# Ensemble forecast of Indo-Pacific SST based on IPCC twentieth-century climate simulations

Qiaoyan Wu[1,3] and Dake Chen[1,2,3]

Received 13 June 2010; revised 8 July 2010; accepted 13 July 2010; published 20 August 2010.

[1] A set of Markov models is developed based on a statistical linearization of 5 coupled ocean-atmosphere general circulation models used in the Intergovernmental Panel on Climate Changes Fourth Assessment Report (IPCC AR4), and is applied to ensemble prediction of the tropical Indo-Pacific sea surface temperature variations. By taking advantage of the long data records of IPCC simulations, the linear model is statistically robust, and exhibits a level of ENSO prediction skill comparable to other forecast models. More importantly, the model shows much higher skill in the western Pacific and the tropical Indian Ocean than previously achieved, thus providing new insight and optimism for the predictability of the short-term climate change in the whole tropical Indo-Pacific region. **Citation:** Wu, Q., and D. Chen (2010), Ensemble forecast of Indo-Pacific SST based on IPCC twentieth-century climate simulations, *Geophys. Res. Lett.*, *37*, L16702, doi:10.1029/2010GL044330.

## 1. Introduction

[2] Forecasts of El Niño and the Southern Oscillation (ENSO), with focus mainly on sea surface temperature (SST) anomalies in the central and eastern Pacific, have been presented by various dynamical and statistical models [e.g., *Zebiak and Cane*, 1987; *Chen et al.*, 1995; *Xue et al.*, 2000; *Xue and Leetmaa*, 2000; *Johnson et al.*, 2000; *Penland and Magorian*, 1993]. Retrospective forecasts by both intermediate coupled model [*Chen et al.*, 2004] and fully coupled general circulation model (CGCM) [*Luo et al.*, 2008] have shown that ENSO can be predicted at lead times of up to 2 years, but there is still a large amount of uncertainty in real-time prediction. *Chen and Cane* [2008] discussed the major limiting factors for dynamical models and suggested several potential areas for improvement. For statistical models, an obvious limitation is the lack of long enough observational data needed for model construction. Because of it, the usefulness of these models for ENSO prediction is probably underestimated [*Johnson et al.*, 2000].

[3] The climate variability in the tropical Indian Ocean is still an issue of considerable debate. It has been suggested that the dominant interannual variability in the Indian Ocean is closely related to ENSO [e.g., *Nigam and Shen*, 1993; *Yu and Rienecker*, 1999], with a basin-wide warming during El Niño, resulting from weakened Walker circulation and surface latent heat flux. But other studies emphasize the importance of an "Indian Ocean Dipole" (IOD), a mode of variability thought to be internal to the Indian Ocean [*Saji et al.*, 1999; *Yamagata et al.*, 2003], which may have a significant influence on El Niño and its predictability [*Luo et al.*, 2010]. It is further argued that ENSO and IOD can be largely unified within the framework of "Indo-Pacific Tripole", an intrinsic mode of tropical climate variability that captures the interaction between the two oceans [*Chen and Cane*, 2008]. In any rate, due to the existence of the huge warm pool in the tropical Indo-Pacific and the associated double-cell Walker circulation, the regional climate variations should be studied and possibly predicted as a whole.

[4] The purpose of this study is to develop a set of linear Markov models based on the coupled ocean-atmosphere general circulation models used in the Intergovernmental Panel on Climate Changes Fourth Assessment Report (IPCC AR4), and to evaluate their skill in predicting the interannual SST fluctuations of the tropical Pacific as well as Indian Oceans. The difference between our approach and previous statistical ENSO forecast models are threefold: First, our models are constructed using long records of dynamical model outputs rather than limited observational data; Second, we simulate and predict the tropical Indo-Pacific variability as a whole instead of ENSO itself; Finally, we use multi-model ensemble to reduce the forecast uncertainties that are inevitable in single model prediction.

## 2. Data and Method

[5] SST, sea surface height (SSH) and sea surface wind data are obtained from the 5 coupled general circulation models (CGCMs) listed in Table 1. Although a total of 25 models have been submitted to IPCC AR4, only 17 of them provide all necessary data at the time of our study, and the 5 models we chose are among those that best simulate the tropical climatology according to *Guilyardi* [2006]. The set of simulations analyzed here is from the Climate of the Twentieth-Century Experiment (20C3M), with the model's external forcing representative of the period between January 1900 and December 1999.

