Simulation and estimation of future precipitation changes in arid regions: a case study of Xinjiang, Northwest China

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Abstract
Precipitation is critical for maintaining the stability of an ecosystem, especially in arid regions. This study primarily focuses on climatic changes during present (from 1985 to 2005) and future (from 2040 to 2059) periods in Xinjiang, Northwest China. In this study, the Weather Research and Forecasting model is implemented in Xinjiang to efficiently predict the future climate. Moreover, the National Climate Research Center Community Climate System Model version 4 is employed for the mid-21st century under representative concentration pathways 4.5 and 8.5 (RCP4.5 and RCP8.5, respectively). Our results indicate that the amount of annual precipitation will increase in the future under RCP4.5 and RCP8.5 in Xinjiang, especially in mountainous areas. The increase in precipitation is predicted to be much smaller under RCP8.5 than under RCP4.5, except in Southern Xinjiang. Moreover, the increasing precipitation predicted in Xinjiang implies that the current humid and warm conditions will persist, thereby further indicating that Xinjiang is still currently suffering from a dry climate. The largest increase in seasonal precipitation is predicted to occur in spring and summer in Tianshan and Northern Xinjiang, whereas this phenomenon is predicted to occur in spring and winter in Southern Xinjiang. In addition, it is predicted that daily heavy precipitation events will occur more frequently in various subregions of Xinjiang, although light rain events will remain dominant. Finally, the relative humidity is closely related to the changes in annual and seasonal precipitation.

Keywords WRF · Projected precipitation · CCSM4 · RCP4.5 · RCP8.5

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1 Introduction

Global climate change and climate variations are significantly affected by anthropogenic activities (Li et al. 2011). From 1850–1900 to 2006–2015, mean land surface air temperature has increased by 1.53 °C (range: 1.38 to 1.68 °C), while the global mean surface (land and ocean) temperature increased by 0.87 °C (range: 0.75 to 0.99 °C) (Shukla et al. 2019). Rising temperatures have greatly increased the number of extreme temperature events, while altering the global precipitation patterns (Kharin et al. 2013). Climate change poses varying risks to ecological environments in different areas, and the degree of influence depends on both the topography of the region and distance from the ocean (Wang et al. 2013).

Xinjiang is located in Northwest China and is far from the ocean; it is surrounded by mountains and exhibits an area of $1.6 \times 10^6$ km$^2$ (Zhang et al. 2012). Xinjiang has a typically continental and arid or semi-arid climate with an annual precipitation that ranges from less than 50 mm in the Tarim Basin to approximately 800 mm in the Tianshan Mountains (Chen et al. 2009; Domrös and Peng 2012; Tan and Shao 2017; Wang et al. 2013). Owing to global warming, although the total amount of annual precipitation in some areas (e.g., Taklamakan Desert) is approaching zero for certain years, Xinjiang has experienced an overall change from a warm and dry climate to a warm and wet climate (Shi et al. 2007; Xu et al. 2010). Specifically, the average surface air temperature in Xinjiang has increased by 0.18 °C per decade in the last century, which is much greater than the global average rate (Chen et al. 2009). Meanwhile, the amount of precipitation has increased by 20–30 mm per decade (Tan and Shao 2017). However, although drought conditions appear to have relieved to a certain extent, the nature of the arid and semi-arid climate regime has not changed. As a result, Xinjiang is still suffering from an arid and semi-arid climate (Wang et al. 2020). The diverse climate in Xinjiang results in a clear difference between the desert and alpine mountain ecosystems (Li et al. 2013; Wu et al. 2010). Based on these considerations, Xinjiang has been a popular study area for exploring the interactions between local ecosystems and local climate changes.

To explain these interactions, Cao et al. (2011) demonstrated that the decrease in annual precipitation (not temperature) was the main factor resulting in the fluctuation of the vegetation coverage in Xinjiang. Fang et al. (2013) showed that the trends observed for changes in vegetation productivity during the growing season were similar to the changes in precipitation. Seddon et al. (2016) proved that the steppe and prairie systems in Xinjiang have strong responses to precipitation anomalies. Huang et al. (2014) estimated the future changes in annual precipitation in Central Asia under different representative concentration pathways (2.6, 4.5, and 8.5) and showed that the amount of precipitation will significantly increase between 2011 and 2100. Briefly, previous studies have proven that climate change is closely related to corresponding ecosystem changes.

