Seasonal Forecast of Antarctic Sea Ice

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1. Introduction

Long-range forecasts of Antarctic sea ice are very much in demand, not only because of the potential importance of sea ice in global climate, but also for the practical purpose of exploring the Antarctic continent. Unfortunately, such forecasts are not yet feasible with any state-of-the-art general circulation models, because the complex air-sea-ice interaction processes on long timescales are still not well understood and are by no means well simulated by these models. An alternative is to apply statistical methods to Antarctic sea ice prediction. The linear Markov model used in this study (Chen and Yuan, 2004) represents one of the first attempts in this direction.

The variability of Antarctic sea ice is likely to be controlled by both remote and local processes. The atmospheric anomalies from low latitudes could excite certain modes of the Antarctic climate system, which then could be amplified and sustained by the local air-sea-ice interaction. Here we explore the possibility of forecasting Antarctic sea ice anomalies using a technique combining multivariate empirical orthogonal function (MEOF) analysis and linear Markov prediction. Our model results indicate that the dominant modes of the Antarctic climate variability is indeed predictable up to one year in advance, and that our simple statistical model can serve as a useful tool for Antarctic sea ice prediction until better dynamical models come along.

2. Model and Data

Our model is constructed in the MEOF space. In other words, the base functions of the model's spatial dependence consist of the MEOFs of several variables that are chosen to define the state of the Antarctic climate, while the temporal evolution of the model is a Markov process with its transition functions determined from the corresponding principal components (PCs). By retaining only a few leading modes of the MEOFs, we can greatly reduce the model space and, more importantly, filter out incoherent small-scale features that are basically unpredictable. This kind of model has been used previously in some ENSO predictability and prediction studies (Blumenthal, 1991; Xue et al., 2000; Canizares et al., 2001).

We chose to define the coupled Antarctic climate system with eight variables: sea ice concentration, surface air temperature, sea level pressure, zonal and meridional surface winds, 300mb geopotential height, and zonal and meridional winds at 300mb level. The sea ice data were obtained from the National Snow and Ice Data Center and then binned into 0.5^{o}lat x 2^{o}long grids and monthly intervals. All other data sets came from the reanalysis product of the National Center for Environmental Prediction, which are monthly data on a 2.5^{o} x 2.5^{o} grid. The model domain covers the southern polar region (50-90^{o}S). Twenty-two years (01/1979-12/2000) of observational and reanalysis data were used in this study. The details of model construction can be found in Chen and Yuan (2004).

3. Results

Hindcast experiments were carried out for the period from January 1979 to December 2000. The Markov model was initialized with observational and reanalysis data in each month and predictions were made for up to 12 months for all model variables. The model showed remarkable skill in predicting the Antarctic dipole, the dominant mode of climate variability in the southern polar region (Yuan and Martinson, 2001), especially in austral winter (JJA). As an example, Figure 1 (front cover) displays the model hindcasts at different lead times for the winter of 2000, when a typical dipole pattern occurred in response to the 1999-2000 La Niña. The top row (0-month lead) is simply the observations represented by the first 7 MEOF modes and thus can be considered as the target. The model did a fairly nice job predicting all of the main features in the observed sea ice and atmospheric variables, though the prediction made 9-months ahead is a bit weak in magnitude.

To prevent artificial skills, the model was evaluated using a cross-validation scheme (Barnston and Ropelewski, 1992), in which the data used to verify the model hindcasts are not used for model training. Figure 2 (page 22)shows the cross-validated model skills in predicting the average sea ice anomaly at DP1 (130-150^{o}W, 60-70^{o}S, the center of the dipole in Pacific). The model beats the persistence prediction by a large amount in terms of both anomaly correlation and rms (root-mean-square) error. Among the four model cases with different numbers of MEOF modes included, the one with 7 modes has the highest overall score. In this case, the anomaly correlation is above 0.6 and the rms error is below 9% for almost all lead times up to almost one year. It is worth noting that the model is not particularly sensitive to the number of modes retained.

We started real-time seasonal forecasting of Antarctic sea ice in the beginning of 2003. Since then we have been providing forecasts on a monthly basis in our experimental sea ice prediction webpage (http:///rainbow.ldeo.columbia.edu/~dchen/sea_ice.html) at Lamont-Doherty Earth Observatory of Columbia University. So far the forecast results are quite encouraging. The gross features of our model predictions have been verified by recent observations.

