Statistical Downscaling of Pattern Projection Using Multi-Model Output Variables as Predictors*

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ABSTRACT

A pattern projection downscaling method is employed to predict monthly station precipitation. The predictand is the monthly precipitation at 1 station in China, 60 stations in Korea, and 8 stations in Thailand. The predictors are multiple variables from the output of operational dynamical models. The hindcast datasets span a period of 21 yr from 1983 to 2003. A downscaled prediction is made for each model separately within a leave-one-out cross-validation framework. The pattern projection method uses a moving window, which scans globally, in order to seek the most optimal predictor for each station. The final forecast is the average of the model downscaled precipitation forecasts using the best predictors and is referred to as DMME. It is found that DMME significantly improves the prediction skill by correcting the erroneous signs of the rainfall anomalies in coarse resolution predictions of general circulation models. The correlation coefficient between the prediction of DMME and the observation in Beijing of China reaches 0.71; the skill is improved to 0.75 for Korea and 0.61 for Thailand. The improvement of the prediction skills for the first two cases is attributed to three steps: coupled pattern selection, optimal predictor selection, and multi-model downscaled precipitation ensemble. For Thailand, we use the single-predictor prediction, which results in a lower prediction skill than the other two cases. This study indicates that the large-scale circulation variables, which are predicted by the current operational dynamical models, if selected well, can be used to make skillful predictions of local precipitation by means of appropriate statistical downscaling.

Key words: precipitation, dynamical model, downscaling, multi-model ensemble

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1. Introduction

East Asian monsoon prediction is still a challenge for current General Circulation Models (GCMs) due to large errors in these models (Kang et al., 2002; Wang et al., 2004; Zhang et al., 2006; Kang and Park, 2007a). Generally, dynamical seasonal prediction errors arise from model deficiencies in the representation of complex terrain, the governing physics and the atmospheric uncertainty (Wilks, 1995). In order to improve the seasonal prediction skill, a multi-model ensemble (MME) system has been developed by reducing the uncertainties from different models in the past decades. It has been demonstrated that MME produces more reliable probability forecasts of seasonal climate anomalies than a single model (Palmer and Shukla, 2000; Krishnamurti et al., 1999; Zhu et al., 2008). Wang et al. (2007) improved the model forecast skill on the Asian summer rainfall through a revised 25-point Shuman-Shapiro spatial filter applied to six atmospheric GCMs and MME predictions. However, MME still has little skill in midlatitude regions. In addition, GCMs generally employ a spatial resolution of $2.5°\times2.5°$ (latitude×longitude), and they are far from being able to provide station-scale climate information needed by users.

Current GCMs, nevertheless, are able to reasonably simulate the large-scale atmospheric variables

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such as sea level pressure (SLP) and 500-hPa geopotential height (Z500) (von Storch et al., 1993; Kang et al., 2004). In some regions, local precipitation has reliable statistical relationships with the large-scale atmospheric variables, and the relationships may reveal robust dynamical and physical mechanisms between the local rainfall and large-scale circulations. Statistical downscaling methods establish an empirical statistical relationship between one or several large-scale meteorological variables, commonly those representing the atmospheric circulation, and local-scale variables (predictand), and then infer local changes by means of sensibly projecting the large-scale information on the local scale (Zorita and von Storch, 1999). A statistical downscaling scheme can also use GCM output as predictor data to make predictions, which is known as model output statistics (MOS; Wilks, 1995).

Based on the MOS and MME techniques, a pattern projection downscaling system (Kang et al., 2007b, 2009) had been developed using the multi-model outputs collected by APEC (Asia-Pacific Economy Cooperation) Climate Center (APCC). APCC has been operationally running MME with the timely contributions of GCM hindcasts and forecasts from 15 institutes of the APEC members. The hindcast datasets are well-suited for an MOS-based downscaling. So far, the statistical method has been successfully applied in predicting precipitation over the Philippines, Thailand, Korea, Malaysia, etc. (Kang et al., 2007b, 2009; Chu et al., 2008; Liew et al., 2010). This paper will review the pattern projection downscaling technique developed at APCC and demonstrate the skill improvement in seasonal prediction using the new case of Beijing, China in comparison with cases of Korea (Kang et al., 2009) and Thailand (Kang et al., 2007b).

This paper is arranged as follows. Section 2 describes the datasets used in this study and introduces the downscaling methodology. Section 3 demonstrates the skills of downscaling prediction using the cases of China, Korea, and Thailand, and goes on to analyze how the prediction skills are improved in the downscaling procedures. A summary is provided in Section 4.