[6] In a manner similar to *Xue et al.* [2000] and *Chen and Yuan* [2004], our Markov models are constructed in the reduced space of multivariate empirical orthogonal functions (MEOFs). The model's spatial structure consists of the MEOFs of SST, SSH and surface vector wind that define the state of the Indo-Pacific climate, while the model's temporal evolution is a Markov process with its transition functions determined from the corresponding principal components

[1]State Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, Hangzhou, China.
[2]Lamont-Doherty Earth Observatory, Earth Institute at Columbia University, New York, New York, USA.
[3]Department of Ocean Science and Engineering, Zhejiang University, Hangzhou, China.


0094-8276/10/2010GL044330

**Table 1.** List of Models Used in This Paper

| Model | Model Institute |
|---|---|
| GFDL-CM2.0 | Geophysical Fluid Dynamics Laboratory |
| GFDL-CM2.1 | Geophysical Fluid Dynamics Laboratory |
| MPI-ECHAM5 | Max Planck Institute for Meteorology (Germany) |
| NCAR-PCM1 | National Center for Atmospheric Research PCM |
| UKMO-HADCM3 | Hadley Center for Climate Prediction and Research |

(PCs). Due to the strong seasonality of tropical climate variability, a seasonal Markov model is more useful than a nonseasonal one [*Xue et al.*, 2000]. Thus a separate Markov transition matrix is constructed for each of the 12 calendar months, which determines the evolution from one month to the next. Through a process of trial and error, we chose 3 leading MEOF modes for Markov model construction, and the truncation errors do not have a significant influence on the model's performance. About 50–70% of the total variance for SST, 40–60% for SSH and 30–40% for wind in these 5 IPCC models are explained by the first three MEOF modes, comparable to those calculated from observations.

[7] As an example, Figure 1 compares the SST pattern of the first MEOF mode from each model with that from observation for the month of November. The percentage of variance explained by the first three MEOFs is also shown. Obviously, this mode represents the mature phase of ENSO. The models are able to pick up the observed pattern of "Indo-Pacific Tripole" [*Chen and Cane*, 2008], characterized by in-phase anomalies in the central-eastern Pacific Ocean and the western Indian Ocean, with out-of-phase anomalies in between. This ability has significant implications for the model's predictive power, as we will discuss later. Nevertheless, the El Niño signal in all models tend to extend too far to the west, leading to large biases in the western equatorial Pacific, especially in the region between 120°E and 160°E.

[8] An outstanding problem in climate forecast is the model-data incompatibility caused by large systematic model biases. The IPCC models used here are no exception. This study adopts the bias-correction method of *Chen et al.* [2000], which is based on the regression of model errors and model states in a reduced space of MEOFs. The regression coefficient matrices are calculated using 30 years (1980–2009) of SST data from *Reynolds and Smith* [1994], SSH and surface wind data from reanalysis products, and predictions of each Markov model for the same period. Then for any given model state, the biases of SST, SSH and wind are determined through regression and are subtracted from the original model fields. In order to reduce the artificial skill arising from using the same period of data for model verification, the bias correction is cross-validated [*Barnston and Ropelewski*, 1992], which means that the data to be corrected is removed from the time series used to calculate the regression coefficients. In the following section, both corrected and uncorrected forecast results will be shown for comparison.

[9] The actual procedure of model prediction follows five steps. First, the initial PCs are obtained by projecting observations to model MEOFs. Second, the predictions of PCs are made at increasing lead times by successively applying the transition matrices. Third, the predicted PCs are combined with the respective MEOFs to give a full forecast. Forth, the bias correction is applied to the forecast of each model. Finally, the bias-corrected forecasts from all models are combined to make ensemble mean forecast. In this paper we will only show ensemble forecasts because on average they are superior to those from individual models. Also, we

