Effects of the Physical Process Ensemble Technique on Simulation of Summer Precipitation over China*

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ABSTRACT

The effects of the physical process ensemble technique on simulation of summer precipitation over China have been studied by using a p-σ regional climate model with 9 vertical levels ($p\sigma$-RCM9). The results show that there are obvious differences among simulations of summer precipitation over China from different individual ensemble members. The simulated precipitation over China is sensitive to different cumulus convection, radiative transfer, and land surface process parameterizations. These differences lead to large uncertainties in the simulation results. The standard deviation of the simulated summer precipitation departure percentage over West China is larger than that over East China, signifying that the simulated precipitation over East China has higher reliability and consistency than that over West China. The Talagrand diagram shows that the ensemble system has reasonable dispersion in the simulated summer mean precipitation over East China. The summer ensemble mean precipitation over East China evaluated by various indices is better than most single simulations. The physical process ensemble technique reduces the uncertainties of the model physics in precipitation and improves the simulation results as a whole. Further, adopting the optimized ensemble mean method can obviously improve the performance of the $p\sigma$-RCM9 model in simulation of summer precipitation over East China.

Key words: regional climate model, physical process ensemble, precipitation, uncertainty

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1. Introduction

The weather is a chaotic system (Lorenz, 1963), whose predictability is limited by errors in the initial conditions and the models (Buizza et al., 2005). These two sources of uncertainty limit the skill of single and deterministic forecasts in an unpredictable way. Ensemble forecasting is a feasible method to integrate a deterministic forecast with an estimate of the probability distribution of atmospheric states. It is based on a statistical sampling approach (Leith, 1974) in which the forecast probability density function is approximated using a finite sample of forecast scenarios. The ensemble systems are often integrated from different initial conditions or using different numerical models to capture initial condition or model-related forecast uncertainties. Ensemble forecasting is introduced into numerical weather prediction (NWP) as a feasible way to reduce influences of initial conditions and model errors on simulation results, and has attracted more and more attention. It has become a new NWP approach (WMO, 1996; Li and Chen, 2002) and led an important direction in the present NWP research and development (Du, 2002).

With the advances of computer science and numerical models, the ensemble forecast technique has been developed from only including the effects of initial conditions to including the impacts of model dynamics and physical processes. Previous studies on the uncertainties of models can be divided into two sorts. The first one is about multimodel ensemble or super ensemble forecasting (Krishnamurti et al., 1999), which generally uses linear methods to produce better predictions by combining several independent forecasts from different numerical models with potentially fundamentally different statistics. The multimodel ensemble considers the impacts of both initial conditions and physical processes. Past studies on

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atmosphere and ocean circulation models have shown that the multimodel ensemble usually produces a more skillful forecast than the individual ensemble members (Doblas-Reyes et al., 2000; Kharin and Zwiers, 2002; Gao and Dirmeyer, 2006). Recent studies of Zhou et al. (2009) showed that the multimodel ensemble simulation had a skill in capturing the leading modes of the interannual variability of the Asian-Australian monsoon. The second sort of model error studies is about physical process ensemble forecasting, in which only one model is used but each member uses a unique version of the model by varying combinations of model physics options and/or perturbed parameterizations (Mullen et al., 1999). Most studies have been conducted on the influences of model physics and physical process ensemble. For example, Kain and Fritsch (1992) found that the simulation of a squall line is affected significantly by the trigger function that determines where and when the model parameterized convection is activated. Wang and Seaman (1997) further showed that different convective parameterization schemes produce different evolutions of convective activity.

When several measures of skill are examined, no one scheme is clearly better than the others. It is well known that model parameterizations can feedback and influence the baroclinic development of the atmosphere (Gyakum, 1983). The sensitivity of forecast accuracy to model parameterizations appears to be greatest for short-range forecasts, as highlighted by our inability to forecast accurately convective weather events during summertime. Houtekamer et al. (1996) applied the physical process ensemble approach by varying four model options (horizontal diffusion, convection/radiation, gravity wave drag, and orography) in a medium-range ensemble system. They found that the physical process ensemble made an obvious improvement. Du et al. (1997) concluded that varying model physics was a potentially powerful method to create an ensemble. The results from Chen et al. (2003, 2006) showed that single determinate predictions of heavy rain were unstable, while physics ensemble predictions could reflect the uncertainties of heavy rain, provide more useful guidance, and had a higher application value. Wang and Duan (2003) simulated three precipitation cases during the 1999 Meiyu period over East China by using a physical process ensemble forecasting system created by choosing four kinds of cumulus parameterization schemes and two kinds of planetary boundary layer (PBL) parameterization schemes. The results showed that stable precipitation forecast could be achieved from the ensemble mean.

