Evaluation and Correction of Sub-seasonal Forecast of Precipitation in Eastern China

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Research Article

Keywords: Error correction, Sub-seasonal precipitation forecast, Rainfall-belt, Rainy days correction

Posted Date: May 11th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1565356/v1

Version of Record: A version of this preprint was published at Climate Dynamics on May 19th, 2023. See the published version at https://doi.org/10.1007/s00382-023-06788-6.

Abstract

Assessing the capability of sub-seasonal dynamic model forecast of precipitation and proposing probable correction method is quite an important topic in current climate research field. From the perspective of rainfall amount, rainy days and rainfall-belt evolution, the sub-seasonal forecast ability of the European Centre for Medium-Range Weather Forecasts (ECMWF) model for the main rainy-season precipitation in eastern China is evaluated up to 4-week (25–31 days) lead time. The evaluation results show that the forecast biases increase gradually with the increase of forecast lead time, characterized by the predicted rainfall amount obviously higher than observation and the rainy days much longer than observation. In order to decrease the forecast biases of rainfall amount and rainy days, the rainy day based correction (RDC) method is proposed in this study. Cross validation results of the RDC method indicate that the spatial correlation coefficient (SCC) of rainfall amount forecast of the ECMWF model with the observation increases by 0.61%-1.56% and the root mean square error (RMSE) decreases by 3.5%-7.6% up to 4-week lead time. While RDC method also modifies the number of rainy days, the SCC of rainy days increases by 12.96%-18.62%, and the RMSE decreases by 56.49%-63.78%. Furthermore, the problem of the number of continuous rainy days being too long in the model forecast is also improved by using the RDC method. Therefore, the RDC method presents the pretty good performance to improve the sub-seasonal forecast on rainfall amount, total rainy days and maximum continuous rainy days, which may be further applied in other models' sub-seasonal forecasts.

1. Introduction

According to the atmospheric initial conditions and boundary conditions, weather forecast's upper limit of predictability about 2 weeks (Baldwin et al. 2003; Black et al. 2017; Zhu et al. 2014) and climate forecast has certain predictability in its seasonal mean state (Jia et al. 2011; Li and Mao 2018; Yamagami and Matsueda 2020). The sub-seasonal to seasonal (S2S) forecast, between the weather and climate forecast, is sufficiently long to lose much of the memory of atmosphere and is probably too short for variability in lower boundary. S2S forecast has been widely concerned by international and domestic meteorological scientists (Brunet et al. 2010; Robertson et al. 2015; Vitart et al. 2017) and its improvement of forecast ability of precipitation, temperature and other factors can provide better support for agriculture, energy, health and meteorological services.

To improve the predictive performance of S2S forecast, the World Weather Research Program (WWRP) and the World Climate Research Program (WCRP) established the S2S forecast dataset (Becker et al. 2014; Robertson et al. 2015; Vigaud et al. 2017). This dataset consists of real-time ensemble forecast and hindcast ensemble forecast data, up to 60 days of forecasts from 11 global long range forecasting centers. i.e., the European Centre for Medium-Range Weather Forecasts (ECMWF), the China Meteorological Administration (CMA), the US National Center for Environmental Prediction (NCEP) etc. The establishment of S2S dataset can promote the understanding of the mechanism of S2S scale variation, and thus improve the skills of S2S scale forecasting (Fan et al. 2008; Lang et al. 2020; Lin et al. 2016).

With the rapid development of S2S forecast model, it is particularly important to objectively access the forecast ability of S2S models. Numerous scholars have evaluated the forecast performance of the model, providing references for forecasters to grasp the forecast ability of the model. Liang and Lin (2017) evaluated the east Asian summer precipitation and 2m temperature forecasted by ECCC model, and found out the precipitation forecasting skills are limited to 5–11 days, while the temperature forecast could maintain a high level in 26–32 days. Olaniyan et al. (2018) evaluated the precipitation forecast ability of ECMWF model during the peak of the West African monsoon in Nigeria. Phakula et al. (2020) compared the model assessment skills of ECMWF, UKMO and CNRM for maximum and minimum temperatures in South Africa, and found out that the ECMWF model had better forecast effects in 11–30 days than the other two models, but there are systematic errors and random errors in all models (Jung 2010; Wu and Jin 2021). The forecast skills, error stability and similarity of numerical forecast models in the long-term forecast process may provide some useful information for long-term forecast (Gong et al. 2016; Liu et al. 2015; Wang et al. 2021). Therefore, model simulation and hindcast results need to be compared with observations to identify the systematic biases of the model for correction. In addition, many hindcast studies have compared the model results with observations, and as for the model itself, the factors that may lead to model bias in different schemes have not yet been clearly investigated (Xiangrui et al. 2019).

As for model error correction, meteorologists have put forward a series of methods on how the forecast skill of the climate model can be effectively improved through the dynamic-statistic combined approach (Gong et al. 2016; Huang et al. 1993; Wang et al. 2012). Plenty of statistic-dynamic combined forecast strategies have been developed and applied in operational applications(Fan et al. 2012; Lang and Wang 2010; Liu and Fan 2013). Zhang et al. (2013) pointed out the defects of dynamic and statistical methods, and discussed the probable ways to combine them. Chen and Lin (2006) proposed a correction method that demonstrates the ENSO dependence of the model (IAP-DCP) systematic biases. The statistical alone forecast method and the statistical and model combined forecast method, are proposed to improve forecast skill (Gong et al. 2016). Considering the sea surface temperature (SST) is one of atmosphere predictability sources, the summer precipitation predicted by the model is revised by using precursor SST, and the forecast skill can be improved to 30 days in some areas (He et al. 2020). There are also revision methods based on precipitation levels. For instance, Li (2019) sorted the predicted rainfall amount and used a superior bias revision method to correct the S2S precipitation bias in hydrological forecast. In the model forecast process, the model interpolation will lead to false forecast of precipitation in some certain place due to the influence of surrounding precipitation. It is easy to lead to the abnormal number of continuous rainy days in the precipitation forecast. Therefore, it is possible to improve the forecast ability of the model by adding the correction of rainy days in precipitation forecast process. Liu et al. (2020) proposed that there are two main rainfall-belts in eastern China during April-September, among which the southern rainfall-belt reflected the advance and retreat of monsoon and carried out a series of research work on the rainfall-belt. At present, how to carry out the forecast and evaluation research on the main rainy-season precipitation and the evolution of the rainfall-belt in China based on the S2S model forecast data will help us better understand whether the model can effectively predict the intra-seasonal variation

characteristics of the main rainy-season precipitation in eastern China and the northward advance of the rainfall-belt.

Based on the S2S forecast results of the ECMWF model, this paper intends to evaluate the model forecast ability of precipitation in the main rainy-season in eastern China and develop an error correction method based on the rainy days. The second part of this paper mainly introduces the data and proposes the rainy day based correction (RDC) method. The third part is to compare the precipitation predicted by the ECMWF model with the observation given by the National Meteorological Information Center, and systematically evaluate the forecast performance of the model. In the fourth part, the rainfall-belt is analyzed to test the forecast ability of the model to the seasonal precipitation evolution during April-September. The fifth part, the model forecast error correction is carried out by using rainfall systematic error correction (RSC) method and RDC method, respectively. The sixth part is an independent sample experiment to verify the practical significance of these two correction methods. Finally, a brief summary and discussion of this paper is given at the last part of this paper.

2. Data And Methods

2.1 Data

The observed precipitation data are obtained from China surface climate daily dataset developed by the National Meteorological Information Center of China (http://data.cma.cn).The forecast data are derived from European Centre for Medium-Range Weather Forecasts (http://apps.ecmwf.int/datasets/data/s2s). The model system is coupled by land, ocean and atmosphere (Lang et al. 2020; Robertson et al. 2015; Yang et al. 2021). Ensemble forecast provide a variety of atmospheric variables, including precipitation, 2m temperature, sea level temperature, wind field at each layer, geopotential height, dew point temperature and so on. The forecast duration can reach 46 days. The forecast results are given on Monday and Thursday (Buizza et al. 2006; Vigaud et al. 2017). In this study, the forecast of each Thursday is selected to systematically evaluate the main rainy-season precipitation forecast in eastern China during April-September in 1995–2014, which is divided into four weeks forecast with advanced time (Liang and Lin 2017). That is, the weekly average forecast of 1 week (4–10 days) lead, 2 weeks (11–17 days) lead, 3 weeks (18–25 days) lead and 4 weeks (26–32 days) lead.

2.2 Forecast error correction method

Due to the influence of surrounding precipitation during model forecast, model interpolation will lead to false forecast of precipitation in some certain place (Liu et al. 2021; Ding et al. 2019). It is easy to cause the problem of abnormally large number of consecutive rainy days. Therefore, based on the number of rainy days, an error correction method named the Rainy days based Correction (RDC) is proposed in this paper.

