Dynamics and Predictability of Hemispheric-Scale Multidecadal Climate Variability in an Observationally Constrained Mechanistic Model

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ABSTRACT

This paper addresses the dynamics of internal hemispheric-scale multidecadal climate variability by postulating an energy-balance (EBM) model comprising two deep-ocean oscillators in the Atlantic and Pacific basins, coupled through their surface mixed layers via atmospheric teleconnections. This system is linear and driven by the atmospheric noise. Two sets of the EBM model parameters are developed by fitting the EBM-based mixed-layer temperature covariance structure to best mimic basin-average North Atlantic/Pacific sea surface temperature (SST) covariability in either observations or control simulations of comprehensive climate models within the CMIP5 project. The differences between the dynamics underlying the observed and CMIP5-simulated multidecadal climate variability and predictability are encapsulated in the algebraic structure of the two EBM model versions so obtained: EBM_{CMIP5} and EBM_{OBS} . The multidecadal variability in EBM_{CMIP5} is overall weaker and amounts to a smaller fraction of the total SST variability than in EBM_{OBS} , pointing to a lower potential decadal predictability of virtual CMIP5 climates relative to that of the actual climate. The EBM_{CMIP5} decadal hemispheric teleconnections (and, by inference, those in CMIP5 models) are largely controlled by the variability of the Pacific, in which the ocean, due to its large thermal and dynamical memory, acts as a passive integrator of atmospheric noise. By contrast, EBM_{OBS} features a stronger two-way coupling between the Atlantic and Pacific multidecadal oscillators, thereby suggesting the existence of a hemispheric-scale and, perhaps, global multidecadal mode associated with internal ocean dynamics. The inferred differences between the observed and CMIP5 simulated climate variability stem from a stronger communication between the deep ocean and surface processes implicit in the observational data.

1. Introduction

Decadal climate variability (DCV) generated internally within the climate system can give rise to significant modulations of regional-to-global warming trends and may be associated with useful near-term climate predictability (Latif et al. 2006; Smith et al. 2012; Kirtman et al. 2013; Meehl et al. 2014; Yeager and Robson 2017; Cassou et al. 2018). At longer, multidecadal time scales, a tantalizing property of both observed DCV (Kravtsov and Spannagle 2008; Wyatt et al. 2012; Deser and Phillips 2017) and DCV simulated by the state-of-the-art climate models

(Dommenget and Latif 2008; Barcikowska et al. 2017; Ghil et al. 2019) is its tendency to exhibit a truly global character, forming a “network of teleconnections, linking neighboring ocean basins, the tropics and extratropics, and the oceans and land regions” (Cassou et al. 2018, p. 479), although the overall magnitude and spatiotemporal structure of these teleconnections in models versus observations appears to be different (Kravtsov et al. 2014; Kravtsov 2017; Kravtsov et al. 2018).

The two prominent regional modes of DCV with pronounced sea surface temperature (SST) expressions that have been receiving a great deal of attention are the Atlantic multidecadal oscillation [AMO: Kerr 2000; Delworth and Mann 2000; Enfield et al. 2001; Knight et al. 2005; alternatively, Atlantic multidecadal variability (AMV): Zhang 2017] and the Pacific decadal oscillation/variability (PDO/PDV: Mantua et al. 1997; Minobe 1997; Schneider et al. 2002; Deser et al. 2012;

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Newman et al. 2016). The PDO is not entirely synonymous but is still very closely connected with the so-called interdecadal Pacific oscillation/variability (IPO/IPV; see, e.g., Dong and Dai 2015); it is on those long, multidecadal time scales where the AMO and PDO appear to be most strongly interrelated (d'Orgeville and Peltier 2007; Wu et al. 2011; Wyatt et al. 2012; Kravtsov et al. 2014); see below.

The overwhelming evidence from a combination of statistical analyses and first-principle climate modeling [in particular, but not solely, from control simulations of global climate models (GCMs) subject to preindustrial conditions] suggests that both AMO and PDO/IPO are associated with internal climate dynamics largely independent from the variability in the external forcing (DelSole et al. 2011, 2013; Newman 2007, 2013; Trenary and DelSole 2016; Yan et al. 2018, among others). The AMO mechanisms are thought to centrally involve the internal (but, possibly, excited by the stochastic atmospheric noise; see, e.g., Delworth et al. 2017) multidecadal (50–70 yr) variability of the Atlantic meridional overturning circulation (AMOC; Buckley and Marshall 2016; Zhang et al. 2019) aided, perhaps, by coupled air–sea feedbacks in the tropics (Bellomo et al. 2016; Brown et al. 2016; Yuan et al. 2016) and on basin scale (Li et al. 2013; Sun et al. 2015). The PDO/IPO is likely to be a superposition of a suite of distinct processes rather than a single physical mode (Newman et al. 2016), although some studies highlight the singular importance, on time scales of 20–30 years, of tropical–extratropical interactions involving the shallow subtropical oceanic meridional overturning circulation cell in the Pacific (Meehl and Hu 2006; Farneti et al. 2014a,b).

The *multidecadal* component of PDO/IPO, on the other hand, may reflect the hemispheric imprint of the AMO variability via extratropical or tropical atmospheric teleconnections (see Kucharski et al. 2016; Sun et al. 2017; Zhang et al. 2019, section 4.2, and references therein). This follows from the so-called pacemaker experiments using global coupled climate models, in which forcing the model SST in the whole of or a subregion of the Atlantic Ocean via some sort of data assimilation to match the observed SST evolution there allows one to faithfully reproduce the observed multidecadal variability in the rest of the world. It is noteworthy, however, that this seems also to be the case for the Pacific pacemaker experiments (Kosaka and Xie 2016), highlighting two-way interactions between Atlantic and Pacific basins as being likely instrumental in the hemispheric-scale multidecadal climate variability (see McGregor et al. 2014; Meehl et al. 2016).

Finally, initialized near-term prediction systems [see Cassou et al. (2018) for a recent summary] show a larger

skill of predicting AMO compared to PDO/IPO, although the skill for the former seems to be confined to the Atlantic Ocean region due, tentatively, to underestimated magnitude of multidecadal variability in AMOC (Yan et al. 2018) combined, as discussed above, with misrepresentation, in climate models, of air–sea feedbacks that shape and energize the observed basin-scale AMO signature. The resulting weaker-than-observed basin-scale multidecadal AMO signals in coupled climate GCMs (Kravtsov and Callicutt 2017; Kravtsov 2017; Kim et al. 2018; Yan et al. 2019) are consistent with weak interbasin coupling in free runs of these models (despite an apparent teleconnectivity demonstrated via pacemaker experiments), the loss of potential AMO-related skill in predicting the PDO/IPO, as well as with the lack, in these models, of the global-scale multidecadal variability matching the magnitude and spatiotemporal structure of such variability diagnosed in the reanalysis data (Kravtsov et al. 2018).

In this paper, we develop a minimal model conceptualizing the dynamics and predictability of hemispheric-scale multidecadal climate variability. Such models play an important role in climate modeling hierarchy (Ghil and Robertson 2000; Held 2005, 2014; Jeevanjee et al. 2017; Ghil and Lucarini 2019). They have been used, among many other things, to formulate the red-noise null hypothesis for low-frequency climate variability (Hasselmann 1976), to identify reduced thermal damping as the basic effect of ocean–atmosphere thermal coupling (Barsugli and Battisti 1998), to interpret the behavior of comprehensive (Bretherton and Battisti 2000) and intermediate-complexity climate models (Kravtsov et al. 2008), and to study DCV in the single-basin context (e.g., Marshall et al. 2001 and references therein). We extend the latter energy-balance model (EBM) studies to include two ocean basins coupled linearly via atmospheric teleconnections; aside from this coupling, the SST variability in each basin is a combination of the fast component due to mixed-layer passive response to atmospheric noise (Barsugli and Battisti 1998) and the slow component associated with the tendency of the oceanic circulation and heat transport to act as a delayed negative feedback on thermal perturbations, thereby leading to DCV (Marshall et al. 2001). The EBM model parameters are constrained in a way for this model to reproduce the covariance structure of the Atlantic/Pacific SSTs in either observations or an ensemble of preindustrial control simulations of global climate GCMs. The differences between the observed structure of the hemispheric multidecadal climate variability and the one simulated by GCMs thus become encapsulated in the algebraic structure of the two versions of the EBM model. These differences point to very different predictability

FIG. 1. Cartoon of the energy-balance model (EBM) geometry. The model is a two-basin extension of a slab ocean–atmosphere model of Barsugli and Battisti (1998). Within each basin, the ocean model also has a thermocline component, which exchanges heat with the ocean mixed layer and, advectively, with a fixed-temperature deep ocean (not shown). The two basins are coupled via parameterized atmospheric teleconnections.

characteristics of the actual climate and its virtual, GCM simulated counterpart.

In section 2, we formulate our multiscale two-basin EBM model and estimate its parameters. Section 3 compares the algebraic structure of the EBM models tuned to represent the observations and GCMs and shows how the differences in this structure affect decadal variability and predictability of the two EBMs. Implications of our analysis and potential future applications of the EBM models developed here are discussed in section 4.

2. Model development

We consider the hemispheric system of two ocean basins (namely, the North Atlantic and North Pacific Oceans) coupled via the atmosphere (Fig. 1). The atmospheric model has one layer representing the midlatitude atmospheric boundary layer, while the oceans are divided in the vertical into the mixed-layer and thermocline components; deep-ocean temperature below the thermocline is assumed to be fixed. The atmospheric boundary layer temperature, surface atmospheric temperature, ocean mixed-layer temperature, and thermocline temperature anomalies with respect to climatology are denoted as $\mathbf{T}_a = (T_{a,1}, T_{a,2})^T$, $\mathbf{T}_{sf} = (T_{sf,1}, T_{sf,2})^T$, $\mathbf{T} = (T_1, T_2)^T$, $\mathbf{T}_o = (T_{o,1}, T_{o,2})^T$, respectively, with the superscript T indicating the transpose operator (making the temperatures two-valued column vectors) and subscripts 1

and 2 referring to the North Atlantic and North Pacific basins. The surface atmospheric temperature is assumed to be linearly related to the boundary layer temperatures

$$\mathbf{T}_{sf} = c\mathbf{T}_a, \quad (1)$$

and we used the fixed value of $c = 1$ throughout the paper, following Barsugli and Battisti (1998).

a. Ocean mixed layer–atmosphere component

The equations governing the evolution of the ocean mixed layer and atmospheric temperature anomalies represent the coupled system's energy balance achieved via radiation and heat exchange processes and are completely analogous to those developed by Barsugli and Battisti (1998), except for the inclusion of interbasin communication through atmospheric teleconnections and heat exchange between oceanic mixed layer and thermocline:

$$\gamma_a \dot{\mathbf{T}}_a = \lambda_{sa}(\mathbf{T} - \mathbf{T}_{sf}) - \lambda_a \mathbf{T}_a + \Lambda_c \mathbf{T} + \mathcal{F}_T, \quad (2)$$

$$\gamma_o \dot{\mathbf{T}} = -\lambda_{so}(\mathbf{T} - \mathbf{T}_{sf}) - \lambda_o \mathbf{T} - \Lambda_{do}(\mathbf{T} - \mathbf{T}_o), \quad (3)$$

$$\Lambda_c = \begin{pmatrix} \lambda_c & \lambda_{c2,1} \\ \lambda_{c1,2} & \lambda_c \end{pmatrix}; \quad \Lambda_{do} = \begin{pmatrix} \lambda_{do,1} & 0 \\ 0 & \lambda_{do,2} \end{pmatrix}. \quad (4)$$

The fixed parameters in (2)–(4), which are, once again, the same as in Barsugli and Battisti (1998), are listed

TABLE 1. Fixed geometrical and physical parameters.