It is well known that summer precipitation forecast is still one of the most difficult tasks in NWP (Zhou and Li, 2002). China is located in the East Asian summer monsoon region where summer precipitation has a great variability (Zhou and Yu, 2005; Yu and Zhou, 2007). Improving the predictability of summer precipitation over China is meaningful for climate disaster prevention. Most recent physical process ensemble studies are focused on short-range weather events or heavy rain cases by using NWP models, but little such work has been done for climatic precipitation simulations.

On the other hand, initial perturbation ensemble is very important for weather forecast, but not for climate system prediction. It has limited impacts on the real uncertainty of precipitation forecast. In contrast, different physical parameterization schemes are set up on different assumptions and the uncertainties related to model physical processes are supposed to be significant to the climate system. The results from Stensrud et al. (2000) showed that the influences of model physics became much larger than those of initial conditions when considering mesoscale, sensible weather phenomena in the warm season. Thus, in this paper, we will focus on the physical process ensemble through simulating and validating the summer precipitation over China based on a p-σ regional climate model with 9 vertical levels ($p\sigma$-RCM9) (Huang, 2007). Our objectives are to answer such questions as follows: Is the physical process ensemble technique applicable to the simulation of summer precipitation over China? Can the physical process ensemble technique improve the performance of the $p\sigma$-RCM9 in simulating the summer precipitation over China than any of its individual members?

This paper is organized as follows: The $p\sigma$-RCM9 model and numerical experiment schemes are described briefly in Section 2. Data and analysis methods are introduced in Section 3. The simulation results are presented in Section 4. Finally, the concluding remarks are given in Section 5.

2. Model description and numerical experiment design

2.1 Model description

The $p\sigma$-RCM9 regional climate model used in this study is based on a primitive equation model with a p-σ vertical coordinate. It was firstly developed by Kuo and Qian (1981, 1982) for investigating the diurnal changes of weather and climate in the development of monsoon circulation over East Asia. It was further developed by Qian (1985), Zhang and Qian (1999), Liu and Qian (1999), Liu et al. (2002), Wang and Qian (2002), Huang and Zhang (2007), and Huang (2007). The model has 9 vertical levels with a horizontal resolution of $1°\times1°$. The pressure coordinate is used above 400 hPa with four uniform layers. Below 400 hPa, the σ and σ_b coordinates are adopted. Four σ layers are uniformly divided, and only one layer is defined as the atmospheric boundary layer with 50-hPa thickness in the σ_b coordinate. The model domain is from 0° to 60°N and 70° to 140°E, including the Tibetan Plateau, the Bay of Bengal, the South China Sea, and part of western Pacific. The model includes a PBL parameterization (Businger, 1973); four cumulus convective parameterization schemes, namely, the Kuo scheme (Kuo, 1974), the Anthes-Kuo scheme (Anthes, 1977), the Grell scheme (Grell, 1993), and the Betts-Miller scheme (Betts and Miller, 1993); two radiative transfer schemes, the KQ scheme (Qian et al., 1988) and the NCEP/NCAR CCM3 CRM (column radiation model) radiative transfer scheme (Kiehl et al., 1996); and two land surface process parameterization schemes, HBTS (heat balance temperature scheme) (Qian, 1988) and BATS1e (biosphere-atmosphere transfer scheme version 1e) land model (Dickinson et al., 1993). The $p\sigma$-RCM9 model and its previous versions are used extensively and successfully in simulating large-scale circulations and investigating the impacts of air-sea feedback on the atmospheric circulation (Wang and Qian, 2002; Zhang et al., 2006; Huang et al., 2007; Huang et al., 2008).

2.2 Numerical experiment design

Twelve different configurations of the $p\sigma$-RCM9 regional climate model are used to produce a 12-member ensemble of simulations starting from identical model initial conditions. Studies of Du et al. (1997) showed that the ensemble mean can obtain 90% improvement with ensemble sizes as small as 8 to 10 members. We are able to investigate a wide range of model configurations and still remain within our computational limitation by using 12 members in the ensemble. We choose different model physical process parameterization schemes to construct 12 various versions of the $p\sigma$-RCM9 regional climate model (shown in Table 1) and produce an ensemble of simulations that start from the same initial and lateral boundary conditions. Each simulation is carried out from 16 May to 31 August in each year from 1996 to 2005. We choose the results in the last 92 days from the model outputs in each simulation for each summer. The