Although current literature has been sufficiently improved with regard to the exploration data on future climate change in Central Asia and spatial patterns of precipitation, a critical issue remains to be solved. Specifically, global climate models (GCMs) with coarse resolutions (i.e., >100 km) have primarily been used in previous research. Consequently, detailed characteristics such as precipitation on the regional scale cannot be fully reflected. To overcome this drawback, regional climate models with high resolutions have been utilized for dynamic downscaling by using the GCMs outputs as a forcing condition to achieve detailed dynamic descriptions of regional precipitation. This approach has been proven to be efficient for Spain, the Canary Islands, China, and Central Asia (Argueso et al. 2012; Exposito
et al. 2015; Liu et al. 2013; Qiu et al. 2017). However, this method has not been applied to Xinjiang for regional climate downscaling. Thus, a detailed understanding of the characteristics in Xinjiang, including precipitation and temperature, remains unknown. Consequently, the trends in future climate changes cannot be efficiently determined. More importantly, the changes in hydrology and ecosystems caused by climate change cannot be reasonably addressed.

To overcome this limitation, this study is aimed at investigating the changes in the intensity and frequency of precipitation under different emission scenarios in Xinjiang for the future decades of the 21st century. Specifically, we obtained climate change data by using the Weather Research and Forecast (WRF) model version 3.8.1 at 10 km resolutions in the mid-21st century in Xinjiang (Skamarock et al. 2008). The initial and boundary conditions of the WRF model were derived from simulations performed using National Climate Research Center (NCAR) Community Climate System Model version 4 (CCSM4) under representative concentration pathways 4.5 and 8.5 (RCP4.5 and RCP8.5, respectively). RCP4.5 and RCP8.5 represent long-term global greenhouse gas emissions that stabilize the radiation at 4.5 W/m² (approximately 650 ppm CO₂ equivalent) and 8.5 W/m² (approximately 1370 ppm CO₂ equivalent) (Gent et al. 2011).

The structure of this paper is organized as follows. Section 2 describes the details of the WRF configuration and GCM output. Section 3 presents the validation of the WRF model in Xinjiang and the predicted precipitation between the mid-21st century and the past 20 years, analyzes the differences from the current climate conditions, and details the atmospheric processes of these changes. Section 4 discusses the uncertainty of the modern-era retrospective analysis for research and applications (MERRA) data, the difference between WRF and CCSM4, and the effect of topography on precipitation. Finally, Section 5 summarizes the key findings.

2 Experimental design, data, and methodology

2.1 WRF model and experimental design

The WRF model is a high-resolution mesoscale prediction model and data assimilation system that is widely used in climate change research (Bao et al. 2015; Exposito et al. 2015). In this study, WRF version 3.8.1 was employed to dynamically downscale the GCM outputs with coarse resolutions and to generate high-resolution data for physical processes on the regional scale, especially in complex surface areas with heterogeneous land cover and topography (Chen and Frauenfeld 2016). The initial and lateral boundary conditions used to drive the WRF model were derived from CCSM4 RCP4.5 and RCP8.5, which exhibit horizontal resolutions of 0.9°×1.25° (longitude and latitude) for the years 2039–2059. The average precipitation in the future was compared with the average precipitation from 1985 to 2005, which was also dynamically downscaled by WRF using historical CCSM4 data. The starting years of the present and future simulation (i.e., 1985 and 2039) were regarded as the model spin-up and consequently discarded. As shown in Fig. 1, two one-way nested model domains with 124×135 and 241×199 horizontal grid points and spatial separations of 30 km and 10 km were configured with 28 vertical levels reaching 50 hPa. The map projection was Lambert conformal, and the central point was located at 41.4°N, 84.8°E. The inner domain provides full coverage of the Xinjiang region. Based on prior research (Qiu et al. 2017), the following
parameterization schemes were used in WRF configuration: the Betts-Miller-Janjić scheme for cumulus parameterization (Janjić 1994); cloud microphysics scheme of Thompson (Thompson et al. 2008); land surface parameterization scheme using the Noah land surface model (LSM), which provides the four-layer soil temperature and moisture model (Chen and Dudhia 2001); and the Mellor-Yamada-Janjić scheme for the planetary boundary layer (Janjić 2002). In addition, the NCAR community atmosphere model (CAM) was used to calculate the atmospheric longwave and shortwave radiation transfer (Collins et al. 2004).

