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Predicting the Atlantic Meridional Overturning Circulation (AMOC) Variability Using Subsurface and Surface Fingerprints

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In this study, a linear statistical predictive model of observed fingerprints of Atlantic Meridional Overturning Circulation (AMOC) variability is developed, which predicts a weakening of AMOC strength in the coming years. Recent studies have suggested that the leading modes of North Atlantic subsurface temperature (Tsub) and sea surface height (SSH) anomalies are induced by AMOC variations and can be used as fingerprints of AMOC variability. Here, we show that in the GFDL coupled general circulation model assimilated with observed subsurface temperature data, including recent Argo network data (2003-2008), the leading mode of the North Atlantic Tsub anomalies is similar to that found with the objectively analyzed Tsub data and highly correlated with the leading mode of altimetry SSH anomalies for the period 1993-2008. A statistical auto-regressive (AR) model is fit to the timeseries of the leading mode of objectively analyzed detrended North Atlantic Tsub anomalies (1955-2003) and is applied to assimilated Tsub and altimetry SSH anomalies to make predictions. A similar statistical AR model, fit to the timeseries of the leading mode of modeled Tsub anomalies from the 1000-years GFDL CM2.1 control simulation, is applied to modeled Tsub, SSH, and AMOC anomalies to make predictions. The two AR models show comparable skills in predicting observed Tsub and modeled Tsub, SSH and AMOC variations.

1. Introduction

Recent studies have demonstrated tele-connections between the North Atlantic and regional climate variability at multidecadal timescales [e.g. Enfield et al., 2001; Knight et al., 2006; Zhang and Delworth, 2006]. Low frequency variability in the North Atlantic is often thought to be linked to Atlantic Meridional Overturning Circulation (AMOC) variability [Delworth and Mann, 2000; Knight et al., 2005; Zhang, 2008]. Griffies and Bryan [1997] have shown that AMOC variations provide decadal predictability of simulated North Atlantic variability. However, estimating the AMOC variability has been a major challenge. Instantaneous surveys across 25°N suggest a long-term slowdown of the AMOC [Bryden et al., 2005], but these snapshots could be aliased by large intra-annual variations [Cunningham et al., 2007]. To reconstruct the past variability of the AMOC when no direct observations are available, as well as to evaluate future AMOC impacts, it will be very useful to develop fingerprints for AMOC variations. The fingerprints need to be quantities that can be derived from both climate models and observations. The development of AMOC fingerprints would link the ocean circulation with variables that are observed extensively. The identification of such AMOC fingerprints will contribute to the interpretation of AMOC variations, and improve assessments of the impacts of AMOC variability on global climate change.

Previous studies have suggested that basin averaged North Atlantic sea surface temperature (SST) anomalies could be taken as a fingerprint of the multidecadal AMOC variability [Latif et al., 2004; Knight et al., 2005]. The anti-correlated relationship between the tropical North Atlantic SST and subsurface temperature anomalies has also been shown as a signature of the AMOC variability [Zhang, 2007]. The North Atlantic SST anomalies might be influenced by high frequency synoptic atmospheric variability and changes in the radiative forcing [Mann and Emanuel, 2006], thus their linkage to the AMOC variability is highly debated. A recent study [Zhang, 2008] found that the leading mode of altimeter SSH data is highly correlated with that of instrumental subsurface ocean temperature data in the North Atlantic, and both show opposite signs between the subpolar gyre and the Gulf Stream path. Such a dipole pattern is a distinctive fingerprint of AMOC variability, as shown by a millennial coupled ocean-atmosphere model (GFDL CM2.1) simulation. The fingerprint using modeled and observed SSH/subsurface temperature data suggests that, contrary to previous interpretations, the recent slowdown of the subpolar gyre is a part of a multidecadal variation and linked to a strengthening of the AMOC. With recent advancement in measurement of subsurface oceans by the ARGO network and satellite altimetry, it may be possible to monitor AMOC variability using this fingerprint.

