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Predicting Atlantic meridional overturning circulation (AMOC) variations using subsurface and surface fingerprints

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ABSTRACT

Recent studies have suggested that the leading modes of North Atlantic subsurface temperature (T_{sub}) and sea surface height (SSH) anomalies are induced by Atlantic meridional overturning circulation (AMOC) variations and can be used as fingerprints of AMOC variability. Based on these fingerprints of the AMOC in the GFDL CM2.1 coupled climate model, a linear statistical predictive model of observed fingerprints of AMOC variability is developed in this study. The statistical model predicts a weakening of AMOC strength in a few years after its peak around 2005. Here, we show that in the GFDL coupled climate model assimilated with observed subsurface temperature data, including recent Argo network data (2003–2008), the leading mode of the North Atlantic T_{sub} anomalies is similar to that found with the objectively analyzed T_{sub} 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 time-series of the leading mode of objectively analyzed detrended North Atlantic T_{sub} anomalies (1955–2003) and is applied to assimilated T_{sub} and altimetry SSH anomalies to make predictions. A similar statistical AR model, fit to the time-series of the leading mode of modeled T_{sub} anomalies from the 1000-year GFDL CM2.1 control simulation, is applied to predict modeled T_{sub}, SSH, and AMOC anomalies. The two AR models show comparable skills in predicting observed T_{sub} and modeled T_{sub}, SSH and AMOC variations.

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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 variations. However, estimating AMOC variations 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 seasonal variations (Cunningham et al., 2007). To reconstruct the past AMOC variations when no direct observations are available, as well as to evaluate future AMOC impacts, it would 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 identification of AMOC fingerprints would link the ocean circulation with well-observed variables and contribute to the interpretation of AMOC variations, allowing improved assessments of the impacts of AMOC variations 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 variations (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 anomalies in the subpolar gyre and the Gulf Stream path. A millennial control simulation using a coupled ocean–atmosphere model (GFDL CM2.1) suggests that such a dipole pattern is likely to be a distinctive fingerprint of AMOC

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variations. The fingerprint using modeled and observed SSH/subsurface temperature data suggests that the recent slowdown of the subpolar gyre is a part of a multidecadal variation and linked to a strengthening of the AMOC. Note that the relationship between the subpolar gyre and AMOC has not been universally established in all models, and one ocean-only modeling study suggests a contrary in-phase relationship between the two (Böning et al., 2006). Nonetheless, with recent advancement in measurement of subsurface oceans by the Argo network and satellite altimetry, it may be possible to monitor AMOC variations 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 variations. In particular, we take into account the observed ocean subsurface temperature from the Argo network to establish a new framework for monitoring and predicting AMOC variations using the observed subsurface temperature fingerprint. We apply the Argo data through the GFDL coupled data assimilation (CDA) product (Zhang et al., 2007b). Furthermore, we make predictions of AMOC variations using a statistical auto-regressive (AR) model fit to the time-series of the observed 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 strength in the coming decade. A similar statistical AR model, fit to the time-series of the leading mode of modeled subsurface temperature anomalies from a 1000-year 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 index anomalies to make predictions. The two AR models show comparable skills in predicting observed subsurface temperature and modeled subsurface temperature, SSH and AMOC index variations. As a caveat, the simulated AMOC varies considerably in different climate models in terms of mean intensity, time-scale and amplitude (Stouffer et al., 2006). Hence, the results from the GFDL CM2.1 model are likely to be model dependent. However, the AR2 model used to make future predictions in the real world is independently computed from the observed time-series of the AMOC fingerprints, and thus is not dependent on the GFDL CM2.1 model time series.

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. Following (Zhang, 2008), we use subsurface temperature anomalies at a depth of 400 m in our analysis. 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 secular 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 variations and to reconstruct the past AMOC variations using the method shown in Zhang (2008).

To obtain continuously updated AMOC variations, we take advantage of the recent measurement of ocean subsurface temperature by the Argo network. The Argo network is a global array of 3000 free-drifting profiling floats deployed since 2000, allowing continuous monitoring of the temperature, salinity, and velocity (estimated from the drift of the floats on resurfacing) of the upper 2000 m of the ocean. We employ the recent Argo subsurface temperature data through the GFDL coupled data assimilation (CDA) product (Zhang et al., 2007b). The GFDL coupled model assimilation system consists of an Ensemble Filter applied to the GFDL fully coupled climate model (CM2.1). The data assimilated into the coupled model includes the Argo network data along with moored ocean buoy data from 2001 onwards (Chang et al., 2009). Prior to 2001, the assimilation primarily incorporates data from the expendable bathymetry thermographs (XBTs) (Zhang et al., 2007b). The inclusion of high quality Argo network observations has considerably increased the skill of the assimilation (Chang et al., 2009). Ongoing assimilation of Argo data will lead to an increased record length, giving the potential to monitor the current and future ocean state.

The altimeter SSH data, also used to define a fingerprint of AMOC variations, are obtained from the DUACS (Data Unification and Altimetry Combination System) product (Le Traon et al., 1998), distributed by AVISO (Archiving, Validation and Interpretation of Satellite Oceanographic data). The dataset merges the TOPEX/Poseidon (T/P), Jason-1, ERS-1/2, and Envisat satellite measurements, and is available from 1993 onwards. To compare with the altimetry SSH data, we analyze the subsurface temperature data from the CDA product over the period of 1993–2008.

In addition, to establish the robustness of the use of the linear statistical model applied to observed fingerprints of AMOC, we also build a linear statistical model using the 1000-year control simulation of the GFDL CM2.1, which exhibits decadal AMOC variability (Delworth et al., 2006).

