Article ID: 1006-8775(2021) 02-0136-12

Intercomparison of CRA−Interim Precipitation Products with ERA5 and JRA−55

YE Meng-shu (叶梦姝)[1], YAO Xiu-ping (姚秀萍)[1], ZHANG Tao (张 涛)[2], XU Xiao-feng (许小峰)[3], WANG Shi-gong (王式功)[4]

(1. Training Center, China Meteorological Administration, Beijing 100081 China;
2. National Meteorological Information Center, China Meteorological Administration, Beijing 100081 China;
3. China Meteorological Administration, Beijing 100081 China;
4. Chengdu University of Information Technology, Chengdu 610103 China)

Abstract: Based on the hourly observational data during 2007−2016 from surface meteorological stations in China, this paper compares the influence of 3-hourly precipitation data, mainly from the Chinese Reanalysis-Interim (CRA-Interim), ECMWF Reanalysis 5 (ERA5) and Japanese Reanalysis-55 (JRA-55), on the simulation of the spatial and temporal distribution of regional precipitation in China and the bias distribution of the simulation. The results show that: (1) The three sets of reanalysis datasets can all reflect the basic spatial distribution characteristics of annual average precipitation in China. The simulation of topographic forced precipitation in complex terrain by using CRA-interim is more detailed, while CRA-interim has larger negative bias in central and East China, and larger positive bias in southwest China. (2) In terms of seasonal precipitation, the three sets of reanalysis datasets overestimate the precipitation in the heavy rainfall zone in spring and summer, especially in southwest China. According to CRA-interim, location of the rain belt in the First Rainy Season in South China is west by south, and the summer precipitation has positive bias in southwest and South China. (3) All of the reanalysis datasets can basically reflect the distribution difference of inter-annual variation of drought and flood, but overall the CRA-Interim generally shows negative bias, while the ERA5 and JRA-55 exhibit positive bias. (4) For the diurnal variation of precipitation in summer, all the reanalysis datasets perform better in simulating the daytime precipitation than in the night, and the bias of CRA-interim is less in the Southeast and Northeast than elsewhere. (5) The ERA5 generally performs the best on the evaluation of quantitative precipitation forecast, the JRA-55 is the next, followed by the CRA-Interim. The CRA-Interim has higher missing rate and lower threat score for heavy rains; however, at the level of downpour, the CRA-Interim performs slightly better.

Key words: reanalysis datasets; temporal and spatial distributions of precipitation; CRA; ERA5; JRA-55
CLC number: PP459 **Document code:** A
https://doi.org/10.46267/j.1006-8775.2021.013

1 INTRODUCTION

The atmospheric reanalysis dataset has been widely used as basic data for research in various fields of atmospheric sciences (Zhao et al. [1]; He et al. [2]). However, previous studies have shown that the assimilation scheme, model framework, data source and bias correction in different reanalysis datasets are different, and moreover, the quality of a single reanalysis product also varies in different regions, elements, and time periods. Therefore, reanalysis data cannot fully and accurately reflect the distribution patterns and characteristics of meteorological elements. Before applying reanalysis data to climate monitoring, seasonal prediction, and research on climate change, it is necessary to compare it with observational data and fully analyze the spatial-temporal characteristics of corresponding errors. A comprehensive understanding of its applicability could provide important reference for the application of reanalysis data.

In recent years, the assessment and analysis of precipitation products based on reanalysis datasets is one of the research hotspots in the field of numerical prediction in the world. The possibility of using reanalysis datasets to simulate precipitation is mainly evaluated in terms of total amount, the spatial distribution and the annual (seasonal or daily) variation trend of precipitation.

For example, Kalnay [3] have pointed out that the global distribution of precipitation in reanalysis datasets is consistent with that measured by the microwave instrument, and the consistency is better at low latitudes, but the precipitation in reanalysis datasets is relatively small. By comparing three

Received 2021-01-10 **Revised** 2021-02-15 **Accepted** 2021-05-15

Funding: National Natural Science Foundation of China (42030611, 91937301); Second Tibetan Plateau Scientific Expedition and Research (STEP) Program (2019QZKK0105)

Biography: YE Meng-shu, Senior Engineer, primarily undertaking research on climatology.

Corresponding author: YAO Xiu-ping, e-mail: yaoxp@cma.gov.cn

reanalysis datasets with the precipitation product from weather stations in China, Li et al. [4] conducted an assessment on the precipitation field using NCEP/DOE, ECMWF Reanalysis (ERA) and Japanese Reanalysis (JRA). It has been revealed that the distribution characteristics of precipitation in China can be basically represented in three datasets. However, in the NCEP products, an artificial rainfall center is produced, and the precipitation characteristics in western regions is poorly simulated. Meanwhile, the overestimation of weak precipitation and underestimation of strong precipitation can be found in all the three datasets. For all the three reanalysis datasets, the Threat Score (TS) score is around 0.6, while the Bias (BS) score is around 1.5. By comparing the mean values, correlations, and characteristics of temporal variation for precipitation products in three reanalysis datasets with the observations in China, Cheng et al. [5] have found that in the NCEP reanalysis dataset, the precipitation is significantly overestimated, and the maximum bias occurs in southwest China. It has been revealed that the locations of rain belts in China can be basically reproduced in terms of monthly average precipitation in reanalysis datasets of ERA-40 and NCEP-2. Similar studies have also found that for the precipitation in the three reanalysis datasets, there is little difference in the regions north of the Yangtze River compared with the observations, but the precipitation from JRA-25 in the regions to south of the Yangtze River, especially in South China, is obviously larger (Lu et al. [6]).

From the aspect of monthly variation, Su et al. [7] have demonstrated that the precipitation in reanalysis datasets is very close to that in observations, and so is the annual variation trend. Zhao et al. [8, 9] have found that the NCEP reanalysis dataset performs well in simulating the summer precipitation and the annual average rainfall, but the winter precipitation is not simulated very well. Based on the four-times-daily reanalysis data in summer, the reproduction ability for characteristics of the diurnal variation of summer precipitation in the three reanalysis datasets are compared with those in station observations during the same period (Dai et al. [10]). The applicability of the NCEP reanalysis data for temperature and precipitation along the Qinghai-Tibet railway were described, and it has been revealed that the reanalysis data can well depict the characteristics of the annual variation of precipitation, but the precipitation values are overestimated, and there is a huge difference in the spatial distribution for the applicability of precipitation data (Wei and Li [11]).

At the same time, the difference in the applicability of different reanalysis datasets in a specific region is also one of the foci for the evaluation on reanalysis datasets. The applicability of different reanalysis data has been compared in arid regions of China, Xinjiang and Central Asia, respectively (Chen et al. [12]; Hu et al. [13]). Comparisons on the characteristics of precipitation simulation in Arctic and Antarctic among different reanalysis datasets have also been conducted (Hurley [14]; Palerme et al. [15]). East Asia is of the most frequent human activities, the most sensitive global climate changes, and the most vulnerable climate ecology. Therefore, it is of great significance to study the climatic characteristics over East Asia.

In 2018, a reanalysis dataset named CRA-Interim (Chinese Reanalysis-Interim) has been developed independently in China, which is the first high-resolution atmospheric reanalysis data with regional characteristics of East Asia (China) in the world. Therefore, for precipitation products in the CRA-Interim reanalysis dataset, which is at the promotion stage, it is necessary to evaluate its representativeness in China (Zhao et al. [16]; Li et al. [17]). To better present the characteristics and advantages of China's atmospheric reanalysis data, two sets of more advanced reanalysis data (ERA5 and JRA-55 (Dragani et al. [18]) in the world and the observed precipitation data in China are selected in this paper for cross comparisons, aiming to provide references for relevant research and development works.

