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Forced and Internal Variability of Ocean Temperature Diagnosed via Multi-Model Ensemble Linear Dynamical Mode (M-ELDM) Decomposition

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Abstract

State-of-the-art Earth System Models (ESM) produce variability in the simulated ocean temperatures mostly consistent with the observed, historical climate behavior but can have divergent trajectories in their future-climate projections. Any attempts to constrain this projection uncertainty require, first of all, a careful examination and comparison of the models' performance over the historical period. Here we develop a new objective methodology for such an intercomparison rooted in the Linear Mode Mode (LDM) decomposition and apply it to the analysis of sea-surface temperature (SST) and upper-ocean heat content (OHC) anomalies generated by a multi-model ensemble of historical climate simulations. The resulting multi-model ensemble LDM (M-ELDM) method is shown to be an

efficient tool for identifying the optimal low-dimensional subsets of forced and internal climate modes with patterns and characteristic time scales shared across the individual models and the associated time series encapsulating the differences between the models. We present examples of the M-ELDM based model intercomparison in terms of their dominant forced response, as well as their interannual-to-subdecadal and multidecadal internal variability. We also devise a strategy for ranking these behaviors against observations and demonstrate, in particular, the absence in the models of a pronounced multidecadal signals evident in the observational data.

Keywords: Climate change, Earth System Models, ocean temperature, forced response, internal variability

1 Introduction

The ocean is absorbing about 90% of the excess heat produced by the radiative forcing due to climate-system adjustments to natural and anthropogenic drivers, such as increasing concentrations of greenhouse gasses (GHGs) in the atmosphere (Hansen et al. 2011; Trenberth et al. 2009). Observations of the global ocean heat content (OHC) and sea-surface temperature (SST) in recent decades show clear upward trends (Domingues et al. 2008; Levitus 2012; Cheng et al. 2019). These trends, while largely forced, are nonuniform in space and time and apparently modulated by internal climate modes operating on a wide range of scales (Ting et al. 2009; DelSole et al. 2011; Trenberth and Fasullo 2013). Examples of the latter modes include the predominantly interannual El Niño–Southern Oscillation phenomenon (ENSO: see, for example, Wang et al. 2017) in the tropical Indo-Pacific, Pacific Decadal Variability (PDV: Di Lorenzo et al. 2023) and low-frequency variability in the North Atlantic associated with the Atlantic Multidecadal Oscillation (AMO: Zhang et al. 2019). Recent studies (e.g., von Schuckmann et al. 2020) have argued that OHC is a more relevant metric than SST to track the forced component of the global climate change.

Irrespective of the metric (SST or OHC), accurate delineation of the forced signal from the background internal variability is key to our understanding of future climate change. This task is nontrivial due to the sheer size and complexity of the climate system (see, for example, Palmer 1999). A standard solution utilizes Earth System Model (ESM) ensembles, in which multiple climate realizations are obtained using single-model simulations with independent or perturbed initial conditions, yet driven by an identical history of the external forcing. For a large enough single-model ensemble, the forced signal is associated with the mean across the ensemble, while the internal variability is encapsulated in the deviations from the ensemble mean; these deviations are statistically uncorrelated between the individual climate realizations within the ensemble (Deser et al. 2014; Frankcombe et al. 2018). The number of realizations required to faithfully isolate the forced response depends on the climate variable, geographical location, and spatiotemporal scales of interest (Deser et al. 2012; Screen et al. 2014; Kravtsov and Callicutt 2017). The individual (single) model ensembles within the Coupled Model Intercomparison Project (CMIP), phases 5 or 6

(Taylor et al. 2012; Eyring et al. 2016) typically have 5–10 realizations. Some large ensemble collections, with 40–100 realizations per model, such as Multi-Model Large Ensemble Archive (MMLEA) Version 1 and 2 (Deser et al. 2020; Maher et al. 2025), Large-Ensemble project (LENS: Kay et al. 2015) and Max Planck Institute’s Grand Ensemble (MPI-GE: Maher et al. 2019), are also available.

The state-of-the-art ESMs are known to exhibit differences in the simulated climate behavior due to their different spatial resolutions and different parameterizations of sub-grid scale physical processes. These differences translate to a large uncertainty of future climate projections, with similar uncertainty levels throughout all generations of the ESM models to date (Hawkins and Sutton 2009; Lehner et al. 2020). In attempts to reduce this uncertainty, it is therefore important to identify which aspects of the forced response and internal variability are robust across multiple climate models and how realistic these aspects are in comparison with the observed climate behavior. Wills et al. (2026) documented a concerted effort to address these questions within an ambitious ForceSMIP project, which evaluated state-of-the-art forced-response identification methods using large multi-model ESM ensembles, with the ultimate goal of devising an optimal strategy for estimating the forced signal from a single climate realization, either simulated or observed.

The forced-signal estimation methods discussed in Wills et al. (2026) are typically based on certain assumptions about spatiotemporal differences between the forced response and the internal variability of the simulated climates. For example, the dynamical adjustment methods seek to remove the influence of high-frequency (typically atmospheric) internal variability on a variable of interest (such as near-surface atmospheric temperature) by regression against a “dynamical” variable representing the effects of atmospheric circulation (e.g., mean sea-level pressure) (Wallace et al. 2012; Smoliak et al. 2015; Deser et al. 2016). Such a procedure may increase the forced-signal-to-internal-noise ratio in the residual trends, with some caveats related to the need of differentiating between the impacts from multiple sources of internal variability (for example, ENSO: Thompson et al. 2009). Another class of methods assume significant time-scale separation between the forced and internal climate variability by postulating the forced signal to be associated with a set of patterns that vary on time scales longer than those of the internal variability (Schneider and Held 2001; Frankignoul et al. 2017; Wills et al. 2018). One of the most efficient methods to isolate the forced trends that are common across the single-model ensemble of simulations from the internal variability is the signal-to-noise maximizing pattern (S/NP) analysis of Wills et al. (2020), which seeks the fingerprinting patterns that maximize the ratio of ensemble-mean-to-total variance in the variable of interest. This method is free of any assumptions about characteristic time scales of forced or internal variability, but, to be effective, still requires the two kinds of variability to have distinct spatial patterns.

The pattern recognition technique we focus on in this paper is based on the Linear Dynamical Mode (LDM) decomposition (Gavrilov et al. 2019, 2020, 2024) of the observed or simulated climate variability into the set of spatiotemporal modes ranked by their respective time scales. The latter property makes the LDM methodology conceptually similar to such alternative linear decomposition methods as optimal persistence patterns (OPP: DelSole 2001), average predictability time (APT: DelSole and

Tippett 2009a,b) and dynamic mode decompositions (DMD: Mezić 2005; Williams et al. 2015; Mankovich et al. 2025, 2026). However, the LDM methodology is not obtained via rotation of the original data, and all of the requisite LDM parameters, including the number of distinct modes and their time scales, are instead determined objectively within a Bayesian framework, which ensures the decomposition of optimal complexity void of overfitting. The original version of the method (Gavrilov et al. 2019) did not distinguish in any way between the forced and internal climate modes. Gavrilov et al. (2020) extended this methodology by specifying, additionally, the temporal shape of the single forced component based on a separate analysis of a multi-model ESM ensemble of historical simulations. The spatial pattern of the forced component, as well as the remaining LDM modes of the residual, nominally internal variability in the near-surface air-temperature, were jointly computed by the LDM algorithm. Finally, Gavrilov et al. (2024) developed a version of the LDM method — ensemble LDM method (ELDM)— for the use with an ensemble of single-model climate simulations. This most complete method provides data-adaptive, self-consistent decomposition of the simulated climate variability into the forced signal and internal variability modes with their own spatial patterns and time scales. The forced signal is postulated to be the same in each of the simulated climate realizations, whereas the internal variability modes have the same patterns but different time dependence across multiple model runs. The major distinction of LDMs from the dynamical adjustment, time-scale separation and other variance-ratio based pattern recognition methods is thus the absence of any *a priori* assumptions about spatiotemporal differences between the forced and internal modes.

In this work we adapt the single-model (S) ELDM method of Gavrilov et al. (2024) for the analysis of the forced and internal variability in SST and OHC across a multi-model (M) ensemble of historical climate simulations. In the resulting M-ELDM method, the forced signal and internal variability modes are each postulated to have common (*a priori* unknown) patterns but different component time series across the models; for a given model, the forced-signal components are also postulated to be the same across this model’s climate realizations, thereby naturally delineating them from the internal modes (which have different time dependence in different realizations), as in the original S-ELDM method. The new method thus constructs an optimal, low-dimensional representation of the forced signal and internal variability simulated by multiple models in the common spatial basis. The differences between the models are encapsulated in those between the component time series associated with each (forced or internal) LDM pattern, which provides a useful lens for comparing the model behaviors across the multi-model ensemble. We also develop an LDM-based recipe for evaluating similarities and differences between the simulated and observed climate modes derived from the gridded observational products.

The M-ELDM decomposition developed in this work provides a succinct characterization of the model uncertainty in representing the forced global warming trends, and offers a useful framework for assessing the role of the different physical drivers underlying the observed climate change, including, for example, the much debated role of anthropogenic and natural aerosols in forcing the North Atlantic SST variability (Booth et al. 2012; Zhang et al. 2013; Murphy et al. 2017; Bellomo et al. 2018;

Birkel et al. 2018). It also helps assess and compare key aspects of the internal climate variability associated with ENSO, PDV and AMO across models, in particular those related to the ENSO asymmetry and diversity (Planton et al. 2021), as well as to the teleconnections of the Pacific Decadal Oscillation (Fasullo et al. 2020) which, together with multidecadal AMO-like signal, arguably represent a globally connected mode of climate variability associated with the so-called Global Stadium Wave (GSW: Wyatt et al. (2012); Kravtsov et al. (2018, 2024, 2025)).

The rest of the presentation is organized as follows. Section 2 introduces the historical simulations and gridded observational products used here and outlines the data pre-processing steps (section 2.1). It also describes the M-ELDM decomposition (section 2.2), the methodology for analyzing the M-ELDM filtered data subsets (section 2.3), as well as our LDM-based treatment of the observational data (section 2.4). Section 3 analyzes and compares our estimates of the climate’s observed and simulated forced response (section 3.1), the residual low-frequency (decadal and longer time scale) variability (section 3.2) and ENSO variability (section 3.3). Section 4 summarizes and discusses the results and outlines some perspectives for future research.

2 Data and methods

2.1 Data sets

2.1.1 Model simulations

We analyzed output from historical climate simulations produced by $K = 6$ state-of-the-art climate models, focusing on the analysis of sea surface temperature (SST) and sea water potential temperature on a global grid. Five of these models — CESM2 Danabasoglu (2019), HadGEM3-GC31-LL Ridley et al. (2019), CanESM5 Swart et al. (2019), MPI-ESM1-2-LR Wieners et al. (2019), and INMCM5 Volodin et al. (2019) — are a part of the CMIP6 multi-model ensemble, while the sixth model is a new version of the INMCM climate model (INMCM6P) with improved parametrization of clouds, large-scale condensation, and aerosols (Volodin 2023; Volodin et al. 2024). The upper ocean heat content (OHC) data are obtained by the vertical integration of potential temperature over the top 0–300 m layer at each grid node:

$$OHC = \rho C_p \int_0^{300} \theta(z) dz, \quad (1)$$

where $\rho = 1026 \text{ kg/m}^3$ and $C_p = 3990 \text{ J/(kgK)}$ are sea-water density and heat capacity, respectively, and $\theta(z)$ is the vertical profile of potential temperature.

