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Evaluating the added values of regional climate modeling over China at different resolutions

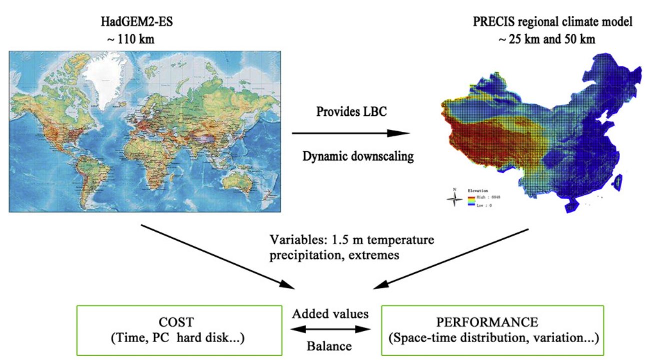
Junhong Guo [a,c], Guohe Huang [b,c,*], Xiuquan Wang [d,**], Yinghui Wu [a,c], Yongping Li [e], Rubing Zheng [a], Limin Song [a]

[a] Key Laboratory of Regional Energy and Environmental Systems Optimization, Ministry of Education, North China Electric Power University, Beijing 102206, China
[b] Institute for Energy, Environment and Sustainable Communities, University of Regina, Regina, Saskatchewan S4S 0A2, Canada
[c] SC Institute for Energy, Environment and Sustainability Research, North China Electric Power University, Beijing 102206, China
[d] School of Climate Change and Adaptation, University of Prince Edward Island, Charlottetown, Prince Edward Island C1A 4P3, Canada
[e] School of Environment, Beijing Normal University, Beijing 100875, China

HIGHLIGHTS

- Evaluating whether a fine-resolution model has more added value for understanding regional climatology.
- PRECIS model is used to conduct long-term climate simulations for China at two different spatial resolutions.
- Regional climate models with higher resolution cannot always produce more accurate output.

GRAPHICAL ABSTRACT



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ABSTRACT

Previous studies have suggested that dynamical downscaling to global climate models can produce improved climate simulations at regional and local scales. However, the expensive computational requirements of dynamical downscaling inevitably add a limit to the spatial resolution of the resulting regional climate simulations. In order to find a balance between computational requirements and simulation improvements, it is extremely important to investigate how the spatial resolution of regional climate simulation affects the added values of dynamical downscaling; yet, it is still not well understood. Therefore, in this study, we conduct long-term climate simulations for the entire country of China with the PRECIS regional climate model at two different spatial resolutions (i.e., 25 and 50 km). The purpose is to evaluate whether a fine-resolution model simulation, given its considerable requirements for computational resources, would add more valuable information for understanding regional climatology than a coarse-resolution model simulation. Our results show that the PRECIS can reasonably reproduce the spatial distribution of seasonal and monthly mean temperature and precipitation over the most of regions in China. However, in the process of downscaling, RCM with higher resolution cannot always produce more accurate output. In regard to precipitation simulations, compared with the host GCM, it is difficult to determine exactly a homogeneous improvement of performance in downscaling, both in terms of spatial patterns as well as magnitude of errors. For interannual variability, variations in temperature are closer to observation than

* Correspondence to: G. Huang, Institute for Energy, Environment and Sustainable Communities, University of Regina, Regina, Saskatchewan S4S 0A2, Canada.
** Corresponding author.
E-mail addresses: huang@iseis.org (G. Huang), xxwang@upei.ca (X. Wang).

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precipitation and the high-resolution R25 has better skills over the northwest than R50. Moreover, except for the west, it is shown that PRECIS is able to better reproduce the probability distribution function of precipitation and some impact-relevant indices such as the number of consecutive wet days and simple precipitation intensity index in spatial distribution.

1. Introduction

China is one of the regions highly vulnerable to climate change, with complicated climatic conditions, fragile ecological environment and frequent natural disasters. In recent years, China has experienced many disasters due to climate change. According to the Global Climate Risk Index 2019, there are more than 11,500 extreme weather events (i.e., storms, floods, heat waves, etc.) around the world, resulting in 5,260,000 deaths approximately and US$ 3.47 trillion economic losses from 1998 to 2017, wherein China ranked second for the losses in the world list. In 2017, losses caused by natural disasters are 301.87 billion yuan and affect 140 million people in China (David Eckstein, 2019; Jia and Yun, 2018). Scientific understanding for the process of the past climate changes can obtain the cognition of contemporary climate warming and further provide a reference for adapting to future climate change.

It is widely acknowledged that GCMs are the primary and most authoritative information on climate change, which have been widely used to assess impact, explore reasons and develop adaptive measures of global warming. However, owing to the coarse resolution, GCMs cannot reflect some characteristic information (i.e., vegetation and soil types, complex topography, land-sea contrasts, etc.) in local areas exactly, which play an important role in the formation of the microclimate uniqueness. Therefore, researchers prefer to a transformed version at higher horizontal resolutions instead of GCM.

Dynamic downscaling technology is one of possible solutions available. With realistic details by the representation of fine-scale surface forcing, driven at the lateral boundaries by atmospheric variables obtained from interpolation of coarse-resolution GCMs, regional climate models (RCMs) allow the reproduction of small-scale processes that are unresolved by the low-resolution GCMs. Some popular RCMs, including National Center for Atmospheric Research (NCAR) Weather Research and Forecasting Model (WRF), and Abdus Salam International Centre for Theoretical Physics (ICTP) Regional Climate Model (RegCM), have been widely used for studies on climate simulation and projection in China (Liu et al., 2015; Shi et al., 2015; Wang and Yu, 2013; Zhang et al., 2005).

Previous studies have demonstrated that RCMs can add value to GCMs over different regions of the world because of their higher resolution to some extent, but it is unclear as to whether or not the dynamical downscaling has an overwhelming superiority in reproducing the observed climate change. In addition, there still exists an open question on whether RCMs with higher resolution have better performance than those with lower resolution. For example, Cantet et al. (2014) found that the high resolution showed remarkable advantages in simulating the temperature over the small islands. Lee and Hong (2014) thought the finer resolution model was more efficient in generating the main features of air temperature and precipitation. Tolika et al. (2016) concluded that the higher resolution model presented a better skill in generating low winter temperatures and precipitation over complex terrain. On the other hand, downscaling is not always able to improve the simulation skills of large-scale GCMs (Dosio and Panitz, 2016). Castro (2005) discussed the question when downscaling may be a valid tool to enhance spatial resolution and when it is not, through a Regional Atmospheric Modeling System (RAMS) with a set of six basic experiments. They concluded that there were greater errors as both horizontal grid spacing and domain size increase in RCM, owing to the failure to correctly retain the value of the large scale GCM. Hong and Kanamitsu (2014) found that RCMs inherited the biases from the lateral boundary conditions in driving GCMs and the mismatch of parameterization and resolution often resulted in an inferior simulation. Hasson (2016) used eight CORDEX South Asia RCMs against their six driving CMIP5 experiments to analyze rainfall seasonality over Himalayan watersheds and concluded that RCM results had higher bias than their corresponding driver. In simulations of Indian summer monsoon rainfall, Singh et al. (2017) thought there was no obvious improvement in the RCM simulations with respect to their host GCMs for any of the characteristics of Indian monsoon except the spatial variation.

Generally, the higher the ability of a model to accurately reproduce the present climate, the higher the credibility of the future climate projection (Corney et al., 2013; Liang et al., 2008; Racherla et al., 2012). However, the regional climate model with higher resolution will consume more computing and storage resources. We need to find a balance between computational requirements and simulation improvements. Thus, given its considerable requirements for computational resources, scientific evaluation on the performance of RCM before using the dynamically downscaled climate change projections for policy decisions is very necessary and meaningful.

In this paper, an RCM (PRECIS) is run at two different horizontal resolutions over the entire country of China, and the output is then examined with respect to the effects on temperature and precipitation of the regional topography. The objectives of this study are to: (1) validate the performance of PRECIS in simulating temperature and precipitation over China, (2) assess the added value to GCM at different resolutions in dynamic downscaling, and (3) given the requirements for computational resources, answer whether higher-resolution RCM has more advantages in downscaling. The remainder of the paper is organized as follows: in Section 2, brief descriptions of the methods and data are introduced. Section 3 compares the seasonal climatology, annual cycles, interannual variations and extremes of temperature and precipitation in two RCM runs and their driving GCM. A summary of the key findings is presented in Section 4.

2. Methods and data

2.1. Regional climate model

The model used in this study is the Providing Regional Climate for Impacts Studies (PRECIS), which is developed by Meteorological Office, Hadley Centre. Owing to its ease of use and flexibility, PRECIS has been employed to conduct climate simulation and projection in different parts of the world (Buontempo et al., 2014; Wang et al., 2015a; Wang et al., 2015b). It uses atmospheric boundary and initial condition from GCM to generate two high-resolution climate data, which are $0.44° \times 0.44°$ (~50 km) and $0.22° \times 0.22°$ (~25 km) at the equator of the rotated regular latitude-longitude grid. It contains 19 levels in a vertical hybrid-coordinate system, the lowest at ~50 m and the highest at 0.5 hPa with terrain following σ-coordinates used for the bottom four levels, purely pressure coordinates for the top three levels and a combination in between (Noguer et al., 2003). The lateral buffer zone contains a four-point zone at longitude and latitude using a relaxation technique. In addition, as a highly encapsulated and integrated visualization model system, PRECIS uses a mass flux penetrative convective scheme with an explicit downdraught and includes the direct impact of vertical convection on momentum (Gregory, 2011; Gregory et al., 2010). The radiation scheme includes the seasonal and diurnal cycles of insolation, computing six short wave bands and eight long wave bands (Slingo, 1989; Slingo and Wilderspin, 2010). The land surface scheme employs Met Office Surface Exchange Scheme 2.2 (MOSES 2.2) (Essery and Cox, 2001). More detailed information about the physical processes is given in Noguer et al. (2003). PRECIS requires certain boundary conditions at the surface and through the depth of the atmosphere. These binary files are in UM format and contain constant, time-series or annual cycle data which are read as the model progresses (Table 1). In this paper, HadGEM2-ES, which is an earth system model of Hadley Centre Global Environment Model version 2, is used to provide the initial and lateral boundary conditions to drive the PRECIS. For its atmospheric component, there is 38 levels extending to ~40 km height in the vertical direction and $1.25° \times 1.875°$ at horizontal resolution.

2.2. Evaluation methods

In this paper, we look at the relative error (RE) and pattern correlation coefficient (R) relative to the observation to assess the overall performance of simulations, including PRECIS runs and HadGEM2-ES.

In order to quantify the ability of PRECIS to improve (or not) over the HadGEM2-ES, we follow a method from (Dosio et al., 2015; Fotso-Nguemo et al. (2017)), who defined an Added Value (AV):

$$AV = \frac{(X_{GCM} - X_{OBS})^2 - (X_{RCM} - X_{OBS})^2}{Max\left((X_{GCM} - X_{OBS})^2, (X_{RCM} - X_{OBS})^2\right)} \quad (1)$$

where X_{GCM} is the GCM (HadGEM2-ES), X_{OBS} is the observation (CN05.1), and X_{RCM} are the simulations (PRECIS runs with different resolution). As defined above, the AV value is positive where RCM's squared error is smaller than its driving GCM, suggesting PRECIS model improves over the corresponding HadGEM2-ES. By contrast, the negative value represents more errors in RCM.

