1. Introduction

Near-term climate prediction has been studied extensively using the models participated in the decadal prediction experiments of the Coupled Model Intercomparison Project Phase 5 (CMIP5) [1]. The North Atlantic is one of the regions that have shown improved skill due to initialization in most models [2–6]. The Atlantic multi-decadal oscillation (AMO) was a benchmark to assess the capability of decadal forecast systems, which impacts temperature and precipitation over the land [7]. The prediction skills in AMO and climate over the land associated with the AMO are, however, model dependent [8]. Still, some models, such as the Beijing Climate Center climate system model version 1.1 (BCC-CSM1.1), had poor prediction skill in the AMO although they are skillful in the tropical Pacific and tropical Atlantic oceans [9,10].

Decadal climate predictability depends on both initial conditions and external forcings arising from changes in atmospheric composition [11,12]. Since the external forcing is the same for all CMIP5 models [13], different prediction skills of these models may mainly originate from their initial conditions. Currently, modeling groups use different techniques and methodology to initialize decadal climate prediction, as summarized in Meehl et al. [6]. It is hard to identify which technique is better through comparing these model outputs. Carrying out re-forecasts using one model and different techniques of initialization is a good approach, although it is a huge task for any modeling group.

In the ongoing CMIP6, one of the grand science challenges is to improve near-term climate predictions. It is urgent to study how to improve the prediction skill of BCC-CSM climate model. This paper aims to investigate the influence of assimilated data used in the initialization upon the prediction skill of BCC-CSM1.1. First, we...

Improved decadal climate prediction in the North Atlantic using EnOI-assimilated initial condition

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generate a new dataset through assimilating the sea surface temperature (SST) of the Hadley Centre Sea Ice and Sea Surface Temperature (HadISST) dataset [14] via the Ensemble Optimum Interpolation (EnOI). Then a suite of re-forecasts was carried out with the new assimilated data used in the initialization. Results of the re-forecasts will be compared with the previous CMIP5 forecast focusing on the North Atlantic.

2. Model, experiments and methodology

2.1. Model

Climate model BCC-CSM1.1 was developed by Beijing Climate Center (BCC) of China Meteorological Administration (CMA). The horizontal resolution of the atmospheric model BCC_AGCM2.1 is about 2.8° (T42), and there are 26 layers in the vertical [15,16]. The ocean component is based on the Modular Ocean Model version 4.0 (MOM4) [17], which has 40 levels in the vertical and is hence abbreviated as MOM4_L40 [18]. The horizontal resolution of the ocean model is 1° longitude by 1/3° latitude with tripolar grid. Detailed description about BCC-CSM1.1 was provided by Wu et al. [19].

2.2. Experiments

The initialization of CMIP5 decadal prediction experiments with BCC-CSM1.1 [20] employed a full-field nudging method to relax modeled ocean temperature to Simple Ocean Data Assimilation (SODA) data [21]. The time period for the restoration is one day. This study uses the EnOI method to assimilate the observation data to MOM4_L40, and generates a new dataset for the initialization of decadal prediction experiments. EnOI is a simplified form of the Ensemble Kalman Filter (EnKF) [22,23], which has an advantage in computational cost. In the assimilation, background error covariance controls the magnitude and structure of adjustment to the observations. The background error covariance used in EnOI is estimated from a prescribed static ensemble instead of dynamic ensembles used in EnKF. This ensemble is kept unchanged through the assimilation cycle and is referred as “static ensemble”. It is usually generated by using a large historical ensemble composed of model states sampled over a long-time integration.

A control run (CNTR) from 1949 to 2008 is firstly carried out with MOM4_L40 model driven by the daily NCEP/NCAR reanalysis [24]. The instantaneous fields of CNTR on the 15th day of each month from 1990 to 1999 are selected to generate the static ensembles, because previous study indicated that 100 or so static samples are more appropriate than other sample numbers [25]. Then the HadISST data were assimilated to MOM4_L40 model using the EnOI method from January 1949 to December 2008. The time window for assimilation is one month. Outputs generated by the EnOI assimilation are named ASSIM.