In this paper, we extend the analysis of Zhang [2008] to include more recent measurements and highlight the link between these new measurements and the capability of estimating AMOC variability. In particular, to obtain a continuously updated AMOC variability and to establish a new framework for monitoring the AMOC variability in the future using the observed subsurface temperature fingerprint, we take advantage of the recent measurement of ocean subsurface ocean temperature by the ARGO network. We employ the recent ARGO subsurface temperature data through the GFDL coupled data assimilation (CDA) product [Zhang et al., 2007b]. Furthermore, we make predictions of the AMOC variability using a statistical auto-regressive (AR) model fit to the time-series of the fingerprints of the AMOC. Schneider and Griffies [1999] apply discriminant analysis to North Atlantic decadal variability of SSH and conclude that the *predictive power* of AR models, as applied here, is comparable to that of climate models. Applying the AR model to the assimilated subsurface temperature and altimetry SSH anomalies predicts a decline of the AMOC in the coming decade. A similar statistical AR model, fit to the timeseries of the leading mode of modeled subsurface temperature anomalies from a 1000-years control simulation of the fully coupled ocean-atmosphere model (GFDL CM2.1, Delworth et al. [2006]), is applied to modeled subsurface temperature, SSH, and AMOC anomalies to make predictions. The two AR models show comparable skills in predicting observed subsurface temperature and modeled subsurface temperature, SSH and AMOC variations.

2. Description of Data and Models

In this study, the observed North Atlantic ocean subsurface temperature data are derived from the publicly available yearly averaged dataset of objectively analyzed ocean temperature anomalies [Levitus et al., 2005] based on instrumental data for the period of 1955-2003. A quadratic monotonic function is fit to the time series of the basin averaged subsurface temperature anomaly in the North Atlantic to estimate the long term global warming trend over the past decades. The subsurface temperature anomaly is detrended by removing this quadratic regression fit at each grid point. This nonlinear detrended North Atlantic subsurface temperature anomaly is used to define a fingerprint of AMOC variability and to reconstruct the past AMOC variability using the method shown in Zhang [2008].

To obtain a continuously updated AMOC variability, we take advantage of the recent measurement of ocean subsurface ocean temperature by the Argo network. We employ the recent Argo subsurface temperature data through the GFDL coupled data assimilation (CDA) product [Zhang et al., 2007b] (briefly described in supplementary material). The inclusion of high quality ARGO network observations has considerably increased the skill of the assimilation [Chang et al., 2009]. Ongoing developments of assimilating the latest ARGO network data into the coupled model with increased data record length in the future have the potential for monitoring the current and future ocean climate.

The altimeter SSH data used in this study is obtained from AVISO (Archiving, Validation and Interpretation of Satellite Oceanographic data) [Le Traon et al., 1998] (briefly described in supplementary material). This altimetry SSH data is available from 1993-2008 and is used to define a fingerprint of the AMOC variability. To compare with the altimetry SSH data, we analyze the subsurface temperature data from the CDA product over the same period of 1993-2008.

3. AMOC Fingerprints

The spatial pattern of the leading empirical orthogonal function (EOF1) of detrended North Atlantic subsurface temperature anomalies at a depth of 400m (Tsub) displays a dipole pattern (Figure 1a), i.e. warming in the subpolar gyre and cooling near the Gulf Stream path; the principal component of the leading mode (PC1) of the Tsub is strongly correlated with that of the altimetry SSH for the period (1993-2003) (Figure 1d), as discussed in Zhang [2008]. Figure 1b shows the spatial pattern of the leading mode of CDA subsurface temperature at a depth of 400m for the period 1993-2008. The PC1 is highly correlated with that of the objectively analyzed Tsub for the period 1993-2003 (Figure 1d). However, the spatial pattern shows differences in and around the Gulf Stream region near the North American eastern coast. These differences can be attributed to the inherent model biases of the coupled climate model (GFDL CM2.1) and the short length of data-record for assimilation, which limits the convergence of the assimilation product.

The spatial pattern of the leading mode of altimetry SSH (Figure 1c) shows a similar dipole pattern, i.e. increasing SSH in the subpolar gyre and reduced SSH near the Gulf Stream path. A high correlation is also seen between PC1s of CDA Tsub and SSH (Figure 1d), establishing the robustness of the coherence between Tsub and SSH discussed in Zhang [2008], where it was proposed that these fingerprints of the AMOC could be used as proxies for estimating AMOC variability on decadal scales. An intensification of the AMOC is associated with a weakening of the subpolar gyre and a southward shift of the Gulf Stream and a strengthening of the northern recirculation gyre (NRG). The weaker subpolar gyre is associated with warmer subsurface temperature and increased SSH over subpolar North Atlantic, while colder subsurface temperature and lower SSH are seen in Gulf Stream region associated with the southward shift of the Gulf Stream.

