea-level rise if segments either do not adapt or follow a proactive retreat strategy. If segments construct protective seawalls, then wetland services are assumed to be totally lost because wetlands no longer have inland space to migrate away from advancing sea levels. Wetland costs are computed as:

\[ WetlandCost = \begin{cases} 
    wv \text{ area} \left( \frac{dSLR}{dt} \right)^2, & \text{if Retreat or No Adaptation and } \frac{dSLR}{dt} < \lambda \\
    wv \text{ area}, & \text{if Protect or } \frac{dSLR}{dt} \geq \lambda 
\end{cases} \]

where \( wv \) represents the annual value of wetland services (Brander et al., 2006), \( dSLR/dt \) is the rate of sea-level rise, \( \lambda \) is a threshold for wetland migration, and \( \text{area} \) is the inundated wetland area (Hoozemans, 1993; Spalding, 1997). Wetland value is also assumed to increase with income and population density.

Flood costs are computed as the expected damages over the distribution of extreme sea levels, \( s \):

\[ FloodCost = \mathbb{E}[\text{Damage}(s)] = \int_{A}^{S_{\text{max}}} \text{Damage}(s)f(s)ds \]

where \( f(s) \) is the probability density function for extreme sea level \( s \), \( A \) is the current adaptation level for this segment, \( S_{\text{max}} \) is a maximum plausible surge level for this segment, and \( \text{Damage}(s) \) gives the flood damages associated with the incidence of extreme sea level \( s \). \( f(s) \) is assumed to follow a generalized extreme value distribution (Diaz, 2016). We conduct sensitivity experiments to compare updated surge exposure data sets (Muis et al., 2016) against this original surge exposure data (see Text S3). \( \text{Damage}(s) \) is given by:

\[ \text{Damage}(s) = (1 - \rho) \int_{x_{\text{min}}}^{S_{\text{max}} + s} \text{area}'(x) \cdot \left( \sigma_k \phi(h(x)) + \sigma_l \mu VSL \right) dx, \]

where \( x_{\text{min}} \) is the lower bound of elevation for this segment, \( \rho \) is a national resilience index parameter (which is tied to national gross domestic product), \( x \) is vertical elevation, \( lslr \) is the change in local mean sea level from the start of the model simulation, \( h \) is flood water height, \( \phi(h) \) is a depth-damage function (Hinkel et al., 2014), \( \mu \) is a flood mortality factor (Jonkman and Vrijling, 2008), and \( VSL \) is the national value of a statistical life for the country in which the given segment is located. \( VSL \) is based on national per capita income (216 times per capita income), which is consistent with how (for example) the FUND integrated assessment model computes the value of a statistical life (200 times per capita income) (Cline, 1992).

We note that there are, of course, many parametric uncertainties (e.g., \( VSL \) or the flood mortality factor) and structural uncertainties (specific data sets used, the form of extreme value distribution for surge exposure, or the parameterization of each component of overall damages). This work is not meant to be an attempt to minimize or constrain these uncertainties. Rather, it is our aim to characterize how these uncertainties propagate through the coupled geophysical (sea-level change) and human (coastal risk) system. This characterization of uncertainty is conditioned on a particular set of structural
and parametric assumptions that are consistent with numerous previous studies spanning the previous decade of research. These uncertainties, while potentially reducible, are inherent and unavoidable. No study can reduce them to zero, which elevates the importance of improving our understanding of how they influence our characterizations of coastal risk.

Text S3. Sensitivity to surge exposure data set

We conduct a supplemental experiment to assess the sensitivity of the modeled adaptation costs to the specific data set used for storm surge return levels for each CIAM coastal segment. The Original CIAM model uses the DINAS-COAST (“DC”) surge exposure data as provided by the DIVA database (Vafeidis et al., 2008). We compare the DC data set to two alternative surge data sets, based on the Global Tide and Surge Reanalysis (GTSR) data set (Muis et al., 2016). We construct one data set that applies a multiplicative bias correction to the DC surge level data. This bias factor is equal to the ratio of the 100-year return level from GTSR to the 100-year return level from DC for each particular coastal segment. Then, we multiply each return level from the DC data set by this factor. Thus, in this “GTSR/DC” data set, the 100-year return level matches those from GTSR exactly, and the other return levels (10-year and 1000-year) are stretched/contracted to account for biases (e.g., that DC return level distributions are too high and too flat (Hunter et al., 2017)). We also compare a GTSR-based data set for each segment by using the nearest GTSR data point to each DIVA segment’s centroid. The GTSR data (GTSR, 2016) does not include the “1-year” return level (annual maximum high tide level (Diaz 2016), so we use the GTSR/DC return levels for that datum.