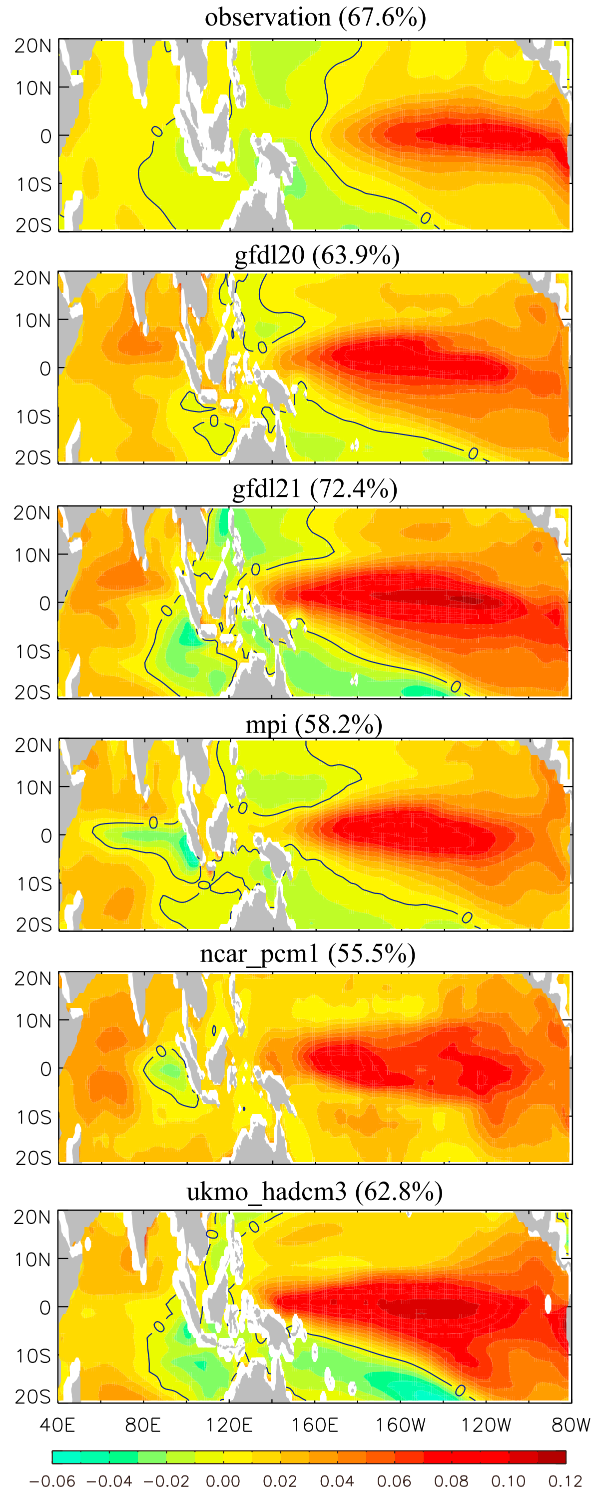


**Figure 1.** The first MEOF pattern for SST in November. Data are from observation and five IPCC models. Unit is nondimensional. The percentage of SST variance explained by the first three MEOFs is shown on top of each plot.