Focusing on the fact that the number of rainy days predicted by the model are more than observed, the revised method is divided into three steps. Firstly, cross average bias of rainy days (E_d) is achieved by

calculating bias of rainy days between the model (F_d) and the observation (O_d). Secondly, the revised total number of rainy days of the model (F^*d) is obtained by minus the average bias (E_d). The Eqs. (1) and (2) are the process to revise ECMWF model's total number of rainy days in each year.

$$E_d(z,j) = \frac{1}{n-z}\sum_{i=1}^{n-z}(F_d(i,\ j) - O_d(i,\ j)),\ (i = 1,2,3....n-z, j = 1,2,3....M)$$

1

$$F_d^*(i,j) = F_d(i,j) - E_d(z,j),\ (i = 1,2,3....n-z, j = 1,2,3....M)$$

2

Where *i* and *j* present time and space point, respectively. M are total space points, z is the current year, n are total years, n-z means total year exclusion the current year.

Thirdly, the most significant step is to adjust ECMWF model's rainy day at per week. Comparing total number of rainy days of original model forecast (F_d) with revised (F^*d), prioritizing rainy days according to rainfall amount, the rainy days with high values of rainfall amount are kept and rainy days with low values are removed. Where < *a*, *b* > in Eq. (3) means prioritizing element of *a* and *b* at each time zone.

$$R^*(i,j) =< F_d(i,j), F^*{}_d(i,j) >,\ (i = 1,2,3....n-z, j = 1,2,3....M)$$

3

Thus, the total number of new revised rainy days (R^*) same as the number of rainy days through systematic error correction (F^*d) at per week, and the weekly rainy days are more closed to the real distribution.

Model forecast always produces systematic bias, which is characterized by the bias of the measurement results in one direction, and its value changes according to a certain rule, with repeatability and unidirectional characteristics(Rozante et al. 2014; Wu and Jin 2021). In order to analyze the advantages and disadvantages of the RDC method, the normal systematic error correction based on rainfall amount is also carried out for the ECMWF forecast.

3. Evaluation Of Precipitation In Eastern China

3.1 Evaluation of forecasting ability of rainfall

The spatial distribution of observed total rainfall amount during April-September in Eastern China is shown in Fig. 1 (*a*), displaying decreasing trend from south to north. The ECMWF forecast of total rainfall amount for 1-week, 2-week, 3-week and 4-week in advance are respectively provided in Fig. 1 (*b*1-*b*4), which can also better reproduce the decreasing characteristics of rainfall amount from south to north.

Differences between ECMWF model forecast and observation in four lead weeks are given in Fig. 1 (*c*1-*c*4), which all depict that model forecast of rainfall amount are much more than observation in most area. Comparing four period forecast fields, the forecast effect of 1-week lead is the best. What's more, forecast error increases with the increase of the forecast lead time.

The inter-annual variation of Spatial Correlation Coefficient (SCC) of rainfall amount forecasted by the ECMWF model in eastern China is shown in Fig. 2 (*a*). The 1-week lead forecast passes the significance test in 1995–2014, and average SCC of rainfall amount is 0.49, 0.32, 0.27 and 0.26 respectively in four lead forecast weeks. Therefore, the average forecast skill of ECMWF for main rainy-season precipitation decreases with the increase of lead time, but SCC has some fluctuation in different years.

The spatial distribution of the Temporal Correlation Coefficient (TCC) of rainfall amount forecasted by the ECMWF model in eastern China is shown in Fig. 3 (*a*1-*a*4). It can be seen that TCC of 1-week lead forecast of rainfall amount is best, the significance test passing almost the whole eastern China (Fig. 3a1). TCC of 2-week lead forecast of rainfall amount is decreased in the southeastern coastal areas, but TCC in the Huanghe river region and the northern part of northeast China are obtained high level (Fig. 3a2). TCC of 3-week lead forecast of rainfall amount is smaller in Huanghe river region, and TCC turns from positive correlation to negative in the northern northeast of China (Fig. 3a3). The 4-week lead forecast of rainfall amount is similar to the 3-week lead forecast, and the overall forecast credibility is low (Fig. 3a4). That is forecast reliability is further reduced with the increase of lead time.

The spatial distribution of Root Mean Squared Error (RMSE) of rainfall amount forecast by the ECMWF model in eastern China is shown in Fig. 4 (*a*1-*a*4). RMSE of rainfall amount is greater than 50mm in southern China, such as South China, southwest China and the middle and lower reaches of the Yangtze River. RMSE of rainfall amount in North China and Northeast China is generally less than 35mm (Fig. 4a1). After 1-week, RMSE of rainfall amount increases more obvious in the southern region (Fig. 4a2-*a*4). Due to the reason of the model itself, RMSE of rainfall amount in 2-week lead is larger than that in 3-week and 4-week lead, which is also consistent with the characteristics of rainfall amount shown in Fig. 1 (*c*1-*c*4).

3.2 Evaluation of forecasting ability of rainy day

Previous model evaluation focused on the forecast ability evaluation of rainfall amount (Liang and Lin 2017; Liang et al. 2018). However, grid interpolation is required for the model, which will inevitably lead to the forecast bias of a large number of consecutive rainy days, and the evaluation work in this aspect is relatively few (Olaniyan et al. 2019; Zhou et al. 2018). The ability of ECMWF sub-seasonal forecast to predict the number of rainy days is briefly evaluated following.

The spatial distribution of forecast bias of number of rainy days shows that model forecast is significantly more than observation in eastern China (Fig. 5a1-*a4*), which is coherent with the more rainfall amount forecast (Fig. 1c1-*c*4). The spatial distribution of forecast bias of frequency of continuous rainy days shows that the frequency of continuous rainy days predicted by the model is less

than that observed in the area south of the Yangtze River, especially in south China. While in the region north of the Yangtze River, the frequency of continuous rainy days predicted by the model is generally more, especially in northeast China, but slightly less in Inner Mongolia (Fig. 5b1-*b*4). The forecast bias of maximum continuous rainy days is less in Inner Mongolia and western Northeast China, while the forecast of maximum continuous rainy days is more in southern China (Fig. 5c1-*c*4). However, the bias of maximum continuous rainy days is opposite to frequency of continuous rainy days. That is owing to in a fixed period of time, if there is a long continuous precipitation phenomenon, then the statistical continuous precipitation frequency will be less, and vice versa. With the increase of lead time, the bias of the four forecast periods also increases gradually.

The inter-annual variation of SCC of rainy days is shown in Fig. 2 (*b*). It can be seen that SCC score of rainy days is basically below 0.6. However, different from SCC of rainfall amount, the four predicted periods basically pass the significance test. The average SCC of rainy days of 1-week, 2-week, 3-week and 4-week lead is 0.54, 0.39, 0.378 and 0.376, respectively, which is generally higher than that of rainfall amount.

The spatial distribution of TCC of rainy days is given in Fig. 3 (*b*1-*b*4). It shows that forecast lead time in 1-week is best, almost the entire eastern region has passed the test of significance. TCC in 2-week is down at once, only Hetao area and parts area of northeast passed by significance test. TCC in 3-week and 4-week is higher than in 2-week over the southern region. While in the northern region, TCC in 3-week and 4-week is lower than in 2-week.

The spatial distribution of RMSE of rainy days is reflected in the (Fig. 4b1-*b*4). It shows that 1-week is relatively low, and the forecast error of the other three weeks are similar. The largest errors are concentrated in south China, southwest China and north-Northeast China, with an error of more than 30 days.

4. Evaluation Of Forecast Ability Of Main Rainfall-belt

In the precipitation process of the main rainy-season, the ECMWF model forecast fields of four periods show the climate characteristics of rainfall-belt advance (Fig. 6b1-*b*4). The precipitation enters the pre-flood season in southern China in the mid- May. And then it experiences the meiyu rainfall in Jianghuai, the rainy-season in north-central China and the rainy-season in northeast China during June-August. Finally, it begins to retreat southward, and enters the post-flood season in southern China in late August. In mid-September, it enters the Autumn rainy-season in Huaihe River (Liu et al. 2020).

The forecast of main rainfall-belt in four periods shows the same characteristics (Fig. 6c1-*c4*). From April to June, the forecast precipitation is generally more than observed. It is slightly less than reported only in the area of 20°N-22°N. From June to the mid-August, there is less precipitation in the south of 40°N than in the north of 40°N. After late August, rainfall amount is overreported again. Therefore, it can be concluded that precipitation is reported less in flood season, while forecast precipitation is more than

observation in non-flood season. At the meanwhile, the error increases significantly with the increase of forecast lead time.

The inter-annual variation of SCC of the main rainfall-belt shown in Fig. 2 (*c*). The 1-week lead forecast passes the significance test during 1995–2014. The average SCC of 1-week is 0.53, which is far higher than the other three weeks forecast. The average SCC of 2-week lead, 3-week lead and 4-week lead are 0.32, 0.24 and 0.21, respectively. Similarly, the forecast techniques decrease as the lead time increases.

The spatial distribution of TCC (Fig. 7a1-*a*4) and RMSE (Fig. 7b1-*b*4) of ECMWF model forecast for main rainfall-belt during 1995–2014 are presented. The most obvious feature is that TCC decreases and RMSE increases with the increase of forecast lead time. TCC is the best and RMSE is lowest between early April and early May. With the advance of the rainfall-belt, RMSE also increases when it enters the pre-flood season in Southern China after the mid-May. The error reaches the maximum after the meiyu in Jianghuai, the rainy-season in North China and the rainy-season in northeast China. After September, the error gradually decreases. That is, the forecast bias is large during the advance of the rainfall-belt.