3. AMOC fingerprints

The spatial pattern of the leading empirical orthogonal function (EOF1) of detrended North Atlantic subsurface temperature anomalies at a depth of 400 m (T_{sub}) displays a dipole pattern (Fig. 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 T_{sub} is strongly correlated with that of the altimetry SSH for the period 1993–2003 (r=0.95, Fig. 1D), as discussed in Zhang (2008). Fig. 1B shows the spatial pattern of the leading mode of CDA subsurface temperature at a depth of 400 m for the period 1993–2008. The PC1 is highly correlated with that of the objectively analyzed T_{sub} for the period 1993–2003 (r=0.97, Fig. 1D), partly resulting from the similar trends present in the two time-series during the period. 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 (Fig. 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 T_{sub} and SSH (r = 0.91, Fig. 1D), establishing the robustness of the coherence between T_{sub} and SSH discussed in Zhang (2008), where it was proposed that these features are fingerprints of the AMOC that could be used to estimate decadal AMOC variations. In the GFDL CM2.1 control simulation, 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 increased subsurface temperature and increased SSH over the

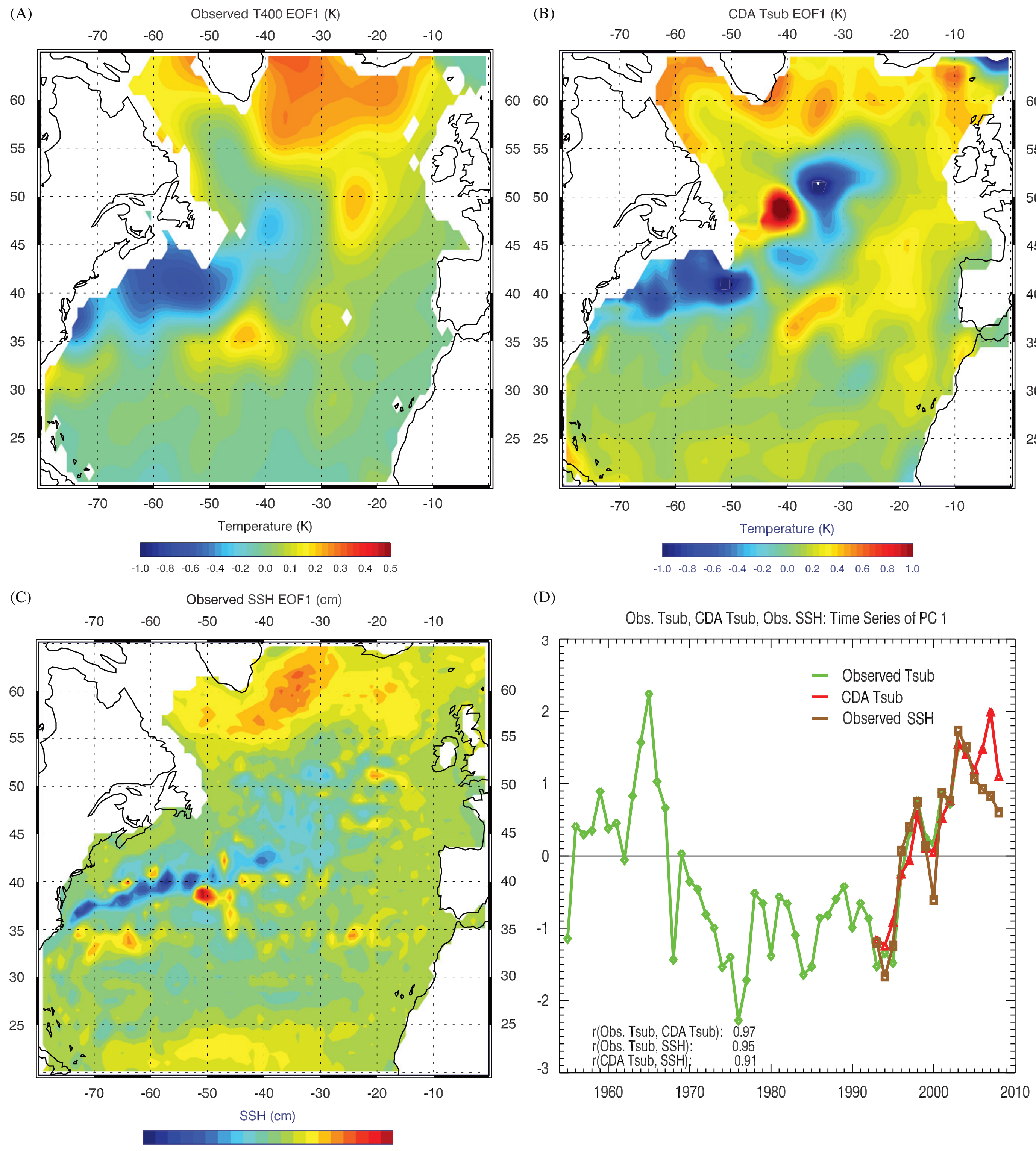

Fig. 1. EOF1 of (A) objectively analyzed T_{sub} anomalies at 400 m for 1955–2003, (B) CDA T_{sub} anomalies at 400 m for 1993–2008, (C) altimetry SSH anomalies for 1993–2008, and the corresponding (D) standardized PC1s. The cross-correlations between PC1s are listed in (D).

subpolar North Atlantic, while decreased subsurface temperature and lower SSH are seen in the Gulf Stream region associated with the southward shift of the Gulf Stream. It should be noted, however, that while the above-mentioned fingerprints of the AMOC are a feature of the GFDL CM2.1, they may not be universal. It remains to be established if such fingerprints of the AMOC exist in other climate models.

