A New Scheme for Improving the Seasonal Prediction of Summer Precipitation Anomalies

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ABSTRACT

A new scheme is developed to improve the seasonal prediction of summer precipitation in the East Asian and western Pacific region. The scheme is applied to the Development of a European Multimodel Ensemble System for Seasonal to Interannual Prediction (DEMETER) results. The new scheme is designed to consider both model predictions and observed spatial patterns of historical “analog years.” In this paper, the anomaly pattern correlation coefficient (ACC) between the prediction and the observation, as well as the root-mean-square error, is used to measure the prediction skill. For the prediction of summer precipitation in East Asia and the western Pacific (0°–40°N, 80°–130°E), the prediction skill for the six model ensemble hindcasts for the years of 1979–2001 was increased to 0.22 by using the new scheme from 0.12 for the original scheme. All models were initiated in May and were composed of nine member predictions, and all showed improvement when applying the new scheme. The skill levels of the predictions for the six models increased from 0.08, 0.08, 0.01, 0.14, −0.07, and 0.07 for the original scheme to 0.11, 0.14, 0.10, 0.22, 0.04, and 0.13, respectively, for the new scheme.

1. Introduction

Seasonal time-scale dynamical climate predictions based on climate models are of great value to society for agriculture, water resource management, flood and drought disaster reduction, and many other uses. These models, both experimental and operational, were first developed in the early 1990s (Zeng et al. 1990; Ji et al. 1996; Kumar et al. 1996), based on the successful predictions of El Niño by prototype coupled ocean–atmosphere models (Zebiak and Cane 1987).

“Two tier” approaches have been applied from the very beginning of dynamical seasonal climate prediction. In these models, the predictions are made by the atmospheric general circulation model (AGCM) forced with prescribed (or forecasted) sea surface temperatures (SST) and other boundary conditions. Multimodel superensemble predictions have been used in climate prediction to produce more reliable probability forecasts in recent years (Krishnamurti et al. 1999; Palmer 2001). Two well-known projects have been undertaken in Europe and the United States, respectively, namely the Prediction of Climate Variations on Seasonal to Interannual Timescales (PROVOST) project and the Dynamical Seasonal Prediction (DSP; Palmer and Shukla 2000), to validate the skill of multimodel ensemble predictions. The results of these projects showed the large spatial differences of the skill, as well as the considerable intermodel variability of the SST-forced seasonal-mean signal, plus seasonal-mean “noise” (Straus and Shukla 2000; Pavan and Doblas-Reyes 2000).

Coupled ocean–atmosphere–land surface process models have been used in the operational prediction (i.e., “one tier” approach) over the last 10 yr (e.g., Stockdale et al. 1998; Mason et al. 1999). The Development of a European Multimodel Ensemble System for Seasonal to Interannual Prediction (DEMETER) project was conceived to produce a series of 6-month multimodel ensemble hindcasts by running a number of state-of-the-art global coupled ocean–atmosphere models on a single supercomputer with common archiving and diagnostic software (Palmer et al. 2004).

The models used in the DEMETER project are those of Météo-France; the Max-Planck Institut für Meteorologie (MPI), Germany; the U.K. Met Office (UKMO), and the European Centre for Medium-Range Weather Forecasts (ECMWF), United Kingdom; the Istituto Nazionale de Geofisica e Vulcanologia, Italy; and the Laboratoire d’Océanographie Dynamique et de
Climatologie (LODYC) and the European Centre for Research and Advanced Training in Scientific Computation, France (CNFC) [the models used are, respectively, the Centre National de Recherches Météorologiques coupled model (CNRM), the MPI coupled model (SMPI), the UKMO coupled model, the SCWF model, the SCNR coupled model, LODY model, and the CNFC model].

The DEMETER hindcasts cover the same period as the 40-yr ECMWF Re-Analysis (1958–2001), and are started from 1 February, 1 May, 1 August, and 1 November. Each hindcast is integrated for 6 months and comprises an ensemble of nine members.

In this paper, hindcasts for the period 1979–2001 will be discussed for the summer precipitation prediction skill for the East Asian and Western Pacific (EAWP) region. The hindcasted June–August (JJA) precipitation results integrated from 1 May are employed for the analysis. Six models (all except the CNFC model) have the hindcasts covering this period. Since the CNFC model contains results only after the year 1980, this model is excluded from our analysis. The Climate Prediction Center’s (CPC) Merged Analysis of Precipitation (CMAP) dataset (Xie and Arkin 1997) is used for the validation of the models’ prediction skill.