5. Correction Of Precipitation Forecast In Eastern China

5.1 Rainfall forecast systematic error correction

The RSC method, as a traditional systematic error correction method, can properly correct the overestimated model precipitation (Miyakoda and Sirutis 1990). After using RSC method, SCC and RMSE are changed. In terms of time changes, obvious reduction effect of SCC is shown during 1995–2014 (Fig. 8a). In terms of spatial variation, RMSE in the south of 35°N has decreased to less than 50mm, and in the north 35°N have decreased to less than 30mm in four weeks lead (Fig. 9a1-*a*4). After using RSC method, average SCC of rainfall amount has increased by 2.04%, 9.38%, 16.98% and 13.64% in the four weeks (Fig. 10a) while average RMSE of rainfall amount has decreased by 34%, 41%, 32% and 30% at corresponding time (Fig. 10c).

5.2 Rainy days based correction

Considering continuity of rainy days predicted by the ECMWF model, the RDC method is given. This method not only corrects overestimated rainfall amount, but also modifies the number of rainy days.

In the process of adjusting rainfall amount, average SCC of rainfall amount have increased by 0.61%, 1.56%, 1.13% and 1.14% in four weeks after revised by RDC method (Fig. 10a). Average RMSE of rainfall amount have decreased by 3.5%, 7.6%, 2.9% and 3.9% in four weeks after revised by RDC method (Fig. 10c). However, the effect of RDC method modification on rainfall amount is not as significant as that of RSC method, which is also reflected on time range of SCC (Fig. 8b) and spatial distribution of RMSE (Fig. 9b1-*b*4).

In the process of adjusting rainy days, average SCC of rainy days have increased by 12.96%, 23.08%, 18.52% and 18.62% in four weeks after revised by RDC method (Fig. 10b). Average RMSE of rainy days

have decreased by 63.78%, 56.49%, 56.72% and 58.47% in four weeks after revised by RDC method (Fig. 10d). There are significant reduction effects of SCC in the four weeks (Fig. 8c), and RMSE have dropped below 15 days in southern of Eastern China and 12 days in the northern of Eastern China (Fig. 9c1-*c*4).

After the two revision methods, SCC increase and RMSE decrease. The RSC method has a significant revision effect on rainfall amount, while the RDC method has a significant revision effect on the number of rainy days. In addition, the RDC method significantly improves the forecast of precipitation process.

Continuous phenomenon is formed in the process of rainy day forecast, that is, the number of rainy days forecasted by the ECMWF model are much more than observation. Revised by RDC method, the number of rainy days is closed to the observation in most areas (Fig. 11a1-*a*4). The change of frequency of continuous rainy days number is more obvious in the northern part of Northeast China (Fig. 11b1-*b*4). And maximum number of continuous rainy days are weakened more apparently in South China (Fig. 11c1-*c*4).

6. Independent Sample Validation

To further illustrate the validity of RSC method and RDC method, independent sample validation is used to verify whether rainfall amount and rainy days actually being improved in independent years.

The comparison of unrevised forecast of rainfall amount and revised forecast of rainfall amount respectively by RSC method and RDC method in independent years are shown. In 2015, average differences of forecast rainfall amount minus observation are reduced by 73%, 82%, 196% and 71% in four weeks after RSC method while are reduced by 17%, 32%, 56% and 17%, respectively after RDC revision (Fig. 12a). In 2016, the differences are corresponding reduced by 190%, 117%, 106% and 162% after RSC method while are reduced by 44%, 43%, 35% and 37%, respectively after RDC revision (Fig. 12b). In 2017, differences are reduced by 298%, 103%, 103% and 93% after RSC method while are reduced by 63%, 36%, 33% and 23%, respectively after RDC revision (Fig. 12c).

Obviously, RSC method has an inverse effect, causing differences are changed from positive to negative. Compared with the traditional RSC method, RDC method is based on the slight change of adjusting precipitation process. Therefore, modified intensity of RDC method is much weaker than that of RSC, and instead cause effect of rainfall amount correction is better than RSC method.

Accordingly, comparison of unrevised forecast of rainy days and revised forecast of rainy days respectively by RSC method and RDC method in independent years are shown. In 2015, average differences of forecast rainy days minus observation decreases by 117%, 126%, 151% and 150% respectively after RDC method (Fig. 12d). In 2016, the differences are corresponding decreased by 99%, 94%, 115% and 113% after RDC method (Fig. 12e). In 2017, differences are decreased by 101%, 109%, 114% and 147%, respectively after RDC method (Fig. 12f).

When revising the number of rainy days, the phenomenon that differences change from positive to negative also displayed in RDC method. It becomes more obvious after 3-week lead. Therefore, the modification effect of the RDC method on the number of rainy days is better within 2-week lead, which belongs to the acceptable range of revision.

7. Summary And Discussion

The forecast skills of the ECMWF model in the 1-4 lead weeks are analyzed by using hindcast data in 1995-2014 in this paper. The RDC method is proposed to revise rainfall amount and rainy days, and compare its correction effect with the normal RSD method. The results are tested in the real-time forecast to verify whether it is feasible. Main conclusions of this study are summarized as follows,

1. Main rainy-season precipitation in eastern China is systematically evaluated. It is found that rainfall amount and the number of rainy days predicted by the ECMWF model are much higher in the most eastern China. The forecast of main rainfall-belt in flood period is less than that of in non-flood period. The forecast effect of 1-week lead is better, but with the increase of the time lead, the forecast effect becomes worse gradually.
2. Comparing with the ECWMF model original forecast, SCC of the revised rainfall amount forecast have increased by 2.04%-16.98% and RMSE have decreased by 30%-34% by the RSC method. This method can effectively improve the ECMWF model forecast bias of rainfall amount, but has limitation in correcting the continuous precipitation forecast process.
3. In the model forecast, rainy day, as an important factor in meteorological statistics, hasn't been fully considered in the previous model correction studies. By systematically evaluating S2S forecast bias of rainy days of the ECMWF model and combining historical rainy days bias with real time forecast, RCD method is proposed in this paper. It is shown that the number of predicted rainy days and rainfall amount are both can be properly improved by using RDC method, i.e., rainfall amount SCC have increased by 0.61%-1.56% and RMSE have decreased by 3.5%-7.6%, rainy days SCC have increased by 12.96%-18.62% and RMSE have decreased by 56.49%-63.78%.
4. The RDC method not only appropriately improves the model rainfall amount forecast bias mainly reflected by the change of TCC and RMSE, but also overcomes the problem of the number of continuous rainy days being too long in the model forecast. Therefore, RDC method presents the pretty good performance on improving the sub-seasonal forecast of rainfall amount, rainy days and maximum continuous rainy days, which may be further applied in other models' sub-seasonal forecasts.

Independent sample validations of RSC method and RDC method indicate that two correction methods can properly improve sub-seasonal forecast of ECMWF model. RSC method is effective in improving rainfall amount forecast while RDC method both have distinct effect on modifying rainy days and rainfall amount forecast. Therefore, RDC method proposed in this study shows potential application in operational forecast.

Declarations

Acknowledgments

This work was supported by the National Key Research and Development Program of China (2018YFA0606301), the National Natural Science Foundation of China Project (41875100, 42075057, and 41875093). The numerical calculations in this paper have been done on the supercomputing system in the Supercomputing Center of Nanjing University of Information Science & Technology.

Data Availability Statement

The ECMWF model forecast data can be achieved from European Centre for Medium-Range Weather Forecasts (http://apps.ecmwf.int/datasets/data/s2s). The observation data are provided by the National Meteorological Information Center of China (http://data.cma.cn).

Declaration of competing interest. The authors declare no conflict of interest.