We considered $M = 10$ ensemble members for each model over the January 1950 – December 2014 period, to match the length of the available OHC observational record (see section 2.1.2). Thus, the full multi-model ensemble consisted of $KM = 60$ realizations for both the SST and OHC fields. The resulting monthly data were interpolated onto a common $2^\circ \times 2^\circ$ spatial grid, and, after subtracting the mean seasonal

cycle, aggregated into non-overlapping 3-month averages to form the seasonally averaged data; thus, each input realization has $N = 260$ maps sampled with the 3-month sampling interval.

2.1.2 Observational products

To compare the simulated and observed climate variability, we made use of two state-of-the-art gridded observational products obtained via objective analyses of the observed data: the extended reconstructed SST (ERSST) data set, version 5 (Huang et al. 2017) and the OHC data set based on the Institute of Atmospheric Physics’ ocean temperature analysis (IAPv4: Cheng et al. 2024); both data sets have a monthly resolution. The IAPv4 OHC data are available since 1940 but are most reliable after 1950s, mainly due to an improved quality of global measurement networks and, as a result, reduced sampling errors. For this reason, we chose to restrict our analysis to the 1950–2014 period for all data sets considered here, whether simulated or observed. The observed gridded data were pre-processed in the same way as the simulated data (see section 2.1.1).

2.1.3 Data pre-processing

The multi-model LDM analysis (section 2.2) was performed separately on the SST and OHC anomalies in the phase space of their leading ensemble Empirical Orthogonal Functions (EOFs). Specifically, we stacked all of the available $KM = 60$ realizations of either field (hereafter, $k = 1, \dots, K$ is the model index and $m = 1, \dots, M$ is the realization index) along the time axis ($n = 1, \dots, N$), resulting in the sample of size KMN and computed the D leading EOFs of this data normalized, at each grid node, to have unit variance and, additionally, weighted by the square root of the cosine of latitude to account for meridian convergence on a spherical grid. The D leading principal components (PCs) so obtained were then unstacked to form the D -dimensional input multi-model data set $\mathbf{X} = \{(\mathbf{x}_1^{(m,k)}, \dots, \mathbf{x}_N^{(m,k)})\}_{m=1, \dots, M}^{k=1, \dots, K}$ to be further subjected to the M-ELDM analysis (see section 2.2.3). We used $D = 20$ EOFs for the SST data and $D = 50$ EOFs for the OHC data, describing, in each case, about 55% of their total variance (as computed for the original, non-normalized SST and OHC fields), but a vast majority of large-scale low-frequency climate variability.

Regarding the observational data, we also performed LDM analysis separately for the SST and OHC anomalies in the reduced phase space spanned by the $D = 20$ (for both SST and OHC data) leading EOFs that captured about 70% of the total SST/OHC variance.

2.2 Multi-model ensemble LDM (M-ELDM) decomposition

We start with the single-model ensemble LDM (S-ELDM) decomposition (Gavrilov et al. 2024; Buyanova et al. 2025). This method generalizes, in turn, the original single-realization LDM approaches of Mukhin et al. (2015) and Gavrilov et al. (2016, 2020) to include automatic identification of the forced and internal components from ensembles of climate-model realizations. From a machine-learning perspective, all LDM versions

can be described as a dimensionality reduction technique with specific dynamical Bayesian priors on the latent-space variables.

2.2.1 Single-Model Ensemble LDM (S-ELDM) decomposition

The S-ELDM decomposition seeks to represent a single-model M -member ensemble time series (PCs) $\mathbf{X} = \{(\mathbf{x}_1^{(m)}, \dots, \mathbf{x}_N^{(m)})\}_{m=1, \dots, M}$ of a multidimensional variable $\mathbf{x}_n^{(m)} \in \mathbb{R}^D$ as follows:

$$\mathbf{x}_n^{(m)} = \mathbf{A} \mathbf{p}_n^{(m)} + \mathbf{B} \mathbf{f}_n + \mathbf{c} + \sigma \boldsymbol{\xi}_n^{(m)}. \quad (2)$$

Here the latent low-dimensional time series (components) $\mathbf{p}_n^{(m)} \in \mathbb{R}_{d_p}$ and $\mathbf{f}_n \in \mathbb{R}_{d_f}$ are associated with the internal variability and forced signal, respectively, while the columns of matrices $\mathbf{A}$ and $\mathbf{B}$ store the corresponding spatial patterns; $\mathbf{c}$ is an intercept, and σ controls the amplitude of the Gaussian white-noise residual $\boldsymbol{\xi}_n$. Note that the internal components $\mathbf{P} = \{(\mathbf{p}_1^{(m)}, \dots, \mathbf{p}_N^{(m)})\}_{m=1, \dots, M}$ are different in each ensemble member, whereas the forced components $\mathbf{F} = (\mathbf{f}_1, \dots, \mathbf{f}_N)$ are the same in all M realizations; the latter assumption is the fundamental property which allows one to distinguish between the forced-signal and internal-variability modes.

In the absence of the forced component ($d_f = 0$) and for the case of a single realization ($M = 1$), the decomposition (2) has the same form as in the standard linear dimension reduction methods such as the principal component analysis (PCA) [also known as the Empirical Orthogonal Function (EOF) analysis] and its modifications (Jolliffe 1986; Hannachi et al. 2007), all of which minimize the residual variance in (2). However, even in this case, the LDM decomposition would, in general, be different from the EOF decomposition, as the former also stratifies the components by their characteristic time scales (see below).

2.2.2 LDM loss function

All the parameters $\boldsymbol{\mu} = (\mathbf{P}, \mathbf{F}, \mathbf{A}, \mathbf{B}, \mathbf{c}, \sigma)$ in Eq. (2) above are fit using an LDM-specific loss function $\psi(\boldsymbol{\mu})$ derived within a Bayesian probabilistic framework (Gavrilov et al. 2024; Buyanova et al. 2025). This function consists of three parts:

$$\psi(\boldsymbol{\mu}) = \mathcal{L}_{main}(\boldsymbol{\mu}) + \mathcal{L}_{smooth}(\mathbf{P}, \mathbf{F}) + \mathcal{L}_2(\mathbf{A}, \mathbf{B}, \mathbf{c}). \quad (3)$$

The main loss term is a negative log-likelihood of a model (2):

$$\mathcal{L}_{main}(\boldsymbol{\mu}) = \frac{1}{2\sigma^2} \sum_{m,n} |\mathbf{x}_n^{(m)} - \mathbf{A} \mathbf{p}_n^{(m)} - \mathbf{B} \mathbf{f}_n - \mathbf{c}|^2 + \frac{MND}{2} \ln(2\pi\sigma^2), \quad (4)$$

which corresponds to the minimization of the residual variance (cf. EOF methods).

The second, smoothing regularization term for the time series $\mathbf{P}$ and $\mathbf{F}$ — $\mathcal{L}_{smooth}(\mathbf{P}, \mathbf{F})$ — is the signature feature of the LDM approach. It implements the prior assumption that the LDM components $\mathbf{p}_n^{(m)}$ and $\mathbf{f}_n$ belong to a class of linear

stochastic processes with (unknown) time scales $\boldsymbol{\tau}_p \in \mathbb{R}^{d_p}$, $\boldsymbol{\tau}_f \in \mathbb{R}^{d_f}$ and standard deviations $\boldsymbol{\sigma}_p \in \mathbb{R}^{d_p}$, $\boldsymbol{\sigma}_f \in \mathbb{R}^{d_f}$:

$$\mathcal{L}_{smooth}(\mathbf{P}, \mathbf{F}) = \sum_m l_s(\mathbf{p}_1^{(m)}, \dots, \mathbf{p}_N^{(m)} | \boldsymbol{\tau}_p, \boldsymbol{\sigma}_p) + l_s(\mathbf{f}_1, \dots, \mathbf{f}_N | \boldsymbol{\tau}_f, \boldsymbol{\sigma}_f). \quad (5)$$

Here the function $l_s(\mathbf{z}_1, \dots, \mathbf{z}_N | \boldsymbol{\tau}_z, \boldsymbol{\sigma}_z)$ given by

$$l_s(\mathbf{z}_1, \dots, \mathbf{z}_N | \boldsymbol{\tau}_z, \boldsymbol{\sigma}_z) := \frac{1}{2} [\mathbf{z}_1^T \boldsymbol{\Sigma}_z^{-1} \mathbf{z}_1 + \ln \det(2\pi \boldsymbol{\Sigma}_z)] + \frac{1}{2} \sum_{n=2}^N \left[(\mathbf{z}_n - \hat{\alpha}_z \mathbf{z}_{n-1})^T \tilde{\boldsymbol{\Sigma}}_z^{-1} (\mathbf{z}_n - \hat{\alpha}_z \mathbf{z}_{n-1}) + \ln \det(2\pi \tilde{\boldsymbol{\Sigma}}_z) \right] \quad (6)$$

is the negative log-PDF of a d_z -dimensional time series $\mathbf{z}_1, \dots, \mathbf{z}_N$ generated by the first-order linear autoregressive stochastic process with the time scales $\boldsymbol{\tau}_z \in \mathbb{R}^{d_z}$ and standard deviations $\boldsymbol{\sigma}_z \in \mathbb{R}^{d_z}$; the diagonal matrices $\hat{\alpha}_z$ and $\boldsymbol{\Sigma}_z$ are such that $(\hat{\alpha}_z)_{ii} = e^{-\frac{1}{(\boldsymbol{\tau}_z)_i}}$, $(\boldsymbol{\Sigma}_z)_{ii} = (\boldsymbol{\sigma}_z)_i^2$, while $\tilde{\boldsymbol{\Sigma}}_z = \boldsymbol{\Sigma}_z - \hat{\alpha}_z \boldsymbol{\Sigma}_z \hat{\alpha}_z^T$. In plain terms, (6) represents a log-rescaled joint distribution of samples of size N drawn from a smooth linear stochastic AR-1 processes with parameters $\boldsymbol{\tau}_z$ and $\boldsymbol{\sigma}_z$: $z_{i,n+1} = \hat{\alpha}_{ii} z_{in} + \sqrt{(\boldsymbol{\sigma}_z)_i^2 (1 - \hat{\alpha}_{ii}^2)} \eta_{in}$.

Finally, the last term in (3) is a classic L2-regularization for the model weights $\mathbf{A}, \mathbf{B}, \mathbf{c}$ wrapped into a negative Gaussian log-prior:

$$\mathcal{L}_2(\mathbf{A}, \mathbf{B}, \mathbf{c}) = \sum_{s,i} l_2(A_{si} | \lambda_s \sigma_A^2) + \sum_{s,i} l_2(B_{si} | \lambda_s \sigma_B^2) + \sum_s l_2(c_s | \lambda_s \sigma_c^2), \quad (7)$$

$$l_2(z | \lambda \sigma_z^2) := \frac{z^2}{2\lambda \sigma_z^2} + \frac{1}{2} \ln(2\pi \lambda \sigma_z^2).$$

Here λ_s is the scaling coefficient taken to be equal to the variance of the s -th input ensemble PC, which renders tunable hyperparameters $\sigma_A, \sigma_B, \sigma_c$ dimensionless.

