
TOP-OF-ATMOSPHERE RADIATION FIELDS OVER THE LAST MILLENNIUM RECONSTRUCTED FROM PROXIES

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ABSTRACT

Earth’s energy imbalance at the top of the atmosphere is a key climate system metric, but its variability is poorly constrained by the short observational record and large uncertainty in coupled climate models. While existing ocean heat content reconstructions offer a longer perspective, they cannot separate the contributions of shortwave and longwave radiation, obscuring the underlying processes. We extend the energy budget record by reconstructing the top-of-atmosphere radiation and related surface variables over the last millennium (850–2000 CE). Our method combines proxy data and model dynamics using seasonal, gridded data assimilation, exploiting the covariance of radiation with proxies sensitive to surface temperatures. The method validates well in a pseudoproxy experiment and against instrumental observations. We find that a last-millennium cooling trend coincides with heat loss that gradually slowed, although there are intermittent multidecadal periods of energy gain. The cooling trend is associated with a southwestward shift of Indo–Pacific convection and growth of sea ice, with seasonal sea ice trends following orbital-scale changes in polar insolation. We also find that the upper-ocean heat content following large volcanic eruptions does not begin to recover until 5–10 years later, suggesting the initiation of the Little Ice Age by decadal-paced eruptions in the early 1100s and late 1200s. Indeed, the latter period marks the decade of largest energy loss over the last millennium. Our reconstruction reveals that the energy imbalance for all 20-yr periods after 1980 is unprecedented in the pre-industrial period.

1 Introduction

Earth’s energy imbalance (EEI) at the top of the atmosphere (TOA) is a fundamental climate system metric, governing the total energy inventory and constraining global temperatures, the hydrological cycle, sea levels, and ice cover [von Schuckmann et al., 2016]. Much of the EEI is forced, over the last millennium mostly by volcanic eruptions, solar irradiance, and changes in Earth’s orbit, and more recently by anthropogenic greenhouse gases and aerosols. In addition, there is internal, unforced variability in the energy budget at all timescales. Seasonal variability is primarily due to extratropical storms and the Madden–Julian oscillation, while the El Niño–Southern Oscillation (ENSO) explains most interannual variability [Trenberth et al., 2015]. However, decadal to centennial variability in the energy budget remains poorly understood [Wills et al., 2021, Trenberth et al., 2014]. This complicates, for example, the interpretation of recent albedo trends [Goessling et al., 2025, Mauritsen et al., 2025, Hodnebrog et al., 2024, Raghuraman et al., 2021] and the warming hiatus [Medhaug et al., 2017, Xie et al., 2016, Trenberth and Fasullo, 2013], both of which are not reproduced well by coupled climate models. A better understanding of Earth’s energy budget would also help to attribute historical climate change [Lean, 2018] and constrain future warming [Sherwood et al., 2020].

Our understanding of EEI variability is limited by the short satellite observational record of around 25 years [Loeb et al., 2024], which prohibits the investigation of low-frequency variability and the response to rare, episodic forcings. Additionally, it is difficult to disentangle forced and internal variability of Earth’s energy budget due to the strong anthropogenic greenhouse gas forcing and the uncertain aerosol forcing during the observed period. Therefore, coupled climate models have been used to investigate aspects like radiative feedbacks [Sherwood et al., 2020] and decadal

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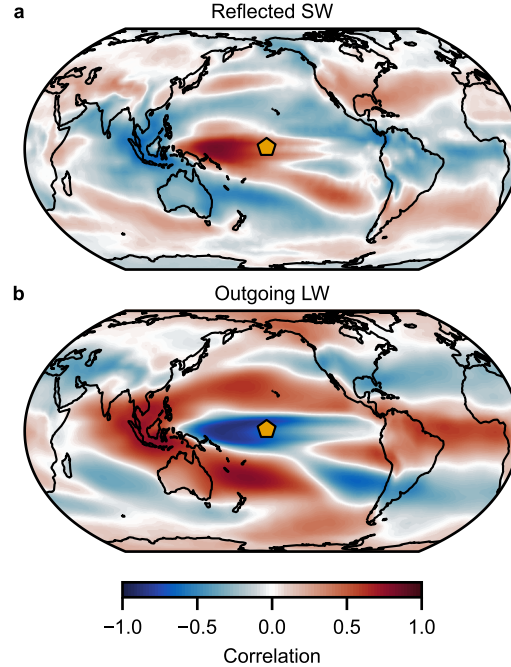


Figure 1: Annual-mean correlation between the SST at a point in the Niño 3.4 region (yellow pentagon; e.g., location of a coral proxy) and the TOA (a) reflected SW and (b) outgoing LW radiation globally. The correlation is from last-millennium simulations over 850–1850, averaged over four models.

variability [Palmer and McNeall, 2014, Brown et al., 2014, Zhou et al., 2016a], more recently through coordinated experiments [Schmidt et al., 2023, Webb et al., 2017]. However, even models of the latest generation produce a large spread in TOA radiation, on the order of $5\text{--}20\text{ W m}^{-2}$ for most components [Wild, 2020], and systematically underestimate the radiative response [Olonscheck and Rugenstein, 2024]. In addition, simulations of the last millennium disagree with proxy evidence on global temperature trends, their realization of internal variability often differs from the true climate history, and specified forcings may not be accurate [Lean, 2018, Lücke et al., 2023, Fyfe et al., 2021]. Other studies have extended the energy budget record by reconstructing the ocean heat content (OHC). For example, Zanna et al. [2019] and Wu et al. [2025] derive the global-mean OHC over the historical period, while Gebbie and Huybers [2019] reconstruct the gridded OHC over the Common Era. Further OHC reconstructions from the Last Glacial Maximum to present are reviewed in Gebbie [2021]. On interannual to decadal timescales, the OHC is a more reliable indicator of global change than surface temperatures [Palmer and McNeall, 2014, Allison et al., 2020]. However, the ocean perspective, particularly in the global mean, obscures the atmospheric processes that cause heat content changes, and the role of clouds and sea ice in mediating them. Rather, a top-of-atmosphere perspective that separates shortwave (SW) and longwave (LW) components is needed to improve the process understanding of energy budget variability.

Here, we reconstruct Earth’s energy budget over the last millennium (850–2000 CE) from proxies. The reconstruction is seasonally and spatially resolved, and partitions the TOA radiation into SW and LW components. We use data assimilation, which combines proxy observations with model dynamics, and has been used successfully to reconstruct past climates [e.g., Goosse et al., 2010, Perkins and Hakim, 2021, Meng et al., 2025, Hakim et al., 2016, Valler et al., 2024, Judd et al., 2024, Cooper et al., 2025]. Our method exploits the covariance of TOA radiation and OHC with surface temperatures, to which the proxies are sensitive. For example, if a proxy in the Pacific Warm Pool indicates warmer sea surface temperatures (SSTs), the atmospheric response there is to enhance deep convection, which mediates an increase in reflected SW and a decrease in outgoing LW radiation (Fig. 1; e.g., Dong et al., 2019). Similarly, changes in temperature gradients can affect the overturning atmospheric circulation with implications for subtropical low clouds, which have a strong SW effect. Besides clouds, snow/ice cover and solar surface heating play a role, and establish a temperature–radiation relationship over much of the globe [Trenberth et al., 2015]. In addition to this physical underpinning, Loeb et al. [2020] demonstrates that the current generation of atmosphere-only climate models can skillfully simulate TOA radiation when SST and sea ice are prescribed; both of these variables can be reconstructed from proxies.

We take two perspectives on the TOA energy balance. The first perspective involves a partition of the EEI into insolation S , reflected SW radiation (RSR), and outgoing LW radiation (OLR):

$$\text{EEI}^\downarrow = S^\downarrow - (\text{RSR}^\uparrow + \text{OLR}^\uparrow).$$

By our chosen sign convention, EEI is positive downwelling (energy gain), while RSR and OLR are positive upwelling (energy loss). Separating the SW and LW radiation fields allows us to infer the physical processes governing the EEI, particularly clouds. The reconstructed partitioning is derived from emulators of last-millennium climate simulations and is therefore not aimed at long-term trends during periods of strong anthropogenic forcing from greenhouse gases and aerosols (i.e., the 1900s).

The second perspective on the TOA energy balance emphasizes the relation to the global-mean surface temperature T in a one-layer energy balance model [Geoffroy et al., 2013]:

$$\text{EEI} = C \frac{dT}{dt} + \gamma T, \quad (1)$$

where EEI is the global-mean TOA energy imbalance, C is the heat capacity of the upper ocean, and γ is the heat uptake coefficient of the deep ocean. On short timescales the deep-ocean heat uptake is relatively small, so we can approximately compare OHC and EEI by differentiation or integration. A third perspective on EEI involves the forcing–feedback framework [e.g., Sherwood et al., 2015]. Both forcings and feedbacks correlate with temperature-sensitive proxies, forcings through their cumulative effect on heat content, feedbacks through a temperature-mediated response. However, we can only reconstruct their sum using our method. Separating forcings and feedbacks requires climate model simulations and is beyond the scope of this study.

The remainder of the paper is organized as followed. We first describe the data assimilation method (Section 2). After validating this method in a pseudoproxy experiment and the real-proxy reconstruction against instrumental datasets (Section 3), we present our reconstructed energy budget over the last millennium (Section 4), then illustrate applications to the pre-industrial energy budget variability and the response to volcanic eruptions (Section 5).

2 Methods

We use online paleoclimate data assimilation (DA) to reconstruct gridded climate fields at seasonal resolution. DA combines proxy information with forecasts from a model in a statistically optimal way [e.g., Kalnay et al., 2024]. Our ensemble DA system comprises linear inverse models (LIMs), an ensemble Kalman filter (EnKF), and proxy system models (PSMs). The methodology for our seasonal-resolution DA is similar to Meng et al. [2025] and based on the prior work from Perkins and Hakim [2021] and Hakim et al. [2016].

Ensemble DA represents the distribution of the state in each season using samples, each of which is equally likely. The procedure starts with a climatological prior. During the update step, the EnKF updates the prior ensemble with available proxy data to obtain the posterior ensemble. During the forecast step, the LIM propagates all posterior ensemble members to the next season, where the forecast serves as prior for another update with available proxies. The posteriors from this repeated forecast–update cycle comprise the reconstruction.

2.1 Forecasts using linear inverse models

We use LIMs as efficient emulators of the dynamics and statistics of coupled climate models. Using such emulators allows us to run large ensembles and incorporate the dynamics of different climate models. The LIM dynamics have the form

$$\frac{d\mathbf{x}}{dt} = \mathbf{L}\mathbf{x} + \mathbf{S}\boldsymbol{\eta},$$

where $\mathbf{x}$ is the state vector, $\mathbf{L}$ is a constant matrix representing the linear dynamics, $\mathbf{S}$ is the noise amplitude matrix, and $\boldsymbol{\eta}$ is a vector of Gaussian white noise with unit variance. Together, $\mathbf{L}$ and $\mathbf{S}$ encode, for example, how surface temperatures and TOA radiation are related. The full equations for determining the matrices and for ensemble forecasts are presented in the Supplemental Information.

The state vector $\mathbf{x}$ represents seasonal anomalies of atmospheric and oceanic climate variables. We include 2-m surface air temperature (SAT), sea surface temperature (SST), TOA energy imbalance (EEI), TOA reflected SW radiation (RSR), TOA outgoing LW radiation (OLR), ocean heat content of the upper 300 m (OHC300), Arctic sea ice concentration (SIC), and Antarctic SIC. We integrate the OHC over 300 m, which is the depth required to close the seasonal energy budget [Johnson et al., 2023] and is sufficiently deep to remove surface noise [Allison et al., 2020]. The OHC also imparts memory to the LIM forecasts since anomalies persist longer than in atmospheric fields.

The training data are regridded to the same $2^\circ \times 2^\circ$ grid, converted to anomalies relative to their own 1961–1990 climatology, then linearly detrended by season to remove the orbital precession signal. Any trend in the reconstruction is therefore due to proxies. The full gridded state has significant spatial correlations at seasonal resolution, motivating a large dimensional reduction for the LIM. We accomplish this reduction by using empirical orthogonal functions (EOF) on the area-weighted gridded data, and constructing the state vector from the truncated principal components (PCs):

$$\mathbf{x} = [\tilde{\mathbf{x}}_{20}^{\text{SAT}}; \tilde{\mathbf{x}}_{20}^{\text{SST}}; \tilde{\mathbf{x}}_{30}^{\text{EEI}}; \tilde{\mathbf{x}}_{15}^{\text{RSR}}; \tilde{\mathbf{x}}_{10}^{\text{OLR}}; \tilde{\mathbf{x}}_{15}^{\text{OHC300}}; \tilde{\mathbf{x}}_{10}^{\text{SICn}}; \tilde{\mathbf{x}}_{10}^{\text{SICs}}],$$

where semicolons denote vertical stacking, and $\tilde{\mathbf{x}}_n^{\text{var}}$ represents the leading n PCs for variable var, standardized by the square root of the retained variance after truncation. SICn/SICs refer to Arctic/Antarctic SIC. The truncation ranks n were chosen subjectively based on the cumulative variance explained, trading off reconstruction fidelity and degrees of freedom required for LIM training. We use the same number of PCs for each model prior, despite differences in the explained variance (Fig. S1). This ensures a fair comparison since the number of degrees of freedom is comparable.

The dynamical and stochastic components of the LIM are determined from climate model simulations. We train LIMs on the CMIP6 last-millennium simulations (past1000 and past2k; Jungclaus et al., 2017) from the following models: MPI-ESM1-2-LR, CESM2-WACCM-FV2, and MRI-ESM2-0. These are the “model priors”, hereafter referred to as MPI, CESM, and MRI [Mauritsen et al., 2019, Danabasoglu et al., 2020, Yukimoto et al., 2019]. We exclude MIROC-ES2L (MIROC) from LIM training due to its Antarctic sea ice low bias [Hajima et al., 2020]. Last-millennium simulations from other models exist but either lack needed variables, like SIC, have issues with the implementation of forcings, or have not been published. Previous reconstructions like Perkins and Hakim [2021] and Meng et al. [2025] train LIMs on CMIP5 models. However, only since the CMIP6 generation are these models able to faithfully simulate TOA radiation, mainly due to better representations of the low-cloud SW effect [Loeb et al., 2020].

Each LIM is used separately in the DA algorithm to assimilate proxies, yielding three reconstructions, each containing 400 members (details provided below). Multi-model ensembles have proven effective in reducing reconstruction error, particularly in regions distant from proxies [Parsons et al., 2021].

2.2 Data assimilation using an ensemble Kalman filter

The Kalman filter is a DA algorithm that optimally combines a prior state, such as a forecast, with available proxy observations, weighted by their uncertainties. In an ensemble Kalman filter (EnKF), the prior and posterior distributions of the state are approximated as normal distributions using samples. Multiple flavors of the EnKF exist. Here, we use a serial ensemble square root filter [Whitaker and Hamill, 2002].

The EnKF combines the prior ensemble mean $\bar{\mathbf{x}}_b$ and a proxy observation y into the posterior ensemble mean $\bar{\mathbf{x}}_a$:

$$\bar{\mathbf{x}}_a = \bar{\mathbf{x}}_b + \mathbf{K}(y - \mathbf{H}\bar{\mathbf{x}}_b), \quad (2)$$

where $\mathbf{K}$ is the Kalman gain matrix, and $\mathbf{H}$ is the forward operator for estimating the observation from the prior. The individual ensemble members are updated such that the posterior covariance (i.e., their spread), estimates the uncertainty consistently with respect to the full Kalman filter. The Kalman gain matrix encodes covariances between the observation and the state, which allows us to estimate any field that covaries with surface temperature. The full equations for determining $\mathbf{K}$ and for updating the ensemble members are presented in the Supplemental Information.

Seasonally resolved proxies are assimilated in the season they represent. Assimilating annually resolved proxies is complicated by the fact that the proxy seasonality can span multiple seasons. Our DA strategy in this case is to update all seasons within this time window when the proxy can be estimated by the ensemble (i.e., once the end of the window is reached), similarly to Meng et al. [2025]. For example, a proxy with seasonality MAMJJA is assimilated during the JJA step to update the MAM and JJA values. The update to the last season (JJA) then informs future seasons through the LIM forecast, while updates to past seasons are not propagated forward in time. To perform the EnKF update of multiple seasons simultaneously, we use the time-averaging algorithm from Huntley and Hakim [2010]. This algorithm uses the time mean over multiple seasons as $\bar{\mathbf{x}}$ in Eq. (2), then adds the deviations of each season around that prior time mean to the posterior time mean.

We perform DA in EOF space, as opposed to the gridded physical space, which is computationally efficient, since the LIM and the EnKF operate on the same vectors and thus no mapping between spaces is necessary. While this means we cannot mitigate sample and model error using covariance localization [e.g., Anderson, 2012], we instead use a large ensemble and an EOF space that is low-dimensional compared to the ensemble size. Moreover, we perform separate reconstructions with three different LIMs to account for model error. The operator $\mathbf{H}$ first maps from the EOF space to the temperature at the proxy location, then maps to the proxy value using the PSM. We map all posteriors from EOF space to physical space as a postprocessing step. We also obtain absolute SIC values by anchoring the anomalies to the merged model–satellite 1961–1990 climatology from Cooper et al. [2025], then clip values outside the interval between zero and one.

We repeat the reconstruction procedure 20 times for each LIM using a Monte Carlo approach. In each iteration, we assimilate a random sample of 80% of the available proxy data. This allows us to sample over uncertainty in the proxy error estimates by randomly removing proxies that may have an outsized impact [Tardif et al., 2019]. The remaining 20% of proxies in each iteration are used for independent validation of reconstruction skill in the pre-instrumental period. Each of the 20 iterations uses 400 ensemble members. We reduce the full 8000-member ensemble to 400 members per model prior by subsampling 20 members from each iteration. The analysis below is performed on the resulting 1200-member multi-model ensemble derived from reconstructions from all three model priors.

2.3 Proxy system models

The EnKF requires a PSM that estimates the proxy value from the current state, corresponding to $\mathbf{H}\bar{\mathbf{x}}_b$ in Eq. (2). We use linear univariate PSMs that are calibrated over the instrumental period. Such statistical PSMs allow us to estimate the proxy error needed for DA from regression residuals while sacrificing little skill compared to process-based PSMs [Dee et al., 2016, Sanchez et al., 2021].

The linear model takes as input the temperature (SAT or SST, depending on the proxy type) at the nearest gridpoint. For seasonally resolved proxies, we fit one PSM for each season. For annually resolved proxies, we objectively determine the proxy seasonality based on the Bayesian information criterion (as in Tardif et al., 2019), then fit a single PSM that takes the mean over those seasons as input. Seasonal DA allows us to explicitly update seasonal temperatures rather than the annual-mean temperature, whereas annual DA can suffer from seasonality biases [Lücke et al., 2021].

The PSMs are calibrated on GISTEMP v4 [Lenssen et al., 2024, GISTEMP Team, 2025] and ERSSTv5 [Huang et al., 2017]. We truncate these temperature datasets to the same EOF basis used for each LIM to include representativeness error in the proxy estimate. We remove GISTEMP data before 1900 since there are spatial discontinuities that may affect the calibration. The full calibration procedure is described in the Supplemental Information.

2.4 Proxy dataset

We assimilate the proxies included in the PAGES2k [PAGES 2k Consortium, 2017] and CoralHydro2k [Walter et al., 2023] databases, and add the Palmyra coral record from Dee et al. [2020]. Duplicates are removed based on time resolution, geographical location, and time series correlations. We average all subseasonal proxies to seasonal resolution, and remove proxies that have a time resolution longer than one year since we cannot assimilate them easily. Proxies are excluded if their overlap with the instrumental period is too short (< 25 years) or their calibration correlation is too low (< 0.05). The resulting proxy network comprises 647 records, most of which derive from tree rings (64%) and corals (28%; Fig. S2).

The proxy network is relatively sparse before around 1500. In fact, there are less than 10 seasonally resolved proxies before 1650. Importantly, we are still able to reconstruct the seasonal climate since annual proxies are sensitive to certain seasons, and the LIM propagates information to proxy-sparse seasons.