2 DATA AND METHODS

2.1 *Data*

The hourly observational data from the weather stations in China are derived from the platform of China Integrated Meteorological Information Service System (CIMISS) of China Meteorological Administration (CMA), including the hourly precipitation data from 2411 national surface stations (Zhang [19]). Through the real-time quality control of hourly observational data from surface meteorological stations in China, the availability rate of data for each element exceeds 99.9%, and the correctness rate is close to 100%, indicating good quality of this dataset.

In this paper, precipitation products from three newly released reanalysis datasets are selected for comparative study. The reanalysis datasets include the fifth generation of ECMWF atmospheric reanalysis of the global climate from the European Centre (ERA5), the third-generation reanalysis data from Japanese Meteorological Agency (JRA-55), and the CMA's global atmospheric reanalysis data (CRA-Interim), which is at the stage of trial operation. For NCEP reanalysis data, as the resolution is quite different from those of other datasets, it is not selected for analysis in this paper (Kistler et al. [20]).

The atmospheric prediction model used in the CRA-Interim is a global spectrum model (NCEP / GSM) with spherical harmonic function. The horizontal resolution is T574, which is about 34 km at the equator, and the top layer of the model (64 layers in total) is up to 0.27 hPa (about 55 km). The global spectral model in the integrated forecasting system (IFS for short, version CY41r2) of ECMWF is used for the ERA5 reanalysis data, with a horizontal resolution of T639 (31 km) and 137 layers in the vertical direction with the top layer of 0.01 hPa. The assimilation scheme consists of a set of four-dimensional variational method and EDA technology. A global spectrum model (JMA2002) is adopted in JRA-55, with a horizontal resolution of T319, 60 layers (equal δ surface) in the vertical direction (0.1 hPa on the top layer), and 4D-Var semi-Lagrangian assimilation schemes (Liu et al. [21]; Liang et al. [22]).

A time period ranging from January 1, 2007 to December 31, 2016 is selected for the above datasets. In addition, the three-hourly precipitation is obtained from the composite of hourly precipitation (0000–0300, 0300–0600, 0600–0900, 0900–1200, 1200–1500, 1500–1800, 1800–2100, 2100–0000 UTC).

2.2 *Methods*

In order to facilitate the comparison of observed precipitation, the bilinear interpolation method is used to interpolate the grid data into data from national stations. Thus, three sets of reanalysis precipitation data at 2411 surface observation stations are obtained.

In this paper, two basic statistics are used to describe the bias of reanalysis data, namely the mean error (ME) and root mean square error (RMSE). The calculation formulas are as follows:

$$\mathrm{MEAN}=\frac{1}{N}\sum_{t=1}^{N}(\mathrm{Observed}_t-\mathrm{Predicted}_t), \qquad (1)$$

and

$$\mathrm{RMSE}=\sqrt{\frac{1}{N}\sum_{t=1}^{N}(\mathrm{Observed}_t-\mathrm{Predicted}_t)^2}. \qquad (2)$$

where Observed denotes the observed value, Predicted denotes the precipitation value in reanalysis datasets, and t is the data time.

3 COMPARISONS FOR PRECIPITATION PRODUCTS IN THREE REANALYSIS DATASETS

3.1 *Spatial distribution characteristics*

3.1.1 ANNUAL PRECIPITATION

Based on the interpolated precipitation data from the three reanalysis datasets and the observed precipitation at stations, the spatial distributions of ten-year-averaged annual precipitation in China during 2007–2016 are shown in Fig. 1. It can be seen that the basic distribution of the annual average precipitation in China, which exhibits the characteristic of increasing from northwest to southeast in observations, are slightly different among the three reanalysis datasets. Specifically, in northwest regions, CRA-Interim and ERA5 overestimate the annual precipitation in the Tianshan Mountains and the Altai mountains. For the Tibet Plateau, the CRA-Interim and ERA5 overestimate the precipitation over the southern Tibet southeast of the Himalayas, and the average annual precipitation in Tibet is higher than that of JRA-55. In the northeast and north of China, the annual precipitation in reanalysis datasets is about 200 mm higher than the total observed precipitation for the same year. The CRA-Interim performs more detailed simulation of precipitation triggered by topographic forcing in the Changbai Mountains and Lesser Khingan Mountains in Northeast China, Taihang Mountains and Lüliang mountains in North China. In the coastal areas of South China, Southwest and Southeast China, the precipitation over complex terrain in the CRA-Interim dataset is closer to the observation in depicting the details of the precipitation distribution.

The regional distribution characteristics of the precipitation bias vary in three reanalysis datasets. From Fig. 2, it can be seen that the simulated precipitation in the CRA-Interim shows negative bias in China, indicating that the precipitation is underestimated by the reanalysis data. The center of negative bias is located in the middle and lower reaches of the Yangtze River, with a maximum of about −400 mm. In regions of Sichuan, Yunnan, Guizhou, Guangxi and Guangdong, the CRA-Interim shows positive bias, and the center is located near the Sichuan Basin, with a maximum of more than 1000 mm. ERA5 generally shows positive bias across China, indicating an overestimation of the precipitation. Positive bias can be found in Hunan and Hubei in ERA5. Meanwhile, contrary to the other two reanalysis datasets, the negative center of precipitation bias in ERA5 is located in the coastal areas of Guangdong and Fujian, with the maximum of about −200 mm. Precipitation in JRA-55 also shows positive bias in China, and the area with positive bias is larger than that in ERA5. Meanwhile, the area with maximum bias is mainly distributed in the south of the Tibet Plateau, Sichuan Basin and Yunnan-Guizhou Plateau, with a maximum value of more than 800 mm, whereas relatively smaller positive bias occur in the northwest and northeast regions.

Further analysis has been conducted on the spatial distributions of the RMSEs of the total annual precipitation in the three reanalysis datasets. It is shown that, due to the particularity of the precipitation data, the area with large RMSEs is basically consistent with the area with large total annual precipitation (Yang and Smith[23]; Jia [24]). The RMSEs of precipitation in the CRA-Interim in southwest and southeast regions are larger than those in ERA5 and JRA-55, while the RMSEs in JRA-55 in northwest and northeast regions are slightly larger than those in ERA5 and CRA-Interim. Overall, the RMSEs of precipitation in ERA5 are the smallest.