4. Predicting the AMOC Variability Using Subsurface Temperature and SSH Fingerprints

We now take a step further by forecasting the variability of the AMOC in the near future using linear statistical models. The two identified indices of AMOC variability, namely, SSH and Tsub PC1s, respectively provide slightly different initial conditions for conducting forecasts. Recent extensive observations of altimetry SSH and ARGO network are too short to reconstruct the AMOC variability in the past several decades. Our approach here is to construct one AR model for AMOC variability using the much longer standardized PC1 of the objectively analyzed North Atlantic Tsub anomalies (1955-2003), and apply it to the standardized PC1s of the CDA Tsub and altimetry SSH anomalies to conduct forecasts of near future AMOC variations.

Our application of the same statistical model for different standardized data is pinned on the strong correlation between these data over the past 15 years, discussed in the previous section, and also supported by the strong model evidence about the correlation and physical link between the two variables [Zhang, 2008]. Hence, we assume that the AR model parameters estimated from the PC1 of objectively analyzed Tsub anomalies are the best estimate for the PC1s of the CDA Tsub and altimetry SSH anomalies in the North Atlantic. In order to focus on the low frequency decadal variability of AMOC, we perform a running mean smoothing with a bandwidth of five years on the three time-series before we fit the model and make predictions.

A computation and comparison of the Schwarz Bayesian criterion (SBC) [Schwarz, 1978] using the ARfit software [Schneider and Neumaier, 2001] reveals that an AR model of order two (AR2) would serve as the best fit for the smoothed PC1 of the objectively analyzed detrended North Atlantic Tsub anomalies among the class of AR models of higher orders. A lower order AR model also has the advantage of reduced risk of overfitting associated with higher order models. Our chosen AR2 model can be represented as:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \epsilon_t \tag{1}$$

where, X_t represents the value of the time-series at time t, ϵ represents white noise with a mean of zero, and ϕ_1 and ϕ_2 represent the auto-regressive parameters estimated from a least squares fit to the PC1 of the observed North Atlantic Tsub anomalies.

Validation of the AR2 model from hindcasts is shown in the supplementary material. A similar AR2 model, fit to the first 500 years of modeled Tsub PC1 from the 1000-years GFDL CM2.1 control simulation, is applied to the second 500 years of modeled Tsub PC1, SSH PC1, and AMOC Index of the control simulation to make predictions. The two AR models show comparable skills (Figure 2a) in predicting observed Tsub PC1 and modeled Tsub PC1, SSH PC1 and modeled AMOC Index. This comparison justifies the application of the AR2 model, constructed from Tsub PC1, to highly correlated quantities (SSH PC1 and AMOC Index) to make predictions. Figures 2b and 2c show examples of hindcasts of standardized Tsub PC1 of the GFDL CM2.1 control simulation using the AR2 model, and the comparison with modeled standardized AMOC anomalies. The modeled Tsub PC1 is in phase with modeled AMOC variations. AR2 model skills are found to be better than persistence and damped persistence (AR1) forecasts of GFDL CM2.1 AMOC index from the GFDL CM2.1 control simulation.

Figure 2d shows the AR2 model predictions of PC1 of the objectively analyzed Tsub anomalies for the next ten years. Also, shown are the 66% and 95% prediction confidence intervals based on the stochastic prediction error and the sampling error of the least squares fit to estimate model parameters assuming Gaussian white noise (Wilks [1995], supplementary material). A decline in the time-series is predicted, implying a decline in AMOC strength in the near future [Zhang, 2008]. Both forecasts of PC1 of the CDA

Tsub PC1 and altimetry SSH PC1 from 2008 onwards, using the same AR2 model (Figures 2e, f) predict a decline, implying a decline in AMOC strength in the coming years. It should be noted that all three forecasts have different initial conditions. A consistent prediction from all three independently derived timeseries indicates the robustness of the predictions. Predictions from the leading mode of variability from the SVD analysis of the cross-covariance matrix of CDA Tsub and altimetry SSH anomalies also reveal a decline in the AMOC in the coming years (not shown).