3 Validation of reconstruction skill

We validate our method using a pseudoproxy experiment (PPE) and the real-proxy reconstruction against instrumental datasets. PPEs help to establish an upper bound on reconstruction fidelity in an idealized scenario [Smerdon, 2012], while the instrumental validation assesses the real reconstruction, albeit over a limited time period and against uncertain verification sources.

3.1 Pseudoproxy experiment

PPEs are particularly useful to assess the feasibility of reconstructing new target variables such as TOA radiation. A climate model simulation serves as “truth,” to be reconstructed based on sparse pseudoproxies that mimic the characteristics of the real proxy network. The challenge is analogous to the real problem, which is to reconstruct the full climate fields given only sparse and noisy proxy observations.

For our PPEs, truth consists of the concatenated last-millennium and historical simulations from the MIROC model. We then reconstruct MIROC fields using LIMs trained on the MPI, CESM, and MRI model priors. This constitutes an imperfect-model experiment, which includes error from a mismatch in LIM dynamics and the EOF basis relative to the truth simulation, analogous to the real reconstruction where the true dynamics are unknown. For each real proxy, the pseudoproxy is drawn from the truth simulation using the real PSM with added noise consistent with the estimated

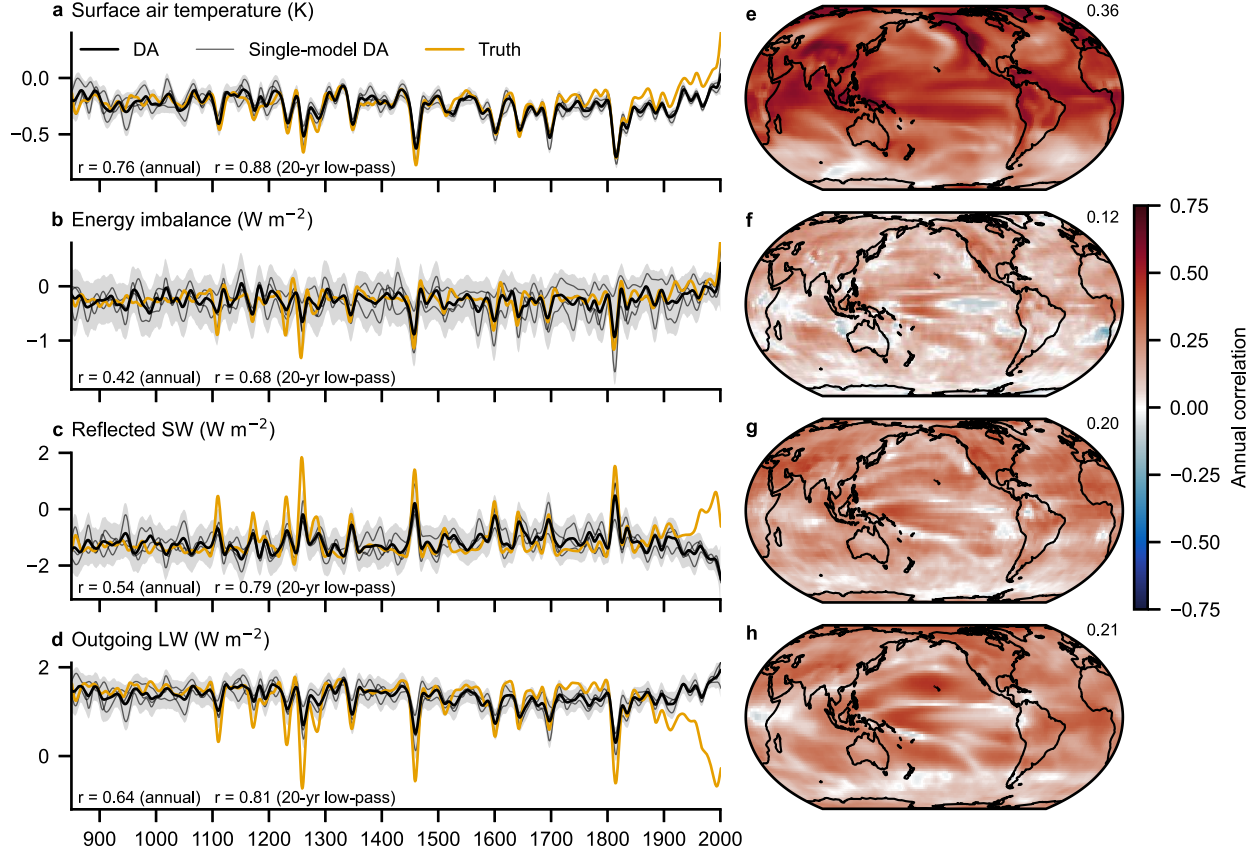


Figure 2: Comparison of the pseudoproxy imperfect-model reconstruction with the truth simulation. (a–d) Global-mean time series and their correlation coefficients r over 850–1850. The reconstruction (black) and the truth (yellow) are anomalies with a 20-yr low-pass filter. The truth anomalies are relative to 1961–1990, and the reconstruction has been shifted to match the truth in the 850–1850 mean. DA is the mean of the three single-model reconstructions with the MPI, CESM, and MRI model priors. Shading denotes the 5th–95th percentile range. (e–h) Spatial correlation of annual anomalies over 850–1850. Numbers in the top right corners represent global-mean values.

error. The pseudoproxies mimic the real proxies in location, temporal availability, seasonal sensitivity, signal-to-noise ratio, and temperature field sensitivity (SAT or SST).

Results show that the global-mean reconstructions for the fields of interest correlate highly with the truth simulation (Fig. 2a–d). For SAT, decadal variability is tracked well, and the truth is generally within the ensemble spread. The modern warming is somewhat underestimated, possibly because patterns of warming are different in the MIROC model compared to the LIMs, or because the EOF basis, which is derived from the pre-industrial period, cannot represent well the 20th-century trend. The reconstruction is also skillful for the TOA radiation fields. Interannual and decadal variability in the surface temperature induces a radiative response, and the volcanic forcing is partitioned well into RSR and OLR fields, although its magnitude is underestimated. In contrast, while the EEI in the 1900s due to anthropogenic forcing is reconstructed well, the partition into RSR and OLR contributions is flawed. This is because the historical period is not included in the LIM training data, and therefore the LIMs are not aware of the greenhouse gas and aerosol forcing of this period.

The PPE also demonstrates spatial reconstruction skill over the last millennium (Fig. 2e–h). Correlations with the truth simulation are positive over most of the globe, although they are smaller over the Southern Ocean, which is relatively sparse in proxies. Like for the global mean, annual skill is highest for SAT and lowest for EEI.

3.2 Instrumental validation of real-proxy reconstruction

Validation against other datasets allows us to assess the real reconstruction. The SAT, SST, and OHC reconstructions are highly correlated with instrumental products and other reconstructions (Figs. S3 and S5a,b). The SIC reconstruction

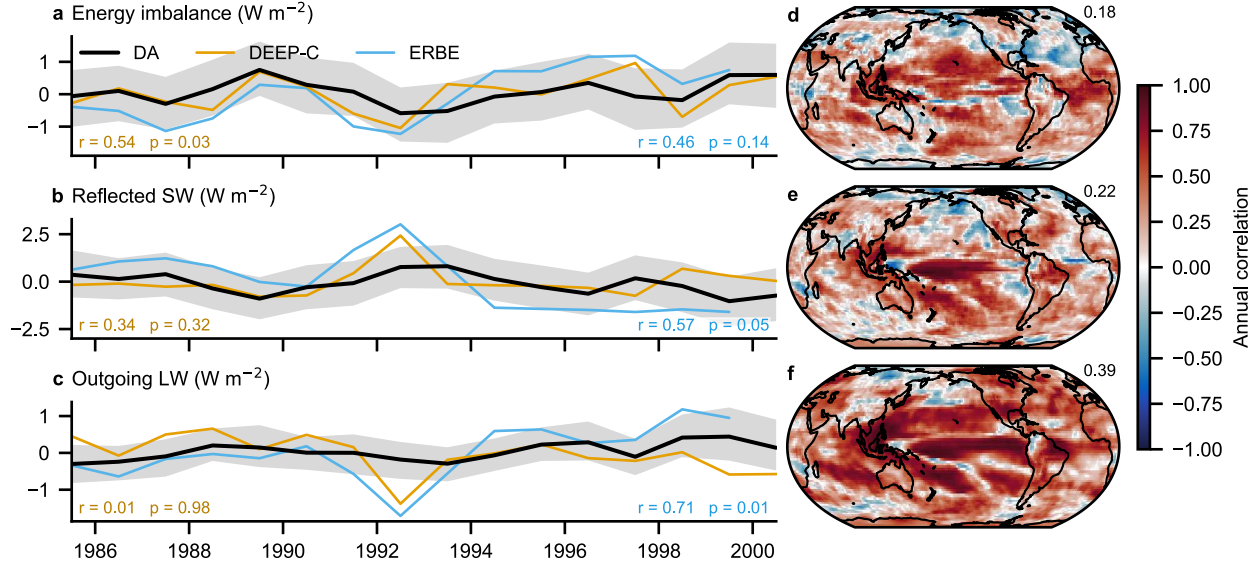


Figure 3: Annual TOA radiation anomalies from our reconstruction, the DEEP-C combined product, and ERBE satellite measurements. The anomalies are relative to 1985–1999. Shading denotes the 5th–95th percentile range. (a–c) Global-mean time series and their correlation coefficients r . The p -values indicate if r is different from zero. (d–f) Spatial correlation with DEEP-C. Numbers in the top right corners represent global-mean values.

is skillful at annual and seasonal scales when compared to satellite observations (Figs. S4 and S5c–f). Unassimilated proxies (20% withheld for validation), which are predicted from the reconstruction and compared directly to proxy values, correlate significantly, indicating skill over the whole last millennium (Fig. S6).

The Earth Radiation Budget Experiment (ERBE) satellite observations of TOA radiation overlap with our reconstruction over 1985–1999. We validate against the DEEP-C v5 dataset [Liu and Allan, 2022, Liu et al., 2020], which combines these satellite observations with atmospheric reanalyses and atmosphere-only model simulations. We also validate against the ERBE WFOV Edition 4.1 datasets [ERBE Science Team, 2020a,b], which are direct, recently recalibrated observations but lack some spatial and temporal coverage. The statistical significance of correlations is determined using the random-phase test, a nonparametric test that generates surrogate time series with the same spectral density [Ebisuzaki, 1997].

Correlations of the reconstructed global-mean TOA radiation with the DEEP-C and ERBE data reflect generally skillful tracking of interannual variability (Fig. 3a–c). Much of the skill comes from the tropics and subtropics, but large regions in the higher latitudes have positive correlations as well (Fig. 3d–f). The reconstructed seasonal TOA radiation is skillful as well, but with correlations slightly less than the annual values (Fig. S7). Compared to the PPE, the correlations of the global mean are similar, but the skill mostly comes from the tropics, while it is more uniform in the PPE. The correlations are not always statistically significant and sensitive to small variations because of the short overlap period and high temporal autocorrelation.

Our reconstruction also tracks well decadal variations in the upper-ocean heat content due to volcanic eruptions (Fig. 4). The timescale and amplitude of OHC300 changes agree closely with the Cheng et al. [2017] instrumental dataset, which is derived from in-situ temperature profiles. The recovery from the 1963 Agung eruption took twenty years, possibly prolonged by the 1968 Fernandina eruption. We conclude that the reconstruction is generally skillful, despite the spatiotemporal sparseness of the proxy network and the complex relationship between surface temperature and TOA radiation.

4 Reconstruction over the last millennium

Our reconstruction consists of gridded, seasonal climate fields over 850–2000 CE. Results labeled as DA are the combined ensemble of the three single-model reconstructions. Annual means are taken from December to the following November. While we also reconstruct EEI directly, we found that the sum of its constituents $-(\text{RSR} + \text{OLR})$ has higher skill (Fig. S9a), and is thus shown as EEI here. Uncertainties refer to the very likely range (5th to 95th ensemble percentile, i.e., the 90% median credible interval).

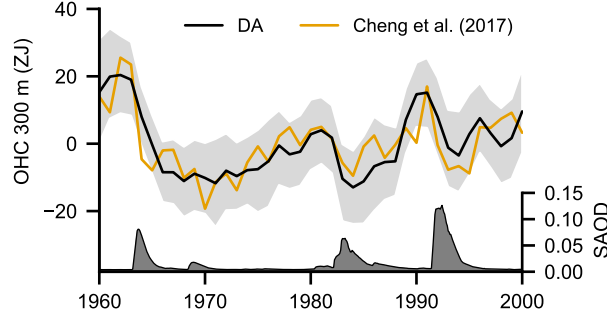


Figure 4: Annual upper-ocean heat content from our reconstruction and the Cheng et al. [2017] instrumental dataset. The linear trend over 1960–2000 has been removed to emphasize interannual to decadal variations as in Church et al. [2005]. Stratospheric aerosol optical depth (SAOD) at 550 nm is from the CMIP7 historical volcanic forcing dataset [Aubry and CMIP Climate Forcing Task Team, 2025].

4.1 Global means of temperature and radiation

The reconstructed global-mean SAT has a cooling trend over much of the last millennium, followed by warming over the 1900s (Fig. 5a). The SAT transition from a warm Medieval Climate Anomaly (MCA; c. 800–1200) into a colder Little Ice Age (LIA; c. 1300–1850) is a feature often found in last-millennium proxy reconstructions [e.g., Mann et al., 1999, Esper et al., 2002, Mann et al., 2009, PAGES 2k Consortium, 2019] and simulations [e.g., Fernández-Donado et al., 2013, Otto-Bliesner et al., 2016, Ljungqvist et al., 2019]. Based on linear regression over 850–1850, we find a cooling trend of -0.30 K kyr^{-1} (see also Fig. 8a). There is also considerable multidecadal variability, some of which coincides with large volcanic eruptions; we will consider these events in greater detail in Section 4.5. The global-mean SST, OLR, and OHC300 are highly correlated with SAT ($r > 0.90$; Fig. S8). The reconstruction is about 0.1 K warmer over 850–1850 than the multi-method ensemble from PAGES 2k Consortium [2019] but agrees within uncertainty.

The absolute EEI governs changes in the energy budget, while we only reconstruct anomalies. We make the EEI anomalies absolute by shifting them to an 1600–1900 average of zero, chosen to coincide with relatively constant temperature and OHC, and thus no significant energy gain or loss over this period. Before 1600, the absolute EEI oscillates just below zero but has a slight positive trend (Figs. 5c and S9). This trend is due to a decrease in OLR, partially offset by a small increase in RSR. Note that this increase in EEI does not contradict the cooling temperature trend since the EEI remains negative. There is substantial interannual variability, occasionally on the order of 0.5 W m^{-2} . Over the historical period, our results correlate well with the rate of change in 2000-m OHC from Wu et al. [2025]. However, the multidecadal variability and the last-millennium trend show little in common with the rate of change in full-depth OHC from Gebbie and Huybers [2019, version OPT-0015], often having antiphased changes and differences as large as 1.0 W m^{-2} . Further, the integrated energy imbalance, or energy inventory, disagrees with their OHC (Fig. S9). Note that the energy inventory is sensitive to the offset used to make the reconstructed EEI anomalies absolute, since any offset adds a linear function upon integration. Gebbie and Huybers [2019] obtain the OHC by subtracting SSTs into the deep ocean. Their subtracted SSTs, based on the Ocean2k proxy network [McGregor et al., 2015], are around 0.3 K colder in the pre-industrial period and show modern warming earlier than our SST anomalies (in the 1700s rather than the 1900s).

The global-mean RSR and OLR are dominated by multidecadal variability, often associated with volcanic eruptions (Fig. 5c). The RSR is anticorrelated with SAT (annual $r = -0.72$), while the OLR has a strong positive correlation (annual $r = 0.94$). These correlations are about 50% stronger than in the last-millennium simulations, likely since we rely on temperature to reconstruct the radiation. In contrast, the correlation of EEI with SAT is weakly positive (annual $r = 0.15$), and similarly in the models. The ensemble spread for RSR is twice as large, mostly due to spread between the different model priors. The reconstructed RSR and OLR mostly agree with atmosphere-only simulations over the late 1800s, but then have opposite trends over the 1900s, similar to the PPE.

4.2 Context for recent energy imbalance

We consider the recent energy imbalance and its trend in the context of pre-industrial, natural variability. The EEI over 20-yr periods over 850–1850 in our reconstruction ranges from -0.36 to $+0.27$ (Fig. 6a). The distribution of this pre-industrial EEI provides context for the modern EEI, taken from CERES EBAF [Loeb et al., 2018], the 2025 update to the IPCC AR6 report [Forster et al., 2025, Smith et al., 2025], and Wu et al. [2025]. In all datasets, the EEI over all

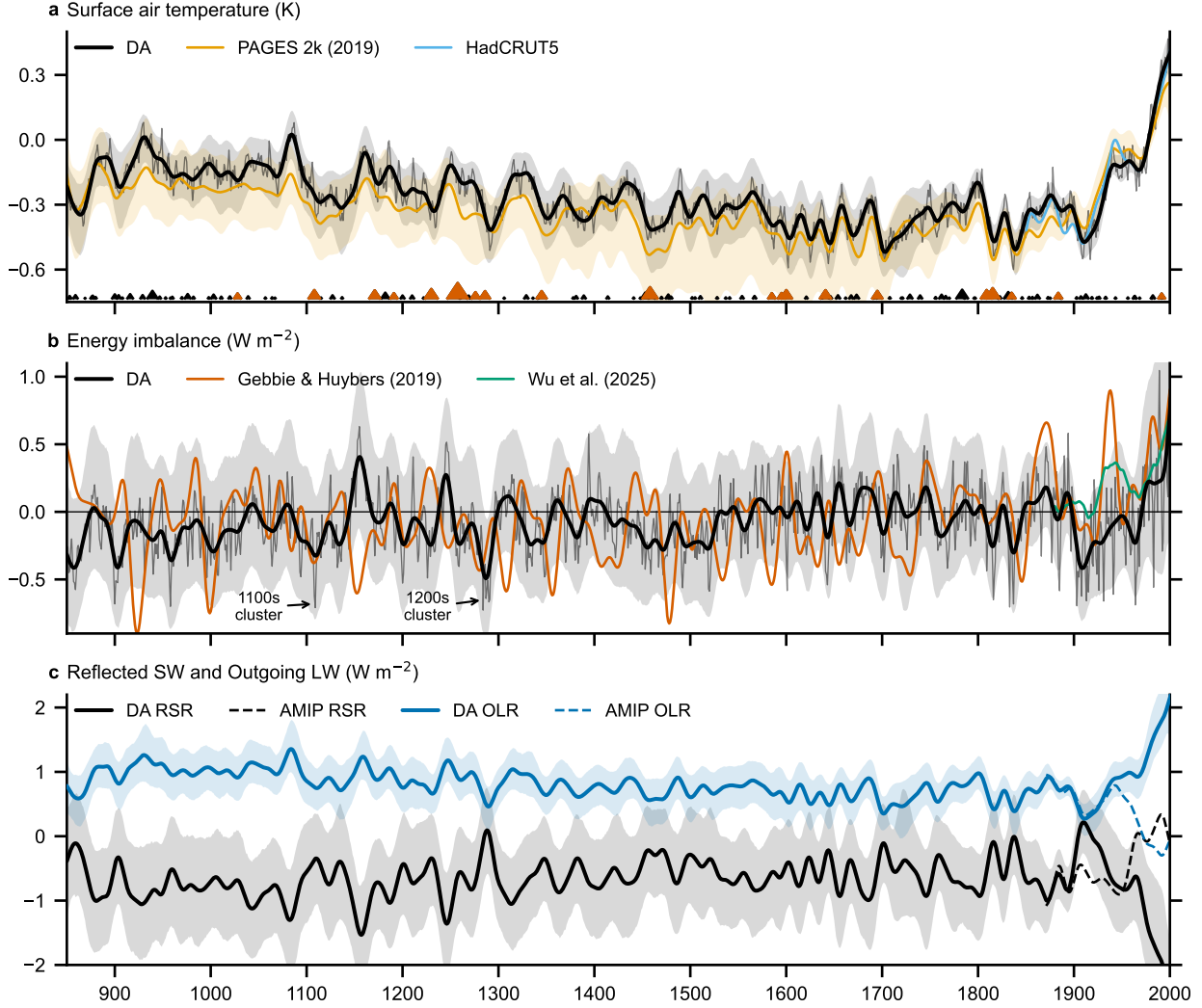


Figure 5: Global-mean time series over the last millennium. DA refers to the combined ensemble of the multi-model reconstructions. Shading denotes the 5th–95th percentile range. Bold lines have a 20-yr low-pass filter, thin gray lines are annual values. (a) SAT anomalies relative to 1961–1990, comparing to the multi-method ensemble and median from PAGES 2k Consortium [2019] and the HadCRUT5 instrumental dataset [Morice et al., 2021]. Carets indicate volcanic eruptions, scaled by their volcanic stratospheric sulfur injection, from the eVolv2k [Toohey and Sigl, 2017] and the CMIP7 historical volcanic forcing datasets (Aubry and CMIP Climate Forcing Task Team, 2025; small eruptions with a VSSI below 0.5 Tg S removed). Those marked in orange are composited in Fig. 10. (b) Absolute energy imbalance. The DA EEI anomalies are made absolute by shifting to a zero-mean during 1600–1900, chosen to coincide with a period of relatively constant temperature. Colored lines show the rate of OHC change from the Gebbie and Huybers [2019] and Wu et al. [2025] reconstructions, expressed as equivalent EEI. The early 1100s and late 1200s volcanic clusters are annotated. (c) RSR and OLR. Atmosphere-only simulations (amip-hist; Zhou et al., 2016b), averaged over seven models, are shown in dashed lines as anomalies relative to 1961–1990. The DA anomalies in (c) are shifted to match the simulation 1871–1900 mean.