Parameters	Value, units	Description
(H_a, h_o, H_o)	(1000, 150, 1000) m	Layer thicknesses: (atmosphere, ocean mixed layer, thermocline)
(Σ_1, Σ_2)	$(16 \times 10^{12}, 36 \times 10^{12}) \text{ m}^2$	Areas: (Atlantic, Pacific)
(ρ_a, ρ_w)	(1, 1000) kg m^{-3}	Densities: (air, water)
(c_a, c_w)	(1000, 4000) $\text{J kg}^{-1} \text{K}^{-1}$	Heat capacities: (air, water)
σ	$5.7 \times 10^{-8} \text{ W m}^{-2} \text{K}^{-4}$	Stefan-Boltzmann constant
ε	0.76	Atmospheric emissivity
λ	$20 \text{ W m}^{-2} \text{K}$	Ocean-atmosphere heat exchange coefficient
$(\bar{T}_a, \bar{T})$	(270, 285) K	Climatological temperatures: (atmosphere, ocean mixed layer)
$(\Delta T_1, \Delta T_2)$	(20, 10) K	Effective vertical temperature gradient: (Atlantic, Pacific)
τ_d	100 yr	Ocean circulation spin-down time scale

and described in Tables 1 and 2 and the dot denotes the time derivative. The last two terms in (2) parameterize unresolved dynamics, which is partly due to oceanic feedback onto the atmosphere $\Lambda_c \mathbf{T}$ and partly due to internal atmospheric variability $\mathcal{F}_T$, to be modeled as a white noise process. Local (within-basin) and remote (interbasin) feedbacks are represented by diagonal and off-diagonal elements of the ocean-atmosphere coupling matrix Λ_c . The exchange rates between ocean mixed layer and the thermocline below [last term in (3)] can be different between the basins; see the expression for Λ_{do} in (4). The within-basin ocean-atmosphere coupling parameter λ_c is the same as in Barsugli and Battisti (1998), while the parameters $\lambda_{c2,1}$, $\lambda_{c1,2}$, $\lambda_{do,1}$, $\lambda_{do,2}$ will be determined by model tuning (see section 2d).

Using the time scale $[t] = \gamma_o/\lambda_{so}$ and temperature anomaly scale of 1 K (Table 2), the dimensionless version of the system (1)–(4) can be written as (keeping for dimensionless temperatures the same notations as for the dimensional temperatures)

$$\beta^{-1} \mathbf{T}_a = -a \mathbf{T}_a + \mathbf{B} \mathbf{T} + A \mathbf{N}, \quad (5)$$

$$\dot{\mathbf{T}} = c \mathbf{T}_a - d \mathbf{T} - \mathbf{E}(\mathbf{T} - \mathbf{T}_o), \quad (6)$$

$$\mathbf{B} = \begin{pmatrix} b & f_{2,1} \\ f_{1,2} & b \end{pmatrix}; \quad \mathbf{E} = \begin{pmatrix} e_1 & 0 \\ 0 & e_2 \end{pmatrix}. \quad (7)$$

Here $\mathbf{N}$ is spatially uncorrelated (two-valued) Gaussian-distributed white noise with zero mean and unit standard deviation and A is the dimensionless amplitude; Table 3 lists the definitions and values of the parameters β^{-1} , a , b , c , d , e_1 , e_2 , $f_{2,1}$, and $f_{1,2}$. Using the fact that $\beta^{-1} \ll 1$ and neglecting the heat storage in the atmosphere, we can eliminate the atmospheric temperature $\mathbf{T}_a$ from (5) and (6) and obtain the single approximate equation for the low-frequency evolution of the ocean mixed-layer temperature $\mathbf{T}$; this equation in the component form is

$$\frac{a}{c} \dot{T}_1 = \left[b - \frac{a(d + e_1)}{c} \right] T_1 + f_{2,1} T_2 + \frac{ae_1}{c} T_{o,1} + A N_1, \quad (8a)$$

$$\frac{a}{c} \dot{T}_2 = f_{1,2} T_1 + \left[b - \frac{a(d + e_2)}{c} \right] T_2 + \frac{ae_2}{c} T_{o,2} + A N_2. \quad (8b)$$

The system (8) with e_1 , e_2 , $f_{2,1}$, and $f_{1,2}$ set to zero reduces, in each basin, to the Barsugli and Battisti (1998) model.

b. Thermocline component

The equations proposed below for the evolution of the basin-scale thermocline temperature anomalies represent, in a mechanistic fashion, slow ocean dynamics involving advective heat transports by the oceanic circulation. For conceptual simplicity, we further discuss these transports as being primarily associated with the meridional overturning circulation (MOC), by assuming that its anomalies q are acting on the mean vertical temperature gradient ΔT between the thermocline and deep ocean to induce changes in the thermocline

TABLE 2. Derived (fixed) dimensional parameters and scales.

Parameter	Formula	Value/comments
γ_a	$\rho_a c_a H_a$	$1 \times 10^6 \text{ J m}^{-2} \text{K}^{-1}$
γ_o	$\rho_w c_w h_o$	$6 \times 10^8 \text{ J m}^{-2} \text{K}^{-1}$
γ_d	$\rho_w c_w H_o$	$4 \times 10^9 \text{ J m}^{-2} \text{K}^{-1}$
λ_{sa}	$\lambda + 4\varepsilon\sigma\bar{T}^3$	$24.01 \text{ W m}^{-2} \text{K}^{-1}$
λ_a	$4\varepsilon\sigma(2\bar{T}_a^3 - c\bar{T}^3)$	$2.81 \text{ W m}^{-2} \text{K}^{-1}$
λ_{so}	$\lambda + 4\varepsilon\sigma\bar{T}_a^3/c$	$23.41 \text{ W m}^{-2} \text{K}^{-1}$
λ_o	$4\sigma(\bar{T}^3 - \varepsilon\bar{T}_a^3/c)$	$1.87 \text{ W m}^{-2} \text{K}^{-1}$
$[t]$	γ_o/λ_{so}	0.81 yr (time scale)
$[T]$	—	1 K (temperature scale)
$[q]$	—	1 Sv (1 Sv $\equiv 10^6 \text{ m}^3 \text{s}^{-1}$) (ocean circulation anomaly scale)

TABLE 3. Dimensionless parameters.

Parameter	Formula	Value/comments
β^{-1}	$\gamma_a \lambda_{so} / \gamma_o \lambda_{sa}$	0.0016
a	$(\lambda_a / \lambda_{sa}) + c$	1.11
b	$(\lambda_c / \lambda_{sa}) + 1$	0.5
c	—	1
d	$(\lambda_o / \lambda_{so}) + 1$	1.08
e_k	$\lambda_{do,k} / \lambda_{so}$	To be tuned; $k = 1, 2$
$(f_{2,1}, f_{1,2})$	$(\lambda_{c2,1}, \lambda_{c1,2}) / \lambda_{sa}$	To be tuned
A	—	To be tuned
ε_h	$(\gamma_o / \gamma_d) = (h_o / H_o)$	0.15
$(\tau_{q,1}, \tau_{q,2})$	$\gamma_d [q] / H_o \lambda_{so} (\Delta T_1 / \Sigma_1, \Delta T_2 / \Sigma_2)$	(0.2136, 0.0475)
$q_{T,k}$	$Q_{T,k} [t] / [\varepsilon_h [q]]$	To be tuned; $k = 1, 2$
k_q	$[t] / \varepsilon_h \tau_d$	0.0542
B	—	To be tuned
C	—	To be tuned

temperature: $\dot{T}_o \sim -q\Delta T$. We also assume that the basin-scale thermocline temperature anomalies are representative of changes in the meridional temperature gradient and force the changes in the MOC (Marshall et al. 2001); hence, $\dot{q} \sim +T_o$. The corresponding equations for each ocean basin thus have the following form:

$$\gamma_d \dot{T}_o = -\frac{\gamma_d}{H_o \Sigma} (q\Delta T + \bar{q}T_o) - \lambda_{do}(T_o - T) + \mathcal{F}_{T_o}, \quad (9)$$

$$\dot{q} = Q_T T_o - \frac{q}{\tau_d} + \mathcal{F}_q. \quad (10)$$

In the above, the term proportional to $\bar{q}T_o$ describes the advection of temperature anomalies by the mean meridional overturning. While this is a valid physical process, we would set this term to zero (thus, formally, setting $\bar{q}$ to 0) to reduce the number of adjustable parameters in the model, since, mechanistically, it is merely another linear damping term. Our linear thermocline model additionally incorporates the heat exchange between the thermocline and ocean mixed layer [the term $\lambda_{do}(T_o - T)$ in (9)], linear drag $-q/\tau_d$ in the momentum equation (10), and features both thermal and mechanical stochastic forcing $\mathcal{F}_{T_o}$ and $\mathcal{F}_q$, both of which will also be modeled as white-noise processes.

The dimensionless version of (9) and (10) for each ocean basin is

$$\varepsilon_h^{-1} \dot{T}_{o,k} = -\tau_{q,k} q_k - e_k (T_{o,k} - T_k) + B N_{T,k}, \quad (11)$$

$$\varepsilon_h^{-1} \dot{q}_k = q_{T,k} T_{o,k} - k_q q_k + C N_{q,k}, \quad k = 1, 2, \quad (12)$$

where $N_{T,k}$ and $N_{q,k}$ are given by the Gaussian distributed white noise with zero mean and unit standard deviation, and all of the parameters are defined in Table 3; note that the coefficient $\tau_{q,1} > \tau_{q,2}$, reflecting both larger area of the Pacific Ocean and its weaker heat-transport efficiency (Talley 1984; Hsiung 1985). Note also that the coefficient

$\varepsilon_h \ll 1$, which explicitly shows, in nondimensional equations (11) and (12), that the thermocline component of the model represents the slow dynamics of the system, in contrast to fast dynamics modeled by the ocean mixed layer/atmosphere component (8). Finally, (11) and (12) is mathematically a set of equations describing damped linear oscillators with (dimensional) internal periods of

$$P_i = \frac{2\pi[t]}{\varepsilon_h \sqrt{q_{T,k} \tau_{q,k}}}. \quad (13)$$

These oscillators are coupled through the interbasin teleconnections incorporated in the ocean mixed layer/atmosphere model (8).

c. Separation into the fast and slow dynamical systems

To simplify further tuning and analysis of the model (8), (11), and (12), we derive the approximate closed equations for the evolution of the fast and slow components of the system. In particular, we decompose the ocean mixed-layer temperature as

$$\mathbf{T} = \mathbf{T}_f + \mathbf{T}_s, \quad (14)$$

where $\mathbf{T}_f$ and $\mathbf{T}_s$ represent the fast and slow dynamical subsystems. On short time scales, it follows from (11) and (12) that $\dot{T}_{o,i}$ and $\dot{q}_i$ are both $O(\varepsilon_h) \ll 1$, so on these time scales the approximate evolution of the fast system is given by (8) with $T_{o,1}$ and $T_{o,2}$ set to zero:

$$\frac{a}{c} \dot{T}_{f,1} = -D_1 T_{f,1} + f_{2,1} T_{f,2} + A N_1, \quad (15a)$$

$$\frac{a}{c} \dot{T}_{f,2} = f_{1,2} T_{f,1} - D_2 T_{f,2} + A N_2, \quad (15b)$$

$$D_k = \frac{a(d + e_k)}{c} - b, \quad k = 1, 2. \quad (15c)$$

By contrast, on long time scales, the left-hand side of (8) becomes small—as can be shown, for example, by rescaling dimensionless time to $t' = \varepsilon_h t$, so that $d/dt = \varepsilon_h(d/dt')$ —and the ocean mixed layer temperature evolution is effectively dictated by that of the thermocline. Neglecting also the noise terms in (8), assuming that their low-frequency contribution to the slow evolution of $\mathbf{T}_s$ is smaller than the thermocline-induced variability, we can solve (8) with $\dot{T}_1 = \dot{T}_2 = A = 0$ to obtain

$$T_{s,1} = \frac{a/c}{D_1 D_2 - f_{s1,2} f_{s2,1}} (e_1 D_2 T_{o,1} + e_2 f_{s2,1} T_{o,2}), \quad (16a)$$

$$T_{s,2} = \frac{a/c}{D_1 D_2 - f_{s1,2} f_{s2,1}} (e_1 f_{s1,2} T_{o,1} + e_2 D_1 T_{o,2}). \quad (16b)$$

Note that in (16a) and (16b) we introduced new parameters $f_{s2,1}$ and $f_{s1,2}$, which govern interbasin coupling

through atmospheric teleconnections in the slow system; these parameters are analogous to the fast system's parameters $f_{2,1}$ and $f_{1,2}$, but, in general, $f_{s2,1} \neq f_{2,1}$ and $f_{s1,2} \neq f_{1,2}$. In doing so, we implicitly assumed that the surface expressions of the slow and fast systems have different spatial patterns, which both contribute to the basin-mean temperatures, but cause different atmospheric responses across the hemisphere. Such an interpretation of the coupled system developed here in terms of the individual modes (here, fast and slow modes) of the ocean–atmosphere system and their (implicit) spatial patterns is, indeed, one of the possible ways of making connections between the present low-dimensional model and observed or GCM simulated climate variability (cf. Barsugli and Battisti 1998).