The optimal sets of time scales $\boldsymbol{\tau}_p$ and $\boldsymbol{\tau}_f$ of the dominant LDM components, as well as the other hyperparameters $\boldsymbol{\sigma}_p, \boldsymbol{\sigma}_f, \sigma_A, \sigma_B, \sigma_c$, are optimized within a Bayesian framework, as described in Sec. 2.2.4. The dimensions d_p and d_f are optimized by trial and error, which may results in substantial increases in the computational burden when these dimensions are high. However, it can also be shown that there exist threshold values of d_p and d_f , beyond which all the new LDM components are equal to zero, meaning that increasing these dimensions further would produce no change in the resulting LDM decomposition.

2.2.3 Multi-model LDM modifications

Consider now a multi-model ensemble of climate simulations by K Earth system models (ESMs) that includes M climate realizations produced by each model: $\mathbf{X} = \{(\mathbf{x}_1^{(m,k)}, \dots, \mathbf{x}_N^{(m,k)})\}_{m=1, \dots, M}^{k=1, \dots, K}$. Ensemble LDM decomposition (2) is straightforwardly modified in this case as follows:

$$\mathbf{x}_n^{(m,k)} = \mathbf{A} \mathbf{p}_n^{(m,k)} + \mathbf{B} \mathbf{f}_n^{(k)} + \mathbf{c} + \sigma \boldsymbol{\xi}_n^{(m,k)}. \quad (8)$$

Note that for each model, the forced components are still assumed to be the same in all of this model’s realizations. However, both internal and forced components are different in different models. Another important assumption underlying (8) is that all the parameters fixed in time — in particular, the internal-variability and forced-response patterns $\mathbf{A}$ and $\mathbf{B}$ — are postulated to be the same in all realizations and thus do not depend on either the model number k , or on the realization number m . In this way, the M-ELDM decomposition represents the entire multi-model ensemble in a common low-dimensional subspace, which permits a like-to-like comparison between the forced and internal components of different models, while ensuring robustness as new ESM models are included in this ensemble. For these reasons, the M-ELDM decomposition was chosen to form the foundation for the forced-signal estimation Method 23 in the ForceSMIP intercomparison project (Wills et al. 2026).

The loss function used in the M-ELDM decomposition is essentially the same as that for the single-model decomposition (3), with an additional summation over K models in the loss terms (4) and (5), now written as follows:

$$\mathcal{L}_{main}(\boldsymbol{\mu}) = \frac{1}{2\sigma^2} \sum_{k,m,n} |\mathbf{x}_n^{(m,k)} - \mathbf{A}\mathbf{p}_n^{(m,k)} - \mathbf{B}\mathbf{f}_n^{(k)} - \mathbf{c}|^2 + \frac{KMND}{2} \ln(2\pi\sigma^2); \quad (9)$$

$$\mathcal{L}_{smooth}(\mathbf{P}, \mathbf{F}) = \sum_{k,m} l_s(\mathbf{p}_1^{(m,k)}, \dots, \mathbf{p}_N^{(m,k)} | \boldsymbol{\tau}_p, \boldsymbol{\sigma}_p) + \sum_k l_s(\mathbf{f}_1^{(k)}, \dots, \mathbf{f}_N^{(k)} | \boldsymbol{\tau}_f, \boldsymbol{\sigma}_f). \quad (10)$$

The overall optimization procedure is also the same in both the single-model and multi-model versions of the ensemble LDM decomposition.

2.2.4 Bayesian selection of hyperparameters

As noted in section 2.2.2, the LDM hyperparameters $H = (d_p, d_f, \boldsymbol{\tau}_p, \boldsymbol{\tau}_f, \boldsymbol{\sigma}_p, \boldsymbol{\sigma}_f, \sigma_A, \sigma_B, \sigma_c)$ are optimized within a Bayesian framework. Specifically, the following loss function is to be minimized over H :

$$\Psi = \left[\psi + \frac{1}{2} \ln \det \left(\frac{1}{2\pi} \nabla \nabla^T \psi \right) \right] \bigg|_{\boldsymbol{\mu}^*} \longrightarrow \min_H. \quad (11)$$

Here $\boldsymbol{\mu}^*$ is the set of parameters $\boldsymbol{\mu}$ corresponding to the minimum of the LDM loss $\psi(\boldsymbol{\mu})$ as per (3), and $\nabla \nabla^T \psi$ is its Hessian matrix with respect to $\boldsymbol{\mu}$.

This framework was originally developed for the nonlinear version of the decomposition by Mukhin et al. (2015) and Gavrilov et al. (2016) and then adapted for the various LDM versions. In a nutshell, the minimization of Ψ corresponds to maximization of the marginal likelihood of the data $\mathbf{X}$ given the hyperparameters H , often called the Bayesian evidence (Jeffreys 1998; Gavrilov et al. 2017). Marginalization over $\boldsymbol{\mu}$ was performed here via Laplace approximation method.

2.2.5 Implementation details

To find the optimal hyperparameters of multi-model LDMs, we implemented the same numerical procedure as in the other versions of the LDM decomposition. This procedure is based on the annealing Markov Chain Monte Carlo (MCMC)-like iterations searching for the minimum of (11) (Gavrilov et al. 2020, 2024; Buyanova et al. 2025). A more recent development used here (and in Wills et al. 2026, method 23) is a new numerically efficient parameter-fitting algorithm for minimizing (3) at the fixed values of hyperparameters. This algorithm utilizes the property of the loss function to be quadratic with respect to each of the parameters $\mathbf{P}$, $\mathbf{F}$ and the triplet $\mathbf{A}, \mathbf{B}, \mathbf{c}$ to compute a partial minimum with respect to each of them in one matrix–vector multiplication operation. Thus, the fitting procedure iteratively performs analytical minimization sequence over $\mathbf{P}$, $\mathbf{F}$, $(\mathbf{A}, \mathbf{B}, \mathbf{c})$, σ in a loop, until the loss-function decrease reaches the numerical-precision threshold. This procedure is much faster than a lazy gradient descent minimization, especially for large data sets; the readers are referred to Gavrilov et al. (2020) (Appendices A, B) for further algorithmic details.

2.3 Analysis strategy

The M-ELDM method optimally decomposes the input multi-model time series in the modal subsets associated with the forced and internal climate variability, each mode within these subsets being characterized by its dominant time scale. These modes, however, are not necessarily associated with substantial variance and, when looked at in isolation, may not appear to be climatologically important. To bypass this restriction, we further analyze the forced and internal variability subsets separately by reconstructing their fast (interannual) and slow (decadal and longer time scale) components via summation of the corresponding modes, and then utilizing the EOF analysis of the subsets so reconstructed. The M-ELDM decomposition is thus interpreted as, first, dynamical and, second, spatiotemporal filter able to disentangle the contributors to the total climate variability simulated by ESMs.

We used subjectively chosen thresholds of $\tau_{ia}^* = 72$ and $\tau_{md}^* = 96$ months to define the interannual ($\tau < \tau_{ia}^*$; see section 3.3) and interdecadal/multidecadal modes ($\tau > \tau_{md}^*$; see sections 3.1 and 3.2) in both the forced and internal-variability subsets identified by the E-LDM decomposition of the SST and OHC fields. Their estimated forced response is vastly dominated by the low-frequency modes in each case and is essentially one-dimensional, with the leading ensemble EOF of the reconstructed forced response describing 95% and 85% of the SST and OHC forced-signal variance (across the entire model ensemble), respectively (see section 3.1). In contrast, the internal variability subsets are dominated by the interannual ENSO-like variability, which are further analyzed via the EOF analysis in section 3.3. In the same vein, the low-frequency subsets of the internal variability are analyzed using the rotated EOF analysis analogous to that in Kravtsov et al. (2024) to visualize the dominant multidecadal variability present in the data (section 3.2).

2.4 LDM treatment of observational data

To identify and analyze forced and internal variability subsets of the observational data, we relied on the version of the LDM analysis developed by [Gavrilov et al. \(2020\)](#), which specifies the time series of the forced response based on the prior analysis of the multi-model ensemble and finds the associated pattern, alongside the patterns and time series of the residual (nominally, internal) LDM modes via Bayesian optimization. In the present study, the time series of the forced signal supplied to the LDM algorithm was naturally taken as the ensemble-mean of the leading PC of the M-ELDM identified multi-model forced signal.

3 Results

3.1 Estimated forced response

The M-ELDM method identified $d_f = 7$ forced modes in the SST data and $d_f = 8$ modes in the OHC data. Most of these modes are low-frequency modes, with only two of the SST modes (3 and 4) characterized by fast, seasonal and interannual time scales, respectively. The spatial patterns and component time series of all modes are shown in Figs. S1–S2 of the *Supplementary Information*. The SST response is dominated by two leading modes associated with the largest contributions to the total SST variance, while the OHC response is largely represented by the single leading mode. Of all modes, the leading mode in both the SST and OHC has the highest signal-to-noise ratio (computed, for example, as the ratio of the standard deviation of this component’s ensemble-mean to the ensemble spread) and describes the overall global warming trend, which is likely dominated by the forced response to increasing concentrations of greenhouse gases (GHG; cf. [Andrews et al. 2012](#); [Wills et al. 2022](#); [Armour et al. 2024](#)). This trend is relatively uniform in space and time for SST, while it is more spatially heterogeneous and only starts in the 1980s for the OHC data. Higher-order modes with relatively large signal-to-noise ratios describe forced-response corrections due to a combination of anthropogenic and volcanic aerosol forcings (e.g., modes 2 and 5 for SST and modes 4 and 5 for OHC), reflecting the well known mid-century cooling trend before the 1980s and pronounced short-term cooling episodes which are synchronized with the major volcanic eruptions (1963 Agung, 1982 El Chichón and 1991 Pinatubo).

The total forced response in both fields is vastly dominated by the leading multi-model ensemble EOF of their total M-ELDM reconstructed signal, which describes 95% and 85% of the total forced-signal variance in the SST and OHC, respectively (Fig. 1). Based on the visual inspection of its time series (upper row) and patterns (middle row), this EOF seems to encapsulate the summative effect of the forced responses to the individual forcing agents: the overall positive trend associated with the GHG forcing, little-to-no warming before 1980s due to anthropogenic aerosols, as well as local volcanic minima punctuating either time series.