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Figures

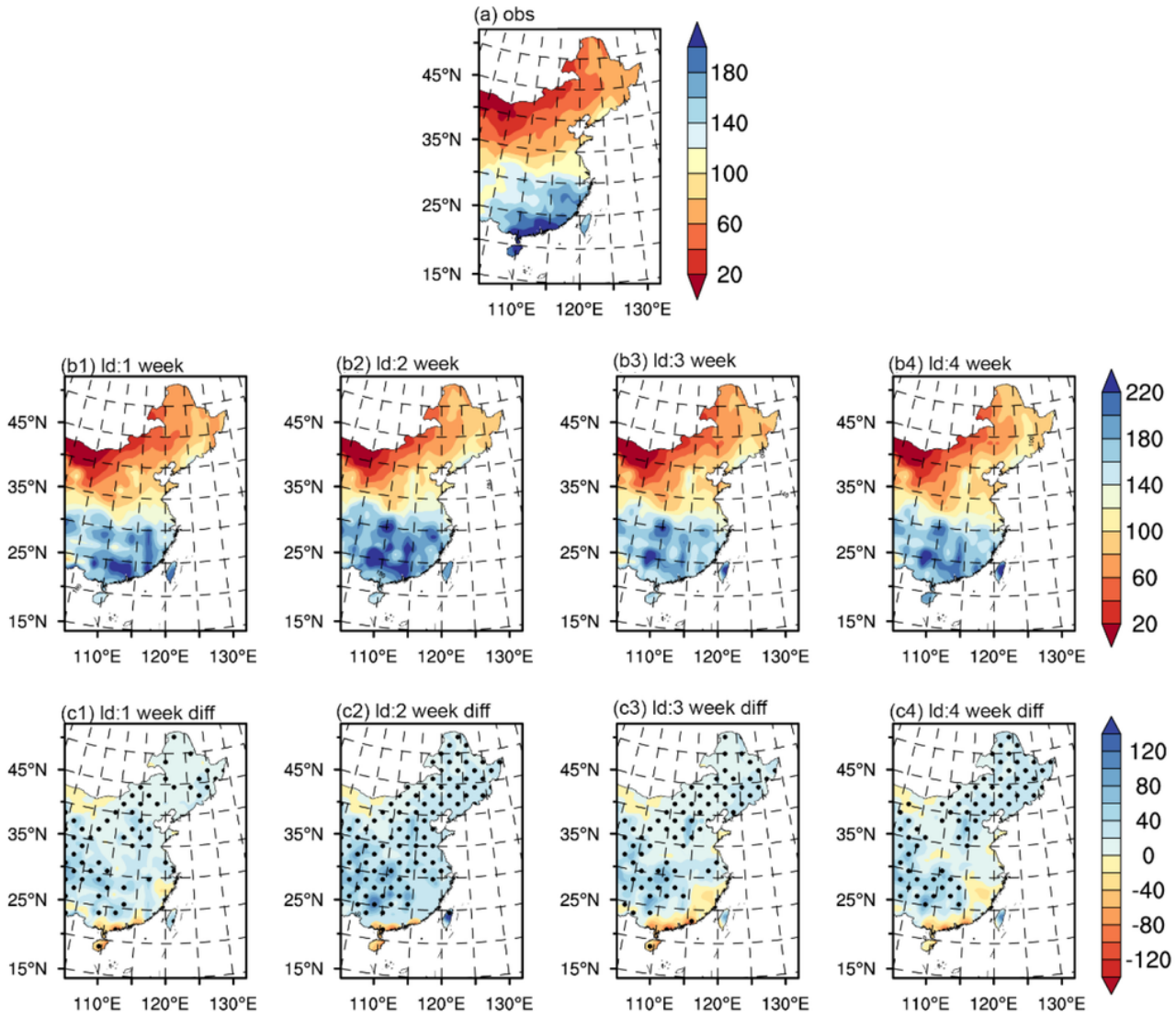

Figure 1

Spatial distribution of total rainfall amount (unit: mm) during April-September. (a) observation; (b1-b4) ECMWF forecast model for 1-week, 2-week, 3-week and 4-week in advance, respectively; (c1-c4) difference of ECMWF model forecast minus observation. Dots indicate the 90% significance level

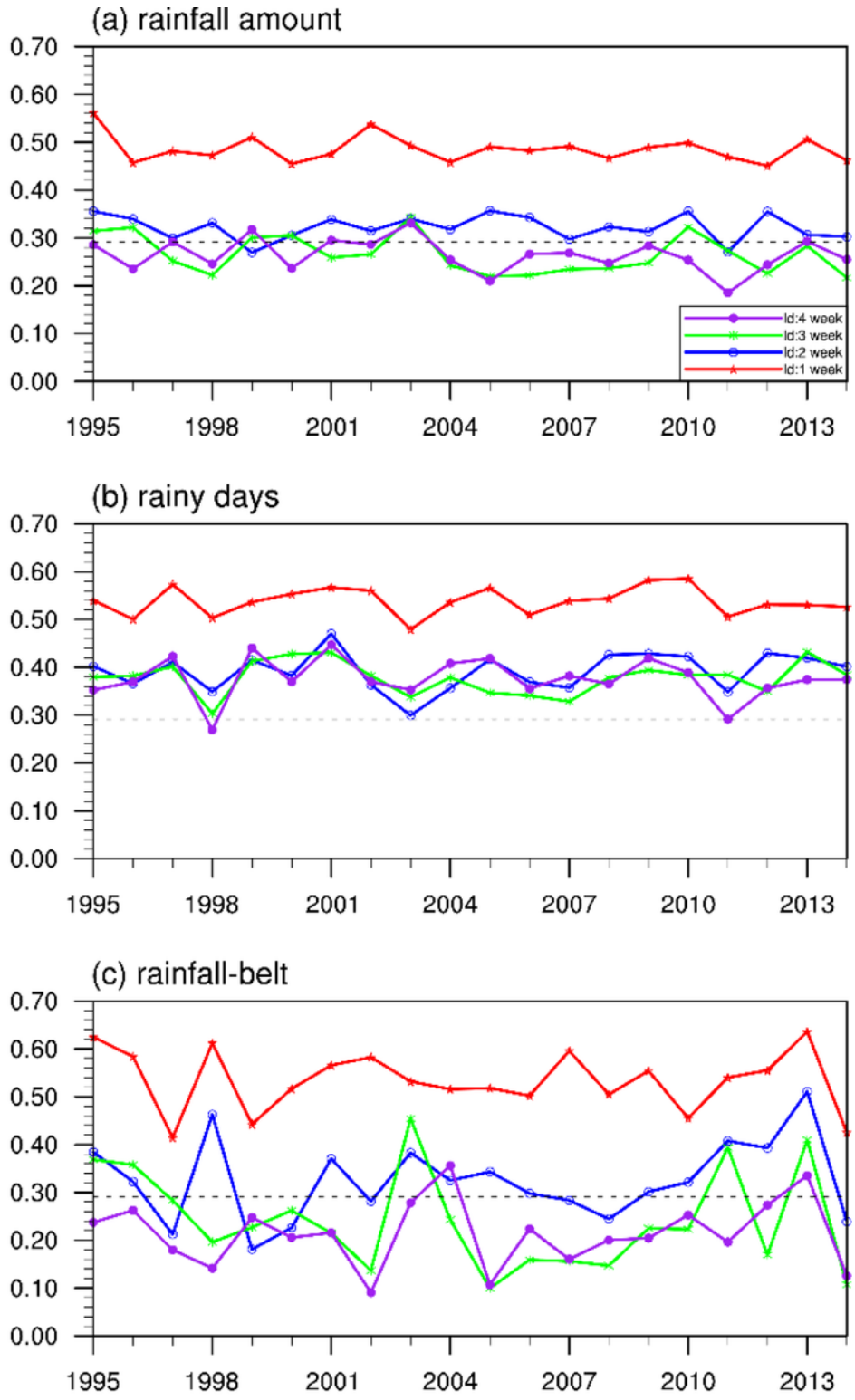

Figure 2

Inter-annual variation of SCC of main rainy-season (April-September) precipitation forecast in eastern China during 1995-2014. (a) rainfall amount, (b) rainy days, and (c) cross section of rainfall-belt