A coefficient of variation is used to calculate interannual variability of climatology defined as the ratio of the standard deviation to the mean (Fotso-Nguemo et al., 2017; Saini et al., 2015). With respect to the standard deviation of the seasonal and mean climatology, the coefficient of variation removes the dependency on the mean.

$$CV = \frac{X_{std}}{X_{mean}} \quad (2)$$

where X is the daily temperature or precipitation, X_{std} is the annual standard deviation of X and X_{mean} is the annual mean value of X.

In addition, two ECTCDI precipitation indices based on daily precipitation are used in this paper. The consecutive wet days (hereafter, CWD), defined as the maximum number of consecutive wet days, indicates precipitation frequency (Eq. (3)), and the simple precipitation intensity index (hereafter, SDII), defined as the mean precipitation on wet days, represents precipitation intensity (Eq. (4)).

$$CWD = Max(W_i) \quad (3)$$

$$SDII = \frac{\sum_{w=1}^{W} RR_w}{W} \quad (4)$$

Table 1
Boundary conditions of PRECIS.

Data type	Name	Spatial resolution
Lateral boundary conditions	HadGEM2-ES historical: ta, ps, ua, va, hus	$1.25° \times 1.875°$
Surface boundary conditions	Orographic fields	$1.25° \times 1.875°$
	Vegetation and soil fields	$0.5° \times 0.5°$
	SST and SICE	$1.0° \times 0.333°$
	DMS and SO2 emissions	$1.25° \times 1.875°$

where *RR* presents daily precipitation amount is more than 1 mm (wet days), W_i is the ith number of consecutive wet days, *W* presents total number of wet days.

2.3. Data

The CN05.1 dataset, which is developed by the China Meteorological Administration, is used as the observation to validate the performance of simulations in this study. The dataset is based on 2416 national meteorological stations and covers the period 1961 to 2012, and then they are interpolated onto spatial grids with $0.25° \times 0.25°$ horizontal resolution. Its variables contain daily mean/maximum/minimum temperature, precipitation, evaporation, mean wind speed and relative humidity (Wu and Gao, 2013). The data has been widely employed in many studies in assessment on past climate change in China (Guo and Wang, 2016; Wu et al., 2017; Xu et al., 2018). Here, we extract the successive 30-years data, including daily mean temperature and precipitation, from 1976 to 2005 to represent the observations of present-day climate over China. The HadGEM2-ES is also used as a benchmark to examine the improvement of dynamic downscaling through PRECIS.

The experiment domain of PRECIS covers the entire China region as shown in Fig. 1. Based on different typical geographical climate features, the domain is divided into six sub regions, which are the northwest (NE), north central (N), northeast (NE), west (W), central (C) and southeast (SE) of China (Fig. 1 and Table 2). In total, the grid points are about 40,000 in 25-km resolution, and one quarter points in 50-km one. A long-term continuous run covering the period of 1950 to 2005 is performed as the present-day climate. In this paper, we selected the continuous 30-years daily dataset of the period 1976–2005 as the baseline period for model validation. Two experiments (R50 and R25) differ only in spatial resolution, all other land parameters are the same, and their running time and hard disk space are list in Table 3. All RCM and GCM output are validated separately in annual (ANN) and seasonal (December–January-February, DJF; June–July-August, JJA). In order to conduct a homogenous comparison, the simulations are remapped into the same resolution as the CN05.1 dataset.

3. Results

In this section, we analyze the ability of PRECIS with different resolutions to reproduce the climatic characteristics over China, and identify the added values of RCM by comparing with observation and its host GCM. Firstly, we discuss the spatial and temporal distribution of mean temperature and precipitation in annual and different seasons, and calculate their spatio-temporal statistics (i.e., R, RE and AV). Then, annual cycles and interannual variations of mean temperature and precipitation are investigated over China and sub regions. Finally, the probability distribution functions (PDFs) and two extreme indices of daily precipitation are also computed.

3.1. Seasonal climatology

The spatial distributions of simulated and observed mean temperature in annual, winter and summer are shown as Fig. 2. Compared to the observation, the major cold (i.e., the northeast and Tibet Plateau) and warm centers (i.e., the northwest and southeast) are well simulated by HadGEM2-ES and PRECIS. The simulated annual mean temperature by PRECIS shows colder regions in the northwest corner edges. Correspondingly, the biases between observation and simulations are presented in Fig. 3. Except for summer, the mean temperature from HadGEM2-ES is colder than observation over most regions in China, especially in the margin of Kunlun Mountains with about 8 °C cold bias, however, the temperature in the Ili River Valley is overestimated compared to observation. The temperature simulated by GCM over the north of Xinjiang in winter is colder, while it is warmer in summer. Bounded on Tianshan Mountains, the bias in

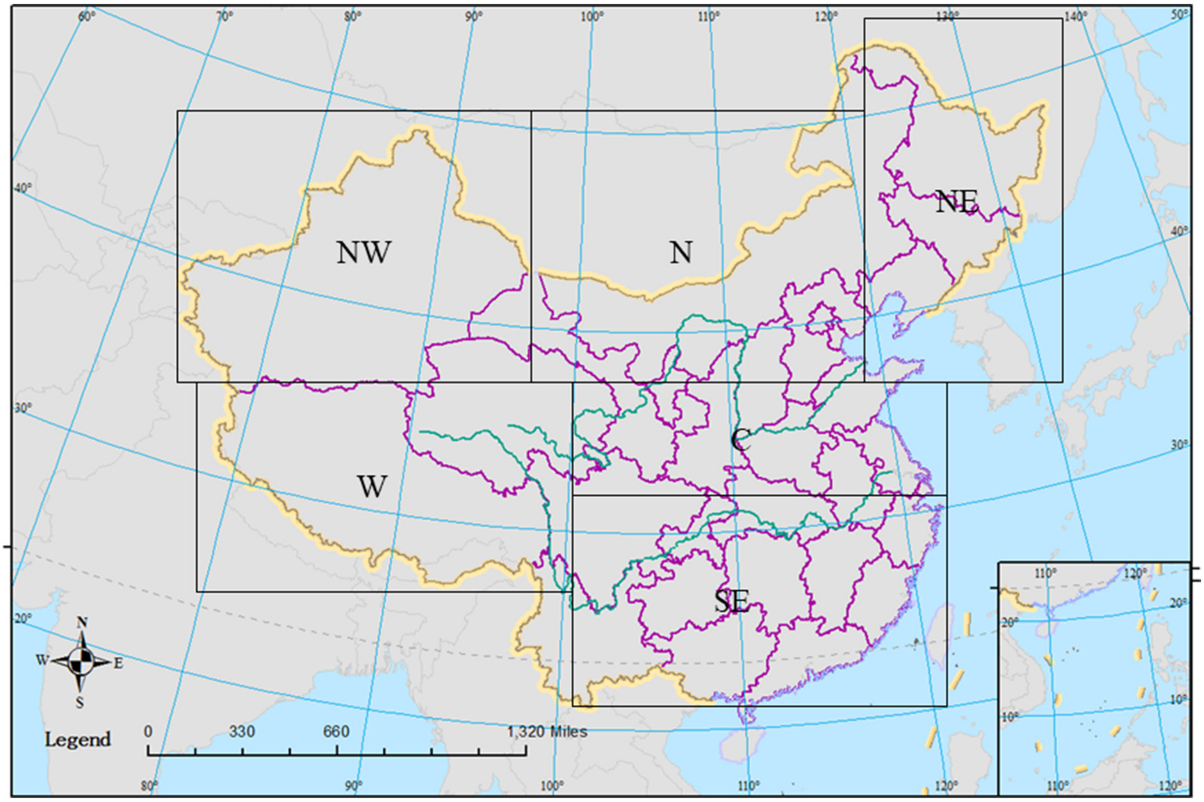

Fig. 1. Study domain in PRECIS climate simulation experiment.

the south and north of Xinjiang is also opposite in summer. PRECIS shows a distinctly more reasonable result than its forcing GCM. The cold biases in annual temperature are corrected in most of areas except for the northwest edges of Xinjiang, even though the RCM results seem a bit hypercorrect in summer and winter. For example, in winter, the cold bias from HadGEM2-ES over the east of Xinjiang is well corrected, while the bias is changed from cold to warm in the north through PRECIS downscaling. In summer, the boundary line (Tian Shan Mountains) between cold and warm biases from GCM is eliminated obviously by RCM over the northwest of China, and instead, many warm biases are overwhelming, especially in the south of Xinjiang. Over the northeast of China, the simulated annual mean temperature by GCM also shows a similar spatial distribution and the boundary line between cold and warm biases is the Greater Khingan Mountains. Compared with the observation, there is apparent colder temperature in winter and warmer in summer from GCM in the whole northeastern plain of China, while PRECIS shows a lot of improvements and that is especially true in the northernmost region for R25. Relative to its driving data, PRECIS also shows significant advantages in temperature simulation over the southeast of China, where significantly reducing the regions of cold bias, especially in annual and summer. However, the mean temperature in winter is still slightly underestimated in Sichuan Basin, despite all the improvements. In the Tibetan Plateau region of western China, the performance of PRECIS in annual mean temperature is not better than HadGEM2-ES, because both R50 and R25 definitely underestimate the mean temperature in nearby the Himalayas and some southeastern regions of Tibet. The mean temperature simulated by PRECIS in summer is better than that in winter, when the temperature is obviously colder than observation over the Tibet Plateau.

Overall, compared to the observation, the mean temperature simulated by GCM has more biases than PRECIS, who corrects considerable cold biases over most areas in China, especially in the east. However, PRECIS has a phenomenon of overcorrection in some regions, such as the northern Xinjiang. In addition, higher-resolution R25 in some high altitudes and complex terrains (i.e., Tianshan or Greater Khingan Mountains) can present more detail information than its driving data in spatial distribution.

Table 2
Climatic characteristics of sub regions in China.

Sub region	Abbreviation	Coordinates	Climatic characteristics
Northwest China	NW	73.2°~97.6°E 36.2°~49.5°N	Arid continental climate
Northcentral China	N	96.7°~123.3°E 36.2°~49.5°N	Temperate continental monsoon climate
Northeast China	NE	123.3°~135.2°E 36.2°~53.7°N	Temperate monsoon climate
West China	W	78.2°~103.1°E 26.8°~36.2°N	Plateau mountain climate
Central China	C	103.1°~123.1°E 30.8°~36.2°N	Warm temperate zone and semi-clouding monsoon climate
Southeast China	SE	103.1°~123.1°E 20.9°~30.8°N	Subtropical monsoon climate

Table 3
Computational resources consumption.

Experiments	Resolution	Grids	Elapsed time	Disk space requirement
R50	50 km	~10,000	~1 month	~1.4 TB
R25	25 km	~40,000	~3 months	~4.1 TB

Note that the above statistics are summarized from the testing results of a professional Oracle Server with a 2.3 GHz Intel 36-core processor and 384 GB memory.