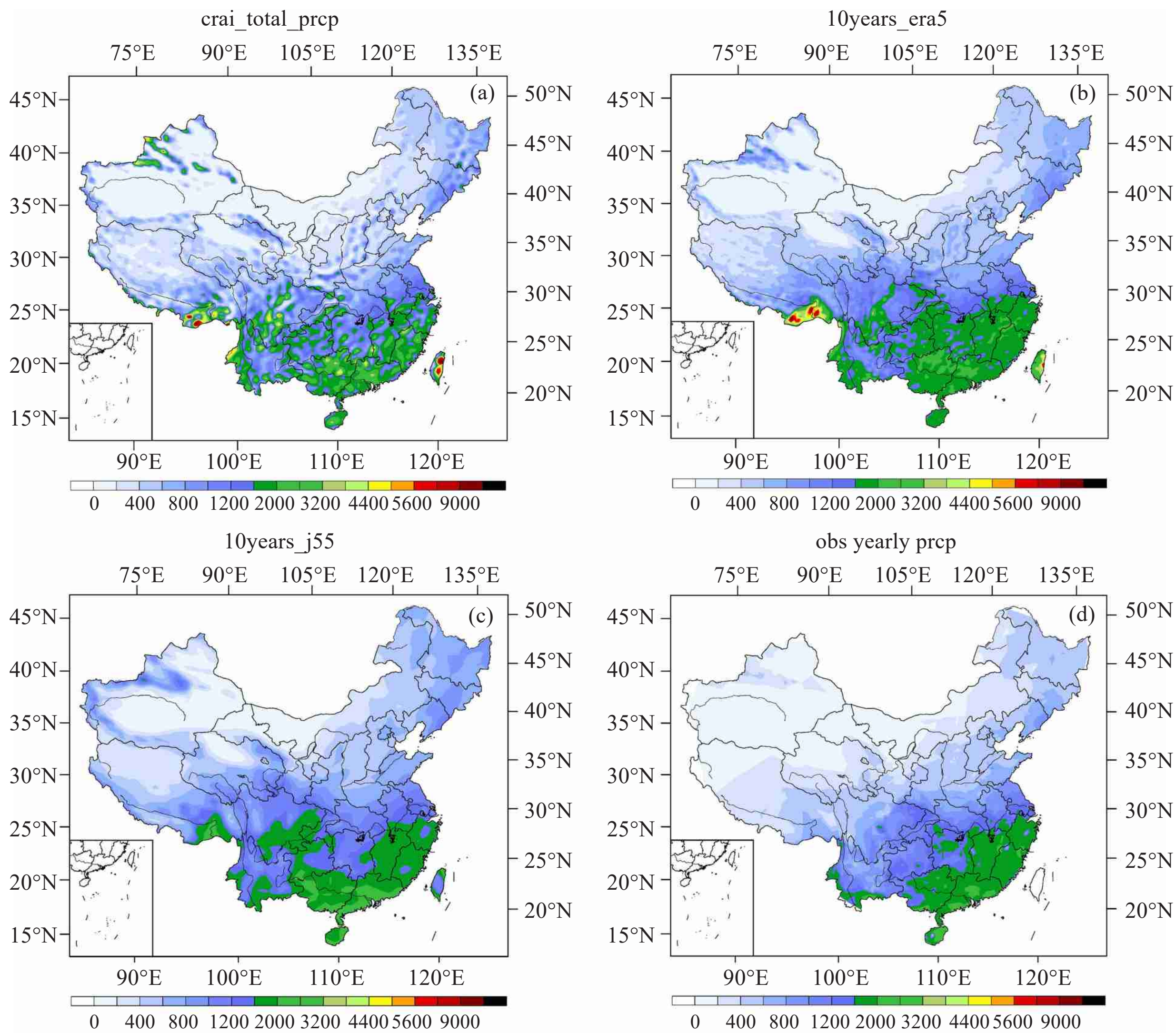

Figure 1. Climatological annual total precipitations (mm year) 2007-2016 in CRA-Interim (a), ERA5 (b), JRA-55 (c), Observation (d).

3.1.2 SPATIAL DISTRIBUTIONS OF PRECIPITATION IN EACH SEASON

Based on above analyses, the spatial distribution of daily-average precipitation rate in four different seasons in China during the 10 years is further obtained by using the reanalysis and observed precipitation data.

It can be seen that in spring, the precipitation is mainly concentrated in South China. Compared with the observations, the western boundary of the rain belt in spring simulated by the CRA-Interim is more westward, and the northern boundary is more southward. The overestimation of precipitation rate in the CRA-Interim mainly appears in Southwest China (Sichuan, Chongqing, Yunnan and Guizhou), while the underestimation appears in Central and East China (Hubei, Hunan, Anhui and Zhejiang), with both the bias of about 2 mm d^{-1}. The simulation results of ERA5 in Southwest China are similar to those of CRA-Interim, and so are the bias (2 mm d^{-1}). However, the northern boundary of the rain belt is more accurately simulated in ERA5, which coincides with the observations very well. Basically, the distribution of the rain belt in spring simulated by JRA-55 is relatively more accurate, of which the range is slightly larger and the intensity is slightly stronger. The overestimation of precipitation appears in Southwest China (Sichuan, Chongqing, Yunnan, Guizhou), Guangdong and Guangxi, with bias of about 2 mm d^{-1}.

Precipitation in China is most concentrated in summer, which gradually increases from northwest to southeast. Fig. 3 shows the spatial distributions of summer-averaged daily precipitation in the three reanalysis datasets and observations. Compared with the observations, the summer-averaged daily precipitation simulated by the CRA-Interim is overestimated in Southwest and South China, which is the region with most precipitation, with bias of about 4 mm d^{-1}. However, for regions with second-most precipitation in summer, the daily precipitation is

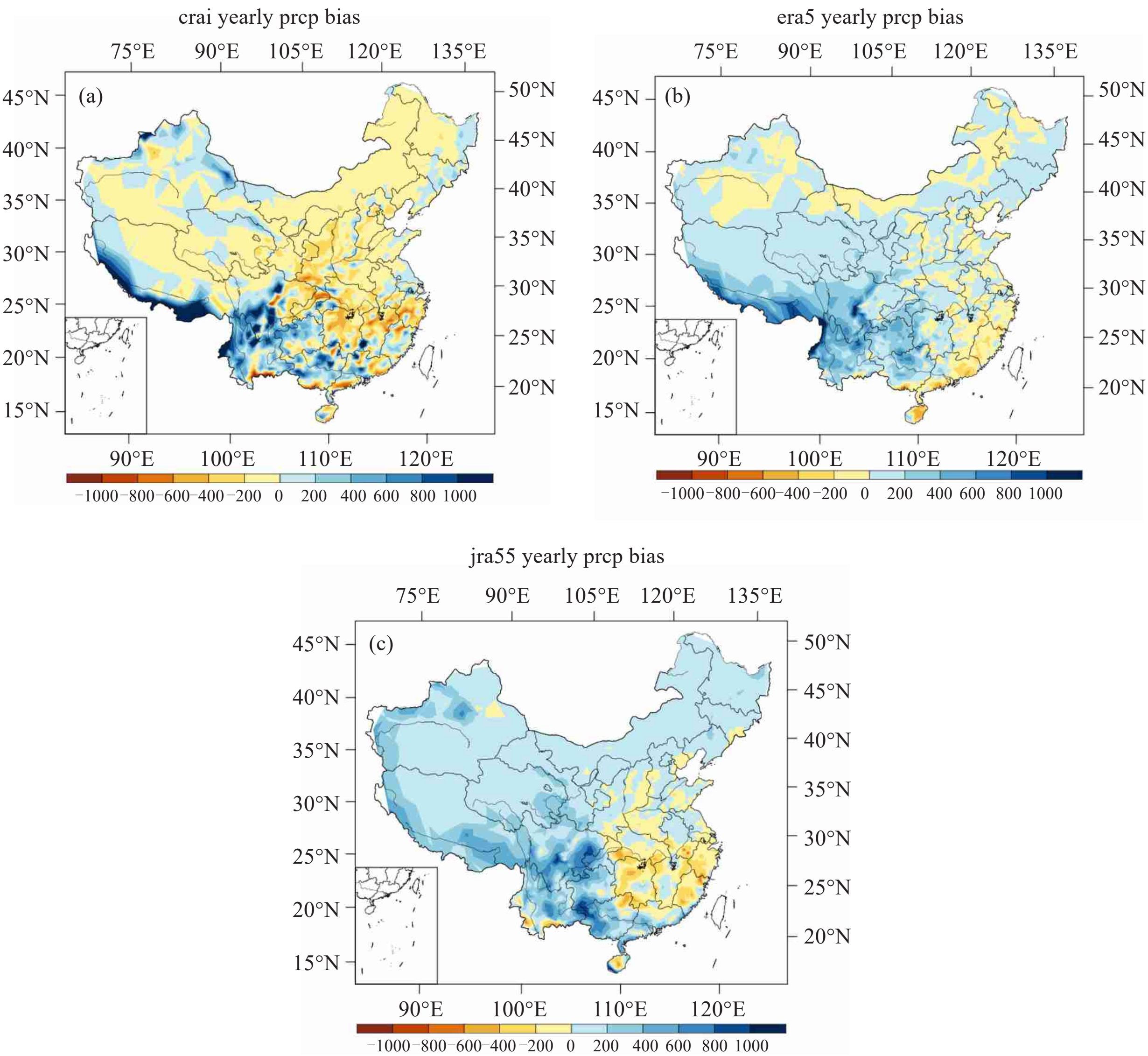

Figure 2. Climatological annual total precipitations mean error(mm/year)2007–2016 in CRA-Interim (a), ERA5 (b), JRA-55(c). (reanalysis data minus observation).

underestimated, with bias of about 2 mm d^{-1}. For rest regions in China, the simulated precipitation is similar to the observations. ERA5 generally shows positive bias in summer, with an overestimation in the key rain belt. The simulation shows that there are positive bias of about 4 mm d^{-1} in the southern Tibet, Sichuan and Yunnan. Meanwhile, JRA-55 also overestimates the range and intensity of rain belt in summer of China, and shows positive bias of about 4 mm d^{-1} in the southwest and northeast of China.

