Ocean-Atmosphere Dynamical Coupling Fundamental to the Atlantic Multidecadal Oscillation

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ABSTRACT

The North Atlantic has shown large multidecadal temperature shifts during the 20th century. There is ongoing debate about whether this variability arises primarily through the influence of atmospheric internal variability, through changes in ocean circulation, or as a response to anthropogenic forcing. This study isolates the mechanisms driving Atlantic sea-surface temperature variability on multidecadal timescales by using low-frequency component analysis (LFCA) to separate the influences of high-frequency variability, multidecadal variability, and long-term global warming. This analysis objectively identifies the North Atlantic subpolar gyre as the dominant region of Atlantic multidecadal variability. In unforced control runs of coupled climate models, warm subpolar temperatures are associated with a strengthened Atlantic Meridional Overturning Current (AMOC) and anomalous local heat fluxes from the ocean into the atmosphere. Atmospheric variability plays a role in the intensification and subsequent weakening of ocean overturning and helps to communicate warming into the tropical Atlantic. These findings suggest that dynamical coupling between atmospheric and oceanic circulations is fundamental to the Atlantic Multidecadal Oscillation (AMO) and motivate approaching decadal prediction with a focus on ocean circulations.

1. Introduction

In both observations and climate models, North Atlantic sea-surface temperatures (SSTs) show spatially coherent variability at multidecadal timescales. Periods of higher than average SSTs are associated with warmer summers over North America and western Europe (Sutton and Hodson 2005), Arctic sea-ice loss (Mahajan et al. 2011; Day et al. 2012; Zhang 2015; Yeager et al. 2015), drought in the United States (Enfield et al. 2001; McCabe et al. 2004; Nigam et al. 2011), drought relief in the Sahel (Gray 1990; Zhang and Delworth 2006), and a higher frequency of landfalling Atlantic hurricanes (Gray 1990; Goldenberg et al. 2001; Zhang and Delworth 2006). Multiple physical mechanisms have been put forth to explain this variability. Most studies have focused on the role of internal variability in ocean circulation, principally AMOC (Delworth et al. 1993; Delworth and Mann 2000; Latif et al. 2004; Knight et al. 2005; Medhaug and Furevik 2011; Wang and Zhang 2013; Zhang and Wang 2013; MacMartin et al. 2013; Ba et al. 2014; O’Reilly et al. 2016; Kim et al. 2018). However, multidecadal temperature variability can also arise in response to stochastic atmospheric forcing of temperature anomalies stored in the ocean mixed layer (Hasselmann 1976; Clement et al. 2015; Cane et al. 2017).

Additionally, some of the observed North Atlantic temperature variability over the 20th century is thought to result from a response to external forcing (Booth et al. 2012; Tandon and Kushner 2015; Si and Hu 2017; Bellucci et al. 2017; Bellomo et al. 2018), such as from greenhouse gasses, anthropogenic and volcanic aerosols, and stratospheric ozone. Several recent studies have suggested that atmospheric teleconnections and cloud feedbacks are essential for multidecadal variability in the tropical North Atlantic (Yuan et al. 2016; Brown et al. 2016; Bellomo et al. 2016). Do these different mechanisms make up one coherent mode of variability or are they distinct mechanisms operating on different timescales and in different geographic locations?

Atlantic temperature variability is traditionally characterized by the North Atlantic SST index (NASSTI), the spatially averaged SST anomaly over the North Atlantic basin (0-60°N, 0-80°W), with the influence of global warming removed through linear detrending (Enfield et al. 2001) or by subtracting the global-mean SST (Trenberth and Shea 2006). NASSTI appears to vary on multidecadal timescales, and is thus often lowpass filtered and referred to as the Atlantic Multidecadal Oscillation (AMO). Recent work has shown that the amplitude and phase of the AMO are sensitive to the method of detrending (Ting et al. 2009; Frankcombe et al. 2015). Moreover, the choice of averaging region is problematic, as no physical mecha-
nism has been postulated that dictates that multidecadal SST variability should be coherent between the equator and 60°N. The use of the current NASSTI/AMO index is based solely on the history of its introduction and, as we will show, mixes multidecadal temperature variability with other forms of temperature variability on shorter timescales.

Here, we seek to determine the mechanisms driving multidecadal variability of Atlantic SSTs without a priori assumptions about its spatial or temporal structure. To do so, we use low-frequency component analysis (LFCA), introduced by Wills et al. (2018) (cf. Schneider and Held 2001), an objective method to find spatial anomaly patterns with the highest ratio of low-frequency to total variance. We apply this method to Atlantic SST anomalies in observations and in unforced pre-industrial control simulations with comprehensive climate models. We use the results to identify the physical mechanisms that are important for unforced Atlantic multidecadal variability in climate models and develop a mechanistic understanding of the AMO. While a number of other studies have investigated the mechanisms of Atlantic multidecadal variability based on its manifestations on the subsurface ocean and sea level (Zhang 2008, 2010; Buckley et al. 2014; Zhang and Zhang 2015; Yan et al. 2018), we focus in particular on the surface manifestation of Atlantic multidecadal variability (i.e., the AMO) to address the large body of literature taking this perspective.

Section 2 describes the analysis methods, data sets, and climate model simulations used. Section 3 describes the low-frequency components of Atlantic SST variations in observations and climate models. In Section 4, we discuss how LFCA provides insight into the mechanisms of unforced Atlantic multidecadal variability in climate models, and in particular how these mechanisms differ from the mechanisms of variability at shorter timescales. In Section 5, we compare different indices of Atlantic multidecadal variability and the AMO. Section 6 discusses how these results compare to recent studies using slab-ocean models. The key findings are summarized in Section 7. In the Appendices, we explore how AMO variability differs across models and discuss the next lowest frequency mode of Atlantic SST variability.

2. Methods

a. Low-frequency component analysis.

LFCA isolates the low-frequency variability in a data set by finding low-frequency patterns (LFPs) that are linear combinations of the leading empirical orthogonal functions (EOFs) and sorting them by the ratio of low-frequency to total variance in their corresponding time-series, called low-frequency components (LFCs). We define low-frequency variance based on a lowpass filter with a cutoff at 10 years. This type of analysis can be used to find the spatial pattern that best discriminates between some type of variance representing a “signal” compared to “noise” that exists within internal variability or between realizations, and has been variously called optimal filtering or signal-to-noise maximizing EOF analysis (Allen and Smith 1997; Venzke et al. 1999; Schneider and Griffies 1999; Schneider and Held 2001; Ting et al. 2009). These methods take advantage of any spatial structure of covariance in the “noise” to optimally filter it out.