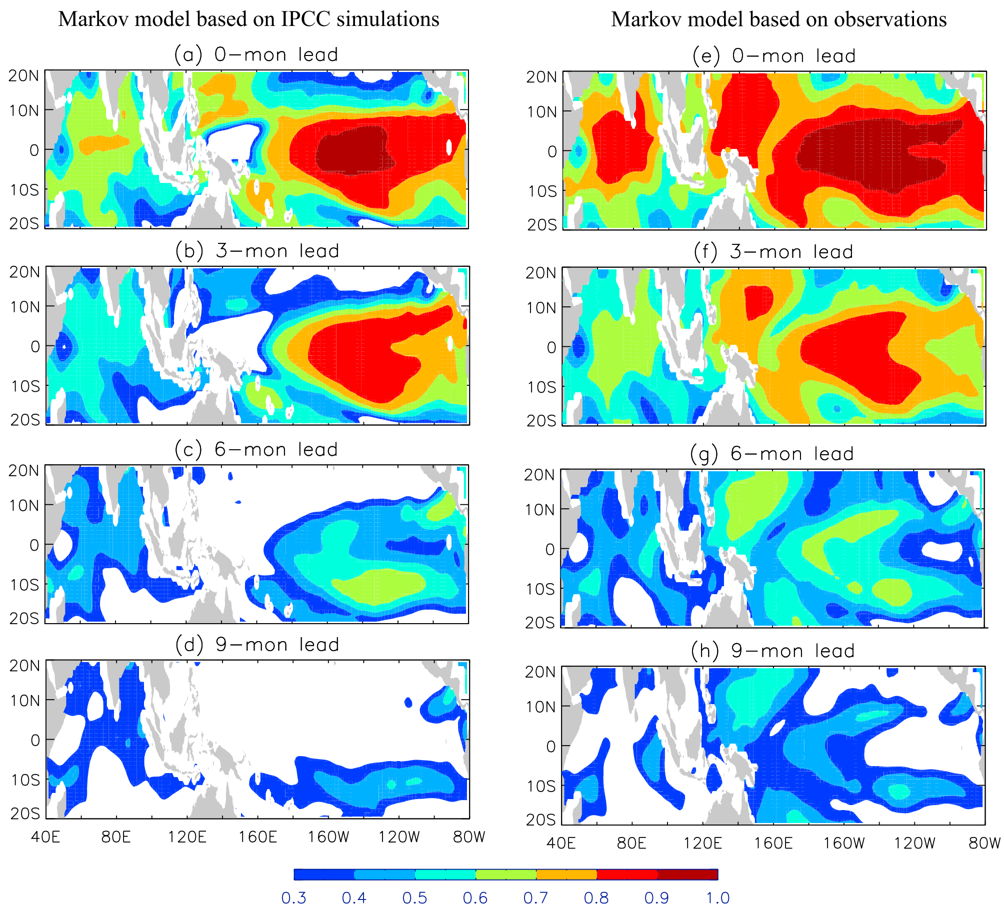


**Figure 2.** (a–d) Correlation skill for SST anomalies without bias correction based on the ensemble forecasts initiated from every month between January 1980 and December 2009 at 0, 3, 6 and 9 month leads. (e–h) Corresponding skill of an observation-based Markov model with no cross-validation.

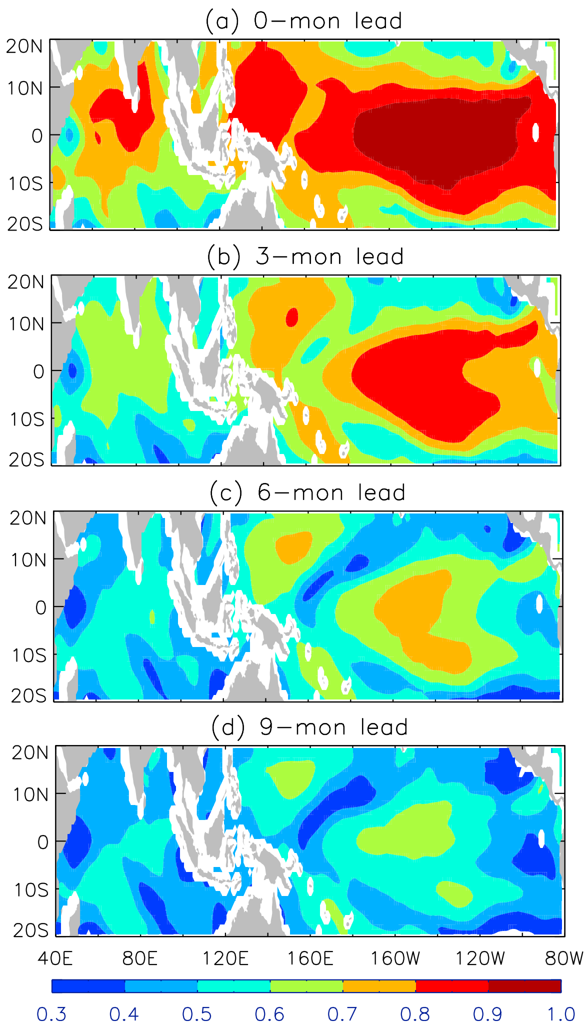


**Figure 3.** Same as Figures 2e–2h except for model skill with bias correction.

focus our attention on SST fields here, although predictions of all model variables are automatically generated.