The sea surface temperature (SST) bias of ASSIM is compared to that of CNTR to examine the performance of the EnOI assimilation (Fig. 1). The observation data used to estimate the bias is from the Extended Reconstructed Sea Surface Temperature (ERSST) Version 3b (ERSST V3b) dataset [26]. As can be seen in Fig. 1, the SST bias of ASSIM is lowered globally than that of CNTR, especially in the tropical Indian Ocean, the western Pacific Ocean and northward of 40°N in the North Pacific Ocean, with the bias less than 0.5°C. In the North Atlantic, the SST bias of CNTR is about 2.0°C, while the bias of ASSIM is reduced by about 0.5–1.0°C. So the EnOI assimilation is able to reduce the SST bias simulated by the ocean model.

The ASSIM data are used in the initialization of the re-forecasts of BCC-CSM1.1, while other conditions remain the same as in the CMIP5 forecasts. As the CMIP5 forecasts, the re-forecasts started each year over the time periods of 1961–2005 and predicted the next 10 years. This new suite of decadal forecasts is named as EnOI_HadInit. The CMIP5 decadal prediction using the SODA data in the initialization is referred to as SODAInit, while the historical simulation without initialization is referred to as NoInit. The external forcing of the two suits of forecasts are the same as the NoInit with the greenhouse gases, ozone, aerosols, volcanoes and solar variability evolving with time. The two suites of forecasts and NoInit all have three ensemble realizations with difference in initial states. The ensemble mean of the three realizations for each experiment were used in the analysis.

The ASSIM data have less bias than the modeled SST, and are more coordinated with the ocean component of BCC-CSM1.1 than
the SODA reanalysis. Application of ASSIM data in the initialization tends to reduce the model drift generated by the full-field relaxation in the decadal prediction experiments. EnOI_HadInit will be compared with SODAInit to investigate whether the assimilation can improve the prediction skill in the North Atlantic.

2.3. Methodology

To avoid the influence of model drift in the analysis, a usual method in evaluating decadal forecast is to compare the anomalies after removing the climatology. Here, a standard approach is used to compute anomalies for the two suites of decadal predictions based on the World Climate Research Program (WCRP) recommendations, as used in previous studies [2,3,8]. The climatological mean for each forecast year \((n = 1, 2, 3, \ldots, 10)\) of all prediction experiments \((1960 + n, 1961 + n, 1962 + n, \ldots, 2004 + n)\) is calculated. The monthly anomalies of each forecast year are computed by subtracting the predicted climatology of the corresponding forecast year. The forecast years beyond 2005 of the prediction experiments are excluded from the calculation, because the prediction of the years after 2005 is beyond the observed external forcing period. This study focuses on the forecast years 2–5. So there are 41 years’ hindcast results denoted as 1962, 1963, ..., 2002. A 4-year running mean is applied to the observed and historical simulations to validate the decadal predictions.

The observed SST used in the analysis is the ERSST V3b [26]. The meridional current data from the European Centre for Medium-Range Weather Forecasts (ECMWF) Ocean Reanalysis System 4 (ORA-S4) [27] are used to calculate the observed Atlantic meridional overturning circulation (AMOC). The AMOC index is defined as the maximum of zonally-integrated annual-mean overturning stream function at 45 °N. The AMO index is defined as the SST anomaly in the North Atlantic (80 °W-0 °, 0 °-60 °N) minus the global-mean SST (60 °S to 60 °N) [28]. Root-mean-square error (RMSE) and anomaly correlation coefficient (ACC) relative to the global-mean SST are used in the comparison. The statistical significance of ACC is verified by two-tailed Student-\(t\) test. The effective sample size of the test is calculated after removing the autocorrelation [29]. This study focuses on the prediction skill for forecast years 2–5.