In order to ensure that the LFPs correspond to variability that actually occurs within the data set, the LFPs are required to be linear combinations of the N leading EOFs. For an $n \times p$ spatiotemporal data matrix $X$ with zero time mean (e.g., $n$ time steps of SST anomalies at $p$ grid points) we compute the EOFs $\mathbf{a}_k$, which are the eigenvectors of the sample covariance matrix of the unfiltered data,

$$\mathbf{C} = (n-1)^{-1} \mathbf{X}^T \mathbf{X}. \quad (1)$$

The EOFs are normalized $||\mathbf{a}_k|| = 1$, such that the corresponding eigenvalues $\sigma_k^2 = \mathbf{a}_k^T \mathbf{C} \mathbf{a}_k$ give the variance associated with the $k$th EOF and the principal components $\mathbf{PC}_k = \sigma_k^{-1} \mathbf{X} \mathbf{a}_k$ have unit variance. The data matrix $X$ is weighted by the square root of grid cell area such that the covariance is area weighted.

We look for linear combinations of the first $N$ EOFs,

$$\mathbf{u}_k = \begin{bmatrix} a_1  & a_2 & \ldots & a_N \end{bmatrix} \mathbf{e}_k, \quad (2)$$

such that the ratio of low-frequency to total variance

$$r_k = \frac{\left(\mathbf{X} \mathbf{u}_k^T\right) \mathbf{X} \mathbf{u}_k}{\left(\mathbf{X} \mathbf{u}_k^T\right) \left(\mathbf{X} \mathbf{u}_k\right)} = \frac{\mathbf{u}_k^T \tilde{\mathbf{C}} \mathbf{u}_k}{\mathbf{u}_k^T \mathbf{C} \mathbf{u}_k}. \quad (3)$$

is maximized when the data matrix is projected onto them. The coefficient vectors $\mathbf{e}_k$ are normalized such that $||\mathbf{e}_k|| = 1$. Here, $\tilde{X}$ is the pointwise lowpass filtered spatiotemporal data matrix and $\tilde{\mathbf{C}}$ is the covariance matrix of the lowpass filtered data,

$$\tilde{\mathbf{C}} = (n-1)^{-1} \tilde{X}^T \tilde{X}. \quad (4)$$

We use a linear Lanczos filter with a 10-year lowpass cutoff and reflected boundary conditions to focus on variability at decadal and longer timescales (i.e., multidecadal variability).

The normalization factors $\sigma_k^{-1}$ in (3) ensure that the covariance in the denominator of (3) is equal to 1. Using (2), (3), and the definition of a principal component, we find that the coefficient vectors $\mathbf{e}_k$ are eigenvectors of the covariance (cov) matrix $R$ of the first $N$ lowpass filtered principal components,

$$R_{ij} = \text{cov}(\mathbf{PC}_i, \mathbf{PC}_j). \quad (5)$$

The matrix $R$ has $N$ eigenvectors, $R \mathbf{e}_k = r_k \mathbf{e}_k$. The eigenvalues $r_k$ give the fraction of the variance in the $k$th mode
that occurs at low frequencies. The projection of the unfiltered data onto the linear combination vectors $u_k$ gives the low-frequency components:

$$LFC_k = Xu_k.$$  \hspace{1cm} (6)$$

The regression of the unfiltered data onto the $k$th LFC gives the $k$th low-frequency pattern (LFP):

$$v_k = X^T LFC_k = [\sigma_1 a_1 \sigma_2 a_2 \ldots \sigma_N a_N] e_k.$$  \hspace{1cm} (7)$$

The LFCs are sorted by their variance ratio $r_k$ such that the leading LFCs describe modes of low-frequency variability. The LFPs and LFCs are analogous to EOFs and principal components, respectively, in that the LFCs have unit variance and the LFPs describe the anomaly pattern associated with a 1-standard-deviation anomaly in the LFC.

LFCA has two parameters, the number of EOFs included $N$ and the lowpass cutoff $T$ (or more generally the properties of the filter used). Our results are insensitive to the exact values of $N$ and $T$ used, at least for $N$ between 10 and 50 and for $T > 5$ years. We have limited our analysis of observed SSTs to $N < 50$, because for 50 or more EOFs the number of spatial degrees of freedom becomes comparable to the number of temporal degrees of freedom in the 10-year lowpass filtered data, even when including observations back to 1900. A detailed discussion of the robustness of LFCA to the choice of parameters can be found in Wills et al. (2018).

While filtering is used to define the linear combination of EOFs, the resulting LFCs are unfiltered, and can thus display seasonal variations and rapid transitions. Unlike principal component analysis of lowpass filtered data, LFCA uses information about spatiotemporal covariance at all timescales (e.g., in computing the EOFs $a_k$). LFCA thus provides a method to isolate the regions and physical mechanisms important at long timescales while avoiding the issues with attributing lead-lag relationships based on filtered data (Cane et al. 2017).

**b. Data sets and climate model simulations.**

We analyze observed SSTs over the period 1900-2016 from the NOAA Extended Reconstructed SST (ERSST) data set, version 3b (Smith et al. 2008), and output from pre-industrial control simulations of 26 fully coupled climate models from the Coupled Model Intercomparison Project phase 5 (CMIP5, Taylor et al. 2012). External forcing from greenhouse gases, aerosols, ozone, and solar variability is fixed at pre-industrial levels throughout the simulations. We use pre-industrial control simulations to focus on understanding the mechanisms of unforced variability in Atlantic SSTs without mixing in information about forced changes, for which the mechanisms are likely different. We include 500 years from each model’s control simulation, shown in Table 1. We use model output of surface temperature (TS), sea-level pressure (SLP), ocean meridional overturning streamfunction (MOC), and sensible-heat, latent-heat, and radiative fluxes contributing to the net surface heat flux (SHF). MOC data (including both mslfmyz and msftyyz in the standard CMIP5 notation) is only available for a subset of the models (16 in total), as noted in Table 1. BCC-CSM1.1 and INMCM4.0 have missing SHF data and are omitted from the analysis of net surface heat fluxes. We remove quadratic trends from all outputs of the pre-industrial control simulations in order to remove the effects of model drift. However, trends are included in the ERSST analysis: Linear trends are removed before filtering, but then added back into the data matrix $\tilde{X}$, such that linear trends are included in the definition of low-frequency variance.

**c. Data processing for CMIP5 ensemble.**

All model output is interpolated to a common analysis grid. For surface fields, we use the 2° grid of ERSST. For MOC, we use a 1° grid in latitude and 52 vertical levels extending to 5250 meters depth. Rather than interpolate model output of SST from the irregular ocean grids to the 2° analysis grid, we use TS, which is output on each model’s atmospheric grid. In order to obtain SST data from TS, we set all temperatures below the freezing point of seawater (where sea ice is present) to the freezing point. After interpolation, we exclude all grid points that are over land.