Table 1. Model configurations used in the physics process ensemble

Ensemble member	Cumulus convective parameterization scheme	Land surface parameterization scheme	Radiative transfer scheme
S1	Kuo	HBTS	KQ
S2	Anthes-Kuo	HBTS	KQ
S3	Grell	HBTS	KQ
S4	Betts-Miller	HBTS	KQ
S5	Kuo	BATS1e	KQ
S6	Anthes-Kuo	BATS1e	KQ
S7	Grell	BATS1e	KQ
S8	Betts-Miller	BATS1e	KQ
S9	Kuo	HBTS	CRM
S10	Anthes-Kuo	HBTS	CRM
S11	Grell	HBTS	CRM
S12	Betts-Miller	HBTS	CRM

initial and boundary conditions, including wind, air temperature, specific humidity, and geopotential height fields are specified by the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis (Kalnay et al., 1996) daily mean data. The NCEP/NCAR reanalysis weekly mean OISST data offer the oceanic boundary forcing. The SST is interpolated onto the $p\sigma$-RCM9 grids by using the bilinear interpolation method. The nudging technique is applied only to 10 outer grids of the lateral boundary.

3. Data and analysis methods

3.1 Data

The following data are used in this paper: a) The NCEP/NCAR reanalysis daily mean data from 1996 to 2005, including air temperature, specific humidity, wind, and geopotential height fields. b) The observed daily precipitation over 738 stations in China from 1996 to 2005.

3.2 Analysis methods

The analysis methods, including standard deviation, spatial correlation coefficient (SCC), rate of the same anomaly sign (RSAS), prediction correctness, and root mean square error (RMSE), are adopted to assess the model results. Detailed descriptions of these methods are given below.

3.2.1 Standard deviation

The standard deviation of an ensemble of simulations is given by

$$D_{\mathrm{s}} = \sqrt{\frac{\sum_{i=1}^{n}(x_i/\overline{x}-1)^2}{n}}, \tag{1}$$

where n denotes the ensemble number, e.g., $n = 12$ in this study; x_i is the precipitation of the ith simulation; $\overline{x}$ is the ensemble mean and can be calculated by

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i. \tag{2}$$

The standard deviation D_{s} is a good index for measuring the reliability of model results. High D_{s} indicates low reliability and high dispersion of the ensemble simulations, while low D_{s} shows high reliability and consistency of the ensemble simulations.

3.2.2 Spatial correlation coefficient (SCC)

We adopt SCC to reveal similarity in the spatial distribution between the model simulations and the observation. The SCC can be expressed as:

$$r = \frac{\sum_{I=1}^{N}(R_{\mathrm{F}I}-\overline{R}_{\mathrm{F}})(R_{\mathrm{O}I}-\overline{R}_{\mathrm{O}})}{\sqrt{\sum_{I=1}^{N}(R_{\mathrm{F}I}-\overline{R}_{\mathrm{F}})^2\sum_{I=1}^{N}(R_{\mathrm{O}I}-\overline{R}_{\mathrm{O}})^2}}, \tag{3}$$

where N denotes the grid number in an investigated domain; $\overline{R}_{\mathrm{F}}$ and $\overline{R}_{\mathrm{O}}$ are the area-averaged simulation and observation, respectively.

3.2.3 Rate of the same anomaly sign (RSAS)

The RSAS is given by:

$$A = N_t/N, \tag{4}$$

where N is the total grid number in an investigated domain; N_t is the number of grids where the anomaly signs of the precipitation in simulated results are the same as those in observation. The RSAS primarily shows the tendency of simulations. It cannot reflect the intensity of simulations.

3.2.4 Prediction correctness

The prediction correctness in a rainy season is defined by Zhao (1996):

$$P_{\mathrm{c}} = \frac{N_1+N_2+N_3+N_4}{N+N_3+N_4}\times 100\%, \tag{5}$$

where N is the total number of grids being assessed to calculate P_{c}. N_1 denotes the number of grids where the simulated and observed anomalous precipitation have the same sign. N_2 is the number of grids where 1) signs of the simulated and observed anomalous precipitation are opposite; 2) the simulated precipitation anomaly bears an absolute value of less than 20% of the climate mean. N_3 and N_4 correspond to the number of grids where 1) signs of the simulated and observed anomalous precipitation are the same; 2) the simulated precipitation anomaly bears an absolute value of between 20% and 50% for N_3, and greater than 50% for N_4 of the climate mean.

3.2.5 Root mean square error (RMSE)

The four indices introduced above primarily reflect the tendency of the model results. We adopt

RMSE to reveal the intensity of the model simulations. The *RMSE* is given by:

$$RMSE = \left\{ \frac{1}{M} \sum_{i=1}^{M} (E_i - \overline{E})^2 \right\}^{1/2}, \quad (6)$$

where $E_i = E_{\mathrm{F}i} - E_{\mathrm{O}i}$ is the differences between the model simulation and the observation; $\overline{E} = \frac{1}{M} \sum_{i=1}^{M} E_i$; M is the total grid number. The *RMSE* primarily indicates the intensity of similarity between the simulation and the observation, Low *RMSE* indicates that the intensity of the simulation is close to the observation, while high *RMSE* reflects great differences in intensity between the simulation and the observation.