Zhang (2008) showed that these fingerprints have a robust relation to the AMOC in the GFDL CM2.1 model. The standard deviation of the AMOC index, defined as the maximum Atlantic meridional overturning stream function at 40°N, in the GFDL CM2.1 1000 years control simulation is 1.8 Sv (Zhang, 2008). We can roughly estimate the amplitude of the real world AMOC variations using the observed subsurface temperature fingerprint

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of AMOC variations, assuming that the standard deviation of PC1 of subsurface temperature anomalies is linearly proportional to that of AMOC variations and their ratio is the same in both observations and the coupled model. The standard deviations of PC1 of subsurface temperature anomalies at 400 m are 8.4 and 13.63 K, respectively, in observations (1955–2003) and in the GFDL CM2.1 1000 years control simulation, given normalized EOF1s. Hence, a first-order estimate of the standard deviation of the real world AMOC variations at 40°N is found to be 1.1 Sv. However, the observed period is too short to estimate the AMOC variability accurately. Sampling twenty 50-year nonoverlapping segments from the control run indicates that the ratio of standard deviation of PC1 of subsurface temperature anomalies to the standard deviation of AMOC index ranges from 10.3 to 5.2, suggesting that the standard deviation of the real world AMOC index might range from 0.8 to 1.6 Sv. Also, this estimate of the variability of the real world AMOC index is highly model-dependent and is based on the behavior of the GFDL CM2.1 model.

4. Predicting AMOC variations using subsurface temperature and SSH fingerprints

We now take a step further by forecasting AMOC variations in the near future using linear statistical models. The two identified indices of AMOC variations, namely, SSH and T_{sub} PC1s, respectively, provide slightly different initial conditions for conducting forecasts. Satellite altimetry and Argo data provide extensive observations for the recent past, but are too short to reconstruct AMOC variations in the past several decades. Our approach here is to construct a single AR model for AMOC variations using the much longer standardized PC1 of the objectively analyzed North Atlantic T_{sub} anomalies (1955–2003), and apply it to the standardized PC1s of the CDA T_{sub} and altimetry SSH anomalies to conduct forecasts of near future AMOC variations. The choice of using the AR model class over the generalized auto-regressive integrated moving average (ARIMA) class of time-series models is based on the slowly decaying auto-correlation function of the T_{sub} PC1 at increasing lead times, which is indicative of an AR process, and to avoid overfitting of the short time-series and nonuniqueness of model coefficients.

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 T_{sub} anomalies are also the best estimates for the PC1s of the CDA T_{sub} and altimetry SSH anomalies in the North Atlantic. In order to focus on the low-frequency decadal variability of AMOC, we perform a five-year running mean smoothing on the three time-series before we fit the model and make predictions. Such filtering reduces the high frequency inter-annual noise of the time-series and retains the low-frequency variability, thus reducing irregularity. Low-order AR model parameters estimates are found to be more robust for regularly behaved smoothed time-series and such time-series are hence found to be more predictable (Press et al., 1988). While computing the end-points of the running mean time-series, we assume that values beyond the time-series are mirror image of the time-series about the end-point, i.e. the beginning and end of the time-series are extrapolated to have zero slopes at the end points. Our results show little sensitivity to different smoothing methods and we limit our discussion here to the analysis of the running mean smoothed time-series.

A computation and comparison of the Schwarz Bayesian criterion (SBC) (Schwarz, 1978) using the ARfit software (Schneider and Neumaier, 2001) reveal 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 T_{sub} 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

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

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 T_{sub} anomalies. For the observed T_{sub} PC1 time-series, samples ϕ_1 and ϕ_2 are estimated to be 1.62, and -0.69, respectively. The variance of the two parameters is approximately given by $(1-\phi_2^2)/n$, where n is the sample size, for sufficiently large samples (Wilks, 1995), and decreases with increase in sample size. For a sample size of $n=49$, for the objectively analyzed PC1 of T_{sub} anomalies, the standard deviation of both, ϕ_1 and ϕ_2, is about 0.1.

4.1. AR model validation

Validation of the AR2 model from hindcasts, conducted as follows, shows considerable skill. The first 30 years (1955–1984) of smoothed PC1 time-series of observed objectively analyzed subsurface temperature anomalies (T_{sub}) are used to estimate the initial AR2 model parameters. The AR2 model is applied to compute the forecasts and their errors for the next 10 years (1984–1994). Another year (1985) from the original time-series is then added to the initial PC1 time-series and the AR2 model parameters are re-estimated. Forecasts and their errors are computed again for the next 10 years from the new AR2 model. The process is repeated until the end of the time-series. The AR2 model forecast absolute errors for 10 such forecasts conducted from 1984 to 1993 are shown in Fig. 2. Also, shown are the mean absolute errors and the standard deviation of these 10 forecasts, indicating the growth of the error at increasing lead times. AR2 model skill with respect to climatology forecast for lead time, j, is computed from the prediction errors of the independent part of

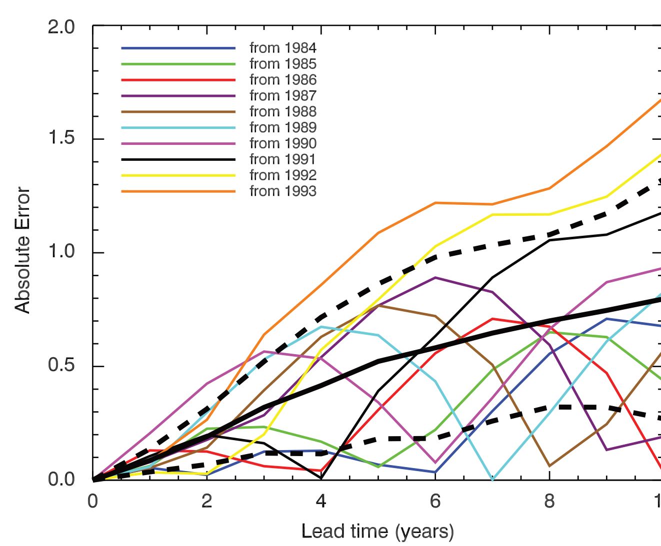

Fig. 2. Absolute errors of 10 AR2 model hindcasts as a function of lead time, of the PC1 time-series of objectively analyzed subsurface temperature anomalies, initialized each year from 1984 to 1993. The initial AR2 model parameters are computed from the 1955–1984 time-series. The thick solid black line shows the mean of the absolute errors for the 10 hindcasts and the thick dashed black line represents their standard deviation.