2. Data and methodology

2.1 Data

The predictand is station-based monthly rainfall. The observed data from 1983 to 2003 are used not only for the development of the statistical downscaling technique, but also for validating the prediction scheme using a cross-validation framework.

The predictor data are taken from operational seasonal prediction model outputs. The hindcast data of one-month lead predictions are outputs from Seasonal Prediction Model Intercomparison Project (SMIP) type experiments (Kobayashi et al., 2000). Table 1 gives a basic description of the models and their hindcast datasets. HFP indicates Historial Forecasting Project. BCC and NCEP models are coupled models (tier-1) while other models are tier-2 systems. Based on the evaluation of the collected models, we selected different models for different cases. The predictors are taken from 8 variables of GCM outputs: Z500, SLP, 850-hPa temperature (T850), 2-m air temperature (T2M), 850-hPa zonal and meridional velocity (U850, V850), and 200-hPa zonal and meridional velocity (U200, V200). The hindcast data also span the 21-yr period from 1983 to 2003 and have a spatial resolution of 2.5 degrees in both latitude and longitude.

Table 1. Description of the GCMs used in this study

Model	Institution (member economy)	Data type	Sea surface temperature
BCC	Beijing Climate Center (China)	SMIP/HFP	Forecast
CWB	Central Weather Bureau (Chinese Taipei)	SMIP/HFP	Forecast
GCPS	Korea Meteorological Administration (Korea)	SMIP/HFP	Forecast
GDAPS	Korea Meteorological Administration (Korea)	SMIP/HFP	Forecast
HMC	Hydrometeorological Center (Russia)	SMIP/HFP	Forecast
JMA	Japan Meteorological Agency (Japan)	SMIP/HFP	Forecast
MGO	Main Geophysical Observatory (Russia)	SMIP/HFP	Observation persistence
NCEP	Climate Prediction Center/NCEP (United States)	SMIP/HFP	Forecast

2.2 Methodology

The downscaling prediction includes three steps as follows.

2.2.1 Coupled pattern selection and projection

Pattern projection is based on the premise that local precipitation variation is related to the variation of large-scale patterns. The latter can be well simulated by dynamical models, hence local precipitation forecasts may be retrieved from the information in the coupled pattern using a proper transfer function. Suppose that the predictand and predictor are $Y(t)$ and $X(i,j,t)$, respectively. Here, $Y(t)$ is local station precipitation, and $X(i,j,t)$ is model predicted large-scale variable at the grid point (i,j) at the same time. Then,

$$Y(t) = \alpha X_p(t) + \beta, \tag{1}$$

where $X_p(t)$ is the projection of the predictor in an optimal window. The optimal window refers to the area in which the sum of the correlation coefficients between the predictor field and the predictand at the target station reaches the maximum,

$$X_p(t) = \sum_{i,j} \mathrm{COR}(i,j) \times X(i,j,t). \tag{2}$$

The correlation coefficient based on the training period is obtained as

$$\begin{aligned}\mathrm{COR}(i,j) = \Big\{\frac{1}{N}\sum_{i,j}(Y(t)-Y_m) \times (X(i,j,t) \\ -X_m(i,j))\Big\}/\Big\{\sigma_x(i,j) \times \sigma_y\Big\},\end{aligned} \tag{3}$$

where N is the number of training years; the subscript m means the average of the variable during the training period; σ denotes the variance (Kug et al., 2007; Kang et al., 2007b, 2009).

One important step in the downscaling procedure is the selection of the optimal window. It has been documented that GCM predictions, whose large-scale circulation variables are used as predictors in downscaling, commonly suffer from substantial drifts away from the observed climate, and these drifts are quite different for each model (Kang et al., 2002; Kang and Schukla, 2006). In order to avoid these model biases, a movable window with a size of 15(longitude)×10(latitude) grid points is set to scan over the globe. The optimal window is the most sensible area in which the sum of correlation coefficients of a predictor in the window with the precipitation at the target station reaches the maximum. Through this step, the large-scale signals related to the variability of local precipitation may be captured, and the precipitation at the target station is ultimately specified by the large-scale information in the optimal window.

2.2.2 Multi-predictor optimal selection

In the Korean case, through the empirical orthogonal function (EOF) analysis, we found that the precipitation over the 60 stations shows quite different interannual variations owing to the influence of the local terrain. Consequently, using only one predictor to specify the variations of rainfall at 60 stations is not enough; one needs to search for more signal-bearing predictors and select the best one for different stations. In this study, eight model output variables are used for downscaling, and the predictor is the one with the best downscaling prediction skill; therefore, the predictor for one station may be different from that for another.