In order to apply LFCA to an ensemble of climate-model simulations, we concatenate the individual-model monthly SST anomaly matrices $X_i$ into one ensemble anomaly matrix,

$$X_E = [X_1^T X_2^T \ldots X_n^T]^T.$$  \hspace{1cm} (8)$$

The climatological seasonal cycle is subtracted from each data matrix $X_i$ separately such that we remove differences
Fig. 1. Atlantic Low Frequency Components in ERSSTv3b. (a) The first and (b) second low-frequency patterns (LFPs) of Atlantic SST anomalies over the historical period from the ERSSTv3b data set, using low-frequency component analysis (LFCA) with 25 EOFs retained and a 10-year lowpass cutoff. (c) The first and second low-frequency components (LFCs) of Atlantic SST, which correspond to the spatial anomaly patterns in (a) and (b). The North Atlantic SST Index (NASSTI), based on linearly detrended SSTs, is shown for comparison. Dashed vertical lines show years with major AMO transitions. Black lines show each index filtered with a 10-year lowpass filter; $r$ is the ratio of low-frequency (greater than 10 years) to total variance. Note that using global-mean SST to remove the global warming signal from NASSTI further reduces its variance ratio $r$ to 0.51 without qualitatively changing its SST pattern. (d) Regression of Atlantic SST anomalies on NASSTI.

in climatology between models. Here, $n_E$ is the number of models in the CMIP5 pre-industrial ensemble. In lowpass filtering the ensemble data matrix $X_E$, we do not filter over discontinuities between models; the data from each model is filtered separately then concatenated,

$$
\tilde{X}_E = [\tilde{X}_1^T \tilde{X}_2^T \ldots \tilde{X}_{n_E}^T]^T.
$$

(9)

LFCA is then applied to find the SST anomaly pattern that maximizes the ratio of low-frequency to total variance over the entire ensemble.

When computing lead-lag regressions and correlations with the corresponding SST indices, significance levels are computed by analyzing the lag-0 regressions or correlations with 500 phase randomized samples of each SST index, following Ebisuzaki (1997). Phase randomization is applied to the concatenated multi-model index such that it also randomizes phase across different models.

3. Multidecadal variability of the subpolar North Atlantic

The two leading LFPs/LFCs of monthly Atlantic SST anomalies (from the climatological seasonal cycle) between 40°S and 75°N in the observations (ERSST, Smith et al. 2008), over the period 1900-2016, correspond to basin-wide long-term warming and subpolar North Atlantic multidecadal variability (Fig. 1). We retain 25 EOFs in the LFCA to capture 85% of the total Atlantic SST variance. LFC 1 is highly correlated (0.94) with global-mean SST and thus represents the impact of global warming on Atlantic SSTs. LFP 2 shows large-scale warming of the North Atlantic, concentrated in the North Atlantic subpolar gyre. Its timeseries (LFC 2, Fig. 1c) shows a pronounced warm phase from 1924 to 1965 followed by a pronounced cold phase from 1966 to 1997 and a weaker warm phase since 1998. This agrees well with the multidecadal shifts in NASSTI (correlation of 0.74, coher-
ence greater than 0.85 for periods greater than 12 yr), but LFC 2 has a much larger ratio of low-frequency to total variance than does NASSTI ($r = 0.76$ versus 0.55). While the temperature patterns associated with LFC 2 and NASSTI are similar in the subpolar gyre (Figs. 1b and 1d), LFC 2 has a much weaker relationship with tropical Atlantic SSTs. Together, these results suggest that the AMO is confined to the subpolar North Atlantic, while the tropical Atlantic varies primarily on shorter (intradecadal) timescales, adding noise to the traditional NASSTI/AMO definition.

LFP/LFC 2 is similar to proposed SST-based indices of AMOC (Rahmstorf et al. 2015; Caeser et al. 2018), and similarly shows a negative trend over the 20th century ($-0.6$ standard deviations per century). However, the magnitude of negative trend in LFC 2 is sensitive to the time period analyzed. Other aspects of the results in Fig. 1 are robust across different choices of time periods and can be recovered by transferring trends between LFCs 1 and 2, as long as we include data back to 1960 [We also obtain similar results from an analysis of the Hadley Centre Global Sea Ice and Sea Surface Temperature data set version 1.1 (HadISSTv1.1, Rayner et al. 2003); LFCs 1 and 2 of HadISSTv1.1 show aspects of the long-term SST trends and LFC 3 has a 0.75 correlation with LFC 2 of ERSST]. Time periods shorter than about 60 years contain less than one full cycle of AMO variability such that this statistical analysis mixes the AMO with the secular trend. Statistical analysis of SST anomalies cannot by itself distinguish the relative influences of external forcing and internal variability on observed Atlantic SST variability. Distinguishing forced from unforced components in observations requires a better understanding of the physical mechanisms of AMO variability, which we will develop (based on coupled climate models) in the next section.

The observational record of ocean circulation (Cunningham et al. 2007) and air-sea heat fluxes (Chou et al. 2003; Yu and Weller 2007; Berry and Kent 2009) is too short to constrain mechanisms of variability on multidecadal timescales, particularly since lead-lag relation-

![Comparison of LFC 1 and NASSTI in coupled climate models](image_url)

**Fig. 2. Comparison of LFC 1 and NASSTI in coupled climate models.** (a and b) Spatial pattern of SST anomalies associated with a 1-standard-deviation anomaly in (a) LFC 1 and (b) NASSTI, computed over the CMIP5 pre-industrial ensemble; the insets show the autocorrelation of the associated indices. (c and d) Regression of net sea-surface heat-flux anomalies on (c) LFC 1 and (d) NASSTI. Positive values denote an anomalous heat flux from the ocean into the atmosphere. Insets show the lead-lag regression of heat-flux anomalies (averaged over the box in the corresponding figure) on each index. Lag 0 is the time where the temperature pattern is maximum; positive lags indicate heat-flux anomalies that lag the index. Dashed grey lines give the 95% significance levels based on phase randomization. Averaging is done over all 26 CMIP5 models used in this study; see Table 1.
FIG. 3. Lead-lag regressions of regional air-sea heat-flux anomalies on AMO indices. (a) The autocorrelation of and (b–d) lead-lag regression of heat-flux anomalies on LFC 1, NASSTI, 10-year lowpass filtered NASSTI, and the subpolar (40-60°N, 20-60°W) SST index. Heat-flux anomalies are averaged over (b) the subpolar box shown in Fig. 2c, (c) the full North Atlantic box shown in Fig. 2d, and (d) the northeast Atlantic (30-65°N, 0-30°W). The heat-flux regressions in the top two rows of (b) and (c) break up the differences in heat-flux regressions show in Figs. 2c and 2d into differences in averaging region and differences in SST index. Heat fluxes are in units of W m⁻² per standard deviation of the associated index. Lag 0 is the time where the temperature pattern is maximum; positive lags indicate heat-flux anomalies that lag the index. Dashed grey lines give the 95% significance levels based on phase randomization.

ships with the AMO are dominated by the two major AMO transitions in the observational record, during 1966-68 and 1995-98. We thus turn our focus to numerical simulations with fully-coupled atmosphere-ocean models. To identify mechanisms of unforced variability, we analyze CMIP5 pre-industrial control simulations, where greenhouse gases and aerosols are kept fixed at pre-industrial levels. We include 500 years from each of 26 different models such that we analyze a total of 13,000 years of unforced variability (Table 1). To reduce the dimensionality of this large dataset, we compute the leading 50 EOFs of monthly Atlantic SST anomalies (from each model’s climatological seasonal cycle, with quadratic trends removed) across the entire multi-model ensemble (capturing 72% of the total variance) and input these to the LFCA. By including 50 EOFs, we include information about variability at small spatial scales (e.g. ocean frontal zones) that could not be captured by a large-scale average such as NASSTI. Rather than trying to assess which models best simulate Atlantic multidecadal variability, we focus on multi-model composites that illustrate the representative mechanisms within the ensemble.