However, it should be noted that all class of sample AR model predictions asymptotically lead to the mean of the sample time-series with increasing lead times, while the variance of prediction approaches the variance of the sample time-series itself [Wilks, 1995]. Hence, the statistical AR model for the AMOC then performs no better than the climatological predictions. The large variance of the prediction as seen in the confidence intervals of the forecasts at increasing lead times indicate that the possibility of a stronger AMOC in the coming years cannot be completely ruled out. Dynamical constraints on the AMOC variability could reduce the prediction uncertainty associated with stochastic AR models, emphasizing the need for coupled climate models to predict the AMOC variability more precisely.

5. Summary and Discussion

The potential impacts of AMOC on global and regional climate, including hemispheric scale surface temperature variations [Zhang et al., 2007a], Atlantic hurricane activities, Sahel and Indian summer monsoons [Knight et al., 2006; Zhang and Delworth, 2006], North American and West European precipitation [Enfield et al., 2001; Sutton and Hodson, 2005], make it crucial to accurately monitor and predict the AMOC variability to improve global and regional climate predictions. Recent modeling and observational studies suggest the existence of the low frequency variability of the AMOC in the 20th century, and its fingerprints are tangible in observational data. The task of estimating the AMOC variability directly from observations suffers from poor sampling of direct observations of the circulation in the past. Hence, we rely on its fingerprints. Here, we extend the analysis initiated in [Zhang, 2008], to use the leading modes of the North Atlantic Tsub and SSH anomalies as fingerprints of the AMOC by analyzing more up to date data including the recent Argo sub-surface temperature data. Our analysis suggests that the current Argo network, along with satellite altimetry SSH data could be used to estimate AMOC variability.

A simple auto-regressive statistical model derived from these fingerprints predicts that the AMOC would decline in the near future. A weakening AMOC would tend to reduce oceanic heat transport and cool the North Atlantic, although radiative forcing changes could overwhelm that tendency. It should be noted, however, that our model is simply based on historical observations of only the past five decades, which is considerably short for estimating decadal scale variability, and our predictions should be considered with that caveat.

Global climate models predictions of the AMOC variability depend critically on the initial state of the AMOC in the model climate. However, model biases and lack of an accurate knowledge of the initial state of the global climate lead to large uncertainties in the prediction of AMOC variability in the real world and climate model predictions are expensive. While our predictions are clearly not near the ultimate goal of a prediction system for AMOC, they certainly serve as a first step in that direction. The robust fingerprints of the AMOC variability established by [Zhang, 2008] and in this study can be used to establish better initial conditions of the AMOC anomalies in coupled climate models. Constraining the AMOC variability in coupled climate models to that of the real world provides an opportunity to improve climate model predictions and projections.

Observations of SST alone have a weak AMOC signal to background noise ratio, as the surface is considerably influenced by the atmosphere and radiative forcings. Monitoring the AMOC variability using subsurface measurements, emphasizes the necessity for subsurface observing networks like ARGO in addition to satellite network. Analyses of the North Atlantic SSH and Tsub would provide independent indirect estimates of the low-frequency AMOC variability to compare with direct observations using the ongoing RAPID moorings measurements [Cunningham et al., 2007].

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References

Bryden, H. L., H. R. Longworth, and S. A. Cunningham, 2005: Slowing of the Atlantic meridional overturning circulation at 25°N. *Nature*, **438 (7068)**, 655–657.

Chang, Y.-S., A. J. Rosati, S. Zhang, and M. J. Harrison, 2009: Objective analysis of monthly temperature and salinity for the world ocean in the 21st century: Comparison with world ocean atlas and application to assimilation validation. *J. Geophys. Res.*, **114**, C02 014.

Cunningham, S. A., et al., 2007: Temporal variability of the Atlantic meridional overturning circulation at 26.5degreesn. *Science*, **317 (5840)**, 935–938.

Delworth, T. L., et al., 2006: GFDL's CM2 global coupled climate models. Part I: Formulation and simulation characteristics. *Journal of Climate*, **19 (5)**, 643–674.

Delworth, T. L. and M. E. Mann, 2000: Observed and simulated multidecadal variability in the northern hemisphere. *Climate Dynamics*, **16 (9)**, 661–676.

