Granger Causality of Coupled Climate Processes: Ocean Feedback on the North Atlantic Oscillation

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ABSTRACT

This study uses a Granger causality time series modeling approach to quantitatively diagnose the feedback of daily sea surface temperatures (SSTs) on daily values of the North Atlantic Oscillation (NAO) as simulated by a realistic coupled general circulation model (GCM). Bivariate vector autoregressive time series models are carefully fitted to daily wintertime SST and NAO time series produced by a 50-yr simulation of the Third Hadley Centre Coupled Ocean–Atmosphere GCM (HadCM3). The approach demonstrates that there is a small yet statistically significant feedback of SSTs on the NAO. The SST tripole index is found to provide additional predictive information for the NAO than that available by using only past values of NAO—the SST tripole is *Granger causal* for the NAO. Careful examination of local SSTs reveals that much of this effect is due to the effect of SSTs in the region of the Gulf Steam, especially south of Cape Hatteras. The effect of SSTs on NAO is responsible for the slower-than-exponential decay in lag-autocorrelations of NAO notable at lags longer than 10 days. The persistence induced in daily NAO by SSTs causes long-term means of NAO to have more variance than expected from averaging NAO noise if there is no feedback of the ocean on the atmosphere. There are greater long-term trends in NAO than can be expected from aggregating just short-term atmospheric noise, and NAO is potentially predictable provided that future SSTs are known. For example, there is about 10%–30% more variance in seasonal wintertime means of NAO and almost 70% more variance in annual means of NAO due to SST effects than one would expect if NAO were a purely atmospheric process.

1. Introduction

The North Atlantic Oscillation (NAO)[1] is one of the leading modes of large-scale climate variability. It has received much scientific attention in recent years (e.g., Hurrell 1995; Wanner et al. 2001; Stephenson et al. 2003; and references therein), not least because of its important impacts on the North Atlantic Ocean and surrounding continents (Marshall et al. 2001; Hurrell et al. 2003). However, despite many studies, several aspects of the time evolution of the NAO still remain unclear. Historical time series of the NAO reveal a particularly complex and noisy evolution that exhibits intriguing persistence on short time scales less than a season (e.g., Baldwin et al. 2003; Charlton et al. 2003) and marked long-term (e.g., multiannual and decadal) nonmonotonic stochastic trends (Stephenson et al. 2000). The short-term persistence and longer-term trends present possible windows of opportunity for prediction of the NAO if only the factors controlling such behavior could be clearly isolated. This study attempts to quantitatively assess the role of the ocean on the NAO by applying econometric time series modeling methods to the output from coupled model simulations.

[1] Or, more generally, NAO/Arctic Oscillation (AO).

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One hope is that the slow evolution of oceanic variables may provide predictability of the NAO at lead times longer than synoptic weather events (1–2 weeks). This requires a causal ocean to atmosphere influence in either the North Atlantic region or the existence of some "bridge" from another ocean basin. Here, we consider only the former more regional mechanism. Many empirical studies have explored the association of the underlying sea surface temperatures (SSTs) with the NAO (Bjerknes 1964; Rodwell and Folland 2002; Czaja and Frankignoul 2002; Czaja et al. 2003; and references therein). In particular, a robust pattern known as the SST tripole has been found to be associated with the NAO (Bjerknes 1964; Deser and Timlin 1997). This pattern is considered to be predominantly the ocean response to latent heat fluxes and wind stress forcing associated with the NAO. However, the amount of feedback of the SST tripole on the NAO has not been formally assessed in previous studies and hence is a major focus of this study. Several empirical studies have used multivariate statistical methods to look for other possible predictors of the NAO. Rodwell and Folland (2002) identified a predictor pattern in May SSTs that enables a linear prediction of the following winter NAO. Saunders and Qian (2002) also investigated the predictability of the NAO based on a linear regression forecast from summer SST to the following winter NAO. Qian and Saunders (2003) investigated other predictors, such as summer snow cover. Numerical modeling studies of the response of the atmosphere to various changes in the North Atlantic Ocean remain rather inconsistent (see Kushnir et al. 2002).

Because of their simplicity, stochastic time series models provide useful tools for understanding climate variability and predictability. Such models have been used in several studies to investigate various aspects of ocean–atmosphere interaction (e.g., Davis 1976; Hasselmann 1976; Frankignoul and Hasselmann 1977). The complexity of the coupled system is reduced in these models by modeling atmospheric variations as serially uncorrelated random noise. Barsugli and Battisti (1998, hereafter BB98) used energy balance assumptions to develop a simple yet elegant two-variable coupled model of the midlatitude coupled system. BB98 modeled the time evolution of a pair of atmosphere and ocean temperature variables using two first-order linearly coupled differential equations. The atmospheric temperature equation included Gaussian white noise forcing to represent fast time-scale atmospheric variations. Using this model, BB98 demonstrated that coupling enhanced the variance of both variables and reduced the air–sea fluxes compared to those simulated by an uncoupled system having prescribed ocean temperatures. Bretherton and Battisti (2000, hereafter BB00) went on to use this model to interpret studies of NAO variability simulated by atmosphere models with prescribed sea surface temperatures. By means of simulations with the BB98 model, they demonstrated that an atmosphere-only version of the model with prescribed SSTs from a fully coupled run could simulate longer-term variations (seasonal to decadal) of NAO that were well correlated with those in the original coupled run. However, the NAO variations were considerably reduced in amplitude compared to those in the coupled simulation and arose from short time-scale interactions less than 6 months between the SSTs and NAO rather than any underlying long-lead forecast skill. In other words, BB00 demonstrated that long-term changes in NAO (e.g., seasonal and decadal) are only *potentially predictable* in that they can only be predicted given knowledge of future SSTs, which in practice are unlikely to be predictable more than 6 months in advance. Nevertheless, potential predictability is important for understanding the amount of long-term trending in NAO—the short-term effect of SSTs on NAO cause NAO to have more long-term trends than would be expected if NAO were purely an atmosphere-only process. Eden et al. (2002) extended the BB98 model by coupling the stochastic atmosphere component to a realistic ocean general circulation model for the Atlantic region. They found an oscillatory behavior in annual mean ocean temperatures that could not be modeled assuming the BB98 first-order Markov process. As with BB98 and BB00, Eden et al. (2002) assumed a known positive feedback of ocean temperatures on the atmosphere based on simplified physical arguments.