2. Prediction skills for summer precipitation in Asia and the western Pacific

Since reliable global precipitation data are available only after 1979, the evaluation of the hindcast skill in this study for the JJA mean precipitation covers only the period of 1979–2001. The anomaly pattern correlation coefficient (ACC) between the predictions and the observations, as well as the root-mean-square error (RMSE), is used for evaluating the model skill. In this paper, all the anomaly fields refer to deviations relative to 1979–1996 averages.

First, we depict the June–August precipitation climatology of the models and the observations averaged for 1979–96 (Fig. 1). The bottom two diagrams show the
multimodel ensemble (MME) and the observations, and show good agreement between the observations and the MME in terms of the spatial pattern of the summer precipitation in East Asia and the western Pacific. The MME closely reproduces the climatological rainfall amount and the spatial distribution in mainland China. However, the MME underestimates the large amount of precipitation in the South China Sea (SCS) and the Bay of Bengal. The CNRM, SCNR, and SMPI models have a similar bias, while the LODY, SCWF, and UKMO models tend to simulate even larger amounts of precipitation in the South China Sea and the Bay of Bengal.

Figure 2 shows the ACCs for the six models’ ensemble hindcasts and the MME prediction for the East Asian and western Pacific region for the years 1979–2001. The average skill for the multimodel ensemble is 0.12, with considerable year-to-year variation. The highest skill levels appear in 1983, 1991, and 1998 (ACCs of 0.45, 0.41, and 0.48, respectively). The years 1981, 1993, and 1997 have the lowest skill levels (ACCs of −0.13, −0.18, and −0.16, respectively). In most years, the ACC of the MME is significantly higher than zero; thus, the MME shows reasonable forecast skill for the JJA precipitation in the East Asian and western Pacific region.

Meanwhile, most of the individual models have no skill for their JJA precipitation forecasts for the EAWP region. The exception is SCWF, which has a 1979–2001 average ACC of 0.14, slightly higher than the MME. The ACCs for the other five models (CNRM, LODY, SCNR, SMPI, and UKMO) are 0.08, 0.08, 0.01, −0.07, and 0.07, respectively. The MME has a higher level of skill than most of the individual models for the EAWP region, although the skill of the MME is still limited. Therefore, seasonal predictions for the summer precipitation in the EAWP region are very difficult to make accurately. The reason for this low skill of prediction is primarily the coarse correlation with the ENSO cycle.

Figure 3 shows the correlation coefficients between the JJA precipitation and the Southern Oscillation index (SOI) in March–May and JJA for 1979–2001. No clear signals of the spring or summer SOI are found in the JJA precipitation in the EAWP region. However, the skill of the precipitation predictions in the tropical region (TR; 30°S–30°N, 0°–180°E) is much higher than in the EAWP region.
better, with a multiyear average spatial anomaly correlation coefficient between the observation and the MME prediction of 0.34. In addition, the precipitations in the two regions are closely correlated, with a correlation coefficient (CC) of 0.58.

Therefore, we have designed a new scheme to make use of the tropical prediction skill to improve the East Asian prediction skill. This is the major reason for developing the “analog” idea to address the difficult prediction problem in the EAWP region. There is an additional consideration. The major patterns of precipitation variability are limited and frequently occur in East Asia. For example, if the precipitation in the South China Sea is above (below) normal, the precipitation in south China is usually below (above) normal. This feature is illustrated well in the empirical orthogonal function (EOF) analysis (Fig. 4). The first two modes can explain 17% and 11% of the total variance, respectively.

Therefore, it might be possible to increase the prediction skill for individual models (most of which have no prediction skill), and even the MME, by adopting some kind of correction scheme based on the tropical predictability and its linkage with the East Asian variability.

3. A simple scheme for improving the prediction

We consider the prediction of the precipitation anomaly in this way: a similar spatial pattern of the precipitation anomaly for the coming year has already occurred in the past for most of the cases (except for an extremely anomalous year). In addition, the above section and many other studies have indicated that the empirical orthogonal function analysis of the precipitation shows a well-organized spatial pattern in this region (e.g., Chen and Huang 2008), indicating that there were frequently a limited number of empirical patterns. Therefore, if we consider the spatially most similar year and the most dissimilar year in the tropical region, we may give a quite reasonable outlook on the spatial pattern of the precipitation anomaly for the coming year in the EAWP region.