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the data from 1984 to 2003 as

$$1-\frac{MSE_j^{AR2}}{MSE_j^{clim}} \tag{2}$$

where MSE_j^{AR2} is the mean squared error of the AR2 model predictions for lead time, j, and MSE_j^{clim} is the mean squared error of predictions for lead time, j, if the predictions are taken to be the climatological mean of the time-series up to the beginning of the year of forecast. A model skill value of one indicates a perfect model, whereas a value of zero implies no skill. The AR2 model skill for PC1 of observed subsurface temperature anomalies with increasing lead times is shown in Fig. 3, and the skill falls below 0.7 after a lead time of three years.

A similar AR2 model ($\phi_1=1.82, \phi_2=-0.92$), fit to the first 500 years of the five-year running mean modeled T_{sub} PC1 from the 1000-year GFDL CM2.1 control simulation, is applied to the second 500 years of modeled T_{sub} PC1, SSH PC1, and AMOC index of the control simulation to make predictions. The two AR models show comparable skills (Fig. 3) in predicting observed T_{sub} PC1 and modeled T_{sub} PC1, SSH PC1 and modeled AMOC index. The comparable skills of the AR2 model in predicting different time-series justifies the application of the AR2 model, constructed from T_{sub} PC1, to highly correlated quantities (SSH PC1 and AMOC index) to make predictions. AR2 model skills are found to be better than persistence and damped persistence (AR1) forecasts of AMOC index from the GFDL CM2.1 control simulation.

The standard deviation of prediction errors computed from predictions of 1984–2003, when the initial AR2 model is trained on the period 1955–1984 also provides an estimate of the statistical significance of AR2 predictions. Fig. 4 shows 10-year hindcasts initialized at 1963, 1966, 1969, 1975, 1988 and 1992. Also, shown are the 66% and 95% confidence intervals of these predictions, which are computed as σ_j and $2\sigma_j$ of the actual prediction errors of the AR2 model from the period 1984 to 2003 for lead time, j. Fig. 5 shows 10-year hindcasts and their

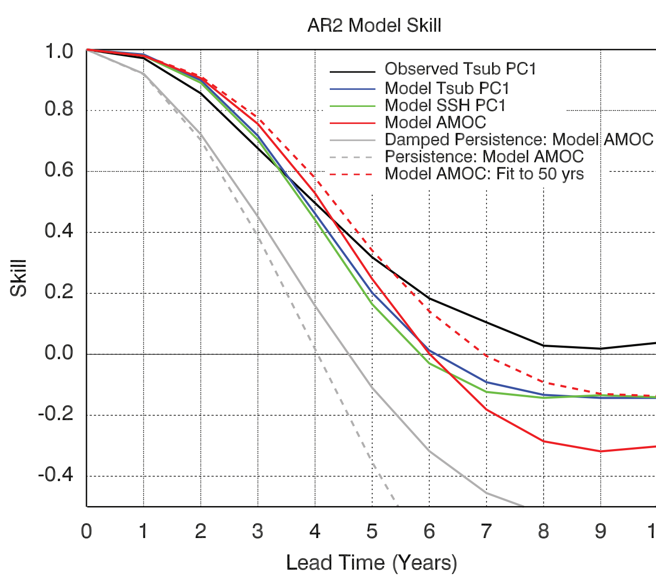

Fig. 3. Skill of the AR2 model constructed from the first 30 years of the objectively analyzed T_{sub} PC1 to predict the objectively analyzed T_{sub} PC1 (black) of the latter 19 years. Also, shown are the skill of the AR2 model constructed from the first 500 years of the T_{sub} PC1 of GFDL CM2.1 control simulation to predict T_{sub} PC1 (blue), AMOC index (red) and SSH PC1 (green) of the latter 500 years of the control simulation, and skill of persistence (dashed gray) and damped persistence (solid gray) forecast of the AMOC index computed from the latter 500 years of the control simulation. Skill of an AR2 model fit to only 50 years of AMOC index from the year 450 to 499 of the control simulation to predict modeled AMOC index of the latter 500 years is shown by the dashed red line.

confidence intervals of standardized T_{sub} PC1 time-series from the 1000 years control simulation of GFDL CM2.1 coupled climate model for selected years, and the comparison with modeled standardized AMOC anomalies. The modeled T_{sub} PC1 is in phase with modeled AMOC variations. The parameters of the AR2 model used to compute the hindcasts are estimated from the first 500 years of T_{sub} PC1 time-series of the control simulation, and the confidence intervals are estimated from the actual prediction errors of the AR2 model for the latter 500 years.

Fig. 6A shows the scatter plot of absolute errors of AR2 model hindcasts at five-year lead time against the initial observed T_{sub} PC1 values used for the hindcasts. AR2 model parameters computed from the whole PC1 time-series are applied to derive these hindcasts, adding some artificial skill to the hindcasts. It is apparent that the skill of forecasts is independent of the initial values. A similar scatter plot (Fig. 6B) from the GFDL CM2.1 model reveals little correlations between forecast errors and the initial values. Similar scatter plots for different lead times also reveal little correlations between forecast errors and the initial values.