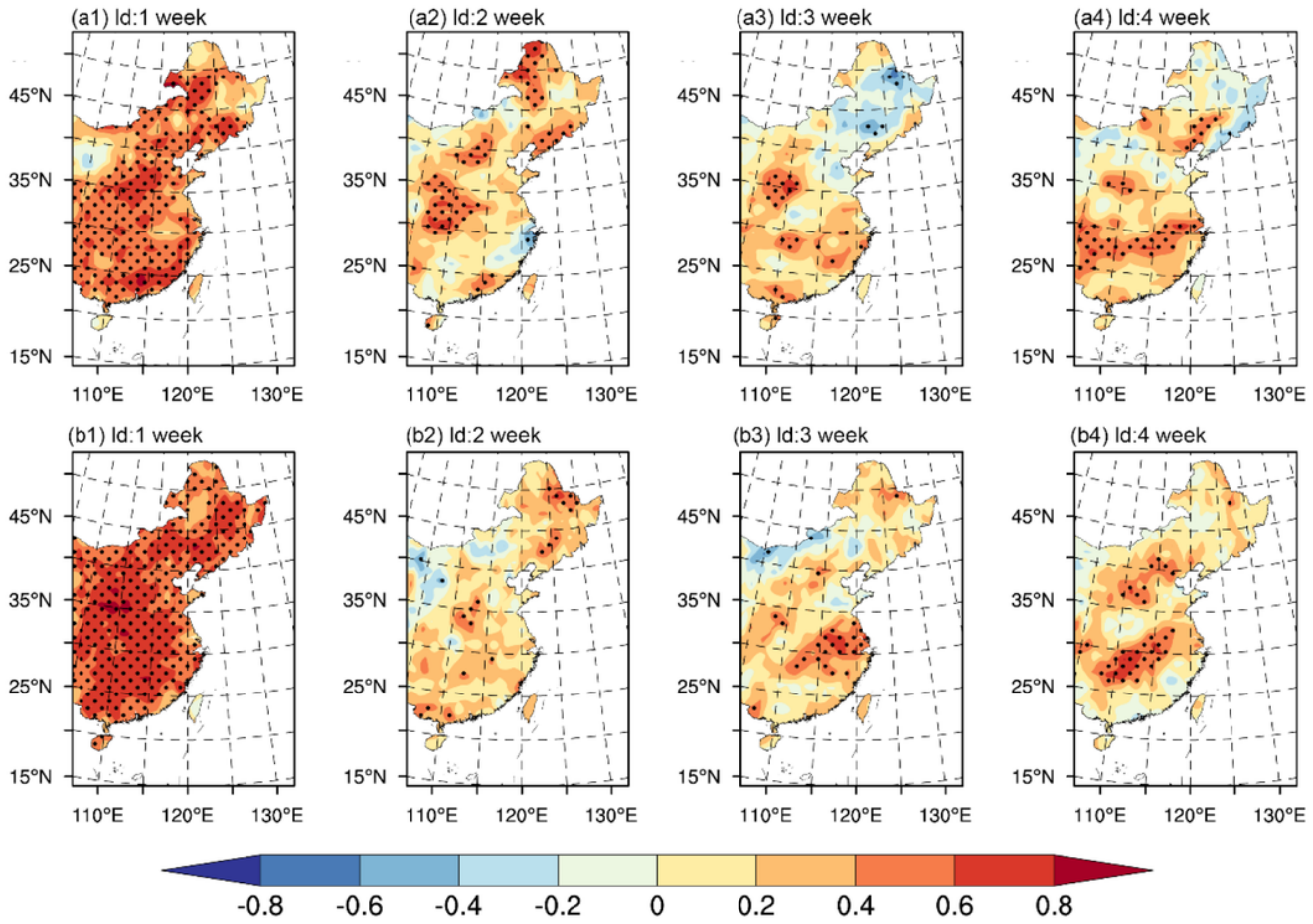

Figure 3

Spatial distribution of TCC of main rainy-season precipitation forecast in Eastern China. (a1-a4) rainfall amount and (b1-b4) rainy days. Dots indicate the 90% significance level

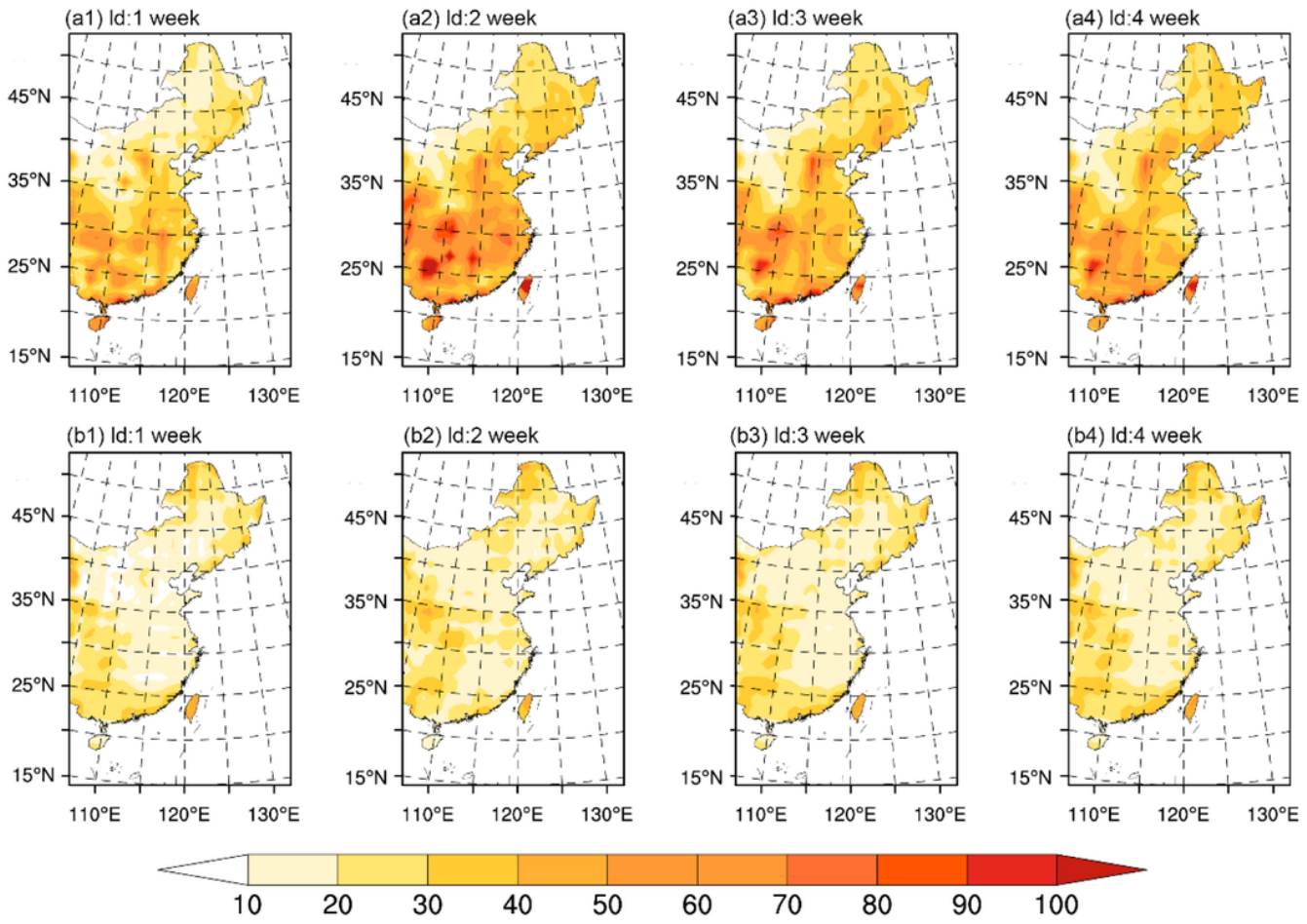

Figure 4

Spatial distribution of RMSE (unit: mm) of main rainy-season precipitation forecast in Eastern China. (a1-a4) rainfall amount and (b1-b4) rainy days

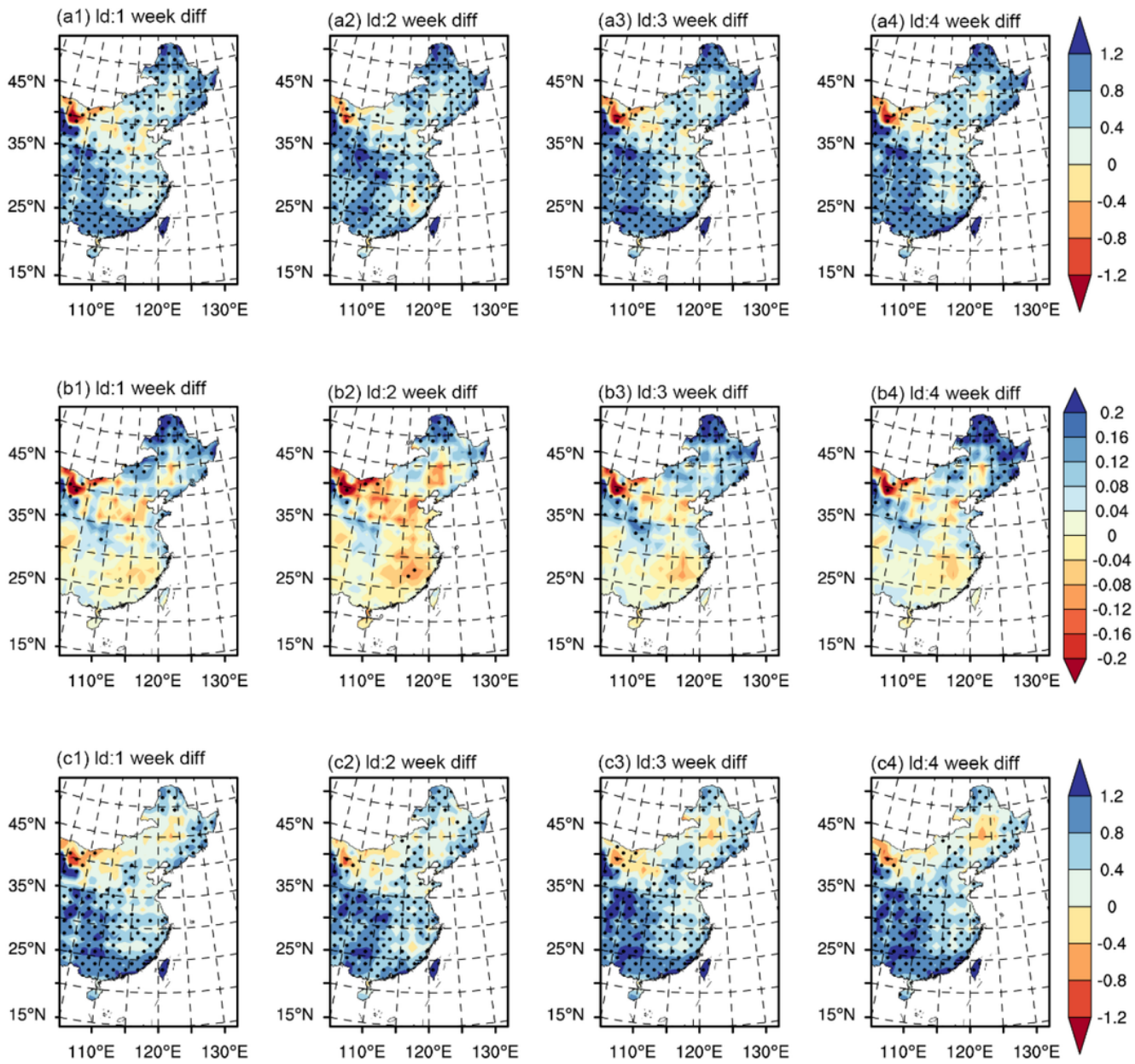

Figure 5

Same as Fig. 1 (c1-c4) but for (a1-a4) Rainy days (unit: day), (b1-b4) frequency of continuous rainy days (unit: times) and (c1-c4) maximum number of continuous rainy days (unit: day). Dots indicate the 90% significance level