4. Results

Figure 1 shows spatial distributions of the summer precipitation over China averaged from 1996 to 2005, as simulated by the 12 ensemble members, respectively. It is found that the SCC between each simulation and observation ranges from 0.21 to 0.55, indicating that the simulations from the ensemble members are significantly different from each other. Ensemble members S1, S2, S4, S9, and S10; S3 and S11; S5, S6, and S7 produce similar spatial distributions of summer precipitation over East China, respectively, but the precipitation intensity differs greatly. Some ensemble members have a good performance in simulating precipitation over some special regions, but cannot simulate precipitation over other regions. It indicates that summer precipitation over China is sensitive to cumulus convection, radiative transfer and land surface physical process parameterizations under the same initial and boundary conditions. Physical process parameterizations have large uncertainties in summer precipitation simulations.

Figures 2a and 2b display the summer ensemble mean precipitation from the 12 ensemble members and the observed summer precipitation over China averaged from 1996 to 2005, respectively. As shown in Fig. 2b, the observed summer precipitation over East China is reduced from south to north dramatically and the maximal precipitation center is located in South China. However, the ensemble mean (shown in Fig. 2a) fails to capture the maximal precipitation center in South China, and the summer ensemble mean precipitation over southern Yangtze and Huaihe valley is larger than the observation. Compared with single simulations (shown in Fig. 1), the distribution of the simulated summer ensemble mean precipitation over China with a high SCC of 0.5 in Fig. 2a is much closer to the observation than most single simulations. The physical process ensemble technique is effective in reducing the uncertainties of the physical process parameterizations.

Figure 3 shows the distribution of standard deviation of summer precipitation simulated by the 12 ensemble members according to Eq. (1). It is found that the standard deviation over East China is lower than that over West China. A minimal standard deviation center below 50% is located in southern Yangtze and Huaihe valley, signifying that the simulated summer precipitation over this region is highly consistent and reliable. However, the standard deviation over West China is over 150%, indicating that the simulation over this area is highly dispersed and less reliable. Compared with West China, the climate model has a relatively stable and reliable performance in simulating the summer precipitation over East China. Meanwhile, as shown in Fig. 2, it should be noted that the simulated precipitation over East China is much closer to the observation than that over West China. We thus concentrate on analyzing the simulation of the summer precipitation over East China (east of 105°E), which falls into the East Asian summer monsoon region and is an important region for summer precipitation forecast. The simulated summer precipitation is interpolated onto the observation stations in East China by using the bilinear interpolation method.

Firstly, we discuss the dispersion among each individual simulation to measure how well these ensemble simulations cover the reality. This is a necessary step toward further discussion of the ensemble simulation. As is well known, the Talagrand distribution or the rank histogram (Talagrand et al., 1997; Candilie and Talagrand, 2005) provides a good index of frequency and dispersion within the ensemble simulations. It gives the relative magnitude between observation and