In autumn, the intensity and range of the rain belt are greatly weakened. Compared with observations, the simulation bias in the CRA-Interim is similar to that in spring. The overestimations in the CRA-Interim appear in Southwest China (Sichuan and Yunnan), while the underestimations appear in the Central and East China (Hubei, Hunan, Anhui, and Zhejiang), with both bias of about 2 mm d^{-1}. ERA5 shows overestimations in the range and intensity of the rain belt in autumn. Positive bias, which are similar to those in the CRA-Interim, appear in the southwest region; however, few negative bias can be found in Hainan Island, which may be attributed to the poor performance in rainfall simulation caused by typhoon. The rain belt in autumn simulated by JRA-55 is similar to that by ERA5, but the negative bias appear in Hubei, Hunan and Anhui instead of Hainan.

In winter, the intensity and range of the rain belt along the southeast coast continue to weaken. The simulated range of the rain belt in winter is underestimated in CRA-Interim and overestimated in JRA-55. However, it coincides well with ERA5.

In general, all the three reanalysis datasets show overestimations of precipitation in spring and summer, especially in Southwest China, where positive bias can be found in all the three reanalysis datasets. This may

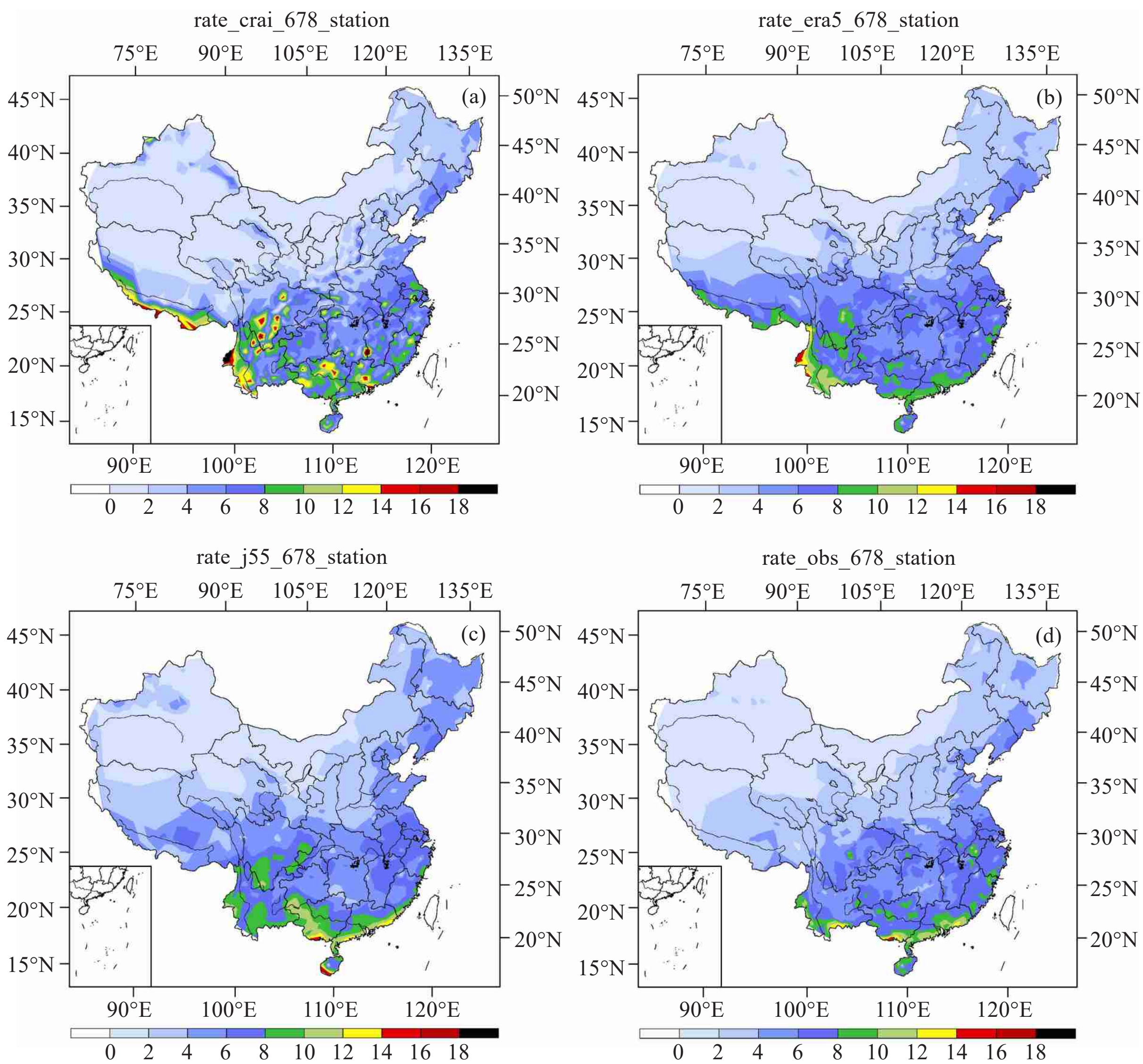

Figure 3. Spatial distribution of average daily precipitation (mm d^{-1}) in summer in CRA-Interim(a), ERA5(b), JRA-55(c), Observation (d).

be related to the large simulation bias of numerical model in the lower reaches of the Tibet Plateau. The CRA-Interim shows a range of negative bias in the central region, which may be due to the assimilation schemes adopted in the CRA-Interim. With more ground information added in the schemes, more detailed simulation of precipitation triggered by topographic forcing would be obtained; however, detailed distribution of observed precipitation cannot be reflected as there is not enough observation over complex terrain. There are few or no stations in mountainous areas (especially in the western mountainous areas); however, the corresponding topographic information has been added into the model, leading to some artificial precipitation triggered by topographic forcing.

3.2 *Temporal distribution characteristics of precipitation*

3.2.1 ANNUAL-MONTHLY VARIATION OF PRECIPITATION

As shown in Fig. 4, based on the monthly precipitation averaged at all the stations in China, the monthly-annual variation of monthly average precipitation is obtained. It can be seen that as most of China is located in the East Asian monsoon area, the distributions of precipitation show obvious seasonal differences. From 2007 to 2016, the monthly average precipitation in summer all exceeds 150 mm, with the maximum of more than 180 mm. Meanwhile, the monthly average precipitation in winter is less than 40 mm, with a minimum of lower than 10 mm.