The leading LFP of monthly Atlantic SST anomalies (between 40°S and 75°N) in the CMIP5 pre-industrial ensemble shows warming throughout the high-latitude North Atlantic (Fig. 2a), particularly at latitudes greater than 40°N, with the largest warming within the subpolar gyre. The corresponding LFC has considerable persistence out to decadal timescales (inset in Fig. 2a). This bears qualitative similarity with LFCA applied to individual models (Appendix A), where each model emphasizes warming in a slightly different region of the subpolar North Atlantic. Compared to the pattern of low-frequency variability in ERSST (Fig. 1b), the multi-model composite SST pat-
Oceanic and atmospheric circulation anomalies associated with AMO in coupled climate models. (a and b) Regression of Atlantic Meridional Overturning Circulation (AMOC) streamfunction anomalies on (a) LFC 1 and (b) NASSTI. Black contours show the climatological AMOC streamfunction (contour interval: 2 Sv). (c and d) Regression of sea-level pressure (SLP) anomalies on (c) LFC 1 and (d) NASSTI. Averaging is done over the 16 models with AMOC data for (a) and (b) and all 26 models for (c and d); see Table 1. Circulation anomalies shown correspond to a 1-standard-deviation anomaly in the respective index.

tern (Fig. 2a) has larger SST anomalies in the Arctic and a weaker connection with Southern Hemisphere temperatures. Averaged over the full Atlantic domain, the pattern correlation between them is 0.64, higher than for any individual model’s SST pattern associated with LFC 1 variability. This suggests that the multi-model composite is a better representation of the real world than any individual model. The decadal persistence is somewhat smaller in the CMIP5 pre-industrial ensemble (LFC 1 autocorrelation e-folding time of 4 years) than in ERSST (LFC 2 autocorrelation e-folding time of 10.5 years). This corresponds to a reduced ratio of low-frequency to total variance in CMIP5 compared to ERSST ($r = 0.60$ vs. $0.76$) and could indicate either that Atlantic multidecadal variability operates on shorter timescales in models than in observations or that external forcing contributed to the observed variations of North Atlantic SSTs over the 20th century.

For comparison, the SST pattern associated with the traditional NASSTI/AMO definition shows a horseshoe-like warming pattern within the 0-60°N latitude range used to define it (Fig. 2b) and has markedly less persistence, similar to our findings in the observational SST data (Fig. 1). NASSTI explains 26% more of the total Atlantic SST variance than LFC 1, but 59% less of the variance on decadal and longer timescales, owing to its lower ratio of low-frequency to total variance. LFC 1 and NASSTI are both associated with sea-ice loss and warming over Europe, eastern North America, and northwestern Africa, giving surface temperature anomalies that are locally larger than the SST anomalies (not shown, cf. Sutton and Hodson, 2005; Mahajan et al., 2011). The model derived LFC 1 and NASSTI give two representations of Atlantic SST variability that can be used to give two perspectives on the associated mechanisms, focusing in particular on how the mechanisms differ between timescales. Because these indices capture some of the same multidecadal variability (see Section 5), we will refer to them both as indices of the AMO.

The second LFP of monthly Atlantic SST anomalies in the pre-industrial ensemble shows a tripolar SST anomaly between the Gulf Stream, the subpolar gyre, and the Norwegian Seas (see Appendix B). The corresponding LFC varies on 8-20 year timescales. In Appendix B, we discuss how it could be related to subpolar gyre variability in response to wind-stress forcing [as discussed in previous work by Curry and McCartney (2001) and Sun et al. (2015)]. Neither of the leading LFPs are sensitive to the domain or LFCA parameters used, and our analysis is broadly consistent with an analogous analyses of annual or seasonal SST anomalies\(^1\). Moreover, we can find similar

\[^1\]The area-weighted pattern correlation between LFP 1 of annual SST anomalies (not shown) and LFP 1 of monthly SST anomalies is 0.98, for analysis of Atlantic SST anomalies in the CMIP5 pre-industrial control ensemble.
indices by applying LFCA to global, rather than Atlantic, SST anomalies (not shown).

4. Mechanisms of ocean–atmosphere dynamic coupling within the AMO

We use lead-lag relationships between air-sea heat-flux anomalies (including sensible heat, latent heat, and radiative components) and SST anomalies to determine whether SST variability is driven by direct atmospheric forcing or by ocean circulation changes (which can result either from internal ocean variability or from prior atmospheric wind and buoyancy forcing). The lag-0 regressions of air-sea heat-flux anomalies on LFC 1 and NASSTI show striking differences (Figs. 2c and 2d). Positive LFC 1 anomalies are associated with anomalous net heat fluxes from the ocean into the atmosphere in the Labrador Sea, subpolar gyre, and Barents-Kara Sea (Fig. 2c) – all regions of positive SST anomalies. This suggests that these SST anomalies are maintained by ocean circulation changes and anomalous ocean heat transport.

Averaging heat-flux anomalies over the subpolar North Atlantic, we find that the ocean is losing energy to the atmosphere for more than 10 years surrounding a maximum in LFC 1 (inset in Fig. 2c). This is only possible if anomalous ocean heat-flux convergence sustains the warm temperatures, because these surface heat-flux anomalies would otherwise act to cool the ocean surface. The reduction in upward heat fluxes a few years before the maximum warming and subsequent heat-flux spike in the year following indicates that atmospheric heat fluxes contribute some additional warming on shorter timescales. Specifically, there is a region of the northeast Atlantic, extending from the southern coast of Iceland towards Great Britain, where the anomalous net heat flux is into the ocean during and in the years preceding a warm event (Figs. 2c and 3d).

In contrast, NASSTI anomalies are associated with anomalous heat fluxes from the atmosphere into the ocean throughout much of the 0-60°N latitude range (Fig. 2d). Averaged over these latitudes, heat-flux anomalies are into the ocean immediately before a temperature maximum and out of the ocean immediately following, consistent with direct atmospheric forcing of this variability. The lead-lag relationships of LFC 1 and NASSTI with air-sea heat-flux anomalies differ partly because these indices identify heat-flux variability in different regions, but the lead-lag relationships remain qualitatively different even if consistent averaging regions are used (Fig. 3).

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2We describe the AMO mechanisms focusing on the warm phase for clarity of explanation, but since this analysis is based on regressions on the LFC 1 index, all mechanisms apply also with opposite sign. In this way, ocean heat-flux convergence contributes to the variance of SST. Note however, that because the SST tendency due to ocean heat-flux convergence is opposite in sign to the tendency due to surface heat fluxes, ocean heat-flux convergence does not necessarily increase the total variance of SST compared to a slab-ocean model.

LFC 1 shows anomalous heat loss from the ocean throughout warm events, an indication that SST anomalies are sustained by anomalous ocean heat-flux convergence.