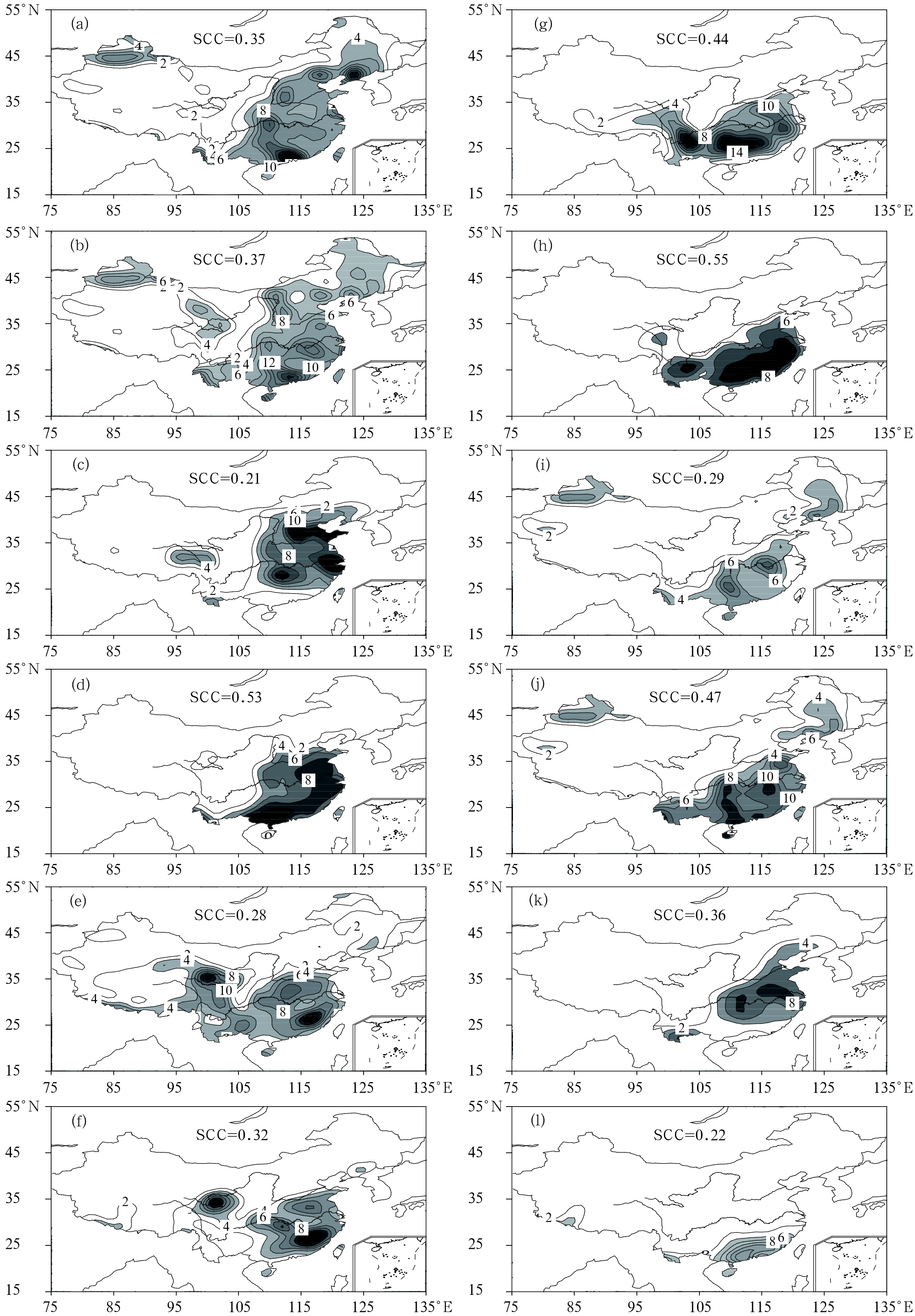

Fig. 1. Summer precipitation (mm day^{-1}) distributions over China simulated by 12 ensemble members averaged over 1996–2005. Regions with precipitation > 4 mm day^{-1} are shaded. The spatial correlation coefficients (SCC) between simulation and observation are marked in each panel.

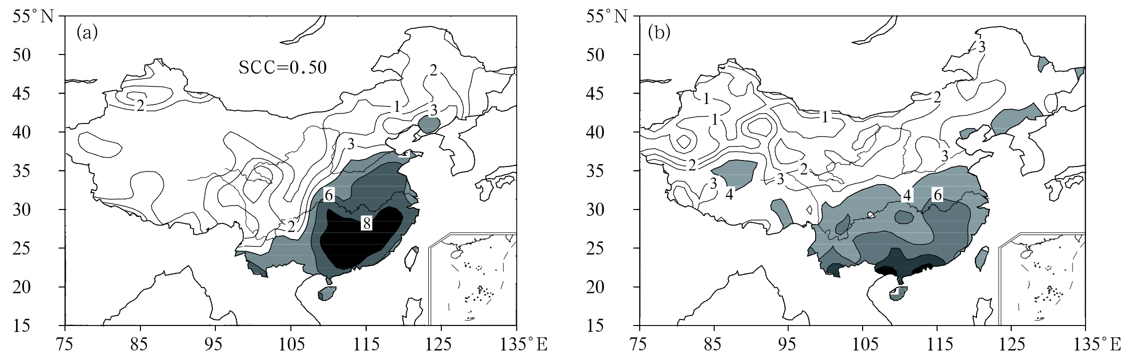

Fig. 2. Summer precipitation (mm day^{-1}) distributions from the ensemble mean (a), and the observation (b) over China averaged from 1996 to 2005. Regions with precipitation > 4 mm day^{-1} are shaded.

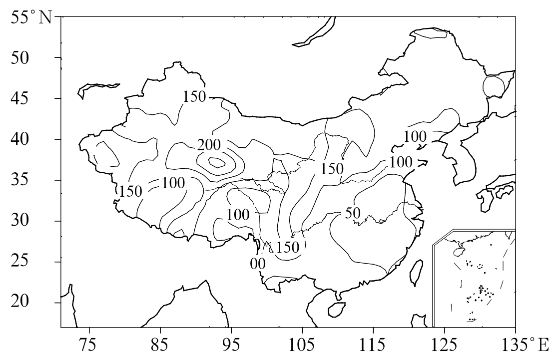

Fig. 3. The distribution of the standard deviation (%) of the summer precipitation simulated by the 12 ensemble members.