Equations (11) and (12) for the thermocline temperature evolution, which complete the formulation of the slow subsystem of our model, remain unchanged:

$$\varepsilon_h^{-1} \dot{T}_{o,k} = -\tau_{q,k} q_k - e_k (T_{o,k} - T_{s,k}) + BN_{T,k}, \quad (17)$$

$$\varepsilon_h^{-1} \dot{q}_k = q_{T,k} T_{o,k} - k_q q_k + CN_{q,k}, \quad k = 1, 2. \quad (18)$$

The system (14)–(18)—with the parameters defined in Table 3 and stochastic forcing $\mathbf{N}$, $\mathbf{N}_T$ and $\mathbf{N}_q$ represented by the Gaussian distributed spatially uncorrelated white noise—can be used to mimic the evolution of the basin-mean mixed-layer temperatures in the North Atlantic and North Pacific. However, 11 of the model parameters, namely e_1 , e_2 , $f_{2,1}$, $f_{1,2}$, $f_{s2,1}$, $f_{s1,2}$, $q_{T,1}$, $q_{T,2}$, A , B , and C , are still undefined. In the next subsection, we will estimate these parameters by matching the lag-covariance structure of the temperatures in our energy-balance model (EBM) (14)–(18) with that in observations and control simulations of the state-of-the-art climate models within phase 5 of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012).

d. Model tuning

To compute the analytical power spectra of the solutions of (14)–(18), we first take the Fourier transform of these equations, for example,

$$T(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{T}(\omega) e^{i\omega t} d\omega, \quad (19)$$

and then solve the resulting linear algebraic systems for the corresponding $\hat{T}$. From (15) we have

$$\hat{T}_{f,1} = A \frac{\sigma_2 \hat{N}_1 + f_{2,1} \hat{N}_2}{\sigma_1 \sigma_2 - f_{1,2} f_{2,1}}, \quad \hat{T}_{f,2} = A \frac{\sigma_1 \hat{N}_2 + f_{1,2} \hat{N}_1}{\sigma_1 \sigma_2 - f_{1,2} f_{2,1}}, \quad (20)$$

where

$$\sigma_k = D_k + i \frac{a}{c} \omega, \quad k = 1, 2 \quad (21)$$

and D_k are given by (16c). The corresponding power spectra and cross-spectrum are then

$$P_{T_{f,1}} = \frac{|\sigma_2|^2 + f_{2,1}^2}{|\sigma_1 \sigma_2 - f_{1,2} f_{2,1}|^2} A^2; \quad P_{T_{f,2}} = \frac{|\sigma_1|^2 + f_{1,2}^2}{|\sigma_1 \sigma_2 - f_{1,2} f_{2,1}|^2} A^2; \\ P_{T_{f,2} T_{f,1}} = \frac{\sigma_2 \bar{\sigma}_1 f_{1,2} + \bar{\sigma}_1 f_{2,1}}{|\sigma_1 \sigma_2 - f_{1,2} f_{2,1}|^2} A^2, \quad (22)$$

where the bar denotes complex conjugate. In comparing the EBM spectra with those of the observed or CMIP5 simulated temperatures, we will be working with the annually averaged data, in which case the spectra (22) need to be multiplied by the $\text{sinc}^2(\omega \bar{t}/2)$, where $\bar{t}$ is the dimensionless time corresponding to 1 year.

In an analogous way, eliminating all $\hat{q}_k$ and $\hat{T}_{s,k}$ from the Fourier transform of (16)–(18) and solving for $\hat{T}_{o,k}$, we can compute the power and cross spectra of $T_{o,k}$ as follows:

$$P_{T_{o,1}} = \frac{1}{|\tilde{D}|^2} \left\{ \left[B^2 + C^2 \frac{\tau_{q,1}^2}{k_q^2 + \left(\frac{\omega}{\varepsilon_h} \right)^2} \right] |\sigma_{s,2}|^2 + \left[B^2 + C^2 \frac{\tau_{q,2}^2}{k_q^2 + \left(\frac{\omega}{\varepsilon_h} \right)^2} \right] \chi_{12}^2 f_{s2,1}^2 \right\}; \\ P_{T_{o,2}} = \frac{1}{|\tilde{D}|^2} \left\{ \left[B^2 + C^2 \frac{\tau_{q,2}^2}{k_q^2 + \left(\frac{\omega}{\varepsilon_h} \right)^2} \right] |\sigma_{s,1}|^2 + \left[B^2 + C^2 \frac{\tau_{q,1}^2}{k_q^2 + \left(\frac{\omega}{\varepsilon_h} \right)^2} \right] \chi_{12}^2 f_{s1,2}^2 \right\}; \\ P_{T_{o,2} T_{o,1}} = \frac{\chi_{12}}{|\tilde{D}|^2} \left\{ \left[B^2 + C^2 \frac{\tau_{q,1}^2}{k_q^2 + \left(\frac{\omega}{\varepsilon_h} \right)^2} \right] \sigma_{s,2} f_{s1,2} + \left[B^2 + C^2 \frac{\tau_{q,2}^2}{k_q^2 + \left(\frac{\omega}{\varepsilon_h} \right)^2} \right] \bar{\sigma}_{s,1} f_{s2,1} \right\}, \quad (23)$$

where the following notations are used:

$$\tilde{D} = \sigma_{s,1}\sigma_{s,2} - f_{s1,2}f_{s2,1}, \quad (24a)$$

$$\sigma_{s,1} = i\frac{\omega}{\varepsilon_h} + e_1 - \chi_1 D_2 + \frac{\tau_{q,1} q_{T,1}}{k_q + i\frac{\omega}{\varepsilon_h}};$$

$$\sigma_{s,2} = i\frac{\omega}{\varepsilon_h} + e_2 - \chi_2 D_1 + \frac{\tau_{q,2} q_{T,2}}{k_q + i\frac{\omega}{\varepsilon_h}}, \quad (24b)$$

$$\chi_{12} = \left(\frac{a}{c}\right) \frac{e_1 e_2}{D_1 D_2 - f_{s1,2} f_{s2,1}}; \quad \chi_k = \left(\frac{a}{c}\right) \frac{e_k^2}{D_1 D_2 - f_{s1,2} f_{s2,1}};$$

$$k = 1, 2. \quad (24c)$$

Since the slow system's power spectra above are strongly red and have negligible power at subannual frequencies, no additional windowing is required here for comparison with the annually averaged data. The spectra of $T_{s,k}$ — $P_{T_{s,1}}$, $P_{T_{s,2}}$, and $P_{T_{s,2}T_{s,1}}$ —can be easily computed from (23) and (24) by exploiting its linear relationship with $T_{o,k}$ [(16a) and (16b)]. Finally, the full spectra of T_k governed by the model (14)–(18) can be found as the sum of the slow and fast subsystem's spectra.

We further computed, analytically, the lag-covariance structure of the model solutions—that is, the auto- and cross-covariances of T_1 and T_2 denoted as $r_{T_1}(\tau)$, $r_{T_2}(\tau)$, and $r_{T_1 T_2}(\tau)$ —by taking the Fourier transform (19) of the power spectra and cross-spectra computed above [here t in (19) should be interpreted as the time lag τ , which can be both positive and negative]. This computation is tedious, but conceptually simple and standard; it involves contour integration in the complex plane using the residue theorem. Programmed as a MATLAB function, the resulting formulas provide values of $r_{T_1}(\tau)$, $r_{T_2}(\tau)$, and $r_{T_1 T_2}(\tau)$ for any lag τ given a set of 11 missing parameters we still need to estimate (see section 2c).

For the latter parameter estimation, we utilized 1) long control simulations (>500 yr each) of 10 CMIP5 models and 2) estimates of the internal SST variability in the North Atlantic and North Pacific SST observations, with the forced signal subtracted using a 17-model ensemble of historical CMIP5 simulations (1880–2005); all of these datasets are the same as used or developed in Kravtsov (2017). The corresponding annual SST anomaly time series were computed for the AMO (Atlantic multidecadal oscillation) and PMO (Pacific multidecadal oscillation) indices, defined as SST area averages over the 0°–60°N, 80°W–0° and 0°–60°N, 120°E–100°W regions, respectively (Steinman et al. 2015; Kravtsov et al. 2015), to be compared with our EBM variables T_1 and T_2 . The online supplemental material provides details of the

datasets and preprocessing procedures used in this study, explores alternative/additional datasets (in particular, historical CMIP5 simulations), and demonstrates that the AMO and PMO indices used here are strongly related, in terms of their time dependence and spatial patterns, to their siblings studied previously (in particular, the internal component of the PMO bears a strong resemblance to PDO/IPO variability).

We computed the sample autocovariance and cross-covariance functions based on each dataset and took their multimodel average to obtain the best estimates of these functions for the observed and CMIP5 simulated internal SST variability for the lags τ between –40 and 40 years; we will refer to these estimates as $r_{T_1, \text{ref}}(\tau)$, $r_{T_2, \text{ref}}(\tau)$, and $r_{T_1 T_2, \text{ref}}(\tau)$, with ref = obs or ref = CMIP5, as appropriate. Finally, we selected the unknown model parameters by minimizing the functional

$$F(e_1, e_2, f_{2,1}, f_{1,2}, f_{s2,1}, f_{s1,2}, q_{T,1}, q_{T,2}, A, B, C)$$

$$= \sum_{\tau} \left\{ \left[\frac{r_{T_1}(\tau) - r_{T_1, \text{ref}}(\tau)}{r_{T_1, \text{ref}}(0)} \right]^2 + \left[\frac{r_{T_2}(\tau) - r_{T_2, \text{ref}}(\tau)}{r_{T_2, \text{ref}}(0)} \right]^2 \right.$$

$$\left. + \left[\frac{r_{T_1 T_2}(\tau)}{\sqrt{r_{T_1}(0)r_{T_2}(0)}} - \frac{r_{T_1 T_2, \text{ref}}(\tau)}{\sqrt{r_{T_1, \text{ref}}(0)r_{T_2, \text{ref}}(0)}} \right]^2 \right\}, \quad (25)$$

using the *fminsearch* function of MATLAB initialized from a cloud of first-guess initial conditions. We selected, for both cases, ref = obs and ref = CMIP5, ~20 possible sets of parameters using the empirically determined thresholds of $F < 1.27$ and $F < 0.09$, respectively. A larger threshold value for ref = obs compared to ref = CMIP5 effectively documents larger net deviations of the observed covariances from the analytical fit, reflecting both a larger sampling variability of the observed covariance estimates due to shortness of the observational record, but also a larger span of time lags with substantial nonzero covariances in observations compared to CMIP5 models (see section 3a). The average values of all tuned parameters, as well as their standard deviations over the respective sample are all given in Table 4; the last two rows of Table 4 also contain the derived estimates of the North Atlantic and North Pacific slow-system internal periods P_1 and P_2 [see (13)].