Precipitation simulations in three reanalysis datasets show different bias. The JRA-55 presents positive bias in almost the entire periods, whereas the CRA-Interim shows negative bias in almost the entire time periods. The ERA5 presents overestimations in spring and autumn for some years, and

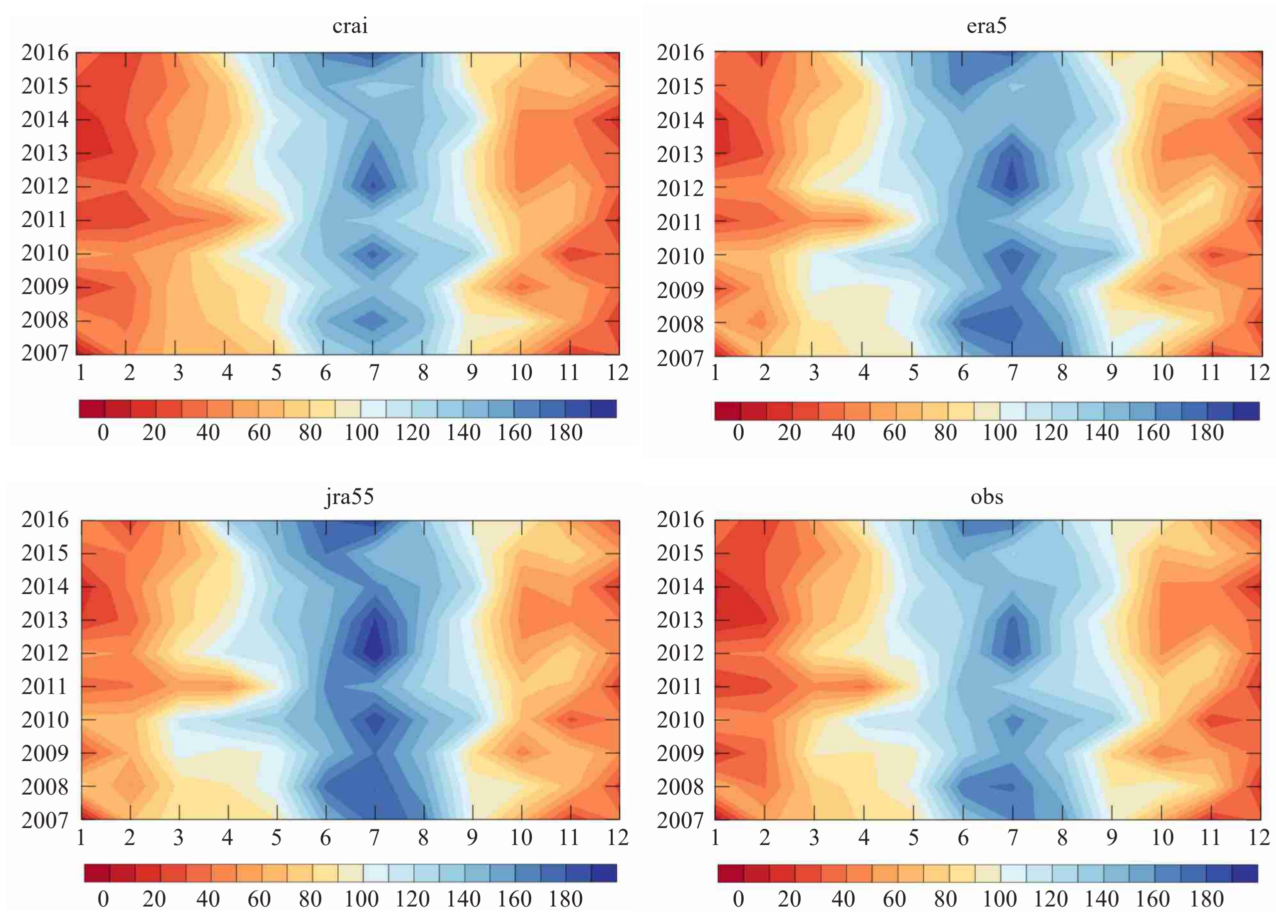

Figure 4. Interannual variation of average monthly precipitation (mm momth^{-1}) of all stations 2007–2016 in CRA-Interim (a), ERA5 (b), JRA-55(c), Observation (d).

underestimations in other periods.

The inter-annual variation of the monthly precipitation is relatively accurately simulated in three reanalysis datasets, reflecting the distribution difference of drought and flood in different years. It is shown that the precipitation in the summers of 2008, 2010, 2012, 2013 and 2016 is more than that in other years, while that of 2009 and 2011 is significantly less. As the difference in the time series of precipitation bias in three reanalysis datasets, the time series of monthly precipitation bias in three reanalysis datasets are obtained by subtracting observational data from the simulated precipitation in three reanalysis data sets.

As shown in Fig. 5, the monthly precipitation averaged at all stations in the CRA-Interim during 2007–2016 generally shows negative bias, with an average of −2 mm. The seasonal variation of the bias is not obvious. The maximum negative bias occurs in spring (March), summer (August) and autumn (November), with a magnitude of more than 20 mm, while the maximum positive bias occurs in summer (July and August), with a maximum of more than 20 mm. In terms of bias characteristics, it might be occasional errors caused by typical weather processes.

ERA5 and JRA-55 show similar bias variations in the 10 years, both of which generally exhibit positive bias. The average bias in ERA5 is 7 mm, with a maximum positive value of 18 mm, while the average bias in JRA-55 is 10 mm, with a maximum positive value of 23 mm. The bias in ERA5 and JRA-55 present certain seasonal variations, which might be due to the systematic bias.

From the temporal variations of the RMSE of the monthly precipitation averaged at all stations in three reanalysis datasets, it can be seen that, in summer, the RMSE of precipitation in the CRA-Interim is the largest, followed by JRA-55, and that in ERA5 is the smallest. The trends of the RMSE in three reanalysis datasets are basically the same, which almost coincides with the variations of the monthly precipitation averaged at all stations. The RMSE in summer is significantly higher than that in winter, which is almost the same in spring and autumn.

3.2.2 CHARACTERISTICS FOR DIURNAL VARIATIONS OF SUMMER PRECIPITATION

Summer is the season with most precipitation in China. The simulation on diurnal variations of precipitation involves many physical processes in the

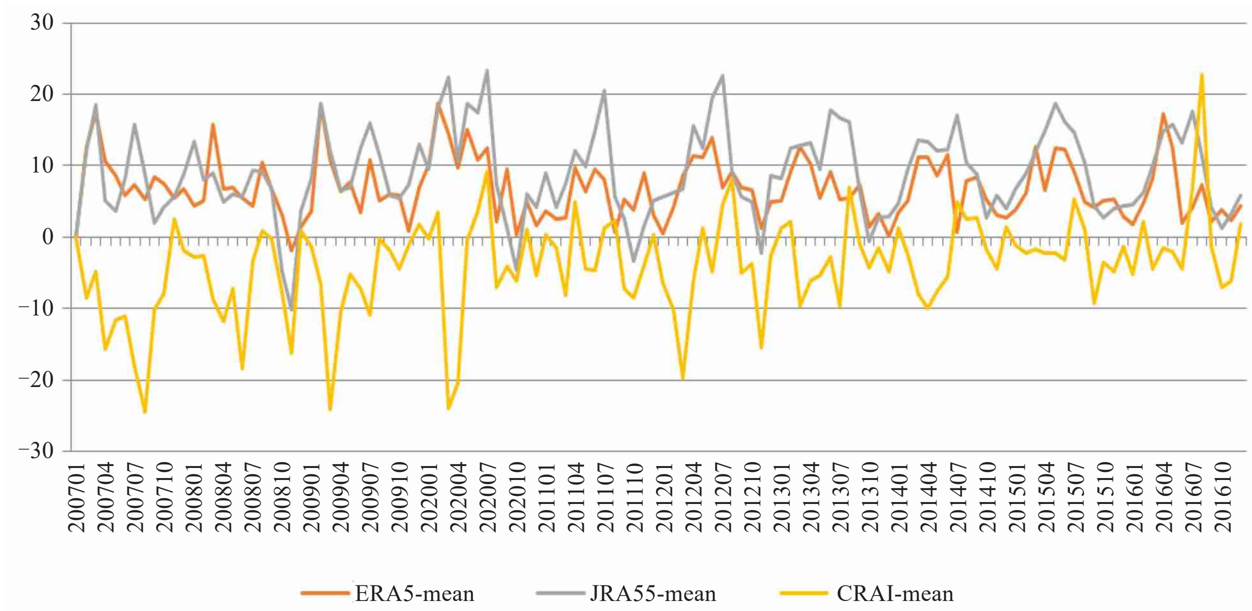

Figure 5. Mean error of monthly accumulated precipitation of all stations Jan 2007-Dec 2016 of 3 reanalysis data.

model, such as the convection, radiation transfer, cloud physical process, terrain difference, flux exchange between the surface and boundary layer, etc. Therefore, it is an ideal method to evaluate the physical process of the model (Trenberth et al.[25]; Cui et al. [26]; Sun et al.[27]; Wei[28]). To further study the applicability of precipitation products from China's atmospheric reanalysis data, comparisons among three reanalysis datasets are conducted on the distribution characteristics for diurnal variations of summer precipitation.

