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North Atlantic climate model bias influence on multiyear predictability

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ABSTRACT

The influences of North Atlantic biases on multiyear predictability of unforced surface air temperature (SAT) variability are examined in the Kiel Climate Model (KCM). By employing a freshwater flux correction over the North Atlantic to the model, which strongly alleviates both North Atlantic sea surface salinity (SSS) and sea surface temperature (SST) biases, the freshwater flux-corrected integration depicts significantly enhanced multiyear SAT predictability in the North Atlantic sector in comparison to the uncorrected one. The enhanced SAT predictability in the corrected integration is due to a stronger and more variable Atlantic Meridional Overturning Circulation (AMOC) and its enhanced influence on North Atlantic SST. Results obtained from preindustrial control integrations of models participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5) support the findings obtained from the KCM: models with large North Atlantic biases tend to have a weak AMOC influence on SAT and exhibit a smaller SAT predictability over the North Atlantic sector.

1. Introduction

Multiyear predictability of surface air temperature (SAT) in the North Atlantic sector has been studied in many climate models. The models suggest that the multiyear predictability is largely related to multidecadal variability of sea surface temperature (SST) (DelSole et al., 2013; Jia and DelSole, 2012; Wu et al., 2015), which is sometimes referred to as the Atlantic Multidecadal Oscillation (AMO) (Kerr, 2000). Here we use the more general term Atlantic Multidecadal Variability (AMV). Results from the models participating in the Coupled Model Intercomparison Project phase 5 (CMIP5; Taylor et al., 2012) show that the role of internal variability cannot be ignored in multidecadal SST variations over the North Atlantic (Flato et al., 2013). The underlying mechanism of the AMV, however, is still under debate. Some recent studies have attributed the AMV to stochastic atmospheric forcing without the need to involve active ocean dynamics (Clement et al., 2015, 2016; Srivastava and DelSole, 2017), which has been disputed in other studies (O'Reilly et al., 2016; Zhang et al., 2016). In fact, in many climate models, the AMV, at least in part, is driven by the Atlantic Meridional Overturning Circulation (AMOC) through changes in northward heat transport (Ba et al., 2014). As the main northward heat-carrying component in the ocean, AMOC thus potentially is a large source of the multiyear SAT predictability over the North Atlantic (Collins et al., 2006). The level of multiyear North Atlantic sector SAT predictability, however, strongly varies among models, and the source of this diversity in multiyear predictability remains unclear.

A common problem in global climate models is large biases in the North Atlantic Ocean (Flato et al., 2013; Wang et al., 2014). These model biases, which are seen, for example, in both sea surface salinity (SSS) and SST, strongly impact the representation of decadal to multidecadal variability in the North Atlantic sector (Menary et al., 2015; Park et al., 2016). Menary et al. (2015) show that models exhibiting large fresh and cold biases tend to simulate salinity-controlled AMOC variability, while models with salty and warm biases temperature-controlled AMOC variability. By employing a freshwater flux correction over the North Atlantic, which strongly reduces North Atlantic SSS and SST biases in the Kiel Climate Model (KCM), Park et al. (2016) report a more realistic AMOC simulation in comparison to the limited instrumental observations and a more robust link between the AMOC and North Atlantic SST as well as Northern Hemisphere SAT. The purpose of this study is to investigate the impact of these improvements on multiyear North Atlantic sector SAT predictability in that freshwater flux-corrected model version of the KCM. We additionally compare our results with results derived from preindustrial control integrations of a set of CMIP5 models.