3. Results

a. Lagged correlations and spectra of AMO and PMO

Both observed and CMIP5 simulated AMO and PMO time series exhibit a multiscale behavior characterized

TABLE 4. Tuned parameters.

Parameter	Tuned to CMIP5 control	Tuned to observations
e_1	0.26 ± 0.02	1.48 ± 0.17
e_2	0.38 ± 0.03	0.61 ± 0.08
$f_{1,2}$	-0.30 ± 0.03	-0.40 ± 0.10
$f_{2,1}$	0.45 ± 0.02	1.26 ± 0.20
$f_{s1,2}$	0.25 ± 0.04	0.32 ± 0.03
$f_{s2,1}$	1.21 ± 0.13	0.90 ± 0.02
$q_{T,1}$	1.83 ± 0.36	1.80 ± 0.04
$q_{T,2}$	0.82 ± 0.13	2.53 ± 0.21
A	0.23 ± 0.004	0.32 ± 0.01
B	0.12 ± 0.02	0.27 ± 0.02
C	0.24 ± 0.06	0.25 ± 0.06
P_1	55 ± 7 yr	55 ± 1 yr
P_2	174 ± 14 yr	99 ± 4 yr

by fast decay of autocorrelations at lags on the order of a few years and slower decay at larger lags, reflecting decadal and longer persistence of SST anomalies (Fig. 2); cf. Zhang (2017). However, the observed low-frequency variability (Fig. 2, right) is characterized by higher decadal autocorrelations than the CMIP5 simulated variability (Fig. 2, left) and bears a signature of a multidecadal oscillation, with negative autocorrelations at large lags, most pronounced in the AMO time series (Fig. 2b). It should be noted that the oscillatory nature of this variability is impossible to deduce or confirm given a short length of the observational record, which is comparable to the apparent “oscillation” period, as reflected by large error bars in Figs. 2b, 2d, and 2f; these error bars correspond, approximately, to the standard uncertainty of the correlation estimates.

The same qualitative discussion applies to the structure of the observed and CMIP5 simulated cross-correlations (Figs. 2e,f). In both CMIP5 models and observations, on short time scales, PMO variability leads AMO variability by about 1 year (corresponding to positive lags in Figs. 2e,f); there is also a local minimum in the AMO/PMO cross-correlation at small negative lags of 1–2 years, hinting at the AMO effect on PMO. These correlations involve, at least partly, tropical–extratropical teleconnections, as demonstrated in the supplemental material by considering the cross-correlations between AMO/PMO anomalies linearly independent of the equatorial Pacific SSTs.

At larger lags, the observed AMO/PMO cross-correlation (Fig. 2f) is much more pronounced, more “oscillatory,” and more asymmetric compared to its CMIP5-based analog. The latter asymmetry manifests in a faster decay of the observed cross-correlations for positive lags between 5 and 20 years (where PMO leads AMO), compared to the cross-correlations for the corresponding negative lags.

The above multiscale behavior is also naturally apparent in the spectra of the observed and CMIP5 simulated

variability (Fig. 3), which exhibit a “two-step bending” (Zhang 2017), with the classical red-noise spectrum at high frequencies plateauing at interannual time scales accompanied by further enhancement of spectral power at interdecadal time scales. In both CMIP5 models (Figs. 3a,c) and observations (Figs. 3b,d), the interdecadal variability in the Atlantic dominates that in the Pacific; however, once again, the observed multidecadal variability is more energetic compared to the CMIP5 simulated variability (cf. Swanson et al. 2009; Zhang and Wang 2013; Kravtsov et al. 2014, 2018; Kravtsov 2017; Kravtsov and Callicutt 2017; Zhang 2017; Yan et al. 2019).

All of these features of the observed and CMIP5 simulated AMO and PMO time series are, by construction, well reproduced by the corresponding versions of our EBM model (14)–(18); see Figs. 2 and 3 (red curves).

b. Differences between EBM versions tuned to mimic CMIP5 models and observations

We next perform a detailed analysis of the differences in the behavior of our EBM metaphors of the observed and CMIP5 simulated AMO/PMO data; hereafter, we will refer to these two versions of the EBM model, with the parameters set at the ensemble-mean values from Table 4, as EBM_{OBS} and EBM_{CMIP5}, respectively. Let us first decompose the EBM-based AMO/PMO autocorrelations (ACF) and cross-correlations (CCF) (Fig. 2) into contributions from the fast and slow subsystems, as per (14) (Fig. 4). The fast-subsystem contributions (blue curves) are substantial at small lags of a few years for both EBM models; however, they are much more pronounced, relative to the slow-subsystem contributions, for the EBM_{CMIP5} (left panels) compared to the EBM_{OBS} (right panels). Furthermore, the e -folding time scales of $T_{f,1}$ and $T_{f,2}$ in EBM_{OBS} are shorter than those in EBM_{CMIP5}, as can be seen from comparing the characteristic widths of the ACFs in Fig. 4a versus Fig. 4b and in Fig. 4c versus Fig. 4d. This is a direct consequence of a much stronger implied efficiency e_1 , e_2 of the heat exchange between the thermocline and ocean mixed layer in EBM_{OBS} over EBM_{CMIP5} (Table 4), which is, indeed, a major difference between the parameter sets characterizing the two EBM models. The resulting damping rates in the fast-sub-system Eqs. (15) are $D_1 = 1$ and 2.36 , $D_2 = 1.14$ and 1.39 ; here the first figure in each pair corresponds to the EBM_{CMIP5} and the second figure to the EBM_{OBS}.

The differences in the fast component of AMO/PMO cross-correlation between EBM_{CMIP5} and EBM_{OBS} (Figs. 4e,f; blue curves) stem from both an enhanced mixed-layer temperature damping rate (due, mostly, to a larger e_1) and a larger Pacific/Atlantic coupling parameter $f_{2,1}$ in EBM_{OBS} compared to EBM_{CMIP5}, as can

FIG. 2. Lagged correlations of the AMO and PMO time series based on (left) the CMIP5 control simulations and on (right) the estimates of observed internal variability obtained by subtracting, from raw observations, forced signals derived from multiple CMIP5 historical runs. Blue curves show results using either CMIP5 simulated or observed data, as appropriate, with error bars representing the standard uncertainty associated with the multimodel spread (of CMIP5 internal variability characteristics and estimated forced signals, respectively). Multiple red curves (~ 20 curves in each panel, for each EBM parameter set) show analytical lagged correlations for the EBM model tuned to represent either CMIP5 control runs or observations. Gray shading shows uncertainty in the correlation estimates (95% spread on the left and 70% spread on the right) associated with the finite length of the available input time series (~ 500 years for the control runs and ~ 120 years for historical time series); these estimates were obtained by using surrogate samples of a given length from numerical simulations of the corresponding EBM model.

FIG. 3. Fourier spectra of the CMIP5-simulated, observed, and EBM-based AMO and PMO time series; same setup, symbols, and conventions as in Fig. 2. An additional black dashed curve in each panel shows the ensemble-mean spectrum from the surrogate numerical simulations of the corresponding EBM model. The numerical spectra were computed by the Welch periodogram method using the window size of 64 years for observations and 128 years for the CMIP5 control runs. Raw spectra were divided by the empirically determined factor of 0.8 to compensate for the variance reduction due to window tapering.

be demonstrated via sensitivity experiments involving these two parameters (not shown). In particular, a combination of these factors results in a larger AMO/PMO positive correlation at short positive lags (Pacific leading Atlantic), but much smaller negative correlation at short negative lags (Atlantic leading Pacific) in the EBM_{OBS} over EBM_{CMIP5} (Figs. 4e,f), despite a similar (negative) value of the Atlantic/Pacific coupling parameter $f_{1,2}$ in the two models.

The most striking differences between the EBM_{OBS} and EBM_{CMIP5} results manifest in a much more pronounced low-frequency variability and interbasin connections in EBM_{OBS}. This is primarily achieved, once again, via a much stronger coupling between the thermocline and mixed layer in the latter model controlled by the parameters e_1 , e_2 (Table 4). Higher levels of the total mixed-layer temperature variability in EBM_{OBS} over EBM_{CMIP5} despite a larger mixed-layer damping in the former model are due to a larger amplitude of the

effective stochastic driving for both fast and slow subsystems there (parameters A and B in Table 4, respectively), while a larger proportion of the low-frequency variability in the mixed-layer temperature of EBM_{OBS} relies on both the stronger thermocline–mixed layer coupling and a higher amplitude of the slow-subsystem stochastic driving; namely, the ratio of the slow-to-fast subsystems’ stochastic forcing amplitudes B/A is approximately 1 in EBM_{OBS} and is only around 0.5 in EBM_{CMIP5}. Accordingly, the resulting relative variances of the slow/fast subsystems in EBM_{OBS} (EBM_{CMIP5}) are about 55%/45% (20%/80%) for AMO (Figs. 4a,b; lag 0) and 30%/70% (10%/90%) for PMO (Figs. 4c,d).

Structurally, the low-frequency variability in EBM_{OBS} exhibits a much more pronounced oscillatory character than that in EBM_{CMIP5}, with the former model’s ACFs and CCF in Figs. 4b, 4d, and 4f having much more substantial negative lobes at decadal lags compared to those of the latter model (Figs. 4a, 4c, and 4e). Furthermore,

FIG. 4. Contributions of the fast (blue curves) and slow (red curves) subsystems to the EBM simulated AMO/PMO auto- (ACF) and cross-correlations (CCF), for the EBM model tuned to represent (left) CMIP5 models and (right) observations. For both of the EBM models here we used the ensemble-mean values of all the parameters (see Table 4). The sum of the blue and red curves in all panels is close to the ensemble-mean of the corresponding red curves in Fig. 2 (not shown).

the AMO/PMO CCF is more asymmetric in EBM_{OBS} and, in particular, exhibits, in the range of lags between -15 and 15 years, larger positive values at negative lags (AMO leads PMO) compared to the values at the corresponding positive lags (PMO leads AMO). To better understand this structure, we can decompose the auto- and cross-covariances $r_{T_{s,1}}, r_{T_{s,1}}, r_{T_{s,1}T_{s,2}}$ of the

slow-subsystem part of the Atlantic and Pacific mixed-layer temperatures $T_{s,1}$ and $T_{s,2}$ into the contributions from the auto- and cross-covariances $r_{T_{o,1}}, r_{T_{o,1}}, r_{T_{o,1}T_{o,2}}$ of the Atlantic and Pacific thermocline temperatures $T_{o,1}$ and $T_{o,2}$ (which drive the variability of the slow subsystem), using (16). The resulting expressions are as follows:

$$r_{T_{s,1}} = \left(\frac{a/c}{D_1 D_2 - f_{s1,2} f_{s2,1}} \right)^2 \left[e_1^2 D_2^2 r_{T_{o,1}} + e_2^2 f_{s2,1}^2 r_{T_{o,2}} + e_1 e_2 D_2 f_{s2,1} (r_{T_{o,1} T_{o,2}} + r_{T_{o,2} T_{o,1}}) \right], \quad (26a)$$

$$r_{T_{s,2}} = \left(\frac{a/c}{D_1 D_2 - f_{s1,2} f_{s2,1}} \right)^2 \left[e_1^2 f_{s1,2}^2 r_{T_{o,1}} + e_2^2 D_1^2 r_{T_{o,2}} + e_1 e_2 D_1 f_{s1,2} (r_{T_{o,1} T_{o,2}} + r_{T_{o,2} T_{o,1}}) \right], \quad (26b)$$

$$r_{T_{s,1} T_{s,2}} = \left(\frac{a/c}{D_1 D_2 - f_{s1,2} f_{s2,1}} \right)^2 \left[e_1^2 D_2 f_{s1,2} r_{T_{o,1}} + e_2^2 D_1 f_{s2,1} r_{T_{o,2}} + e_1 e_2 (D_1 D_2 r_{T_{o,1} T_{o,2}} + f_{s1,2} f_{s2,1} r_{T_{o,2} T_{o,1}}) \right]. \quad (26c)$$

Note that the auto- and cross-covariances $r_{T_{s,1}}$, $r_{T_{s,1} T_{s,2}}$ above are nontrivial only if at least one of the parameters e_1 or e_2 is greater than zero. Furthermore, the cross-covariance $r_{T_{s,1} T_{s,2}}$ can only be asymmetric with respect to lag if both e_1 and e_2 are greater than zero.