2.2.3 Multi-model ensemble

The uncertainties of MOS forecasts are in general caused by internal variability of the climate system, the GCMs and the statistical downscaling models (Benestad, 2001; Chen et al., 2006). Benestad (2002) found that uncertainties in monthly and annual precipitation scenarios associated with GCM realizations tended to be greater than those associated with the downscaling strategies. In order to reduce the uncertainties associated with GCMs, an MME prediction is performed using the average of the precipitation downscaled from the best predictor of the GCMs (henceforth referred to as "DMME"). For comparison, we create another MME using the average of the precipitation directly predicted by these GCMs (henceforth referred to as "RMME"). RMME precipitation, which has the same resolution of 2.5°×2.5° as that of the GCMs, is interpolated to station points using the method of 9-grid inverse distance to a power. As a result, the precipitation from both DMME and RMME can be verified against the station observation; moreover, the skills of both types of MME predictions can be compared with each other.

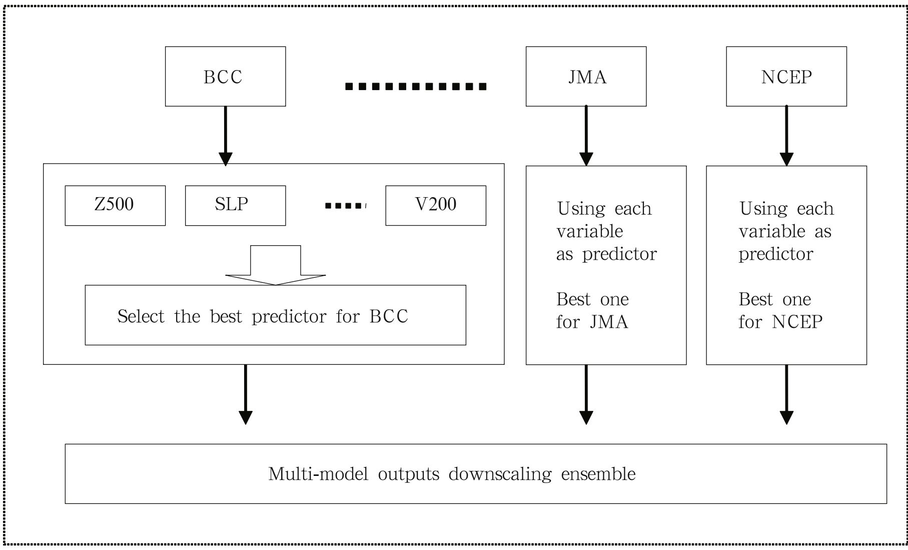

Fig. 1. The flow chart of the downscaling strategy.

Figure 1 shows the flow chart of the downscaling strategy. For each model, the downscaling is first carried out using each of the eight variables as predictor, separately. The downscaling procedure is tested within a leave-one-out cross-validation framework, where one year used as forecast year is removed, leaving other 20 years as the training period for developing the statistical relation (WMO, 2002). In this way, the downscaling forecast is performed in turn for each of the 21 years. Then, DMME is generated by averaging the downscaled rainfall from the best predictor of GCMs. Finally, both DMME and RMME predictions are compared with the observed precipitation at each station.

3. Results

3.1 Beijing

The data of monthly mean precipitation of Beijing in August 1983–2007 are obtained from the China Meteorological Administration. The predictors are from the outputs of all the models described in Table 1 except MGO. A cross-validation verification is made during the 21-yr period of 1983–2003, then the independent forecasts for 4 yr from 2004 to 2007 are made and the forecast results are verified against the observation.

Figure 2 shows that raw MME generally predicts wrong signs of precipitation anomalies for August in Beijing in the cross-validation period and independent forecast years. The correlation coefficient between observed and simulated precipitation anomalies is only 0.04 during the hindcast period (1983–2003). In the four independent forecast years, raw MME predicts wrong signs for three years. Thus, users cannot obtain any valuable prediction information from the selected GCMs for the Beijing station.

Figure 3 shows that downscaled MME predictions are in quite good agreement with respective observed precipitation anomalies during the cross-validation period (1983–2003). The correlation coefficient between observed and downscaled precipitation anomalies in the 21 years is 0.71. In the four independent forecast years, downscaled MME successfully predicts correct signs. By comparing Fig. 3 with Fig. 2, it is found that downscaled MME achieves considerable improvement in prediction skill than raw MME. However, downscaling fails to predict the reasonable amplitude of the precipitation anomalies. During the period of cross-validation, the selected predictor for different years is different even for one station, and the predictor also changes among these models; but T850, SLP, and V850 are commonly selected as the best predictor in most of the years.