In addition to being able to simulate the coupled climate system, stochastic models also provide extremely useful tools for estimating the feedbacks in such systems. Unlike descriptive correlation and covariance approaches, stochastic models can be used to diagnose direct and indirect feedbacks in complex systems. For example, Junge and Stephenson (2003) used a multiple linear regression model to distentangle the direct and indirect effects of the ocean and NAO on central England temperature variations. BB98 concluded by "hoping that their model, or refinements of it, will be applied to the quantitative diagnosis of more realistic GCM runs . . . ." This suggestion was taken up by Mosedale et al. (2005), who used an AR(1) discrete version of the BB98 model to diagnose the influence of daily ocean mixed layer temperatures on daily lower-tropospheric air temperatures as simulated by the Hadley Centre coupled model. Mosedale et al. used the model to estimate the coupling and showed that it was significantly positive in a region over the eastern extension of the Gulf Stream. Wang et al. (2004) extended the BB98 model by using higher-order time series models to test the coupling of monthly mean SSTs on monthly mean NAO in observations and reanalyses from 1948 to 2000. Using an approach known as *Granger causality* testing (see section 2c of this article for more details), they demonstrated that preceding season mean SSTs in the Gulf Stream extension have a statistically significant effect on wintertime mean NAO. However, since much of the ocean–atmosphere feedback takes place on time scales less than a season, it is more revealing to apply Granger causality on more frequently sampled data.

This study aims to extend the work of Mosedale et al. (2005) to assess the SST feedback on NAO in daily output from the Hadley Centre coupled model. Rather than imposing a first-order Markov model restriction as done by BB98 and BB00, the more flexible Granger causality approach is used to determine the best time series models for modeling the coupled system. The order of the autoregressive model that best fits the data is estimated using the data. Section 2 of the paper describes the coupled model and the Granger causality and potential predictability methodologies. These procedures are then applied to investigate the interaction between the NAO and the SST tripole in section 3, and NAO and local North Atlantic SSTs in section 4. Section 5 presents conclusions and suggestions for future directions.

2. Models and methodology

The aim of this study is to introduce new techniques for diagnosing coupled interactions and apply these techniques to the ocean–atmosphere system, focusing on the influence of SST on the future evolution of the NAO. The techniques involve fitting time series models to daily SST and sea level pressure (SLP) data from a 50-yr simulation of the Third Hadley Centre Coupled Ocean–Atmosphere GCM (HadCM3; Gordon et al. 2000; Collins et al. 2001). The methods presented in this study are in no way restricted to examining daily GCM data and can equally well be applied to observations and data with different sampling rates.

a. *The coupled general circulation model: HadCM3*

HadCM3 has 3.75° × 2.5° resolution in the atmosphere and 1.25° × 1.25° resolution in the ocean. A 50-yr-long control simulation of HadCM3 has been performed with SLP and SST fields archived daily (see Mosedale 2004). This daily resolution allows investigation of both short- and long-term effects of SST on the NAO.

A simple yet robust NAO index has been formed by taking the difference in area-weighted averaged SLP between two large boxes, stretching from 20° to 55°N, 55°N to the North Pole, both from 90°W to 60°E. This gives an NAO index based on simple pressure differences rather than more complicated procedures such as empirical orthogonal functions. This approach also has the advantage of being more robust to variations in the centers of action of the NAO than station-based indices, although there is some evidence that area-averaged indices can occasionally result in misleading physical conclusions (Slonosky and Yiou 2002). However, tests performed by us showed that the results presented here were not overly sensitive to the size of box used to define the NAO index. An SST index is obtained by aggregating the top layer of the model ocean, giving an SST index for each atmospheric grid point.

Mean annual cycles are removed from the time series of the NAO and those of the SST at each grid point over the North Atlantic domain to obtain climate anomalies. These cycles are estimated as the sum of the annual and semiannual harmonics fitted to the data. In this study only the cold half of the year is considered, from October to March. This block season approach has the advantage of separating wintertime processes from summertime processes, at the expense of ignoring processes by which summertime SSTs might affect wintertime NAO. Finally, each anomaly time series is standardized by removing its mean and dividing by its standard deviation, to give an index time series with zero mean and unit variance.

b. *The time series modeling approach*

Following Mosedale et al. (2005), vector autoregressive (VAR) time series models are fitted to the GCM output. The pth-order vector autoregressive VAR(p) time series model is defined by

$$N_t = \sum_{i=1}^{p} \alpha_i N_{t-i} + \sum_{i=1}^{p} \beta_i S_{t-i} + \varepsilon_t \tag{1}$$

$$S_t = \sum_{i=1}^{p} \gamma_i N_{t-i} + \sum_{i=1}^{p} \delta_i S_{t-i} + \eta_t, \tag{2}$$

where N_t is the NAO index at day t, S_t is the SST index at day t, and $p \geq 1$ is the order of the model. The terms ε_t and η_t are noise residuals in the regression. This model is related to that of BB98, which was used by Mosedale et al. (2005) in a precursor to this study. However, unlike the VAR(1) model, the higher-order

VAR(p) model is able to realistically reproduce the lag covariance structure seen in the GCM data.

Three time series models are investigated here, each based on this VAR(p) model. The full model is that given above, which contains both directions of interaction. The effect of the ocean on the atmosphere is investigated by comparing this full model with a null model of no ocean to atmosphere influence. This model is obtained by setting the $\{\beta_i; i = 1, 2, \ldots, p\}$ parameters to zero so that SSTs can no longer directly affect the NAO. A third model is also considered, in which the atmospheric forcing of the ocean is turned off by setting the atmosphere-to-ocean parameters $\{\gamma_i; i = 1, 2, \ldots, p\}$ to zero. Since it is well known that the atmosphere plays a major role in forcing the ocean, this model can be rejected immediately and so cannot be considered to be a good choice of null model for the process. However, this restricted model can be used to investigate the effects of atmospheric forcing on the ocean on the predictability of the NAO. For simplicity, the three models will be referred to as $a \leftrightarrow o$ for the full model, $o \nrightarrow a$ for the null model, and $a \nrightarrow o$ for the third model: in each case the symbolic representation is of the interactions between the atmosphere and ocean that are present in the model.