20-yr periods starting after 1970 exceeds any pre-industrial 20-yr-average EEI. Considering the 20th-century EEI from our reconstruction, this holds for all 20-yr periods starting after 1980.

The EEI trend over 24-yr periods over 850–1850 in our reconstruction ranges from -0.30 to $+0.37 \text{ W m}^{-2} \text{ dec}^{-1}$ (Fig. 6b). The trend over the 24-yr CERES period (2001–2024) as observed from satellites and constrained by OHC observations in CERES EBAF is $+0.45 \text{ W m}^{-2} \text{ dec}^{-1}$. Even a trend of $+0.25 \text{ W m}^{-2} \text{ dec}^{-1}$, corresponding to the lower uncertainty bound of the CERES EBAF trend, is in the 97th percentile of pre-industrial variability.

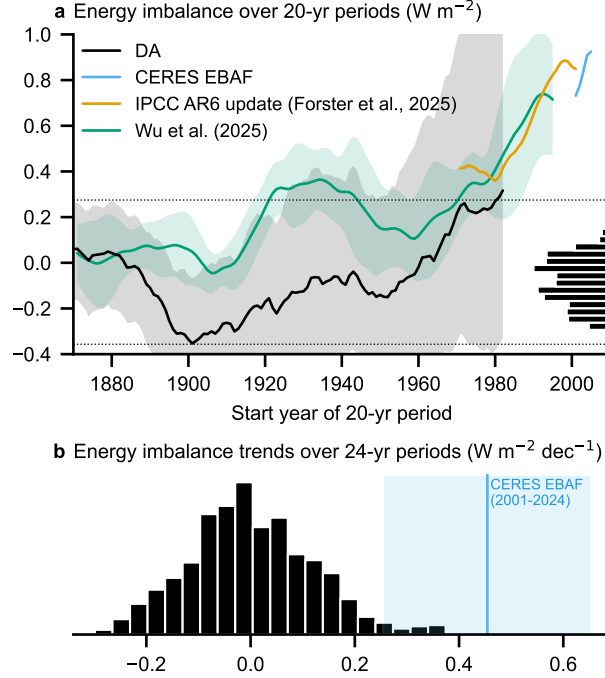


Figure 6: Recent energy imbalance in the context of pre-industrial variability. (a) Absolute energy imbalance over 20-yr periods. The EEI reconstructed in this study is compared to CERES EBAF 4.2.1 data [Loeb et al., 2018] and to the 20-yr sliding window trend in the energy inventory reconstructions of Forster et al. [2025] and Wu et al. [2025]. Shading denotes the 5th–95th percentile range. The histogram shows the distribution of 20-yr-mean, ensemble-mean EEI from our reconstruction over 850–1850, and dotted lines its minimum and maximum. The DA EEI anomalies used for the distribution are set to zero-mean during 1600–1900, chosen to coincide with a period of relatively constant temperature. (b) Energy imbalance trends over 24-yr periods, which is the number of full years in the CERES record. The histogram shows the distribution of 24-yr trends in the ensemble-mean EEI from our reconstruction over 850–1850. The trend from CERES EBAF is shown in blue, with an uncertainty of $\pm 0.20 \text{ W m}^{-2} \text{dec}^{-1}$ as in Raghuraman et al. [2021].

4.3 Sea ice

Sea ice influences high-latitude TOA radiation through surface albedo, lapse rate, and cloud feedbacks [Jenkins and Dai, 2021]. Therefore, we reconstruct the SIC, from which the Arctic and Antarctic sea ice area (SIA) can be derived. While Arctic sea ice reconstructions over the last millennium exist [e.g., Brennan and Hakim, 2022, Meng et al., 2025], Antarctic sea ice has so far been elusive [Thomas et al., 2019].

SIA in both hemispheres increased with the cooling trend over the last millennium (Fig. 7). Arctic SIA agrees closely with Brennan and Hakim [2022], which is a proxy-based reconstruction using offline DA (no model forecasts). Over 850–1850, the annual-mean Arctic SIA grows by $0.5 \times 10^6 \text{ km}^2$, mostly in the Barents Sea, while $0.9 \times 10^6 \text{ km}^2$ are lost over 1850–2000 (Figs. S4 and S10). Antarctic SIA has less variability and more uncertainty when compared to Arctic SIA. Interannual to decadal variability in Antarctic SIA over 1700–2000 correlates highly with Dalaiden et al. [2023], another proxy-based reconstruction using offline DA. The annual-mean Antarctic SIA shrinks by $0.8 \times 10^6 \text{ km}^2$ over 1850–2000. This shrinking is not present in Dalaiden et al. [2023]’s sea ice area, but similar to Cooper et al. [2025]’s reconstruction over 1900–2000 (Fig. S4).

During the growth period, the amplitude of the seasonal cycle in Arctic sea ice decreases, with a smaller boreal winter SIA and a larger summer SIA, peaking in JJA, relative to the annual mean. In contrast, the amplitude of the seasonal cycle in Antarctic sea ice increases during the last millennium, with peak growth in SON. The seasonal sea ice trends are synchronous with high-latitude insolation trends, which differ between the hemispheres (Fig. 7c,d). Extremes of insolation trends are smoothed in the seasonal averages, which obscures lead–lag relationships at monthly timescales.

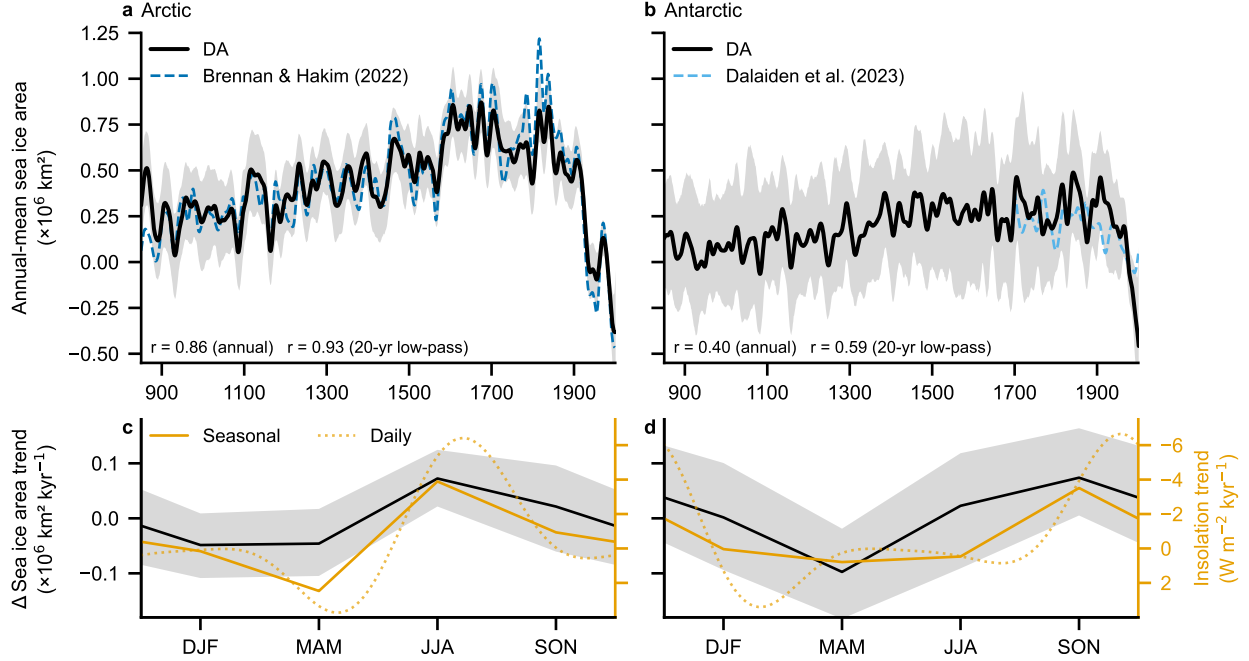


Figure 7: Sea ice area over the last millennium for the Arctic and Antarctic. Anomalies are relative to 1961–1990, and shading denotes the 5th–95th percentile range. (a,b) Annual-mean SIA with 20-yr low-pass filter (bold lines). Arctic sea ice area is compared to Brennan and Hakim [2022]’s reconstruction. (c,d) Departures in seasonal trends from the annual-mean trend over 850–1850. The high-latitude ($> 60^\circ$) insolation trend (yellow) from Berger and Loutre [1991] is shown with an inverted y-axis.

4.4 Last-millennium trends

The global-mean cooling trend from the MCA into the LIA is a prominent feature in our reconstruction. Associated with it are regional variations, which we summarize here in terms of zonal-mean trends. Latitude–longitude gridded trends are shown in Fig. S11.

While all regions cool from the MCA into the LIA, polar amplification is evident in the SAT trend (Fig. 8a). Arctic amplification, measured by the ratio of the 67°N – 90°N trend to the global-mean trend in SAT, is 3.9, similar to recent decades [Rantanen et al., 2022]. Cooling is stronger in the Northern Hemisphere (NH; -0.37 K kyr^{-1}) than in the Southern Hemisphere (SH; -0.22 K kyr^{-1}). In comparison, global-mean temperature trends in the four CMIP6 last-millennium simulations range from -0.1 to $+0.3 \text{ K kyr}^{-1}$.

Trends in SST and OHC are closely related to each other (Fig. 8b,c), with cooling at all latitudes, particularly in the North Pacific, North Atlantic, and the tropical Pacific. However, there is significant uncertainty in the magnitude of reconstructed cooling in the northern mid-latitudes across model priors. Warming occurs around the Kuroshio–Oyashio Extension and the Gulf Stream (not shown).

Trends in TOA radiation have a more complex spatial structure (Figs. 8d–f). The OLR trend is strongly negative and mostly confined to the tropics and subtropics, whereas the RSR trend is positive and extends globally. Together, this makes the global-mean EEI trend positive (toward energy gain). We find that the RSR and EEI trends are not significantly different from zero, and vary strongly by location and season (Figs. 9 and S11). The EEI trend is positive in the equatorial region and negative in mid-latitudes. The trend is most positive in MAM, driven by a tendency to gain energy in the equatorial east Pacific in both RSR and OLR. The opposite is the case in JJA, although the energy loss is offset by energy gain over the Maritime Continent.

4.5 Volcanic eruptions

We composite pre-industrial tropical eruptions larger than Pinatubo, i.e., eruptions with a volcanic stratospheric sulfur injection (VSSI) of at least 7.5 Tg S and a latitude below 30° . If a second eruption with a $\text{VSSI} > 1 \text{ Tg S}$ occurs within the composite window, we remove all data following that second eruption to capture the undisturbed response. Eruption

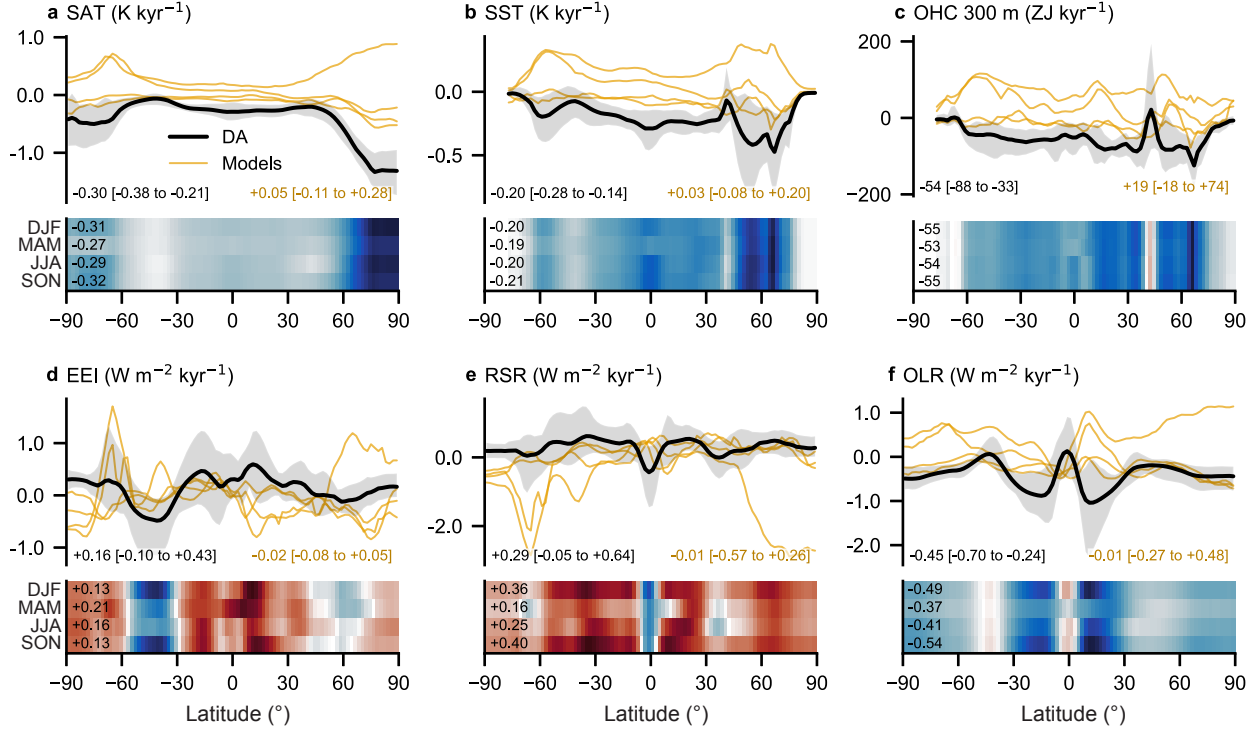


Figure 8: Zonal-mean linear trends over 850–1850. Each panel shows (top) the annual mean and (bottom) the seasonal means. Yellow lines correspond to the CMIP6 last-millennium simulations from the MPI, CESM, MRI, and MIROC models. Numbers denote the global-mean trend (reconstruction in black with 5th–95th percentile range, models in yellow with min–max range). Shading denotes the 5th–95th percentile range.

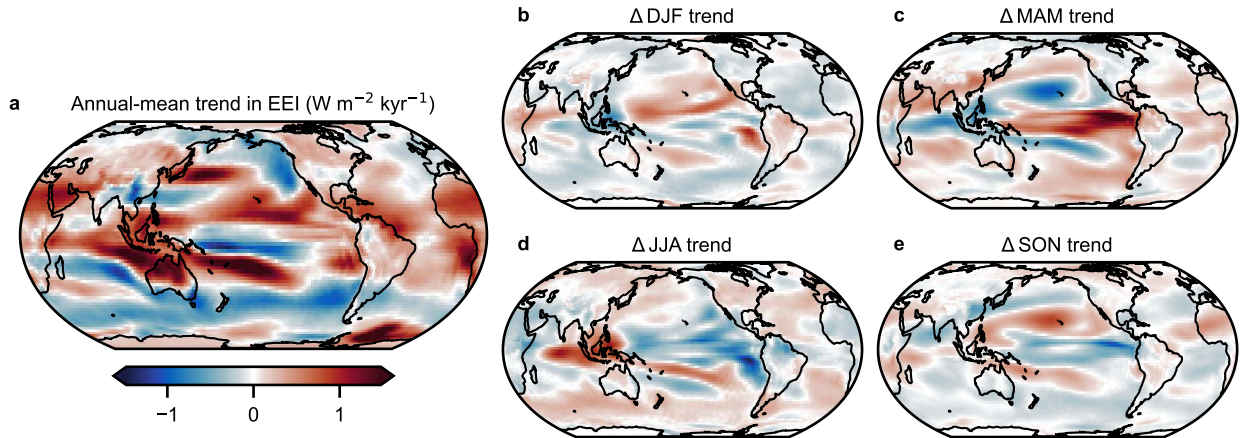


Figure 9: Linear trend in EEI over 850–1850. (a) Annual-mean trend and (b–e) departures in seasonal trends from the annual-mean trend. The constituent RSR and OLR trends are shown in Fig. S11.

dates, latitude, and VSSI are taken from the eVolv2k dataset [Toohey and Sigl, 2017], which is derived from ice core records.