Table 4 presents the statistics of correlation coefficient (R), relative error (RE) and added value (AV) in domain-averaged temperature over China and sub regions. It can be seen that the correlation coefficients in R50 and R25 are higher than their driving GCM. The R values in annual and winter are exceeding 0.9 over most of regions in China. However, over the NE region, the values in downscaling results are lower in summer (about 0.8). Similar with the spatial distribution, over the NW region, although the correlation coefficients between simulations and observation are lower than that over other regions, PRECIS still makes dramatic improvements, for example, the R value increases from 0.6 in GCM to 0.8 in RCMs approximately in winter. Furthermore, RCMs also obviously decrease the relative errors in the largest part of China, except in the western region, and the relative errors become smaller with the increase of spatial resolution. Nevertheless, over the

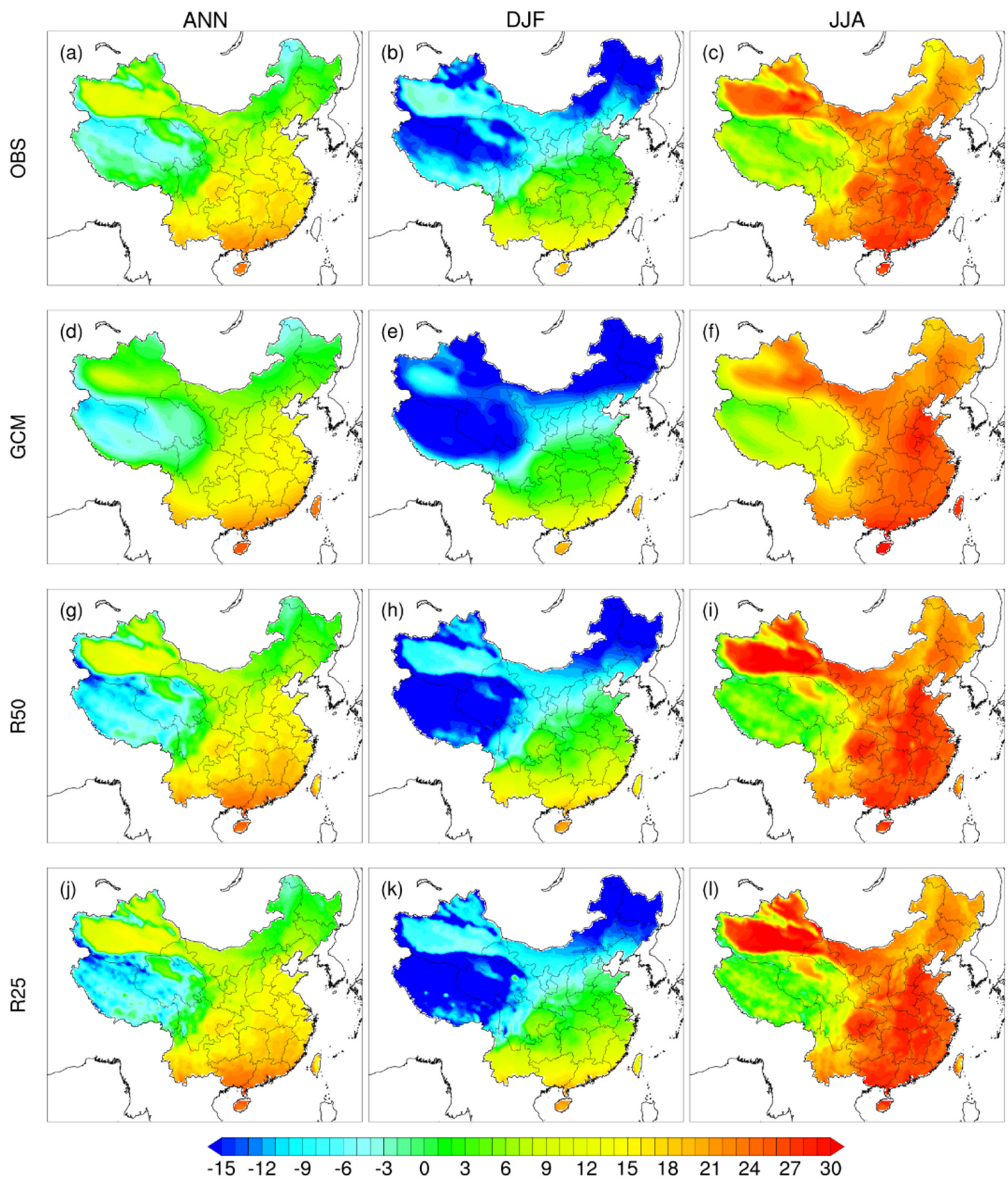

Fig. 2. Spatial distribution of mean temperature in annual (first column), winter (second column) and summer (third column). The CN05.1 data is shown as observation (first row), and the simulations are GCM (second row), R50 (third row) and R25 (forth row), respectively. (Unit: °C).

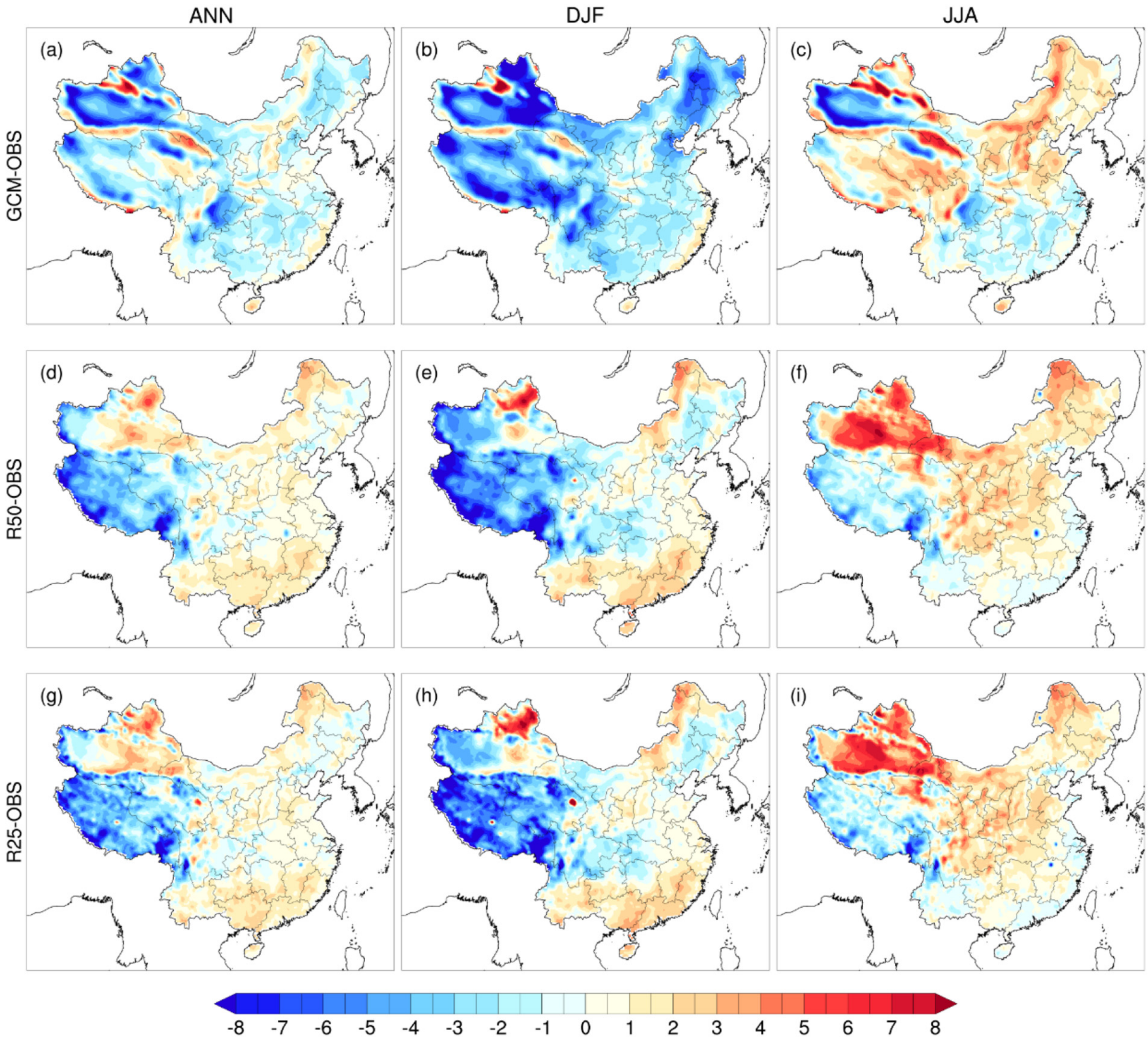

Fig. 3. Biases of mean temperature in annual (first column), winter (second column) and summer (third column), compared to CN05.1 (used as observation), for the GCM (first row), R50 (second row) and R25 (third row), respectively. (Unit: °C).

Table 4
Statistics of correlation coefficient (R), relative error (RE) and added value (AV) in temperature over different regions.

Reg.	Sim.	R			RE (%)			AV		
		ANN	DJF	JJA	ANN	DJF	JJA	ANN	DJF	JJA
China	GCM	0.95	0.96	0.93	−20.91	45.53	2.93			
	R50	0.97	0.96	0.97	−3.68	16.13	6.65	0.08	0.29	−0.02
	R25	0.97	0.95	0.97	−4.47	14.12	5.87	0.09	0.30	0.00
NE	GCM	0.92	0.90	0.90	−49.84	22.36	6.79			
	R50	0.94	0.95	0.82	24.17	−0.46	10.02	0.20	0.77	−0.35
	R25	0.94	0.95	0.81	15.21	−0.14	7.82	0.22	0.78	−0.12
N	GCM	0.91	0.92	0.89	−15.18	29.64	8.72			
	R50	0.96	0.94	0.96	7.86	3.22	9.15	0.26	0.55	−0.03
	R25	0.96	0.93	0.95	5.05	1.91	7.72	0.29	0.54	0.06
C	GCM	0.91	0.92	0.90	−5.63	−169.25	2.03			
	R50	0.98	0.94	0.97	3.77	−30.93	7.33	0.11	0.49	−0.13
	R25	0.97	0.94	0.95	3.03	−13.81	6.94	0.13	0.49	−0.10
SE	GCM	0.88	0.91	0.86	−5.87	−18.20	−3.39			
	R50	0.96	0.94	0.92	6.42	13.89	1.96	0.04	0.16	0.21
	R25	0.96	0.95	0.92	6.00	14.22	1.88	0.07	0.17	0.21
NW	GCM	0.80	0.59	0.77	−57.74	46.47	−5.33			
	R50	0.95	0.78	0.97	−0.02	17.08	16.77	0.46	0.32	−0.06
	R25	0.95	0.77	0.97	4.17	10.91	15.91	0.39	0.36	−0.10
W	GCM	0.89	0.91	0.82	86.67	37.41	16.47			
	R50	0.96	0.92	0.86	232.73	44.47	−19.63	−0.41	−0.08	0.05
	R25	0.90	0.92	0.83	238.02	45.71	−19.26	−0.42	−0.11	0.01

Tibet Plateau, there is more uncertainties in dynamic downscaling, where the relative errors are larger than its corresponding driver, and the relative error even changes sign in summer.

From the analysis of the added value, PRECIS succeeds at reducing or correcting the bias from its forcing GCM over eastern regions, especially in winter. The added values in the north are larger than those in the south. However, the biases are still present or even larger portions over the western region, where the negative AV of temperature in annual and winter implies that the biases in downscaling are larger than its GCM, relative to the observation.