The parameters α_i, β_i, γ_i, and δ_i in each model are separately fitted to NAO and SST data from the HadCM3 simulation. The regression procedure used is an efficient method of generalized least squares estimation known as *seemingly unrelated regression* (Zellner 1962). In the case of the full model, this reduces to an ordinary least squares regression for each model equation. Simulations of the three time series models are then made using white noise forcing, scaled appropriately such that the ratio of atmospheric to oceanic forcing is the same as that of the GCM.

c. Granger causality

In 2003, Clive W. J. Granger was awarded the Nobel prize in economics for his work on analyzing economic time series with common trends (cointegration). In a pivotal study, Granger (1969) defined causality as follows:

> A variable Y is causal for another variable X if knowledge of the past history of Y is useful for predicting the future state of X over and above knowledge of the past history of X itself.

So if the prediction of X is improved by including Y as a predictor, then Y is said to be *Granger causal* for X. Granger presented a clear time series approach for testing for such causality that has since been used in many econometric studies.

A predictive definition of causality is highly relevant to climate science but has not yet been used in many studies. Notable exceptions include the studies by Kaufmann and Stern (1997), Stern and Kaufmann (1999), and Triacca (2001). Recently, Granger causality has also been applied to seasonal mean interaction between the ocean and the atmosphere in the North Atlantic region (Wang et al. 2004). Wang et al. found some evidence that preceding season SSTs were Granger causal for the winter mean NAO.

The procedure for testing Granger causality is as follows (see Mills 1999):

1) Granger causality testing applies only to statistically stationary time series. If the time series are nonstationary, then the time series model should be applied to temporally differenced data, $\Delta X_t = X_t - X_{t-1}$, rather than the original data.
2) The best order p for the VAR time series model on which Granger causality is based must be selected. Here this is achieved by minimizing the Schwarz criterion (Schwarz 1978),

$$\mathrm{SC} = -2\frac{l}{n} + 2(1 + 2p)\frac{\log(n)}{n}, \tag{3}$$

where

$$l = -\frac{n}{2}[2(1 + 2\log\pi) + \log|\Omega_p|] \tag{4}$$

is the log likelihood of the VAR(p) model, n is the sample size ($n = 9000$ for 50 years of long winter daily data), and $|\Omega_p|$ is the determinant of the covariance matrix of the residuals. When the time series model fits the GCM data well, $|\Omega_p|$ is small, making the first term of the Schwarz criterion large and negative. The second term penalizes large-order models and is required to avoid the model becoming overparameterized (i.e., becoming overly complex).
3) Granger causality tests a complete model against a null model with no possible causality; this null model has the possible causal variables removed. A test statistic is obtained by comparing the residuals of the full model with those of the model in which the parameters of interest are set to zero. To identify Granger causality of the ocean on the NAO, the model with $\beta_i = 0$ is used as the null model. In other words, the NAO is not influenced by any previous SST values. The two models are compared using the log likelihood ratio statistic:

$$L_{S\rightarrow N} = n(\log|\Omega_{p,\beta_i=0}| - \log|\Omega_p|). \tag{5}$$

If this statistic is close to zero, then the restricted model does equally as well as the full model in representing the data and, therefore, SST has no Granger causal impact on the NAO. If the statistic is large, then the addition of the interaction terms helps to describe the variability in the data and thus there is Granger causality. The Granger causal impact of the NAO on SST can also be assessed, using the statistic

$$L_{N\to S} = n(\log|\Omega_{p,\gamma_i=0}| - \log|\Omega_p|). \tag{6}$$

4) Statistical significance is assessed by comparing the L statistic against the χ_p^2 null distribution. If the p value is smaller than 0.05, then the null hypothesis is rejected and the SST measure is Granger causal for the NAO at the 5% level of significance.

Granger causality applied to the daily time series described herein decides whether the use of the ocean as a predictor will improve the one-day-ahead prediction of the NAO. We may expect that most of the residual variance will be concentrated at short time scales, so the Granger causality statistic will be dominated by the effect of daily prediction errors.

d. Potential predictability

Longer-term time behavior is evaluated here using the potential predictability framework based on variance ratios of long-term means (see Madden 1976; Zwiers 1987). In this approach, one expresses a weather time series variable as the sum of a slow signal and a fast noise component: $Y = Y_{\text{signal}} + Y_{\text{noise}}$. The slow signal is considered to be potentially predictable whereas the noise component is only considered to be predictable over short weather time scales (e.g., less than a month ahead). One then assesses whether there is more variance in the long-term means (e.g., seasonal means) of the series $\overline{Y} = \overline{Y}_{\text{signal}} + \overline{Y}_{\text{noise}}$ than one could expect from averaging just the noise (pure weather) component (von Storch and Zwiers 1999).

A major difficulty in defining potential predictability is how best to define weather noise. Here, however, the noise component is taken naturally to be the evolution of NAO in the absence of any SST forcing as described by the $o \nrightarrow a$ model. One can then ask how much more variance there is in simulations with the full model than there is in simulations with the atmosphere-only model. Following Stephenson et al. (2000), potential predictability is presented here in terms of *aggregated variance*—the variance of k-day time means as a function of averaging period k:

$$\text{var}(\overline{Y}) = \frac{1}{n}\sum_{i=0}^{(n/K)-1}\left[\sum_{j=0}^{K-1} Y_{t+iK+j}\right]^2. \tag{7}$$

For uncorrelated signal and noise $\text{var}(\overline{Y}) = var(\overline{Y}_{\text{signal}}) + \text{var}(\overline{Y}_{\text{noise}})$, so potential predictability can be defined as the percentage of total variance attributable to the signal:

$$p = \left(1 - \frac{\text{var}(\overline{Y}_{\text{noise}})}{\text{var}(\overline{Y})}\right) \times 100\%. \tag{8}$$

It is a necessary and sufficient condition that the ocean is Granger causal for NAO ($\beta_i \neq 0$) for the NAO to have potential predictability ($\text{var}\overline{Y} > var\overline{Y}_{\text{noise}}$). Note that potential predictability is a necessary but not sufficient condition for long-term predictive skill: for predictability one also requires predictability of the signal component.

3. The role of the SST tripole

Many previous studies of ocean–atmosphere interaction in the North Atlantic region have highlighted the role of the SST tripole pattern (e.g., Bjerknes 1964; Deser and Timlin 1997; Czaja and Frankignoul 1999; Peng et al. 2003; Cassou et al. 2004). In particular, these studies argue that the tripole is a response to atmospheric forcing by the NAO pattern, and many have also discussed the influence of the tripole upon the NAO. This section investigates the role of the tripole in responding to and forcing the NAO pattern in HadCM3.

The SST tripole pattern is defined here as the contemporaneous correlation between the NAO index and the SST at each grid point. A tripole index can be formed by summing the SST at each grid point, weighted by the correlation at that grid point. Figure 1 shows the NAO pattern and its associated tripole pattern.