There is a clear global cooling signal, albeit with large scatter, peaking one to two years after the eruption at -0.15°C (NH: -0.22°C , SH: -0.09°C) and fully recovering after 10–15 years (Fig. 10). The stronger NH cooling, particularly in summer (Fig. S12a), is possibly due to proxy distribution and seasonality, but model simulations also suggests a hemispherically asymmetric response [Pauling et al., 2021]. The OHC300 is reduced by 22 ZJ after five years, although most heat is lost in the first two years after the eruption. This heat loss is driven by enhanced RSR (up to $+0.7 \text{ W m}^{-2}$), counteracted by a small reduction in OLR (up to -0.3 W m^{-2}). This leads to a negative EEI of up to -0.4 W m^{-2} ,

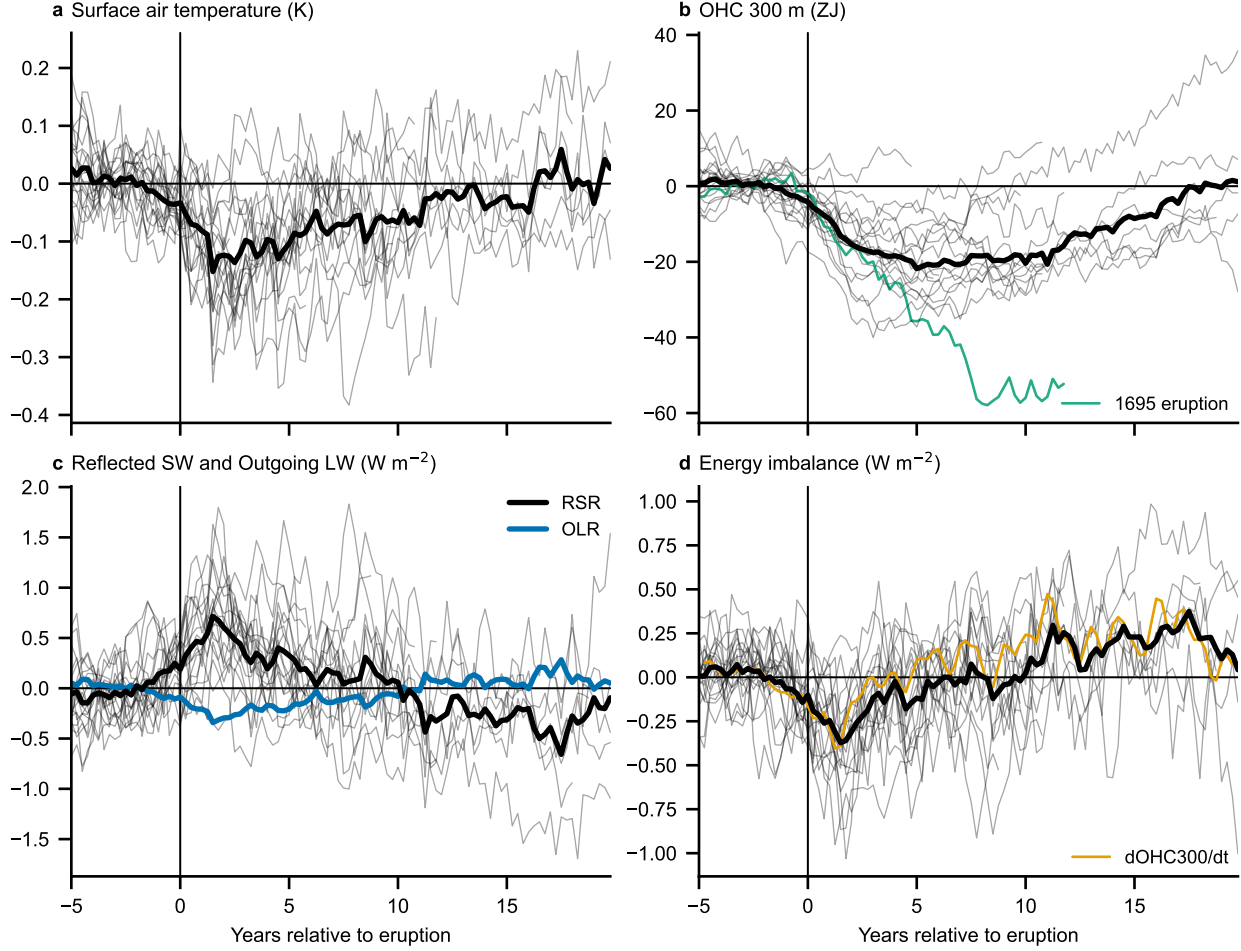


Figure 10: Composite analysis of global-mean seasonal anomalies for tropical volcanic eruptions larger than Pinatubo (1991) over 850–1850 ($n = 19$). Eruptions have a VSSI of at least 7.5 Tg S , a latitude below 30° , and are marked in orange in Fig. 5a. Anomalies are computed relative to the 5 years prior to each eruption. The blue and green lines in (b) correspond to eruptions causing large OHC losses. The orange line in (d) is the 3-point moving average of the time derivative of OHC300, rescaled by Earth’s ocean fraction (71%) to make it comparable to EEI.

which approximately aligns with the rate of OHC loss. Most OHC is lost over the north Atlantic and the equatorial west Pacific (Fig. S13). EEI becomes positive after 5–10 years, coinciding with the recovery of OHC. Time scales for sea ice expansion are similar to those of surface temperature, and there is no discernible impact on ENSO (Fig. S12), consistent with the analysis of Zhu et al. [2022]. Compared to coupled-model simulations, the volcanic response in all fields is damped and lagged (Fig. S14).

Multiple large eruptions spaced a few years to a decade apart can initiate periods of prolonged OHC loss (Fig. S15, and colored line in Fig. 10b; Gupta and Marshall, 2018). For example, the 1693 and 1695 eruptions caused a 10-year period of OHC loss. After a loss of 55 ZJ, the recovery took 40 years due to five additional, smaller eruptions.

4.6 Consistency between OHC and EEI

Approximately 90% of the heat absorbed due to a non-zero EEI is stored in the ocean [von Schuckmann et al., 2023]. Recently, 42% of the accumulated OHC has been stored in the upper 300 m [Pan et al., 2025]. Therefore, a strong correlation between the EEI and the rate of change of the upper-ocean heat content ($d\text{OHC}_{300}/dt$) is expected, particularly at seasonal to interannual timescales. This can provide insight into the connection between Earth’s energy budget at the TOA and at the surface, but also serves as a consistency check for the DA procedure. By Eq. (1), a difference between $d\text{OHC}/dt \approx C(dT/dt)$ and the EEI may be due to heat uptake γT by the deeper ocean, or components of the climate system other than the ocean. We multiply $d\text{OHC}/dt$ by Earth’s ocean fraction (71%) to obtain

the equivalent EEI over the total surface area. The derivative is calculated using a central difference as in [Trenberth et al., 2014].

Reconstructed EEI and $d\text{OHC}_{300}/dt$ are correlated annually at 0.69 (Fig. S16), and the volcanic response is similar (Fig. 10d). At seasonal timescales, the correlation is 0.60, but $d\text{OHC}/dt$ leads EEI by one season. With increasing timescale, the two quantities decorrelate. Interpreting the difference as deep ocean heat uptake, the deep ocean is releasing heat over most of the last millennium.

5 Discussion and Conclusions

We presented a reconstruction of Earth’s energy budget over the last millennium, comprising both the TOA radiation and upper-ocean heat content, in addition to radiatively relevant surface variables. In contrast to previous reconstructions, ours is spatially and seasonally resolved at the surface and at the TOA, separates the SW and LW components, and is constrained by proxies. The reconstruction can be used to investigate seasonal to decadal variability, millennial trends, and episodic events like volcanic eruptions.

5.1 Reconstruction skill and limitations

The reconstruction presented here is the first proxy-constrained dataset of TOA radiation over the last millennium. We use the fact that radiation covaries with surface temperature, to which the proxies are sensitive. However, the proxy information is temporally and spatially sparse, and the link to TOA radiation is mediated by complex and noisy physical processes. Therefore, we rely on a pseudoproxy experiment, instrumental validation, and internal consistency to establish TOA radiation reconstruction skill. As in previous reconstructions, surface variables agree well with instrumental products and other reconstructions (Figs. S3–S5), and withheld proxies for independent validation over the whole last millennium have significant positive correlations (Fig. S6).

Of the three TOA radiation fields, OLR has the highest correlations in the PPE and with the ERBE satellite record for the real-proxy reconstruction (Figs. 2 and 3). This is not surprising since OLR covaries strongly with TAS through the Planck response, especially in association with ENSO and other modes of internal variability. RSR has slightly lower correlations because it is generally noisier at seasonal timescales. EEI skill may be lower because it is the small difference of two opposing quantities of similar magnitude. While there is skill at seasonal and annual timescales in all fields, it is higher at interannual to decadal timescales.

Consistency between the TOA radiation and OHC, even though not explicitly enforced, is further evidence of reconstruction skill (Figs. S16 and 10d). EEI and $d\text{OHC}_{300}/dt$ should correspond since much of the energy imbalance is absorbed into the ocean [von Schuckmann et al., 2023, Palmer and McNeall, 2014]. Indeed, their seasonal and annual correlation is high, with a correlation peak at a timescale of 4 years. Up to timescales of 20 years, the correlation is above 0.60, with a trend toward decorrelation for longer timescales. We speculate that the multidecadal correlation might be higher if OHC were to include the deeper ocean. At seasonal timescales, the EEI lags $d\text{OHC}/dt$ by one season.

One caveat of our method is that the partitioning of EEI into RSR and OLR only works well over the last millennium, and not over the historical period. This is because the temperature–radiation relationship in the LIM is learned from last-millennium simulations, which are dominated by volcanic forcing rather than greenhouse gases and tropospheric aerosols. In the training data, a cooling (warming) is thus usually associated with a negative (positive) SW forcing, which in response reduces (increases) the OLR. This is in contrast to anthropogenic greenhouse gas forcing, for which warming is associated with reduced OLR, opposite of what the LIM has learned. Interannual variability over the historical period does not suffer from this issue, however, as evident from the satellite comparison (Fig. 3).

We conclude that our reconstruction is generally skillful, despite the spatiotemporal sparseness of the proxy network and the complex relationship between temperature and radiation. Most reliable are global means at interannual to decadal timescales, although even seasonal fields have considerable skill. The spatial reconstruction fidelity is highest in the tropical and subtropical Pacific, but non-negligible in most regions. Over the historical period, the partitioning at decadal timescales is inaccurate, but the total EEI and non-radiation fields do not lose skill.

5.2 Earth’s energy budget over the last millennium

Reconstructions and models agree that there was a global-mean cooling trend over the last millennium, although the patterns of cooling may not be globally synchronous [PAGES 2k Consortium, 2019, Neukom et al., 2019]. This cooling was driven primarily by volcanic forcing, with a potential minor role of greenhouse gas and solar forcing [Schurer et al., 2014, Büntgen et al., 2020, Wanner et al., 2022, Esper et al., 2012], then amplified by positive feedbacks [Atwood et al., 2016]. However, the climate system is stable due to the strongly negative Planck feedback, which responds to cooling

with reduced OLR. Indeed, the OLR decreased by $0.42 \text{ W m}^{-2} \text{ kyr}^{-1}$, while the RSR only increased by $0.29 \text{ W m}^{-2} \text{ kyr}^{-1}$, which explains the increasing EEI trend of $0.16 \pm 0.26 \text{ W m}^{-2} \text{ kyr}^{-1}$, although it is not significantly different from zero. To sustain the cooling trend, the EEI needs to remain negative on average despite the increasing trend, leading to a slowdown of cooling over centuries. In our reconstruction, this implies an 1850–1900 EEI mean of at most $0.15 \pm 0.25 \text{ W m}^{-2}$ (cf. Fig. S9b). If we let the relatively constant SAT and OHC over 1600–1900 imply an average EEI of zero over this period, the 1850–1900 EEI mean would be $0.07 \pm 0.21 \text{ W m}^{-2}$, similar to the estimate of $0.2 \pm 0.2 \text{ W m}^{-2}$ from Forster et al. [2021]. In comparison, the EEI inferred from the OHC reconstruction of Gebbie and Huybers [2019] is 0.24 W m^{-2} over this period. The energy imbalance over any 20-yr period after 1980, and possibly after 1970, is unprecedented in the context of the last millennium, similar to temperatures [PAGES 2k Consortium, 2019]. This provides further evidence that the global warming that started in the 20th century is anthropogenic rather than natural [Masson-Delmotte et al., 2021].

While both our reconstruction and that of Gebbie and Huybers [2019, described further in Gebbie, 2021] show sustained energy loss before around 1600, theirs starts with a higher energy content and cools more into the LIA (Fig. S9). The discrepancy may be explained by the much colder pre-industrial SSTs prescribed by Gebbie and Huybers [2019] than we reconstruct (Fig. S8). Their reconstruction then agrees well with the reconstruction from Wu et al. [2025] over the historical period since both are instrumental-based, while our EEI is likely too low in the early 1900s, even though it matches in the later decades. Our reconstructions agree that the energy inventory was higher during the MCA than in 2000, and that there was significant multidecadal variability with intermittent periods of energy gain. However, both reconstructions come with large uncertainties that preclude definite conclusions about the last millennium energy budget.

By comparing the spatial structure of the radiation trends (Figs. 9 and S11), we can infer the physical processes involved. The OLR trend is negative almost everywhere, presumably due to the Planck feedback. Superimposed is a La Niña-like response (cf. Fig. 1), with a westward shift of the Indo–Pacific convection region toward the Maritime Continent, causing negative OLR trends in regions with enhanced deep convection [Hartmann, 2016]. The increased EEI south of the convective region points to a southward shift of the Intertropical Convergence Zone accompanying the westward shift, likely because the SH cools less and thus more heat is transported northward [e.g., Donohoe et al., 2013]. In addition to these shifts, the RSR and EEI have trends in the subtropical east Pacific and Atlantic, likely associated with the subtropical stratus decks. Northeast Pacific low cloud cover appears enhanced and thus more reflective, while southeast Pacific and Atlantic low clouds appear somewhat suppressed. There also is a clear-sky RSR contribution from enhanced Antarctic sea ice (Fig. S11a).

5.3 Seasonality due to orbital precession

The last-millennium trends of all fields differ consistently by season. The seasonal cycle in the global-mean cooling trend ranges from -0.27 K kyr^{-1} in MAM to -0.32 K kyr^{-1} in SON (Fig. 8). The timing is latitude-dependent since insolation trends are most extreme in MAMJJJA in the NH and SONDJF in the SH (Fig. 7c,d; cf. Fig. 2d in Lücke et al., 2021). Sea ice area trends are synchronous with these high-latitude insolation trends, with lower insolation coinciding with more sea ice. These seasonal trends are associated with a reduced (enhanced) amplitude of the seasonal sea ice cycle in the Arctic (Antarctic). The same pattern is also evident in the radiation fields (Fig. 8d–f).

The insolation trends are caused by axial precession [Lücke et al., 2021]. While the annual-mean insolation is approximately constant over the last millennium, there are latitude-dependent seasonal trends in insolation due to shifting of the solstices relative to the apsides of Earth’s orbit around the sun. MAM thus tends to occur closer to perihelion, attenuating the cooling, while SON tends to occur closer to aphelion, amplifying the cooling (Fig. 8a). This has previously led to a wrong interpretation of trends in annual proxy reconstructions [Lücke et al., 2021], while our seasonal DA approach explicitly accounts for such seasonality.

5.4 Climate response to volcanic eruptions

Large volcanic eruptions are the dominant pre-industrial climate forcing [Büntgen et al., 2020]. Clusters of them are thought to be the main cause of the LIA [Miller et al., 2012, Brönnimann et al., 2019] and previous cold periods [Van Dijk et al., 2024]. Sea-surface cooling after eruptions is initially damped by the upper ocean and absorbed into the deeper ocean [Gregory et al., 2016]. The cold anomalies then slowly resurface, extending the cooling well beyond the volcanic aerosol residence time of 1–2 years. A decadal pacing of large eruptions would thus allow OHC anomalies to accumulate and persist [Gupta and Marshall, 2018, Zhong et al., 2011]. In our volcanic composite, the OHC does not begin to recover until 5–10 years after the eruption (Fig. 10b). If another eruption were to occur during this period, the heat loss would compound. We found that this has happened multiple times over the last millennium, e.g., in the early 1100s, late 1200s, early 1700s, and early 1800s, causing upper-ocean heat loss of 50 ZJ or more over 10 years (Fig. S15). The late

1200s cluster is thought to have initiated the LIA [Miller et al., 2012, Zhong et al., 2011]. Indeed, the decade with the lowest EEI over the last millennium is 1283–1292 (0.6 W m^{-2} below 1850–1900 mean), with a minimum in 1284 (0.8 W m^{-2} below 1850–1900 mean). However, the start of the cooling trend and a multidecadal cold period align better with the early 1100s cluster, although the energy loss was less sustained. The LIA may thus have been initiated by multiple clusters (both annotated in Fig. 5b).

The upper-ocean heat loss differs qualitatively between our reconstruction and model simulations (Fig. 10 and S14). The simulated ocean cooling peaks 3 years after the eruption and recovers immediately, while the reconstructed cooling peaks at a lower amplitude. In contrast to the simulations, the reconstructed onset of recovery varies by eruption, occurring 3–10 years post-eruption and resulting in the flatter composite (Fig. 10b). This damped and lagged response is potentially a proxy artifact since the biological memory in tree-ring width proxies, which form the bulk of our network, smooths out the volcanic response [Lücke et al., 2019, Zhu et al., 2020]. However, models are also known to overestimate the cooling after large-magnitude eruptions when prescribing aerosol optical properties rather than simulating interactive aerosols [Marshall et al., 2025]. The discrepancy can be further reduced by accounting for uncertainty in VSSI and timing [Lücke et al., 2023]. The timescale of OHC recovery in our reconstruction agrees with instrumental datasets for three large eruptions (Fig. 4).

The loss of OHC is driven by a negative EEI at the TOA, arising from increased RSR due to stratospheric aerosols (Fig. 10c,d). After 5–10 years, the EEI becomes marginally positive and the OHC recovers over the course of a decade. The recovery is associated with an RSR that is slightly less than pre-eruption, rather than reduced OLR, also evident in coupled model simulations (Fig. S14c). The recovery is aided by deep ocean heat release γT , which results from the difference between the EEI and $d\text{OHC}/dt$ in Fig. 10d.

There is cooling both after volcanic eruptions and in the last-millennium temperature trend, but the spatial patterns of cooling and radiation differ (Figs. S11 and S13). The millennial trend shows strong polar amplification and a colder equatorial Pacific, which induces a La Niña-like OLR response. In contrast, volcanic eruptions cause more cooling over land and actually warm the equatorial Pacific slightly so that the tropical OLR response is El Niño-like, even though the extratropical OLR is reduced in both cases. The volcanic RSR is positive everywhere due to the global dispersal of stratospheric aerosols. While the post-eruption warming of the equatorial Pacific has been observed before, it is indistinguishable from natural variability. Indeed, our Niño 3.4 index does not change significantly after volcanic eruptions (Fig. S12b), consistent with Zhu et al. [2022] and Dee et al. [2020].

Previous modeling studies have found expanded sea ice persisting for more than a century following large eruptions due to sea ice–ocean feedbacks in the Arctic Ocean and North Atlantic [Zhong et al., 2011, Slawinska and Robock, 2018]. In contrast, in our volcanic composite, the sea ice area in both hemispheres returns to the pre-eruption value after 15–20 years (Fig. S12c,d). However, Zhong et al. [2011] find that these sea ice changes following volcanic eruptions depend on the initial state. Centennial sea ice expansion that sustains cold anomalies could thus be important for some eruptions and could have played a role in initiating the LIA [Miller et al., 2012].

5.5 Consistency with simulations

CMIP6 last-millennium simulations disagree markedly among themselves and with our reconstruction. They do not capture the millennial-scale cooling trend (Fig. 8) and the OHC loss after a series of volcanic eruptions differs much in magnitude (Fig. S15). While the lack of a global-mean cooling trend, or even the presence of strong warming, is the main reason for the mismatch in the other fields, they also disagree in the spatial structure, particularly in the mid and high latitudes. While proxy reconstructions have their own issues [Anchukaitis and Smerdon, 2022, Zhu et al., 2020], this potentially highlights the value of DA, which adjusts the model state through time using proxy information.

Since the annual-mean cooling trend is likely volcanically forced [Schurer et al., 2014, Büntgen et al., 2020, Wanner et al., 2022], the lack of a trend may imply that the coupled climate system response to volcanic eruptions, such as post-eruption OHC loss, is not well resolved in climate models [Church et al., 2005]. Other model issues that can lead to discrepancies with proxy reconstructions include uncertainty in the forcing dataset and in the aerosol representation [Lücke et al., 2023, Marshall et al., 2022, Timmreck, 2012]. A false warming trend can also arise from impulsive positive radiative forcing when the prescribed background aerosols from the spin-up run are removed at the start of a last-millennium run [Gregory et al., 2013, Fyfe et al., 2021].

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Center for Atmospheric Research (NCAR), sponsored by the National Science Foundation. This work made use of pyleoclim [Khider et al., 2022] and climlab [E. J. Rose, 2018].

Data availability The reconstruction data and code will be published once this manuscript has been accepted.

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Supplemental Information for

Top-of-atmosphere radiation fields over the last millennium reconstructed from proxies

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- Supporting text
- Figs. S1 to S16
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Supplemental Information Text

Linear Inverse Model

A linear inverse model (LIM) is a dynamical system emulator that explicitly models the linear, deterministic dynamics while parameterizing the non-linear residual as noise that is uncorrelated in time but may be correlated in the state variables. The linear dynamics are stable, so that anomalies decay toward the mean in the long-time limit. The noise forcing maintains the system in statistical equilibrium against the persistent decay from the linear dynamics. In the context of online data assimilation (DA), the linear part propagates the posterior mean forward in time while the noise part contributes to the covariance structure needed for the Kalman filter. The LIM dynamics have the form

$$\frac{d\mathbf{x}}{dt} = \mathbf{L}\mathbf{x} + \mathbf{S}\boldsymbol{\eta} = \mathbf{L}\mathbf{x} + \boldsymbol{\xi},$$

where $\mathbf{x} \in \mathbb{R}^{N_x}$ is the state vector, $\mathbf{L} \in \mathbb{R}^{N_x \times N_x}$ encodes the linear dynamics, $\mathbf{S} \in \mathbb{R}^{N_x \times N_x}$ is the noise amplitude matrix, and $\boldsymbol{\eta} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}) \in \mathbb{R}^{N_x}$ is additive Gaussian white noise with unit variance. Alternatively, the noise term can be written as $\boldsymbol{\xi} \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}/dt) \in \mathbb{R}^{N_x}$, where $\mathbf{Q} = \mathbf{S}\mathbf{S}^T dt$ is the noise covariance matrix. The state vector represents anomalies about a mean state. The state dimension here is $N_x = 130$, which is the sum of the number of principal components retained after EOF truncation.