To investigate the ocean circulation changes associated with these two types of AMO-like variability, we regress monthly anomalies of the AMOC streamfunction onto LFC 1 and NASSTI. LFC 1 anomalies are associated with a maximum AMOC strengthening of 0.41 Sv
Fig. 6. **AMO Evolution.** Regressions of SST (shading) and SLP (contours; contour interval 5 Pa; dashed negative) on LFC 1 for various lead and lag times. Year 0 is the year of maximum warming as characterized by LFC 1. We focus on the 10-years surrounding a maximum in LFC 1, because the statistical significance of these regressions is small for longer lead/lag times (i.e., even though LFC 1 evolves on multidecadal timescales, it is only predictable on decadal timescale).

Both LFC 1 and NASSTI show an AMOC maximum 2-3 years before the maximum North Atlantic warming (Fig. 5a and 5c). Combined with the necessity to invoke ocean heat-flux convergence to explain surface heat-flux anomalies (Fig. 2c), this suggests that AMOC plays a causal role in AMO variability. The relationship with AMOC is stronger for LFC 1; the NASSTI relationship is obscured by a short-lived peak at lag-0, which corresponds to a change in the ocean gyres rather than an increase in ocean overturning. In essence, NASSTI is mixing together information about any variability that leads to warming in the North Atlantic, whether that is strengthened AMOC or a net heat flux from the atmosphere to the ocean due to stochastic atmospheric variability (the latter of which also leads to a change in the ocean gyres).

The regression of sea-level pressure (SLP) anomalies also differs between LFC 1 and NASSTI. The lag-0 regression of SLP anomalies on LFC 1 shows a low-pressure anomaly centered over the region of positive subpolar SST anomalies (Fig. 4c). This atmospheric circulation anomaly acts to weaken the trade winds and communicate the warming into the tropical Atlantic (cf. Yuan et al. 2016; Brown et al. 2016). This basin-wide low pressure anomaly develops only after AMOC has reached its maximum strength (Fig. 6), suggesting that it is a response to AMOC-driven warming of the North Atlantic, either directly or indirectly. The circulation anomaly fits with what is expected from a direct atmospheric response to extratropical thermal forcing (Hoskins and Karoly 1981). The lag-0 regression of SLP anomalies on NASSTI shows a low-pressure anomaly over the subtropical gyre and weak high-pressure anomaly over the subpolar gyre. The weaker subtropical anticyclone weakens the trade winds, reducing evaporative cooling of the subtropics and help-
Fig. 7. Schematic evolution of an AMO warm event. Summary of the atmospheric and oceanic anomalies during the (a) growth, (b) peak, and (c) decay phases of an AMO warm event. Orange shading shows an SST anomaly characteristic of each stage (taken from years −5, −1, and 3 in Fig. 6). Blue and red contours indicate low and high pressure anomalies, respectively. Black arrows indicate strong zonal winds during the growth phase. Upward squiggly arrows indicate anomalous heat fluxes (including radiation) from the ocean into the atmosphere; downward, from the atmosphere into the ocean. The dark red arrow shows the path of the Gulf Stream and North Atlantic Drift; its width corresponds to the magnitude of AMOC anomaly in each phase of the AMO. Note that the heat-flux anomalies in the eastern North Atlantic (southeast of Iceland) and in the subtropical North Atlantic change signs between the peak phase (b) and the decay phase (c) indicating that SST anomalies are driven by the atmosphere in this region (while being driven by the ocean elsewhere).

ing to warm subtropical SSTs (cf. Figs. 2b and 2d). Since this anomaly opposes the climatological atmospheric circulation, it acts to weaken the ocean gyres, leading to the AMOC streamfunction anomaly shown in Fig. 4d.

Variability of the North Atlantic atmospheric circulation can be characterized by the North Atlantic Oscillation (NAO, Hurrell et al. 1995). Both LFC 1 and NASSTI show positive NAO anomalies from 12 to 2 years before peak warming (Fig. 5b and 5d). This is consistent with a proposed mechanism where positive NAO anomalies act to bring cold dry air off the North American continent, enhancing turbulent heat fluxes from the ocean into the atmosphere, stimulating deep-water formation in the Labrador Sea, and strengthening AMOC (Fig. 7a and Fig. 6; years −5 to −2) (e.g., Sun et al. 2015; Delworth and Zeng 2016; Delworth et al. 2016, 2017). In the absence of an ocean circulation response, the heat-flux anomalies associated with a positive NAO anomaly would act to cool the ocean; they can only lead to warming of the North Atlantic if anomalous ocean heat-flux convergence overwhelms the atmosphere-driven cooling.

NASSTI additionally shows a negative NAO anomaly in the year preceding and the year of maximum warming (Figs. 4d and 5d). This negative NAO anomaly reduces heat fluxes from the ocean into the atmosphere, leading to basin-wide warming, but also contributing to the weakening of AMOC. LFC 1 shows muted negative NAO anomalies around lag-0, because the associated circulation anomaly is not well aligned with the NAO SLP pattern (Fig. 4c and Fig. 6; years −1 to 1). These weakly negative NAO anomalies persist for ~25 years (not shown) and eventually lead to a phase reversal of the AMO after 20-45 years (95% confidence interval), but correlations at these lag times are not statistically significant in general, so we do not discuss them further. Over the course of a subpolar North Atlantic warm event (as characterized by LFC 1), the atmospheric circulation evolves from a positive NAO anomaly that helps to strengthen AMOC to a basin-scale low-pressure anomaly that helps to communicate the warming into the subtropics (Fig. 6). The interplay between NAO and AMOC illustrates the role of ocean-atmosphere dynamic coupling in AMO variability.

A summary schematic of the physics of the AMO in coupled climate models, as illuminated by LFCA, is shown in Fig. 7. In the growth phase of an AMO warm event (Years −12 to −2, Fig. 7a), strong zonal winds over the North Atlantic (e.g., associated with stochastic NAO variability) lead to anomalous heat loss from the Labrador Sea, helping to trigger deep-water formation and strengthen AMOC. Because AMOC takes several years to respond to NAO heat-flux anomalies (Delworth and Zeng 2016), even white-noise NAO forcing would result in red-noise AMOC variability extending out to multidecadal timescales (Hasselmann 1976). Ocean heat transport associated with AMOC overcompensates for the initial cooling and leads to warming of the subpolar North Atlantic.

During the peak phase of an AMO warm event (Years −2 to 0, Fig. 7b), AMOC reaches its maximum strength and a low-pressure cell forms over the subpolar gyre, helping to extend the warming to the east and south...
through warm air advection and reduced evaporative cooling. Heat-flux anomalies into the ocean in the eastern North Atlantic (30-65°N, 0-30°W, Figs. 3d and 2c) add buoyancy and contribute to subsequent AMOC weakening, helping to terminate the AMOC-driven warm event. The atmospheric response to the AMOC maximum simultaneously contributes to further North Atlantic warming and to the weakening of AMOC, such that the maximum warming lags the AMOC maximum by two years.