Examples of time series of both the NAO and tripole indices are shown in Fig. 2. Note that the NAO index exhibits much day-to-day variability, but also long-term trends over the course of months and years. Conversely, the tripole index shows a much slower evolution, with the longer-term trending characteristic of the ocean dominating the short time-scale changes.

a. Lag correlations of the NAO and SST tripole

Figure 3a shows the autocorrelation of the daily NAO index. This exhibits high lag-1 autocorrelation followed by a rapid decrease over the first week of lag. This rapid decrease is due to the large amount of short time-scale (daily and faster) variability of the atmosphere in this region (the passing of weather systems). At lags from one week to about one and a half months there is a shoulder in the autocorrelation, where the

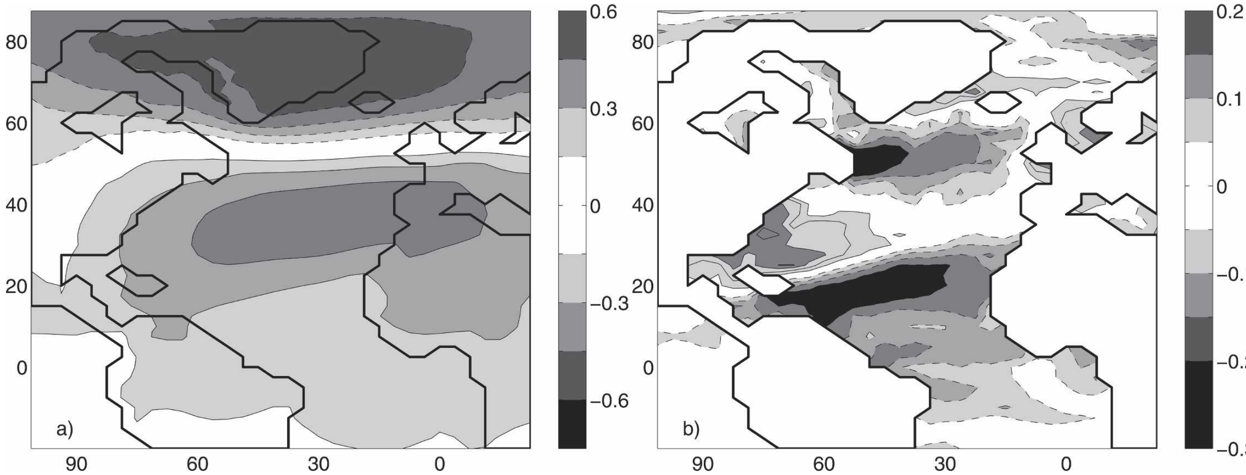

FIG. 1. Spatial patterns describing (a) the NAO and (b) the SST tripole. The patterns are defined as the contemporaneous correlation of the daily NAO index with the sea level pressure and sea surface temperature fields at each grid point. Negative contour lines are dashed.

autocorrelation decreases less rapidly with increasing lag. This autocorrelation, larger than that of a typical exponentially decreasing atmospheric autocorrelation, has been attributed to the effects of the stratosphere for the observed Arctic Oscillation (Charlton et al. 2003; Baldwin et al. 2003). It is possible that the GCM stratosphere may be partly responsible for this shoulder in the NAO index autocorrelation although, because of the relatively few stratospheric levels in the model, this may not be the only mechanism. At lags longer than 40 days, there is a fat tail in autocorrelation extending to a many-months lag. This is comparatively small but cannot be dismissed owing to the long time scale over which it extends. For comparison, the autocorrelation function of the tripole index is shown in Fig. 3b. There is a slow decrease in autocorrelation over the first 3 months, indicative of the long persistence of this oceanic variable, which can potentially provide long-term predictability of the NAO index. Figure 4 shows the cross-correlation between the NAO index and the tripole index. For positive lags, the NAO leads the SST, and for negative lags the SST leads the NAO. The peak in cross correlation occurs where the NAO leads the SST by about 2–3 weeks. This is in agreement with the findings of Deser and Timlin (1997) and Ciasto and Thompson (2004) in their observational studies.

The structure of the autocorrelations of the ocean–atmosphere systems simulated by the time series models can be validated. Each model is fitted to the NAO and tripole time series using *seemingly unrelated regression* to estimate the parameters and the variance of the stochastic forcing terms. A 1000-yr daily simulation of

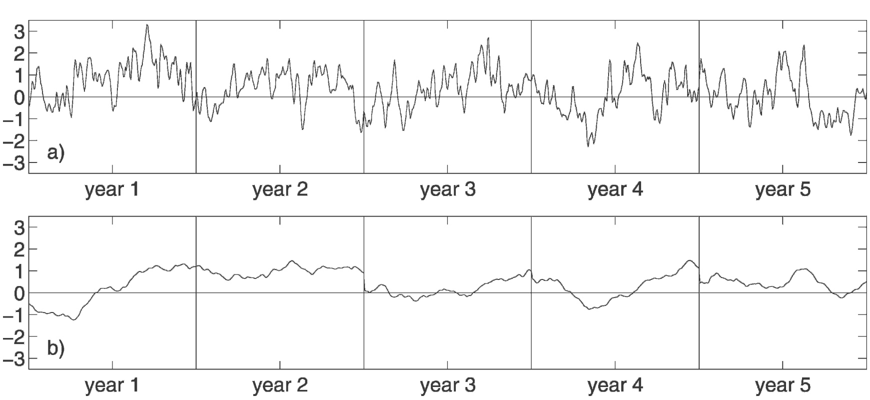

FIG. 2. Time series of the (a) NAO and (b) tripole indices for the first 5 years of the 50-yr HadCM3 simulation. Each index is standardized to have zero mean and unit variance over the full period.