To verify that these data sets produce surge exposure levels that reflect the biases relative to one another that have been previously noted in the literature (e.g., Muis et al., 2017), Figure S10 shows the relationship between the GTSR and the DC 100-year return levels. Muis et al. (2017) found a global mean bias for DC relative to tide gauge data of 0.55 m, and a bias for GTSR of -0.19 m. From the linearity of expectation, the mean bias of DC relative to GTSR should then be 0.74 m. DC surge levels are higher than our GTSR data set, with a mean difference, DC-GTSR, of 0.748 m, in tight agreement with the findings of Muis et al. (2017).

The distributions of the total global net present value of total adaptation costs from 2010-2150 (with a constant 4% discount rate) are not sensitive to the choice of specific storm surge exposure data set (Figure S11). This is potentially counterintuitive based on the apparent differences in the storm surge data sets (Figure S10), but is explained by the CIAM model structure (both in Original CIAM, and retained in our MimiCIAM implementation). Specifically, the first model time step (2010-2020) is a “calibration” or “spin-up” period. This accounts for the relative sparsity of detailed information about coastal adaptation infrastructure on a global scale. In this calibration period, it is assumed that each segment adapts efficiently (least-cost) to the storm surge hazard over this period. The storm surge distributions for each coastal segment are assumed to be stationary (i.e., return levels are the same throughout the model
simulation time period). Thus, the potentially increased or decreased adaptation costs are felt in the first (calibration) time step, and subsequent increases in flood risk are driven entirely by sea-level rise. As noted in the main text, we have subtracted the costs/damages from this calibration period from the results in subsequent time steps.

Text S4. Model validation and limited decision-maker foresight

In a first experiment, we verify that the new MimiCIAM model, coded in Julia, matches the model output from Original CIAM, which was coded in GAMS (Figure S3, no hatch). We post-process the model output to be consistent with the perfect foresight of future sea-level rise that is assumed in Original CIAM (Figure S3, “x” hatch). We also compare the new version of MimiCIAM with limited decision-maker foresight (Figure S3, stippling). As expected, in the no-adaptation scenario, all three versions match (Figure S3a). With least-cost adaptation, for the first adaptation (2010-2050) annual total adaptation costs are slightly lower with limited foresight (Figure S3b). This is because perfect foresight of end-of-century sea-level rise leads to higher levels of protection in the Original CIAM and perfect foresight MimiCIAM cases. This is evident in the relatively lower protect costs in the limited foresight MimiCIAM case, and slightly higher inundation damages (Figure S3b). In subsequent adaptation periods (2050-2090, and 2100 and beyond), higher optimal adaptation costs in the limited foresight case are driven by inundation (dryland loss) and proactive retreat.

In the experiments presented in the main text, we employ GDP and population pathways that follow the SSPs (Riahi et al., 2017) and sea-level projections that use an updated semi-empirical sea-level model (Wong et al., 2022a). Relative to the limited foresight MimiCIAM baseline (Figure S3, stippling), we show under SSP5-8.5 the incremental changes from each of those two updates (Figure S6).

Text S5. Calculation of elementary effects for sensitivity analysis

We use Method of Morris (Morris, 1991) to compute elementary effects (EE) for each BRICK and MimiCIAM input parameter, indexed by \( i = 1, 2, \ldots, 57 \), and for a number of trajectories \( r \), indexed by \( j = 1, 2, \ldots, r \). If \( M(\mathbf{x}) \) denotes the model output of interest (here, net present value of total adaptation costs) when using input parameter vector \( \mathbf{x} \), the model sensitivity to parameter \( i \) is estimated as the mean of the absolute value of the EE as:

\[
S_i = \mu_i^* = \frac{1}{r} \sum_{j=1}^{r} |EE_{i,j}| = \frac{1}{r} \sum_{j=1}^{r} \left| \frac{M([x_{1},x_{2},\ldots,x_{i-1},x_{j}+\Delta_{i,j},x_{i+1},\ldots,x_{57}]) - M([x_{1},x_{2},\ldots,x_{57}])}{\Delta_{i,j}} \right|, \tag{1}
\]

where \( r \) is the number of trajectories used in the estimate.