## 3. Model Results

[10] Figures 2a–2d show the anomaly correlation in the tropical Indo-Pacific region between observed and model-predicted SST at different lead times before bias correction. At 0 month lead, which represents the initial condition for the forecast, the correlation skill is maximized in the eastern and central equatorial Pacific Ocean, and to a lesser extent in the equatorial Indian Ocean and the northwestern tropical Pacific Ocean. The poor correlation in the far western equatorial Pacific is due to the systematic model bias mentioned above. At 3 and 6 month leads, the most predictable regions are the central equatorial Pacific and the south Pacific trade wind area, where the correlation skill is above 0.8 at 3 month lead and above 0.6 at 6 month lead. At 9 month lead, the correlation skill is relatively low for the most of the model domain. It is interesting to note that there is considerable skill in the tropical Indian Ocean at all leads. For comparison, Figures 2e–2h show the correlation skill of a Markov model built from observations of 1980 to 2009, which does a better job than the uncorrected models built from IPCC simulations. Note that the observation-based model is not cross-validated, and thus its skill shown in Figure 2 represents the upper limit of such a model.

[11] The correlation skill for SST anomalies after bias correction is displayed in Figure 3 for different lead times. As compared to uncorrected forecasts, the overall correlation skill has increased by 0.1 to 0.3 at all lead times throughout the model domain. In particular, the far western equatorial Pacific is no longer a problem area, and the forecasts at long lead times are greatly improved. Comparing to the Pacific-only models such as that of *Xue and Leetmaa* [2000], our model not only adds considerable predictive skill for the Indian Ocean, but also has a much higher skill in the western Pacific, indicating co-variability of the two oceans and the influence of the Indian Ocean on the Pacific. As compared to the observation-based model (Figures 2e–2h), the bias-corrected model built from IPCC simulations now has a higher skill at 6 month and longer leads. Our results also suggest that even if the model captures the time evolution of the natural variability, the bias in spatial pattern may prevent it from reaching its predictive potential. Statistical bias correction is a useful tool before the systematic model biases can be largely reduced by improving model physics.

[12] To further demonstrate the predictive ability of our model, the retrospective forecasts of the 1997–98 El Niño and 1998–99 La Niña events are illustrated in Figure 4. In the winter of 1997–98, observed SST anomalies appeared to have a tripole pattern, with warm anomalies in the eastern/central Pacific Ocean and in the western Indian Ocean, separated by cold anomalies in the western Pacific and eastern Indian Oceans. The initial condition at 0 month lead generally agrees with the observation, though the anomalies in the western Pacific and the Indian Ocean are somewhat weaker. The forecasts at 3, 6 and 9 month leads capture the observed anomaly pattern very well, though the longer-lead forecast underestimates the magnitude of the warm event, a common problem with all statistical models. In the winter of 1998–99, observed SST anomalies again showed a tripole pattern, but with cold anomalies in the central equatorial Pacific and in the western Indian Ocean, separated by warm anomalies in between. The model is able to predict this La Niña event as well. Besides the strong cold anomalies in the central pacific, the warm anomalies in the western Pacific and eastern Indian Oceans are also nicely forecasted.

## 4. Summary and Discussion

[13] In this study, we constructed a set of linear Markov models based on the outputs of 5 CGCMs from IPCC AR4, and applied these models to an experiment of retrospective ensemble forecast of tropical Indo-Pacific SST. The model exhibits considerable skill in predicting both El Niño and La Niña. For the 30-year period from 1980 to 2009, the model's predictive skill in terms of anomaly correlation is above 0.6 in the central tropical Pacific at 9-month lead, which measures up to the state-of-the-art of ENSO forecasting. More importantly, our model shows much higher skill in the western Pacific and tropical Indian Ocean than previously achieved, thus providing new insight and optimism for the predictability of the short-term climate change in the whole tropical Indo-Pacific region.