The breakdown (26) is visualized in Fig. 5; note the different scale of ACFs and CCF between EBM_{CMIP5} (left panels) and EBM_{OBS} (right panels), with stronger variances (by about a factor of 3) in the latter. In EBM_{CMIP5}, the Pacific Ocean's thermocline temperature auto-covariance $r_{T_{o,2}}$ is the dominant contributor to all of the $r_{T_{s,1}}$, $r_{T_{s,2}}$, $r_{T_{s,1} T_{s,2}}$, with the Atlantic Ocean's auto-covariance only having a comparable contribution to $r_{T_{s,1}}$ (Figs. 5a,c,e). This is due to the fact that for this model $e_2 > e_1$ and $f_{s2,1} > f_{s1,2}$. Therefore, the EBM_{CMIP5} hemispheric low-frequency variability and, by inference, the low-frequency variability and hemispheric teleconnections evident in mixed-layer temperature of CMIP5 models, are to a large extent controlled by the variability of the Pacific Ocean's thermocline temperature. In EBM_{CMIP5}, the latter variability is represented by a strongly damped ultralow-frequency oscillation excited by the stochastic driving; the period of this oscillation is slightly below 200 years (see Figs. 3c, 4c, and 5c, as well as the estimate of P_2 in Table 4).

By contrast, in EBM_{OBS}, the Atlantic contributions to the hemispheric low-frequency variability are much more pronounced, whereas the influence of the Pacific thermocline temperature is smaller than in EBM_{CMIP5}. In particular, the contribution from $r_{T_{o,2}}$ is only dominant in $r_{T_{s,2}}$ (Fig. 5d); it is essentially negligible in $r_{T_{s,1}}$ (Fig. 5b) and is less than contributions from either $r_{T_{o,1}}$ or $r_{T_{o,1} T_{o,2}}$ in $r_{T_{s,1} T_{s,2}}$ (Fig. 5f). The thermocline temperature variability in both oceans is characterized by damped oscillations with periods relatively close to the corresponding oscillators' natural frequencies (periods

of P_1 and P_2 of around 50 and 100 years, respectively; see Table 4), which results in a more "oscillatory" character of EBM_{OBS} ACFs and CCF (Figs. 4 and 5b,d,f) and the corresponding broad spectral peaks in Figs. 3b and 3d. Finally, for both EBM models, $D_1 D_2 \gg f_{s1,2} f_{s2,1}$, so that the contribution from the last term in (26c) to $r_{T_{s,1} T_{s,2}}$ is very small and the asymmetry in of $r_{T_{s,1} T_{s,2}}$ is dictated by that in $r_{T_{o,1} T_{o,2}}$.

In comparing the properties of EBM_{CMIP5} and EBM_{OBS} in general and understanding the interbasin connections manifest in $r_{T_{o,1} T_{o,2}}$ in particular, it is instructive to explicitly compute and compare the coefficients in the slow-subsystem governing Eqs. (16)–(18) for the two EBM models (Table 5). In (29) and (30), the slow-subsystem mixed-layer temperatures $T_{s,1}$, $T_{s,2}$ present in the original formulation (17) were eliminated using (27) and (28).

The only substantial difference between the two versions of the EBM model in the parameterized thermocline momentum equations (31) and (32) is the coefficient in front of $T_{o,2}$, which controls the period of the low-frequency oscillator in the Pacific, leading to longer P_2 in EBM_{CMIP5} relative to that in EBM_{OBS} (Table 4). The thermocline temperature equations (29) and (30) have a very similar algebraic structure in the two EBM versions: In EBM_{OBS}, a stronger net damping of $T_{o,1}$ and $T_{o,2}$ is compensated by a larger magnitude of the stochastic driving. In (29) [describing the low-frequency evolution of the Atlantic Ocean], the feedback from Pacific thermocline temperatures $T_{o,2}$ has a comparable magnitude with the damping term (proportional to $T_{o,1}$) in each case, while the Atlantic influence on the Pacific in (30) is relatively small (slightly larger in EBM_{OBS}).

To gauge the importance of the latter Atlantic-to-Pacific feedback in the EBM simulated hemispheric teleconnections, we compared the covariance structure of $T_{o,1}$ and $T_{o,2}$ in the original model (29)–(32) with that from two additional sensitivity experiments. In the first experiment, we used the time history of $T_{o,2}$ from the original model to force the Atlantic component (29) and (31) of each EBM. In the second experiment, we integrated the full model (29)–(32), with the coefficient in front of $T_{o,1}$ in (30) set to zero. In both experiments, the variability of Pacific temperatures $T_{o,2}$ does not depend on $T_{o,1}$ and acts as an external forcing in the Atlantic Ocean equation (29), but in the former case, the temporal structure of $T_{o,2}$ reflects the fully coupled interbasin dynamics. The resulting differences in the $T_{o,1}/T_{o,2}$ cross-correlation are substantial in both versions of the EBM model (Figs. 6e,f). The cross-correlation in all cases is asymmetric with respect to the lag, reflecting, for the auxiliary experiments, the memory of the $T_{o,2}$ forcing time series at negative lags ($T_{o,1}$ leads $T_{o,2}$) and forced

FIG. 5. Breakdown of the auto- (ACF) and cross-covariances (CCF) of the slow subsystem's ocean mixed-layer temperatures $T_{s,1}$ (AMO) and $T_{s,2}$ (PMO) (the ACFs and CCF are denoted here as $r_{T_{s,1}}, r_{T_{s,2}}$ and $r_{T_{s,1}T_{s,2}}$; black curves) into contributions from the auto- and cross-covariances of the thermocline temperatures $T_{o,1}$ and $T_{o,2}$ — $r_{T_{o,1}}, r_{T_{o,2}}$ and $r_{T_{o,1}T_{o,2}}$; see (26). The results from EBM models tuned to represent (left) CMIP5 models and (right) observations are shown. The black curves in all panels are the unscaled versions of the corresponding auto- and cross correlations (red curves) in Fig. 4.

oscillatory response of $T_{o,1}$ to $T_{o,2}$ at positive lags. The lowest correlations appear in the “no AMO $\rightarrow$ PMO influence” experiment and the highest in the original experiment with the full interbasin coupling, with the maximum of correlation shifting toward negative lags,

indicating the AMO effect on PMO in the original experiment. There are also the corresponding sizable changes in the auto-covariances in EBM_{OBS} (Figs. 6b,d), but not in EBM_{CMIP5} (Figs. 6a,c). Thus, despite an apparent smallness of the $T_{o,1}$ (AMO) feedback on $T_{o,2}$

TABLE 5. Comparison of the algebraic structure of the EBM_{CMIP5} and EBM_{OBS} equations (16)–(18) governing the slow-subsystem evolution. The coefficients distinct between the two versions of the EBM model are in boldface.

EBM _{CMIP5}	EBM _{OBS}	
$T_{s,1} = \mathbf{0.4} T_{o,1} + \mathbf{0.62} T_{o,2}$	$T_{s,1} = \mathbf{0.76} T_{o,1} + \mathbf{0.21} T_{o,2}$	(27)
$T_{s,2} = \mathbf{0.08} T_{o,1} + 0.51 T_{o,2}$	$T_{s,2} = \mathbf{0.18} T_{o,1} + \mathbf{0.54} T_{o,2}$	(28)
$0.15^{-1} \dot{T}_{o,1} = -0.21q_1 - \mathbf{0.16} T_{o,1} + \mathbf{0.16} T_{o,2} + \mathbf{0.12} N_{T,1}$	$0.15^{-1} \dot{T}_{o,1} = -0.21q_1 - \mathbf{0.36} T_{o,1} + \mathbf{0.31} T_{o,2} + \mathbf{0.27} N_{T,1}$	(29)
$0.15^{-1} \dot{T}_{o,2} = -0.05q_2 - \mathbf{0.19} T_{o,2} + \mathbf{0.03} T_{o,1} + \mathbf{0.12} N_{T,2}$	$0.15^{-1} \dot{T}_{o,2} = -0.05q_2 - \mathbf{0.28} T_{o,2} + \mathbf{0.11} T_{o,1} + \mathbf{0.27} N_{T,2}$	(30)
$0.15^{-1} \dot{q}_1 = 1.83 T_{o,1} - 0.05q_1 + 0.24 N_{q,1}$	$0.15^{-1} \dot{q}_1 = 1.80 T_{o,1} - 0.05q_1 + 0.25 N_{q,1}$	(31)
$0.15^{-1} \dot{q}_2 = \mathbf{0.82} T_{o,2} - 0.05q_2 + 0.24 N_{q,2}$	$0.15^{-1} \dot{q}_2 = \mathbf{2.53} T_{o,2} - 0.05q_2 + 0.25 N_{q,2}$	(32)

(PMO) in (30), it appears to play an important role in setting up hemispheric teleconnections in the present EBM model, especially for the EBM parameter set reflecting the observed data.

Very different relative contributions of the Atlantic and Pacific sectors to the mixed-layer temperature low-frequency variability in Fig. 5 for EBM_{CMIP5} and EBM_{OBS} are ultimately controlled by different hemispheric teleconnections encapsulated in (16a) and (16b), as can be seen from its numerical equivalent (27) and (28), with EBM_{OBS}, once again, featuring larger contributions from the Atlantic ($T_{o,1}$ terms) throughout the globe and weaker teleconnection from Pacific to Atlantic compared to EBM_{CMIP5}, whose mixed-layer temperature low-frequency variability and teleconnections are dominated by the Pacific. This, coupled with smaller relative contribution of the slow subsystem to the total AMO/PMO variability in EBM_{CMIP5} (Fig. 4), leads to drastic differences between covariances and spectra simulated by our two versions of the EBM model (Figs. 2 and 3). All in all, the observed AMO/PMO data suggest a stronger communication between low-frequency subsurface ocean dynamics and the mixed layer relative to the levels underlying implied dynamics of the CMIP5 models.

c. Predictability experiments

Differences in the dynamics of the two EBM models identified above bear implications for decadal predictability of climates simulated by these models, which might in turn highlight the differences in potential predictability of the real climate system and that of virtual climates associated with CMIP5 models. We approach this issue in a standard way by performing self-forecasts of EBM simulated climates in a perfect-model setup, that is, assuming perfect knowledge of all model parameters and initial conditions. To do so, we first ran a

long (15 000 yr) numerical simulation of each EBM model (EBM_{CMIP5} and EBM_{OBS}) with a dimensional time step of 1 month and then made forecasts 50 years out from each of the $15\,000 \times 12$ initial conditions using the corresponding EBM model with the noise terms in (15) and (18) set to zero. To measure the forecast skill, we computed the anomaly correlations (i.e., correlations between the original time series and the time series of all forecasts for a given lead time) (Fig. 7) and root-mean-square (rms) errors (Fig. 8) of the forecasts, for each lead time.