2.2 Data

To assess the capabilities of current climate model simulations in this study, observational data was used to validate the WRF model outputs qualitatively and quantitatively. Ground-based meteorological observation data describing the maximum and minimum daily averages of precipitation from 69 meteorological stations were obtained from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn). The observed data incorporated the period from 1985 to 2005, and we employed the following process for inspecting these data to ensure high quality (Li et al., 2012). First, we eliminated the observed stations that had more than 25% of their data missing. Second, we removed the stations that had missing data for two or more months per year. Through this process, the observed data from 54 meteorological stations were retained and employed in our experiments.

Fig. 1 WRF simulated domains (50 km (D01) and 10 km (D02)), and the ground meteorological stations with consistent precipitation variations in the study area (D02)
and analysis (Table 1). As there are only a few stations located in the mountains, specifically in South Xinjiang, the MERRA data (Rienecker et al. 2011), which most favorably compares multiple datasets with ground observations, were compared with the model results (Hu et al. 2016), as a supplement to the observational data.

2.3 Regionalization method

Numerous climate types are observed in Xinjiang due to its complex topography. Therefore, it is necessary to divide this area into subregions to explore the effectiveness of the WRF. To efficiently identify and classify the subregions with similar climate patterns, we used the cluster analysis method (Duque et al. 2007), which has been proven effective to achieve this objective in Central Asia (Qiu et al. 2017) and the Tianshan Mountains (Chen et al. 2019). The K-nearest neighbor (KNN) method was employed to further divide the region into subregions based on the monthly mean precipitation data from the 54 ground stations. To obtain the optimal spatial constraint parameters, we used a series of K values ranging from 2 to 10. The cluster analysis tool can automatically reveal the number of clusters by identifying the climate characteristics with the highest similarity (Zhang et al. 2018). The Calinski Harabasz pseudo-$F$-statistic can be automatically measured to quantify the similarity and dissimilarity between groups (Caliński and Harabasz 1974; Qiu et al. 2017; Zhang et al. 2018).

\[ F = \frac{R^2}{\frac{n_c - 1}{1 - R^2}}, \]

where \( R^2 = \frac{BGD - WGS}{BGD} \) and a larger value indicates a better clustering result. WGS reflects the within-cluster similarity cluster, and BGD reflects the between-cluster difference. The formulas for WGS and BGD are as follows:

\[ BGD = \sum_{i=1}^{n_c} \sum_{j=1}^{n_i} \sum_{k=1}^{n_j} (y_{ij} - y_{ik})^2, \]

and

\[ WGS = \sum_{i=1}^{n_c} \sum_{j=1}^{n_i} \sum_{k=1}^{n_j} (y_{ij} - y_{ik})^2, \]

| Pattern correlation | CCSM4 | WRF | Relative bias (%) |
|----------------------|-------|-----|-------------------|
| CCSM4               |       |     |                   |
| WRF                 |       |     |                   |
| ANN                  | 0.73  | 0.89| 39                |
| MAM                  | 0.70  | 0.87| 46                |
| JJA                  | 0.80  | 0.92| 33                |
| SON                  | 0.73  | 0.90| 50                |
| DJF                  | 0.68  | 0.82| 57                |

Table 1 Spatial correlation coefficient and relative bias for annual and seasonal precipitation in Xinjiang between CCSM4 or WRF simulation and MERRA data. ANN represents annual, MAM for March-April-May, JJA for June-July-August, SON for September-October-November, and DJF for December-January-February.
where $n = \text{number of objects to be regionalized}$, $n_i = \text{number of objects in cluster } i$, $n_c = \text{number of clusters}$, $n_v = \text{number of variables used to cluster objects}$, $v^i_j = \text{value of the } k\text{th variable of the } j\text{th object in the } i\text{th cluster}$, $v_i = \text{mean value of the } k\text{th variable}$, $v^j_k = \text{mean value of the } k\text{th variable in cluster } j$.