The simulated response patterns should be compared to the LDM-based patterns of the estimated observed forced response (section 2.4) (bottom row of Fig. 1), which corresponds to the ensemble-mean time series of the multi-model response (black curve

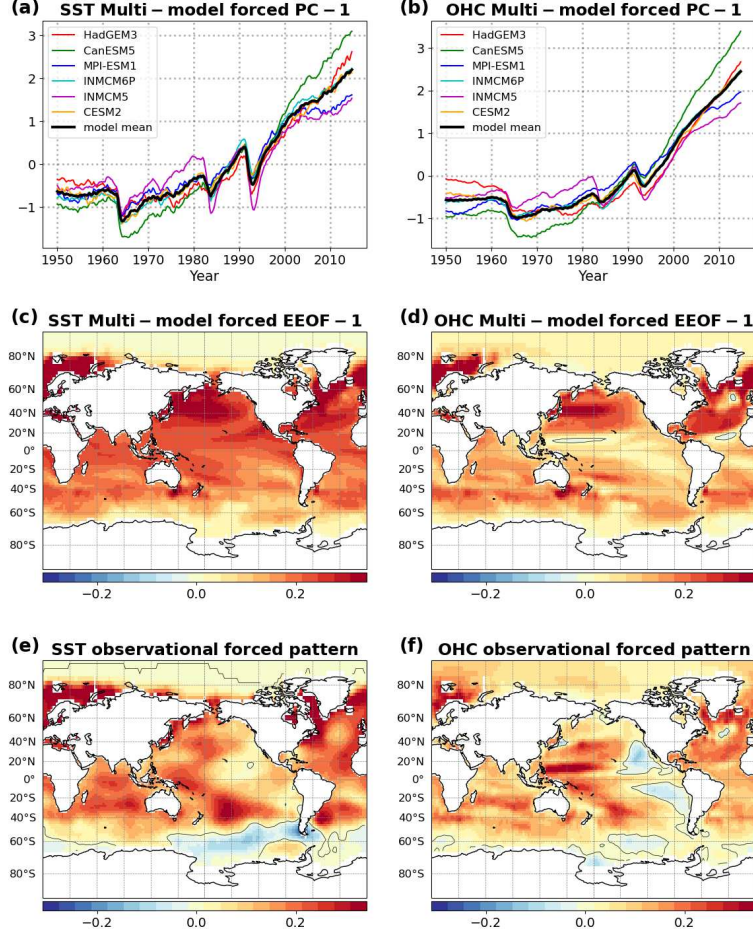


Fig. 1 The leading ensemble EOF of the M-ELDM based forced-signal reconstruction, for SST (left) and OHC (right). Shown are the unit-ensemble-variance PC-1 time series (top row) and the corresponding dimensional EOF-1 patterns (middle row). Bottom row shows the force-signal patterns obtained via the LDM decomposition of the observational data (section 2.4). Units are $^{\circ}\text{C}$ for SST and 10^9 J m^{-2} for OHC.

in the top row of Fig. 1). The observed and simulated patterns match well in the Atlantic and Indian Ocean sectors but are clearly distinct over the Pacific Ocean sector, featuring PDO-like signature in observations that is absent from the simulated forced trends (cf. Trenberth and Fasullo 2013; Wills et al. 2022).

One of the key strengths of the M-ELDM decomposition is in that it provides convenient means for comparing the model behaviors across a multi-model ensemble by associating each LDM mode with a single robust pattern, common for all models. The differences between the models are thus encapsulated in the properties of the corresponding LDM component. For example, the forced responses of individual models

shown in the top row of Fig. 1 feature the differences in the apparent climate-model sensitivity to external forcings. In particular, the INMCM5 and MPI-ESM1 models demonstrate the lowest, whereas the CanESM5 model — the highest rate of the global warming as compared to other models, in both SST and OHC data. Indeed, it is known that the INMCM5 model has the lowest equilibrium climate sensitivity to CO₂ doubling among the CMIP6 models Volodin (2021). On the other hand, this model is characterized by an abnormally strong response to volcanic aerosols, as measured by the depth of the volcanic minima in SST and OHC relative to that of other models.

The climate models’ dominant forced response in SST and OHC is amplified over the Northern Hemisphere’s oceans, including the North Atlantic Ocean (Fig. 1, middle row), thus providing, among other things, a substantial contribution to the North Atlantic SST (and OHC) variability. Now note the apparent multidecadal deviations of the dominant forced-signal component of the individual models (colored curves) from the ensemble-mean forced response (black curve), clearly discernible in the top panels of Fig. 1. Let’s assume that the ensemble-mean response represents the known true response of the climate system to external forcings. If so, subtraction of this true response from a single simulation of an individual climate model would create multidecadal biases that would masquerade as the internal multidecadal variability with a pronounced expression over the North Atlantic Ocean. It is, naturally, also a possible interpretation for the residual (nominally, internal) variability identified by our LDM methodology in the observational data. This thought experiment illustrates two opposing views on the dynamics of the Atlantic Multidecadal Oscillation (AMO), which either emphasize internal dynamics (Zhang et al. 2019) or a possible role of aerosol forcings in driving the observed North Atlantic SST variability (see, for example, Booth et al. 2012; Zhang et al. 2013; Murphy et al. 2017; Bellomo et al. 2018; Birkel et al. 2018). We will address this issue further in section 3.2, following the approach of Kravtsov et al. (2024).

3.2 Multidecadal variability

The M-ELDM procedure identified $d_p = 8$ significant internal modes in both the SST and OHC data (see Figs. S3–S4 of the *Supplementary Information*). The simulated internal variability is dominated by the interannual-to-decadal time scale modes representing ENSO-like behavior (see section 3.3). In this section, however, we focus on the lowest-frequency internal modes, namely, modes 7 and 8 in the M-ELDM decomposition of SST and modes 6 and 8 in that of OHC.

The estimated internal modes of the observational data also exhibit interannual-to-decadal ENSO-like variability (section 3.3), as well as multidecadal variability (Figs. S5–S6), with two out of five significant SST modes (2 and 4) and three out of 8 OHC modes (2, 6, and 7) being associated with the lowest-frequency behavior.

3.2.1 Rotation of multidecadal modes

To visualize and compare the observed and simulated multidecadal variability, we adopted the procedure developed in Kravtsov et al. (2024). This procedure involves computing the rotated EOFs of the low-pass filtered data in such a way that the first

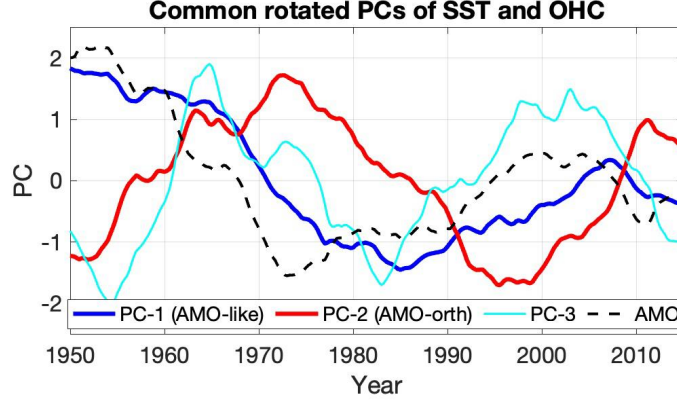


Fig. 2 The rotated PCs of the LDM-reconstructed low-frequency internal variability subset of the observational data (see the legend). The dashed black curve shows the AMO index associated with this subset. All time series are normalized to have unit standard deviation.

rotated EOF (AMO-like) pattern represents the signal maximally correlated with the AMO index (defined as the time series of the $0-60^{\circ}\text{N}$ area averaged North Atlantic SST of the LDM-reconstructed low-frequency data), while the sign of the second rotated EOF (AMO-orth pattern) is chosen so that the corresponding rotated PC-2 lags the rotated PC-1 in time. In applying this procedure here, we first computed the *common* EOFs of the SST and OHC’s reconstructed multidecadal variability (defined through the sum of the corresponding internal LDM modes) via the singular value decomposition of the concatenated PC time series of the individual (SST and OHC) fields normalized by the standard deviation of their respective leading PCs. Upon rotation of the resulting common PCs, the (dimensional) spatial patterns of the corresponding rotated EOFs were computed by regressing the original reconstructed low-frequency subsets of the SST and OHC onto the rotated PCs normalized to have unit variance. In keeping with the conventions used in this paper, the model simulated patterns were computed by appending all of the $MK = 60$ available internal realizations into one single extended time series prior to the analysis.

3.2.2 The Global Stadium Wave (GSW)

The rotated PCs of the LDM-reconstructed low-frequency components of the observational data (Fig. 2) recover essentially the same AMO-like and AMO-orth time series as in Kravtsov et al. (2024) (their Fig. 3) despite a shorter climate record processed (1950–2014 here vs. 1880–2005 in Kravtsov et al.’s work), very different methods to isolate the forced signal and filter out high-frequency noise, and our inclusion of the OHC data alongside the SST data, all of which underscores the robustness of the leading

multidecadal signal referred to, by these authors, as the global stadium wave (GSW: Wyatt et al. (2012); Kravtsov et al. (2018)). The SST expression of the AMO-like mode (Fig. 3a) matches well the pattern identified in Kravtsov et al. (2024) (e.g., their Fig. 4a). The AMO-orth SST pattern also exhibits some similarity with the corresponding pattern in Kravtsov et al. (2024), although this pattern is less coherent in that study, possibly due to their usage of the near-surface air temperature data in lieu of the

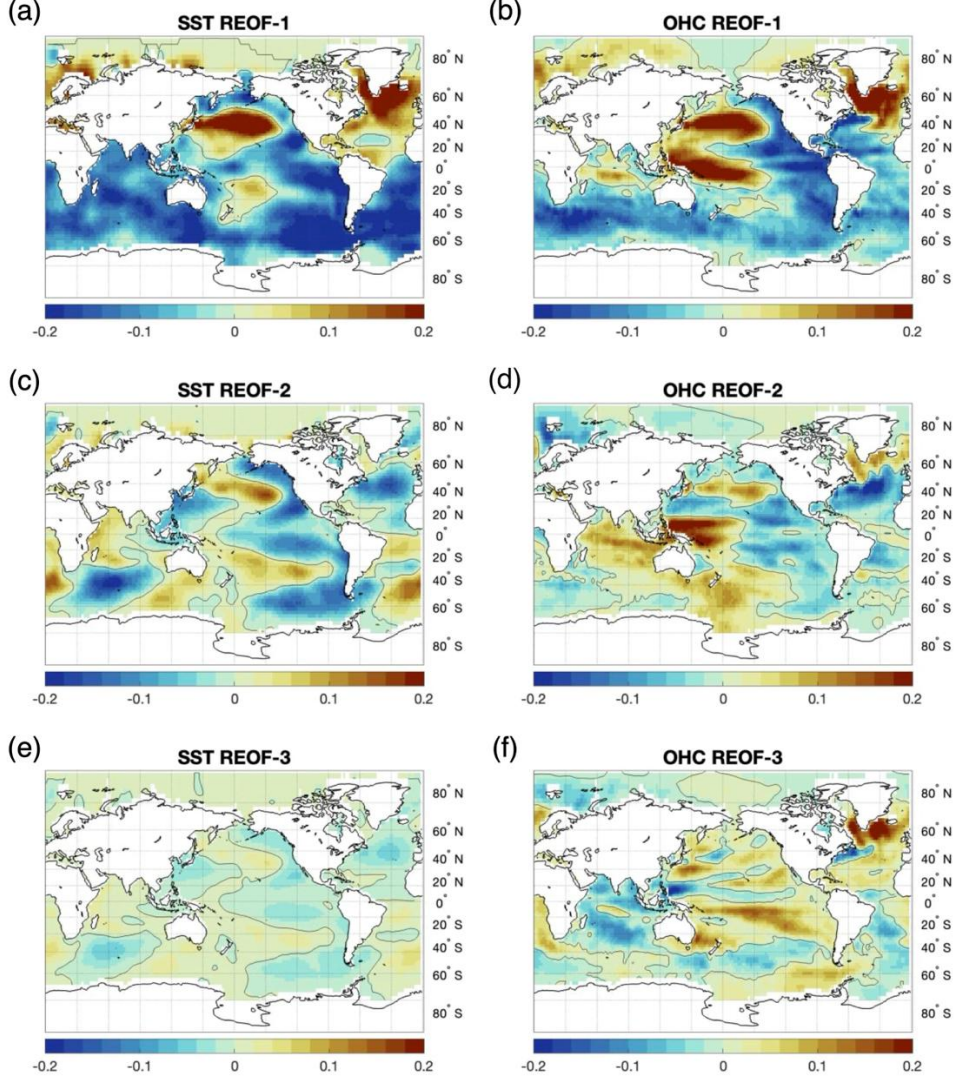


Fig. 3 The rotated EOFs of the LDM-reconstructed low-frequency internal variability subset of the observational data, for SST ($^{\circ}\text{C}$, left column) and OHC (10^9 J m^{-2} , right column) fields. (a, b) AMO-like pattern; (c, d) AMO-orth pattern; (e, f) REOF-3.