Within a year of the maximum warming, AMOC and the North Atlantic atmospheric circulation have returned to near their climatologies. The decay phase (Years 0 to 10, Fig. 7c) is characterized by warm temperatures decaying away through anomalous air-sea heat fluxes. This schematic synthesizes mechanistic understanding of the AMO growth phase (Delworth and Zeng 2016) with mechanistic understanding of AMO’s influence on the tropical Atlantic (Yuan et al. 2016; Brown et al. 2016) and elucidates the role of the atmospheric circulation response in driving buoyancy gain in the North Atlantic current, which helps to terminate AMO warm events. Note that these mechanisms also apply to AMO cold events (with opposite sign).

The NAO index is used for this mechanistic picture not because it provides the ideal AMOC perturbation, but because it is a canonical index that explains a large fraction of the total atmospheric circulation variability over the North Atlantic (Hurrell et al. 1995). Any perturbation that leads to heat loss from the subpolar North Atlantic should also spin up AMOC and lead to a delayed subpolar warming. Future work should consider how these mechanisms differ when Labrador Sea heat fluxes are driven by anthropogenic radiative forcing rather than stochastic atmospheric variability, as this could help to disentangle internal variability from forced responses in observed Atlantic temperatures.

5. Indices of Atlantic multidecadal variability

LFC 1 and NASSTI give two different statistical representations of processes contributing to multidecadal variability of Atlantic SSTs. LFC 1, by definition, has a higher ratio of low-frequency (i.e. multidecadal) to total variance than NASSTI. As a result, it has at least twice as much variance at 30-200 year timescales and half as much at 2-6 year timescales (Fig. 8a). Neither index has any strong spectral peaks in the multi-model mean, besides the peak at annual timescales in LFC 1, which is a consequence of low-frequency AMOC-driven SST anomalies having the largest manifestation in wintertime temperatures. Despite their differences, LFC 1 is relatively coherent with NASSTI at low frequencies (Fig. 8b), meaning that they are capturing much of the same multidecadal variability. This coherence at low frequencies helps to explain why NASSTI still captures the lead-lag relationships with NAO and AMOC on long timescales (Fig. 5c and 5d).

On the timescales where they are coherent, LFC 1 leads NASSTI by about one year (Fig. 5c), suggesting that AMOC-driven low-frequency variability of the subpolar North Atlantic can lead to basin-wide SST anomalies in the following year, likely due to its impact on the subtropical atmospheric circulation and subtropical low clouds (Yuan et al. 2016; Brown et al. 2016). In fact, at lead
times of 1-10 years, LFC 1 is a better predictor of NASSTI than NASSTI itself (Fig. 8d). This makes a strong case that LFC 1 would be a useful index for decadal predictions. It is a crucial point that processes in the subpolar North Atlantic lead to multidecadal variability throughout the Atlantic, since many of the impacts of the AMO are associated with SST anomalies at lower latitudes (Ruprich-Robert et al. 2017).

An alternate index of Atlantic variability, based on the monthly SST anomaly averaged over the subpolar North Atlantic (40-60°N, 20-60°W, Fig. 9a), also obscures the role of AMOC in AMO variability by mixing it with (high-frequency) atmosphere-driven warming of the subpolar gyre. This reduces its ratio of decadal to total variance (such that it is equal to that of NASSTI), causes it to show a correlation with anomalous heat fluxes into the ocean at lag-0 (Fig. 9b), and obscures its covariance with AMOC (Fig. 9c). The regression of SLP onto the subpolar SST index shows a negative NAO anomaly (Fig. 9d). This is associated with heat gain in the Labrador Sea and the eastern North Atlantic (Fig. 9b), both of which contribute to AMOC weakening. Variability of the subpolar SST index is associated with atmospheric variability that drives local warming through air-sea fluxes, but these heat-flux anomalies act to weaken AMOC, resulting in short-lived warm events. This is evident in the rapid decrease in AMOC following the strong negative NAO anomaly (Figs. 5g and 5h). Even though the subpolar SST index focuses on the same region of SST variability as LFC 1, it obscures the mechanisms that are important on decadal and longer timescales. LFCA thus goes beyond simply identifying the relevant region of Atlantic multidecadal variability by providing an improved AMO index that is useful in diagnosing the associated physical mechanisms.

Analyzing physical mechanisms based on a 10-year lowpass filtered NASSTI index, similar to what has been done by a number of other studies (Brown et al. 2016; Zhang et al. 2016; O’Reilly et al. 2016), recovers some of the conclusions as we have with LFCA (compare Fig. 10 with Figs. 2 and 4, Fig. 5e with Fig. 5b, and Fig. 5f with Fig. 5b), but makes strong assumptions about the spatial pattern of AMO SST anomalies and shows a different relationship between atmospheric circulations and the AMO. The SST pattern associated with the lowpass filtered NASSTI resembles that of NASSTI (by construction), but with weight shifted towards the subpolar part.
Fig. 10. Lowpass Filtered NASSTI. (a) SST pattern associated with the 10-year lowpass filtered NASSTI. The autocorrelation of the index is shown in the inset. (b) Net upward surface heat-flux anomaly associated with a 1-standard-deviation anomaly in lowpass filtered NASSTI. The inset shows the lead-lag regression of net surface heat-flux anomalies (averaged over 0-60° N in North Atlantic) and lowpass filtered NASSTI. Lag 0 is the time where the temperature pattern is maximum; positive lags indicate heat-flux anomalies that lag lowpass filtered NASSTI. Dashed grey lines give the 95% significance levels based on phase randomization. (c) AMOC streamfunction anomaly associated with a 1-standard-deviation anomaly in lowpass filtered NASSTI. The AMOC streamfunction climatology is shown in black contours (contour interval: 2 Sv). (d) Sea-level pressure anomaly associated with a 1-standard-deviation anomaly in lowpass filtered NASSTI. The lowpass filtered NASSTI mixes together the positive NAO anomalies driving AMOC variability and the negative NAO anomalies helping to terminate AMOC-driven warm events, such that it shows a weak overall SLP anomaly and obscures the role of ocean-atmosphere dynamic coupling in AMO variability (cf. Figs. 4c and 5c.)

Other studies have used lowpass filtered subpolar SST anomalies (Zhang 2017) or lowpass filtered AMOC streamfunction anomalies (Yan et al. 2018) as indices of Atlantic multidecadal variability. Such indices recover many of the same mechanistic insights as we have with LFCA, but remove all information about sub-decadal variations. LFCA uses information about the spatiotemporal covariance of sub-decadal variability in order to optimally filter it out, obtaining a monthly resolved index of multidecadal variability. Such an index is useful for determining the impact of sub-decadal variations on multidecadal SST variability (e.g., variations in the NAO or in northeast Atlantic heat fluxes; Figs. 5b and 3, respectively). That is not to say this is the only way to get this information. For example, Guan and Nigam (2009) have separated off a subpolar component of the AMO using extended EOF analysis. However, for the purposes of defining indices of multidecadal variability, one clear advantage of LFCA is that it identifies the anomaly pattern with the highest possible ratio of multidecadal “signal” to inter-decadal “noise”.