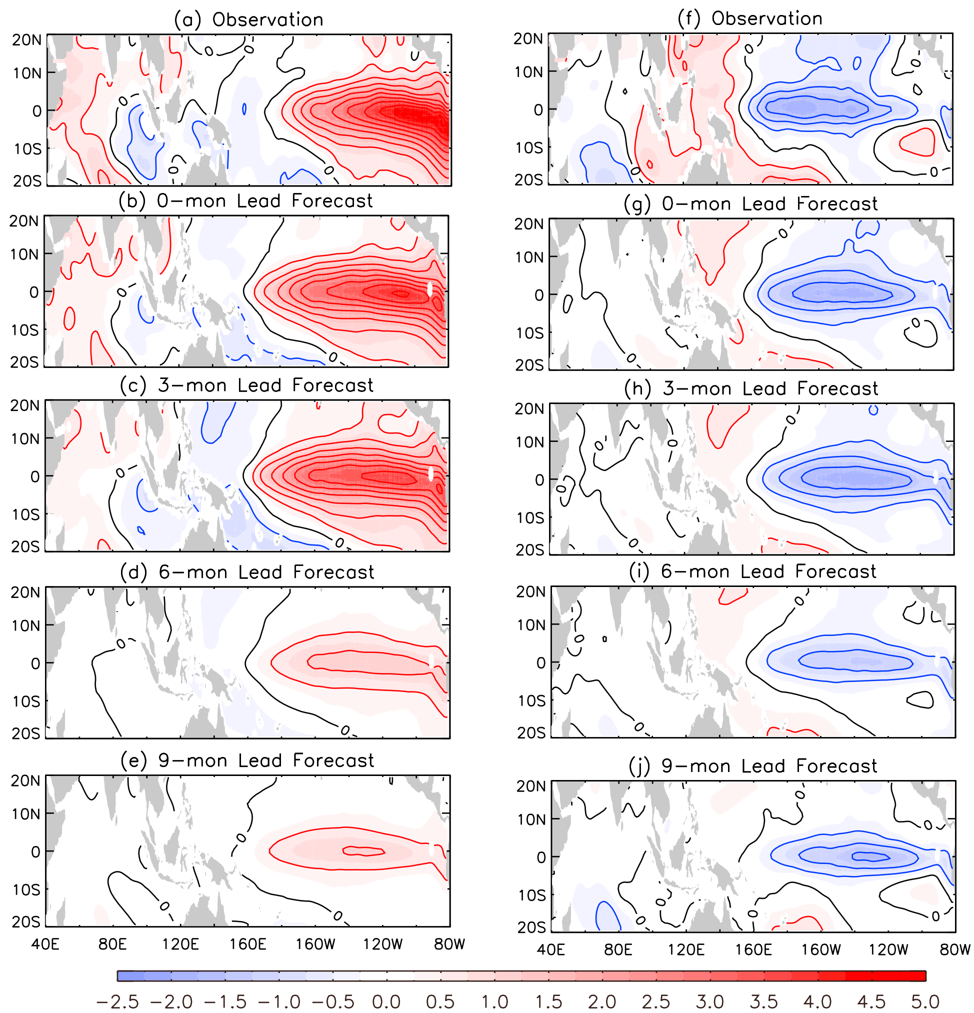


**Figure 4.** Observed and forecast SST anomalies in December (a–e) 1997 and (f–j) 1998. Forecasts are made at lead times of 0, 3, 6, and 9 months and are bias-corrected.

[14] Our approach to construct statistical forecast models using a linearization of multiple CGCMs has several advantages. First, unlike similar models based on observational data such as that of *Xue and Leetmaa* [2000], the length of data records for model training is no longer a limiting factor; thus the model is more statistically robust. Second, while multi-model ensemble forecasts with a group of CGCMs are extremely costly, the same task with our linear models is readily feasible, which makes long retrospective forecast a simple experiment. Third, the linear models constructed this way retain the basic modes of variability in the original CGCMs, and thus reflecting the variety of behaviors of those dynamical models.

[15] The success of our simple model is partly attributable to the low-dimensional nature of the tropical climate variability, meaning that the ocean-atmosphere coupled system here is dominated by a few distinctive modes, with the Indo-Pacific Tripole being the most dominant mode [*Chen and Cane*, 2008]. As long as a model simulates these modes well, which is obviously the case with our Markov models, it should be able to predict the evolution of a reasonably captured initial signal. Of course, the success of our approach also depends on the realism of the internal variability of the CGCMs used for model construction. In a way our results validate the usefulness of a set of IPCC AR4 models for seasonal-to-interannual prediction. The same approach can be easily extended to the models submitted to the upcoming IPCC Fifth Assessment Report (AR5). With the expected improvement of AR5 models, we will no doubt have a better and larger set of simulations to work with, and consequently a more skillful ensemble forecast system to deliver.