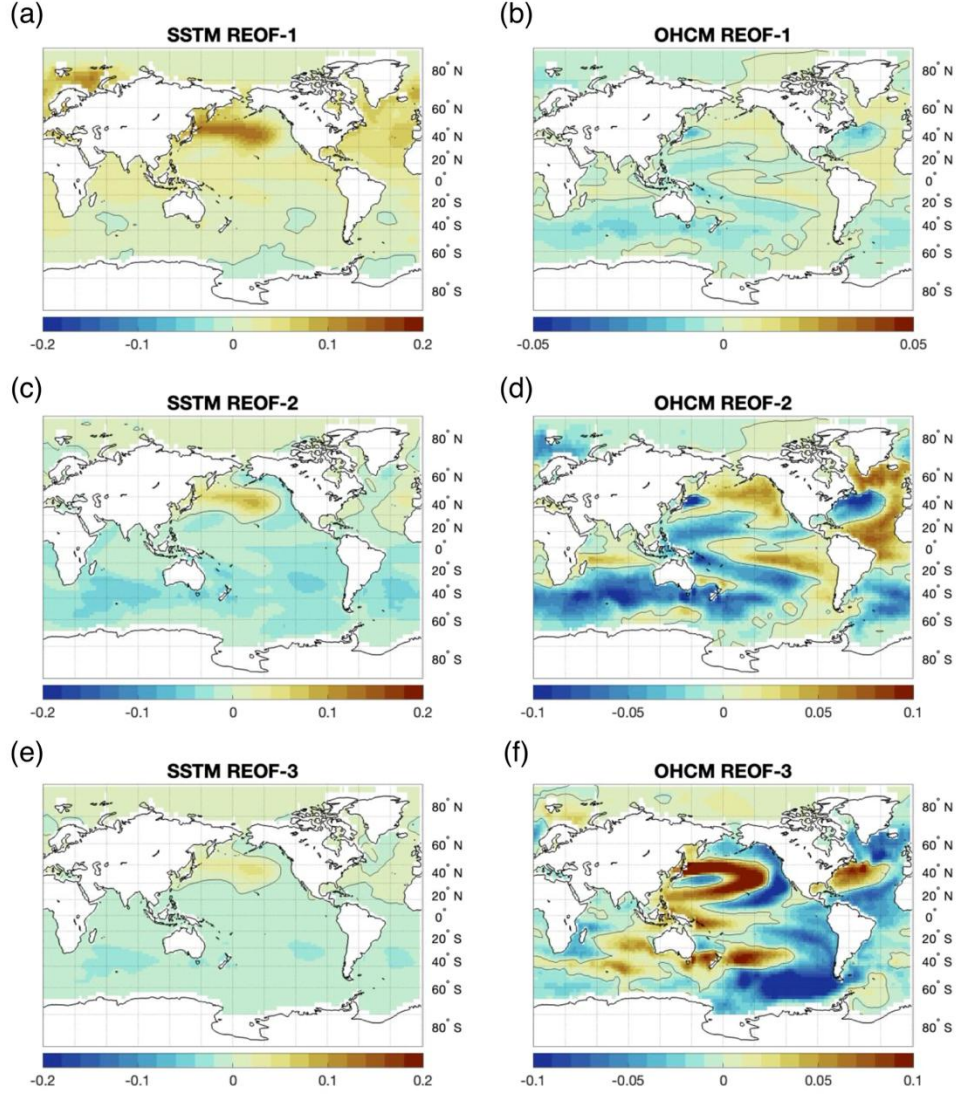


Fig. 4 The same as in Fig. 3 but for the multi-model ensemble.

SST data. Our results thus provide a cleaner view on the SST-based reconstruction of the GSW. The AMO-like component features a large-scale interhemispheric SST contrast, with basin-wide positive SST anomalies in the North Atlantic and North Pacific and negative SST anomalies in the Southern Hemisphere. The AMO-orth component is negatively correlated with the Pacific Decadal Oscillation (PDO: [Trenberth and Fasullo 2013](#), their Fig. 8) time series, and its pattern resembles (although is not identical with) the negative PDO pattern. The AMO-like and AMO-orth OHC patterns

are largely coherent with the corresponding SST patterns, with notable differences in the tropical western Pacific, which exhibits enhanced heat storage and deeper thermocline (cf. [Trenberth and Fasullo 2013](#), their Fig. 12) despite a neutral or cool SST anomalies. Our AMO-like SST and OHC patterns in the North Atlantic are consistent with the observed Atlantic Multidecadal Variability (AMV) fingerprints derived in [Yan et al. \(2019\)](#).

The model simulated AMO-like and AMO-orth patterns (Fig. 4) exhibit some similarities to but, overall, are very different from the observed patterns. The AMO-like SST pattern (Fig. 4a) is characterized by weak positive SST anomalies in the North Atlantic by construction, but has even stronger SST anomalies in the North Pacific and Arctic Ocean, with largely uniform global SST anomalies tapering off towards the south. This SST pattern is both weaker than observed (Fig. 4a) and doesn't really have its own truly coupled OHC covariability, but rather projects weakly on the OHC anomalies associated with the AMO-orth mode (compare Figs. 4b and d). This projection in the North Atlantic region is still consistent with the AMV signature of the CMIP5 models — different from the observed one — in [Yan et al. \(2019\)](#). (Note that our model based LDM reconstruction of the low-frequency variability only has four independent modes, and it appears that AMO-like and AMO-orth rotated EOFs are dominated by the SST and OHC variability, respectively, while the companion field reflects a correlated but, very likely, not genuinely coupled pattern; the same applies to the third rotated pattern of the observational data in Fig. 3e, whose SST expression mirrors the AMO-orth SST pattern and is probably not truly connected to the corresponding OHC pattern in Fig. 3f. We still show these patterns for the sake of completeness.) The AMO-orth SST and OHC patterns (Figs. 4c,d) bear some similarities with the observed patterns in the North Atlantic and North Pacific but are very different elsewhere, including, in particular, tropical Pacific, where the simulated SST anomalies are virtually non-existent and the OHC anomalies are of the opposite sign compared to the observed anomalies (Fig. 3d). One striking difference between the models and observations is thus the absence of a pronounced PDO-like multidecadal variability in model simulations.

Still, the models' internal low-frequency variability, while weaker and spatially distinct from the observed, has similar time scales yet much lower signal-to-noise ratio compared to the observed GSW-type variability (Fig. 5), as evidenced by the much smaller simulated correlations at decadal lags compared to the observed correlations — a property possibly related to the so-called signal-to-noise paradox in climate science [Scaife and Smith \(2018\)](#); [Kravtsov \(2020\)](#).

3.2.3 On the possible forced origin of GSW

We finally explore here a possibility that the observed GSW (Figs. 2 and 3) results or, at least, possesses a substantial contribution from the forced-signal biases (in our estimated “observed” forced response that we subtract from the observational data; this forced signal is represented by the black curves in the top panels in Fig. 1, in conjunction with the LDM identified patterns in the bottom panel of that figure). To address this hypothesis, we first form the M-ELDM reconstructed low-frequency subset of the multi-model ensemble (as the sum of the low-frequency forced and internal

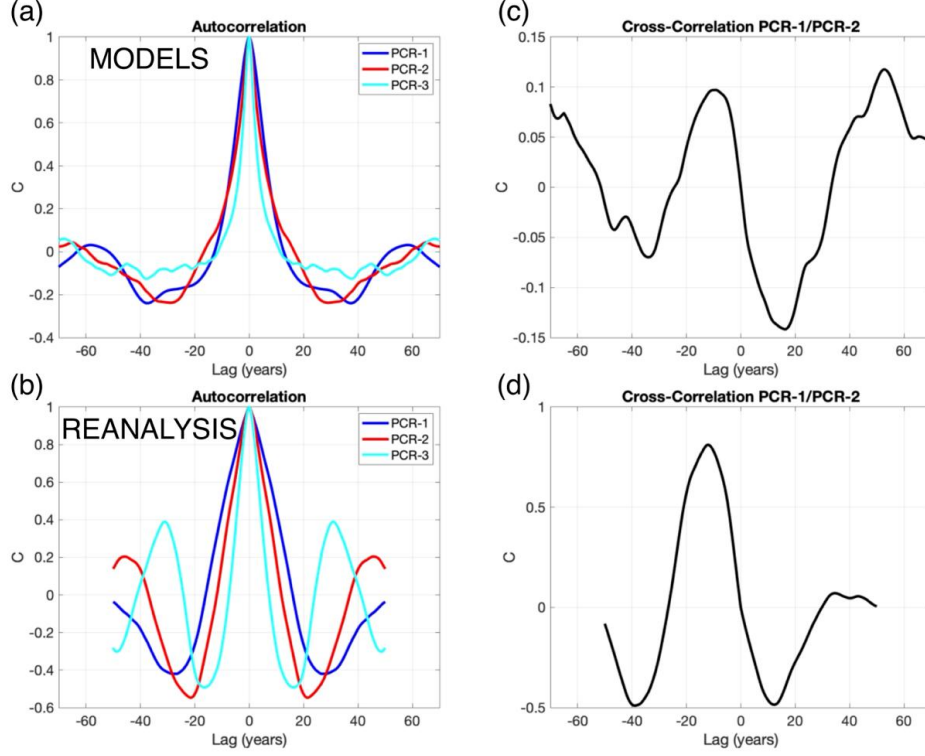


Fig. 5 The auto- (left) and cross-correlations (right) of the AMO-like and AMO-orth components in models (top)/ and observations (bottom).

modes) and then subtract from this subset the ensemble-mean variability associated with the leading EOF of the model simulated forced signal (Fig. 1, middle row). This procedure for constructing the resulting simulated anomalies is thus completely analogous to the one used to define the observed “internal” anomalies. The latter anomalies can, in general, represent the sum of the forced-signal residuals (due to biases in the forced-signal estimation) and internal variability in the climatic data sets considered. Hereafter, we will refer to the simulated data set so constructed as the “F+I” data set. We also considered the M-ELDM based low-frequency forced-signal anomaly data set — the “F” data set, — in which the simulated internal variability was neglected altogether. Both F+I and F data sets were then subjected to the already familiar rotated EOF analysis to isolate the AMO-like and AMO-orth components; this experimental setup is analogous to that used in [Kravtsov et al. \(2024\)](#) to test the GSW forced-origin hypothesis.