6. Slab-ocean models

Our results help to reconcile studies suggesting that the AMO in slab-ocean models (in which ocean circulation cannot vary) is similar to that in comprehensive models...
Both processes contribute to Atlantic SST variability, albeit on different timescales and in different geographic regions. The coupled atmosphere-ocean-variability of the subpolar North Atlantic explains more than twice as much multidecadal SST variance as NASSTI, illustrating the importance of dynamic ocean-atmosphere coupling in Atlantic multidecadal variability.

As a final test of these conclusions, we run our analysis on a pre-industrial control simulation of a slab-ocean model, wherein SSTs are allowed to respond thermodynamically to atmospheric fluxes but no ocean dynamics or heat transport changes are resolved. We use a 901 year simulation of the NCAR CAM5 atmospheric general circulation model coupled to a slab ocean (CESM1 in slab-ocean mode) and run with fixed pre-industrial (year 1850) forcing. This simulation was run as part of the CESM Large Ensemble project (Kay et al. 2015). The leading LFP of Atlantic SSTs in the slab-ocean model shows warming in the subpolar North Atlantic, similar to the fully-coupled models (Fig. 11a). Its ratio of low-frequency to total variance is $r = 0.46$, smaller than but comparable to the coupled version of CESM1 (CESM1-BGC, $r = 0.59$). However, a slab-ocean model cannot have anomalous heat fluxes out of the ocean preceding positive SST anomalies, because there is no ocean heat-flux convergence to sustain this heat loss. Indeed, the lead-lag regression of subpolar heat-flux anomalies on the slab-ocean LFC 1 shows anomalous heat fluxes into the ocean and observations (Clement et al. 2015; Cane et al. 2017), with literature showing the importance of AMOC variability for AMO (Delworth et al. 1993; Delworth and Mann 2000; Latif et al. 2004; Knight et al. 2005; Medhaug and Furevik 2011; Wang and Zhang 2013; Zhang and Wang 2013; MacMartin et al. 2013; Ba et al. 2014; O’Reilly et al. 2016; Kim et al. 2018; Garuba et al. 2018). Atlantic-basin-mean warming (i.e., a positive NASSTI anomaly) is preceded by anomalous heat fluxes from the atmosphere into the ocean, showing that NASSTI is primarily driven directly by atmospheric forcing (and could thus be simulated by slab-ocean models). However, lower-frequency SST variability in the subpolar North Atlantic is primarily driven by ocean circulation changes that sustain anomalous heat transport into the subpolar North Atlantic. These ocean circulation changes are partially a response to prior atmospheric forcing, but are driven by anomalous surface heat fluxes from the ocean to the atmosphere (which by themselves would act to cool the subpolar North Atlantic).

![Fig. 11. Low-Frequency Component of Slab-Ocean Simulation.](image)

(a) LFP 1 of Atlantic SSTs in a pre-industrial control simulation with a slab-ocean version of CESM1. The inset shows the autocorrelation and low-frequency to total variance ratio $r$ of the associated LFC. (b) Regression of sea-surface heat-flux anomalies on LFC 1 in the slab ocean model. The map shows the lag-0 regression. The inset shows the lead-lag regression of heat-flux anomalies averaged over the subpolar box. Lag 0 is the time where the temperature pattern is maximum; positive lags indicate heat-flux anomalies that lag LFC 1. Dashed grey lines give the 95% significance levels based on phase randomization.

![Fig. 12. Lead-lag correlation with NAO.](image)

Lead-lag relationship between DIF NAO anomaly and the AMO-like LFC in (a) fully-coupled CMIP5 models, (b) the CESM1 slab-ocean simulation, and (c) observations. For the observational analysis, we take sea-level pressure from the NCEP Twentieth Century Reanalysis (Compo et al. 2011). NAO is defined as the difference in normalized SLP anomaly between Reykjavik and Lisbon (Hurrell et al. 1995). The cross correlation between AMO and NAO is computed for monthly anomalies then averaged over DJF (based on the month of the SLP field). Dashed grey lines give the 95% significance levels based on phase randomization [of LFC 1 for (a) and (b), of NAO for (c)]. Note the extended time axis in panel (c).
immediately before a warm event and out of the ocean immediately after (inset in Fig. 11b), indicating that the SST variability is atmosphere driven, as it must be in the absence of ocean dynamics.

Heat-flux anomalies into the subpolar ocean in the years preceding a slab-ocean warm event are associated with large negative NAO anomalies (Fig. 12b), in contrast to the positive NAO anomalies that precede warm events in coupled models (Fig. 12a). The lead-lag correlations of the NAO and AMO (as characterized by LFC 1) have opposite signs between coupled and slab-ocean models at most lead times. This raises the question: Can we use this to distinguish which mechanism applies in observations? We calculate NAO over the period 1900-2014 from the NCAR Twentieth Century Renalysis (Compo et al. 2011), and compute its lead-lag correlation with the AMO-like LFC 2 from the ERSST analysis. This analysis shows positive NAO anomalies from 30 to 5 years before the subpolar Atlantic warming and negative NAO anomalies in the decades following (Fig. 12c). This is qualitatively similar to the lead lag relationship between NAO and AMO in the coupled models, albeit larger magnitude and on longer timescales. It is inconsistent with the lead-lag relationship between NAO and AMO in slab-ocean models. In agreement with other recent studies (Zhang et al. 2016; O’Reilly et al. 2016), these results suggest that the mechanisms of Atlantic multidecadal variability in slab ocean models are inconsistent with the mechanisms of Atlantic multidecadal variability in coupled models and observations.

7. Discussion and Conclusions

Low-frequency component analysis (LFCA) identifies the spatial signature of multidecadal Atlantic SST variability, focused in the subpolar North Atlantic. The corresponding index is highly correlated with the AMO as traditionally defined, but has a much higher ratio of interdecadal to intradecadal variance. This allows us to identify which physical mechanisms are important at decadal and longer timescales, filtering out mechanisms that play a role at shorter timescales.

We find that AMO temperature anomalies in unforced coupled climate models are driven by ocean heat-flux convergence in the subpolar North Atlantic, associated with anomalies in AMOC. Stochastic atmospheric variability, such as the NAO, is an important influence on the evolution of AMOC because of its influence on air-sea heat fluxes in the Labrador Sea. A positive NAO anomaly is associated with strengthened westerlies off eastern North America, increasing heat loss from the Labrador Sea and increasing the strength of AMOC. During the peak phase of the AMO, a basin-wide low-pressure anomaly develops in response to the warmer temperatures and helps to spread the warming to the east and south through wind-evaporative and cloud feedbacks. Consistent with previous modeling studies of the impact of extratropical Atlantic SST anomalies on atmospheric circulation (e.g., Hodson et al. 2010; Sun et al. 2015), this anomaly is weak and does not project strongly onto the NAO. However, by using a large multi-model ensemble, we are able to characterize a statistically significant low-pressure anomaly over the North Atlantic and weakly negative NAO in the years during and following a warm subpolar SST anomaly (Figs. 5 and 6). This atmospheric circulation anomaly helps to weaken AMOC and terminate the AMOC-driven warming by adding buoyancy in the eastern North Atlantic. This mechanistic picture of the AMO suggests that ocean circulations provide the main source of inertia in the climate system that sustains SST anomalies on long timescales. Ocean mixed-layer dynamics, which provides the source of inertia in the “slab-ocean” view of the AMO put forth by Clement et al. (2015) and Cane et al. (2017), is not the dominant mechanism in the North Atlantic at multidecadal timescales.