Integrating the LIM dynamics in time, and taking the expectation over the noise forcing yields a deterministic forecast equation between two time steps (Penland and Sardeshmukh, 1995):

$$\hat{\mathbf{x}}(t + \tau) = \exp(\mathbf{L}\tau)\mathbf{x}(t) = \mathbf{G}\mathbf{x}(t), \quad (1)$$

where $\mathbf{G} \in \mathbb{R}^{N_x \times N_x}$ is the linear forecast operator and $\tau = 1$ season is the time step. The forecast is stable (i.e., decays to zero for $\tau \rightarrow \infty$) if all eigenvalues of $\mathbf{L}$ have negative real parts. For probabilistic ensemble forecasts during data assimilation, we use the two-step stochastic integration scheme described by Penland and Matrosova (1994):

$$\begin{aligned} \tilde{\mathbf{x}}(t + \delta t) &= \tilde{\mathbf{x}}(t) + [\mathbf{L}\tilde{\mathbf{x}}(t) + \mathbf{S}\boldsymbol{\eta}_0]\delta t, \\ \mathbf{x}(t + \delta t/2) &= [\tilde{\mathbf{x}}(t) + \tilde{\mathbf{x}}(t + \delta t)]/2, \end{aligned}$$

where $\tilde{\mathbf{x}}$ is an intermediate variable and $\boldsymbol{\eta}_0$ is a sample of the noise $\boldsymbol{\eta}$. The integration time step δt must be chosen much smaller than the corresponding deterministic time step τ . We use 360 integration steps per τ , or $\delta t \approx 6$ hr (Penland and Matrosova, 1994; Perkins and Hakim, 2021). In practice, the whole ensemble can be propagated simultaneously by adding an ensemble dimension to $\mathbf{x}$ and by sampling an $N_x \times N_e$ noise matrix $\boldsymbol{\eta}_0$. We use $N_e = 400$.

The system dynamics $\mathbf{L}$ and $\mathbf{G}$ as well as the noise covariance $\mathbf{Q}$ are determined from training data. The procedure is based on the zero-lag and τ -lag covariance matrices:

$$\mathbf{C}(0) = \langle \mathbf{x}(t)\mathbf{x}^T(t) \rangle \quad \text{and} \quad \mathbf{C}(\tau) = \langle \mathbf{x}(t + \tau)\mathbf{x}^T(t) \rangle,$$

where $\langle \cdot \rangle$ denotes the time average over all training data $\mathbf{x}(t)$. The deterministic forecast operator is

$$\mathbf{G} = \mathbf{C}(\tau)\mathbf{C}(0)^{-1},$$

i.e., the linear regression between the state over a τ -lag interval. The linear dynamics $\mathbf{L}$ required for stochastic integration is then found by rearranging Eq. (1) as

$$\mathbf{L} = \frac{\ln \mathbf{G}}{\tau}.$$

Practically, the logarithm is evaluated using the eigendecomposition of $\mathbf{G}$ (i.e., $\ln \mathbf{G} = \tilde{\mathbf{G}}(\ln \boldsymbol{\Lambda}_{\mathbf{G}})\tilde{\mathbf{G}}^{-1}$). Finally, we can find the noise covariance matrix from the fluctuation–dissipation relation as (Penland and Sardeshmukh, 1995)

$$\mathbf{Q} = -(\mathbf{L}\mathbf{C}(0) + \mathbf{C}(0)\mathbf{L}).$$

The noise amplitude matrix is then (Penland and Matrosova, 1994)

$$\mathbf{S} = \tilde{\mathbf{Q}} \left(\frac{\boldsymbol{\Lambda}}{\delta t} \right)^{1/2}$$

where $\tilde{\mathbf{Q}}$ and $\boldsymbol{\Lambda}$ are the eigenvectors and eigenvalues of the noise covariance matrix $\mathbf{Q} = \tilde{\mathbf{Q}}\boldsymbol{\Lambda}\tilde{\mathbf{Q}}^{-1}$. While covariance matrices are always positive semi-definite, the $\mathbf{Q}$ derived from data may have spurious negative eigenvalues as a result of a small training dataset or significant non-linear dynamics (Penland and Matrosova, 1994). We remove these negative eigenvalues and their respective eigenvectors from $\boldsymbol{\Lambda}$ and $\tilde{\mathbf{Q}}$, then rescale the remaining eigenvalues to retain the total variance.

Ensemble Kalman Filter

Data assimilation applies Bayes' theorem to update a prior (e.g., a LIM forecast) with observations (e.g., proxies), taking into account their respective uncertainties. Since this becomes intractable for arbitrary distributions in high dimensions, Kalman filters assume normally distributed state variables, so that the only the means and covariances need to be updated. In ensemble Kalman filters (EnKFs), the covariances are represented by an ensemble, which comprises equally likely samples. We use a particular flavor of EnKF, the serial ensemble square root filter (EnSRF; Whitaker and Hamill, 2002). A serial filter assimilates observations one-by-one by assuming independent observation error. Square root filters factorize the covariance matrix into its matrix square roots, which simplifies some calculations (Tippett et al., 2003). In combination with serial observations, this becomes a regular scalar square root. See Houtekamer and Zhang (2016) for an extensive review of EnKFs.

The ensemble update given a single observation y , denoted by $\text{EnSRF}(y, \mathbf{x}_b)$, works as follows. First, the prior ensemble is converted into perturbations about the ensemble mean $\bar{\mathbf{x}}_b$:

$$\mathbf{X}_b = [\mathbf{x}_b^1 - \bar{\mathbf{x}}_b \quad \mathbf{x}_b^2 - \bar{\mathbf{x}}_b \quad \dots \quad \mathbf{x}_b^{N_e} - \bar{\mathbf{x}}_b] \in \mathbb{R}^{N_x \times N_e}, \quad (2)$$

where $\mathbf{x}_b^i \in \mathbb{R}^{N_x \times 1}$ are the prior ensemble members and $\bar{\mathbf{x}}_b$ is their mean. We then estimate the expected proxy observation, expressed as perturbation about the ensemble mean observation estimate, based on the prior:

$$\hat{\mathbf{Y}} = \mathbf{H}\mathbf{X}_b \in \mathbb{R}^{1 \times N_e}, \quad (3)$$

which has a single row because we use serial observations and thus the observation operator is $\mathbf{H} \in \mathbb{R}^{1 \times N_x}$. The scalar variance $\hat{\sigma}_b^2$ of the observation estimate is

$$\hat{\sigma}_b^2 = \frac{\hat{\mathbf{Y}}\hat{\mathbf{Y}}^\top}{N_e - 1}$$

and the covariance vector $\hat{\sigma}_{xy}$ between the prior state and the observation estimate is

$$\hat{\sigma}_{xy} = \frac{\mathbf{X}_b\hat{\mathbf{Y}}^\top}{N_e - 1} \in \mathbb{R}^{N_x \times 1}.$$

The proxy error variance, determined during PSM calibration, is σ_o^2 . By the Kalman filter update equation, the posterior ensemble mean is then

$$\bar{\mathbf{x}}_a = \bar{\mathbf{x}} + \mathbf{K}(y - \mathbf{H}\bar{\mathbf{x}}), \quad (4)$$

where y is the actual proxy observation. The Kalman gain

$$\mathbf{K} = \frac{\hat{\sigma}_{xy}}{\sigma_o^2 + \hat{\sigma}_b^2} \in \mathbb{R}^{N_x \times 1}$$

maps back from the observation space into the state space, updating any component of the state that covaries with the observation as determined from the ensemble. The Kalman gain takes the respective uncertainties of the prior and the observation into account: if the observation or its estimate are uncertain ($\sigma_o^2 + \hat{\sigma}_b^2$ large), then the posterior will remain closer to the prior. Notice that, if the actual and estimated proxy are the same, the innovation $y - \mathbf{H}\bar{\mathbf{x}}$ is zero and the prior remains unchanged.

The perturbations about the ensemble mean need to be updated such that the posterior ensemble covariance correctly reflects the prior and observation uncertainties. This requires that the Kalman gain is reduced by a factor α , otherwise the posterior variance is underestimated (Whitaker and Hamill, 2002):

$$\alpha = \left(1 + \sqrt{\frac{\sigma_o^2}{\sigma_o^2 + \hat{\sigma}_b^2}}\right)^{-1} < 1.$$

The posterior perturbations are then

$$\mathbf{X}_a = \mathbf{X}_b - \alpha\mathbf{K}\hat{\mathbf{Y}},$$

which has the same form as Eq. (4), except that $y = 0$ since all observation information is absorbed into the mean, and that the reduced Kalman gain $\alpha\mathbf{K}$ is used. The perturbation update can also be expressed as

$$\mathbf{X}_a = (\mathbf{I} - \alpha\mathbf{K}\mathbf{H})\mathbf{X}_b,$$

which demonstrates that the posterior perturbations are just a linear combination of the prior perturbations. Finally, we combine the updated mean and perturbations to form the posterior ensemble

$$\mathbf{x}_a^i = \bar{\mathbf{x}}_a + \mathbf{X}_a^i,$$

essentially reversing Eq. (2). This concludes the assimilation of a single observation. The algorithm is repeated for all observations available at the current time step, with the posterior after each iteration serving as prior for assimilating the next observation. The final posterior is then propagated forward in time using the LIM to form the prior of the next time step.

As described in the main text, we update a window $\mathcal{T}$ of multiple seasons at once using the algorithm from Huntley and Hakim (2010). This algorithm acknowledges the time-averaged nature of annually-resolved proxies. For example, if a proxy is sensitive to MAMJJA, the MAMJJA average is updated directly, rather than each season individually. The covariance with the annual average is expected to be less noisy, and fewer covariances have to be estimated. The time-mean state is denoted as $\langle \mathbf{x} \rangle$, seasonal perturbations around this mean as $\mathbf{x}'$, and the EnSRF algorithm for a single observation y and the prior ensemble $\mathbf{x}_b^0, \dots, \mathbf{x}_b^{N_e}$ described above as EnSRF($y, \mathbf{x}_b$).

We start by determining all seasons $t \in \mathcal{T}$ that the current observation y is averaged over (i.e., the proxy seasonality). We find the perturbations for each season around the prior time mean $\langle \mathbf{x} \rangle_b$ over $\mathcal{T}$:

$$\mathbf{x}'_b(t) = \mathbf{x}_b(t) - \langle \mathbf{x} \rangle_b, \quad t \in \mathcal{T}.$$

We then apply the EnSRF to the time mean:

$$\langle \mathbf{x} \rangle_a = \text{EnSRF}(y, \langle \mathbf{x} \rangle_b).$$

Note that, for $\hat{\mathbf{Y}}$ in the Eq. (3), Huntley and Hakim (2010) use $\langle \mathbf{H}\mathbf{X}_b \rangle$ rather than $\mathbf{H}\langle \mathbf{X}_b \rangle$. However, this only matters for a nonlinear observation operator, while our linear PSM commutes with the time averaging. Finally, we obtain the posterior ensemble for each season by adding back the prior perturbations to the updated time mean:

$$\mathbf{x}_a(t) = \langle \mathbf{x} \rangle_a + \mathbf{x}'_b(t), \quad t \in \mathcal{T}.$$

An alternative to time averaging for windowed DA is time stacking as done by Meng et al. (2025). They stack the states from all seasons to form $\bar{\mathbf{x}}$, then apply the EnSRF to the stacked state, which requires the estimation of a larger covariance matrix. However, tests showed that this does not lead to different results in practice (not shown).

Proxy system models

For all proxies, we use a linear proxy system model (PSM):

$$y = \mathbf{H}\mathbf{x} + y_0 + \epsilon = h\mathbf{H}^*\mathbf{x} + y_0 + \epsilon,$$

where $\mathbf{H}^* \in \mathbb{R}^{1 \times N_x}$ maps from the state space, which consists of the principal components associated with the EOF basis, to the temperature at the nearest grid point. The linear relationship between that temperature and the proxy value y is characterized by the slope h and the intercept y_0 . Only the slope contains useful information, while the intercept converts from anomalies to absolute proxy values. The parameters are determined using ordinary least squares, and the residuals are used to estimate the observation error $\epsilon \sim \mathcal{N}(0, \sigma_o^2)$, which is then used in the EnSRF. Note that we assume that all observation errors are independent, which is a prerequisite for serial data assimilation.

During calibration, we objectively determine the seasonality of annual proxies and the temperature field that the proxy is sensitive to. We test ten candidate seasonalities that are common in proxies, ranging from a single season to all four. For marine proxies, we test both the surface air temperature and sea surface temperature as candidate field, for land proxies we always take the surface air temperature. The candidate PSM with the lowest Bayesian information criterion, or essentially the maximum likelihood, is then chosen (Perkins and Hakim, 2021). Proxies are excluded if they have less than 25 years of overlap with the calibration data, have correlations below 0.05 with the calibration data, or have residual annual autocorrelations exceeding 0.9, as in Meng et al. (2025).

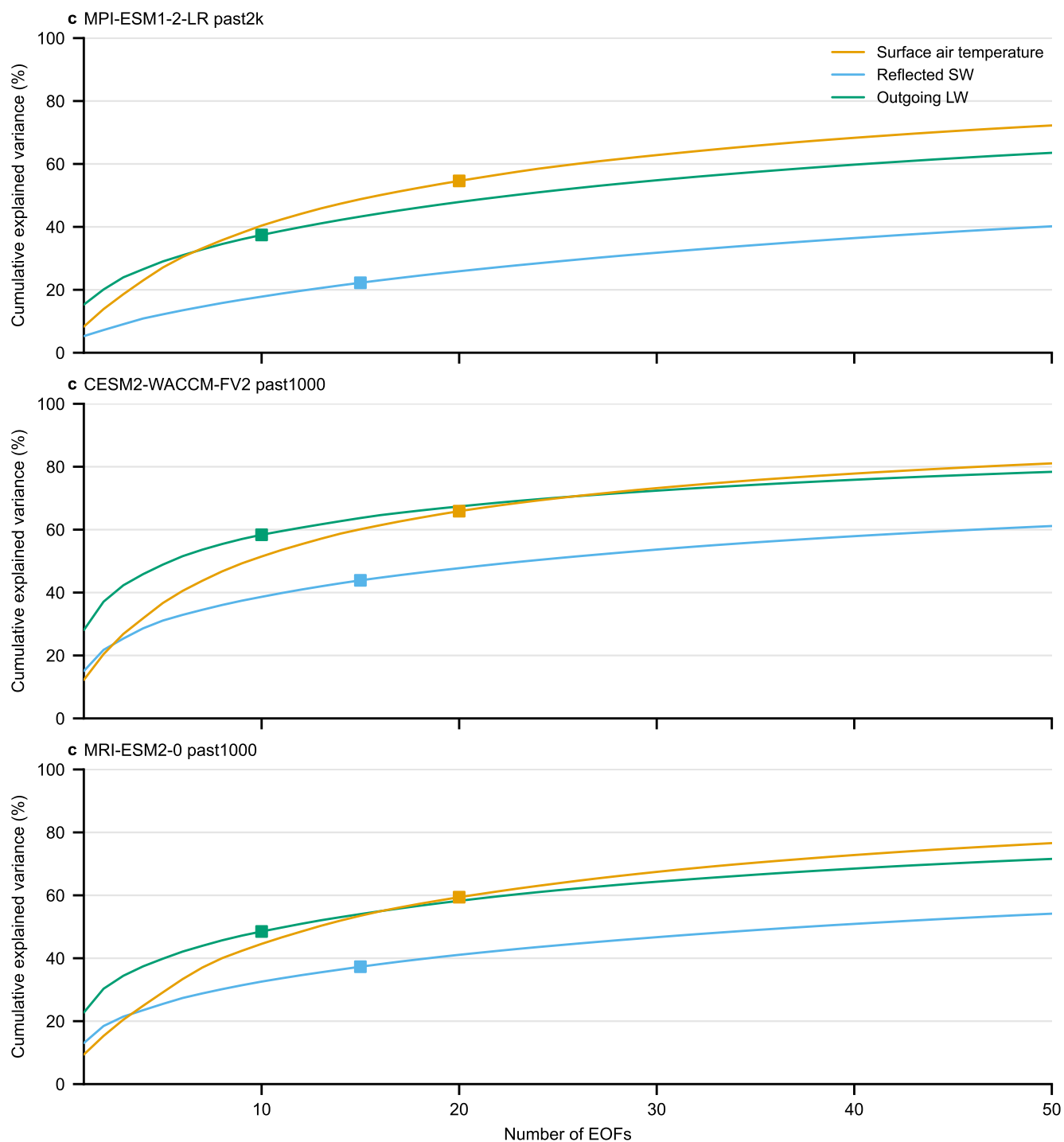


Fig. S1. Fraction of explained variance as a function of the number of EOFs, for three last-millennium simulations (up to 1850) used to train LIMs. We truncate the EOFs as follows, also indicated by the squares: 20 for SAT, 15 for RSR, 10 for OLR, 30 for EEI. SAT and OLR have a few dominant modes, particularly in CESM2. RSR and thus EEI are more noisy, and even with 30 EOFs for EEI, we explain only 35–50% of the variance.

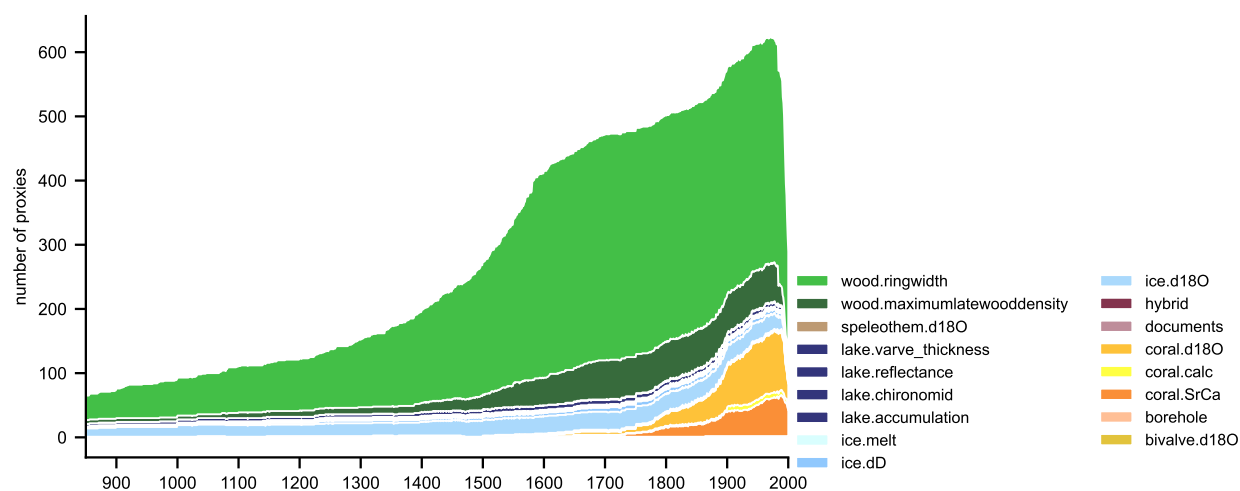
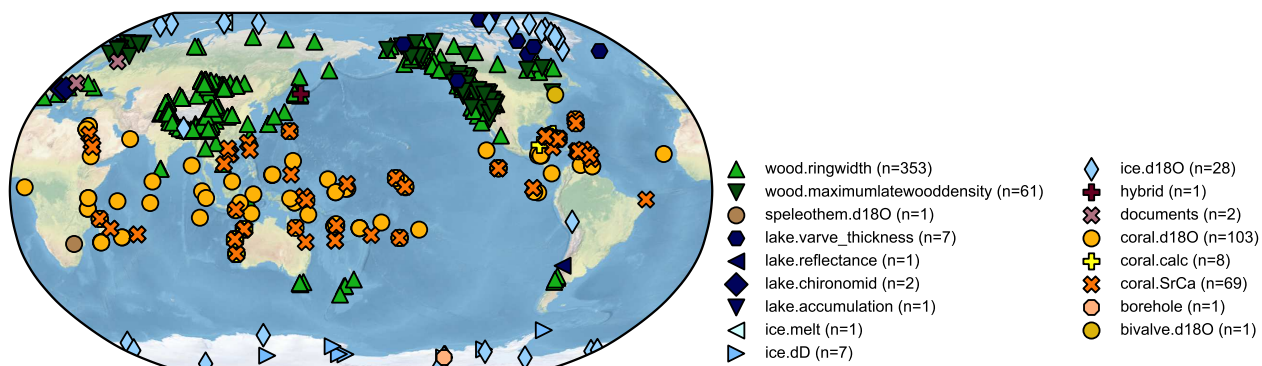


Fig. S2. Proxy network after calibration comprising the PAGES2k (PAGES 2k Consortium, 2017) and CoralHydro2k (Walter et al., 2023) databases, and the Dee et al. (2020) coral proxy. The proxy availability increases drastically after 1500, and most corals only start after 1700.