The F+I subset’s patterns (Fig. 6) all have a larger magnitude yet share common spatial features with the internal-variability patterns in Fig. 4, possibly indicating the presence of a dynamical forced response associated with the adjustment of the climate system’s internal modes to the time-dependent external forcing (cf. [Kravtsov](#)

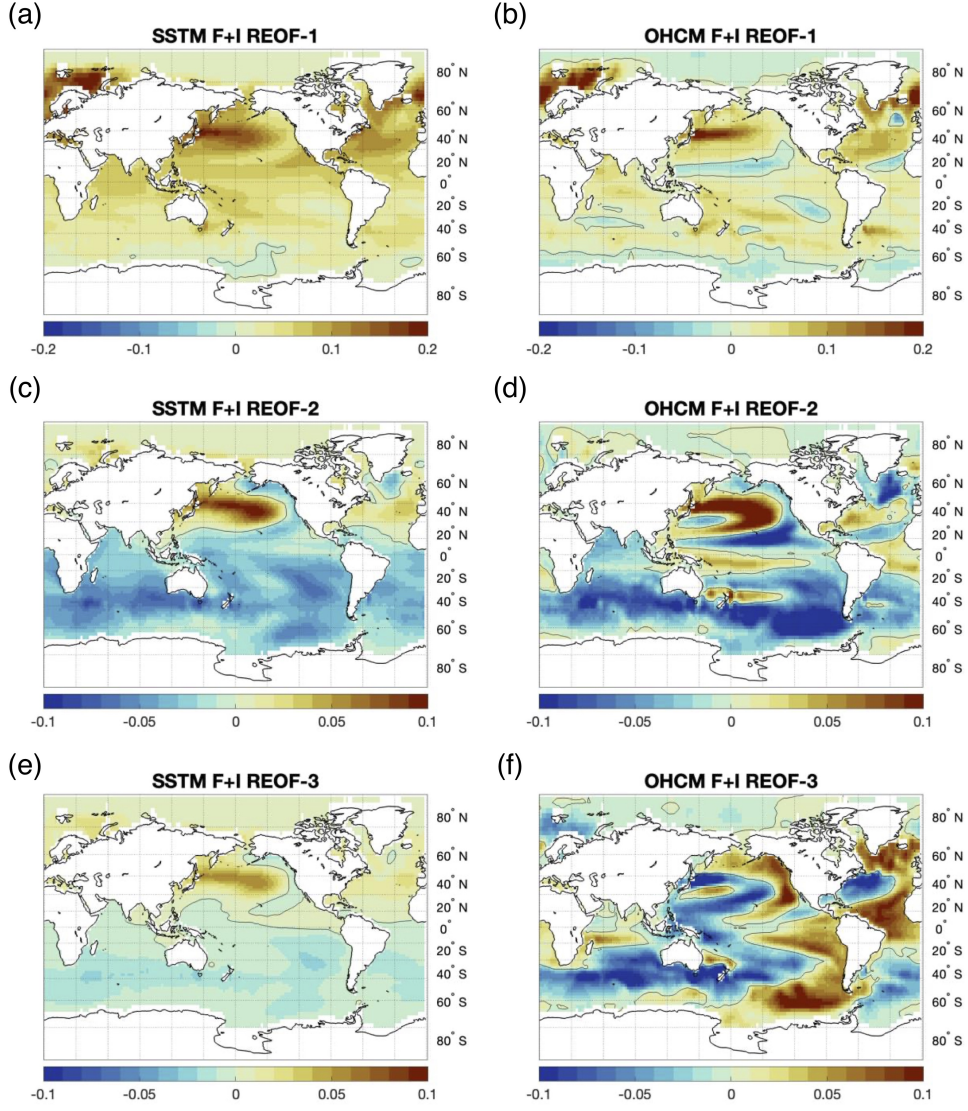


Fig. 6 The same as in Figs. 3 and 4 but for the F+I data set represented by the sum of the models' LDM reconstructed low-frequency modes (forced *and* internal) less the dominant ensemble-mean forced response shown by the black curves in the top panel of Fig. 1 in conjunction with the simulated patterns in the middle panels of that figure.

et al. 2022; Gavrilov et al. 2024). The AMO-like pattern exhibits much more spatial coherence between its SST and OHC expressions than its internal-only counterpart (compare Figs. 6a,b and Figs. 4a,b). On the other hand, the REOF-2 and 3 of the F+I anomalies are switched and most resemble REOF-3 and 2 of the low-frequency

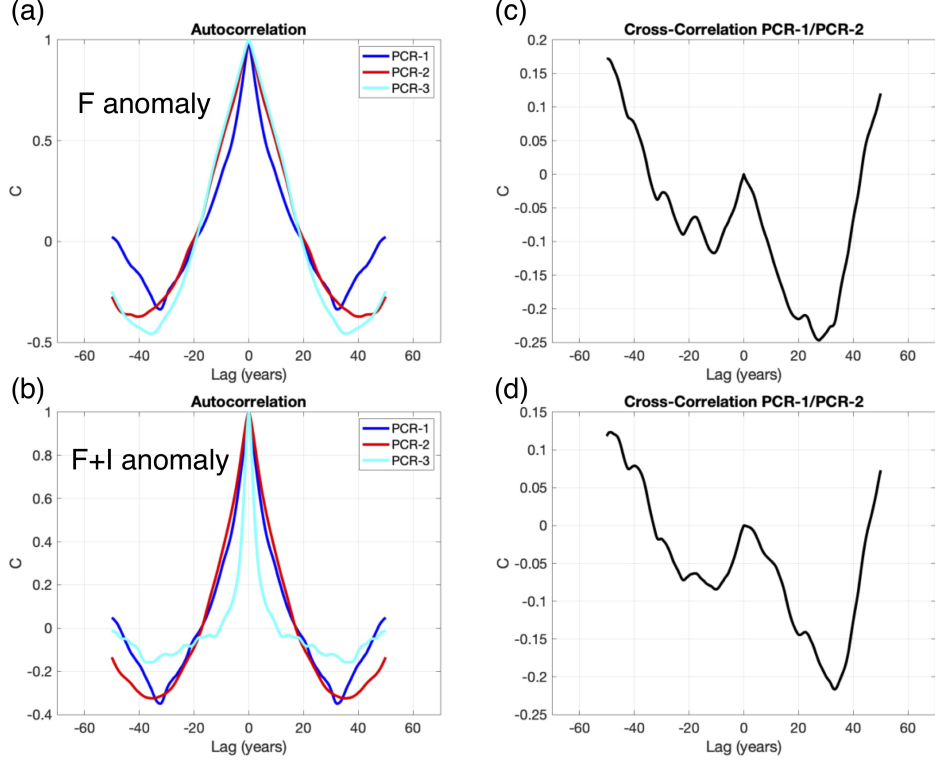


Fig. 7 The auto- (left) and cross-correlations (right) of the AMO-like and AMO-orth components for the simulated low-frequency variability forced-signal anomaly subset F (top), as well as for the F+I subset computed as the sum of the F subset with the low-frequency internal variability subset (bottom: the corresponding patterns are shown in Fig. 6). This figure is analogous to Fig. 5.

internal modes, respectively. The F+I AMO-like (REOF-1) and AMO-orth (REOF-2) patterns are essentially the same in the F-only anomaly subset but have a slightly smaller magnitude and minor spatial differences (figure not shown). Thus, the model simulated AMO-like and AMO-orth patterns in Fig. 6 are predominantly forced.

While these forced patterns have elements resembling some of the features of the observed AMO-like and AMO-orth patterns (Fig. 3), for example, Northern Hemisphere/Southern Hemisphere temperature contrasts, centers of action in the North Atlantic and North Pacific, and so forth, the two sets of patterns are clearly different. For example, the interhemispheric contrast is predominantly a feature of the AMO-like pattern in observations but it is only seen in the AMO-orth pattern in the model simulated F+I subset. Both F+I simulated AMO-like and AMO-orth patterns have a subdued or non-existent PDO-like signature, which is, in contrast, clearly present in the observed patterns. The observed and F+I simulated low-frequency subsets also have very different subsurface patterns. Finally, the time-dependent anomalies of the

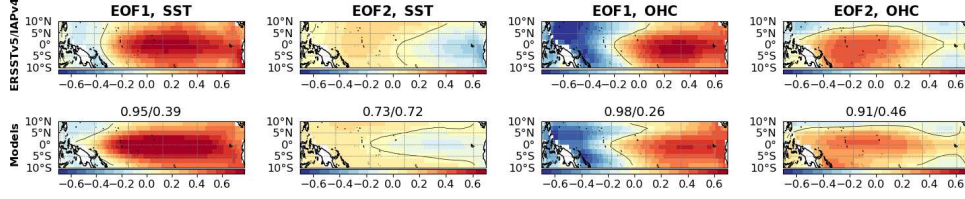


Fig. 8 Dimensional EOF patterns of the observed (top) and model simulated (bottom) fast (ENSO-related) LDM-reconstructed subsets computed via regression of these subsets onto the normalized leading PCs of the 10°S – 10°N data over the tropical Pacific. Shown, from left to right, the EOFs 1 and 2 of SST and EOFs 1 and 2 of OHC. For models, the spatial correlation and root-mean-square distance between the observed and simulated patterns (computed over the domain shown) are listed in panel captions. Units are $^{\circ}\text{C}$ for SST and 10^9J m^{-2} for OHC.

F+I subset have time scales longer than those of the observed AMO-like and AMO-orth signals (compare Figs. 5 and 7). These considerations imply that the observed GSW cannot be rationalized either as the internal mode of low-frequency variability or as the forced response or even as the combination of the two based on the analysis of the climate model simulations considered in the present study, thus suggesting that climate models are missing or misrepresenting the GSW’s requisite dynamics (cf: Kravtsov and Callicutt 2017; Kravtsov et al. 2018, 2024; Yan et al. 2019).

3.3 ENSO variability

The ENSO-like modes identified by the M-ELDM method dominate the internal variability in model simulations. The corresponding spatial patterns and time series (see Figs. S3–S4 of the *Supplementary Information*) indicate that our M-ELDM filter effectively distinguishes between the so-called quasi-biennial (QB: modes 1 and 3 of SST and modes 1,2 and 7 of OHC) and quasi-quadrennial (QQ: modes 2, 4–6 of the SST and modes 3–6 of the OHC) variability in the equatorial Pacific (Jiang et al. 1995; Bejarano and Jin 2008). The ENSO-like modes of observational data (Figs. S5–S6) also capture the QB (modes 1 and 5 of SST and modes 1 and 3 of OHC) and QQ (mode 3 of SST and mode 4 of OHC) components of internal variability on top of substantially more pronounced low-frequency modes that are muted in the historical model runs (see section 3.2).