Enfield, D. B., A. M. Mestas-Nuez, and P. J. Trimble, 2001: The Atlantic multidecadal oscillation and its relation to rainfall and river flows in the continental U.S. *Geophys. Res. Lett.*, **28**, 2077–2080.

Griffies, S. M. and K. Bryan, 1997: A predictability study of simulated North Atlantic multidecadal variability. *Climate Dynamics*, **13 (7)**, 459–487.

Knight, J. R., R. J. Allan, C. K. Folland, M. Vellinga, and M. E. Mann, 2005: A signature of persistent natural thermohaline circulation cycles in observed climate. *Geophys. Res. Lett.*, **32**, L020 708.

Knight, J. R., C. K. Folland, and A. A. Scaife, 2006: Climate impacts of the Atlantic multidecadal oscillation. *Geophys. Res. Lett.*, **33**, L17 706.

Latif, M., et al., 2004: Reconstructing, monitoring, and predicting multidecadal-scale changes in the north Atlantic thermohaline circulation with sea surface temperature. *Journal of Climate*, **17 (7)**, 1605–1614.

Le Traon, P. Y., F. Nadal, and N. Ducet, 1998: An improved mapping method of multisatellite altimeter data. *Journal of Atmospheric and Oceanic Technology*, **15 (2)**, 522–534.

Levitus, S., J. Antonov, and T. Boyer, 2005: Warming of the world ocean, 19552003. *Geophys. Res. Lett.*, **32**, L02 604.

Mann, M. E. and K. A. Emanuel, 2006: Atlantic hurricane trends linked to climate change. *Eos Trans. AGU*, **87 (24)**, 233.

Schneider, T. and S. M. Griffies, 1999: A conceptual framework for predictability studies. *Journal of Climate*, **12 (10)**, 3133–3155.

Schneider, T. and A. Neumaier, 2001: Algorithm 808: ARfit—a Matlab package for the estimation of parameters and eigenmodes of multivariate autoregressive models. *ACM Transactions on Mathematical Software*, **27 (1)**, 58–65.

Schwarz, G., 1978: Estimating the dimension of a model. *Ann. Stat.*, **6**, 461–464.

Sutton, R. T. and D. L. R. Hodson, 2005: Atlantic ocean forcing of North American and European summer climate. *Science*, **309 (5731)**, 115–118.

Wilks, D. S., 1995: *Statistical methods in the atmospheric sciences*. Academic Press.

Zhang, R., 2007: Anticorrelated multidecadal variations between surface and subsurface tropical north Atlantic. *Geophys. Res. Lett.*, **34**, L12 713.

Zhang, R., 2008: Coherent surface-subsurface fingerprint of the Atlantic meridional overturning circulation. *Geophys. Res. Lett.*, **35**, L20 705.

Zhang, R. and T. L. Delworth, 2006: Impact of Atlantic multidecadal oscillations on India/Sahel rainfall and Atlantic hurricanes. *Geophys. Res. Lett.*, **33**, L23 708.

Zhang, R., T. L. Delworth, and I. M. Held, 2007a: Can the Atlantic ocean drive the observed multidecadal variability in northern hemisphere mean temperature? *Geophys. Res. Lett.*, **34**, L02 709.

Zhang, S., M. J. Harrison, A. Rosati, and A. Wittenberg, 2007b: System design and evaluation of coupled ensemble data assimilation for global oceanic climate studies. *Monthly Weather Review*, **135 (10)**, 3541–3564.

6. Figure Captions

Figure 1. EOF1 of (a) Objectively analyzed Tsub anomalies at 400m for 1955-2003, (b) CDA Tsub anomalies at 400m for 1993-2008, (c) altimetry SSH anomalies for 1993-2008, and the corresponding (d) standardized PC1s. The cross correlations between PC1s are listed in (d).