4.2. AR model forecasts

Fig. 7A shows the AR2 model predictions of PC1 of the objectively analyzed T_{sub} anomalies for the next 10 years. Also, shown are the 66% and 95% prediction confidence intervals based on the actual prediction errors estimated from independent hindcasts. 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 T_{sub} PC1 and altimetry SSH PC1 from 2008 onwards, using the same AR2 model (Figs. 7B and C), predict a decline in the time-series and imply a decline in the AMOC in the coming years. It should be noted that although the same AR2 model is used for each of the predictions, all three forecasts have different initial conditions. A consistent prediction from all three independently derived time-series is indicative of the robustness of the predictions. Predictions from a separate AR model of the leading mode of variability from the SVD analysis of the cross-covariance matrix of CDA T_{sub} and altimetry SSH anomalies also imply a decline in the AMOC in the coming years (not shown). As a caveat, the predicted decline in the AMOC is based on the fingerprints of the AMOC established from the GFDL CM2.1 model with some evidence from observational data (Zhang, 2008), but these fingerprints are not well-established in all climate models yet.

It should be noted that at much longer lead times, all sample AR model predictions asymptotically lead to the mean of the sample time-series, 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 at much longer lead times. The large variance of the prediction as seen in the confidence intervals of the forecasts at increasing lead times indicates that the possibility of a stronger AMOC in the coming years cannot be completely ruled out.

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 AMOC variations to improve global and regional climate predictions. Recent modeling and observational studies suggest the existence of the

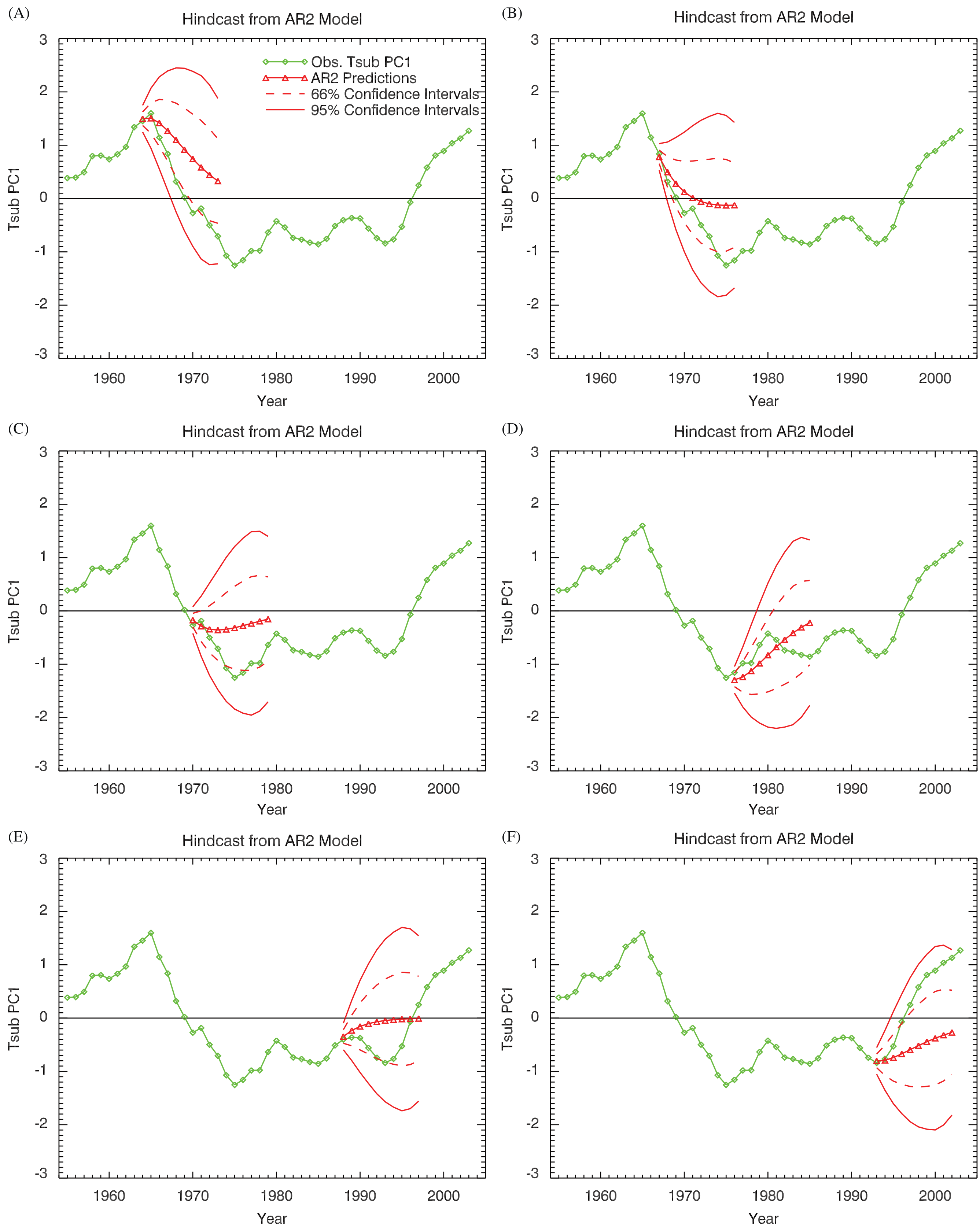

Fig. 4. AR2 model hindcasts of objectively analyzed T_{sub} PC1 (solid red line with triangles) and their 66% and 95% confidence intervals (dashed and solid red lines) initialized at (A) 1963, (B) 1966, (C) 1969, (D) 1975, (E) 1988 and (F) 1992. AR2 model parameters computed from the whole PC1 time-series are used to compute the hindcasts for (A)–(D). AR2 model parameters computed from the PC1 time-series for the period 1955–1984 are used to compute the hindcasts for (E) and (F).