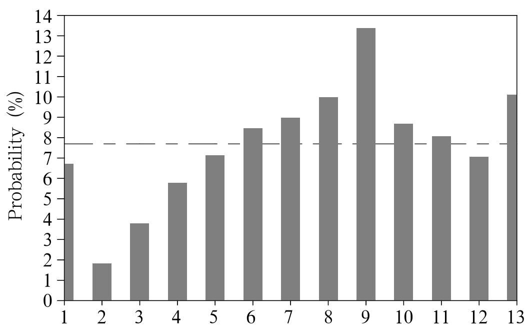

Fig. 4. Talagrand diagram defined by the 12 ordered ensemble members over East China. The dashed line shows the mean probability (7.69%).

forecast without defining any parameters such as event criterion or threshold of category. Suppose there is a forecast system with the ensemble size of n for a set of m independent samples, where $m = 5070$ (10 yr ×507 stations) and $n = 12$ in our case. We have 12 values for a certain physical variable at each grid point for a particular year, which can be sorted in order from small to big to define 12 ranks. The observation will be counted as one more rank. It is expected that each rank should have an equal probability of matching the observation. So a good ensemble should have a uniform distribution. Otherwise, non-uniform shapes may indicate under/over dispersion and bias.

Figure 4 gives the Talagrand distribution of summer mean precipitation over East China. It is shown that the probability values have a little difference from each other and most are very close to the mean probability (7.69%) which is under the ideal situation, signifying that the ensemble system has reasonable dispersion and can well cover the reality.

We then calculated SCC, RSAS, $P_{\rm c}$, and RMSE between the simulation and the observation in order to synthetically validate the performance of the $p\sigma$-RCM9 in simulating the summer precipitation over East China. Figure 5 shows the temporal variation of each evaluating index. In Fig. 5a, the SCCs are over 0.3, indicating that each single ensemble member can well simulate the spatial distribution of the summer precipitation over East China. Meanwhile, it is noted that the SCC values between the summer ensemble mean precipitation and the observation during 1996–2005 are over 0.5, higher than most SCC values between an individual simulation and the observation. The situation shown in Figs. 5b, 5c, and 5d is similar to that in Fig. 5a, denoting that the simulated summer ensemble mean precipitation is closer to the observation than most single simulations. the physical process ensemble technique can reduce the