3. Results

RMSE ratios of SST between the forecasts and the NoInit are shown in Fig. 2. The region with values less than 1 (orange and red) denotes smaller RMSE, namely improved hindcast skill compared with NoInit. EnOI_HadInit improves forecast skill of SST in the subpolar and mid-latitude central area of the North Atlantic compared with NoInit (Fig. 2a), while SODAInit has larger RMSE over most area of the North Atlantic than the NoInit (Fig. 2b). The ratio between RMSEs of EnOI_HadInit and SODAInit indicates that there is less SST error northward of 20 °N in the eastern North Atlantic predicted by EnOI_HadInit (Fig. 2c). The reason for the improvement in EnOI_HadInit may be related to its high skill in AMOC as shown later. There is larger error in the extratropics of the western North Atlantic predicted by EnOI_HadInit than the SODAInit. The dynamics process accounted for this phenomenon remains unclear and needs further investigation.

The ACC skills of SST in the decadal forecasts are explored and shown in Fig. 3. The SST hindcast by EnOI_HadInit is significantly and positively correlated with the observation in the subtropical and subpolar regions of the North Atlantic except for the Gulf Stream area (Fig. 3a). The ACC of SODAInit is negative (positive) to the north (south) of 45 °N in the Atlantic (Fig. 3b). Significant ACC mainly appears in the tropics of the North Atlantic for SODAInit. After detrending the decadal forecasts and observation, the ACC of EnOI_HadInit is still positive and significant in most area of the extratropical North Atlantic, while no significant area is found for SODAInit there (Fig. 3c–d). However, the ACC is still positive and significant for tropical SST of the North Atlantic hindcast by SODAInit.

The EnOI_HadInit has high ACC skills in hindcasting extratropical SST in the North Atlantic, and relatively low skill in the tropical SST in the North Atlantic. This may be related to the assimilation procedure used in this study. In the process of the EnOI assimilation, daily observed atmospheric data are used to drive the ocean model. In the tropics, there is no feedback from the ocean to the atmosphere, where air-sea interaction should be considered. Application of the EnOI assimilation to the coupled system of BCC-CSM1.1 could be a way to improve the ASSIM data and the decadal prediction skill in the region where air-sea interaction exist.

The AMO is an important multi-decadal oscillation signal in the Atlantic Ocean, which can be predicted well by most CMIP5 models [6]. As can be seen in Fig. 4, SODAInit has poor skill in hindcasting the AMO, with the ACC of 0.07. Comparatively, EnOI_HadInit has better skill in predicting the AMO, with the ACC (0.40) significantly at the 10% level. The decreasing trend of AMO in the 1960s and its increase in the early 1990s are well predicted by EnOI_HadInit. After detrending the linear trend of the AMO time series during 1962–2002 (Fig. 4b), the AMO index hindcast by EnOI_HadInit shows better agreement with the observation. The ACC is 0.52 significantly at the 5% level, which is much higher than those by
SODAInit and NoInit. It is inferred that the new assimilated data used in the initialization plays an important role in improving hindcast skill of the AMO in BCC-CSM1.1. The AMOC transports heat and salinity anomalies northward in the North Atlantic and induces the multi-decadal oscillation of the Atlantic thermohaline circulation [30]. The improved skill in decadal prediction of the AMO was thought to be related to skillful prediction of the AMOC resulting from good initialization [31]. The prediction skill of AMOC anomalies by EnOI_HadInit and SODAInit for each forecast year from 2 to 5 is investigated by comparing with the ORA-S4 reanalysis data (Fig. 5). The predicted AMOCs by EnOI_HadInit for forecast years 2, 3, 4, and 5 show obvious decadal variations consistently with the ORA-S4 reanalysis, with the correlation coefficient ranging from 0.39 to 0.55 significantly at the 10% level. Such high skill is not found in SODAInit and NoInit. Moreover, the amplitude of the AMOC anomaly of SODAInit and NoInit are much weaker than those in the ORA-S4 reanalysis. Weak AMOC is also found in the climatology of SODAInit and NoInit (not shown). Skillful forecast of the AMOC by EnOI_HadInit may be the reason for the better prediction skill of the AMO.