Figs. 4 and 5 illustrate simulated precipitation distribution by HadGEM2-ES and PRECIS and their biases compared to observation, respectively. All models capture the gradually decreasing pattern of precipitation from southeastern to northwestern China as shown in observation satisfactorily, though the magnitude of bias was not identical. However, note is that there is artificial precipitation center simulated by HadGEM2-ES over the Taklamakan Desert in southern Xinjiang, and the pseudo-wet center may be a common problem in GCMs on the west of China (Gao et al., 2009; Guo and Wang, 2016), while this error is well corrected by PRECIS in the course of dynamical

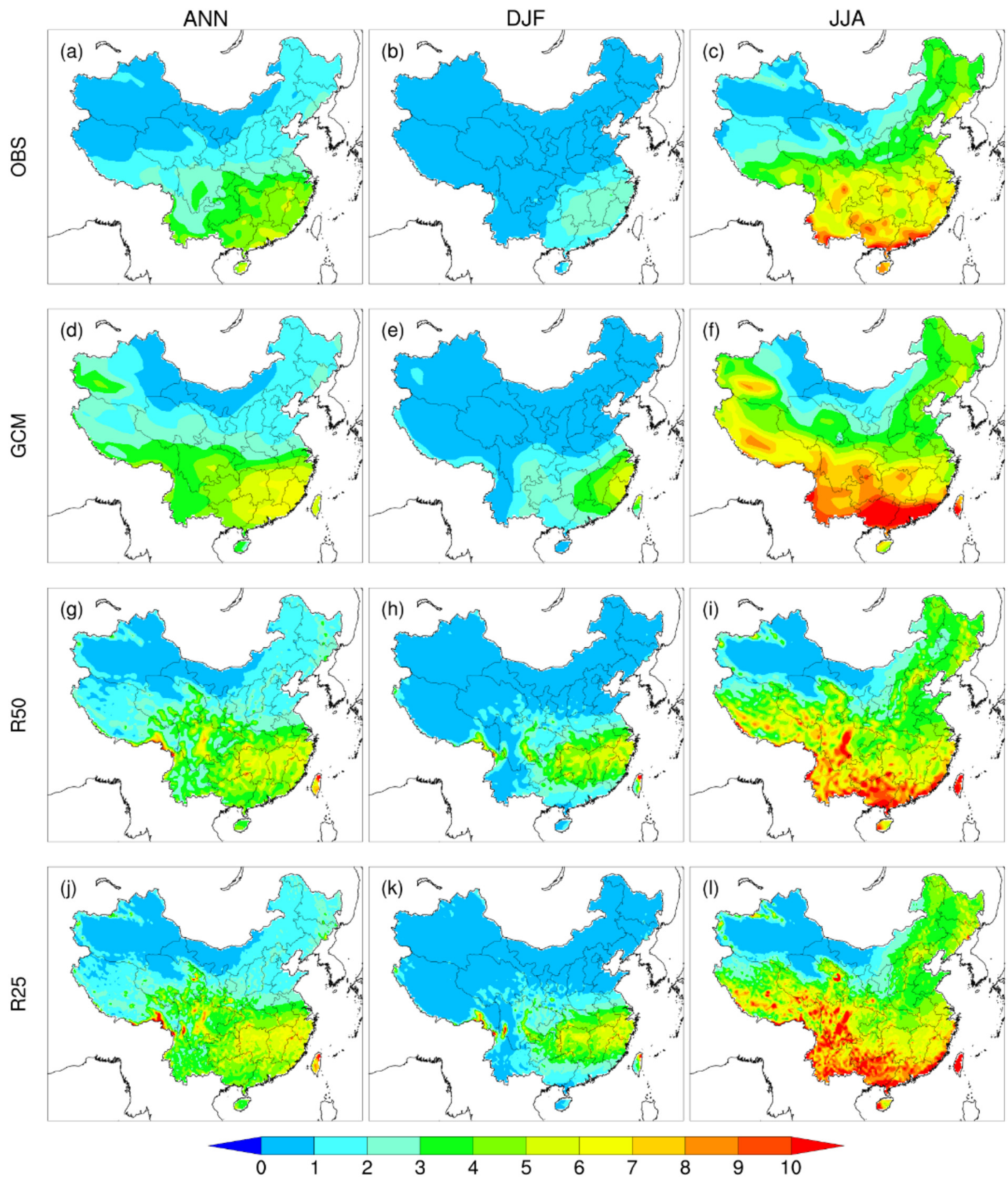

Fig. 4. Spatial distribution of mean precipitation in annual (first column), winter (second column) and summer (third column). The CN05.1 data is shown as observation (first row), and the simulations are GCM (second row), R50 (third row) and R25 (forth row), respectively. (Unit: mm/day).

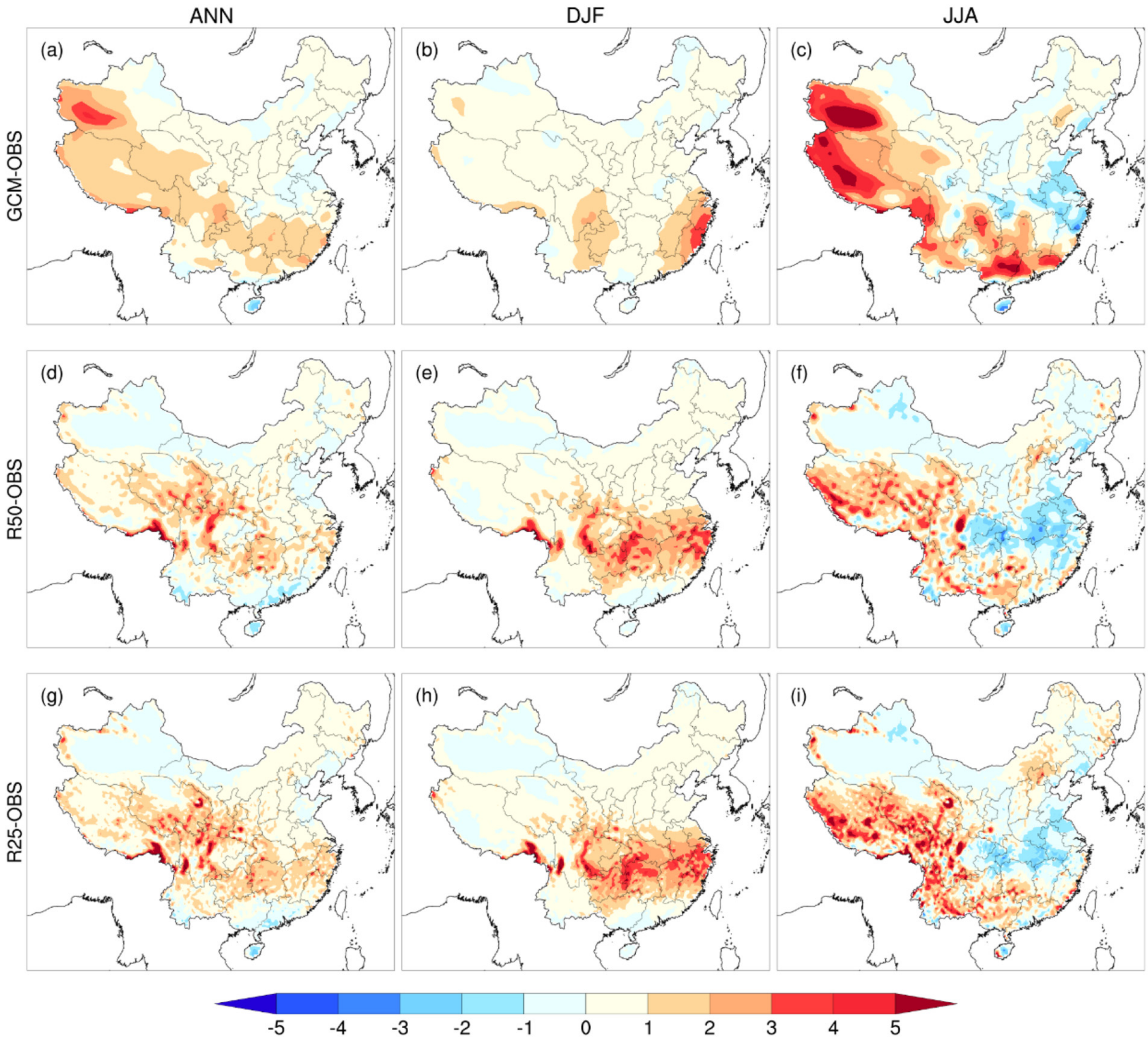

Fig. 5. Biases of precipitation in annual (first column), winter (second column) and summer (third column), compared to CN05.1 (used as observation), for the GCM (first row), R50 (second row) and R25 (third row), respectively. (Unit: mm/day).

downscaling. Other than these, relative to observation the most of southern regions receive more annual mean precipitation both in HadGEM2-ES and PRECIS simulations, but the performance of the latter are better than the former over the southeastern of Tibet Plateau. In winter, mean precipitation simulated by GCM and RCM in the southeast is overestimated. Furthermore, the downscaling results are obviously wetter than observation in the parts of the Yangtze River Basin (above 4 mm/day). On the other hand, PRECIS also is proved its advantage to simulate the summer precipitation. The results simulated by GCM are worse than those from RCM in summer, and some clearly overvalued regions, such as the south of Xinjiang, Tibet, Guangzhou and Guizhou, even exceeding 5 mm/day, are improved by PRECIS. However, the precipitation in the Yangtze River Basin is undervalued in the R50 simulation (about 2 mm/day) but this bias is smaller in the R25 (about 1 mm/day). In addition, it is noted that R25 shows a pronounced wet spot in the Qinghai Lake, which is the biggest inland lake in China. Due to higher resolution in R25, PRECIS can reflect wetter climatic characteristic in lake environments when dynamical downscaling, resulting in more precipitation than R50 and GCM. However, compared with the observation, the finer spatial scale information could generate more "noise" in that lake so that there is an overestimation.

As shown in Table 5, in general, the statistics in domain-averaged precipitation are worse than those in temperature. Specifically, the correlation coefficient in precipitation is smaller and the relative error is larger than that in temperature. Moreover, due to the climatically small precipitation amount in winter, the error is bigger than that in summer. These results are in line with the findings of Xu et al. (2018). However, an improvement is clear for the downscaled results, as shown by the AV values, which is positive in most of regions, especially in winter in the northeast (~0.78 AV value). On the other hand, the correction coefficients in precipitation are lower and the relative errors are larger in RCMs than its forcing GCM. That is to say, the PRECIS has not shown a holistic improvement in seasonally and regionally averaged precipitation for historical decades. Moreover, the positive relative errors of R25 are larger than those of R50 in most regions of China, indicating that 25-km PRECIS produces more precipitation than 50-km one. This may be due to more orographic precipitation formation in the R25 (Tselioudis et al., 2012).

3.2. Annual cycles

Area-averaged annual cycles in mean temperature over China and sub regions are presented in Fig. 6. Whether GCM or RCM, the unimodal distribution of mean temperature in the annual cycle is reproduced satisfactorily, that is, the highest temperature occurs in July and the lowest is in January or December. Fig. 7 shows the biases between simulations

Table 5
Statistics of correlation coefficient (R), relative error (RE) and added value (AV) in precipitation over different regions.