Figure 2. AR2 model predictions. (a) Skill of the AR2 model constructed from the objectively analyzed Tsub PC1 to predict the objectively analyzed Tsub PC1 (black), skill of the AR2 model constructed from Tsub PC1 of GFDL CM2.1 control simulation to predict Tsub PC1 (blue), AMOC index (red) and SSH PC1 (green) of the control simulation, and skill of persistence (dashed gray) and damped persistence (solid gray) forecast of the AMOC index. (b, c) Ten years hindcasts (solid red line with triangles) of standardized Tsub PC1 from GFDL CM2.1 control simulation (diamonds, solid green line) and the 66% and 95% confidence intervals (dashed and solid red lines) starting at simulation year 503 and 516 respectively. The black line represents the modeled standardized AMOC index in the control simulation. (d, e, f) Ten years predictions (solid red lines with triangles) of standardized PC1s of objectively analyzed Tsub, CDA Tsub and altimetry SSH, and the 66% and 95% confidence intervals (dashed and solid red lines).

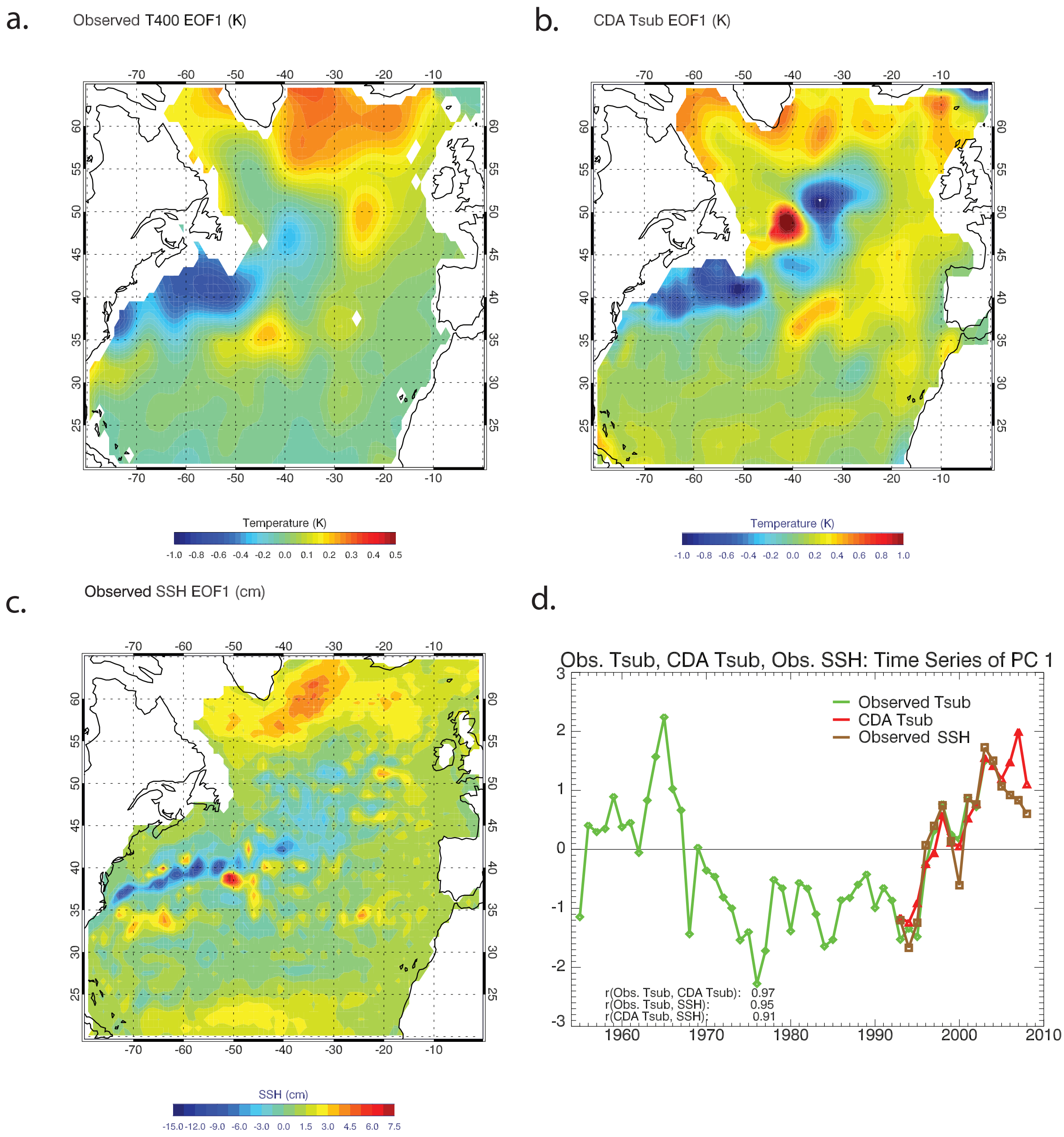
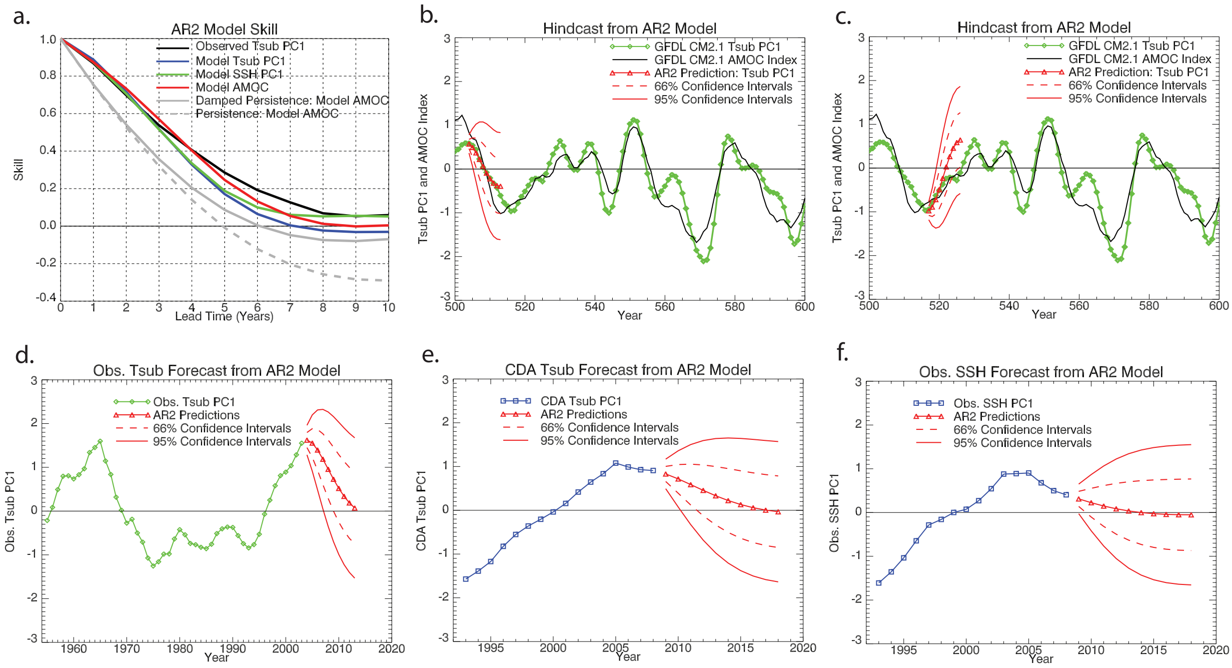