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2. Model and data

The version of the Kiel Climate Model used here consists of the ECHAM5 atmosphere general circulation model (Roeckner et al., 2003) with a spectral horizontal resolution of T42 (2.8° × 2.8°) and with 19 vertical levels. The atmosphere model is coupled through the OASIS coupler to the NEMO ocean–sea ice model (Madec, 2008) and integrated on the global tripolar grid at 2° horizontal resolution (ORCA2). Enhanced meridional resolution of 0.5° is employed in the equatorial region, and the ocean model is run with 31 vertical levels. We note that the standard KCM (Park et al., 2009), which was used in e.g. Ba et al. (2013) and Ba et al. (2014), employs a coarser horizontal resolution of T31 (3.75° × 3.75°) in its atmospheric component. A list of references of published studies conducted with the standard KCM can be obtained from http://www.geomar.de/en/research/fb1/fb1-me/research-topics/climate-modelling/kcms/.

We analyze data from two multi-millennial, about 4000 yr long, control integrations of the KCM, one with and the other without employing a freshwater flux correction over the North Atlantic (Park et al., 2016). These are labeled FWC and CTL, respectively. The CO_2 concentration is set to preindustrial levels in both integrations. Only the last 3000 years of each simulation is used here to account for model spin-up. Relative to the uncorrected control run (CTL), the freshwater flux-corrected simulation (FWC) not only exhibits much less SSS bias in the North Atlantic, as expected, but also strongly reduced North Atlantic cold SST bias which is a common problem in climate models. In general, FWC in comparison to CTL depicts a much better simulation of both the mean state and multidecadal variability in the North Atlantic sector. Further details are discussed in Park et al. (2016).

Data from preindustrial control integrations of 10 CMIP5 models (Taylor et al., 2012) are additionally analyzed: ACCESS1-3, CanESM2, CCSM4, CSIRO-Mk3-6-0, GFDL-ESM2M, MPI-ESM-LR, MPI-ESM-MR, MIROC5, MRI-CGCM3, and NorESM1-M. The data are interpolated onto a common 3°×3° grid. We select the last 300 years from each model and concatenate them to a 3000-yr multi-model time series for analysis. For individual models, the first half of the data is used for training and the second half for verification in Average Predictability Time (APT) analysis. The total sample size for training and verification is equally 1500 yr in both the CMIP5 ensemble and KCM integrations. Annual-mean data is used. To reduce the effects of climate drift, for each model a second-order polynomial is subtracted at each grid point (Boer, 2004). Long-term mean SSS and SST biases are calculated as differences between the simulated values and climatology from NODC World Ocean Atlas 1994 (http://www.esrl.noaa.gov/psd/data/gridded/data.nodc.woa94.html). Although an observed climatology includes some influence of external forcing which is absent in the model data, this difference is likely negligible, as the model biases in the North Atlantic are large compared with the external forcing influences. An AMOC index is defined as the maximum of the Atlantic meridional overturning streamfunction at 30°N. The AMV index used here is defined as the North Atlantic SST anomalies averaged over the region 0°N–70°N.

3. Methods

We identify the most predictable mode of the surface air temperature (SAT) over the Northern Hemisphere from a dataset by applying the Average Predictability Time (APT) method which has been proposed by DelSole and Tippett (2009). APT finds linear combination of variables which maximizes predictability integrated over all lead times. Let $\boldsymbol{x}_t$ be the vector specifying amplitude of the predictor at the time t. In APT analysis, a linear regression model is used for forecast

$$\hat{\boldsymbol{x}}_{t+\tau} = \boldsymbol{L}_\tau \boldsymbol{x}_t, \tag{1}$$

where $\hat{\boldsymbol{x}}_{t+\tau}$ is the predicted vector at time $t+\tau$, and $\boldsymbol{L}_\tau$ is the regression operator at lead time τ. The estimate of the regression operator is obtained by the least squares method with solution $\boldsymbol{L}_\tau = \boldsymbol{C}_\tau \boldsymbol{C}_0^{-1}$, where $\boldsymbol{C}_\tau$ is the time-lagged covariance matrix and $\boldsymbol{C}_0$ is the climatological matrix of the predictor $\boldsymbol{x}$, given that predictors and predictands are the same, which is the case in this study. We denote the weights of the linear combination of $\boldsymbol{x}$ as vector $\boldsymbol{q}$, and $\boldsymbol{q}^T\boldsymbol{x}$ refers to a new predictable mode. We seek the vector $\boldsymbol{q}$ that maximizes APT. The predictability of the predictable mode at a fixed lead time τ as estimated by the squared multiple correlation coefficient R_τ^2 is given by

$$\mathrm{R}_\tau^2 = \frac{\boldsymbol{q}^T \boldsymbol{L}_\tau \boldsymbol{C}_0 \boldsymbol{L}_t^T \boldsymbol{q}}{\boldsymbol{q}^T \boldsymbol{C}_0 \boldsymbol{q}}. \tag{2}$$