The forecasts of the fast-subsystem temperatures $T_{f,1}$ and $T_{f,2}$ are only useful for lead times up to a few months, as measured, for example, by the lead time at which anomaly correlation drops to 0.6 (Figs. 7a,b) or the relative rms error grows to 0.75 of the climatological standard deviation (Figs. 8a,b). Naturally, the slow subsystem's $[T_{s,1}, T_{s,2}]$ (Figs. 7 and 8a,b) and q_1, q_2 (Figs. 7 and 8c,d) predictability times are much longer, on the order of 20–30 years, with the forecast skill curves having the shapes controlled by the low-frequency dynamics (e.g., the dominance of the Atlantic's weakly damped oscillatory mode in EBM_{OBS}). Note that the North Atlantic decadal predictability at such lead times is somewhat higher than that of the North Pacific in both versions of the EBM model. The predictability of the raw (monthly) mixed-layer temperatures T_1, T_2 is in between that of the fast and slow subsystems, with the quick drop of skill at small (increasing) lead times and a heavy tail of enhanced predictability persisting into decadal and longer lead times (Figs. 7 and 8a,b). The enhancement of decadal predictability due to the slow subsystem's dynamics for raw (monthly) mixed-layer data is slight; however, boxcar averaged forecasts quickly alleviate the congestion of the forecast skill by the fast subsystem's high-frequency anomalies (Figs. 7 and 8e,f) and exhibit

FIG. 6. Auto-covariances and cross-correlation of the thermocline temperatures $T_{o,1}$ and $T_{o,2}$ ($r_{T_{o,1}}$, $r_{T_{o,2}}$, and $r_{T_{o,1}T_{o,2}}$) in three versions of each EBM model [(left) EBM_{CMIP5} and (right) EBM_{OBS}]: EBM with original parameters (dubbed “original”); the AMO part of the EBM model (29) and (31) forced by the time history of PMO ($T_{o,2}$) from original model (“forced”); and the EBM model in which the AMO influence on the PMO evolution was artificially suppressed by zeroing out the term proportional to $T_{o,1}$ in (30) (“no AMO $\rightarrow$ PMO influence”). Panel captions and legends define the curves in each panel.

the skills comparable to those of the slow-subsystem anomalies. For example, the forecast skill of decadal averages of the Atlantic mixed-layer temperatures (Figs. 7f and 8f; green curves) is essentially identical with the slow-subsystem self-forecast skill (black curves).

The main difference in the predictability associated with EBM_{CMIP5} and EBM_{OBS} is an enhanced useful

decadal predictability in the latter. Using our predictability thresholds for anomaly correlation and rms error above and concentrating on forecasting decadal means of mixed-layer temperature anomalies in the North Atlantic (Figs. 7f and 8f; green curves), we estimate that these anomalies are predictable for lead times up to about 30 years in EBM_{OBS} and only for lead times up

FIG. 7. Self-forecasts of the two EBM models in the perfect-model setup. Shown are anomaly correlations of various dynamical variables (see figure captions and legends) as a function of the lead time (months) [(left) EBM_{CMIP5} results and (right) EBM_{OBS}]. (e),(f) Anomaly correlations of the original and forecast data for T_1 (AMO) smoothed with a boxcar running-mean filter of different sizes (colored curves; see panel legends) prior to computing the correlations; black curve shows anomaly correlation associated with the slow subsystem's $T_{s,1}$ forecast [the same as the corresponding curves in (a) and (b)].

to about 10 years in EBM_{CMIP5}. This is, once again, due to a larger role of the thermocline driven low-frequency dynamics in the mixed-layer temperature variability of EBM_{OBS} as compared with EBM_{CMIP5} (section 3b).

A larger fraction of predictable variability at decadal and longer time scales in our EBM_{OBS} model versus

EBM_{CMIP5} model leads to the so-called signal-to-noise paradox (Scaife and Smith 2018), which seems to be a generic and ubiquitous property of modern atmospheric and climate models. The essence of the paradox is in that climate models tend to predict observations better than they predict themselves. In particular, forecasts of the time series generated by EBM_{OBS} using EBM_{CMIP5} to

FIG. 8. As in Fig. 7, but for the EBM forecasts' root-mean-square (rms) error. In each case, the error is normalized by the climatological standard deviation of the time series being forecast.

make the forecasts (Fig. 9, yellow curves) are characterized by a higher skill at decadal lead times relative to the self-forecasts of EBM_{CMIP5} (Fig. 9, red curves). Note that our forecast scheme using the EBM models in which the noise terms are suppressed is equivalent to the ensemble forecast with the infinite number of realizations; therefore, the effects of noise only enter the forecast skill via the noise presence in the time series being forecast. Hence, given similar low-frequency dynamics of EBM_{OBS} and EBM_{CMIP5} , higher correlations

between the actual time series and its forecast at decadal lead times are found for the time series that has a more pronounced slow-subsystem contribution (and lesser contamination by the fast-subsystem variability, which is entirely unpredictable at decadal lead times), that is, for the time series produced by EBM_{OBS} , designed to mimic the observed climate variability. Note, however, that the self-forecast skill of EBM_{OBS} (Fig. 9, blue curves) is higher than the forecast skill of EBM_{OBS} time series by EBM_{CMIP5} (Fig. 9, yellow curves), as it should be. It

FIG. 9. Forecast skills of one EBM model predicting itself or the other EBM model. Shown in each case is the correlation of actual data and forecast anomaly as a function of the forecast lead time for (a) AMO (T_1) and (b) PMO (T_2). The line types in the legend follow the convention that the model whose output is being forecast is listed first and the forecast model (model used to perform the forecast) is listed second; for example, OBS/CMIP5 denotes the forecast skill of EBM_{CMIP5} predicting the output of EBM_{OBS} .

should also come as no surprise that decadal forecasts of EBM_{CMIP5} time series by EBM_{OBS} (Fig. 9, purple curves) are the least skillful of all, and, in particular, are less skillful than self-forecasts of both EBM_{OBS} and EBM_{CMIP5} , since in this case we are using a wrong model to try predict the time series that has the lowest signal-to-noise ratio.

4. Summary and discussion

In this paper, we addressed, in a mechanistic fashion, the dynamics of hemispheric-scale multidecadal climate variability. We did so by postulating an energy-balance (EBM) model comprising two deep-ocean oscillators in the Atlantic and Pacific basins, coupled via their surface mixed layers by means of atmospheric teleconnections. This coupled system is linear and driven by the atmospheric random noise forcing (cf. Hasselmann 1976; Barsugli and Battisti 1998). We developed two sets of the EBM model parameters, which were chosen by fitting the EBM-based mixed-layer temperature covariance structure to best mimic either the observed or CMIP5 simulated basin-average North Atlantic/Pacific SST covariability (namely, that of the AMO and PMO SST indices). The differences between the dynamics underlying the observed and CMIP5-simulated multidecadal climate variability and predictability are thus encapsulated in the algebraic structure of the two EBM models so obtained: EBM_{CMIP5} and EBM_{OBS} (see Table 4).

Both EBM models were divided into the fast (15) and slow (16)–(18) subsystems, which only share, in each basin (“1” denoting Atlantic and “2” denoting Pacific), one common adjustable parameter controlling the

surface mixed-layer/thermocline coupling (e_1 , e_2). The main difference between EBM_{CMIP5} and EBM_{OBS} inferred through our optimization procedure is that this coupling is considerably stronger in the latter model for both basins, but especially so for the Atlantic Ocean. Stronger mixed-layer damping in EBM_{OBS} is compensated by a larger magnitude of the stochastic driving A and B for the fast and slow subsystems, respectively, compared to those in the EBM_{CMIP5} model, to achieve the observed higher levels of SST variability relative to those in CMIP5 models. However, the stochastic forcing amplification in EBM_{OBS} is also larger for the slow subsystem (compared to that of the fast subsystem), leading to the slow-to-fast subsystem’s stochastic driving ratio of $B/A \sim 1$ in EBM_{OBS} versus $B/A \sim 0.5$ in EBM_{CMIP5} . The enhanced values of both (e_1 , e_2) and B/A in EBM_{OBS} explains a larger fraction of the slow-subsystem’s contribution to the SST variability in this model relative to that in EBM_{CMIP5} , which results in a larger decadal predictability in the former model (representing observations).

The effective interbasin coupling also works differently in the two EBM models. On short time scales, for the fast subsystem, the basin-scale North Atlantic SST provides a negative feedback on the basin-scale North Pacific SST (parameter $f_{1,2}$) of a similar magnitude in both models, but the positive feedback of the North Pacific on the North Atlantic (parameter $f_{2,1}$), diagnosed by our fitting procedure is about 3 times as strong in EBM_{OBS} , leading, however, in conjunction with the differences in thermocline/mixed layer coupling (e_1 , e_2), to only moderate differences in the fast-subsystem cross-correlation structure between the two EBMs (Figs. 4e,f).

The largest differences between the two models occur, once again, on long time scales characterizing the slow subsystem. The slow-subsystem interbasin coupling parameters $f_{s1,2}$ and $f_{s2,1}$ are both positive (thus corresponding to positive interbasin low-frequency feedback) and have similar magnitudes in the two EBM models, but the effective low-frequency Atlantic→Pacific and Pacific→Atlantic surface coupling in fact depends on the products $e_1 f_{s1,2}$ and $e_2 f_{s2,1}$, respectively (since stronger thermocline/mixed layer coupling would lead to a stronger surface signature of the thermocline temperature anomalies dominating the slow subsystem and vice versa) [see (16)]; these products are very different in EBM_{OBS} and EBM_{CMIP5} [see (27)]. As a result, the hemispheric surface temperature low-frequency variability is dominated by the North Atlantic SSTs in EBM_{OBS} and by the North Pacific SSTs in EBM_{CMIP5}. At the same time, the coupled deep-ocean oscillators feature a stronger net feedback from the Pacific to the Atlantic (29) than that from the Atlantic to Pacific (30); in EBM_{CMIP5}, this is primarily due to large surface imprint of the Pacific SST on the Atlantic SST through the atmosphere (i.e., large $e_2 f_{s2,1}$), whereas in EBM_{OBS} this is due to large efficiency of the Atlantic mixed-layer/thermocline coupling e_1 . Both the Atlantic/Pacific and Pacific/Atlantic feedbacks are, however, important for hemispheric low-frequency variability in each model, both are positive, and both are stronger in EBM_{OBS} than in EBM_{CMIP5}.

Finally, a stronger low-frequency variability of the thermocline temperatures in EBM_{OBS} leads to a stronger, compared to that in EBM_{CMIP5}, oceanic circulation variability in both the Atlantic and the Pacific Oceans through momentum equations (31) and (32); in both EBM models, the Atlantic and Pacific Oceans exhibit multidecadal oscillations, with the Pacific oscillator having a longer period than the Atlantic oscillator; as stated above, the two oscillators are more strongly coupled in EBM_{OBS}, which leads to stronger modifications in their internal (uncoupled) periodicities and covariability in this model (Fig. 6).

Here is the summary of key differences between EBM_{OBS} and EBM_{CMIP5}, which we interpret here as representing the differences between the actual observed and CMIP5 simulated climate variability in the Northern Hemisphere, as seen in the behavior of the AMO and PMO SST indices (keep in mind that the PMO in this paper is not the same with the PDO/IPO):

- Both AMO and PMO have a stronger variability in observations than in CMIP5 models (cf. Swanson et al. 2009; Zhang and Wang 2013; Kravtsov et al. 2014, 2018; Kravtsov 2017; Kravtsov and Callicutt 2017; Zhang 2017; Yan et al. 2019; Zhang et al. 2019).