Reg.	Sim.	R			RE (%)			AV		
		ANN	DJF	JJA	ANN	DJF	JJA	ANN	DJF	JJA
China	GCM	0.82	0.89	0.72	49.13	89.81	33.94			
	R50	0.81	0.82	0.79	35.90	144.45	13.17	0.08	0.29	−0.02
	R25	0.79	0.79	0.77	44.07	152.81	21.83	0.09	0.30	0.00
NE	GCM	0.73	0.54	0.73	13.50	25.01	5.42			
	R50	0.63	0.69	0.56	14.44	65.17	−1.52	0.20	0.77	−0.35
	R25	0.62	0.69	0.52	21.81	68.87	7.58	0.22	0.78	−0.12
N	GCM	0.82	0.76	0.88	21.83	462.27	4.71			
	R50	0.72	0.47	0.83	32.33	181.47	7.99	0.26	0.55	−0.03
	R25	0.62	0.45	0.69	40.75	184.78	16.96	0.29	0.54	0.06
C	GCM	0.71	0.79	0.76	10.88	78.74	−10.16			
	R50	0.50	0.73	0.43	31.39	215.88	−12.54	0.11	0.49	−0.13
	R25	0.55	0.72	0.51	39.63	238.41	−7.84	0.13	0.49	−0.09
SE	GCM	0.64	0.71	0.43	27.63	73.02	19.94			
	R50	0.44	0.56	0.63	17.64	105.05	20.30	0.04	0.16	0.21
	R25	0.44	0.54	0.56	24.18	112.44	8.32	0.07	0.17	0.21
NW	GCM	−0.14	0.00	−0.12	262.58	150.42	214.71			
	R50	0.68	0.67	0.72	22.45	49.19	−10.29	0.45	0.32	−0.06
	R25	0.65	0.61	0.70	21.14	33.36	−8.49	0.39	0.36	−0.10
W	GCM	0.66	0.52	0.44	115.236	244.00	84.31			
	R50	0.62	0.52	0.53	107.056	434.81	65.32	−0.41	−0.08	0.05
	R25	0.60	0.44	0.54	121.108	451.80	81.07	−0.42	−0.11	0.01

(i.e., GCM, R50 and R25) and observation. Overall, the monthly mean temperature simulated by PRECIS is warmer than that by HadGEM2-ES. It is also clear that RCM simulations outperform its forcing GCM over all regions but the west. Specifically, GCM shows considerable biases in colder months, such as January, February and December, but they tend to be identified with greater corrections by the RCM downscaling. On the other hand, GCM is better able to reproduce mean temperature in several warmer months. For example, in the whole of China, the bias is less than 1.0 °C in June, July and August in GCM. On the other hand, over the northeastern and northern regions, the improvement

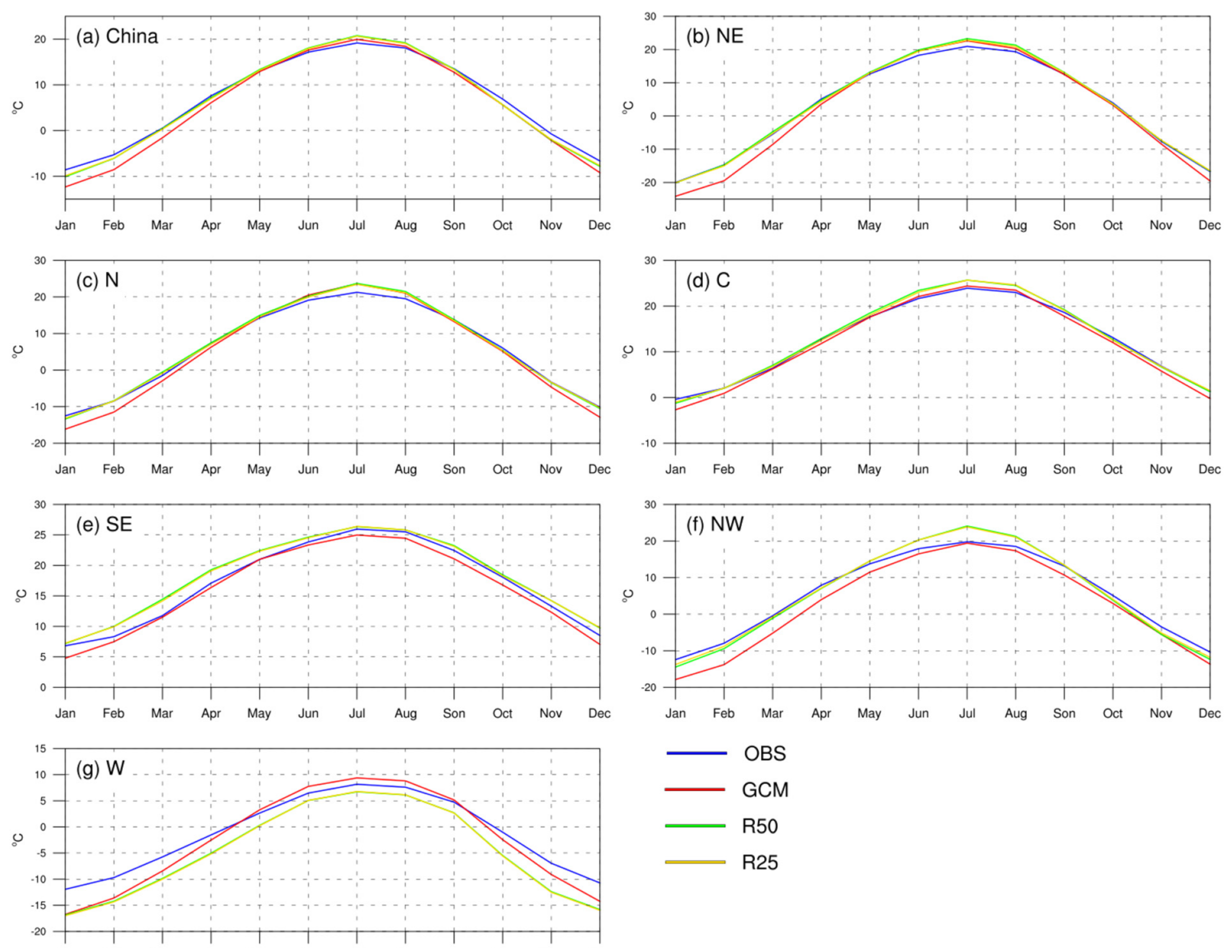

Fig. 6. Mean temperature in annual cycle over China and sub regions.

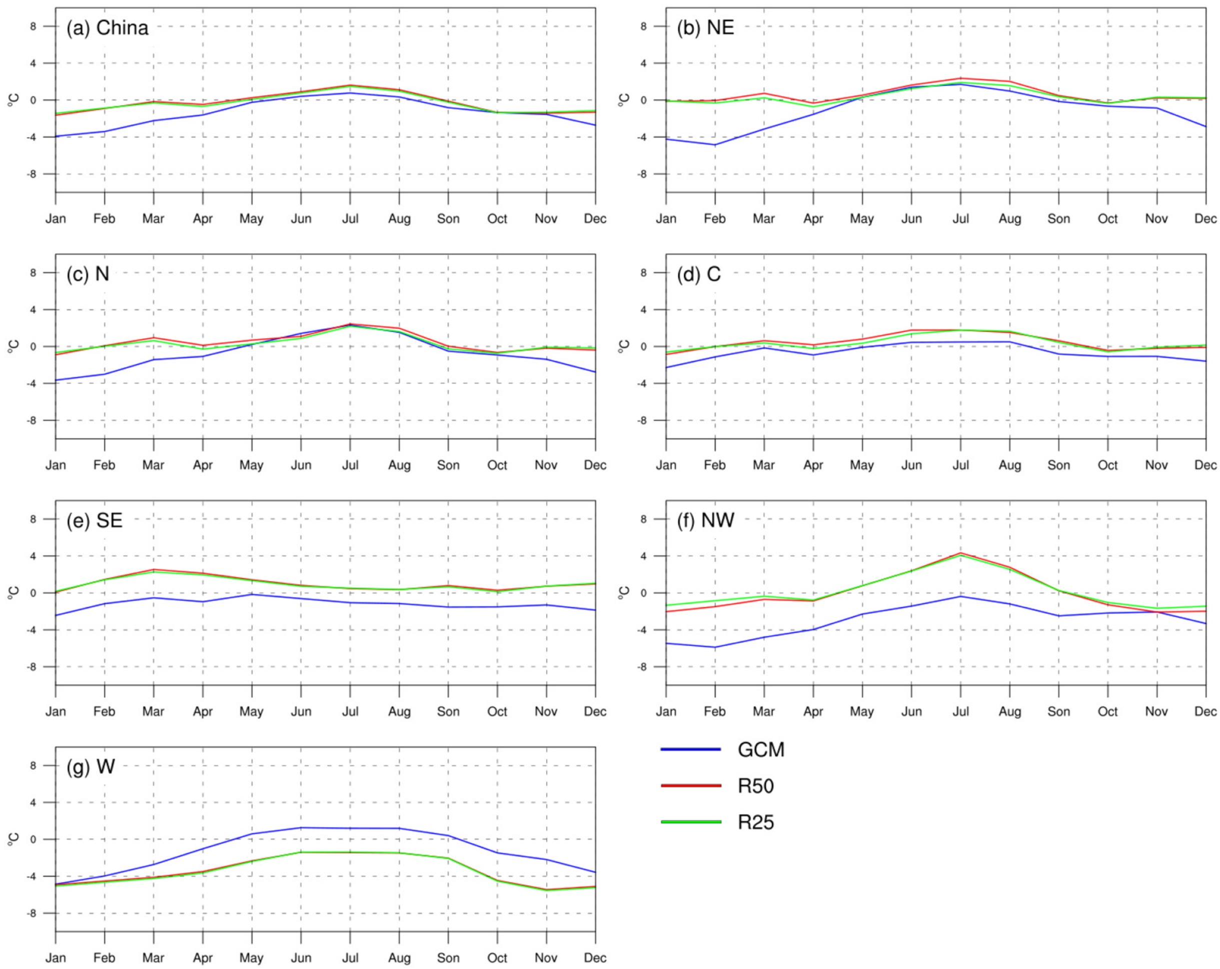

Fig. 7. Biases of mean temperature in annual cycle relative to observation over China and sub regions.

through dynamical downscaling is more visible. For instance, in January and February, the mean temperature simulated by GCM is undervalued about 4.0 °C, while RCM agrees fairly well with observation. Compared with other regions, the simulated mean temperature over central China from RCM is the most consistent with observation, with bias within 1.0 °C. Except for March, PRECIS also shows a good performance over the southeast at most of months. It is very clear that PRECIS tends to correct the bias resulting from its forcing GCM over the northwest, and for most of months, such as from January to May or September to December, these biases are corrected well, however, PRECIS shows a hypercorrection during summer months. Meanwhile, RCM has a worse ability in simulating temperature than GCM over the west, with wildly underestimated values.