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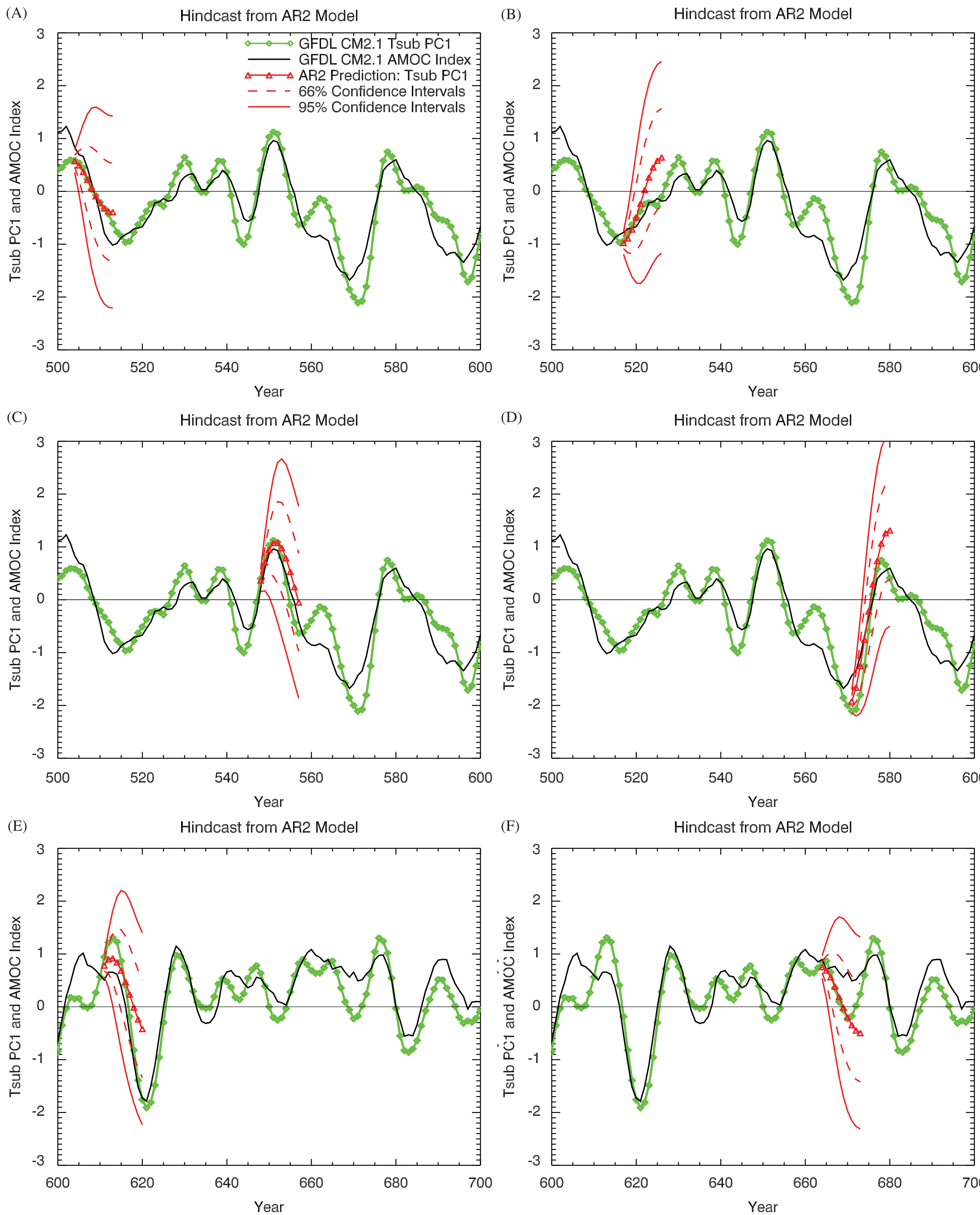

Fig. 5. AR2 model hindcasts of modeled T_{sub} PC1 (solid red line with triangles) and their 66% and 95% confidence intervals (dashed and solid red lines) initialized at years (A) 503, (B) 516, (C) 547, (D) 570, (E) 610 and (F) 663 of the 1000 years GFDL CM2.1 control simulation. AR2 model parameters estimated from the first 500 years of T_{sub} PC1 of the control simulation are used to compute the hindcasts. Also shown is the standardized AMOC index for the GFDL CM2.1 control simulation (black line).