- The signal-to-noise ratios expressed via variances associated with the corresponding EBM's slow/fast subsystems in observations (CMIP5 models) are about 55%/45% (20/80%) for AMO and 30%/70% (10%/90%) for PMO. Hence, AMO seems to be more predictable than PMO in both observations and CMIP5 models (which, indeed, seems to be the case; cf. Cassou et al. 2018), but the CMIP5 models may be underestimating the decadal predictability of the real world for both (Farneti 2016; Scaife and Smith 2018). This leads to the so-called signal-to-noise paradox (Scaife and Smith 2018), in which the models are able to predict observations better than they predict themselves.
- Within the confines of the EBM models developed here, the above properties follow from a stronger communication between the deep ocean and mixed layer implicit in the observed data, coupled with the stronger excitation of the deep-ocean oscillators by the stochastic forcing. These processes are but parameterizations of a multitude of feedbacks operating in realistic CMIP5 models, such as the (underestimated in many CMIP5 models) internal variability of AMOC or its response to the North Atlantic Oscillation (Delworth et al. 2017; Yan et al. 2018) or the generation of basin-scale AMO signature via coupled air–sea feedbacks in response to AMOC variability (Bellomo et al. 2016; Brown et al. 2016; Yuan et al. 2016); see Zhang et al. (2019) for a review.
- From EBM model results, the hemispheric teleconnections and hemispheric-scale multidecadal variability in free runs of CMIP5 models are found to be dominated by PMO, with AMO influence largely confined to the North Atlantic region. This is consistent with apparent regional confinement of the prediction skill associated with AMO in CMIP5 models (Qasmi et al. 2017), and may, in general, be due to weaker-than-observed AMO variability in CMIP5 models (see above). The EBM diagnosis also suggests that the PMO multidecadal variability in CMIP5 models (and, hence, its hemispheric and global expression) is akin to a passive stochastically excited ultralow-frequency hyper mode of Dommenget and Latif (2008).
- By contrast, the AMO plays a much larger role in EBM_{OBS} and, by inference, in the observed hemispheric teleconnections, where two-way interactions between the Atlantic and Pacific are important (cf. McGregor et al. 2014; Meehl et al. 2016). The hemispheric and, perhaps, global multidecadal climate variability features a 50–70-yr oscillation (Minobe 1997; Wyatt et al. 2012; Gulev et al. 2013) with the space–time pattern of global teleconnections missing from CMIP5 models (Kravtsov et al. 2018). The dynamics of this oscillation in the Pacific are presently unknown, with

the current theories predicting shorter periods (Meehl and Hu 2006; Farneti et al. 2014a,b); it is certainly possible that the identification of such an oscillation in our EBM_{OBS} model's fit may be due to sampling variability in the short observational record available.

The present study introduced a minimal conceptual framework for studying global-scale low-frequency variability and decadal predictability, which can be used to address a wide variety of related problems, such as the interpretation of pacemaker experiments (McGregor et al. 2014), multiscale dynamics of global synchronizations (Tsonis et al. 2007), and statistical decadal prediction (Srivastava and DelSole 2017), among many others. These topics will be addressed in a future work.

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REFERENCES

- Barcikowska, M. J., T. R. Knutson, and R. Zhang, 2017: Observed and simulated fingerprints of multidecadal climate variability and their contributions to periods of global SST stagnation. *J. Climate*, **30**, 721–737, <https://doi.org/10.1175/JCLI-D-16-0443.1>.
- Barsugli, J. J., and D. S. Battisti, 1998: The basic effects of atmosphere–ocean thermal coupling on midlatitude variability. *J. Atmos. Sci.*, **55**, 477–493, [https://doi.org/10.1175/1520-0469\(1998\)055<0477:TBEAO>2.0.CO;2](https://doi.org/10.1175/1520-0469(1998)055<0477:TBEAO>2.0.CO;2).
- Bellomo, K., A. C. Clement, L. N. Murphy, L. M. Polvani, and M. A. Cane, 2016: New observational evidence for a positive cloud feedback that amplifies the Atlantic multidecadal oscillation. *Geophys. Res. Lett.*, **43**, 9852–9859, <https://doi.org/10.1002/2016GL069961>.
- Bretherton, C. S., and D. S. Battisti, 2000: An interpretation of the results from atmospheric general circulation models forced by the time history of the observed sea surface temperature distribution. *Geophys. Res. Lett.*, **27**, 767–770, <https://doi.org/10.1029/1999GL010910>.
- Brown, P. T., M. S. Lozier, R. Zhang, and W. Li, 2016: The necessity of cloud feedback for a basin-scale Atlantic Multidecadal Oscillation. *Geophys. Res. Lett.*, **43**, 3955–3963, <https://doi.org/10.1002/2016GL068303>.
- Buckley, M. W., and J. Marshall, 2016: Observations, inferences, and mechanisms of the Atlantic meridional overturning circulation: A review. *Rev. Geophys.*, **54**, 5–63, <https://doi.org/10.1002/2015RG000493>.
- Cassou, C., Y. Kushnir, E. Hawkins, A. Pirani, F. Kucharski, I.-S. Kang, and N. Caltabiano, 2018: Decadal climate variability and predictability: Challenges and opportunities. *Bull. Amer. Meteor. Soc.*, **99**, 479–490, <https://doi.org/10.1175/BAMS-D-16-0286.1>.
- DelSole, T., M. K. Tippett, and J. Shukla, 2011: A significant component of unforced multidecadal variability in the recent acceleration of global warming. *J. Climate*, **24**, 909–926, <https://doi.org/10.1175/2010JCLI3659.1>.
- , L. Jia, and M. K. Tippett, 2013: Decadal prediction of observed and simulated sea surface temperatures. *Geophys. Res. Lett.*, **40**, 2773–2778, <https://doi.org/10.1002/grl.50185>.
- Delworth, T. L., and M. E. Mann, 2000: Observed and simulated multidecadal variability in the Northern Hemisphere. *Climate Dyn.*, **16**, 661–676, <https://doi.org/10.1007/s003820000075>.
- , F. Zeng, L. Zhang, R. Zhang, G. A. Vecchi, and Z. Yang, 2017: The central role of ocean dynamics in connecting the North Atlantic Oscillation to the extratropical component of the Atlantic multidecadal oscillation. *J. Climate*, **30**, 3789–3805, <https://doi.org/10.1175/JCLI-D-16-0358.1>.
- Deser, C., and A. Phillips, 2017: An overview of decadal-scale sea surface temperature variability in the observational record. *PAGES Magazine*, No. 25, Bern, Switzerland, 2–6, <https://doi.org/10.22498/PAGES.25.1.2>.
- , and Coauthors, 2012: ENSO and Pacific decadal variability in the Community Climate System Model version 4. *J. Climate*, **25**, 2622–2651, <https://doi.org/10.1175/JCLI-D-11-00301.1>.
- Dommenget, D., and M. Latif, 2008: Generation of hyper climate modes. *Geophys. Res. Lett.*, **35**, L02706, <https://doi.org/10.1029/2007GL031087>.
- Dong, B., and A. Dai, 2015: The influence of the Interdecadal Pacific Oscillation on temperature and precipitation over the globe. *Climate Dyn.*, **45**, 2667–2681, <https://doi.org/10.1007/s00382-015-2500-x>.
- d'Orgeville, M., and W. R. Peltier, 2007: On the Pacific decadal oscillation and the Atlantic Multidecadal Oscillation: Might they be related? *Geophys. Res. Lett.*, **34**, L23705, <https://doi.org/10.1029/2007GL031584>.
- Enfield, D. B., A. M. Mestas-Núñez, and P. J. Trimble, 2001: The Atlantic Multidecadal Oscillation and its relation to rainfall and river flows in the continental U.S. *Geophys. Res. Lett.*, **28**, 2077–2080, <https://doi.org/10.1029/2000GL012745>.
- Farneti, R., 2016: Modelling interdecadal climate variability and the role of the ocean. *Wiley Interdiscip. Rev.: Climate Change*, **8**, e441, <https://doi.org/10.1002/WCC.441>.
- , F. Molteni, and F. Kucharski, 2014a: Pacific interdecadal variability driven by tropical–extratropical interactions. *Climate Dyn.*, **42**, 3337–3355, <https://doi.org/10.1007/s00382-013-1906-6>.
- , S. Dwivedi, F. Kucharski, F. Molteni, and S. M. Griffies, 2014b: On Pacific subtropical cell variability over the second half of the twentieth century. *J. Climate*, **27**, 7102–7112, <https://doi.org/10.1175/JCLI-D-13-00707.1>.
- Ghil, M., and A. W. Robertson, 2000: Solving problems with GCMs: General circulation models and their role in the climate modeling hierarchy. *General Circulation Model Development: Past, Present, and Future*, D. A. Randall, Ed., Academic Press, 285–325.
- , and V. Lucarini, 2019: The physics of climate variability and climate change. 86 pp., <https://arxiv.org/abs/1910.00583>.
- , Y. Feliks, and J. Small, 2019: Global oscillatory modes in observations and high-end modeling. *Geophys. Res. Abstracts*,