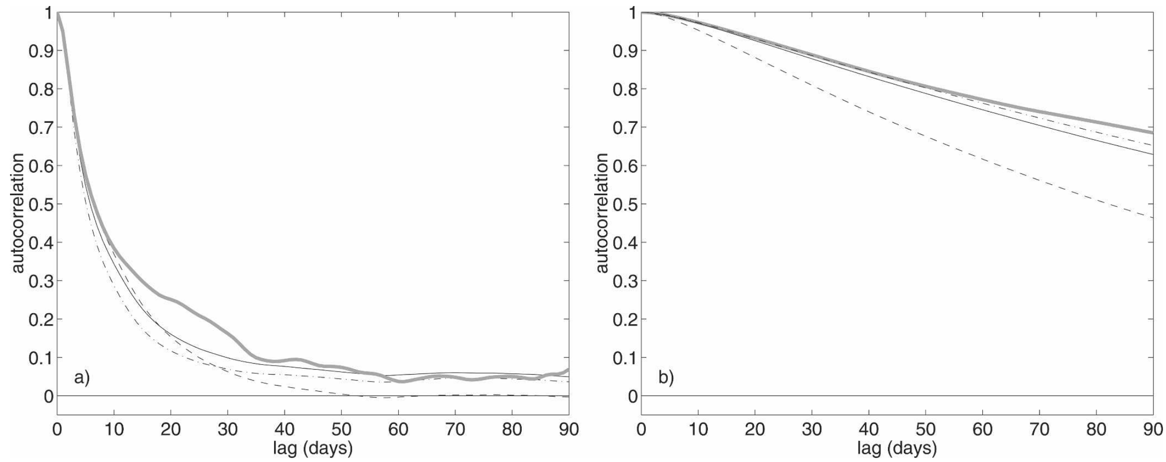

FIG. 3. The autocorrelation of the (a) NAO and (b) tripole indices. In each case the thick gray line gives the autocorrelation of the original GCM output, and the solid black line gives the autocorrelation of a 1000-yr simulation of the full time series model ($a \leftrightarrow o$). Also shown are autocorrelations of the restricted models: no ocean-to-atmosphere influence, $o \nrightarrow a$ (dashed); no atmosphere-to-ocean influence, $a \nrightarrow o$ (dot-dashed).

each model with a white noise forcing is then performed. Each of these simulations replicates winter conditions and so forms a continuous perpetual winter data series. The autocorrelations and cross-correlations of the NAO and tripole as simulated by the three models are shown in Fig. 3 and Fig. 4 as the black lines. These figures show that the full time series model (solid black line) replicates well the lagged characteristics of the two variables for most lags. The only deficiencies are in not being able to replicate the shoulder in the NAO, and in generally underestimating the correlations, particularly the cross-correlations. This underestimate is likely due to nonlinearities not captured by the model, which add to the correlation between the SST and the NAO. There is also the possibility of a third variable affecting both the NAO and the SST tripole not included in the bivariate time series model, such as a lower-stratospheric variable or a remote influence from another ocean basin.

The influence of the two directions of interaction can be assessed by comparing the $a \leftrightarrow o$ model with the two restricted models. The dashed lines of Figs. 3 and 4 show the characteristics of the simulation of the $o \nrightarrow a$ model. In particular, this model entirely fails to reproduce the long tail in NAO autocorrelation, implying that the SST tripole is required in the model to produce this long persistence. In the cross-correlation (Fig. 4), the positive correlation where the SST leads has been totally removed by removing the influence of the ocean on the atmosphere.

The dotted–dashed lines of Figs. 3 and 4 show the effect of removing the influence of the atmosphere on the ocean (the $a \nrightarrow o$ model). The autocorrelation structure of both variables is maintained, but with a reduction of NAO autocorrelation. This implies that atmospheric forcing of the ocean increases the persistence of NAO anomalies, but that this forcing is not necessary for long NAO persistence. Therefore the long memory

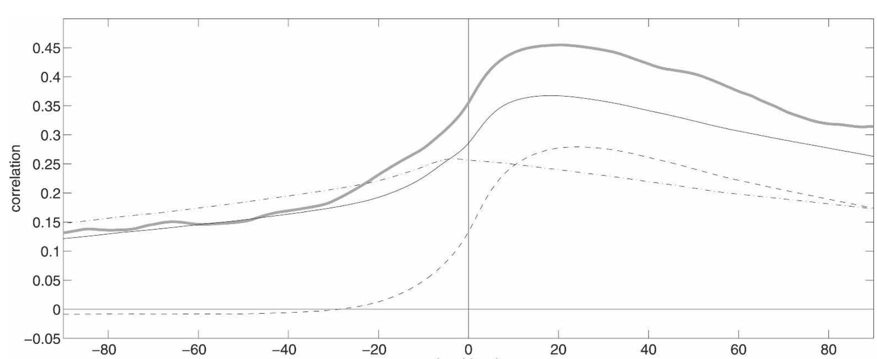

FIG. 4. As in Fig. 3 except with cross-correlations between the NAO and the tripole. Where lag is positive, the NAO leads the tripole, and vice versa.

in the NAO index arises due to the presence of long time-scale oceanic forcing, and to a lesser extent to an NAO→SST→NAO feedback mechanism. The cross-correlation structure of the reduced $a \nrightarrow o$ model shows a peak where SST leads, with the slow decay either side of this caused by the long memory in the ocean.

b. Granger causality and potential predictability

The Granger causality of the interaction between the NAO and the tripole can be assessed using the method described in section 2c. The Schwarz criterion applied to the full model gives an optimum model order of $p = 8$. In other words, the previous 8 days are of particular use in predicting the future evolution of the NAO and the tripole. Tests into the sensitivity of the results to this model order indicate that the choice of order is not critical beyond $p = 5$ (not shown).

The Granger causality statistics for the two directions of interaction are $L_{N\rightarrow S} = 238.1$ and $L_{S\rightarrow N} = 83.0$. Both of these log-likelihood ratio statistics give p values <0.001 and so are statistically significant at the 0.1% level. Hence, there is a (Granger) causal link from the tripole to the NAO and from the NAO to the tripole. Although the statistical significance is impressive, this is heavily influenced by the large number of daily model values. The statistic corresponds to a mean-squared-error improvement in the one-day-ahead forecast of the NAO of only 2% when the ocean is included in the predictive model. The prediction errors of one-day-ahead forecasts are dominated by daily prediction errors, so this Granger causality can be thought of as roughly the skill improvement of a daily NAO forecast when the ocean is included. It will be demonstrated that this ocean effect emerges more clearly in long-term means after averaging over the noisy short-term atmospheric variations.

As described in section 2d, potential predictability is measured as a function of the aggregated variance of the null model (no interaction) and of the full model. Figure 5 shows the aggregated variance for the three models: the $a \leftrightarrow o$ model (solid), the $o \nrightarrow a$ model (dashed), and the $a \nrightarrow o$ model (dotted–dashed). Also included in this figure is the line with a gradient of -1 in this logarithmic representation, indicating the reduction in aggregated variance with averaging period for a white noise process. Figure 5 shows that the full model has excess variance over the model with no oceanic influence on the atmosphere, with this excess increasing at longer averaging periods. Hence for longer averaging periods the influence of the ocean becomes a more important contributor to the total variance of the NAO index. Note that the logarithmic scale in this graph makes the differences between the three models appear smaller than they really are.