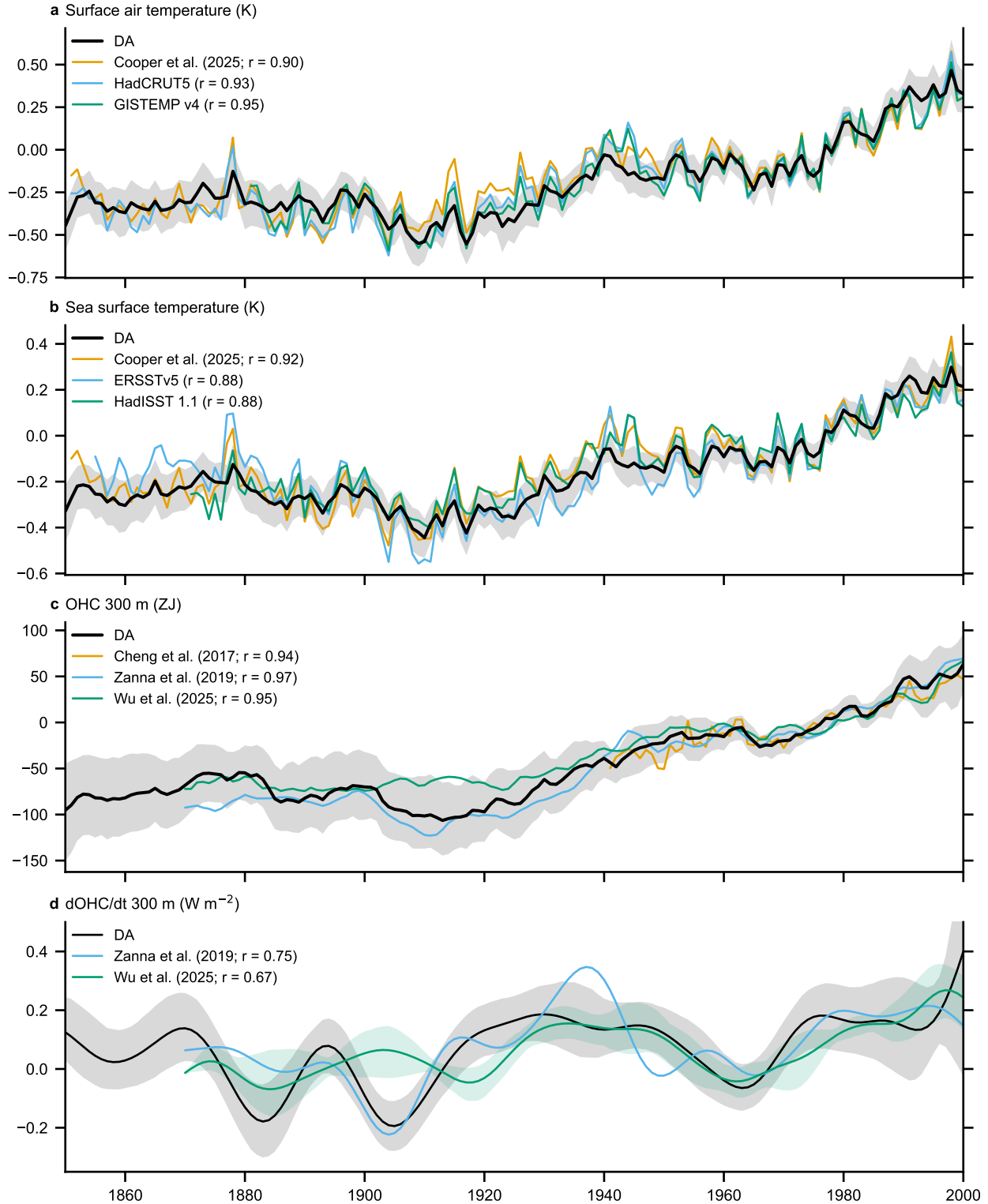


Fig. S3. Annual-mean global-means over 1850–2000. Panels (a–c) show anomalies relative to 1961–1990, (d) shows absolute values. Instrumental/observation-based products and their annual correlation with our reconstruction are shown in color. Shading denotes the very likely range. Compared to the instrumental time series, our proxy-based reconstruction generally has less interannual variability due to the smoothing effect of averaging over the ensemble and the low signal-to-noise ratio in proxies. However, the decadal variability is very similar. The instrumental datasets are Cooper et al. (2025), HadCRUT5 (Morice et al., 2021), GISTEMP v4 (GISTEMP Team, 2025), ERSST v5 (Huang et al., 2017), HadISST 1.1 (Rayner et al., 2003), Wu et al. (2025), Zanna et al. (2019), and Cheng et al. (2017).

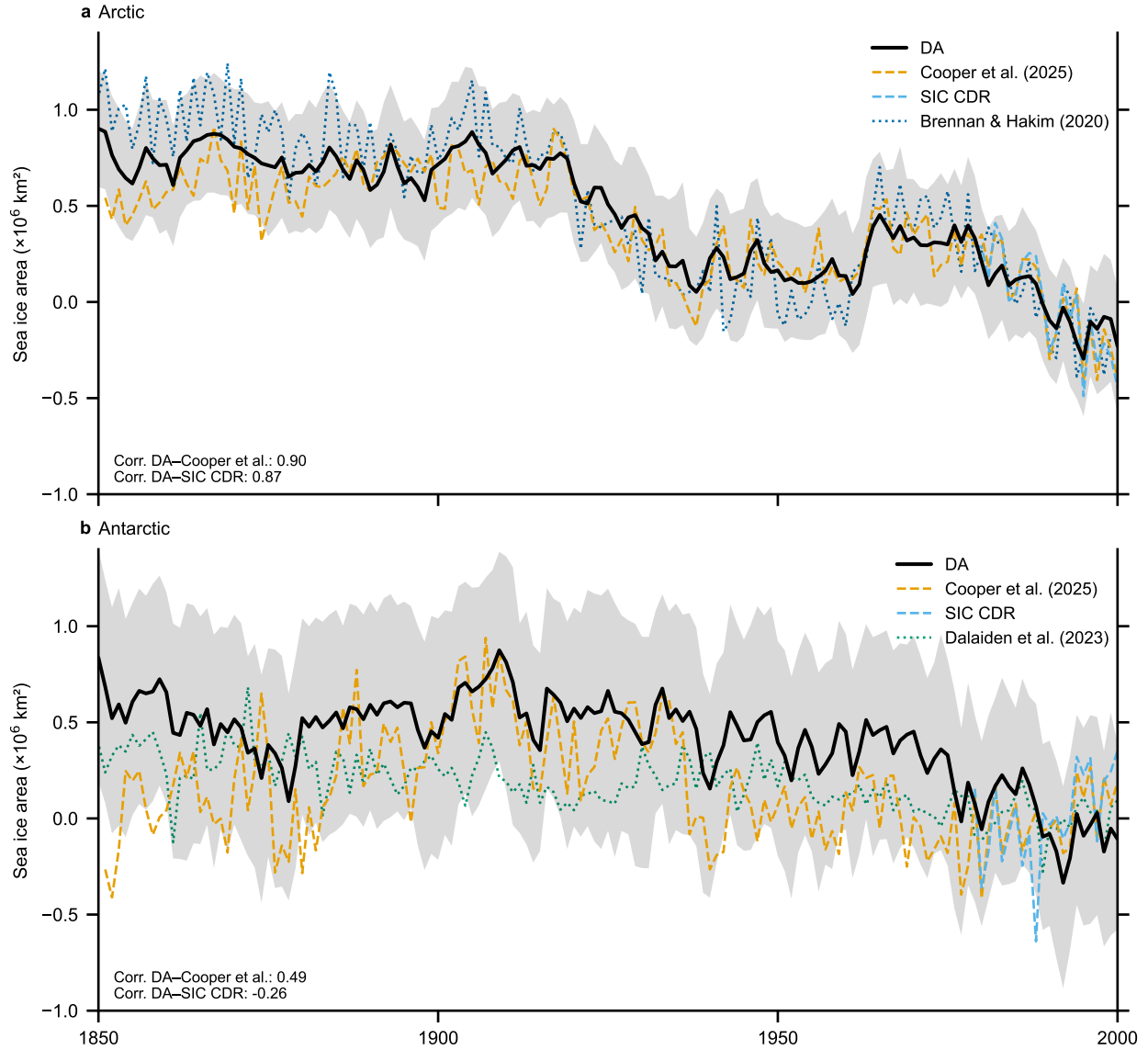


Fig. S4. Annual-mean sea ice area over 1850–2000, expressed as anomalies relative to 1979–2000. Reconstructed Arctic sea ice tracks closely the Cooper et al. (2025) reconstruction, based on DA of instrumental observations, and the NSIDC SIC CDR (Meier et al., 2024, assimilated by Cooper et al., 2025). Antarctic sea ice does not have much interannual skill but has similar decadal variability to Cooper et al. (2025), although their reconstruction relaxes to zero anomaly in the 1800s due to observation sparsity. We also show two other proxy-based reconstructions. The Arctic sea ice area from Brennan and Hakim (2022) agrees well with the other reconstructions, while the Antarctic sea ice area from Dalaiden et al. (2023) appears to be low-biased. Shading denotes the 5th–95th percentile range.

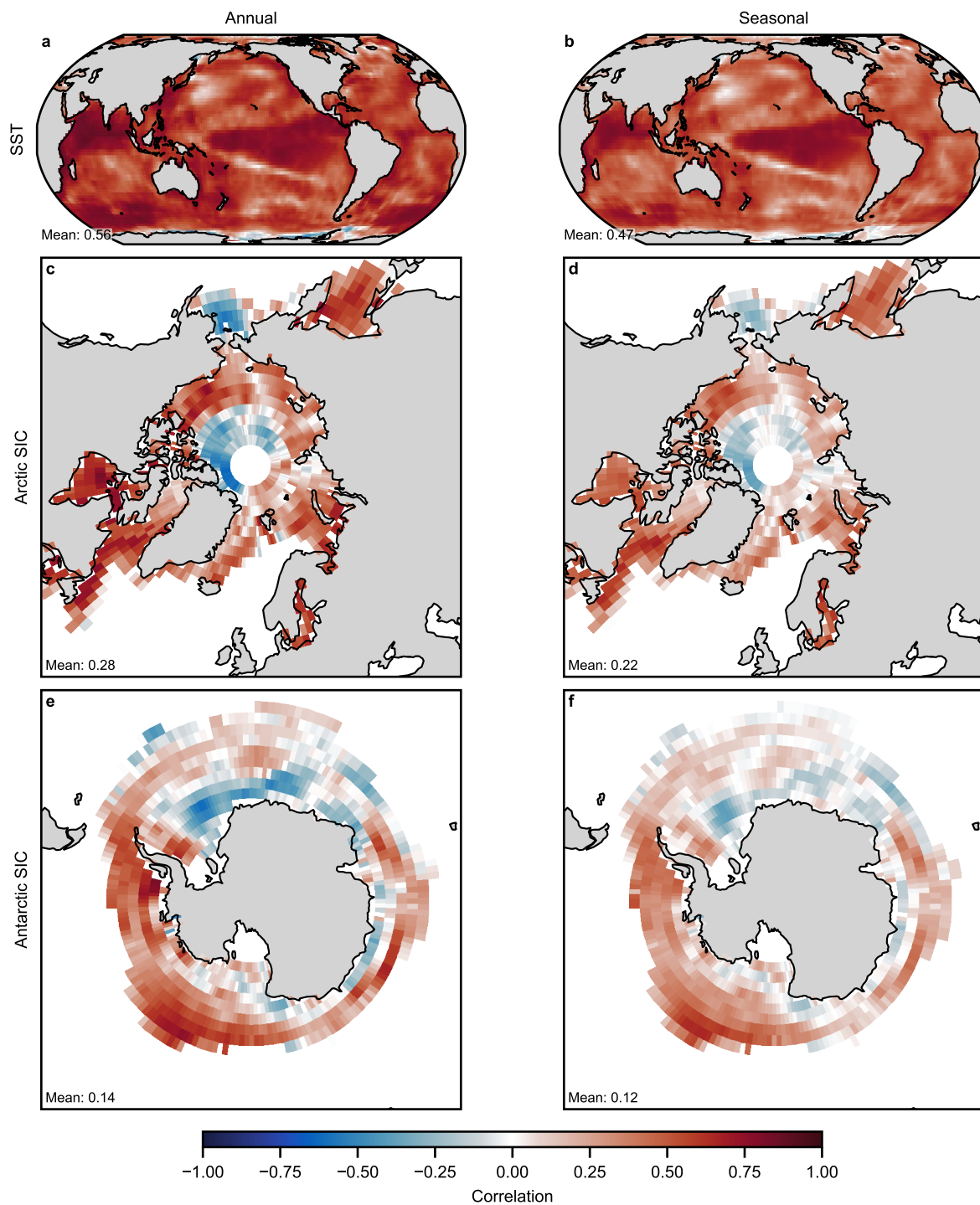


Fig. S5. Correlations of seasonal and annual-mean SST and SIC reconstruction with instrumental products (HadISST 1.1 over 1870–2000, Rayner et al., 2003; NSIDC SIC CDR V5 over 1979–2000, Meier et al., 2024). No satellite SIC data is available for latitudes above 85° due to the pole hole. Lower SIC skill is found in Arctic regions of perennial sea ice and off the coast of East Antarctica and the Weddell Sea. Note that much of the negative correlations for Arctic SIC in (c,d) are in regions of perennial ice cover, for which anomalies are very small.

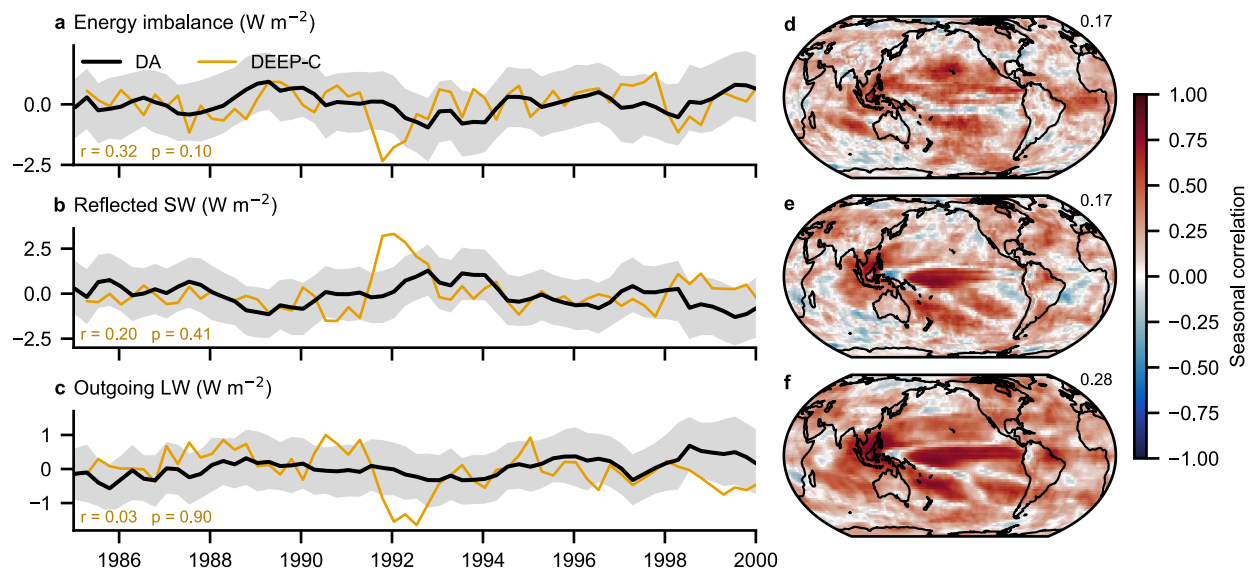


Fig. S7. As in Fig. 3 but at seasonal resolution. The reconstruction agrees with DEEP-C at multiannual timescales but does not capture the 1991 Pinatubo eruption well. We note that proxy availability falls off quickly toward 2000 (see Fig. S2) and that the seasonal correlations are relatively low and not statistically significant due to the short record and high temporal autocorrelation.

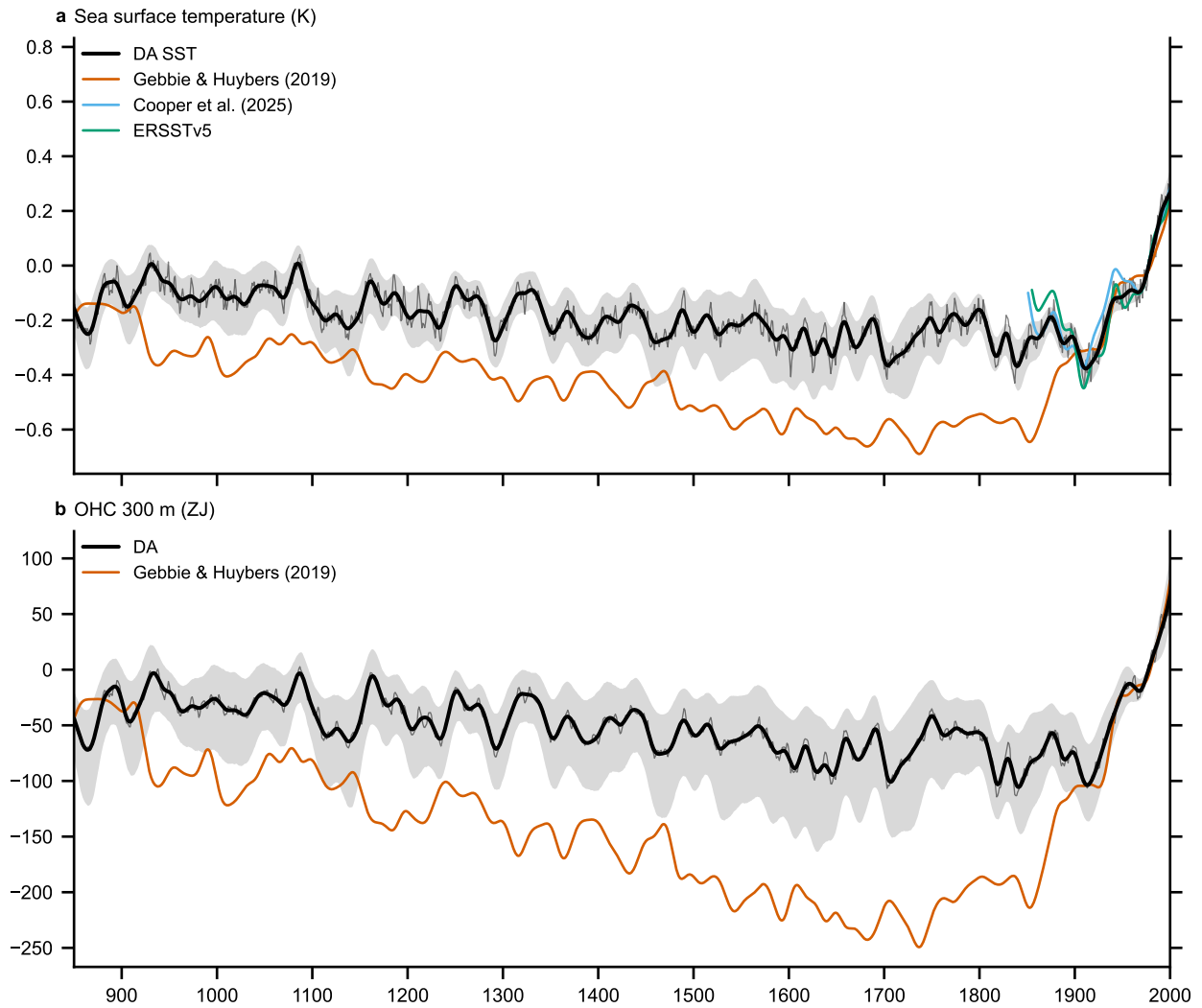


Fig. S8. As in Fig. 5 but for miscellaneous fields, shown as anomalies relative to 1961–1990. The SST and OHC from Gebbie and Huybers (2019), based on SSTs from Ocean2k (McGregor et al., 2015), are systematically colder over the last millennium and start to warm about 200 years before our reconstructed SST and OHC. Over 1850–1900, Gebbie and Huybers (2019) is the only dataset that warms. Possibly this is related to way they prescribe subducted SSTs. They use instrumental winter SSTs when available, but annual-mean SSTs before that, with linear blending over 1870–1950.