In this paper, the total precipitation during 08:00−20: 00 Beijing time is defined as the daytime precipitation, while that during 20: 00−08: 00 Beijing time is defined as night precipitation. The spatial distributions for the percentage of the daytime precipitation to the total daily precipitation averaged in summers of 2007−2016 are shown in Fig. 6.

From Fig. 6, it can be seen that there are some differences between three reanalysis datasets and the observations. Generally, all the three reanalysis datasets have well simulated the distribution characteristics for daily variations of precipitation in southeast coastal areas, the northeast of Inner Mongolia and the northern part of Heilongjiang. The CRA-Interim performs the best, followed by ERA5, while JRA-55 is slightly inferior. All the three reanalysis datasets show slightly poor simulation abilities for the "night rain" in the southwest of China. For the CRA-Interim, the simulated night precipitation in the southwest is basically the same as the daytime precipitation. For ERA5, the "night rain" could only be simulated at the border regions of Sichuan, Chongqing, and Guizhou. The night precipitation simulated by JRA-55 is closer to the observations. In addition, compared with the other two reanalysis datasets, the CRA-Interim overestimates the daytime precipitation in the Shandong Peninsula and the North China Plain, and also overestimates the night precipitation in the Tarim basin.

3.3 *Comparison of simulation ability of precipitation*

By referring to the operational verification methods in National Meteorological Center, indexes of Threat Score (TS), Missing Rate (PO), False Alarm Ratio (FAR), Equitable Threat Score (ETS) and True Skill Statistic (TSS) are selected for verifying the reanalysis datasets (Pan et al. [29]).

Based on the above-mentioned reanalysis products and observations, the results of 24-hour forecast from 00: 00 UTC (i. e., 08: 00 BTC) are analyzed in this study. According to the precipitation value, five levels are defined, namely light rain (⩾ 0.1), moderate rain (⩾ 10), heavy rain (⩾ 25), rainstorm (⩾ 50) and downpour (⩾ 100). If the precipitation is ⩽ 0.1, it is considered that no precipitation events occur.

Indexes for precipitation of five levels in three reanalysis datasets, including TS, PO, FAR, ETS and TSS (table omitted), are calculated. The line chart shows that there are some differences in the scores of different indexes in three reanalysis datasets (Fig. 7).

The results show that the TS decreases with the increase of rainfall. At the level of light rain, the TS scores are all close to 0.6 in three reanalysis datasets, of which ERA5 scores slightly higher, while those of JRA-55 and CRA-Interim are equivalent. At the level of moderate rain, TS has dropped to 0.433 in ERA5, but it is still significantly higher than those of JRA-55 (0.394) and CRA-Interim (0.358). At the level of heavy rain, the TS scores have dropped below 0.3 in all the three reanalysis datasets, whereas the TS of

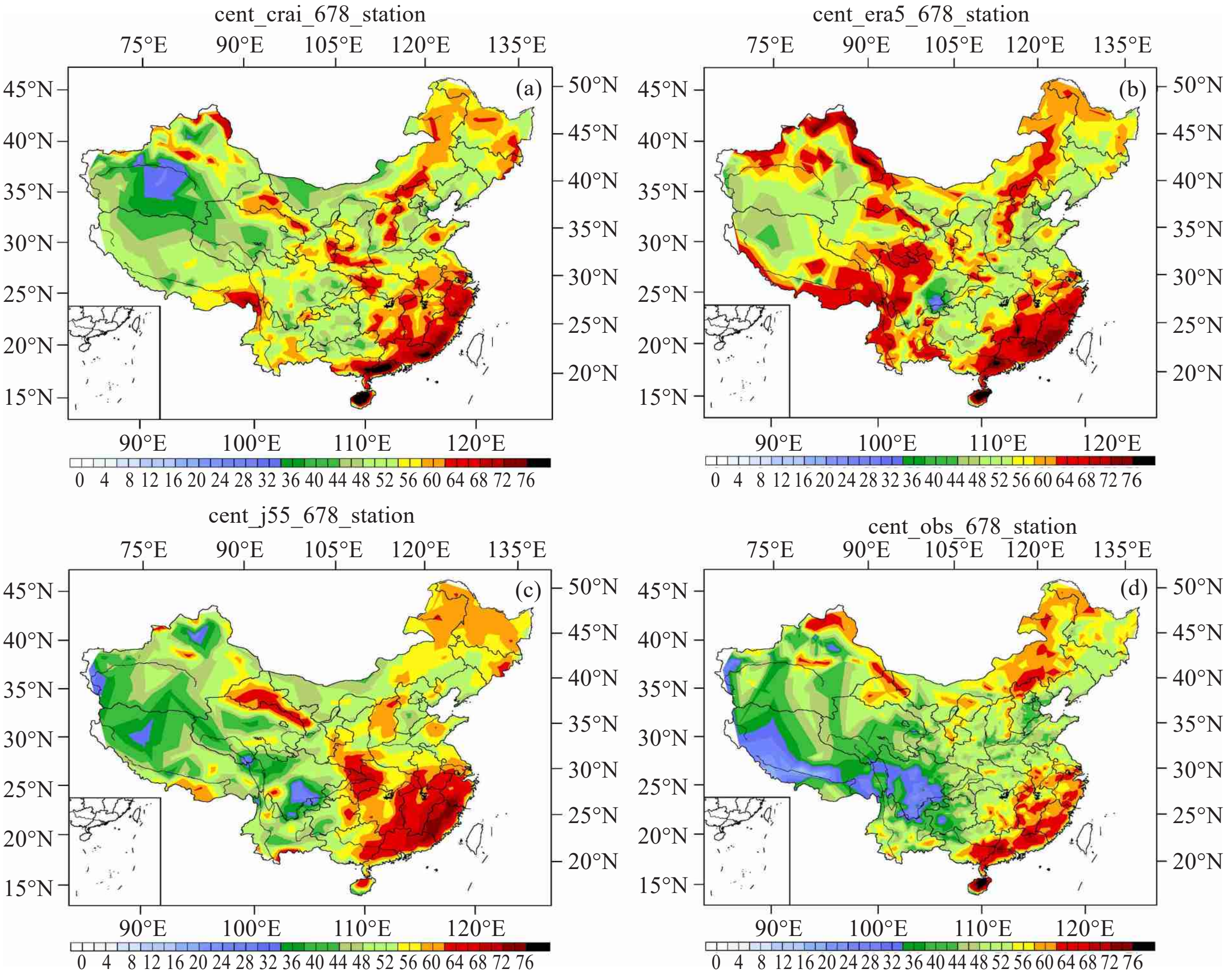

Figure 6. Spatial distribution of average daytime precipitation in summer as a percentage of total daily precipitation (%) in CRA-Interim(a), ERA5(b), JRA-55(c), Observation(d).