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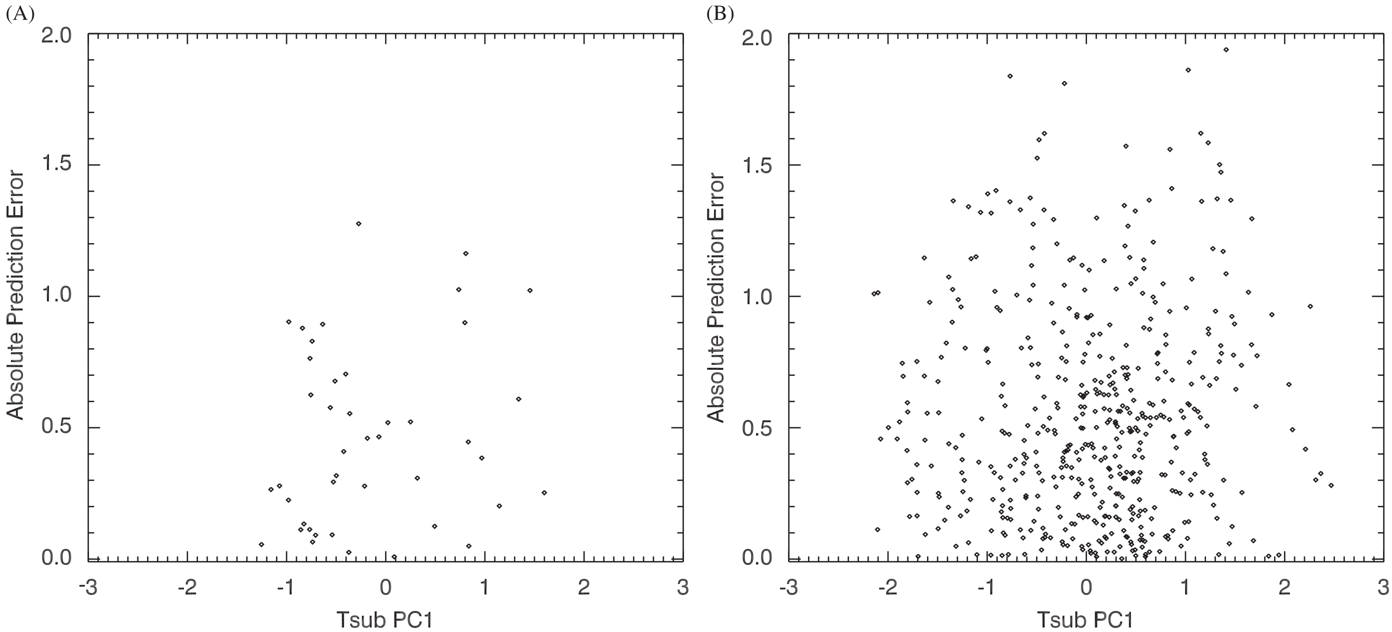

Fig. 6. (A) Scatter plot of the absolute prediction error of AR2 model at a lead time of five years against the amplitude of the objectively analyzed T_{sub} PC1 when the AR2 model is initialized. The AR2 model was constructed from the whole PC1 time-series from 1955 to 2003, and hindcasts were initialized each year from 1956 to 1998. (B) Scatter plot of the absolute prediction error of AR2 model at a lead time of five years against the amplitude of the T_{sub} PC1 of the GFDL CM2.1 control simulation. The AR2 model was constructed from the first 500 years of the PC1 time-series, and hindcasts were initialized each year for the next 495 years.

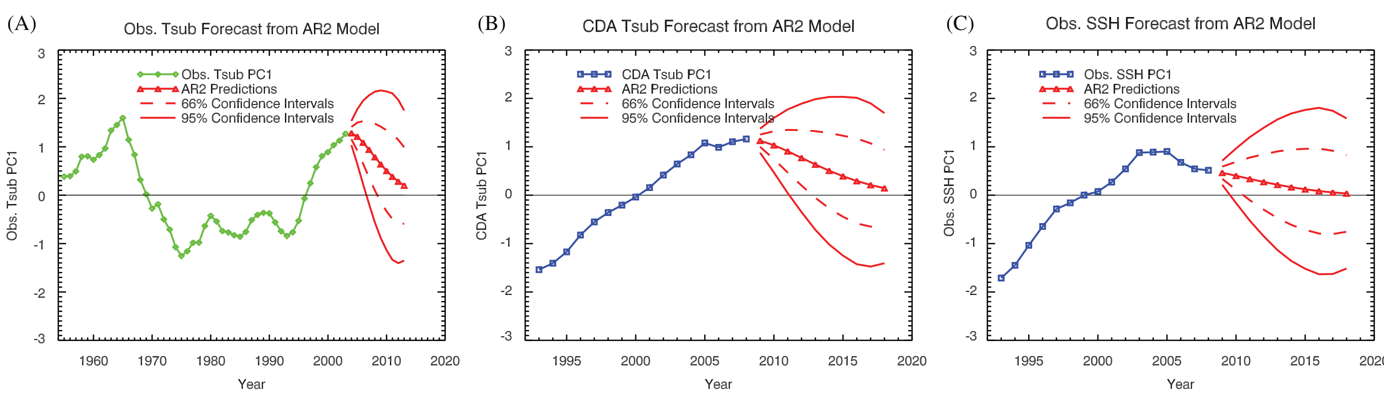

Fig. 7. Ten-year predictions (solid red lines with triangles) of smoothed standardized PC1s of (A) objectively analyzed T_{sub}, (B) CDA T_{sub} and (C) altimetry SSH, and the 66% and 95% confidence intervals (dashed and solid red lines).

low-frequency variability of the AMOC in the 20th century, and its potential fingerprints are tangible in observational data. The task of estimating the AMOC variations 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 T_{sub} and SSH anomalies as fingerprints of the AMOC, based on control simulation results of GFDL CM2.1 model, by analyzing more up to date data including the recent Argo subsurface temperature data. Our analysis suggests that the current Argo network, along with satellite altimetry SSH data could be used to estimate AMOC variations based on the analysis of Zhang (2008).

A simple auto-regressive statistical model derived from these fingerprints predicts that the AMOC strength will 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 the past five decades, which is considerably short for estimating decadal/multidecadal scale variations, and our predictions should be considered with that caveat. However, hindcasts from an AR2 model trained from only a short period (50 years) of the AMOC anomaly of GFDL CM2.1 control simulation show comparable skill to the model trained on 500 years of the T_{sub} PC1 from the GFDL CM2.1 control simulation (Fig. 2A), therefore demonstrating some robustness to our predictions. In the GFDL CM2.1 model, the AMOC demonstrates decadal to multidecadal variability with a peak in the spectrum at a period of about 20 years (not shown). Given the large differences in the multidecadal variations of the AMOC in various climate models, the results of the AR model trained with the GFDL CM2.1 control simulation are hence not universal and are sensitive to the choice of the climate model.

Global climate models' predictions of AMOC variations depend critically on the initial state of the AMOC in the model climate.