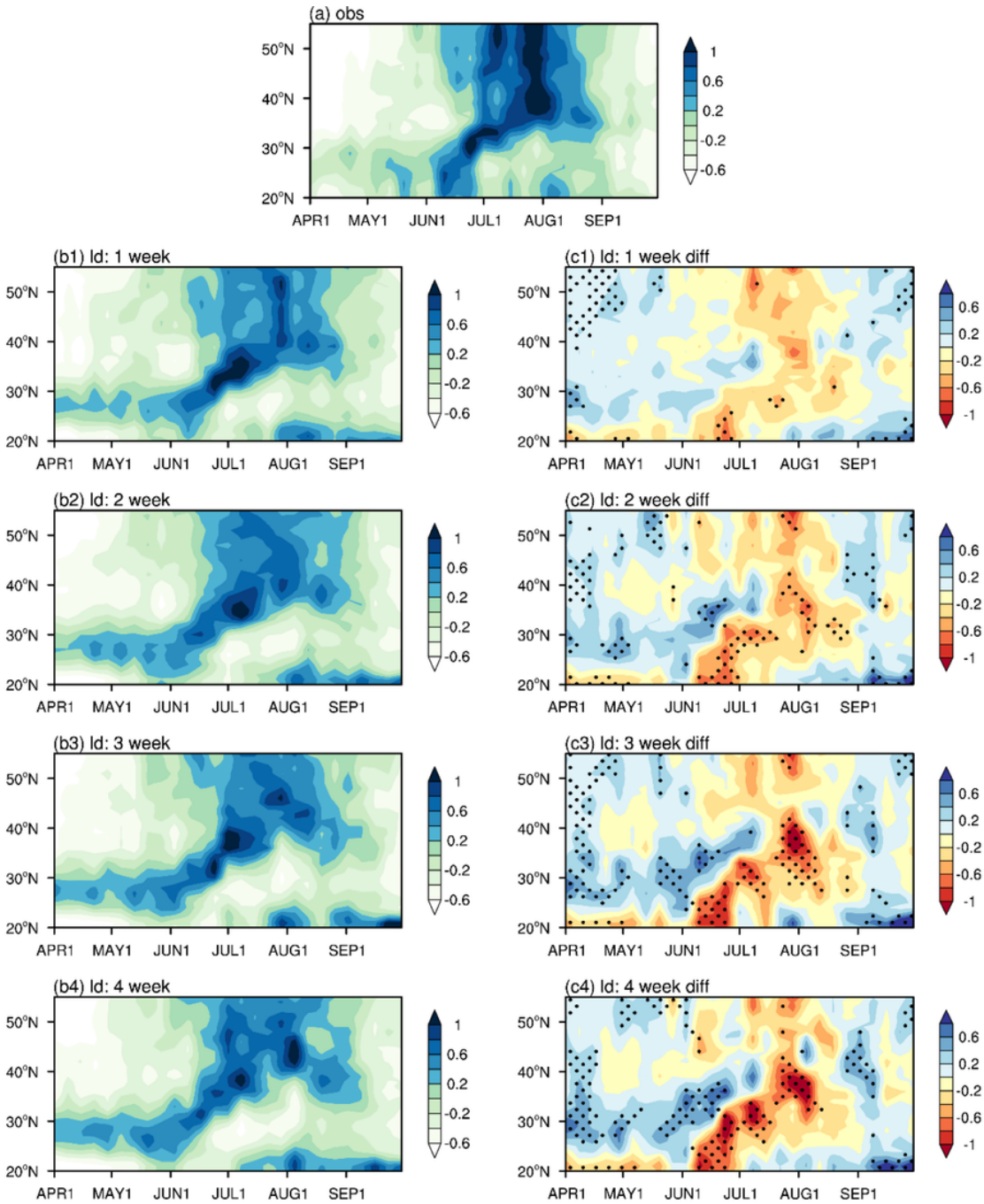

Figure 6

Same as Fig. 1 but for cross section of rainfall amount. Dots indicate the 90% significance level

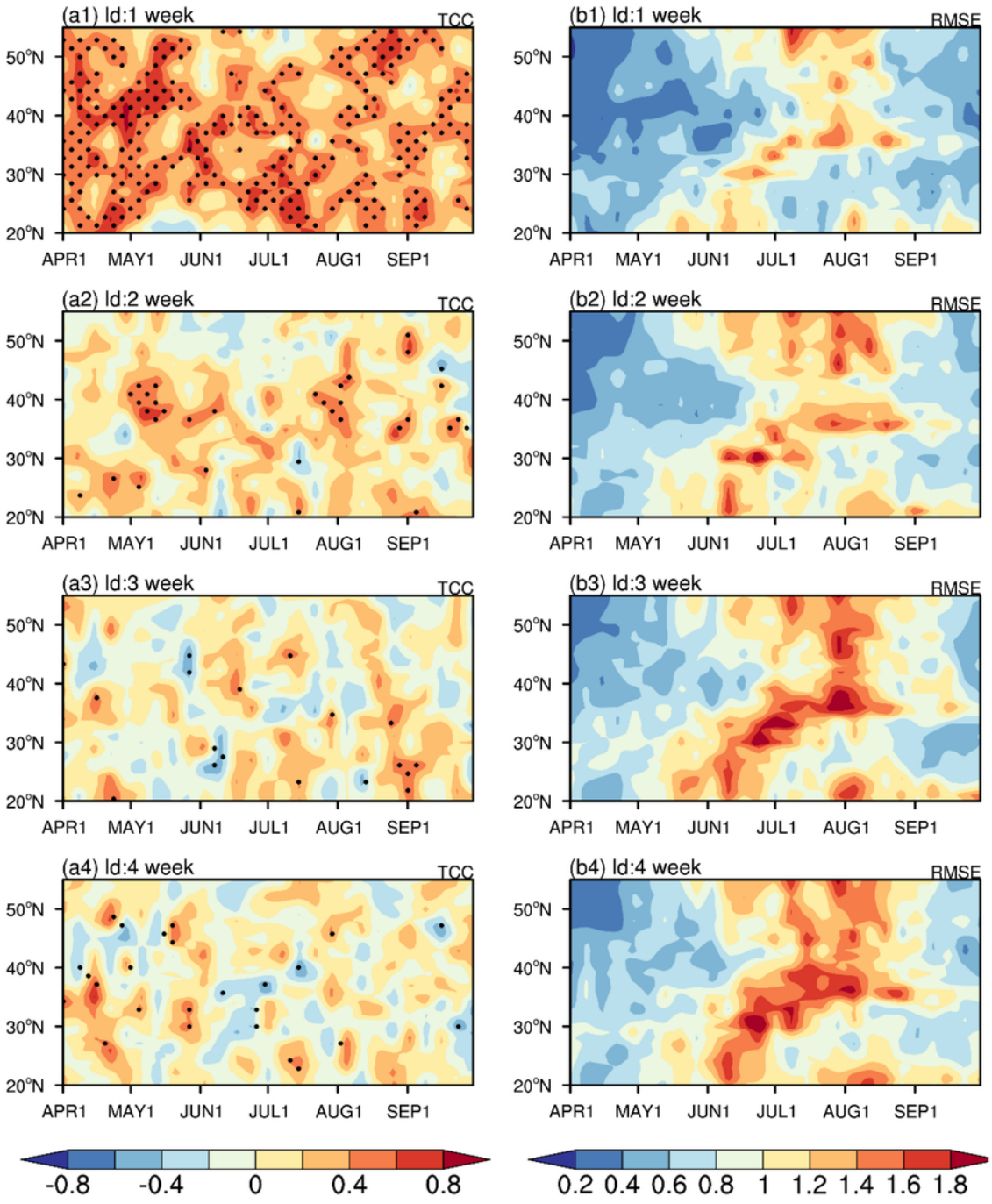

Figure 7

Spatial distribution of (a1-a4) TCC and (b1-b4) RMSE for rainfall-belt forecast in eastern China during April-September. Dots indicate the 90% significance level of TCC