[16] **Acknowledgments.** Funding for Q. Wu is provided by the Talent Recruitment Project of the Second Institute of Oceanography (JR200801) and the National Science Foundation of China (40976018). D. Chen is supported by grants from the National Basic Research Program (2007CB816005), the National Science Foundation of China (40730843), the National Oceanic and Atmospheric Administration, and the National Aeronautics and Space Administration. Comments and suggestions provided by two anonymous reviewers are greatly appreciated.

## References

Barnston, A. G., and C. F. Ropelewski (1992), Prediction of ENSO episodes using canonical correlation analysis, *J. Clim.*, *5*, 1316–1345.

Chen, D., and M. A. Cane (2008), El Niño prediction and predictability, *J. Comput. Phys.*, *227*, 3625–3640.

Chen, D., and X. Yuan (2004), A Markov model for seasonal forecast of Antarctic sea ice, *J. Clim.*, *17*, 3156–3168.

Chen, D., S. E. Zebiak, A. J. Busalacchi, and M. A. Cane (1995), An improved procedure for El Niño forecasting: Implications for predictability, *Science*, *269*, 1699–1702.
Chen, D., M. A. Cane, S. E. Zebiak, R. Cañizares, and A. Kaplan (2000), Bias correction of an ocean-atmosphere coupled model, *Geophys. Res. Lett.*, *27*, 2585–2588.
Chen, D., M. A. Cane, A. Kaplan, S. E. Zebiak, and D. Huang (2004), Predictability of El Niño over the past 148 years, *Nature*, *428*, 733–736.
Johnson, S. D., D. S. Battisti, and E. S. Sarachik (2000), Empirically derived Markov models and prediction of tropical Pacific sea surface temperature anomalies, *J. Clim.*, *13*, 3–17.
Guilyardi, E. (2006), El Niño-mean state-seasonal cycle interactions in a multi-model ensemble, *Clim. Dyn.*, *26*, 329–348.
Luo, J.-J., S. Masson, S. Behera, and T. Yamagata (2008), Extended ENSO predictions using a fully coupled ocean-atmosphere model, *J. Clim.*, *21*, 84–93.
Luo, J.-J., R. Zhang, S. K. Behera, Y. Masumoto, F.-F. Jin, R. Lukas, and T. Yamagata (2010), Interaction between El Niño and extreme Indian Ocean Dipole, *J. Clim.*, *23*, 726–742.
Nigam, S., and H. S. Shen (1993), Structure of oceanic and atmospheric low-frequency variability over the tropical Pacific and Indian oceans. Part I: COADS observations, *J. Clim.*, *6*, 657–676.
Penland, C., and T. Magorian (1993), Prediction of Niño-3 sea surface temperatures using linear inverse modeling, *J. Clim.*, *6*, 1067–1076.
Reynolds, R. W., and T. M. Smith (1994), Improved global sea surface temperature analyses using optimum interpolation, *J. Clim.*, *7*, 929–948.
Saji, N. H., B. N. Goswami, P. N. Vinayachandran, and T. Yamagata (1999), A dipole mode in the tropical Indian Ocean, *Nature*, *401*, 360–363.
Xue, Y., and A. Leetmaa (2000), Forecasts of tropical Pacific SST and sea level using a Markov model, *Geophys. Res. Lett.*, *27*, 2701–2704.
Xue, Y., A. Leetmaa, and M. Ji (2000), ENSO prediction with Markov models: The impact of sea level, *J. Clim.*, *13*, 849–871.
Yamagata, T., S. K. Behera, S. A. Rao, Z. Guan, K. Ashok, and H. N. Saji (2003), The Indian Ocean Dipole: A physical mode, *Bull. Am. Meteorol. Soc.*, *84*, 1418–1422.
Yu, L., and M. M. Rienecker (1999), Mechanisms for the Indian Ocean warming during the 1997–98 El Niño, *Geophys. Res. Lett.*, *26*, 735–738.
Zebiak, S. E., and M. A. Cane (1987), A model El Niño-Southern Oscillation, *Mon. Weather Rev.*, *115*, 2262–2278.

D. Chen and Q. Wu, State Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, 36 North Baochu Rd., Hangzhou, Zhejiang 310012, China. (qwu@sio.org.cn)