Improvement of Long-Term Forecasts Using Multi-Model Superensemble Technique

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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? 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 numerues studies. Krishnamurti et al. (1999, 2000) produced weather and seasonal climate super-ensemble forecasts using different models and a multiple linear regression. The studies have covered forecasts of hurricanes, global NWP, precipitation and seasonal climate. 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.

Yun and Krishnamurti (2001) improved Multi-Model Superensemble model using SVD, EOF, and Z-transformation technique. The new 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 new superensemble techniques reduce the forecast errors below those of the bias-removed ensemble mean and the conventional superensemble technique.

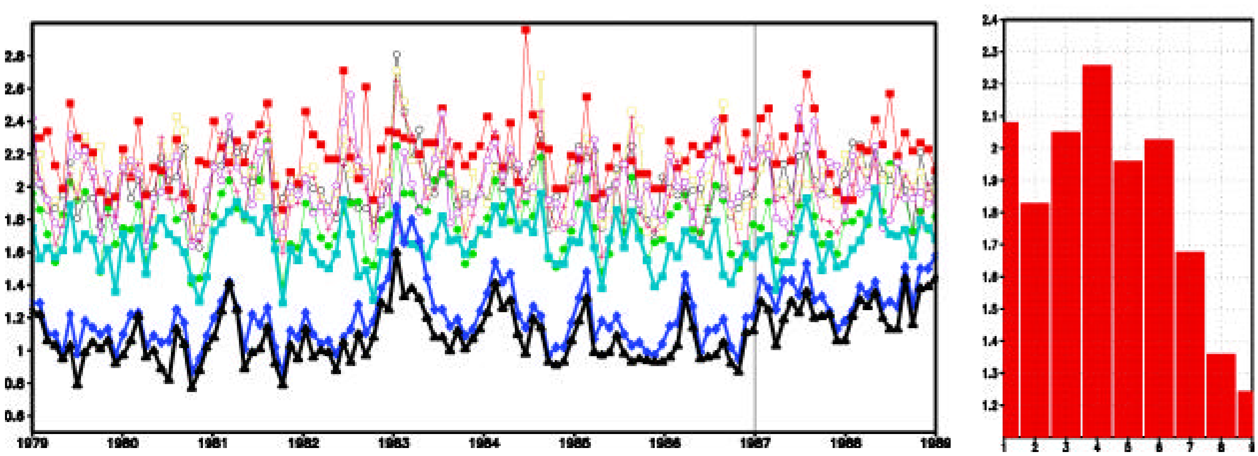

Fig. 1. The RMS errors of global precipitation forecast for the multimodels (marked line) and for the ensemble mean (green line), and conventional (blue line) and new (black line) superensemble method. The numbers from 1 to 6 in the right figure denotes mean RMSE of 6 multi-models and the numbers 7, 8, and 9 indicate the RMSE of the ensemble mean, conventional-, and new method, respectively. Units: mm/day

Using six AMIP models, the performance of the old and new multiple regression methods are compared. The first two approaches utilize a simple pointwise multiple linear regression technique based on Gauss-Jordan and SVD (Singular Value Decomposition) regression models. These were constructed using covariance matrices where the bias and annual cycle were removed. In another new technique, weights were determined for the superensemble forecast using PCs of EOF analyses and low frequency filtered data. The regression is performed in EOF space and in the frequency domain. It is shown that the results of the proposed techniques are clearly better than those of the conventional superensemble method. The superensemble forecast based on the SVD method appears to give the best results due to the computing of the covariance matrix. Obviously, the SVD technique explains the variance in the first case better than the EOF technique in the second case. In the latter, it appears advisable to compute the regression coefficients in the signal space.

Construction of multi-model superensemble using SVD

The singular value decomposition (SVD) is applied to the construction of the superensemble forecast to the computing of the correlation coefficients between different model forecasts, since the SVD is one way of diagonalizing the symmetric covariance matrix. $F_{i,t} = f_{i,1} \cdots f_{i,t}$ describes the model forecast fields in the time domain. The cross-covariance matrix of the anomaly (F') forecast fields with the seasonal cycle-removed is built for both the Gauss-Jordan and SVD methods.

$$C_{i,j} = \sum_{t=1}^{T} \sum_{l=1}^{L} F'_{i,l}(t) F'_{j,l}(t), \tag{1}$$

where, t and l denote time and gridpoint indices, respectively. The SVD of the covariance matrix is its decomposition of the product of three different matrices. This pointwise regression of the SVD method removes the singular vector problem that can't be entirely solved with the conventional Gauss-Jordan elimination method. An aspect of variance analysis, SVD is the method for solving most linear least-squares problems and produces a solution that is the best approximation in the least-square sense. Thus the SVD method explains the maximum variance using the orthonormal basis.

References

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