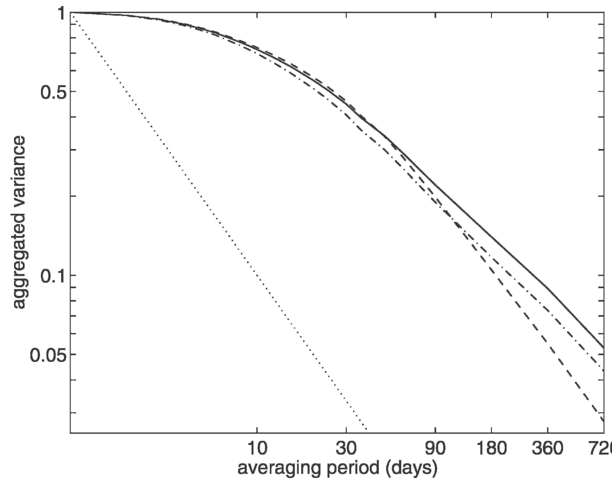

Fig. 5. Aggregated variance of simulations of the three time series models shown on a logarithmic scale: the $a \leftrightarrow o$ model (solid), the $o \nrightarrow a$ model (dashed), and the $a \nrightarrow o$ model (dotted–dashed). The series were standardized prior to calculation to ensure comparability at $K = 1$ (no averaging). The K^{-1} white noise line is also shown for comparison.

The variance of a set of time means can be expressed in terms of autocorrelations (Jones 1975) as

$$\mathrm{var}(\overline{Y}) \approx \frac{\sigma_Y^2}{K}\left[1 + \frac{2}{K}\sum_{j=1}^{K-1}(K-j)r_j(Y)\right] \qquad (9)$$

for averaging period K, where σ_X is the standard deviation of daily X and $r_j(X)$ is the lag-j autocorrelation of X. The aggregated variance is effectively a weighted sum of autocorrelations up to the length of the averaging period, decreasing as K^{-1} for increasing K. When K increases beyond the lag at which the autocorrelation of X goes to zero, the aggregated variance then decays like K^{-1}. This K^{-1} decay is seen in Fig. 5, where for K greater than one and a half months the dashed line ($o \nrightarrow a$) follows the same gradient as the dotted white noise line. This is typical of autoregressive systems, which will have close to zero autocorrelation once all the effects of the fast stochastic noise have been averaged out.

The difference between this model, with no tripole to NAO effect, and the other two models, which both contain this effect, was noted earlier in the autocorrelations. The aggregated variance shows the importance of the autocorrelation tail when longer averaging periods are considered. The gradient of the aggregated variance for the full model is around -0.71, which compares well with the slope of -0.79 obtained for winter mean observed NAO by Stephenson et al. (2000). Eventually,

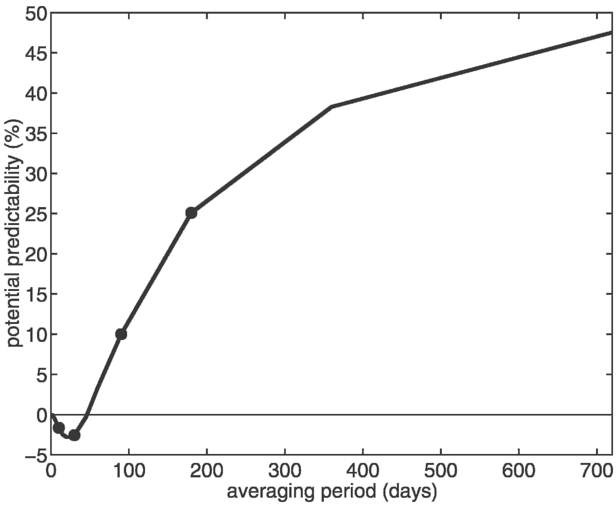

FIG. 6. Potential predictability of the NAO in terms of the percentage of total variance explained by the signal. The $a \leftrightarrow o$ model is compared to the restricted $o \nrightarrow a$ model to identify the effect of SST on NAO predictability. The four key ranges of 10, 30, 90, and 180 days are shown.

given a long enough averaging period, the noisy effects of the ocean on the atmosphere in the full time series model will also average to give the K^{-1} decrease of an autoregressive system (Beran 1992): the $a \leftrightarrow o$ model is still autoregressive but with a much longer time scale than the restricted $o \nrightarrow a$ model.

The potential predictability of the full model NAO index, obtained through comparison of the $a \leftrightarrow o$ and $o \nrightarrow a$ models, is presented in Fig. 6. This is the potential predictability representation of the aggregated variance results presented in Fig. 5. Note that in these two figures the averaging period has been extended to 720 days. This is slightly unnatural for the study of winter climate, where the longest contiguous average that can be made is of 180 days (the cold half of the year). Averages of these values over many winters can give an indication of interannual–decadal predictability, so the behavior of the potential predictability at these time scales is also presented. Four key time scales for NAO potential predictability are highlighted in Fig. 6. These are medium-range weather forecasting (K = 10 days) and monthly (K = 30 days), seasonal (K = 90 days), and annual (K = 180 days) prediction. Potential predictability of the NAO granted by the influence of SST on the NAO is initially close to zero when K is small and becomes greater than zero for seasonal forecasts (K = 90 days). Potential predictability rises to 26% for annual prediction, with close to half of the total variance being potentially predictable at the longer time scale (720 days). The estimate derived for annual predictability is close to that derived by Czaja and Frankignoul (2002) using maximum covariance analysis on observed datasets. This close agreement between studies using different datasets and techniques is encouraging.

Potential predictability at the annual time scale might be slightly further increased by the inclusion of winter-to-winter comparisons in the time series model rather than just the short daily comparisons. Rodwell and Folland (2002) discussed the existence of a small amount of SST reemergence in HadCM3, and it is likely that this reemergence is present in the dataset used here. The fact that our approach fits time series models to variations within winters rather than including all interannual variations means that this additional small amount of persistence is not explicitly modeled. However, the effect of reemergence on subseasonal time scales is taken into account by our approach.

4. The role of local SST

It is of interest to ask whether local SST is able to give more potential predictability than the tripole.