In general, the mean temperature simulated by PRECIS in annual cycle is closer to observation than that from GCM. For RCM, the spatial resolutions do not show a pronounced improvement, maybe just slightly superiority over the northwest, because the distribution lines drawn by R50 and R25 basically coincide with each other.

Relative to the reference data CN05.1, the mean precipitation in annual cycle during the present-day period over China and sub regions is shown in Fig. 8 for PRECIS and its driving GCM, and the corresponding biases are presented in Fig. 9. Basically, the main rainy months are well simulated by PRECIS and GCM. Over the whole of China, PRECIS and HadGEM2-ES show an obvious overestimation in monthly mean precipitation relative to observation, especially for latter part of the year, however, the results from RCMs are better than those from GCM in some rainy months. Specifically, from April to August, there is a bias with over 1.0 mm/day for GCM in mean precipitation, while the bias is smaller for RCM, especially for R50. The precipitation is also well simulated over the northeastern and northern China, with the bias of 0–1.0 mm/day, except for R50 in August. Compared with two regions just noted, the precipitation in the central and southeast is more volatile. For example, in August or September, there is a negative bias (−1.0 mm/day) in simulations, while the bias is positive in other months. For the central, high-resolution results look worse than GCM and the biases of R50 and R25 are even more than 2.0 mm/day. Multiple differences between RCMs and GCM over the south are found. From April to August, the performance in RCM is better than that in GCM and R25 also shows its own advantage in high spatial resolution, whereas in winter months, such as January and February, the biases are larger (near 2.0 mm/day) in PRECIS than its driving data. It is noted that a great improvement for RCM is found in the northwest, and considerable overvalued precipitation in GCM is corrected by R50 and R25. Over the west, the precipitation is totally overestimated throughout the year and the simulated skills for PRECIS and HadGEM2-ES have worse in summer months, in other words, to a certain extent, whether RCM or GCM, they are failed in precipitation simulation in annual cycles over the high-cold Tibet Plateau.

Overall, in annual cycles, the performance in temperature simulation is better than in precipitation. For high-resolution RCM, the precipitation results failed to show an overwhelming superiority than its host GCM like that in temperature simulation.

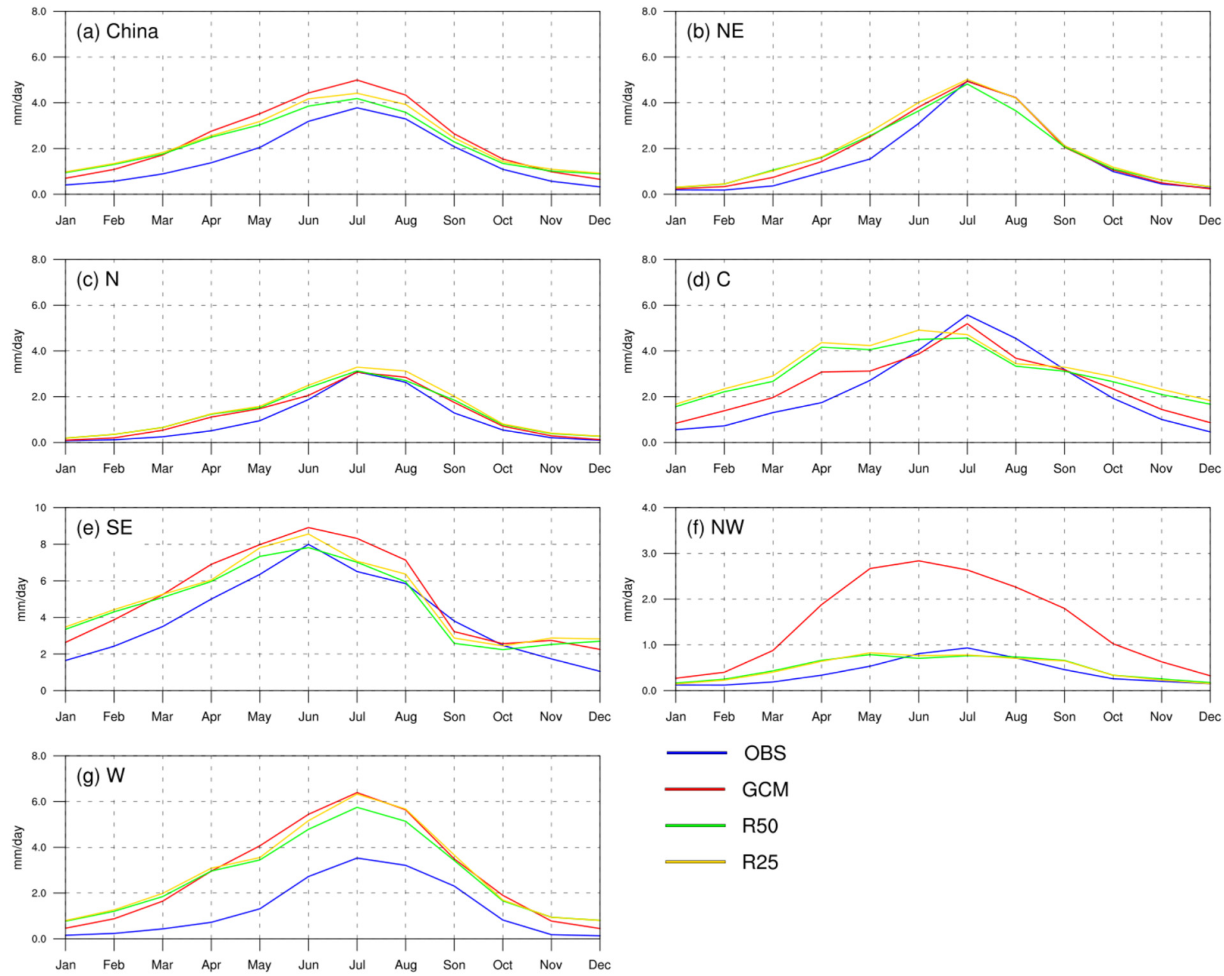

Fig. 8. Mean precipitation in annual cycle over China and sub regions.

3.3. Interannual variation

Fig. 10 presents the interannual variability in temperature and precipitation over China and sub regions. For the entire region of China, the coefficients of variation of temperature simulated by PRECIS and HadGEM2-ES are analogous to the observation, though the latter produces a larger interannual variability than R25 and R50. In the view of sub regions, the NE region shows greater interannual variability as compared to other regions, especially for the driving GCM with exceeding 0.5, suggesting that a broadening of annual temperature distribution and more extremes relative to the mean climate. Different from other regions, the CV value is negative over the western region, because its annual mean temperature is below freezing point. With the exception of central region, the CV of temperature in winter is small (−0.1–0.1). It should be mentioned that the CV value is positive for observation and PRECIS, and the result of R25 is generally in agreement with the observation, while HadGEM2-ES shows an opposite sign over the central region of China. On the other hand, the CV values in summer are smaller than those in winter, and not exceeding 0.05. The largest CV value in winter is presented over the west region while the smallest is shown over the southeast.

With respect to precipitation, the CV values simulated from PRECIS are underestimated in most parts of China relative to the observation, while the values from GCM in the northern regions, such as the northeast and north, are larger than those in the observation. The high-resolution R25 has better skills in simulating the interannual variation over the arid northwest region than R50 and its driving GCM. Seasonally, there is a greater interannual precipitation variability in winter than summer and the CV values are exceeding 0.2 in many regions, because the mean precipitation in winter is smaller. On the other hand, the observed CV is generally larger than in simulations in winter, though the GCM is worse than RCM to some extent. By contrast, the same does not hold true for precipitation in summer, when the overvalued CV values are found in PRECIS and HadGEM2-ES. As the major wet areas, the simulated interannual variability is smaller in the southeast than that in observation. However, the summer precipitation variability is closer to observation with resolution improvement.

3.4. Precipitation extremes

In general, it is more important to simulate or project extreme precipitation rather than mean precipitation because of the significant social and economic impacts associated with it (Liwei Zou, 2013). From above analysis, we found that PRECIS produces a distinctive advance in simulating the general climatology over China. In this section, we examine whether the downscaled precipitation results, especially in extremes, are improved over the large-scale driving ones as well. Fig. 11 presents the probability distribution functions of daily precipitation over China and different sub regions for two downscaled PRECIS runs and their forcing GCM. Over the whole of China, the days of small precipitation (less than 1 mm/day) from observation is more than those simulated by RCMs and GCM. The probability of daily precipitation amount between 1 mm and 4 mm in observation is in close agreement with the simulations. The tails of distribution curves represent the

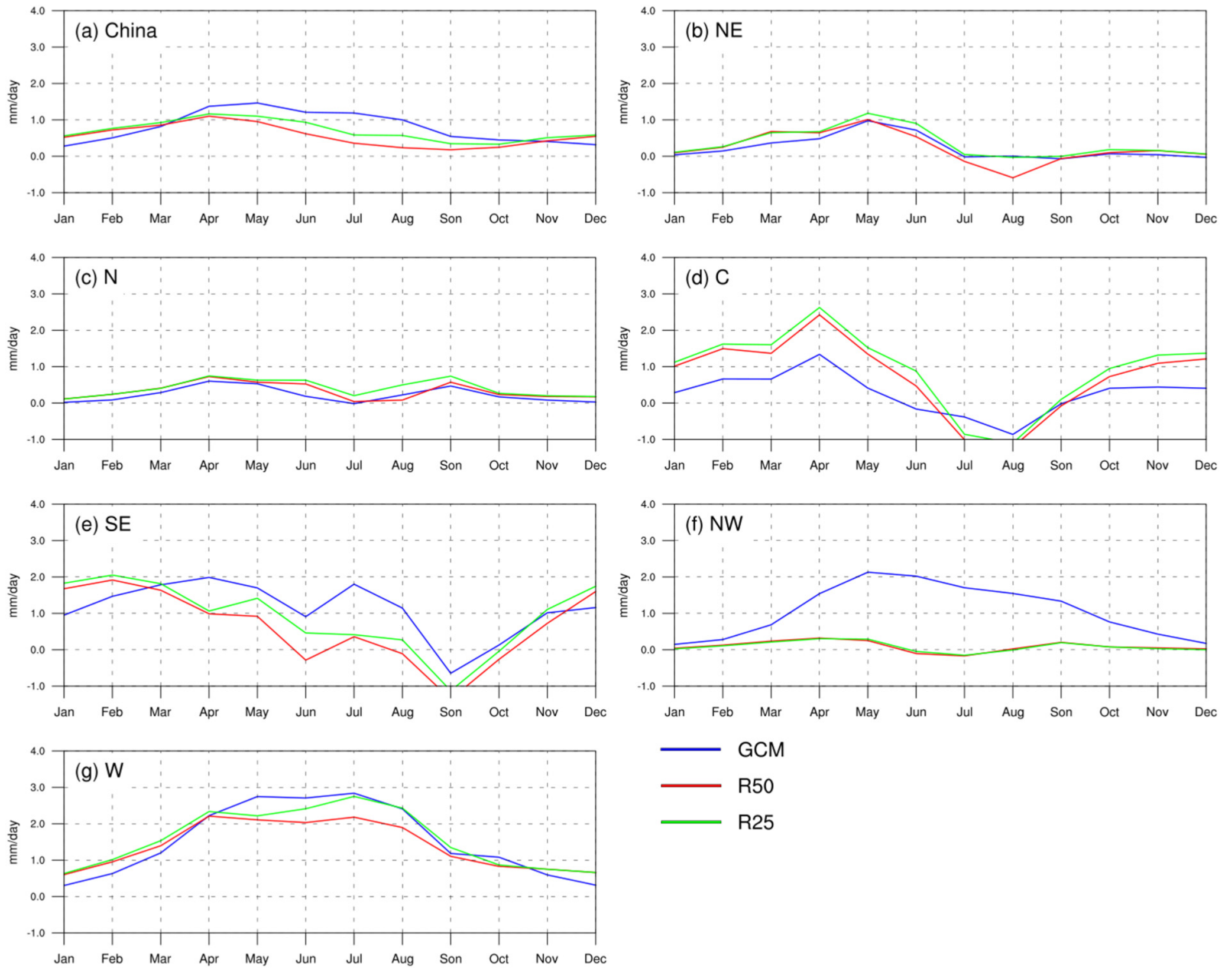

Fig. 9. Biases of mean precipitation in annual cycle relative to observation over China and sub regions.