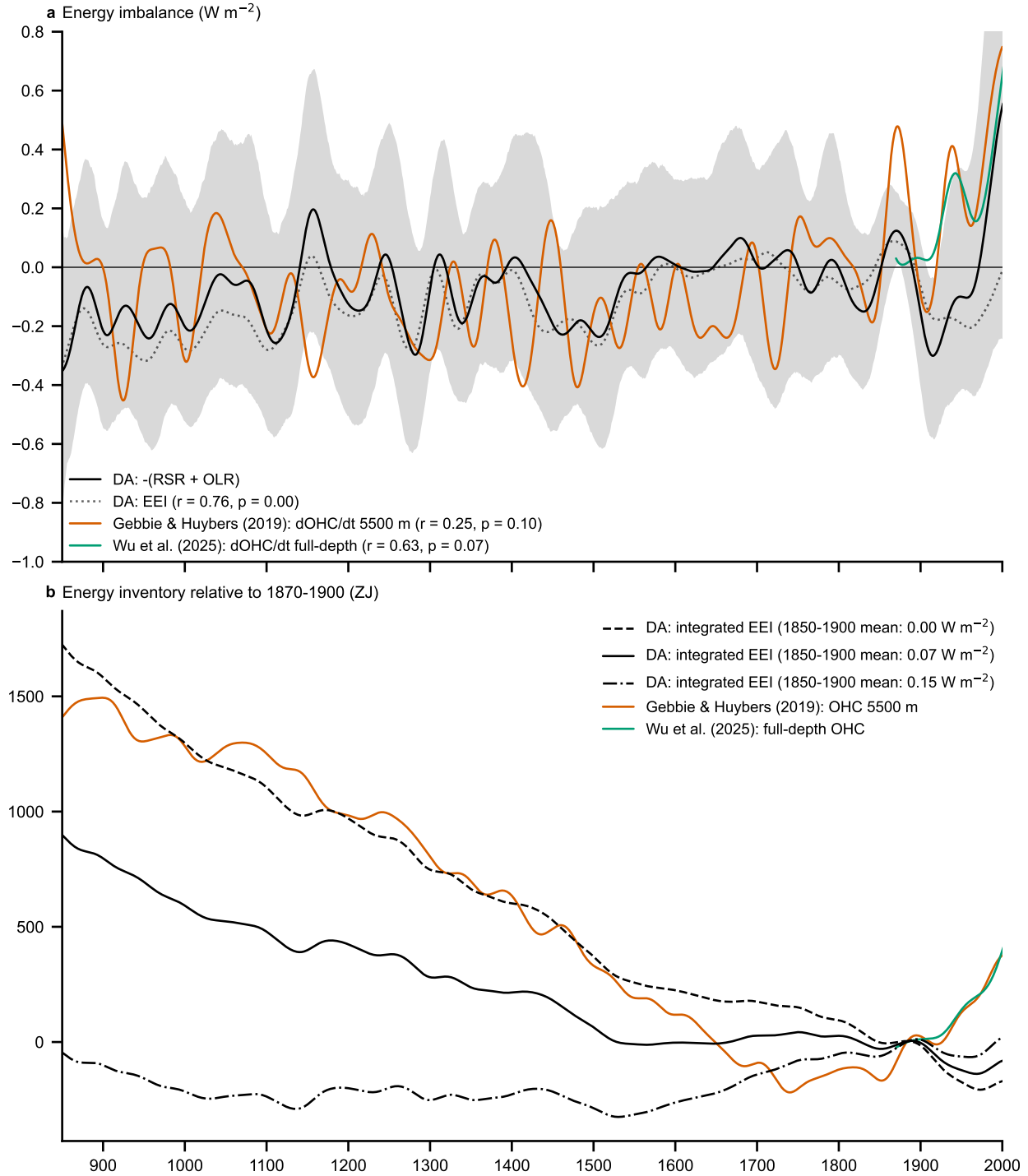


Fig. S9. Estimates of Earth's energy budget over the last millennium. We divide ocean heat content estimates by 90%, which is the fraction of energy imbalance absorbed by the ocean (von Schuckmann et al., 2023). We also rescale dOHC/dt values by Earth's ocean fraction (71%) to obtain the equivalent EEI. (a) EEI, or rate of change of total energy content. For our reconstruction, we show $-(\text{RSR} + \text{OLR})$, which is presented as EEI in the main text, and the EEI that is directly reconstructed but unphysical over the 1900s. We make them absolute by shifting to a zero-mean during 1600–1900 (see below). We compare them to the rate of OHC change from the Gebbie and Huybers (2019) and Wu et al. (2025) reconstructions, who both use Green's functions to subduct surface temperatures into the ocean interior. Correlations are for 50-yr low-pass-filtered values. The p-values test whether the correlations between our EEI and their time series are statistically significantly different from zero, as determined using the random-phase test from Ebisuzaki (1997). (b) Earth's energy inventory, or cumulative energy content, which is closely related to the full-depth ocean heat content. All time series are anomalies relative to 1870–1900. We convert our reconstructed EEI anomalies to absolute values before integration, which amounts to adding a linear function to the cumulative energy content. We show the integration for different values of the offset, expressed as 1850–1900 mean: 0.00 W m^{-2} , which best matches the time series of Gebbie and Huybers (2019); 0.07 W m^{-2} , which corresponds to a zero EEI over 1600–1900, consistent with the constant temperatures over this period, and used in the main text; and 0.15 W m^{-2} , the maximum offset so that there is a net energy loss over 850–1850.

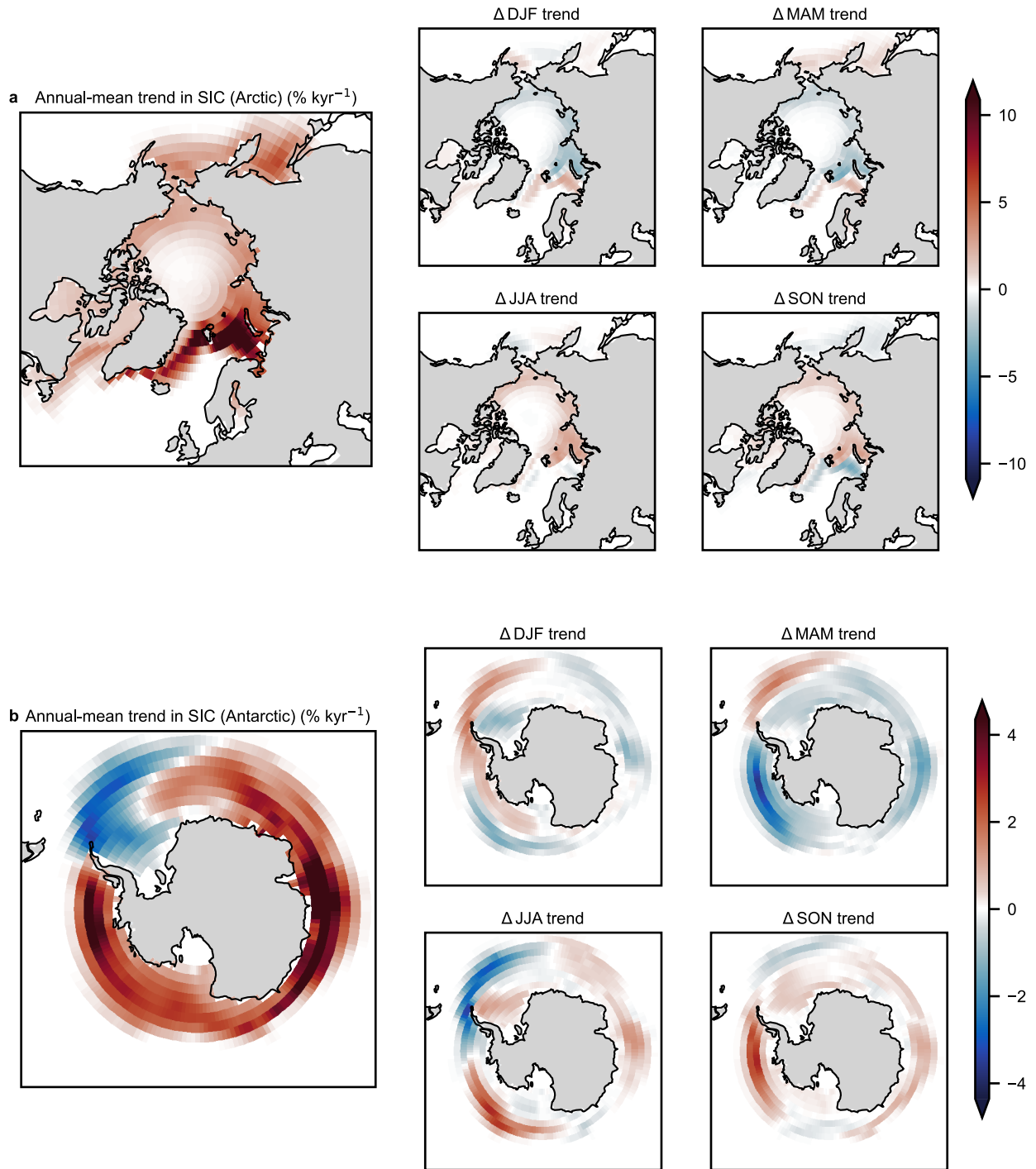


Fig. S10. Linear sea ice trend over 850–1850. (a) Annual-mean trend and (b–e) departures in seasonal trends from the annual-mean trend. Sea ice generally expanded in all seasons in both hemispheres. The reduction in the Weddell Sea may not be real, considering the low reconstruction skill there (cf. Fig. S4), but the ensemble spread is also large in this region.

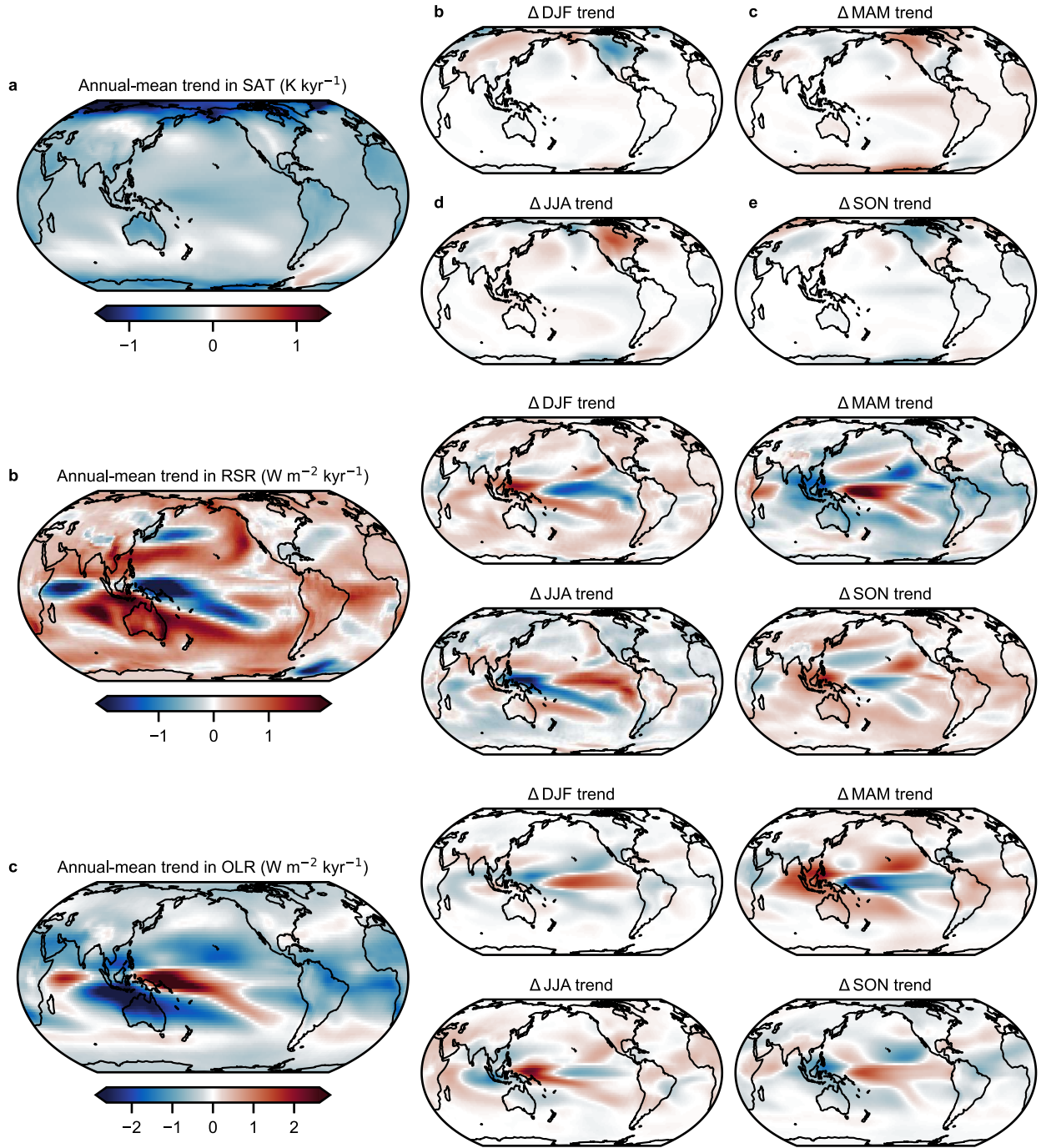


Fig. S11. Linear trends in temperature and radiation fields over 850–1850. (a) Annual-mean trend and (b–e) departures in seasonal trends from the annual-mean trend. The radiation field trends give insight into the physical processes governing the feedbacks and forcings. The OLR trend suggests a southwestward shift of the Indo–Pacific convective region, similar to a negative ENSO phase but with additional hemispheric asymmetry. Stratus cloud decks appear to expand in the Northern Hemisphere but contract in the Southern Hemisphere.

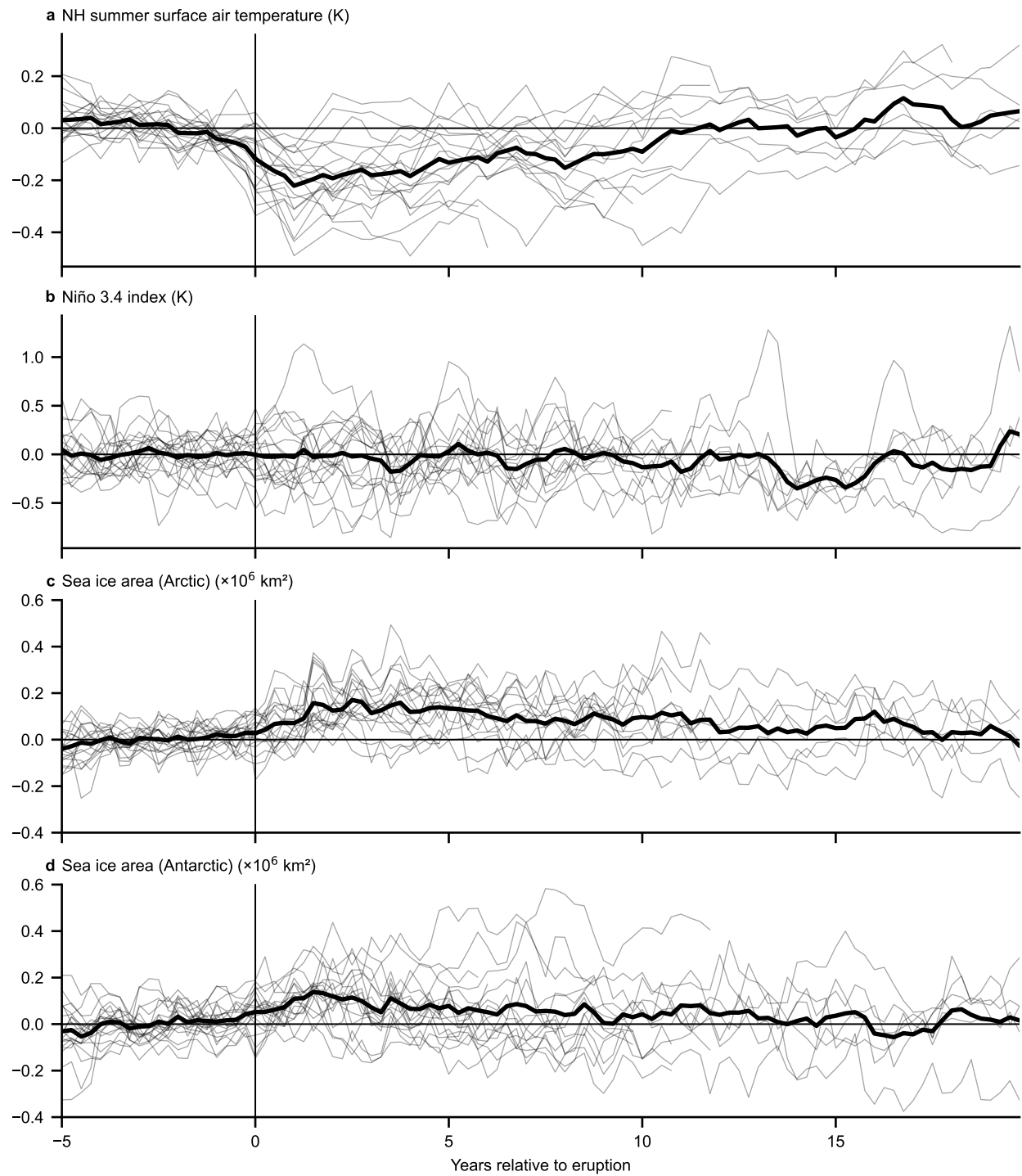


Fig. S12. As in Fig. 9 but for miscellaneous fields.