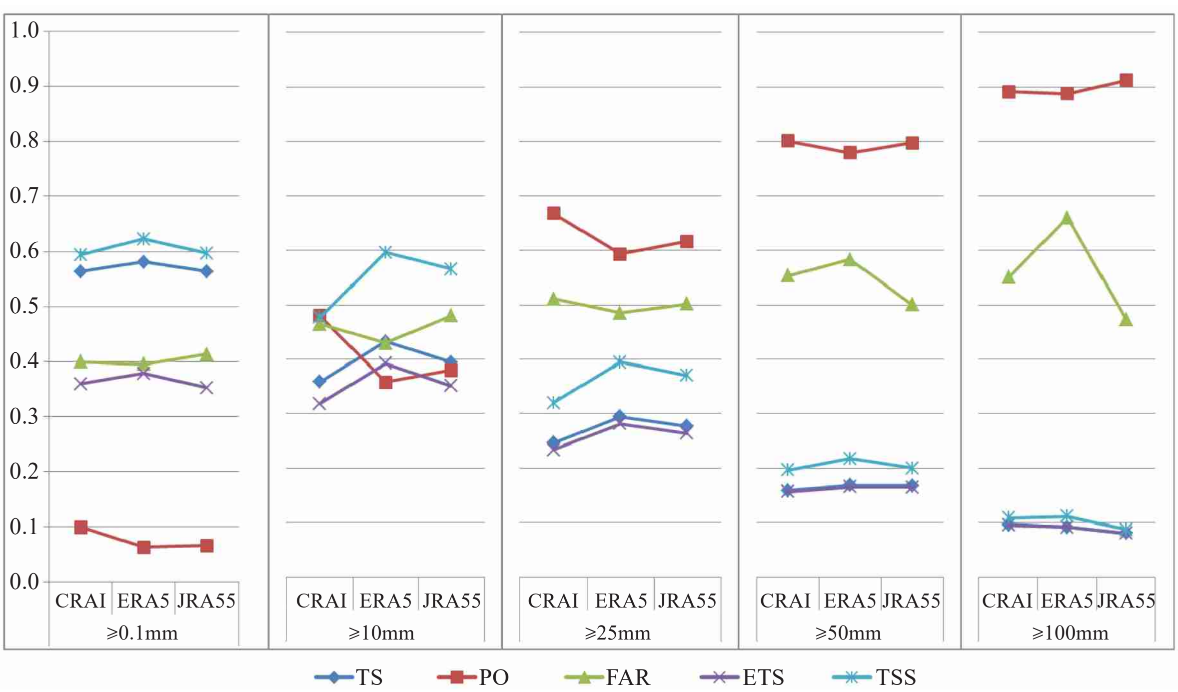

Figure 7. Scores of five indexes for precipitation of five levels in three reanalysis datasets. (Blue: TS, Red: PO, Green: FAR, Purple: ETS, Cyan: TSS).

ERA5 is still higher than those of JRA-55 and CRA-Interim. At the levels of rainstorm and downpour, three reanalysis datasets have comparable performances, with the TS scores between 0.16–0.17 for the level of rainstorm and 0.08–0.10 for downpour.

With the increase of rainfall, the score of PO increases significantly. At the level of light rain, missing events account for less than 10% of the total light rain events in three reanalysis datasets. This percentage increases to 35% – 48% at the level of moderate rain, 60% – 68% at the level of heavy rain, close to 80% at the level of rainstorm, and close to 90% at the level of downpour. Similarly, at the levels of heavy rain or below, the ERA5 performs better than JRA-55 and CRA-Interim, while at the levels of rainstorm and downpour, the PO scores of three reanalysis datasets are basically equivalent, and the CRA-Interim performs slightly better.

The score of FAR increases slightly with the increase of rainfall. Below the level of rainstorm, three reanalysis datasets have comparable performances. The FAR scores are about 0.40, 0.45 and 0.5 at the levels of light rain, moderate rain and heavy rain, respectively. At the level of rainstorm or above, FAR is relatively low in JRA-55, while it is relatively high in ERA5.

The score of ETS also decreases with the increase of rainfall, which is lower than TS score. Moreover, the higher the precipitation level is, the closer the scores of ETS and TS are. The ETS score of ERA5 is slightly higher than those of JRA-55 and CRA-Interim at levels of rainstorm and below. At the levels of rainstorm and above, the scores in three reanalysis datasets are basically the same, where the CRA-Interim performs slightly better at the level of rainstorm.

The variation trends of TSS score at different precipitation levels and the distribution of scores in three reanalysis datasets are basically the same as the performance of TS score. Compared with the TS score, the TSS scores are about 0.030, 0.150, 0.100 and 0.05 higher at the levels from light rain to rainstorm, respectively, and basically the same at the level of downpour.

Through the evaluation on quantitative precipitation forecast, it can be seen that the ERA5 performs the best, followed by the JRA-55 which is better than the CRA-Interim. However, at the level of downpour, the CRA-Interim performs slightly better than the other two.

4 CONCLUSIONS AND DISCUSSION

The present paper compared the data of precipitation observed at the surface meteorological stations of China with the reanalysis datasets of CRA-Interim, ERA5 and JRA-55. The simulations using three reanalysis datasets have some similarities. However, significant differences appear in different regions and at time scales. The main conclusions are as follows.

All the three reanalysis datasets can basically simulate the spatial distribution characteristics of precipitation in China. The simulations of major rain belts in spring and summer mainly show positive bias. CRA-interim has larger negative bias in central and East China, and larger positive bias in Southwest China. Especially, the CRA-Interim exhibits underestimations of the precipitation during the First Rainy Season in South China and the autumn rainfall in West China. However, the CRA-Interim coincides well with the observations in simulating the Meiyu in the middle and lower reaches of the Yangtze River. Besides, the CRA-Interim is more detailed in simulating the precipitation triggered by topographic forcing.

All the three reanalysis datasets perform well in simulating the temporal variations of precipitation of inter-annual variation by basically reflecting the distribution difference of drought and flood in different years. The CRA-Interim mainly shows negative bias, and the seasonal variations of the bias are not obvious. ERA5 and JRA-55 mainly show positive bias with certain seasonal variations. The RMSEs in winter are similar among the three reanalysis datasets, which are significantly lower than those in summer. For the diurnal variation of summer precipitation, the CRA-Interim performs better in simulating the daytime precipitation in most areas, whereas the JRA-55 is better in simulating the night rainfall in southwest China. The bias of CRA-interim is less in the Southeast and the Northeast than in the Southwest.

According to the evaluation on quantitative precipitation forecast, ERA5 generally performs the best, and the JRA-55 is the next, followed by the CRA-Interim. For precipitation at the level of downpour, the CRA-interim is slightly better than the other two. However, at the level of heavy rain (⩾ 25) and rainstorm(⩾ 50) CRA-Interim has higher Missing Rate (PO) and lower Threat Score (TS). The three reanalysis datasets are relatively consistent in simulating weak precipitation.

The above analyses of the precipitation bias of China's atmospheric reanalysis datasets comprehensively show the data applicability at both the climatic and synoptic scales. Therefore, this study could provide some valuable supports for the application of China's atmospheric reanalysis data in climate monitoring, seasonal forecast of precipitation, as well as the research on climate variability, climate change, water cycle and typical rainstorm cases. On the basis of this study, we can continue to study regional climate characteristics, extreme weather, and climate events simulation and evaluation in the future.

Acknowledgments: We thank Nanjing Hurricane Translation for reviewing the English language quality of this paper.

REFERENCES

[1] ZHAO Tian-bao, FU Cong-bin, KE Zong-jian, et al. Global atmosphere reanalysis datasets: current status and resent advances [J]. Adv Atmos Sci, 2010, 25(3): 242-254, https://doi.org/10.11867/j.issn.1001-8166.2010.03.0241.

[2] HE Lang, WU Hong-bao, ZHAO Xiao-chuan, et al. An Intercomparison of basic statistics derived from three kind of reanalysis data [J]. Trans Atmos Sci, 2009, 32: 54-63 (in Chinese), https://doi. org / 10.3969 / j. issn. 1674-7097.2009.01.007.