occurring probability of extreme precipitation. It is evident that the downscaled results outperform those of the driving GCM, whose probability of extreme precipitation is higher than RCMs and observation. In general, the simulated shapes of precipitation distribution curves are closer to the observation over the southeast and north regions than others. On the central of China, PRECIS also shows better performance in simulating the moderate precipitation (14–20 mm/day), while a pronounced underestimation is found in the driving GCM. Moreover, the improvement is especially evident on the northwest region, where large overestimation simulated by GCM is found, while there is very substantial improvement for RCMs, especially for R25 in simulating 4–5 mm daily precipitation. On the other hand, over the Tibet Plateau, whether PRECIS or its driving GCM, an obvious overestimation persists from 3 mm in daily precipitation, even the daily precipitation exceeding 8 mm is simulated in error, compared with the observation.

Two ETCCDI precipitation extreme indices are analyzed in this paper as well. The CWD (consecutive wet days) represents the frequency of precipitation, and the SDII (simple precipitation intensity index) indicates the precipitation intensity. Overall, PRECIS shows better performance in simulating two extreme indices than its forcing GCM over China. As shown in Fig. 12, the CWD in GCM is more 25 days than those in observation over the west of Xinjiang, the edge of Tibet, most parts of Yunnan and the east of Sichuan, while these biases are well corrected by RCMs. On the other hand, two RCMs and their forcing GCM tend to underestimate the consecutive wet days over scattered regions of Sichuan, and it seems that R25 and R50 enlarge these biases. Other than these, the precipitation intensity index (SDII) is also simulated by PRECIS over China, in spite of some biases in spatial distribution (Fig. 13). Again, the PRECIS clearly outperforms its driving GCM, which has large overestimated SDII in the west of China and evidently underestimated one in the east. However, that same dynamic downscaling, the R25 seems to be hypercorrected as compared to R50 in the western China, where scattered regions are overvalued, further suggesting that the downscaling results with higher resolution can simulate more precipitation than observation.

4. Discussion and conclusion

Climate simulations in China through a regional climate model PRECIS at different resolutions were compared to those of its driving GCM. Overall, the PRECIS can reproduce the spatial distribution of annual and seasonal mean temperature and precipitation over the largest part of China, especially in the east. The high resolution in the domain and physical packages of PRECIS play a vital role and contribute to these improvements.

For temperature, the cold biases in HadGEM2-ES have been reduced by PRECIS, in spite of an overcorrection in the northern Xinjiang. In the most regions of China, results with higher resolution show smaller relative errors and larger added values. PRECIS runs have small differences in spatial distribution, and the higher-resolution R25 truly can yield more detail information than R50 and its driving data in high and cold region of western China. However, R25 has colder biases than R50, suggesting that RCM with higher resolution does not always produce more accurate output in the process of downscaling. This finding is also consistent with other studies (Mishra et al., 2017; Xu et al., 2018). An

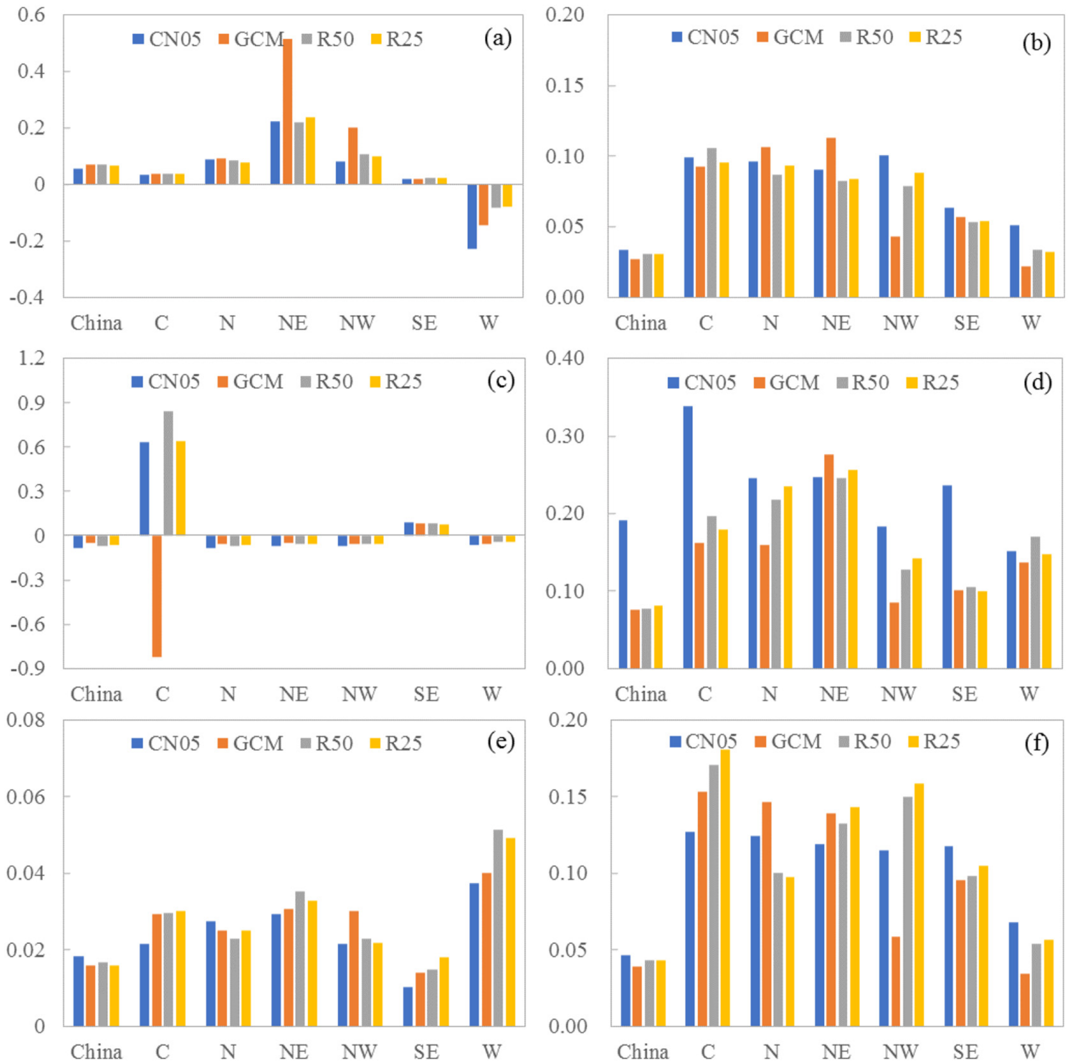

Fig. 10. Coefficient of variation (CV) over China and sub regions. The left column is CV of temperature and the right is CV of precipitation. From top to bottom is annual, winter and summer.

explanation could be that the R25 can represent more land cover types (i.e., snow cover, glaciers and permafrost) than coarse-resolution model. Under the context of global warming, these land cover types will melt and absorb heat from surrounding air further, leading to colder air temperature (Guo and Wang, 2016). In addition, most boundary data of PRECIS have a resolution of 1.25° × 1.875° (about 150 km). Actually, when we design a nested downscaling experiment, a ratio in spatial resolution is generally about 3 between parent domain and sub domain (i.e., WRF). Therefore, this kind of resolution could be more suitable to dynamically downscale to R50 (50 km). This may also be an important reason. Furthermore, there is worse performance for PRECIS over complex terrain areas, such as the western part of China. Except for the model's reason itself, these regions usually have few or no station observations available, which may lead to somewhat inaccurate or at least a large uncertainty when interpolating from stations to grids (Gao et al., 2009; Guo and Wang, 2016).

On the other hand, PRECIS also captured the major spatiotemporal distribution in precipitation roughly, and an artificial precipitation center from HadGEM2-ES in the northwest is well corrected by PRECIS in the course of dynamical downscaling. However, compared to the mean temperature, it is difficult to determine exactly a systematic and homogeneous improvement of performance of the downscaled simulations on its driving GCM, in other words, the PRECIS still lacks of a pretty good capability, which can simulate accurately in seasonally and regionally averaged precipitation for historical decades. It is widely accepted that better performance or larger added value is in temperature than precipitation for climate models (Feser et al., 2011). Mishra et al. (2017) thought the variables (i.e., temperature, winds, humidity, etc.) as the boundary conditions to drive RCM come from the GCM directly, thus it is not surprising that simulated mean temperature tends to have same similar at least near its host GCM. On the other hand, some comprehensive variables, such as precipitation, are mainly affected by the cloud and convective schemes in dynamic and thermodynamic large scale environment. The precipitation is overestimated by PRECIS over many regions in China, especially in annual cycles, and the extent of overestimation in downscaling is larger with the increase of spatial resolution. More detailed landform conditions and local hydrodynamic variability are possible reasons for this (Castro, 2005). In other words, these detailed information may not play such a role or even counteract sometimes. Specifically, RCM with finer resolution could generate more "noise" over special regions, such as great rivers and lakes, resulting in more precipitation in R25 than R50. Furthermore, whether RCM or GCM, they are failed in precipitation simulation in annual cycles over the high-cold Tibet Plateau. Fundamental errors from GCM are one of potential causes. Although the PRECIS has corrected or reduced the errors to some extent, the PRECIS's performance is strongly limited by the skill of its driving GCM (Laprise, 2014; Racherla et al., 2012; Tolika et al., 2016). The PRECIS runs are initialized with dynamic and thermodynamic conditions in HadGEM2-ES, which itself does not capture the spatiotemporal pattern in precipitation well, it is not surprising that