a.
Observed T400 EOF1 (K)
b.
CDA Tsub EOF1 (K)
Temperature (K)
Temperature (K)
c.
Observed SSH EOF1 (cm)
SSH (cm)
d.
Obs. Tsub, CDA Tsub, Obs. SSH: Time Series of PC 1
Observed Tsub
CDA Tsub
Observed SSH
r(Obs. Tsub, CDA Tsub): 0.97
r(Obs. Tsub, SSH): 0.95
r(CDA Tsub, SSH): 0.91

Figure 1.



a.
AR2 Model Skill
Observed Tsub PC1
Model Tsub PC1
Model SSH PC1
Model AMOC
Damped Persistence: Model AMOC
Persistence: Model AMOC
Skill
Lead Time (Years)
b.
Hindcast from AR2 Model
GFDL CM2.1 Tsub PC1
GFDL CM2.1 AMOC Index
AR2 Prediction: Tsub PC1
66% Confidence Intervals
95% Confidence Intervals
Tsub PC1 and AMOC Index
Year
c.
Hindcast from AR2 Model
d.
Obs. Tsub Forecast from AR2 Model
Obs. Tsub PC1
AR2 Predictions
Obs. Tsub PC1
e.
CDA Tsub Forecast from AR2 Model
CDA Tsub PC1
f.
Obs. SSH Forecast from AR2 Model
Obs. SSH PC1

Figure 2.