[3] KALNAY E, KANAMITSU M, KISTLER R, et al. The NCEP / NCAR 40-year reanalysis project [J]. Bull Amer Meteor Soc, 1996, 77(3): 437-471, https://doi.org/10.1175/1520-0477(1996)077<0437:TNYRP>2.0.CO;2.

[4] LI Jian, YU Ru-cong, CHEN Hao-ming, et al. Evaluation and analyses of summer rainfall over mainland China in three reanalysis datasets [J]. Meteor Mon, 2010, 36: 1-9 (in Chinese), https://doi. org / 10.7519 / j. issn. 1000-0526.2010.12.001.

[5] CHENG Xiao-yu, WANG Yan-hua, LI Guo-chun, et al. Evaluation of three reanalysis precipitation datasets in China [J]. Advances in Climate Change Research, 2013, 9: 258-265 (in Chinese), https://doi.org/10.3969/j.issn.1673-1719.2013.04.004.

[6] LV Shao-ning, WEN-Jun, LIU Rong. Applicability and potential of the different precipitation data in mainland China [J]. Plateau Meteor, 2011, 30: 628-640 (in Chinese).

[7] SU Zhi-xia, LV Shi-hua, LUO Si-wei. The examinations and analysis of NCEP / NCAR 40 years global reanalysis data in China [J]. Plateau Meteor, 1999, 18: 209-218 (in Chinese).

[8] ZHAO Tian-bao, AI Li-kun, FENG Jin-ming An Intercomparison between NCEP reanalysis and observed data over China [J]. Clim Environ Res, 2004, 9: 278-294 (in Chinese), https://doi. org / 10.3878 / j. issn. 1006-9585.2004.02.05.

[9] ZHAO Tian-bao, FU Cong-bin. Preliminary comparison and analysis between ERA-40, NCEP-2 reanalysis and observations over China [J]. Clim Environ Res, 2006, 11: 14-32 (in Chinese), https://doi. org / 10.3878 / j. issn. 1006-9585.2006.01.02.

[10] DAI Ze-jun, YU Ru-cong, LI Jian, et al. Characteristics of summer precipitation diurnal variation in three reanalysis datasets over China [J]. Meteor Mon, 2011, 37: 21-30 (in Chinese), https://doi. org / 10.7519 / j. issn. 1000-0526.2011.1.003.

[11] WEI Li, LI Dong-liang. Reliability of NCEP / NCAR reanalysis data in climatic change along Qinghai-Xizang Railway [J]. Plateau Meteor, 2003, 22: 488-494 (in Chinese),

[12] CHEN S, GAN T Y, TAN X Z, et al. Assessment of CFSR, ERA-Interim, JRA-55, MERRA-2, NCEP-2 reanalysis data for drought analysis over China [J]. Clim Dyn, 2019, 53: 737-757, https://doi.org/10.1007/s00382-018-04611-1.

[13] HU Zeng-yun, NI Yong-yong, SHAO Hua, et al. Applicability study of CFSR, ERA-Interim and MERRA precipitation estimates in Central Asia [J]. Arid Land Geo, 2013, 36: 700-708 (in Chinese), https://doi. org / 10.13826/j.cnki.cn65-1103/x.2013.04.011.

[14] HURLEY A R. Comparison and Validation of Arctic Precipitation Fields from Three Atmospheric Reanalyses: CFSR, MERRA, ERA-Interim [D]. Colorado: University of Colorado, 2014.

[15] PALERME C, CLAUD C, DUFOUR A, et al. Evaluation of Antarctic snowfall in global meteorological reanalyses [J]. Atmos Res, 2017, 190: 104-112, https://doi. org / 10.1016/j.atmosres.2017.02.015.

[16] ZHAO B, ZHANG B, SHI C, et al. Comparison of the global energy cycle between Chinese reanalysis interim and ECMWF reanalysis [J]. J Meteor Res, 2019, 33: 563-575, https://doi.org/10.1007/s13351-019-8129-7.

[17] LI C X, ZHAO T B, SHI C X, et al. Evaluation of daily precipitation product in China from the CMA global atmospheric interim reanalysis [J]. J Meteor Res, 2020, 34 (1): 117-136, https://doi.org/10.1007/s13351-020-8196-9.

[18] DRAGANI R, HERSBACH H, POLI P, et al. Recent reanalysis activities at ECMWF: Results from ERA-20C and Plans for ERA5 [C]// AGU Fall Meeting 2015, San Francisco: American Geophysical Union, 2015.

[19] ZHANG Qiang, ZHAO Yu-fei, FAN Shao-hua. Development of hourly precipitation datasets for national meteorological station in China [J]. Torrential Rain and Disasters, 2016, 35: 182-186 (in Chinese), https://doi.org/10.3969/ j.issn.1004-9045.2016.02.011.

[20] KISTLER R, KALNAY E, COLLINS W, et al. The NCEP-NCAR 50-year reanalysis: Monthly means CD-ROM and documentation [J]. Bull Amer Meteor Soc, 2001, 82(2): 247-267, https://doi. org / 10.1175 / 1520-0477(2001)082<0247:TNNYRM>2.3.CO;2.

[21] LIU Z Q, SHI C X, ZHOU Z J, et al. CMA global reanalysis (CRA-40): Status and plans [C]// Proc 5th International Conference on Reanalysis. Rome: Natl Meteor Int Center, 2017: 13-17.

[22] LIANG X, JIANG L P, PAN Y, et al. A 10-Yr Global Land Surface Reanalysis Interim Dataset (CRA-Interim/Land): implementation and preliminary evaluation [J]. J Meteor Res, 2020, 34(1): 101-116, https://doi. org / 10.1007 / s13351-020-9083-0.

[23] YANG S, SMITH E A. Mechanisms for diurnal variability of global tropical rainfall observed from TRMM [J]. J Climate, 2006, 19(20): 5190-5226, https://doi. org / 10.1175/JCLI3883.1.

[24] JIA Peng-qun. Compararion between observational data and grid data of precipitation for the last one hundred years in China [J]. J Appl Meteor Sci, 1999, 10: 181-189 (in Chinese), https://doi.org/CNKI:SUN:YYQX.0.1999-02-005.

[25] TRENBERTH K E, DAI A, RASMUSSEN R M, et al. The changing character of precipitation [J]. Bull Amer Meteor Soc, 2003, 84(9): 1205-1217, https://doi. org / 10.1175/BAMS-84-9-1205.

[26] CUI Mao-chang, ZHU Hai, BAI Xue-zhi, et al. An analysis of daily rainfall variability in China [J]. Chin J Atmos Sci, 2000, 24: 519-526 (in Chinese), https://doi.org/10.3878/j.issn.1006-9895.2000.04.08.

[27] SUN Jia, ZHANG Xin-ping, HUANG Yi-min. Evalution of precipitation from ERA-Interim, CRU, GPCP and TRMM Reanalysiss data in the Dongting Lake Basin [J]. Resources and Environment in the Yangtze Basin, 2015,

24: 1850-1859 (in Chinese), https://doi. org / 10.11870 / cjlyzyyhj201511007.
[28] WEI Fen-fen. Evaluation of Uncertainty in the Regional Climate Simulation Driving by Different Reanalysis over China [D]. Nanjing: Nanjing University, 2013.
[29] PAN Liu-jie, XUE Chun-fang, ZHANG Hong-fang, et al. Comparison of three verification methods for high-resolution grid precipitation forecast [J]. Clim Environ Res, 2017, 22: 45-58, https://doi.org/10.3878/j.issn.1006-9585.2016.16012.

Citation: YE Meng-shu, YAO Xiu-ping, ZHANG Tao, et al. Intercomparison of CRA-Interim precipitation products with ERA5 and JRA-55 [J]. J Trop Meteor, 2021, 27(2): 136-147, https://doi.org/10.46267/j.1006-8775.2021.013.