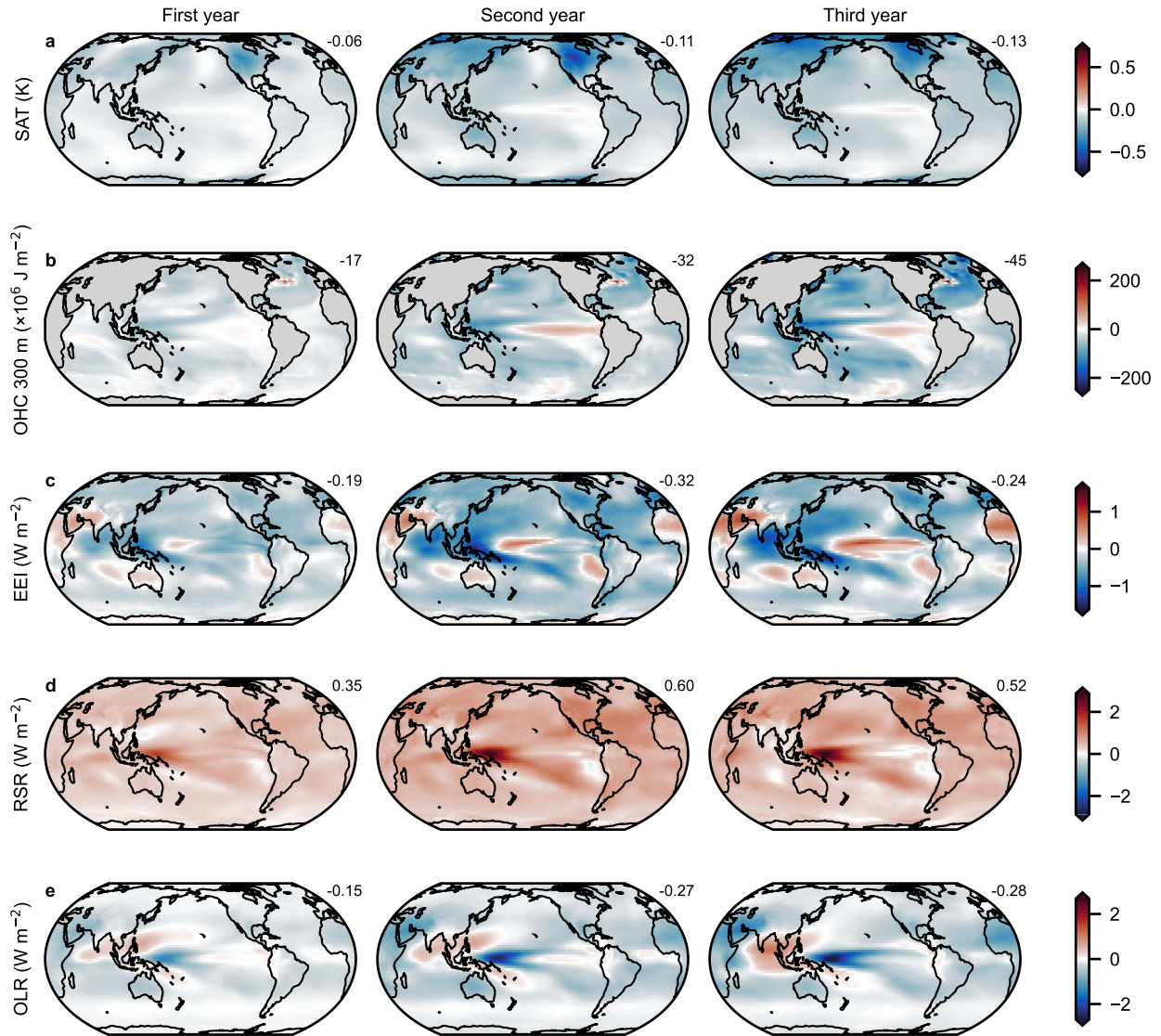


Fig. S13. Composite of volcanic eruption anomalies as in Fig. 9, but gridded and averaged over each post-eruption year. Numbers in the top right corners represent global-mean values. The cooling is global but enhanced over NH continents, which is possibly a result of the proxy distribution. The RSR is positive globally, likely due to the dispersal of stratospheric aerosols, while the OLR response is mostly negative. The net EEI response is slightly positive, owing to the strong RSR forcing.

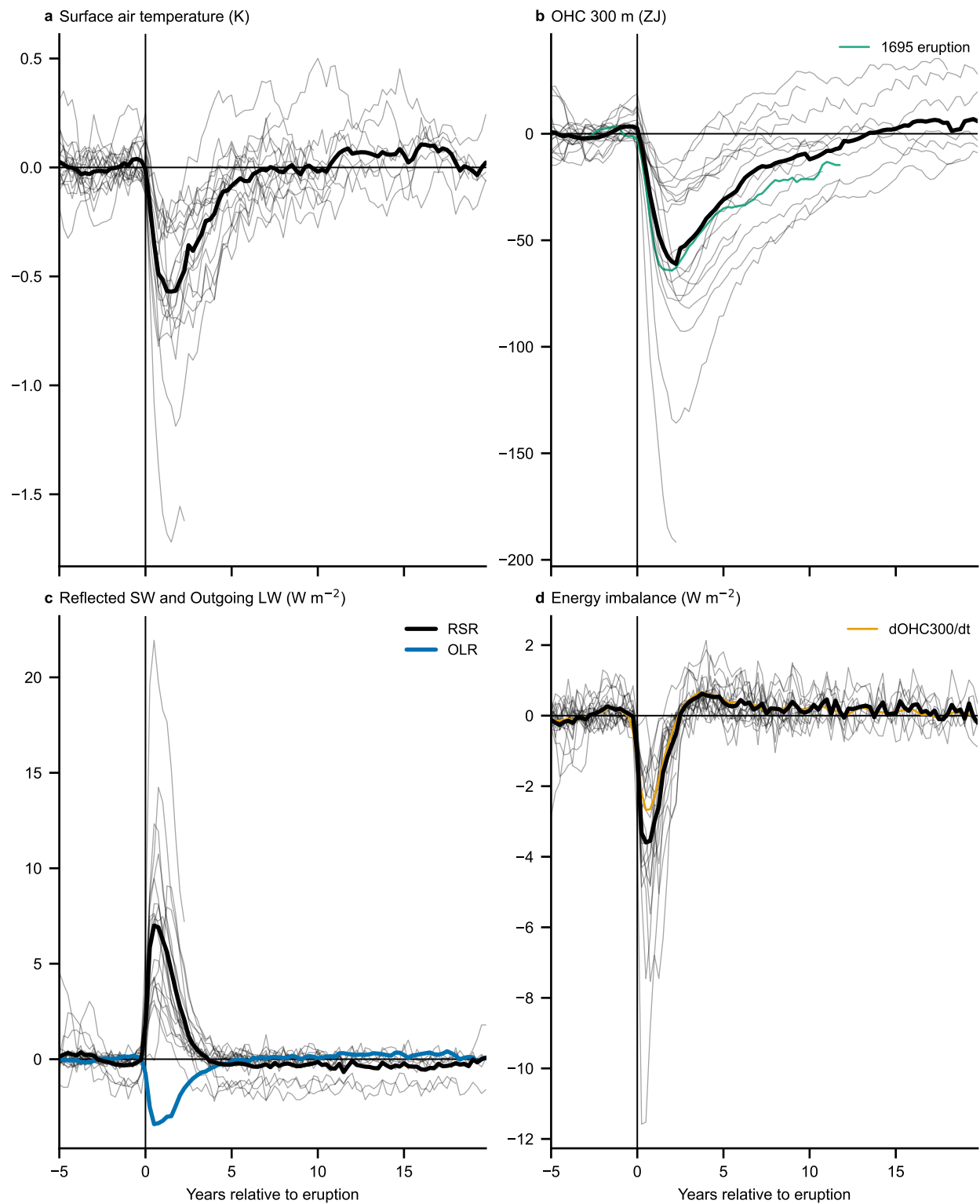


Fig. S14. As in Fig. 9 but for CMIP6 last-millennium simulations, averaged over four models (MPI-ESM1-2-LR, CESM2-WACCM-FV2, and MRI-ESM2-0, MIROC-ES2L).

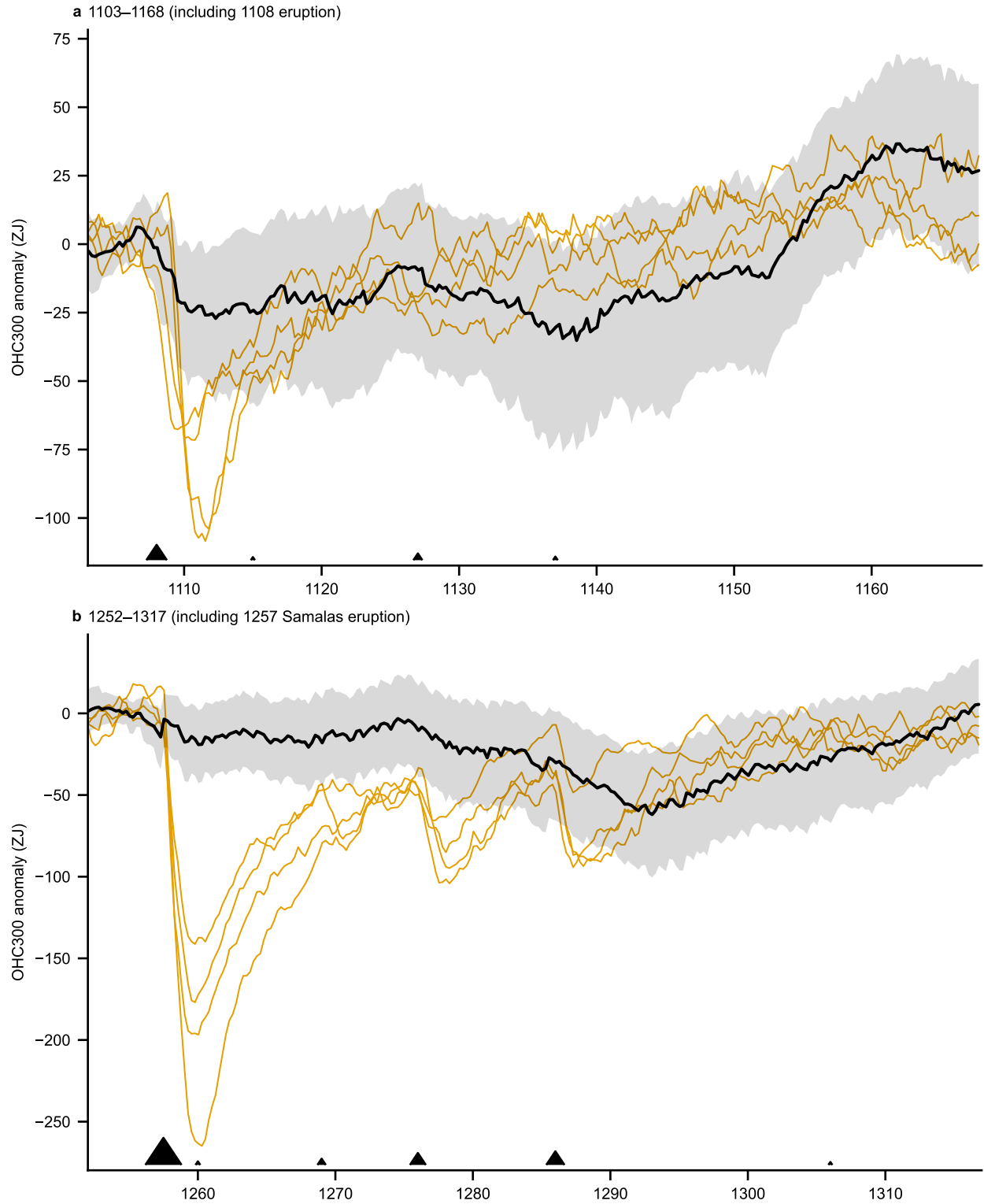


Fig. S15. Upper-ocean OHC anomalies over periods with clusters of volcanic eruptions, relative to the first five years of the periods. Shown are the reconstruction (black) with the very likely range and the CMIP6 past1000 simulations from the MPI, CESM, MRI, and MIROC models (yellow). The carets indicate volcanic eruptions, scaled by their volcanic stratospheric sulfur injection. (a) During 1103–1168, four eruptions occur, leading to an OHC loss of 35 ZJ. (b) During 1252–1317, six eruptions occur. The 1257 Samalas eruption is barely evident in our reconstruction (cf. Zhu et al., 2020), but the compound effect of the 1276 and 1286 eruptions, thought to have initiated the Little Ice Age, leads to large OHC loss. Figure is continued on the next page.

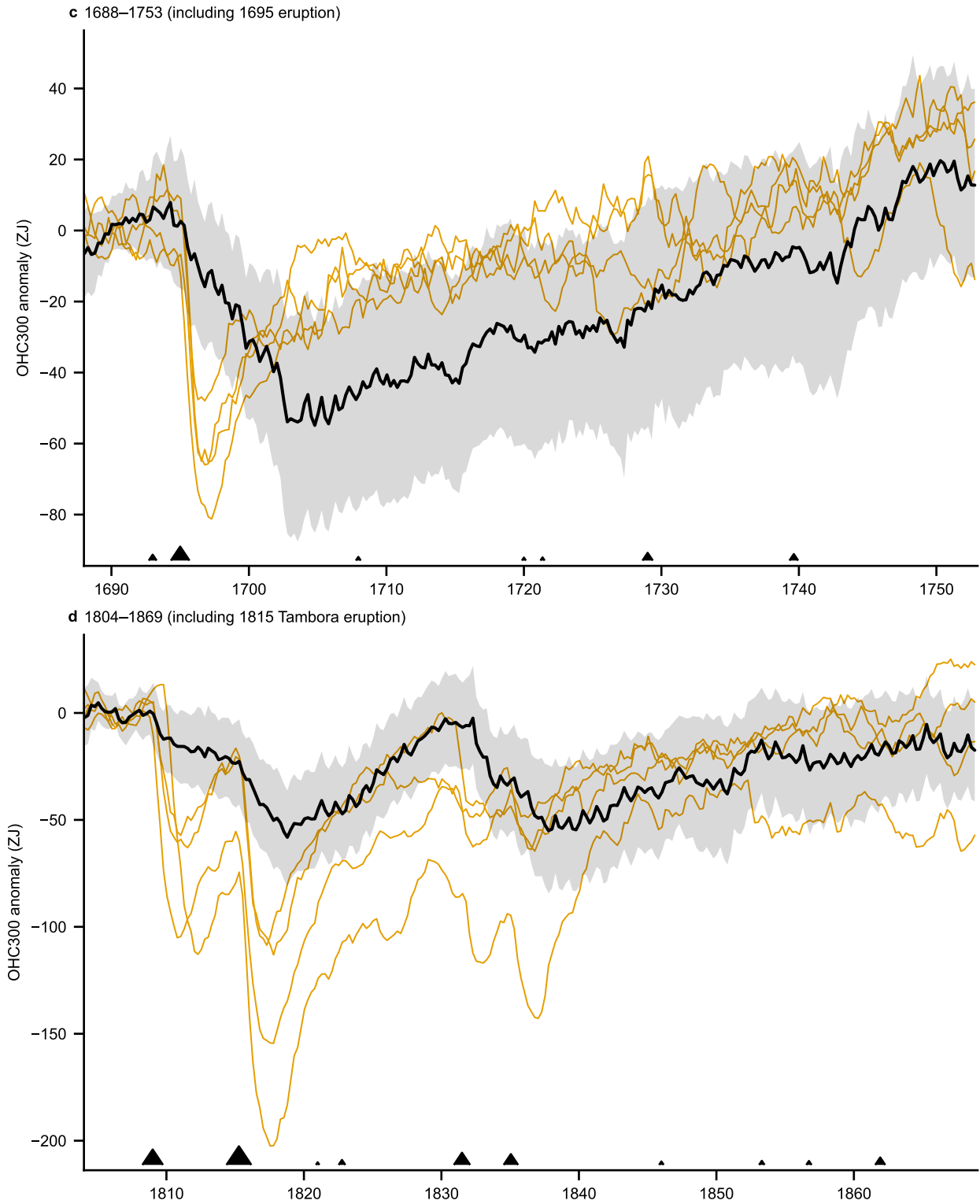


Fig. S15 (cont.). (c) During 1688–1753, seven volcanic eruptions occur, leading to an OHC loss of 55 ZJ over 10 years and a prolonged recovery period of 40 years. (d) During 1804–1869, ten eruptions occur, including the 1815 Tambora eruption. This leads to an OHC loss of 58 ZJ that recovers over 10 years, followed by an OHC loss of similar magnitude that recovers again over 40 years. Also see (Brönnimann et al., 2019) for this period.

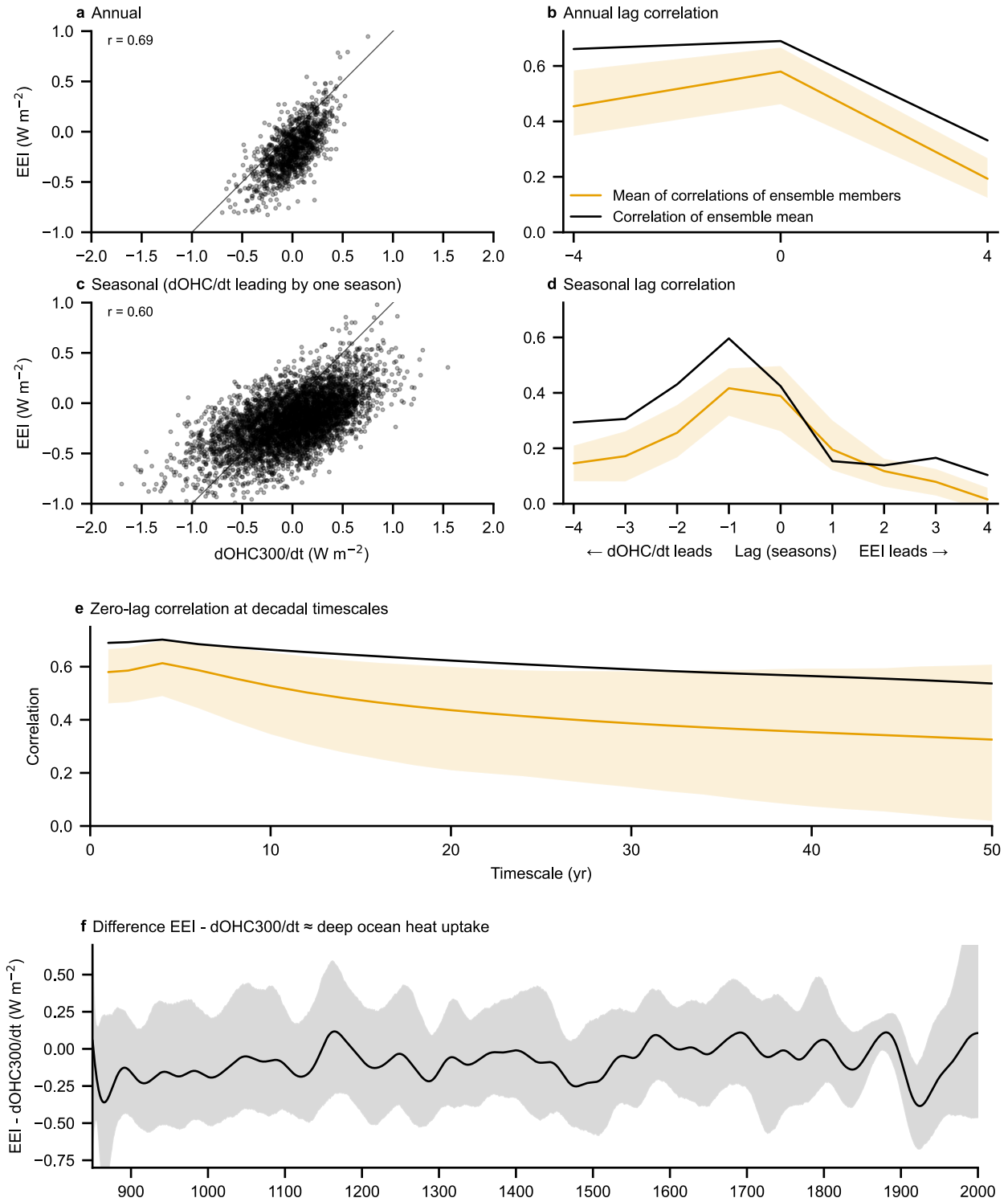


Fig. S16. Comparison of global-mean EEI and dOHC300/dt. We rescale dOHC300/dt by Earth's ocean fraction (71%) to obtain the equivalent EEI. (a,b) At annual timescales, they have a correlation of 0.60 and a similar standard deviation of around 0.25 W m^{-2} . (c,d) At seasonal timescales, dOHC300/dt leads by one season as shown by the maximum lag correlation of 0.50. The scatter plot (c) considers this lag. However, the standard deviations differ: 0.42 W m^{-2} for dOHC300/dt, and 0.27 W m^{-2} for EEI. (e) Zero-lag correlation at decadal timescales, determined by low-pass-filtering both time series. The correlation peaks at 4 years, then slowly decays for longer timescales. (f) Difference between dOHC300/dt and EEI, which can be interpreted as deep ocean heat uptake. The EEI is made absolute by shifting to a zero-mean during 1600–1900. The difference is 50-yr low-pass-filtered. Shading denotes the 5th–95th percentile range.

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