The improved skills of EnOI_HadInit in AMOC and AMO confirm the important role of the new assimilated ocean data in the initialization of the decadal predictions, although EnOI is a simple assimilation method. The EnOI scheme was used in the CMIP5 decadal forecast of GEOS-5 model, which also has good skills in the subtropical and mid-latitude SST of the Atlantic, as well as the AMOC [32]. Results of this study provide reference for whether EnOI scheme could be used in the initialization of climate model in the Decadal Climate Prediction Project (DCPP) of CMIP6.
4. Conclusions

The decadal prediction of BCC-CSM1.1 for CMIP5 had poor hindcast skill in the North Atlantic, which may be caused by using the SODA reanalysis data to initialize its full-field ocean temperature. Here, we used the EnOI to assimilate the HadISST data into the ocean model of BCC-CSM1.1. The re-forecasts were carried out with the new assimilated data according to the protocol of the CMIP5 predictions. Results of these two sets of decadal predictions (SODAInit and EnOI_HadInit) were compared, with a focus on the North Atlantic Ocean.

Comparison showed that the EnOI_HadInit had a higher SST prediction skill in the subtropical and high latitudes of the North Atlantic when measured by both RMSE and ACC. Time evolution of the AMO was better reproduced by the EnOI_HadInit with a correlation coefficient of 0.52 after detrending, significantly above the 5% level. Further investigation showed that this may be related to the enhanced skill of EnOI_HadInit in forecasting the AMOC. The time evolution and strength of the AMOC hindcast by EnOI_HadInit had better resemblance with those of the ORA-S4 reanalysis. In contrast, both SODAInit and NolInit produced weak AMOC. These improvements of the EnOI_HadInit indicated that the assimilation using EnOI provided better initialization data for decadal prediction of BCC-CSM1.1, which could be used in CMIP6 decadal prediction. This study also confirmed that improvement of initial condition is an important way to improve decadal prediction skill of climate models.

Conflict of interest

The authors declare that they have no conflict of interest.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.scib.2017.08.012.