Based on the above considerations, we propose to search the observed precipitation record for the year that is most similar and the year that is most dissimilar to the model forecast in a broad tropical region, TR, as measured in terms of the anomaly pattern correlation. These historical analogs are then linearly combined with the model forecast in the area of interest (EAWP) using empirical coefficients. The new prediction scheme can be expressed as follows:

\[
\text{Predicted precipitation anomaly} = C_1(\text{pattern of the most similar year's observed precipitation anomaly}) - C_2(\text{pattern of the most dissimilar year's observed precipitation anomaly}) + C_3(\text{model output precipitation anomaly}) k_1/k_2.
\]

The coefficients C1, C2, and C3 are the empirical weighting factors, and are set to 0.375, 0.375, and 0.25, respectively, in the current study. In the formula, k1 and k2 are the standard deviations of the observed and the simulated interannual variabilities of precipitation during 1979–1996, respectively. Thus, the term k1/k2 is used to correct the magnitudes of the modeled precipitation anomalies. The reason for doing this is that the
modeled interannual standard deviation of the JJA precipitation is systematically smaller or larger than are those of the observations (see Fig. 5). In searching for the pattern of the most similar (or dissimilar) year, the pattern correlation coefficient between the model output precipitation anomaly and the observed precipitation anomaly computed over TR is used as the criterion.

Thus, this new scheme considers not only the coupled model output but also an observed historical analog pattern—the pattern of the most similar year and the dissimilar year.

We validate the new scheme by verifying the skill of all of the models’ hindcasts in 1979–2001. In this process, the most similar and dissimilar years, as judged by the pattern anomaly correlation coefficient between the modeled and the observed precipitation anomalies, are searched for in the whole 23-yr period, excluding the current year. For example, when considering the hindcast for the year 1979, the years of 1980–2001 are used when searching for the most similar and dissimilar years.

We found that the 23-yr-averaged skill levels for the CNRM, LODY, SCNR, SCWF, SMPI, and UKMO models are 0.11, 0.14, 0.10, 0.22, 0.04, and 0.13 for the new scheme (compared to 0.08, 0.08, 0.01, 0.14, −0.07, and 0.07 for the old scheme). All models show increases in their skill when applying the new scheme. Naturally, the skill of the new scheme is partly dependent on the skill of the old scheme. Thus, the ECMWF model has the highest skill of the six models before or after applying the new scheme.

Figure 6 depicts the pattern anomaly correlation coefficients between the observations and the MME prediction for the years of 1979–2001. In most of the years, the new scheme has larger or very similar ACCs compared with the old scheme, except for the years 1981, 1982, 1983, 1986, and 1999. Therefore, the skill of the prediction could be increased by application of the new scheme. Since the time period is short (only 23 yr), the temporal anomaly correlation coefficient is not computed, as the result may be dominated by some special years.
We now compute the RMSE to further validate the new scheme. The spatially averaged RMSEs are depicted in Fig. 7, as expressed by the percentage of the multiyear precipitation climatology. All models and the MME show decreases in the RMSE. The RMSE is smaller than 30% for all the models in the new scheme.

As an example, we present the spatial distribution of the precipitation anomalies for the year 2001 from the MME predictions obtained by the original scheme and the new scheme, compared with the observations (see Fig. 8). The year 2001 has two major positive precipitation anomalies, located in the Bay of Bengal and the SCS–south China region, whereas the precipitation in central China is substantially below average. The hindcast by the old scheme cannot reasonably reproduce the anomalies in these regions, particularly in the Bay of Bengal and the SCS–south China area. However, the new scheme largely improves the hindcast of the precipitation anomalies, especially in the Bay of Bengal, the SCS, and central China. Therefore, the precipitation patterns of the new scheme are considerably better than are those of the original scheme.

4. Conclusions

In this research, a new seasonal precipitation prediction scheme for the East Asian and Western Pacific region has been proposed based on the results of European coupled climate model predictions. In this scheme, the precipitation anomalies of the most similar year and the most dissimilar year, judged by the similarity between the observed and modeled anomaly patterns in the tropical region, are used to calculate new predicted precipitation anomalies in the EAWP region.

An examination of the new scheme using the DEMETER multimodel hindcast results from Europe was performed. The results show that the new scheme can substantially improve the summer precipitation anomaly predictions in the EAWP region. All six models show increased pattern correlation coefficients between the predictions and the observations averaged for the years of 1979–2001. The largest improvement seen in the new scheme was found in the hindcast by the MME. The averaged ACC for 1979–2001 was 0.12 for the old scheme (direct model output of the precipitation anomalies) and 0.22 for the new scheme. The new scheme also demonstrates decreased root-mean-square errors in every model for the hindcasts of the years 1979–2001, as compared to the old scheme.

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