First, the Granger causality of interactions between local gridpoint SST and the (global) NAO index has been investigated. Best-model fits to the NAO and SST were obtained at each grid point for model orders between 6 (in the extratropics) and 12 (in the Tropics).

Figure 7 shows Granger causality log-likelihood statistics for each grid point. Grid points that failed to pass the 5% level of significance are masked out. Figure 7a shows Granger causality of the NAO on SST, and Fig. 7b shows Granger causality of SST on the NAO. Note that the size of the causality statistics for the tripole are surpassed at only a few of the grid points, suggesting that the tripole is generally a more Granger causal predictor of the NAO than is local SST, and thus that short time-scale ocean–atmosphere interaction is large scale.

The Granger causal effect of the NAO on the SST falls into three main regions. These are collocated with the centers of action of the SST tripole and confirm that the tripole is formed mainly as a response to NAO forcing. The sign of the model parameters in these three regions agrees with this forcing hypothesis. The strongest Granger causal link is in the northernmost lobe of the tripole. The daily NAO can be interpreted in terms of individual storms in the North Atlantic region (Serreze et al. 1997), and the region of strongest Granger causality is collocated with the maximum of the storm track (see Pope and Stratton 2002). Here the storms are at their greatest intensity and thus have a strong effect on the underlying SST.

This study tests whether SST has a Granger causal effect on the NAO in a formal statistical framework. Figure 7b shows that there is a Granger causal effect

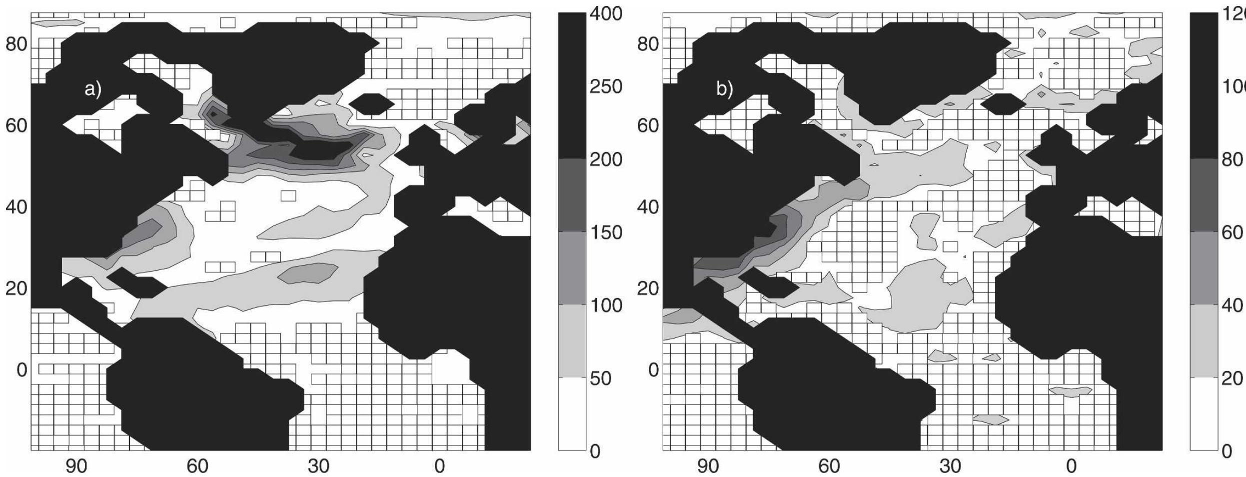

FIG. 7. Local Granger causality log-likelihood statistics for the causality between the NAO and local SST. (a) Causality from the NAO to local SST; (b) causality from local SST to the NAO. Contour levels are 50 and 20, respectively. Grid points failing to pass the 5% level of significance are masked.

and that the most sensitive region is along the eastern seaboard of the United States. This coincides with the positive lobe of the tripole and therefore suggests that this region of the tripole is not solely a response to NAO forcing but also exhibits a feedback, as suggested by Battisti et al. (1995). A possible interpretation of the NAO sensitivity to the SST in this region and on this time scale is through increased cyclone growth due to latent heat processes (Hoskins and Valdes 1990).

Finally, the spatial distribution of potential predictability has been calculated for each of the four key time averaging periods. Figures 8a–d show(a)medium-range, (b) monthly, (c) seasonal, and (d) annual potential predictability of the NAO based on SST to NAO forcing at each grid point. Over short time averages, the potential predictability is small (slightly negative due to model fitting misspecification). It is only once the seasonal prediction time scale is reached that a strong and consistent potential predictability pattern emerges (Fig. 8c). This strengthens for further increases in the averaging period. The dominant pattern of potential predictability resembles (in this squared statistic) the tripole of Fig. 1b, which signifies that the tripole index is the key SST factor for NAO predictability.

5. Conclusions

This study has used a Granger causality time series modeling approach to quantitatively diagnose the feedback of daily sea surface temperatures (SST) on daily values of the North Atlantic Oscillation (NAO) as simulated by a realistic coupled GCM. Bivariate vector autoregressive time series models have been carefully fitted to daily wintertime SST and NAO time series produced by a 50-yr simulation of the Hadley Centre third coupled ocean–atmosphere model: HadCM3. The Granger causality test is based on the goodness-of-fit likelihood ratio of the time series model having both atmosphere to ocean and ocean to atmosphere feedbacks to that of a null time series model having the ocean to atmosphere feedback set to zero. In contrast to BB98 and BB00, this study has used stochastic models to estimate the size of the ocean-to-atmosphere effect rather than to specify it based on simplified physical arguments. In addition, the modeling approach here has allowed us to estimate the order of the autoregressive process rather than assume that it is first order.