R_τ^2 refers to the fraction of the total variance of the predictable mode explained by the linear regression prediction. APT is defined as twice of the integration of R_τ^2 over all lead times:

$$\mathrm{APT} = 2\sum_{\tau=1}^{\infty} \frac{\boldsymbol{q}^T \boldsymbol{L}_\tau \boldsymbol{C}_0 \boldsymbol{L}_t^T \boldsymbol{q}}{\boldsymbol{q}^T \boldsymbol{C}_0 \boldsymbol{q}} = 2\sum_{\tau=1}^{\infty} \frac{\boldsymbol{q}^T \boldsymbol{C}_\tau \boldsymbol{C}_0^{-1} \boldsymbol{C}_\tau^T \boldsymbol{q}}{\boldsymbol{q}^T \boldsymbol{C}_0 \boldsymbol{q}}, \tag{3}$$

where $\boldsymbol{L}_\tau = \boldsymbol{C}_\tau \boldsymbol{C}_0^{-1}$. Hence, APT is independent of the lead time and characterizes an integral property of the climate system. Following DelSole and Tippett (2009), the problem of finding the weight vector to optimize APT in equation (3) leads to a generalized eigenvalue problem:

$$2\sum_{\tau=1}^{\infty} (\boldsymbol{C}_\tau \boldsymbol{C}_0^{-1} \boldsymbol{C}_\tau^T)\boldsymbol{q} = \lambda \boldsymbol{C}_0 \boldsymbol{q}. \tag{4}$$

The eigenvectors of (4) provide the weights to decompose the multivariate time series $\boldsymbol{x}$ into a set of orthography component, and the eigenvalues λ give the associated average predictable time (APT) for each eigenvector. By ordering the eigenvectors decreasingly according to predictability time, the first eigenvector provides the most predictable mode with maximum APT (APT1), and the second eigenvector corresponds to the second most predictable mode (APT2) uncorrelated with the first one, and so on. In simple words, APT method is similar to Empirical Orthogonal Function (EOF) analysis, except that the APT method decomposes predictability instead of variance.

The APT timescale is the integration of R_τ^2. In general, components that are persistent and oscillate in a narrow range of frequencies have large APT. APT has a close connection with Canonical Correlation Analysis (CCA). CCA is a procedure that determines the components in two datasets ($\boldsymbol{x}_t$ and $\boldsymbol{x}_{t+\tau}$ in the present case) that are maximally correlated. The main difference is CCA maximizes the multiple correlation at one lead time τ, while APT maximizes the sum of the squared multiple correlations at all lead times. APT also has some similarities to the Linear Inverse Model (LIM) method. LIM detects the predictable modes with optimal initial condition growth at a fixed lead time. Thus, an eigenvalue problem representing an optimal procedure is investigated in LIM too (Vimont et al., 2014; Capotondi and Sardeshmukh, 2015).

Since the number of grid points exceeds the sample size, as in LIM, the predictors and predictands are projected on the leading EOFs to reduce spatial dimension (DelSole and Tippett, 2009). In this study, we choose 40 principal components (PCs) of SAT over the Northern Hemisphere and the maximum lead time as 20 yr. Also, we test the sensitivity of the APT results by varying the number of the PCs and maximum lead time, but the major results are not sensitive to the choice of parameters. To avoid overestimated predictability, the data are split into two periods of equal length, one for training and the other for verification. The linear regression