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Tropical Seasonal Precipitation Forecasts Using Multi-Model Superensemble Technique

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1. Introduction

A considerable amount of research may be necessary to address the seasonal forecast issue. Can one provide useful guidance on whether a given region will be wet or dry, warmer or colder, during the coming season? Except for some empirical statistical studies on the seasonal guidance of ENSO scenarios, the forecasts in general have rather low skills. Our measures show (Krishnamurti et. al. 2002) that multimodel skills are generally lower than those of climatology, except for some isolated seasonal case studies. That being the state of real-time seasonal climate forecasting, it is necessary to gradually improve the model's data assimilation, physics, resolution, surface parameterizations, and ocean atmospheric coupling aspects. This will at best occur slowly and a continual thrust is necessary. This paper is one such effort to improve the forecast skills of Atmospheric General Circulation models where we show that the use of SVD (Singular Value Decomposition) for the superensemble forecasts of seasonal climate provides an incremental improvement in forecast skills (Yun and Krishnamurti, 2001).

Recently there has been a considerable interest in long-term climate prediction, where the effects of the surface boundaries (the ocean and snow cover) and the internal non-linear dynamics have been explored in numerous studies. Krishnamurti et al. (1999) produced weather and seasonal climate super-ensemble forecasts using different models and a multiple linear regression. Basically, the main result from these studies was that the superensemble-based forecasts were quite superior in comparison to participating member models and the bias-removed ensemble mean. Other studies have also used linear methods to produce deterministic or probability forecasts by combining several independent forecasts.

2. Construction of empirical superensemble forecast model and results

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We have generated the respective weights for each model using the multiple regression technique during the training period. We assume that the long-term behavior, that is, a relationship of the multi-models to the analysis fields, is defined in terms of the temporal resilience of these weights. The forecast skills depend upon these regression coefficients. To obtain the optimal regression coefficients, we have constructed covariance matrices utilizing the following methods:

The simple ensemble method with bias-corrected or biased data respectively, is given by

$$S=\frac{1}{N}\sum_{i=1}^{N}(F_i-\overline{F}_i) \text{ or } S=\frac{1}{N}\sum_{i=1}^{N}(F_i-\overline{O}). \quad (1)$$

The conventional superensemble forecast (Krishnamurti et. al., 2000) constructed with bias-corrected data is given by

$$S=\overline{O}+\sum_{i=1}^{N}a_i\,(F_i-\overline{F}_i) \quad (2)$$

Where, F_i is the i^{th} model forecast, $\overline{F_i}$ is the mean of the i^{th} forecast over the training period, $\overline{O}$ is the observed mean over the training period, a_i are regression coefficients obtained by a minimization procedure during the training period, and N is the number of forecast models involved. The design of an optimal weighting function for a long-term forecast may require detailed knowledge on the natural fluctuation of the climate system, such as low frequency oscillation or physical processes. It is important to obtain good regression coefficients, or weights, for each model.

- In the construction of the covariance matrix for the regression model, for example, one should handle it with the noise-removed or as a low frequency mode
- Another goal is to minimize the variance error of the regression model

3. Results

The performance of the proposed superensemble techniques for the improvement of long-term prediction skill is assessed using skill scores. Fig. 1 illustrates the monthly mean tropic precipitation skill scores for multi-model superensemble techniques. The RMS errors of the individual models lie between 2.5 and 6 mm/day and the RMS errors of the bias-removed ensemble mean are around 2.5 mm/day. The RMS errors of the proposed SVD technique are approximately 0.5 mm/day lower than those of the bias-removed ensemble mean. These results are superior to those of the individual models, as well as the results of bias-removed ensemble mean during each of their respective training and forecast periods.

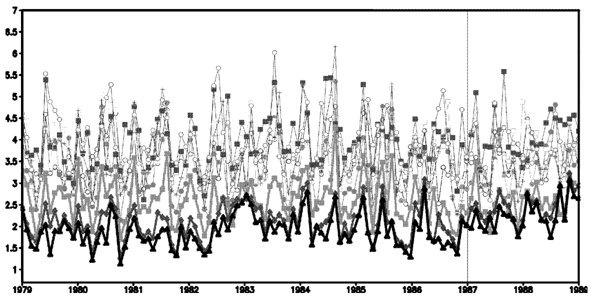

Fig. 1. The RMS errors of tropic (30ºS-30ºN, 50ºE-150ºE) precipitation for the multimodels and for the bias-removed ensemble, and Gauss-Jordan-, SVD methods. Marked line denotes multi-models and the thick marked green- , blue -, and black lines indicate the result of the bias-removed ensemble, Gauss-Jordan-, SVD methods, respectively. Units: mm/day

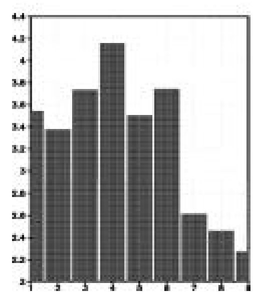

Fig. 2. The mean RMS error of the tropic region (30ºS-30ºN, 50ºE-150ºE) forecasts during the forecast period from 1987-1988. The numbers from 1 to 6 in the figure denotes results of 6 multi-models and the numbers 7, 8, and 9 indicate the result of the bias-removed ensemble mean, Gauss-Jordan -, SVD methods, respectively. Units: Precipitation (mm/day)

In Fig. 2, the monthly mean RMS errors for precipitation in tropic region during the entire two years of the forecast period (Jan. 1987 - Dec. 1988) are compared. These histograms of forecast RMS skill scores include the result of six models, the bias-removed ensemble mean and two different superensemble techniques for tropic region (30ºS-30ºN, 50ºE-150ºE). The conventional method has a lower RMS error compared to the bias-corrected ensemble mean. The skill of the superensemble ethod depends strongly on the covariance matrix error because the weights of each model are computed from a designed covariance matrix. The forecast skill is high if the covariance matrix error is low. The results presented here indicate how close the solution of the proposed techniques to the observed analyzed state.

4. Summary

Our study has focused on improving the prediction skill through the construction of multiple regression models using different approaches for generating superensemble forecasts. We have shown that the results of the proposed techniques are clearly better than those of the conventional superensemble method, and the superensemble forecast that is based on the SVD method demonstrates the best result from computation of the covariance matrix. Obviously, the SVD technique explains the variance better than the other techniques

A postprocessing algorithm based on multiple regression of multi-model solutions toward observed fields during a training period is one of the best solutions for long-term prediction. Due to the cancellation of biases among different models, the forecast superensemble errors are quite small. Our study shows that the proposed techniques reduce the forecast errors below those of the bias-removed ensemble mean and the conventional superensemble technique.

References

Krishnamurti, T. N., C. M. Kishtawal, T. E. LaRow, D. R. Bachiochi, Z. Zhang, C. E. Williford, S. Gadgil, and S. Surendran, 1999: Improved weather and seasonal climate forecasts from multimodel superensemble. *Science*, **285**, 1548-1550.

Krishnamurti, T. N., L. Stefanova, A. Chakraborty, T.S.V. Kumar, S. Cocke, D. Bachiochi, and B. Mackey, 2002: Seasonal forecasts of precipitation anomalies for North American and Asian Monsoons. submitted to *J. Meteor. Soc. Japan*

Yun, W.T. and T. N. Krishnamurti, 2001: Improvement of seasonal and long-term forecasts using multi-model superensemble technique. Submitted to *J. Climate* .