We estimate the standard deviations of the parameters’ elementary effects as:

\[
\sigma_i = \sqrt{\frac{1}{r} \sum_{j=1}^{r} (EE_{i,j} - \overline{EE}_i)^2}, \tag{2}
\]

where \( \overline{EE}_i \) is the mean of the elementary effects for parameter \( i \).
Text S6. Further details regarding the BRICK sea-level rise model

Our version of BRICK is mechanistically identical to the version used by Vega-Westhoff et al. (2019), but implemented in the Julia programming language and written to comply with the Mimi modeling framework. The model takes as input a radiative forcing scenario and a set of model parameters. As output, BRICK yields changes in future global mean sea level (GMSL), and its contributions from glaciers and ice caps, thermal expansion, land water storage, the Greenland ice sheet, and the Antarctic ice sheet. The Antarctic ice sheet model subcomponent of BRICK includes a parameterization to represent the fast dynamical ice loss associated with marine ice sheet and ice cliff instabilities (DeConto et al., 2021; Kopp et al., 2017; Le Bars et al., 2017; Wong, Bakker, & Keller, 2017). Sea-level fingerprints from Slangen et al. (2014) are used to downscale the contributions to global mean sea-level changes to their effects on local mean sea-level change. This local mean sea-level change serves as input to CIAM.

BRICK is a semi-empirical model designed to be flexible and efficient, and thus usable in formal model calibration frameworks. The sea-level projections from (Wong, Rennels, et al., 2022b) were calibrated using a Bayesian model calibration approach that accounts for uncertainty in the model parameters, heteroskedastic uncertainty in the observational data, and autocorrelation in the time series of model-data residuals. The BRICK projections of GMSL are consistent with the estimates of future GMSL change from the Intergovernmental Panel on Climate Change Sixth Assessment Report (IPCC AR6; (Fox-Kemper et al., 2021; their Table 9.8)). Specifically, there is good agreement between the AR6 Marine Ice Cliff Instability (MICI)-based estimates of GMSL change and the BRICK projections (see Figure S2), which is expected given the treatment of the Antarctic ice sheet in BRICK noted above.

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Figure S1. Coupled model structure for BRICK-CIAM.
**Figure S2.** Projections of global mean sea level relative to 1995-2014 mean for the four RCP scenarios used in the main text. The vertical boxes on the right denote the Marine Ice Cliff Instability (MICI) and Structured Expert Judgment (SEJ) estimates for 2150 global mean sea level change from the Intergovernmental Panel on Climate Change Sixth Assessment Report (AR6) under RCP2.6 (blue boxes) and RCP8.5 (red boxes) (Fox-Kemper et al., 2021; their Table 9.8). Shaded areas provide the 17-83% (66%) ranges.
Figure S3. Comparison of total global adaptation costs and damages under RCP8.5, following (a) a no-adaptation scenario and (b) least-cost adaptation by minimizing the NPV of total cost over each 40-50-year adaptation period. Model configurations show how MimiCIAM with perfect foresight ("x" hatching) can match Original CIAM (no hatching), and MimiCIAM with limited foresight (stippling) exhibits higher expected costs. To match Original CIAM, the costs from the first time step reference period have not been subtracted from the overall annual costs.
Figure S4. Shared Socioeconomic Pathways (SSP) population scenarios, relative to the Original CIAM forcing, aggregated globally and for the seven World Bank regions.
Figure S5. Shared Socioeconomic Pathways (SSP) gross domestic product (GDP) scenarios, relative to the Original CIAM forcing, aggregated globally and for the seven World Bank regions.
Figure S6. Comparison of total global adaptation costs and damages under RCP8.5, following (a) a no-adaptation scenario and (b) implementing least-cost adaptation by minimizing the NPV of total cost over each 40-50-year adaptation period. Model configurations shown are MimiCIAM with limited foresight and all original forcings (no hatching, same as Figure S1), MimiCIAM with population and GDP forcing following SSP5 (stippling), MimiCIAM with sea-level rise forcing from the BRICK model under RCP8.5 (diagonal hatching), and MimiCIAM with both BRICK sea-level rise and SSP5 population and GDP (“x” hatching). To compare against the Original CIAM results, the costs from the first time step reference period have not been subtracted from the overall annual costs.
Figure S7. Distributions of net present value of total global adaptation costs and damages over the 2010-2150 time period, where the MimiCIAM socioeconomic parameters (Table S1) are sampled from the original prior distributions (blue curves), distributions whose scale parameters are doubled from the original values (orange curves), and distributions whose scale parameters are half of the original values (gray curves). Shown are the four scenarios (a) SSP1-2.6, (b) SSP2-4.5, (c) SSP4-6.0, and (d) SSP5-8.5.
Figure S8. Quantiles from smaller subsamples of the Monte Carlo ensemble sampling uncertainty in sea-level rise and socioeconomic parameters, under the SSP2-RCP4.5 scenario.
Figure S9. Kernel density estimates of least-cost NPV of total adaptation costs over the 2010-2150 time horizon, aggregated for each of the seven World Bank regions: (a-d) Europe and Central Asia, (e-h) Middle East and North Africa, (i-l) Sub-Saharan Africa, (m-p) Latin America and the Caribbean, (q-t) East Asia and the Pacific, (u-x) South Asia, and (y-ab) North America, under pathways SSP1-2.6 (first column), SSP2-4.5 (second column), SSP4-6.0 (third column), and SSP5-8.5 (fourth column). Shown are distributions of adaptation costs accounting for uncertainty in sea-level rise (blue), accounting for uncertainty in socioeconomic parameters (orange), and accounting for uncertainty in both sea-level rise and socioeconomic parameters (gray).
**Figure S10.** Comparison of the 100-year surge exposure levels from the DINAS-COAST and GTSR data sets.