From Fig. 4, it is found that downscaling substantially improves the prediction skill of each model compared with that of raw models in simulating precipitation. Among raw model predictions, BCC shows the best prediction for Beijing with acorrelation coefficient of 0.29, and other models generally have no prediction skill. After downscaling, all models (except CWB) show considerably higher prediction skills. This indicates that these models have the ability to predict the large-scale circulation well and the method can extract effective information from the large-scale circulation for downscaling prediction.

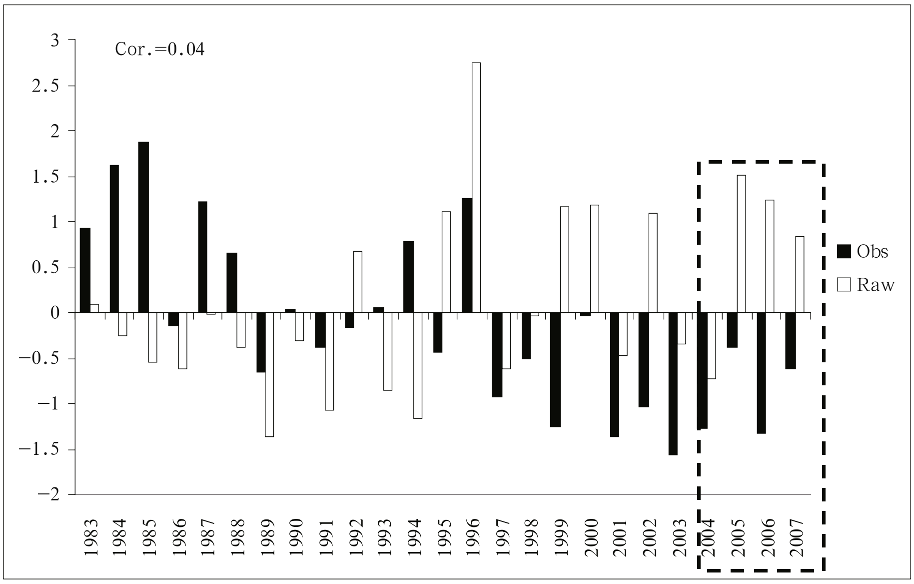

Fig. 2. Precipitation anomalies of observation and raw MME prediction in Beijing in August during the hindcast period (1983–2003) and independent forecast years (2004–2007).

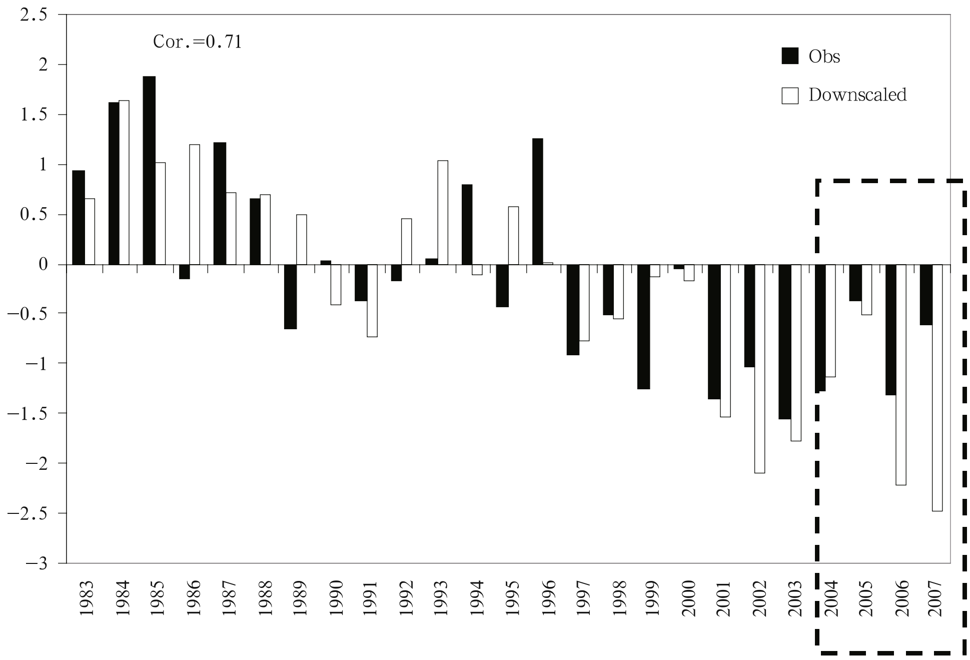

Fig. 3. Precipitation anomalies of observation and downscaled MME prediction in Beijing in August during the hindcast period (1983–2003) and independent forecast years (2004–2007).