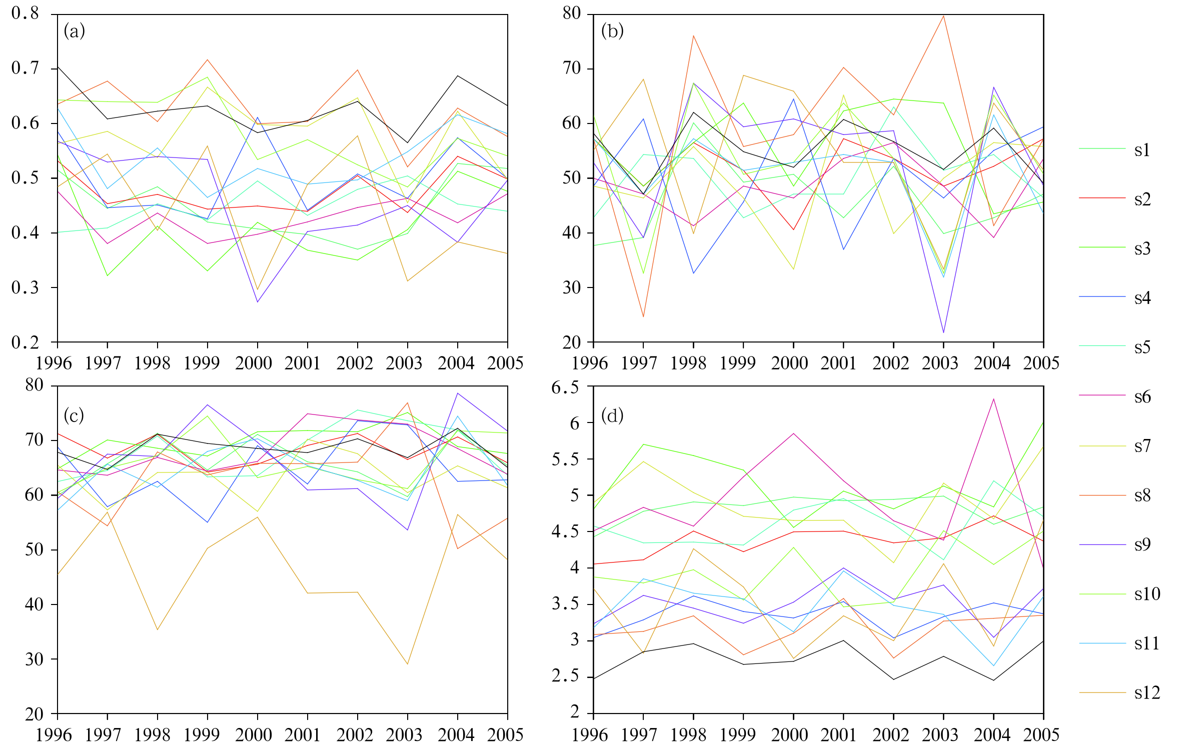

Fig. 5. Temporal variations of each evaluating index of the summer precipitation over East China between model simulation and observation over 1996–2005 (the thick and solid line shows the ensemble mean): (a) spatial correlation coefficient, (b) rate of the same anomaly sign (%), (c) prediction correctness (%), and (d) root mean square error (mm day^{-1}).

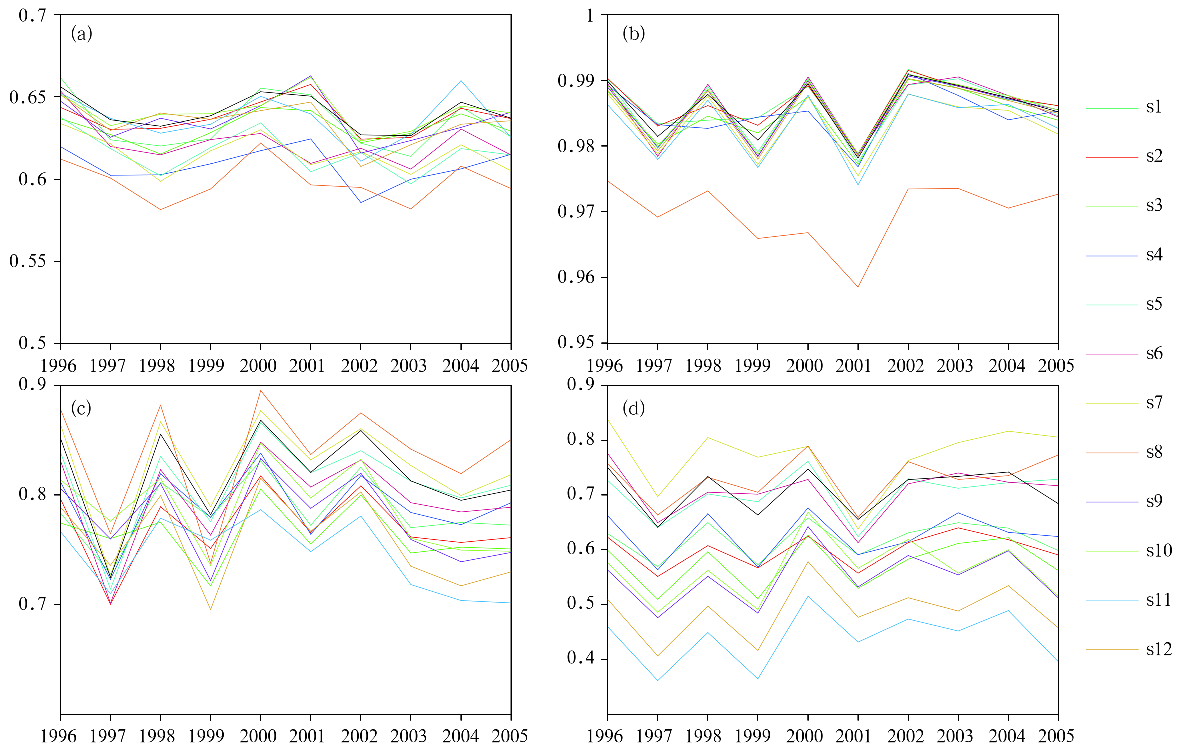

Fig. 6. Temporal variations of the spatial correlation coefficient of surface air temperature (a), 500-hPa height (b), 850-hPa zonal (c), and meridional winds (d) between model simulations and the NCEP/NCAR reanalysis during 1996–2005. The thick solid line shows the ensemble mean.

uncertainties of the model physics and improve the model forecasting skill.

In order to understand the improvement in the ensemble mean, we calculated the SCC of surface air temperature, 500-hPa geopotential height, 850-hPa zonal and meridional winds between model simulations and NCEP/NCAR reanalysis data (Figs. 6a-d). It is shown that the ensemble mean of each meteorological element is much closer to the observation than most single simulations. This is similar to precipitation. It is also noted that the SCC of 500-hPa height and 850-hPa zonal wind between the simulation and observation are over 0.95 and 0.7, respectively, indicating that the $p\sigma$-RCM9 regional climate model has a good performance in simulating 500-hPa geopotential height and 850-hPa zonal wind. Though the SCCs between individual simulations of 850-hPa meridional wind and the observation are significantly different from each other, most SCC values are over 0.65. The meridional wind at 850 hPa is associated with water vapor transport over East China in summer. It is deduced that the improvement in the 850-hPa meridional wind ensemble mean may have contributed to the improvement of summer precipitation ensemble mean simulation over East China.