This study has focused on the mechanisms of unforced AMO variability in CMIP5 models. However, external forcing is thought to play a large role in observed AMO variability over the historical period (Booth et al. 2012; Tandon and Kushner 2015; Si and Hu 2017; Bellucci et al. 2017; Bellomo et al. 2018). Some of the insights about internal variability should also apply to forced changes, because AMOC changes in response to forcing appear to be dominated by changes in surface heat fluxes, rather than changes in surface freshwater fluxes (Gregory et al. 2005). In unforced simulations, AMOC responds to NAO-driven heat-flux anomalies in the Labrador Sea. In forced simulations, additional Labrador Sea heat fluxes due to greenhouse gas and aerosol forcing (including surface radiative fluxes) must be considered in the dynamics of AMOC and AMO.

The LFCA-based description of the AMO is largely consistent with other recent work showing that air-sea heat-flux anomalies are ocean driven on decadal and longer timescales (Zhang et al. 2016; O’Reilly et al. 2016), that positive NAO anomalies can lead to AMOC strengthening and warming with a lag of several years (Sun et al. 2015; Delworth and Zeng 2016; Delworth et al. 2016, 2017), and that wind-evaporative and cloud feedbacks are important for extending warming into the tropical Atlantic (Yuan et al. 2016; Brown et al. 2016; Bellomo et al. 2016). The key benefit of LFCA in this context is that the derived AMO index is not lowpass filtered and can thus resolve rapid transitions and clarify the interactions between high-frequency atmospheric variability (i.e., NAO) and the slowly evolving ocean, including NAO interactions with AMOC (discussed in the main text) and with the Gulf Stream and gyre circulation (Appendix B). Much of the
previous work on the AMO is based on lead-lag regressions on lowpass filtered indices, which can mix together processes leading up to AMO events with those following and hide causal relationships (Cane et al. 2017). Using LFCA, we recover many of these conclusions, while avoiding these pitfalls, adding confidence that dynamical coupling between atmospheric and oceanic circulations is fundamental to the dynamics of the AMO. Our analysis identifies the SST fingerprint of low-frequency AMO/AMOC variability, which may be useful for ongoing efforts to monitor and predict the evolution of AMOC and the AMO.

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APPENDIX A

Differences across models

All results presented in the main text are composite over 26 different CMIP5 models (Table 1). These different models show varying amplitudes and patterns of Atlantic multidecadal variability. In Fig. A1a and A1b, we plot the amplitude (relative to the ensemble mean) and low-frequency to total variance ratio of LFC 1 and NASSTI in each model. Since these indices have unit variance over the entire ensemble, the relative amplitude is the variance of the index in the data segment corresponding to an individual model (i.e. the ratio of variance within a model to the variance within the full ensemble). For ERSST, the relative amplitude is computed by comparing the amplitudes (spatial variance) of the patterns in Figs. 1c and 2a and the variance ratio is the ratio of low-frequency to total variance of the indices in Fig. 1c.
Fig. A2. Characterizing AMO in different models. The LFP with the highest pattern correlation with the full-ensemble LFP 1 (Fig. 2a) from LFCA of each model separately, and the evolution of its corresponding LFC (in units of standard deviation) versus model year. The low-frequency to total variance ratio $r$ is shown with each LFC. Note that some models (especially GFDL-ESM2G) have SST anomalies greater than 1°C that are saturated on the colorscale.
GFDD-ESM (2 models), GISS-E2-R, HadGEM2-ES, INMCM4.0, MIROC5, and MPI-ESM (3 models) show patterns similar to the ensemble mean. A plausible reason for the differences between models is that they differ in their representations of the shape of the subpolar gyre and the geographic locations of deep water formation. Two models are omitted from Fig. A2 for space limitations: GISS-E2-H is similar to GISS-E2-R but with a lower low-frequency to total variance ratio ($r = 0.55$); NorESM1-M shows substantial multidecadal variability, but it is mostly at smaller spatial scales than in other models and none of it resembles the ensemble composite picture of AMO variability. Note that these two models (GISS-E2-H and NorESM1-M) contribute the least to the multi-model composite (Fig. A1).

APPENDIX B

**The second low-frequency component: Tripolar SST anomalies associated with the NAO**

The second LFP of monthly Atlantic SST anomalies (between 40°S and 75°N) in the pre-industrial ensemble shows a tripolar SST anomaly pattern in the high-latitude North Atlantic (Fig. B1a), with warming in the Gulf Stream, cooling in the subpolar gyre, and warming in the Norwegian seas. This is similar to the coupled ocean-atmosphere dynamics of Gulf Stream and gyre circulation variability studied by Taylor and Stephens (1998), Curry and McCartney (2001), Eden and Jung (2001), Sun et al. (2015), Gastineau and Frankignoul (2015) and Nigam et al. (2018), among others.
LFC 2 has a ratio of low-frequency to total variance $r = 0.42$, compared to $r = 0.60$ for LFC 1. While LFCs 1 and 2 are uncorrelated at lag-0 by definition, they have some lead-lag correlations, with negative LFC 1 anomalies tendency to lead to positive LFC 2 anomalies and positive LFC 2 anomalies tendency to lead to positive LFC 1 anomalies (Fig. B1f). However, rather than indicating a casual relationship among LFCs 1 and 2, the cyclical nature of LFC 1/LFC 2 variability likely arises because they represent different timescales of the ocean’s response to a common NAO forcing. There are positive NAO anomalies 0-6 years before a maximum in LFC 2 (Fig. B1e), and 2-15 years before a maximum in LFC 1 (Fig. 5b). Therefore, a persistent positive NAO anomaly would lead to first a positive LFC 2 anomaly, and then, after a lag, a positive LFC 1 anomaly.

As was the case for LFC 1, the net surface heat-flux anomaly associated with LFC 2 indicates an active role of ocean heat transport, because warm temperatures are coincident with a net heat flux from the ocean to the atmosphere and vice versa (Fig. B1b). The lead-lag regression of subpolar gyre heat fluxes against LFC 2 shows heat flux into the ocean when the subpolar gyre is cold (lag-0), as well as anomalies at 10-year lead times and 5-year lag times that are associated with LFC 1 and AMOC. The spatial scale and westward intensification of the SST and net surface heat-flux anomalies suggest that this is a mode of variability in the ocean gyre circulations. However, there is also a high-latitude AMOC streamfunction anomaly associated with LFC 2 (Fig. B1d). It shows a latitudinal shift rather than a strengthening of AMOC and is therefore not well represented by the AMOC index (Fig. B1g). The positive AMOC anomaly associated with LFC 2 spans the latitude range beyond that of the hemispheric AMOC anomaly associated with LFC 1.

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