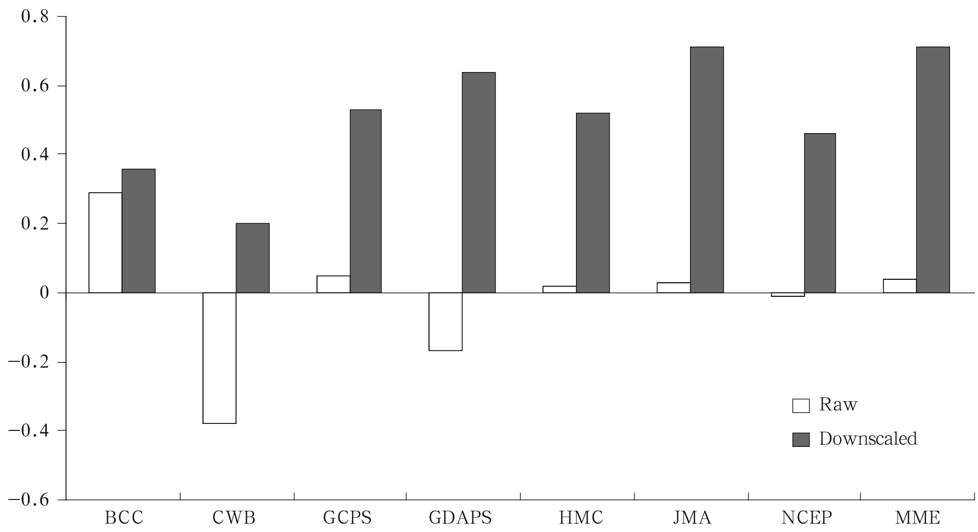

Fig. 4. Correlation coefficients between observed and raw/downscaled precipitation in Beijing during the hindcast period (1983–2003) for seven models and the MME.

3.2 Korea

The predictand is station-based summer rainfall from 1983 to 2003 for 60 stations over Korea. The observation data are taken from the Korea Meteorological Administration. The predictor data are from the outputs of the following six models: CWB, GCPS, GDAPS, JMA, MGO, and NCEP (see Table 1).

Figure 5 presents three time series of station-averaged precipitation anomalies: observation, DMME, and RMME, during the period of 1983–2003. Compared with observation, RMME predicts opposite signs of anomalies in 12 yr. On the other hand, DMME predicts the same sign of rainfall anomalies as in the observation in 17 yr, especially in the heavy rainfall years of 1987, 1998, 2002, and 2003, and in the drought years of 1983, 1988, 1992, and 1994. This indicates that the large-scale variables, which are outputs from the current operational dynamical models, are useful in predicting local rainfall, particularly in extreme years, by means of the downscaling strategy.

Figure 6 shows the distributions of temporal correlation coefficients between observed and predicted precipitation: the panels (a) to (f) are for six models and panel (g) is for RMME; the panels (h) to (m) are for six models using the downscaling strategy and panel (n) is for DMME. It is found that the predictions from these models except GCPS show very poor performance at most of the stations. Even RMME performs poorly. This indicates that the prediction skill cannot be improved through the MME procedure if the participating models have a poor prediction skill. On the other hand, the downscaling predictions by these models have been substantially improved compared with their respective raw model predictions. Moreover, DMME prediction is not only much better than RMME prediction, but also better than any single model downscaling prediction. It is noticed that downscaling predictions by these individual models commonly perform well only in part of Korea, but the combination of these downscaling predictions (DMME) achieves quite good prediction skills at all of the 60 stations. Figure 6 demonstrates clearly that DMME further improves the prediction skill by successfully reducing the uncertainties associated with the individual models.

3.3 Thailand

The observed station monthly precipitation used in this research is taken from the Thailand Meteorological Department (TMD). Our target area is the Bangkok region including eight stations. The predictor data are from SLP outputs of six operational seasonal prediction models: CWB, GCPS, GDAPS, JMA, MGO, and NCEP (see Table 1).