**Figure S11.** Comparison of the net present value of total global adaptation costs and damages over the 2010-2150 time period following SSP5-RCP8.5, using the DINAS-COAST data set (“DC”, blue curve), the DINAS-COAST data set bias-corrected using GTSR (“GTSR/DC”, orange curve), and the GTSR data set (“GTSR”, gray curve).
| Parameter                                                                 | Units                        | Central Value | Distribution                                      | Source                                      |
|--------------------------------------------------------------------------|-----------------------------|---------------|--------------------------------------------------|---------------------------------------------|
| Relocation cost as fraction of income (movefactor)                       | Fraction (0-1)              | 1             | Normal(\(\mu=1, \sigma=1\)), truncated to [0.5, 3] | Anthoff and Tol (2014) and Diaz (2016)     |
| Benchmark land value (dvbm)                                              | Million 2010 USD/km²        | 5.376         | Normal(\(\mu=5.376, \sigma=2.688\)), truncated to [0, Inf] | FUND; originally Darwin et al. (1995)       |
| Population density elasticity of wetland value (wvpdl)                   | Unitless                    | 0.47          | Normal(\(\mu=0.47, \sigma=0.12\)), truncated to [0, 1] | Brander et al. (2006)                      |
| Income elasticity of wetland value (wvel)                                | Unitless                    | 1.16          | Normal(\(\mu=1.16, \sigma=0.46\)), truncated to [0, Inf] | Brander et al. (2006)                      |
| Elasticity of value of statistical life (VSL) (vslel)                    | Unitless                    | 0.47          | Normal(\(\mu=0.47, \sigma=0.15\)), truncated to [0, Inf] | FUND; Viscusi and Aldy (2003)              |
| VSL multiplier on US GDP (vslmult)                                      | Unitless                    | 200           | Normal(\(\mu=200, \sigma=100\)), truncated to [0, Inf] | FUND; originally Cline (1992)              |