4. Summary and Discussion

We have developed a low-order linear Markov model to simulate and predict the short-term climate change in Antarctic, with particular emphasis on sea ice variability. Seven atmospheric variables along with sea ice were chosen to define the state of the Antarctic climate, and the multivariate empirical orthogonal functions of these variables were used as the building blocks of the model. In both hindcast and forecast experiments, the model showed considerable skill in predicting the Antarctic sea ice anomalies up to a year in advance, especially in austral winter and in the Antarctic dipole regions. We are presently using this model for experimental seasonal forecasting of Antarctic sea ice, which is expected to be useful for planning Antarctic field expeditions.

It is somewhat surprising that such a simple statistical model could have fared so well in predicting the interannual variations of the Antarctic sea ice field, a task that has rarely been attempted before. The predictability demonstrated here can be attributed to the domination of the coupled air-sea-ice system by a few distinctive, slowly-changing modes such as the Antarctic dipole, although a self-sustained low-frequency oscillation is not likely to exist in Antarctic. Our understanding of the physical processes operating in the Antarctic climate system is still rather limited, but we do have a good grasp of the statistical characteristics of the system, and a well-constructed statistical model can be a useful forecast tool as long as it contains those dominant climate modes.

This self-evolving Markov model emphasizes the regional air-sea-ice interaction, and as such it does not explicitly simulate the Antarctic-low-latitude teleconnection. However, the success of the model does not compromise in any way the importance of the teleconnection. Since the Antarctic interannual disturbances are likely to be excited in the first place by the influence from low latitudes, as evident in their lagged response to ENSO, any models that simulate the evolution of these disturbances implicitly take into account the teleconnection. What the model does is nothing but to pick out significant signals from observed initial conditions and predict a statistically meaningful path for the movement, growth, or decay of these initial disturbances.

Acknowledgements.

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References:

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

Blumenthal, M. B., 1991: Predictability of a coupled ocean-atmosphere model. *J. Clim.*, 4, 766-784.

Canizares, R., A. Kaplan, M. A. Cane, D. Chen, and S. E. Zebiak, 2001: Use of data assimilation via linear low order models for the initialization of ENSO predictions. *J. Geophys. Res.*, 106, 30947-30959.

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

Xue, Y., A. Leetmaa and M. Ji, 2000: ENSO prediction with Markov models: the impact of sea level. *J. Clim.*, 13, 849-871.

Yuan, X. and D. G. Martinson, 2001: The Antarctic Dipole and its Predictability. *Geophys. Res. Lett.*, 28, 3609-3612.

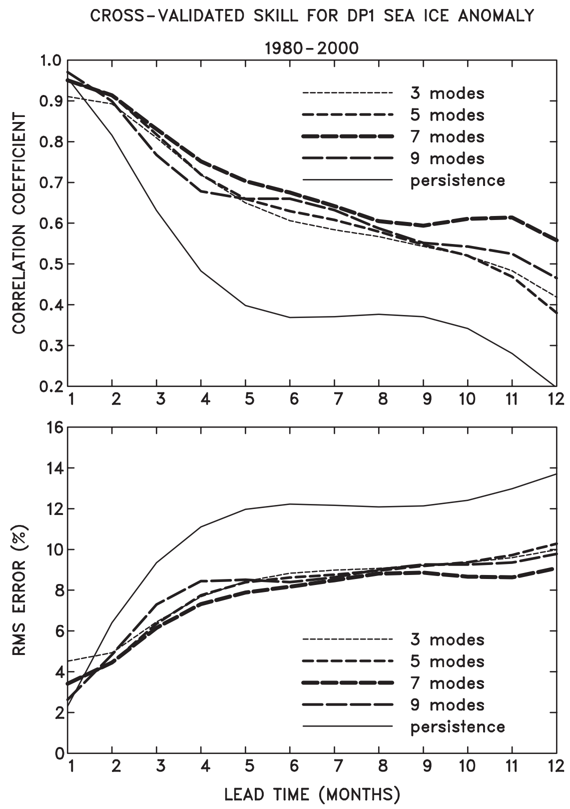

Figure 2. Cross-validated correlation and rms error between hindcast and observed sea ice concentration anomalies averaged in DP1 region (130-150°W, 60-70°S). Compared are four model hindcast experiments with different numbers of MEOF modes included. The skill of persistence prediction is also shown for reference.