Figure 7 shows that the first SVD mode between the observed station precipitation and observed SLP explains 83% of the total covariance, and the correlation coefficient of the expansion coefficients for the leading SVD mode reaches 0.81. It is found that strengthening SLP over the South China Sea, Philippine Sea, and western North Pacific is accompanied by enhanced precipitation in the Bangkok region. This is dynamically reasonable because strengthening SLP centered over the Philippine Sea favors the southeasterly passing over the Bangkok region along the South China Sea and the Gulf of Thailand, bringing about more rainfall in the region. It is noted that the eigenvector values of precipitation at the eight stations

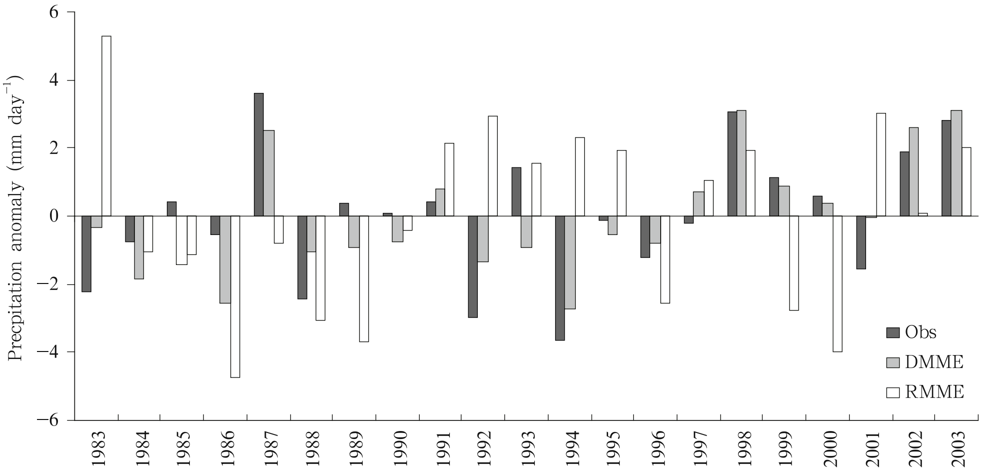

Fig. 5. The station-averaged summer precipitation anomaly time series in Korea from observation, DMME, and RMME during the period of 1983–2003.

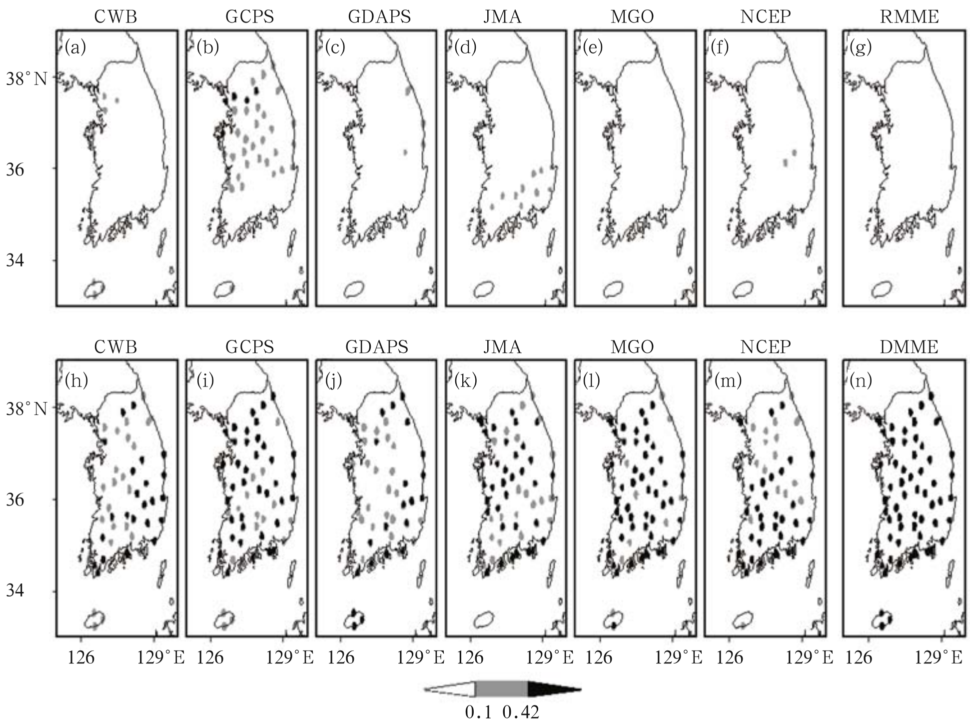

Fig. 6. Distributions of the temporal correlation coefficients between predicted rainfall and observation at each station in Korea. (a) to (f) are for six participating models and (g) is for RMME; (h) to (m) are for downscaling predictions of six model and (n) is for DMME. The darker station points indicate the correlation coefficient at the 5% significance level.