**Table S1.** MimiCIAM parameters varied in the Monte Carlo uncertainty propagation experiments and their distributions. For convenience, the references cited in the above table are provided below.
| Parameter                        | Description                                                                 |
|---------------------------------|------------------------------------------------------------------------------|
| sd_temp                         | Innovation standard deviation for AR1 residuals for temperature (°C)         |
| sd_ocean_heat                   | Innovation standard deviation for AR1 residuals for ocean heat uptake (10^22 J) |
| sd_glaciers                     | Innovation standard deviation for AR1 residuals for glacial sea-level contribution (m) |
| sd_greenland                    | Innovation standard deviation for AR1 residuals for Greenland sea-level contribution |
| sd_antarctic                    | Innovation standard deviation for AR1 residuals for Antarctic sea-level contribution (m) |
| sd_gmsl                         | Innovation standard deviation for AR1 residuals for global mean sea level (m) |
| sigma_whitenoise_co2            | White noise standard deviation for CO2 (ppm)                                |
| rho_temperature                 | Lag-1 autocorrelation coefficient for temperature (-)                        |
| rho_ocean_heat                  | Lag-1 autocorrelation coefficient for ocean heat uptake (-)                  |
| rho_glaciers                    | Lag-1 autocorrelation coefficient for glacial sea-level contribution (-)      |
| rho_greenland                   | Lag-1 autocorrelation coefficient for Greenland sea-level contribution (-)    |
| rho_antarctic                   | Lag-1 autocorrelation coefficient for Antarctic sea-level contribution (-)    |
| rho_gmsl                        | Lag-1 autocorrelation coefficient for global mean sea level (-)               |
| alpha0_CO2                      | Measure of autocorrelation memory for CO2 (-)                                |
| CO2_0                           | Initial CO2 concentration (ppm)                                              |
| N2O_0                           | Initial N2O concentration (ppb)                                              |
| temperature_0                   | Initial temperature anomaly (°C)                                             |
| ocean_heat_0                    | Initial ocean heat uptake (10^22 J)                                          |
| thermal_s0                      | Initial condition for thermal expansion sea level contribution (m SLE)        |
| greenland_v0                    | Initial condition for Greenland ice sheet sea level contribution (m SLE)      |
| glaciers_v0                     | Initial glacier/ice cap volume (m sea level equivalent (SLE))                |
| glaciers_s0                     | Initial condition for glacier/ice cap sea-level contribution (m SLE)         |
| antarctic_s0                    | Initial condition for Antarctic sea-level contribution (m SLE)               |
| Q10                             | Respiration sensitivity (-)                                                  |
| CO2_fertilization               | Carbon fertilization factor (-)                                              |
| CO2_diffusivity                 | Ocean carbon diffusivity (m/y)                                               |
| heat_diffusivity                | Ocean vertical diffusivity (cm^2 s^-1)                                       |
| rf_scale_aerosol                | Aerosol radiative forcing scaling factor (-)                                 |
| climate_sensitivity             | Equilibrium climate sensitivity to doubling CO2 (°C)                         |
| thermal_alpha                   | Global ocean-averaged thermal expansion coefficient (kg m^-3 °C^-1)           |
| greenland_a                     | Equilibrium Greenland ice sheet volume temperature sensitivity (m °C^-1)      |
| greenland_b                     | Equilibrium Greenland ice sheet volume (m SLE)                               |
| greenland_alpha                 | Greenland ice sheet response timescale temperature sensitivity (°C^-1 y^-1)  |
| greenland_beta                  | Greenland ice sheet response timescale temperature sensitivity (y^-1)         |
| glaciers_beta0                  | Initial glacier/ice cap mass balance temperature sensitivity (m y^-1 °C^-1)   |
| glaciers_n                      | Exponent for glacier/ice cap area-volume scaling (-)                         |
| anto_alpha                      | Antarctic ocean temperature sensitivity to global temperature (°C °C^-1)       |
| anto_beta                       | Equilibrium Antarctic ocean temperature (°C)                                 |
| antarctic_gamma                 | Power for relation of Antarctic ice flow speed to water depth (-)             |
| antarctic_alpha                 | Effect of ocean subsurface temperature on ice flux partition parameter (-)    |
| antarctic_mu                    | Parabolic ice surface profile parameter (m^0.5)                              |
| antarctic_nu                    | Antarctic runoff and precipitation proportionality constant (m^0.5 y^0.5)      |
| antarctic_precip0               | Annual Antarctic precipitation for surface temperature 0 °C (m)               |
| antarctic_kappa                 | Coefficient, dependency of Antarctic precipitation on temperature (°C^-1)       |
| antarctic_flow0                 | Antarctic ice flow at grounding line proportionality constant (m y^-1)         |
| antarctic_runoff_height0        | Antarctic runoff line height at 0 °C surface temperature (m)                 |
| antarctic_c                     | Antarctic runoff line height temperature sensitivity (m °C^-1)                |
| antarctic_bed_height0           | Undisturbed bed height at Antarctic continent center (m)                      |
| antarctic_slope                 | Slope of Antarctic ice sheet bed before ice loading (-)                       |
| antarctic_lambda                | Fast Antarctic dynamic disintegration rate (m)                                 |
| antarctic_temp_threshold        | Fast Antarctic dynamic disintegration trigger temperature (°C)                |

**Table S2.** BRICK model parameters varied in the model calibration and sensitivity analysis.
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