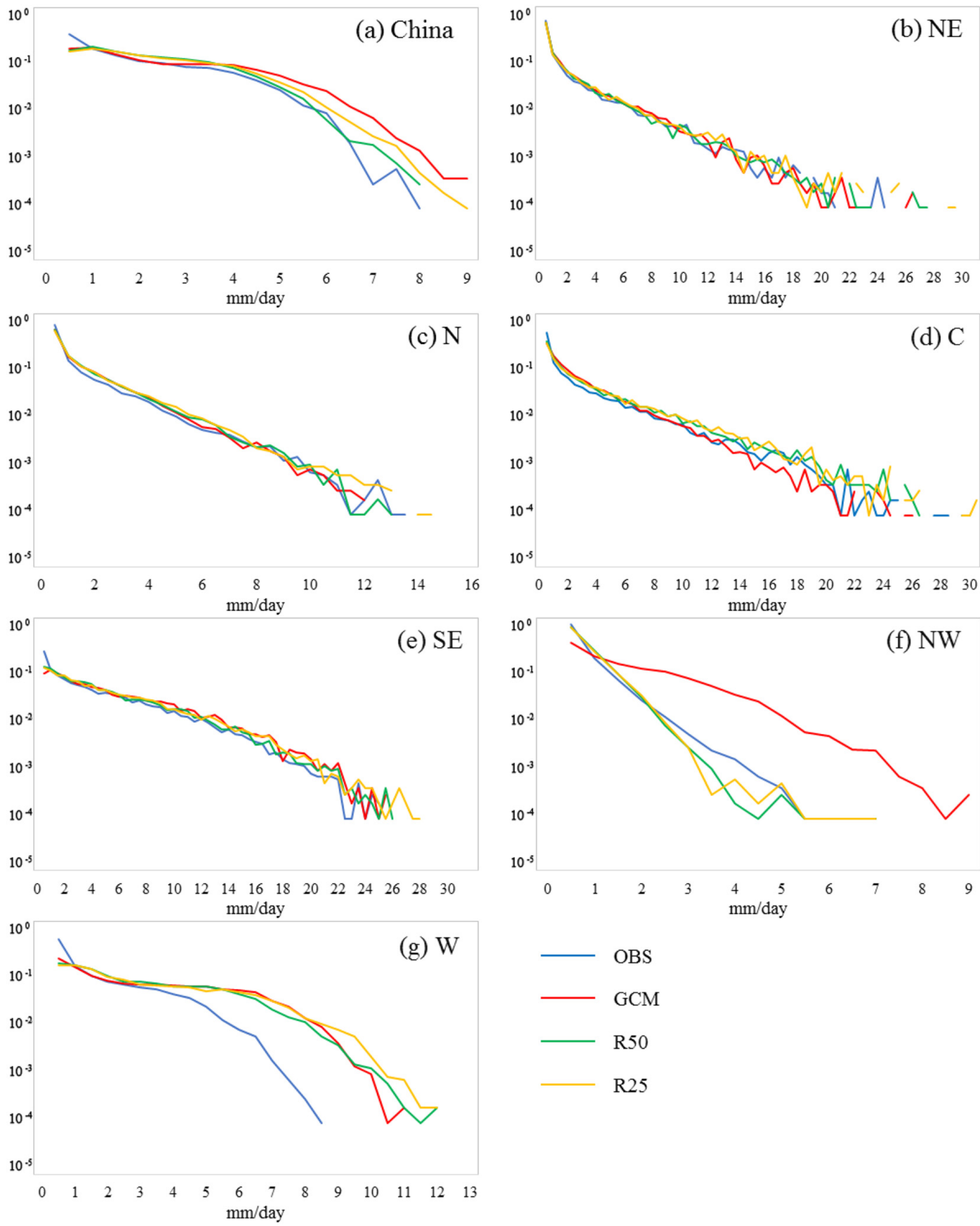

Fig. 11. Probability distribution functions of daily precipitation over China and different sub regions.

PRECIS does not either perfectly. Therefore, it is important to improve the long-range climate ability of GCM or using bias-corrected forcing in downscaling.

Regarding the overall interannual variability, RCMs do not show obviously more advances than their driving GCM in most regions of China, though the results of interannual variability in temperature are better than those in precipitation. For precipitation, the variation is underestimated in summer while the value is overestimated in winter compared to the observation. The HadGEM2-ES used in the present work produced a smaller CV than RCMs in precipitation. This result are also in line with Dosio and Panitz (2016) and Lee and Hong (2014), who compared RCM's results at different resolutions to those of GCM, indicating that the precipitation variance increase with the model resolution. A probable reason for this difference may relate to the uncertainties in PRECIS, which has more detailed land schemes and complex model physical parameterizations. It also means PRECIS will produce more model uncertainties when downscaling in addition to its inherited uncertainties from driving GCM (Corney et al., 2013; Guo and Wang, 2016; Yang et al., 2015). Nevertheless, it is noted that the interannual variability reproduced by the R25 is closer to observation than that in the R50 and its driving GCM over the northwestern arid and semi-arid region, especially for precipitation.

In addition, PRECIS reflects its superiority in simulating precipitation extremes as well. It is evident that the downscaled results outperform those of the driving GCM, whose probability of extreme precipitation is higher than RCMs and observation. Furthermore, it was shown that PRECIS is able to better simulate some precipitation indices such as the number of consecutive wet days and simple precipitation intensity index in spatial distribution, despite some biases in local regions of western China, suggesting that high resolution is important in

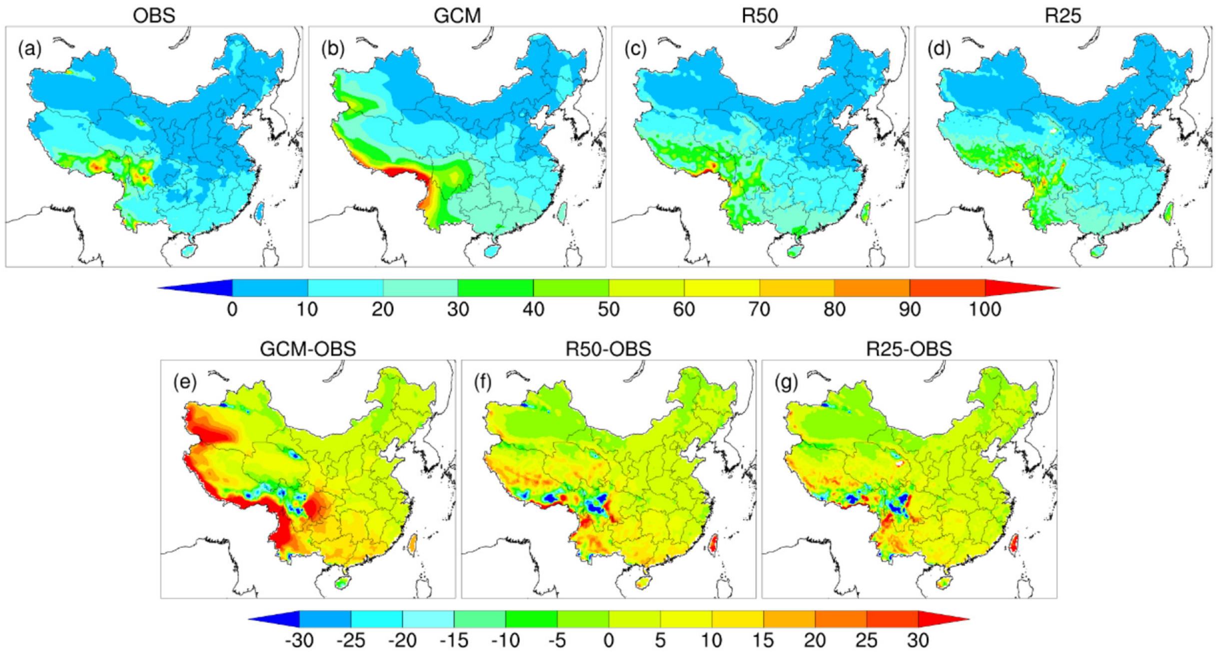

Fig. 12. Spatial distribution for the CWD. The second row is the biases between simulations and observation. (Unit: days).

simulating the precipitation extremes for regional climate models. The results are consistent with other studies. For example, Devanand et al. (2018, 2019) thought that the precipitation bias over the Indian monsoon region was caused by the smoothened topography in the global model and accurate orographic and land-atmosphere representation were necessary to capture the pattern of monsoon rainfall. In addition, similar to the mean precipitation, the R25 seems to simulate more extreme precipitation than R50, further suggesting that the downscaling with higher resolution can simulate more precipitation.

However, in terms of computational resources consumption, the R25 spent about three times as much as time and disk space compared to the R50, suggesting that such a high cost of RCM do not always bring better performance in dynamic downscaling (i.e., precipitation). Thus, it is important to investigate how the spatial resolution of regional climate simulation affects the added values of dynamical downscaling under the limited computational resources.

In future, some issues remain open to further research. For instance, with the development of GCMs, their horizontal resolutions are becoming finer and finer. At that time, whether the added value is not big enough through RCMs, and which is the better approach to get more plausible climate projection, also need investigation. Nevertheless, in this paper, we stress the importance of serious evaluation on the

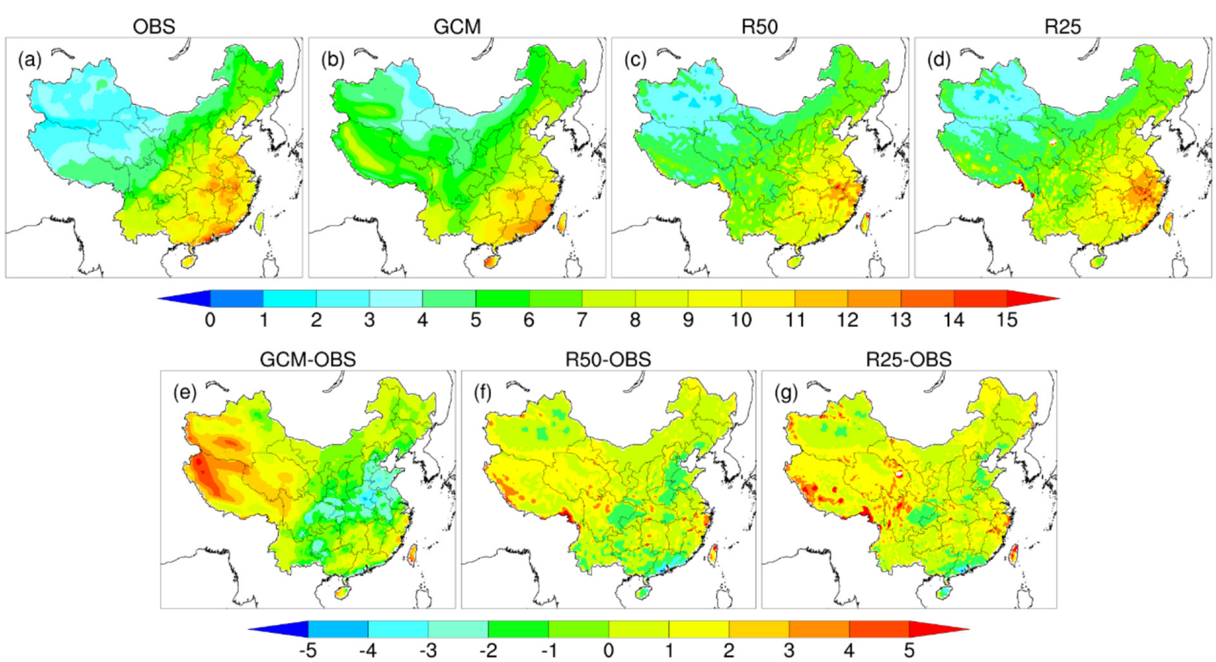

Fig. 13. Spatial distribution for the SDII. The second row is the biases between simulations and observation. (mm/day).

performance of regional climate models before utilizing their output for impacts assessment and subsequent policy making for sustainable climate change adaptation.

Declaration of competing interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

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