The best fit to the NAO and SST tripole index was obtained using an eighth-order vector autoregressive time series model—in other words, the previous 8 days of NAO and the SST tripole index were useful for predicting the current values. This demonstrated that a higher-than-first-order Markov model (e.g., BB98) is needed to accurately model daily variations in NAO and SST simulated by the coupled GCM. Note that the decorrelation time for NAO is not simply 8 days but depends on the values of the eight model parameters. Simulations with this model showed that it was able to convincingly reproduce all the main features in the lag-autocovariances between the NAO and the SST tripole. In particular, the effect of SSTs on NAO was shown to be responsible for the slower-than-exponential decay in lag-autocorrelations of NAO notably at lags longer than typical weather time scales of 1–2 weeks. In addition to an increase in the decorrelation time referred to as *reduced thermal damping* by BB98, the coupling also

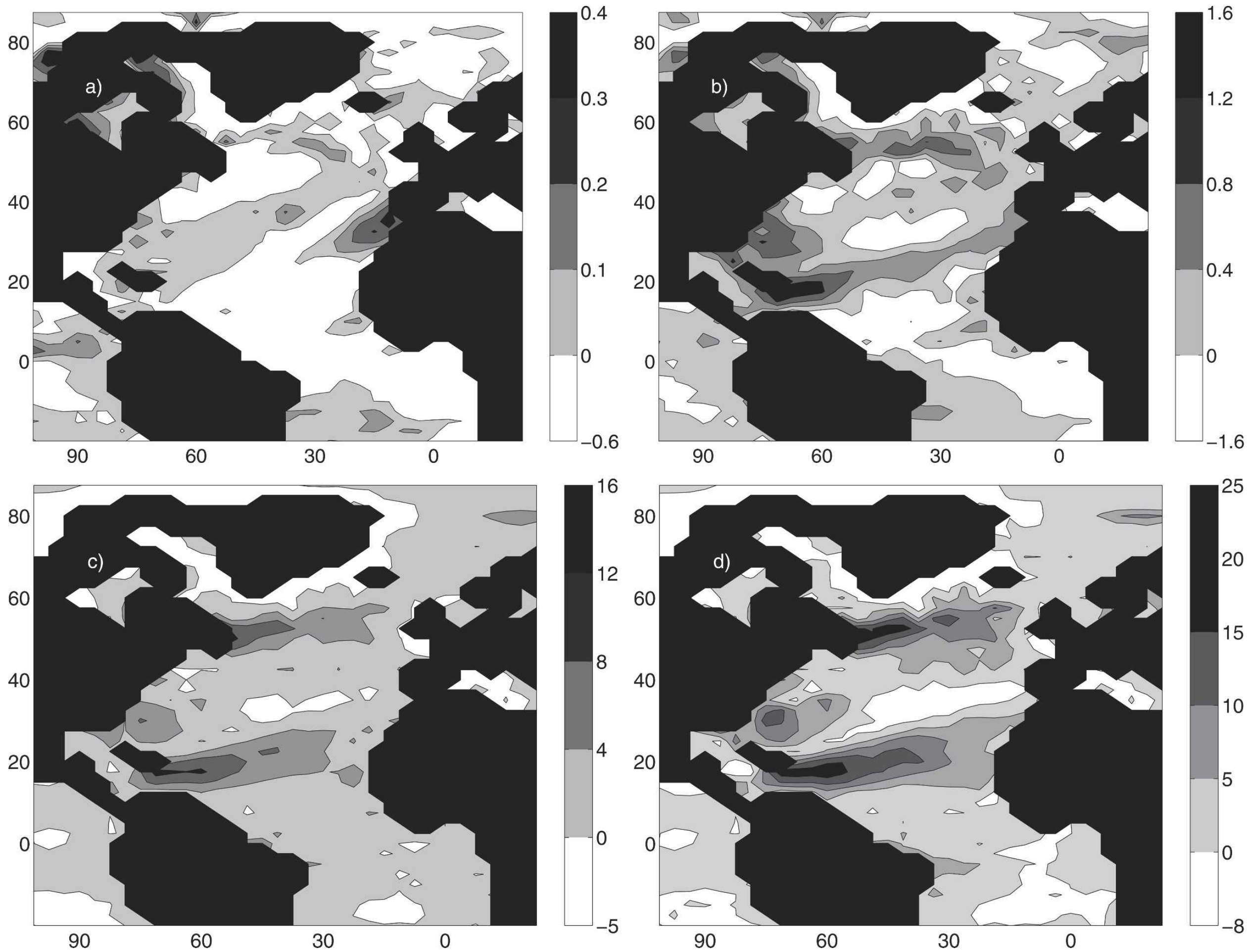

FIG. 8. Potential predictability (%) of the NAO for each local SST on four key time scales: (a) 10 days (medium range), (b) 30 days (monthly), (c) 90 days (seasonal), and (d) 180 days (annual).

changes the shape of the autocorrelation function so that it is no longer exponential. Granger causality testing of this time series model with one in which the ocean to atmosphere feedback was switched off demonstrated a small yet statistically significant feedback of SSTs on the NAO. The SST tripole index was found to provide additional predictive information for the NAO than that available by using only past values of NAO—the SST tripole is *Granger causal* for the NAO. Careful examination of local SSTs revealed that much of this effect on NAO is due to the short-term effect of SSTs in the vicinity of the Gulf Steam, especially south of Cape Hatteras. The local SSTs were not able to provide more predictive skill than that obtainable using the SST tripole index.

The SST effect on NAO leads to greater long-term trends in NAO than can be expected from aggregating just short-term atmospheric noise. The persistence induced in daily NAO by SSTs causes long-term means of NAO to have more variance than expected by averaging NAO noise if there were no feedback of the ocean on the atmosphere. For example, there is about 10%–30% more variance in seasonal wintertime means of NAO and almost 70% more variance in annual means of NAO due to SST effects than one would expect if NAO were a purely atmospheric process. The amount of potential predictability due to SSTs increases monotonically with the length of the averaging periods, and, rather paradoxically, the short-term SST effects on NAO become more apparent in longer-term trends of NAO. The predictability is *potential* since it provides only an upper bound on how much variance *might* be explained *if* one were to know the future values of SST. However, as pointed out by BB00, the future values of SST would not be predictable beyond 6 months if they are purely the response to stochastic midlatitude atmospheric forcing. Nevertheless, other factors such as low-latitude SSTs (e.g., those in the Gulf Stream south of

Cape Hatteras), reemergence of SSTs after one year, and anthropogenic climate change could all help provide some long-term predictability for SSTs and hence for NAO.

This study has investigated SST effects on NAO in simulations made with a coupled GCM. It would be of interest in future studies to repeat this assessment on daily data from other coupled models and also on daily observations and reanalyses. Data sampled more frequently than monthly is ideally required to be able to adequately resolve the key air–sea interaction processes related to the passage of North Atlantic weather systems. The importance of SSTs in the southern part of the Gulf Stream raises interesting questions as to the dynamical mechanisms for such effects. One possible mechanism is via increased humidity in this region invigorating North Atlantic storms, and this could be investigated by performing mechanistic numerical modeling studies. The approach presented here could also be valuable for diagnosing other feedbacks in the coupled earth system such as temperature feedbacks on carbon dioxide concentrations.

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