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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 variations 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 variations, they certainly serve as a first step in that direction using the available data. The fingerprints of AMOC variations proposed 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 might have a weak AMOC signal to background noise ratio, as the surface is considerably influenced by the atmosphere and radiative forcings. Monitoring the AMOC variations using subsurface measurements, emphasizes the necessity for subsurface observing networks like Argo in addition to satellite network. Analyses of the North Atlantic SSH and T_{sub} 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).

An important caveat of this study in using AMOC fingerprints to make predictions is that the relationship between the fingerprints and the AMOC variations is based on a single climate model, the GFDL CM2.1, where the SSH and the subsurface temperature patterns over the North Atlantic are found to be robust fingerprints of the AMOC, and consistent with observed SSH and subsurface temperature anomalies (Zhang, 2008). It remains to be seen if and how these fingerprints are related to the AMOC in other climate models, particularly given the widespread differences in the simulated AMOC from different climate models (Stouffer et al., 2006).

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References

Böning, C.W., Scheinert, M., Dengg, J., Biastoch, A., Funk, A., 2006. Decadal variability of subpolar gyre transport and its reverberation in the North Atlantic overturning. Geophys. Res. Lett. 33 (21) L21S01.

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

Chang, Y.-S., Rosati, A.J., Zhang, S., Harrison, M.J., 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 (February), C02014.

Cunningham, S.A., Kanzow, T., Rayner, D., Baringer, M.O., Johns, W.E., Marotzke, J., Longworth, H.R., Grant, E.M., Hirschi, J.J.-M., Beal, L.M., Meinen, C.S., Bryden, H.L., 2007. Temporal variability of the Atlantic meridional overturning circulation at 26.5°N. Science 317 (5840), 935–938.

Delworth, T.L., Broccoli, A.J., Rosati, A., Stouffer, R.J., Balaji, V., Beesley, J.A., Cooke, W.F., Dixon, K.W., Dunne, J., Dunne, K.A., Durachta, J.W., Findell, K.L., Ginoux, P., Gnanadesikan, A., Gordon, C.T., Griffies, S.M., Gudgel, R., Harrison, M.J., Held, I.M., Hemler, R.S., Horowitz, L.W., Klein, S.A., Knutson, T.R., Kushner, P.J., Langenhorst, A.R., Lee, H.-C., Lin, S.-J., Lu, J., Malyshev, S.L., Milly, P.C.D., Ramaswamy, V., Russell, J., Schwarzkopf, M.D., Shevliakova, E., Sirutis, J.J., Spelman, M.J., Stern, W.F., Winton, M., Wittenberg, A.T., Wyman, B., Zeng, F., Zhang, R., 2006. GFDL's CM2 global coupled climate models. Part I: formulation and simulation characteristics. J. Climate 19 (5), 643–674.

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

Enfield, D.B., Mestas-Nuez, A.M., Trimble, P.J., 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., Bryan, K., 1997. A predictability study of simulated North Atlantic multidecadal variability. Climate Dyn. 13 (7), 459–487.

Knight, J.R., Allan, R.J., Folland, C.K., Vellinga, M., Mann, M.E., 2005. A signature of persistent natural thermohaline circulation cycles in observed climate. Geophys. Res. Lett. 32 (October), L020708.

Knight, J.R., Folland, C.K., Scaife, A.A., 2006. Climate impacts of the Atlantic multidecadal oscillation. Geophys. Res. Lett. 33 (September), L17706.

Latif, M., Roeckner, E., Botzet, M., Esch, M., Haak, H., Hagemann, S., Jungclaus, J., Legutke, S., Marsland, S., Mikolajewicz, U., Mitchell, J., 2004. Reconstructing, monitoring, and predicting multidecadal-scale changes in the North Atlantic thermohaline circulation with sea surface temperature. J. Climate 17 (7), 1605–1614.

Le Traon, P.Y., Nadal, F., Ducet, N., 1998. An improved mapping method of multisatellite altimeter data. J. Atmos. Oceanic Technol. 15 (2), 522–534.

Levitus, S., Antonov, J., Boyer, T., 2005. Warming of the world ocean, 1955–2003. Geophys. Res. Lett. 32 (January), L02604.

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

Press, W.H., Flannery, B.P., Teukolsky, S.A., Vetterling, W.T., 1988. Numerical Recipes in C. Cambridge University Press, New York.

Schneider, T., Griffies, S.M., 1999. A conceptual framework for predictability studies. J. Climate 12 (10), 3133–3155.

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

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

Stouffer, R.J., Yin, J., Gregory, J.M., Dixon, K.W., Spelman, M.J., Hurlin, W., Weaver, A.J., Eby, M., Flato, G.M., Hasumi, H., Hu, A., Jungclaus, J.H., Kamenkovich, I.V., Levermann, A., Montoya, M., Murakami, S., Nawrath, S., Oka, A., Peltier, W.R., Robitaille, D.Y., Sokolov, A., Vettoretti, G., Weber, S.L., 2006. Investigating the causes of the response of the thermohaline circulation to past and future climate changes. J. Climate 19 (8), 1365–1387.

Sutton, R.T., Hodson, D.L.R., 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 (June), L12713.

Zhang, R., 2008. Coherent surface–subsurface fingerprint of the Atlantic meridional overturning circulation. Geophys. Res. Lett. 35 (October), L20705.

Zhang, R., Delworth, T.L., 2006. Impact of Atlantic multidecadal oscillations on India/Sahel rainfall and Atlantic hurricanes. Geophys. Res. Lett. 33 (September), L23708.

Zhang, R., Delworth, T.L., Held, I.M., 2007a. Can the Atlantic Ocean drive the observed multidecadal variability in northern hemisphere mean temperature? Geophys. Res. Lett. 34 (January), L02709.

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