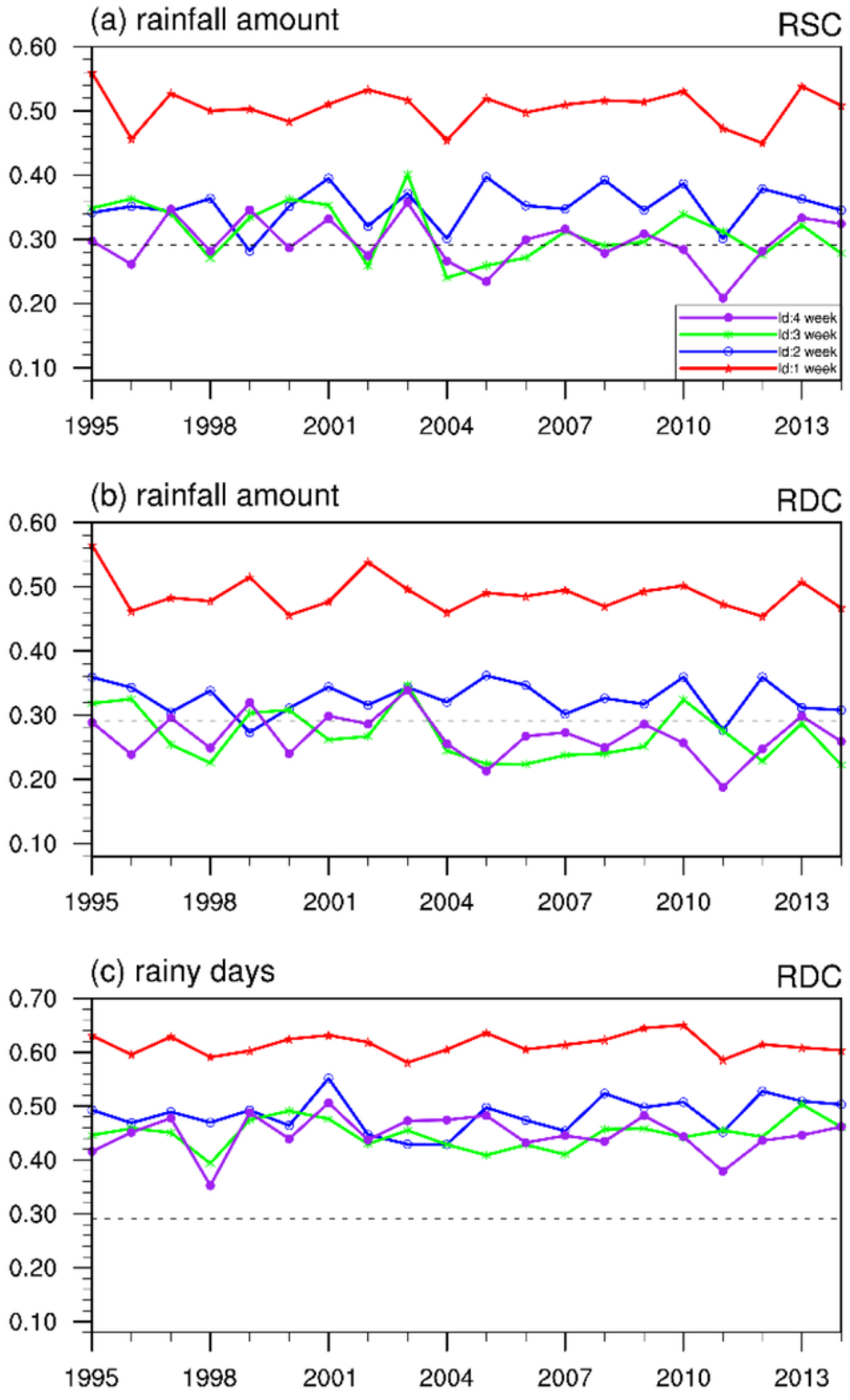

Figure 8

Inter-annual variation of SCC of rainfall amount revised (a) in RSC method, (b) in RDC method, and (c) SCC of rainy days revised in RDC method

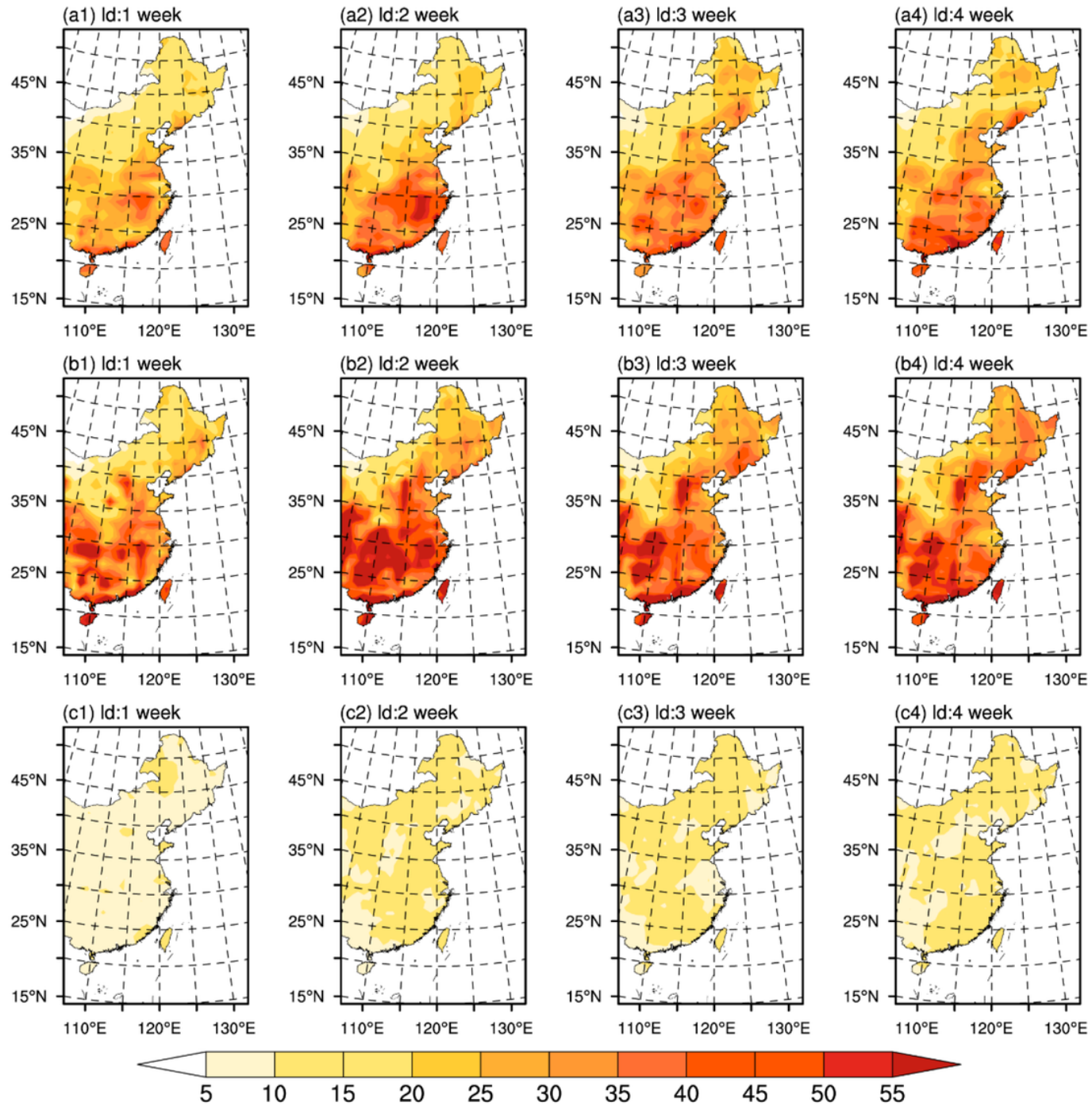

Figure 9

Spatial distribution of RMSE of rainfall amount revised (a1-a4) in RSC method, (b1-b4) in RDC method, and (c1-c4) RMSE of rainy days revised in RDC method

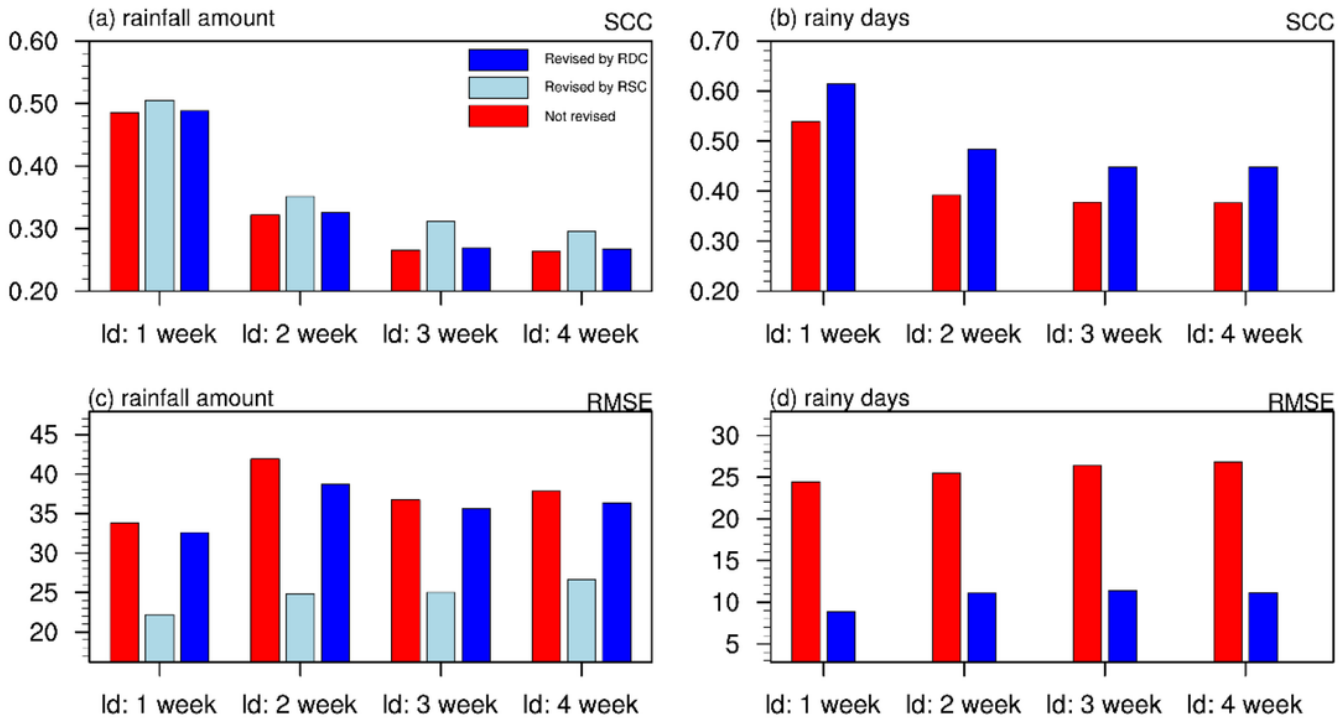

Figure 10

Temporal average of SCC of (a) rainfall amount, (b) rainy days. Spatial average of RMSE of (c) rainfall amount, (d) rainy days