References

[1] Kirtman B, Power SB, Adedoyin AJ, et al. Near-term climate change: projections and predictability. In: Stocker TF, Qin DH, Plattner GK, editors. Climate change 2013: the physical science basis. Contribution of Working Group I to the fifth assessment report of the intergovernmental panel on climate change. New York: Cambridge University Press; 2013. p. 953–1028.
[2] García-Serrano J, Doblas-Reyes FJ. On the assessment of near-surface global temperature and North Atlantic multi-decadal variability in the ENSEMBLES decadal hindcast. Clim Dyn 2012;39:2025–40.
[3] Kim H, Webster PJ, Curry JA. Evaluation of short-term climate change prediction in multi-model CMIP5 decadal hindcasts. Geophys Res Lett 2012;39:L10701. http://dx.doi.org/10.1029/2012GL051644.
[4] van Oldenborgh GJ, Doblas-Reyes FJ, Wouters B, et al. Decadal prediction skill in a multi-model ensemble. Clim Dyn 2012;38:1263–80.
[5] Doblas-Reyes FJ, Andrué-Burillo I, Chikamoto Y, et al. Initialized near-term regional climate change prediction. Nat Commun 2013;4:1715. http://dx.doi.org/10.1038/ncomms2704.
[6] Meehl GA, Goddard L, Boer G, et al. Decadal climate prediction: an update from the trenches. Bull Amer Meteor Soc 2014;95:243–67.
[7] Semenov VA, Latif M, Donnenget D, et al. The impact of north atlantic-arctic multidecadal variability on northern hemisphere surface air temperature. J Clim 2010;23:5668–77.
[8] Gaetani M, Mohino E. Decadal prediction of the Sahelian precipitation in CMIP5 simulation. J Clim 2013;26:7708–19.
[9] Cao F, Xin XG, Wu TW. A study of the prediction of regional and global temperature on decadal time scale with BCC-CSM1.1 model. Chin J Atmos Sci (in Chinese) 2012;36:1165–79.
[10] Han ZY, Wu B, Xin XG. Decadal prediction skill of the global sea surface temperature in the BCC-CSM1.1 climate model. Earth Interact Sci (in Chinese) 2017;32:396–408.
[11] Smith DM, Cusack S, Colman AW, et al. Improved surface temperature prediction for the coming decade from a global climate model. Science 2007;317:796–9.
[12] Keenlyside N, Latif M, Jungclaus J, et al. Advancing decadal-scale climate prediction in the North Atlantic sector. Nature 2008;453:84–8.
[13] Taylor KE, Stouffer RJ, Meehl GA. An overview of CMIP5 and the experiment design. Bull Am Meteorol Soc 2012;93:485–98.
[14] Rayner NA, Parker DE, Horton EB, et al. Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. J Geophys Res 2003;108:4407. http://dx.doi.org/10.1029/2002JD002760.
[15] Wu TW, Yu RC, Zhang F. A modified dynamic framework for atmospheric spectral model and its application. J Atmos Sci 2008;65:2235–53.
[16] Wu TW, Yu RC, Zhang F, et al. The Beijing Climate Center atmospheric general circulation model: description and its performance for the present-day climate. Clim Dyn 2010;34:123–47.
[17] Griffies SM, Gnanadesikan A, Dixon KW, et al. Formulation of an ocean model for global climate simulations. Ocean Sci 2005;1:45–79.
[18] Li QQ, Tan J, Wang LN, et al. Simulation of the natural distribution of carbon and nutrients in the ocean based on the global ocean carbon cycle model MOM4.40. Chin J Geophys 2015;58:1–19.
[19] Wu TW, Li WP, Ji JF, et al. Global carbon budgets simulated by the Beijing Climate Center Climate System Model for the last century. J Geophys Res Atmos 2013;118:1–22. http://dx.doi.org/10.1002/jgrd.50320.
[20] Xin XG, Wu TW, Zhang J. Introduction of CMIP5 experiments carried out with the climate system models of Beijing Climate Center. Adv Clim Change Res 2013;4:41–9.
[21] Carton JA, Giese BS. A reanalysis of ocean climate using Simple Ocean Data Assimilation (SODA). Mon Weather Rev 2008;136:2999–3017.
[22] Oke PR, Allen JS, Miller RN, et al. Assimilation of surface velocity data into a primitive equation coastal ocean model. J Geophys Res 2002;107:3122. https://dx.doi.org/10.1029/2000JC000511.
[23] Evensen G. The ensemble Kalman filter: theoretical formulation and practical implementation. Ocean Dyn 2003;53:343–67.
[24] Kalnay E, Kanamitsu M, Kistler R, et al. The NCEP/NCAR 40-Year Reanalysis Project. Bull Amer Meteor Soc 1996;77:437–71.
[25] Mitchell HL, Houtekamer PL, Pellerin G. Ensemble size, balance, and model-error representation in an ensemble Kalman filter. Mon Weather Rev 2002;130:2791–808.
[26] Smith TM, Reynolds RW, Peterson TC, et al. Improvements NOAAs historical merged land-ocean temp analysis (1880–2006). J Clim 2008;21:2283–96.
[27] Balmaseda MA, Mogensen K, Weaver AT. Evaluation of the ECMWF ocean reanalysis system ORAS4. Quart J R Meteorol Soc 2013;139:1132–61.
[28] Trenberth KE, Shea DJ. Atlantic hurricanes and natural variability in 2005. Geophys Res Lett 2006;33:L12704. http://dx.doi.org/10.1029/2006GL026854.
[29] Bretherton CS, Widmann M, Dymnikov VP, et al. The effective number of spatial degrees of freedom of a time-varying field. J Clim 1999;12:1990–2009.
[30] Vellinga M, Wu PL. Low-latitude freshwater influence on centennial variability of the Atlantic thermohaline circulation. J Clim 2004;17:4498–511.
[31] Swingedouw D, Mignot J, Labetoulle S, et al. Initialisation and predictability of the AMOC over the last 50 years in a climate model. Clim Dyn 2012;40:2381–99.
[32] Ham YG, Rienecker MM, Suarez MJ, et al. Decadal prediction skill in the GEOS-5 forecast system. Clim Dyn 2014;42:1–20.