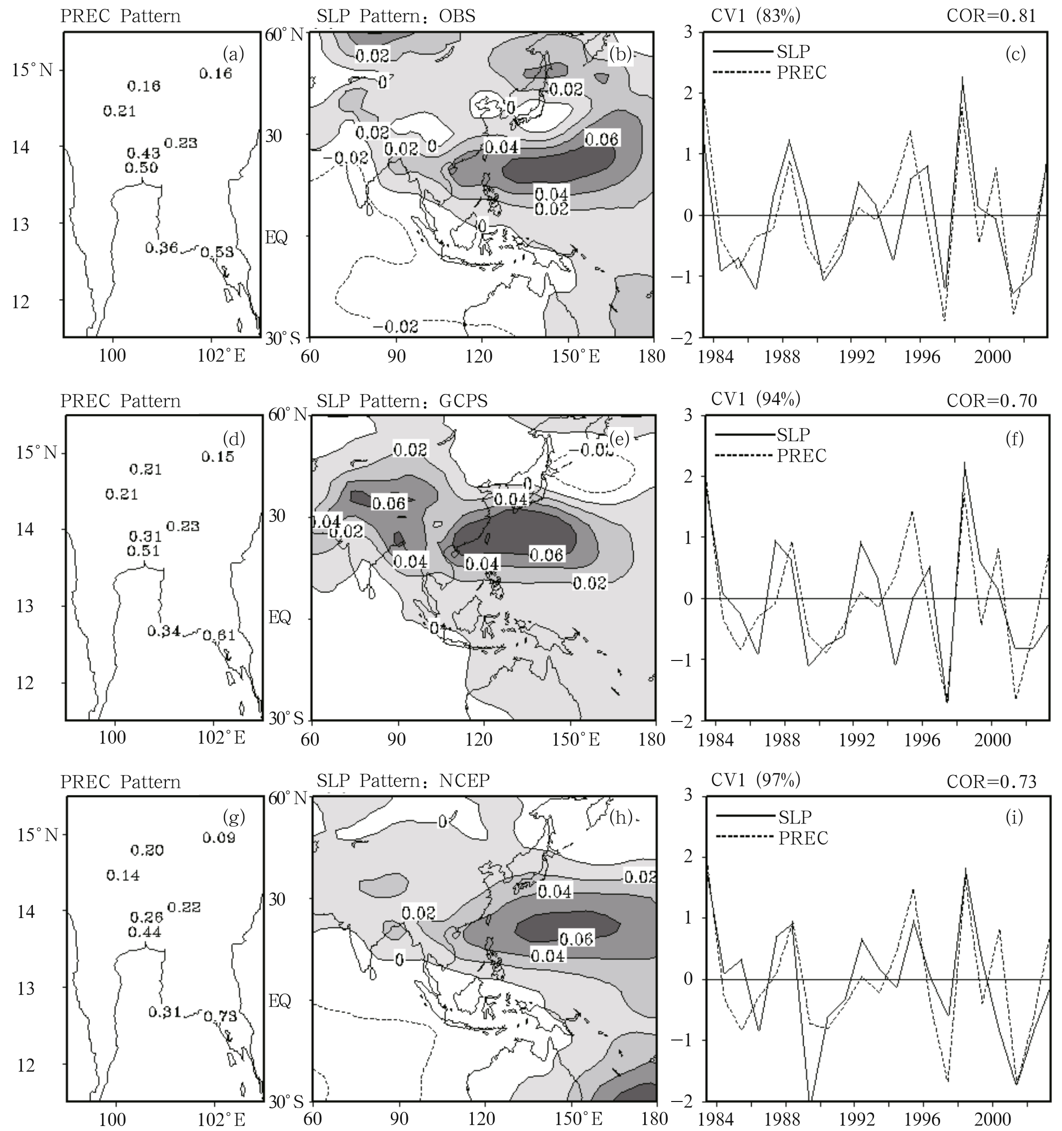

Fig. 7. The first SVD mode between the observed station precipitation in the Bangkok region and observed SLP, and the time series of the expansion coefficient for the leading mode (a, b, c); the first SVD mode and the time series of the expansion coefficient for GCPS (d, e, f); and the first SVD mode and the time series of the expansion coefficient for NCEP (g, h, i).

show the same sign, which suggests that the precipitation at all these stations is controlled by the same large-scale circulation process. This is probably because all the eight stations are located in the same plain which is open to the Gulf of Thailand (see Fig. 7a). We take GCPS and NCEP as examples and show the leading SVD mode between observed precipitation and predicted SLP in Fig. 7. Basically, both models can reproduce the leading mode of the observation well.