- Vol. 21, Abstract EGU2019-9525, <https://meetingorganizer.copernicus.org/EGU2019/EGU2019-9525.pdf>.
- Gulev, S. K., M. Latif, N. Keenlyside, W. Park, and K. P. Koltermann, 2013: North Atlantic Ocean control on surface heat flux on multidecadal timescales. *Nature*, **499**, 464–467, <https://doi.org/10.1038/nature12268>.
- Hasselmann, K., 1976: Stochastic climate models Part I. Theory. *Tellus*, **28**, 473–485, <https://doi.org/10.3402/tellusa.v28i6.11316>.
- Held, I. M., 2005: The gap between simulation and understanding in climate modeling. *Bull. Amer. Meteor. Soc.*, **86**, 1609–1614, <https://doi.org/10.1175/BAMS-86-11-1609>.
- , 2014: Simplicity amid complexity. *Science*, **343**, 1206–1207, <https://doi.org/10.1126/science.1248447>.
- Hsiung, J., 1985: Estimates of global meridional heat transport. *J. Phys. Oceanogr.*, **15**, 1405–1413, [https://doi.org/10.1175/1520-0485\(1985\)015<1405:EOGOMH>2.0.CO;2](https://doi.org/10.1175/1520-0485(1985)015<1405:EOGOMH>2.0.CO;2).
- Jeevanjee, N., P. Hassanzadeh, S. Hill, and A. Sheshadri, 2017: A perspective on climate model hierarchies. *J. Adv. Model. Earth Syst.*, **9**, 1760–1771, <https://doi.org/10.1002/2017MS001038>.
- Kerr, R. A., 2000: A North Atlantic climate pacemaker for the centuries. *Science*, **288**, 1984–1985, <https://doi.org/10.1126/science.288.5473.1984>.
- Kim, W. M., S. Yeager, P. Chang, and G. Danabasoglu, 2018: Low-frequency North Atlantic climate variability in the Community Earth System Model large ensemble. *J. Climate*, **31**, 787–813, <https://doi.org/10.1175/JCLI-D-17-0193.1>.
- Kirtman, B., and Coauthors, 2013: Near-term climate change: Projections and predictability. *Climate Change 2013: The Physical Science Basis*, T. F. Stocker et al., Eds., Cambridge University Press, 953–1028.
- Knight, J. R., R. J. Allan, C. K. Folland, M. Vellinga, and M. E. Mann, 2005: A signature of persistent natural thermohaline circulation cycles in observed climate. *Geophys. Res. Lett.*, **32**, L20708, <https://doi.org/10.1029/2005GL024233>.
- Kosaka, Y., and S.-P. Xie, 2016: The tropical Pacific as a key pacemaker of the variable rates of global warming. *Nat. Geosci.*, **9**, 669–673, <https://doi.org/10.1038/ngeo2770>.
- Kravtsov, S., 2017: Pronounced differences between observed and CMIP5 simulated multidecadal climate variability in the twentieth century. *Geophys. Res. Lett.*, **44**, 5749–5757, <https://doi.org/10.1002/2017GL074016>.
- , and C. Spannagle, 2008: Multidecadal climate variability in observed and modeled surface temperatures. *J. Climate*, **21**, 1104–1121, <https://doi.org/10.1175/2007JCLI1874.1>.
- , and D. Callicutt, 2017: On semi-empirical decomposition of multidecadal climate variability into forced and internally generated components. *Int. J. Climatol.*, **37**, 4417–4433, <https://doi.org/10.1002/joc.5096>.
- , W. K. Dewar, M. Ghil, J. C. McWilliams, and P. Berloff, 2008: A mechanistic model of mid-latitude decadal climate variability. *Physica D*, **237**, 584–599, <https://doi.org/10.1016/j.physd.2007.09.025>.
- , M. G. Wyatt, J. A. Curry, and A. A. Tsonis, 2014: Two contrasting views of multidecadal climate variability in the twentieth century. *Geophys. Res. Lett.*, **41**, 6881–6888, <https://doi.org/10.1002/2014GL061416>.
- , —, —, and —, 2015: Comment on “Atlantic and Pacific Multidecadal Oscillations and Northern Hemisphere temperatures.” *Science*, **350**, 1326, <https://doi.org/10.1126/science.aab3570>.
- , C. Grimm, and S. Gu, 2018: Global-scale multidecadal variability missing in state-of-the-art climate models. *npj Climate Atmos. Sci.*, **1**, 34, <https://doi.org/10.1038/S41612-018-0044-6>.
- Kucharski, F., and Coauthors, 2016: The teleconnection of the tropical Atlantic to Indo-Pacific sea surface temperatures on inter-annual to centennial time scales: A review of recent findings. *Atmosphere*, **7**, 29, <https://doi.org/10.3390/atmos7020029>.
- Latif, M., M. Collins, H. Pohlmann, and N. Keenlyside, 2006: A review of predictability studies of the Atlantic sector climate on decadal time scales. *J. Climate*, **19**, 5971–5987, <https://doi.org/10.1175/JCLI3945.1>.
- Li, J., C. Sun, and F.-F. Jin, 2013: NAO implicated as a predictor of Northern Hemisphere mean temperature multidecadal variability. *Geophys. Res. Lett.*, **40**, 5497–5502, <https://doi.org/10.1002/2013GL057877>.
- Mantua, N. J., S. R. Hare, Y. Zhang, J. M. Wallace and R. C. Francis, 1997: A Pacific interdecadal climate oscillation with impacts on salmon production. *Bull. Amer. Meteor. Soc.*, **78**, 1069–1079, [https://doi.org/10.1175/1520-0477\(1997\)078<1069:APICOW>2.0.CO;2](https://doi.org/10.1175/1520-0477(1997)078<1069:APICOW>2.0.CO;2).
- Marshall, J., H. Johnson, and J. Goodman, 2001: A study of the interaction of the North Atlantic Oscillation with ocean circulation. *J. Climate*, **14**, 1399–1421, [https://doi.org/10.1175/1520-0442\(2001\)014<1399:ASOTIO>2.0.CO;2](https://doi.org/10.1175/1520-0442(2001)014<1399:ASOTIO>2.0.CO;2).
- McGregor, S., A. Timmermann, M. F. Stuecker, M. H. England, M. Merrifield, F.-F. Jin, and Y. Chikamoto, 2014: Recent Walker circulation strengthening and Pacific cooling amplified by Atlantic warming. *Nat. Climate Change*, **4**, 888–892, <https://doi.org/10.1038/nclimate2330>.
- Meehl, G. A., and A. Hu, 2006: Megadroughts in the Indian monsoon region and southwest North America and a mechanism for associated multidecadal Pacific sea surface temperature anomalies. *J. Climate*, **19**, 1605–1623, <https://doi.org/10.1175/JCLI3675.1>.
- , and Coauthors, 2014: Decadal climate prediction: An update from the trenches. *Bull. Amer. Meteor. Soc.*, **95**, 243–267, <https://doi.org/10.1175/BAMS-D-12-00241.1>.
- , A. Hu, B. D. Santer, and S.-P. Xie, 2016: Contribution of the Interdecadal Pacific Oscillation to twentieth-century global surface temperature trends. *Nat. Climate Change*, **6**, 1005–1008, <https://doi.org/10.1038/nclimate3107>.
- Minobe, S., 1997: A 50–70 year climatic oscillation over the North Pacific and North America. *Geophys. Res. Lett.*, **24**, 683–686, <https://doi.org/10.1029/97GL00504>.
- Newman, M., 2007: Interannual to decadal predictability of tropical and North Pacific sea surface temperatures. *J. Climate*, **20**, 2333–2356, <https://doi.org/10.1175/JCLI4165.1>.
- , 2013: An empirical benchmark for decadal forecasts of global surface temperature anomalies. *J. Climate*, **26**, 5260–5269, <https://doi.org/10.1175/JCLI-D-12-00590.1>.
- , and Coauthors, 2016: The Pacific decadal oscillation, revisited. *J. Climate*, **29**, 4399–4427, <https://doi.org/10.1175/JCLI-D-15-0508.1>.
- Qasmi, S., C. Cassou, and J. Boé, 2017: Teleconnection between Atlantic multidecadal variability and European temperature: Diversity and evaluation of the Coupled Model Intercomparison Project phase 5 models. *Geophys. Res. Lett.*, **44**, 11 140–11 149, <https://doi.org/10.1002/2017GL074886>.
- Scaife, A. A., and D. Smith, 2018: A signal-to-noise paradox in climate science. *npj Climate and Atmos. Sci.*, **1**, 28, <https://doi.org/10.1038/s41612-018-0038-4>.
- Schneider, N., A. J. Miller, and D. W. Pierce, 2002: Anatomy of North Pacific decadal variability. *J. Climate*, **15**, 586–605, [https://doi.org/10.1175/1520-0442\(2002\)015<0586:AONPDV>2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015<0586:AONPDV>2.0.CO;2).

- Smith, D. M., A. A. Scaife, and B. P. Kirtman, 2012: What is the current state of scientific knowledge with regard to seasonal and decadal forecasting? *Environ. Res. Lett.*, **7**, 015602, <https://doi.org/10.1088/1748-9326/7/1/015602>.
- Srivastava, A., and T. DelSole, 2017: Decadal predictability without ocean dynamics. *Proc. Natl. Acad. Sci. USA*, **114**, 2177–2182, <https://doi.org/10.1073/pnas.1614085114>.
- Steinman, B. A., M. E. Mann, and S. K. Miller, 2015: Atlantic and Pacific Multidecadal Oscillations and Northern Hemisphere temperatures. *Science*, **347**, 988–991, <https://doi.org/10.1126/science.1257856>.
- Sun, C., J. Li, and F.-F. Jin, 2015: A delayed oscillator model for the quasi-periodic multidecadal variability of the NAO. *Climate Dyn.*, **45**, 2083–2099, <https://doi.org/10.1007/s00382-014-2459-z>.
- , F. Kucharski, J. Li, F.-F. Jin, I. S. Kang, and R. Ding, 2017: Western tropical Pacific multidecadal variability forced by the Atlantic Multidecadal Oscillation. *Nat. Commun.*, **8**, 15998, <https://doi.org/10.1038/ncomms15998>.
- Swanson, K., G. Sugihara, and A. A. Tsonis, 2009: Long-term natural variability and 20th century climate change. *Proc. Natl. Acad. Sci. USA*, **106**, 16 120–16 123, <https://doi.org/10.1073/pnas.0908699106>.
- Talley, L. D., 1984: Meridional heat transport in the Pacific Ocean. *J. Phys. Oceanogr.*, **14**, 231–241, [https://doi.org/10.1175/1520-0485\(1984\)014<0231:MHTTTP>2.0.CO;2](https://doi.org/10.1175/1520-0485(1984)014<0231:MHTTTP>2.0.CO;2).
- Taylor, K. E., R. J. Stouffer, and G. Meehl, 2012: An overview of CMIP5 and the experiment design. *Bull. Amer. Meteor. Soc.*, **93**, 485–498, <https://doi.org/10.1175/BAMS-D-11-00094.1>.
- Trenary, L., and T. DelSole, 2016: Does the Atlantic multidecadal oscillation get its predictability from the Atlantic meridional overturning circulation? *J. Climate*, **29**, 5267–5280, <https://doi.org/10.1175/JCLI-D-16-0030.1>.
- Tsonis, A. A., K. Swanson, and S. Kravtsov, 2007: A new dynamical mechanism for major climate shifts. *Geophys. Res. Lett.*, **34**, L13705, <https://doi.org/10.1029/2007GL030288>.
- Wu, S., A. Liu, R. Zhang, and T. L. Delworth, 2011: On the observed relationship between the Pacific Decadal Oscillation and the Atlantic Multi-decadal Oscillation. *J. Oceanogr.*, **67**, 27–35, <https://doi.org/10.1007/s10872-011-0003-x>.
- Wyatt, M., S. Kravtsov, and A. A. Tsonis, 2012: Atlantic Multidecadal Oscillation and Northern Hemisphere's climate variability. *Climate Dyn.*, **38**, 929–949, <https://doi.org/10.1007/s00382-011-1071-8>.
- Yan, X., R. Zhang, and T. R. Knutson, 2018: Underestimated AMOC variability and implications for AMV and predictability in CMIP models. *Geophys. Res. Lett.*, **45**, 4319–4328, <https://doi.org/10.1029/2018GL077378>.
- , —, and —, 2019: A multivariate AMV index and associated discrepancies between observed and CMIP5 externally forced AMV. *Geophys. Res. Lett.*, **46**, 4421–4431, <https://doi.org/10.1029/2019GL082787>.
- Yeager, S. G., and J. J. Robson, 2017: Recent progress in understanding and predicting decadal climate variability. *Curr. Climate Change Rep.*, **3**, 112–127, <https://doi.org/10.1007/s40641-017-0064-z>.
- Yuan, T., L. Oreopoulos, M. Zelinka, H. Yu, J. R. Norris, M. Chin, S. Platnick, and K. Meyer, 2016: Positive low cloud and dust feedbacks amplify tropical North Atlantic Multidecadal Oscillation. *Geophys. Res. Lett.*, **43**, 1349–1356, <https://doi.org/10.1002/2016GL067679>.
- Zhang, L., and C. Wang, 2013: Multidecadal North Atlantic sea surface temperature and Atlantic meridional overturning circulation variability in CMIP5 historical simulations. *J. Geophys. Res. Oceans*, **118**, 5772–5791, <https://doi.org/10.1002/jgrc.20390>.
- Zhang, R., 2017: On the persistence and coherence of subpolar sea surface temperature and salinity anomalies associated with the Atlantic multidecadal variability. *Geophys. Res. Lett.*, **44**, 7865–7875, <https://doi.org/10.1002/2017GL074342>.
- , R. Sutton, G. Danabasoglu, Y.-O. Kwon, R. Marsh, S. G. Yeager, D. E. Amrhein, and C. M. Little, 2019: A review of the role of the Atlantic meridional overturning circulation in Atlantic multidecadal variability and associated climate impacts. *Rev. Geophys.*, **57**, 316–375, <https://doi.org/10.1029/2019RG000644>.