Here we stick, once again, to our general strategy outlined in section 2.3 and first reconstruct the ENSO-related SST and OHC variability in models or observation via the summation of the corresponding LDM modes, thus optimally isolating the ENSO signals from the background of the forced climate trends (section 3.1) and lower-frequency, interdecadal and multidecadal variability (section 3.2). We then look into some aspects of ENSO multi-scale interactions, asymmetry and diversity by analyzing the two leading EOFs of the M-ELDM reconstructed ENSO-related SST and OHC variability over the equatorial (10°S – 10°N) Pacific (Fig. 8), following Trenberth and Stepaniak (2001) and Takahashi et al. (2011). These EOFs have similar patterns in the observed and model simulated data and feature a combination of largely monopolar and dipolar anomalies along the equator for both SST and OHC fields. For the

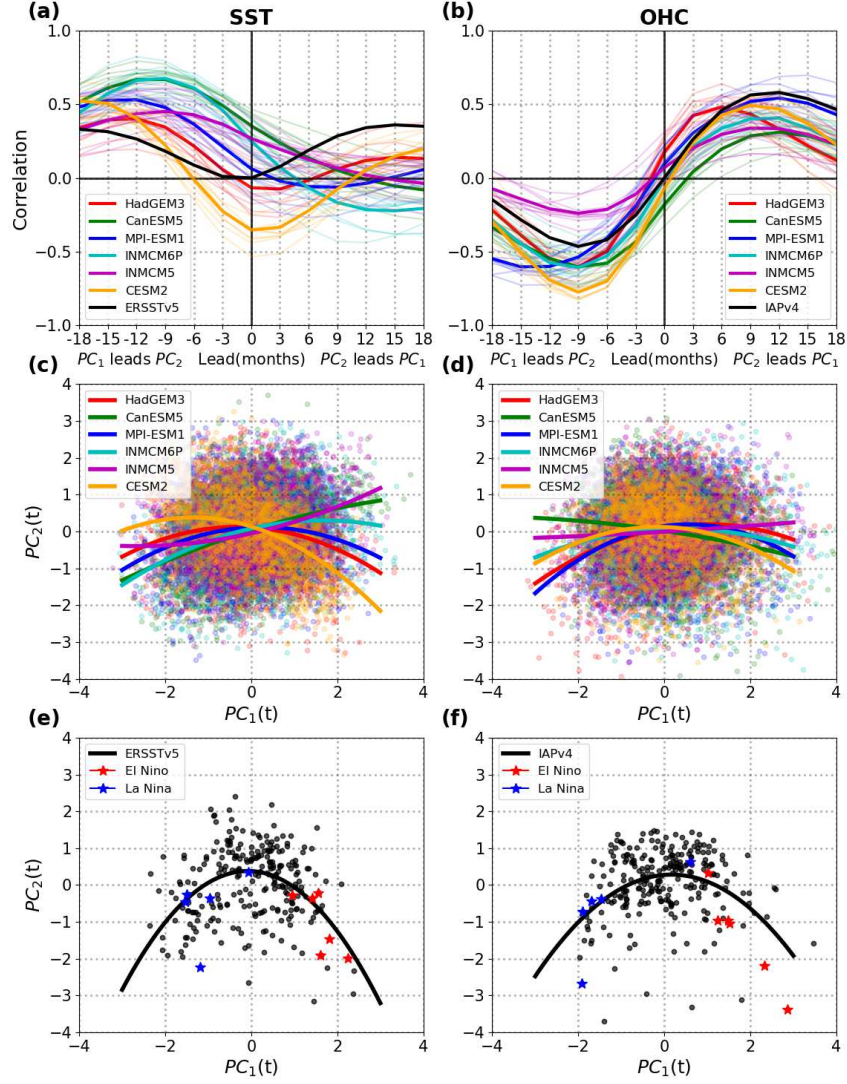


Fig. 9 ENSO in models and observations. Top row: Lagged cross-correlation between the PC_1 and PC_2 of the M-ELDM reconstructed ENSO variability over the equatorial Pacific for (a) SST; and (b) OHC. Thin curves show the results for the individual model realizations, thick curves correspond to the ensemble-mean correlations for either the individual models or observations (see the legend). Middle row: Scatter plots of the model trajectories (dots) alongside the best quadratic-regression fits (12) for individual models (thick curves, see the legend) in the EOF₁–EOF₂ phase space for (c) SST; and (d) OHC. Bottom row: the same as in the middle row but for the observations of (e) SST; and (f) OHC. The red/blue markers correspond to the years of strong El Niño/La Niña events according to <https://ggweather.com/enso/oni.htm>.

subsequent analysis, we broke the multi-model ensemble PC-1 and PC-2 series into

segments associated with each model and each realization. Naturally, the analogous observational analysis used the single available realization of the ENSO variability.

3.3.1 Temporal characteristics

Figures 9a, b show the lagged cross-correlations between the ENSO-related PCs computed above for the SST and OHC, respectively. The observed lagged correlations for the SST PCs (Fig. 9a) are near-symmetric about zero lag and display the enhanced cross-correlations at near-annual lags, thus indicating a predominant biennial time scale. This is also true for some of the models (HadGEM3 and CESM2), but is not so for other models, in which the quasi-quadrennial SST behavior dominates. The observed and simulated behaviors of the OHC modes (Fig. 9b) are more consistent, featuring predominant quasi-quadrennial time scales and slightly sub-annual (in-quadrature) lags between PC-1 and PC-2 time series. The latter phase relationship is consistent with the behavior predicted by the conceptual recharge–discharge oscillator theory (Jin 1997; Vialard et al. 2025). The pronounced quasi-periodicity of the tropical Pacific OHC makes OHC-based predictors preferable to the SST based predictors in data-driven ENSO forecast models (Seleznev and Mukhin 2023).

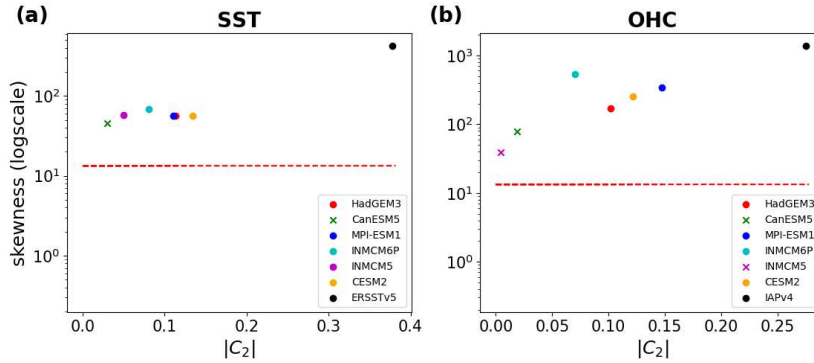


Fig. 10 The scaled multivariate Mardia’s skewness (MARDIA 1970) evaluated in the EOF₁–EOF₂ phase spaces of each model and in observational data, as a function of the absolute value of the corresponding quadratic coefficient C_2 in (12) for (a) SST; and (b) OHC. The horizontal dashed line indicate the 99th percentile of the χ^2 distribution with $\frac{1}{6}D(D+1)(D+2)$ degrees of freedom, which represents that of the Mardia’s skewness for the normally distributed D-variate data (here $D = 2$). The crosses indicate the models for which the C_2 values are statistically indistinguishable from zero according to the test derived and used in Seleznev and Mukhin (2023) and Seleznev et al. (2024).

3.3.2 ENSO nonlinearity

The two-dimensional distributions of the model trajectories in the EOF₁–EOF₂ phase space (middle row of Fig. 9), as well as those of the observed trajectories (bottom row of Fig. 9) are non-Gaussian. To succinctly characterize the ENSO nonlinearity, we computed, following Karamperidou et al. (2017) and Seleznev et al. (2024), the

best-fit quadratic curves

$$PC_2 = C_2 \cdot PC_1^2 + C_1 \cdot PC_1 + C_0 \quad (12)$$

for the scatter-plot data associated with each model and with observations. The observational, as well as most of the model-based best-fit curves for both SST and OHC are convex. However, the model based fits exhibit weaker curvature compared to the observed curvatures, thus indicating substantial differences in the degree of ENSO nonlinearity between models and observations.

The coefficient C_2 in (12) measures, in effect, the non-normality of the ENSO's 2-D probability density function and is related to the degree of asymmetry between the warm and cold ENSO events, which are generally located on different sides with respect to the axis of symmetry of the best-fit parabola in Figs. 9e, f. Indeed, the large values of C_2 generally correspond to more skewed 2-D distributions of ENSO events (Fig. 10), with the model based values, while indicating non-gaussianity of the underlying data, still falling well below the observed values. Thus, we conclude that climate models substantially underestimate the nonlinearity and asymmetry of the observed ENSO events.

3.3.3 ENSO diversity

Finally, we looked at the models' ability to reproduce different ENSO flavors represented by the so-called Central Pacific (C) El Niño and Eastern Pacific (E) El Niño events. To do so, we computed the SST and OHC regression maps (Figs. 10, 11) based on the C and E indices defined by the 45° rotation of the leading SST/OHC PCs:

$$C, E = \frac{1}{\sqrt{2}}(PC_1 \pm PC_2) \quad (13)$$

(Takahashi et al. 2011). For the case of simulated data the rotation was applied, once again, to the entire multi-model PC_1 – PC_2 data set but the regressions were performed separately for each model (by centering and re-normalizing the rotated PC chunks associated with each individual-model ensemble).

The resulting C- and E-ENSO patterns are both characterized by the relative warmth in the tropical Pacific but differ by where the warm SST and OHC anomalies peak. In particular, as implied by their names, the E pattern is amplified in the eastern equatorial Pacific, whereas the C pattern's maximum is shifted to the central equatorial Pacific. Visual inspection of Fig. 11 demonstrates that climate models differ in their ability to represent two different flavors of the observed ENSO events. In particular, of the six models considered, the HadGEM3 and MPI-ESM1 models are able to reproduce relatively well both the spatial pattern and intensity of the observed C and E ENSO modes in both SST and OHC, whereas other models exhibit somewhat more pronounced biases. Among climate models considered here, the INMCM5 is characterized by the lowest magnitude of both the C and E SST/OHC patterns in SST and OHC. Recall that this model also exhibits the lowest global warming trend of the six climate models considered here (see section 3.1). This is consistent with the fact