Based on the correlation analysis and the SVD analysis between observed precipitation and SLP, we think the domain 30°S–60°N, 60°–180°E contains the large-scale circulation information for downscaling over the Bangkok region. We set a movable window to search for the most sensible area, and then make downscaling and MME predictions. Figure 8 shows that the skill of the area-averaged precipitation over

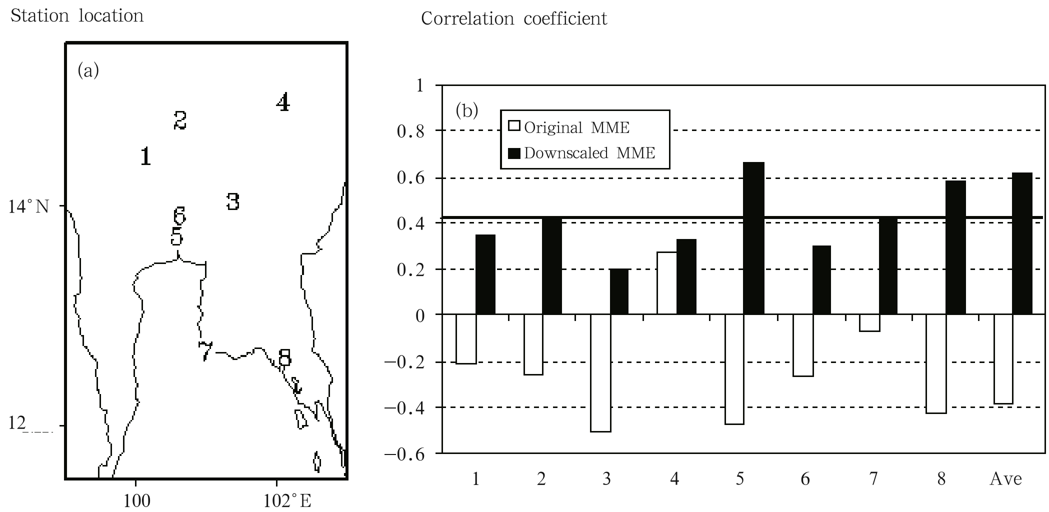

Fig. 8. (a) Station location in the Bangkok region and (b) the correlation coefficients between the observed station precipitation and two MME predictions: one is downscaled MME, and the other is raw model output MME. The solid line in panel (b) indicates the critical value of correlation coefficient at the 5% significance level.

the Bangkok region for downscaled MME reaches 0.62; while for raw MME, the skill is –0.39. For all the stations, the skills have been substantially improved. This is probably because precipitation at all the stations shows a similar covariant scheme with the SLP pattern. In other words, the downscaling from the coupled SLP pattern can predict the variability of precipitation at all the stations if these models have good performance in predicting SLP. It is interesting to note that the correlation coefficient in the capital Bangkok (station No. 5 in Fig. 8) reaches 0.66.

4. Summary

This study uses a multi-model output downscaling technique to predict monthly station rainfall. The hindcast datasets of operational GCMs and station observed data, spanning a period of 21 yr from 1983 to 2003, are employed to develop the downscaling technique under a leave-one-out cross-validation framework. In order to search for a coupled pattern, a movable window is set to scan over a predictor field to find the area that is highly correlated with the station rainfall. Local precipitation can be specified by predicted large-scale information in the optimal window based on the derived statistical relationship in the training period. Single predictor may perform well in the tropical region such as Bangkok in Thailand, where the terrain is relatively simple and rainfall at all stations has a similar relationship with a particular large-scale variable; however, single predictor cannot capture the variations of rainfall at all stations where the rainfall is strongly influenced by local complex mountainous terrain. In our study, eight large-scale variables from GCM outputs are taken as predictors to make downscaling predictions for each station, separately; the best predictor for a model is the one with the best skill. The final prediction, DMME, is the average of all downscaled rainfalls using the best predictors of GCMs. RMME, an average of all GCM predicted rainfall, is also carried out for comparison.

This paper demonstrates that DMME predictions are superior to RMME predictions at 1 station in Beijing of China, 60 stations in Korea, and 8 stations in Bangkok of Thailand. For Bangkok, the correlation coefficient of the prediction by DMME with the observation is improved from –0.39 to 0.61 even using a single predictor; after the multi-predictor optimal selection is applied, the skill for Beijing is improved from 0.04 to 0.71; and for Korea, the skill is improved from –0.21 to 0.75. Downscaling prediction skills are first substantially improved through a coupled pattern projection procedure. Then, the skills are further improved through two steps: (1) multi-predictor optimal selection; and (2) multi-model downscaling ensemble. These skillful DMME predictions indicate that some large-scale variables, which are predicted by current operational GCMs, contain useful information on the local climate variation, and the information can be used to predict local precipitation variability if an appropriate downscaling strategy is applied.

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