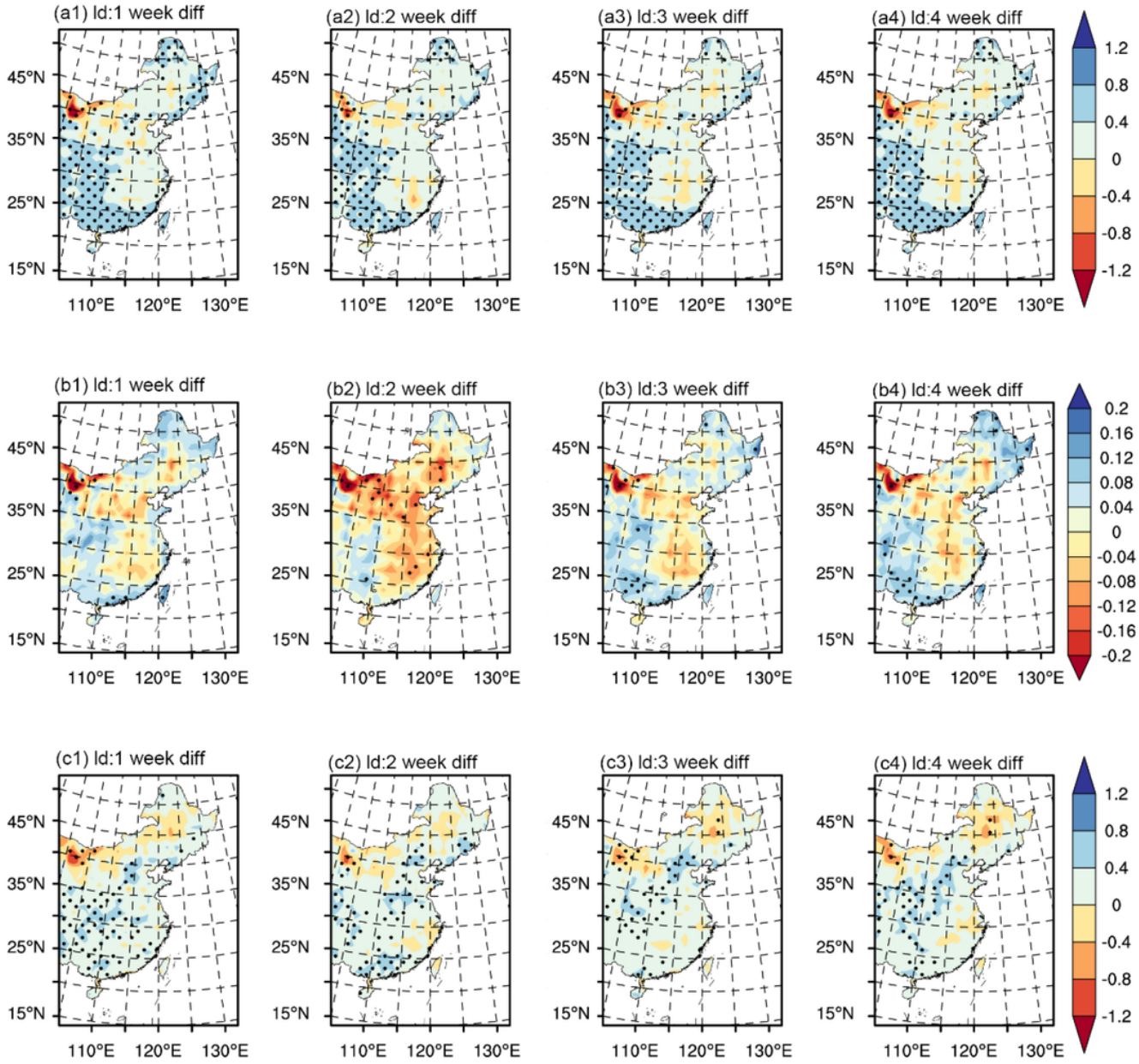

Figure 11

Same as Fig. 1 but for ECMWF model forecast revised by RDC method. (a1-a4) Rainy days (unit: day), (b1-b4) frequency of continuous rainy days (unit: times) and (c1-c4) maximum number of continuous rainy days (unit: day)

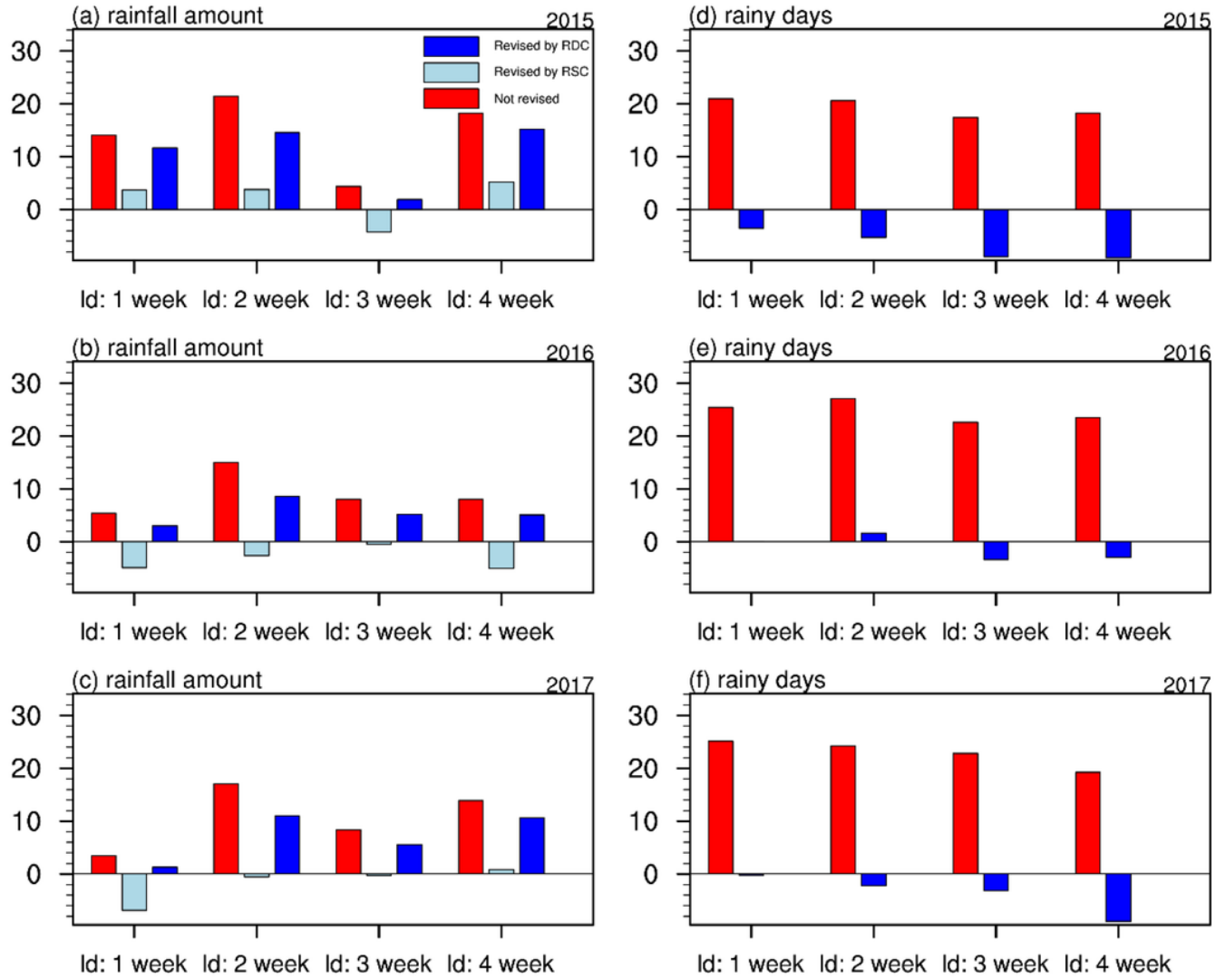

Figure 12

Average difference of model forecast minus observation in 2015, 2016 and 2017 (a-c) rainfall amount and (d-f) rainy days