As discussed above, the ensemble mean is much closer to the observation than most single simulations. There are significant differences between single simulations and the observation, thus the arithmetic (ensemble) mean of all the single simulations must depreciate the quality of some single simulation results. It is necessary to choose single simulations which are close to the ensemble mean at a certain statistical significance level. We call this method the optimized ensemble mean. It is well known that the SCC reflects the similarity of the spatial distribution between the simulation and the observation, while the RMSE reveals the similarity of intensity between the simulation and the observation. In order to choose better single simulations, we calculated the temporal correlation coefficients between the single SCC and ensemble SCC in Fig. 5a and between the single RMSE and ensemble RMSE in Fig. 5d, respectively. The temporal correlation coefficients are listed in Table 2. The underlined labels indicate the correlation coefficients that are over the 95% significance level. Accordingly, seven good single simulations (S1, S2, S4, S8, S9, S10, and S12) are chosen for the optimized ensemble mean.

Table 2. Temporal correlation coefficients (TCC) between the single RMSE and the ensemble RMSE and between the single SCC and the ensemble SCC

Ensemble member	TCC of RMSE	TCC of SCC
<u>S1</u>	0.67	0.52
<u>S2</u>	0.79	0.61
S3	0.32	0.28
<u>S4</u>	0.46	0.61
S5	−0.56	−0.21
S6	0.26	−0.39
S7	0.35	0.61
<u>S8</u>	0.48	0.63
<u>S9</u>	0.54	0.71
<u>S10</u>	0.43	0.56
S11	0.36	0.43
<u>S12</u>	0.44	0.49

The underlined labels signify the correlation coefficients over the 95% significance level.

Compared with Figs. 2a and 2b, the simulated summer optimized ensemble mean precipitation over East China shown in Fig. 7 is much closer to the observation than the simple arithmetic mean. It well captures the maximal precipitation center over South China. This indicates that the optimized ensemble mean can significantly improve the capability of the $p\sigma$-RCM9 model in summer precipitation simulations.

5. Concluding remarks

The effects of the physical process ensemble technique on simulations of summer precipitation over

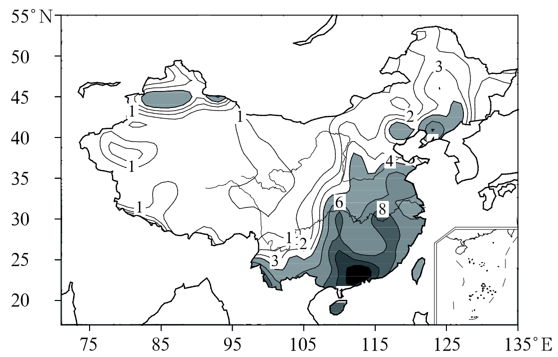

Fig. 7. The optimized ensemble mean of the summer precipitation (mm day^{-1}) in China averaged over 1996–2005. Regions with precipitation over 4 mm day^{-1} are shaded.

China have been studied by using a 12-member physical process ensemble based on the $p\sigma$-RCM9 regional climate model. The main findings are summarized as following:

(1) There are obvious differences among the simulations of summer precipitation over China from different individual ensemble members. The simulated precipitation over China is sensitive to cumulus convection, radiative transfer, and land surface process parameterizations. Adopting different physical process parameterizations in the same model leads to significant differences in summer precipitation predictions.

(2) The standard deviation of the simulated summer precipitation over West China is larger than that over East China, signifying that the simulated precipitation over East China is more reliable and consistent than that over West China. The Talagrand diagram shows that the ensemble system has reasonable dispersion in the simulated summer mean precipitation over East China.

(3) All the evaluating indices reveal that the ensemble mean summer precipitation over East China is better than most single simulations. The physical process ensemble technique can decrease the uncertainties of the model physical processes in the precipitation simulation and improve the simulation results on the whole. It is essential for the short-range climate prediction.

(4) The optimized ensemble mean method can significantly improve the performance of the $p\sigma$-RCM9 model in summer precipitation simulations.

Forecast errors in real applications arise because of not only initial errors, but also the use of imperfect models. We only considered the uncertainties related to model physical processes and explored a so-called optimized ensemble mean method to improve the ensemble simulation in this study. The uncertainties of simulations related to both initial value and model physical processes are our future research focus, on the condition of a significant improvement in our computational power. The results from the present study are encouraging. Meanwhile, this work sheds light on a further investigation of the impacts of physical processes on the diurnal variation of rainfall over eastern China, which has been found with some salient features (Zhou et al., 2008). Some new progress is expected.

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