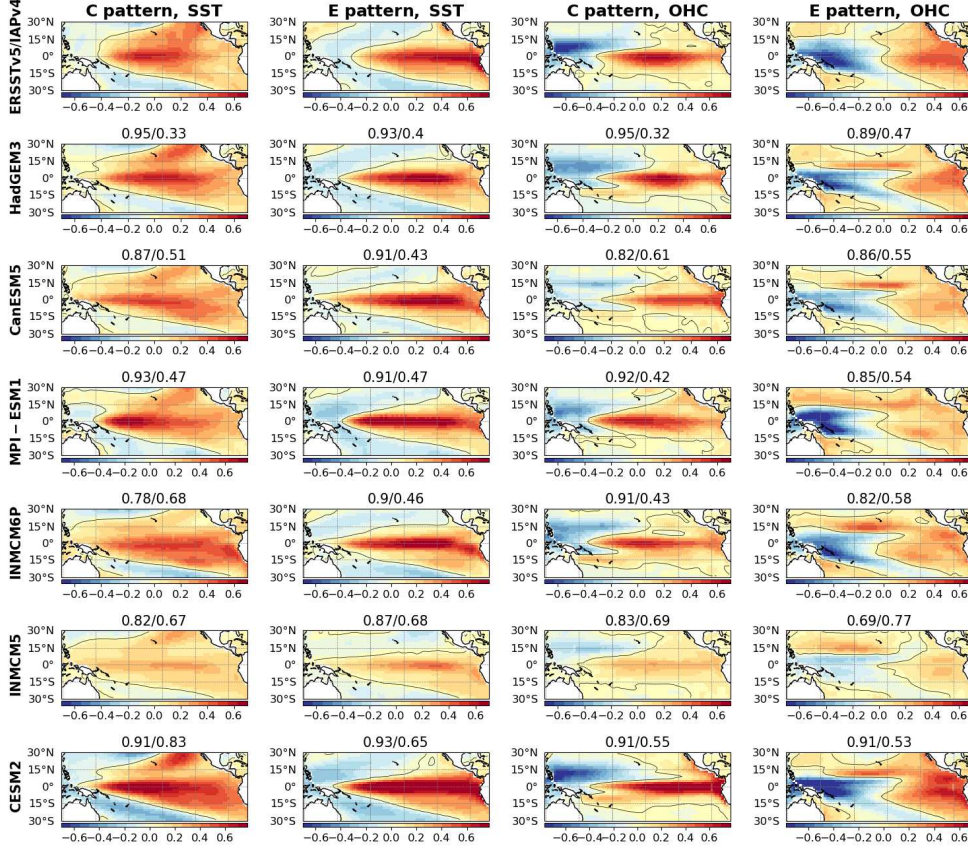


Fig. 11 Spatial patterns obtained by regressing the observed (top row) and individual-model (lower rows) M-ELDM reconstructed ENSO-related variability onto the C- and E-indices (13) (see panel captions). The pattern correlation and root-mean-square distance between the observed and simulated patterns (computed over the domain shown) are also listed in the panel captions for each model. Shown are, from left-to-right, the C and E SST patterns, as well as C and E OHC patterns. Units are $^{\circ}\text{C}$ for SST and 10^9J m^{-2} for OHC.

that models with a higher equilibrium climate sensitivity (ECS) tend to also possess a stronger internal climate variability and vice versa (Cox et al. 2018; Nijssen et al. 2019).

In summary, the M-ELDM method provides a useful framework for identifying the robust behavior across a multi-model ensemble of historical climate simulations and for quantifying the differences between the models, as exemplified in this section by a discussion related to some of the well-known important characteristics of the observed and simulated ENSO-like variability.

4 Summary and discussion

The present work extends the previously developed methodology of the Linear Dynamical Mode (LDM) decomposition for identification and analysis of the forced and

internal dynamics in a single-model ensemble of historical climate simulations (S-ELDM method: [Gavrilov et al. 2024](#)) to the case of a multi-model ensemble, resulting in the new M-ELDM method. This method decomposes the output of multi-model climate simulations into a set of forced and internal modes characterized by their spatial patterns (common across all models) and the corresponding time series (components) associated with their (a priori unknown) dominant time scales. Importantly, unlike other pattern-recognition methods (e.g., [Schneider and Held 2001](#); [Frankignoul et al. 2017](#); [Wills et al. 2018, 2020](#)), the M-ELDM method makes no prior assumptions about the spatiotemporal differences between the forced and internal modes, except for postulating that the forced-response components are the same in all climate realizations within each single-model sub-ensemble comprising the multi-model ensemble considered. All of the decomposition parameters, including the number of forced and internal modes, their spatial patterns, time series and corresponding time scales are determined via a Bayesian optimization procedure. The M-ELDM decomposition thus represents an objective dynamical (through the forced-vs.-internal mode identification), as well as temporal (through the modal time-scale identification) filter that identifies robust spatial features across the entire multi-model ensemble, thereby providing efficient means for comparing the temporal behavior of different climate models across the range of relevant time scales. This methodology was applied before in [Wills et al. \(2026\)](#) (method 23) but never previously described in detail.

The M-ELDM method was used here to analyze, separately, the variability of sea-surface temperature (SST) and 0–300m upper-ocean heat content (OHC) over the 1950–2014 period in historical simulations of six state-of-the-art Earth System Models (ESMs) (with 10 realizations per model) and to compare the simulated variability with the observed (reanalysis based) estimates of climate variability. The choice of the analysis period was dictated by the length of the OHC product and the end date of the ESM runs used here. We reconstructed the fast (interannual, with time scales than 6 years) and slow (decadal and longer, with the time scales exceeding 8 years) climate variability as the sum of the corresponding M-ELDM modes. The simulated (slow) forced response was shown to be vastly dominated by its leading empirical orthogonal function (EOF), which describes 95% and 85% of the total forced SST and OHC variability across the entire multi-model ensemble, respectively. To compare the model simulations with the observed behavior, we followed the approach of [Gavrilov et al. \(2020\)](#) and used the ensemble-mean principal component (PC) of this multi-model simulated M-ELDM reconstructed forced signal as the prescribed time series of the “observed” forced response in the LDM algorithm, which then returned the associated observed forced-response pattern (to be compared with the model simulated pattern), as well as the LDM patterns and time series of the observed residual (nominally, internal) variability. The fast and slow subsets of the observed internal modes so defined were then reconstructed based on their time scales in the same way as for the M-ELDM modes of model simulations.

The simulated leading forced response encapsulates the known cumulative effects of different climatic forcings, including the overall greenhouse-gas induced warming slowed by the anthropogenic aerosols prior to 1980 and punctuated with distinctive cooling episodes due to the volcanic eruptions. This response is also characterized by

the largest intermodel forced-signal uncertainty, with some of the models featuring faster or slower warming rates, as well as by a range of model sensitivities to the volcanic forcing, immediately obvious from the inspection of the multi-model spread of the corresponding component. The simulated response pattern is strongest in the Northern Hemisphere and is largely consistent with the observed pattern in the Atlantic and Indian Ocean sectors but is dramatically different in the Pacific sector, where it lacks a strong signature of the negative Pacific Decadal Oscillation (PDO) pattern present in the observed data (cf. [Trenberth and Fasullo 2013](#); [Armour et al. 2024](#); [Wills et al. 2022](#)).

The slow component of the observed residual variability (with respect to the dominant forced signal above) recovers the so-called Global Stadium Wave (GSW: [Wyatt et al. 2012](#); [Kravtsov and Callicutt 2017](#); [Kravtsov et al. 2018, 2024](#)). The GSW is represented by the AMO-like component associated with the Atlantic Multidecadal Oscillation (AMO: [Zhang et al. 2019](#)), whose North Atlantic SST/OHC signature consistent with that in [Yan et al. \(2019\)](#), and an AMO-orth mode strongly related, as shown here for the first time, to the PDO-like variability ([Trenberth and Fasullo 2013](#)). The AMO-like and AMO-orth modes of the models’ internal or anomalous forced variability subsets (the latter subset computed via the M-ELDM identified forced subset less the ensemble-mean of its leading forced signal) exhibit different patterns and, for the anomalous forced variability, longer time scales compared to observations. Most notably, the model simulated multidecadal variability patterns once again largely miss, in both cases, the PDO-like signature apparent in the observed patterns. The presence of the PDO-like signature in our estimates of both forced and internal observed climate variability is possibly indicative of the so-called dynamical forced response of the climate system to the external forcing, which arises due to the corresponding adjustments of the internal climate modes (e.g., [Kravtsov et al. 2022](#); [Gavrilov et al. 2024](#)). Such response is also implicit in the model simulations, as the patterns of the simulated anomalous forced response are well correlated with the patterns of the simulated internal variability. However, these patterns are, once again, very different from the observed patterns. These results taken together suggest that the observed multidecadal climate variability cannot be unequivocally attributed to either internal or forced dynamics based on the current modeling evidence. The present work thus generalizes the previous results on the multidecadal variability apparently missing from the climate models ([Kravtsov and Callicutt \(2017\)](#); [Kravtsov et al. \(2018, 2024\)](#)) to include additional climatic fields and provides new clues to better delineate the discrepancies between the observed and simulated variability. In particular, we speculate here that the current generation of climate models underestimates the intensity and/or coupling between the internal climate “oscillators” [Tsonis et al. \(2007\)](#) thereby misrepresenting both the internal climate variability and the associated dynamical forced response which possibly underlie the observed GSW.

The fast component of internal variability in SST and OHC is dominated by the ENSO-like modes. Our LDM-based spatiotemporal filtering is efficient in distinguishing between the known quasi-biennial and quasi-quadrennial ENSO signals in the tropical Pacific (cf. [Jiang et al. 1995](#); [Bejarano and Jin 2008](#)); these signals are present in both models and observations. The models are also doing a decent job in replicating

the leading ENSO patterns. However, a closer inspection reveals important differences between the observed and simulated ENSO variability. In particular, the models underestimate the observed ENSO nonlinearity manifested in the non-Gaussianity of its two-dimensional probability distributions and, as a result, also underestimate the observed asymmetry between stronger warm (El Niño) and weaker cold (La Niña) ENSO states, suggesting model deficiencies in representing the nonlinear oceanic feedbacks thought to be important in ENSO dynamics (Jin et al. 2003; An and Jin 2004; An and Kim 2017). Some of the models are also struggling to capture the observed ENSO diversity by misrepresenting the patterns associated with the Central Pacific and Eastern Pacific ENSO events.

The main goal of this paper is to demonstrate the utility of our M-ELDM method in identifying robust aspects of the forced and internal variability in multi-model ensembles of climate simulations to provide an efficient tool for model intercomparison, as illustrated by the examples of the analysis summarized above. The method can be applied to any number of models and climatic fields, and can be easily modified to analyze the joint variability of multiple fields (for example, by utilizing common EOFs of such fields on the data pre-processing stage). The M-ELDM decomposition can also be useful in statistical schemes designed to isolate the forced variability in the observational data, as in our present work (see also Wills et al. 2026, method 23). Finally, the M-ELDM decomposition provides a natural low-dimensional basis for constructing data-driven climate emulators (see, for example, Gavrilov et al. 2019; Mukhin et al. 2021; Seleznev and Mukhin 2023), which can be further used for the dynamical analysis of climate representations across a multi-model ensemble, as well as a lightweight climate forecast tool.

Supplementary information. The Supplementary Information for this manuscript is available online at <https://###>.

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Author contribution. AS and SK: designed the study. AG, EL and AF: formulated M-ELDM methodology. MB: computed M-ELDMs for multimodel ensembles

and LDMs for observational data. AS and SK: performed other supplementary computations. All authors analyzed the results. AS, MB, SK and AG: wrote the first draft of the manuscript, which was then revised by all authors.

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Data availability. The data used in this study is publicly available online at <https://psl.noaa.gov/data/gridded/data.noaa.ersst.v5.html> (a global monthly SST analysis; Huang et al. 2017), <http://www.ocean.iap.ac.cn/> (a global monthly OHC analysis; Cheng et al. 2024), <https://esgf.github.io/index.html> (CMIP6 models output data; Eyring et al. 2016). The output data from the INMCM6P climate model simulations can be made available upon request.

Code availability. The M-ELDM implementation was adopted from Wills et al. (2026). The final code to reproduce all results is available from the corresponding author upon reasonable request.

Conflict of interest. The authors declare that they have no conflict of interest.

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