During the cluster analysis, when $K = 8$ and the number of categories were set to 3, $R^2$ and $F$ reached the optimal values of 0.81 and 83.26, respectively. Hence, in our experiments, $K = 8$ was used as the spatial constraint of the KNN algorithm, and three climate subregions in Xinjiang were obtained: Northern Xinjiang, the Tianshan Mountains, and Southern Xinjiang (Fig. 1). The subregions identified in this area are similar to those described by Zhang et al. (2017).

3 Results

3.1 Evaluation of the simulation results

3.1.1 Annual and seasonal precipitation

Fig. 2 shows the spatial distributions of the annual and seasonal average precipitation in Xinjiang from CCSM4, MERRA, and WRF for 1986–2005. Compared to the CCSM4 data, WRF downscales the annual and seasonal precipitation in Xinjiang, which can provide a more detailed spatial pattern of precipitation. The most striking spatial patterns are observed along the Tianshan Mountains, Altay Mountains, and across the Tarim Basin (desert). In the WRF simulations results, detailed terrain-induced features in precipitation patterns can be observed (Chen et al. 2019). The WRF model clearly reflects the heterogeneous spatial patterns in the precipitation data, especially in the Tianshan Mountains and Tarim Basin (Figs. 2 c, f, i, l, and o). These features are also observed in the MERRA reanalysis results (Figs. 2 b, e, h, k, and n). Although the CCSM4 data slightly underestimates the precipitation in Tianshan, they significantly overestimate the precipitation in Southern and Northern Xinjiang. Therefore, they overestimate the total precipitation in all of Xinjiang. The overestimation of precipitation also occurs in numerous other GCMs (Bao et al. 2015; Flato et al. 2014). Moreover, compared to the CCSM4 data, the precipitation data simulated by the WRF model are more consistent with the MERRA precipitation results, with a high spatial correlation coefficient of 0.82–0.92 (CCSM4, 0.68–0.80) and low relative bias of 12–30% (CCSM4, 33–57%) in annual and seasonal data (Table 1).

3.1.2 Monthly precipitation and daily precipitation events

Figs. 3a–c display the annual cycles of precipitation averaged over the three subregions of the ground-based meteorological observation data. As mentioned in Section 3.1.1, compared with the CCSM4 data, which overestimates the precipitation amounts in Southern and Northern Xinjiang and underestimates the precipitation in Tianshan, the WRF data perfectly captures the annual precipitation change cycles in the three subregions (Figs. 3a–c). The CCSM4 data significantly overestimates the precipitation during the annual cycles in Southern and Northern Xinjiang, which is the main reason that the CCSM4 data overestimates precipitation in Xinjiang, whereas the WRF approach corrects this deviation and the corresponding data agrees with the observations (Figs. 3a and b).
A metric is defined to assess the accuracy of the WRF-simulated daily precipitation. We begin with the precipitation accumulated during daily events in a particular intensity range. These ranges are from 1–5 to 35–40 mm day$^{-1}$ and increase by 5 mm day$^{-1}$. The contribution to the annual precipitation from each intensity group is used as the metric to describe the daily precipitation intensity profile. This metric is analogous to the precipitation probability density function used by Argueso et al. (2012).

Figs. 3d–f show the amount of annual precipitation produced by events over the three subregions. Each value in the Y-axis represents the amount of annual precipitation, which is caused by the precipitation events with specific intensities. Compared to the CCSM4 distribution, the WRF-simulated distribution more closely describes the observed data. Although the WRF-simulated daily precipitation events are still overestimated or underestimated in all
three subregions, the differences are generally small. Moreover, Figs. 3(d–f) demonstrate that the precipitation in each subregion has a gamma distribution with precipitation from light rain events contributing the most to the annual precipitation.

To summarize, the precipitation in Xinjiang during 1986–2005 is reasonably well simulated by our configured WRF model, on daily, monthly, seasonal, and annual scales. Although some large differences exist in the transition area from the Tarim Basin to the Tibetan Plateau and in the complex terrain of the Tianshan Mountains, the WRF model still provides better correction compared with the CCSM4 data.
3.2 Annual precipitation

Figs. 4a and f show the changes in annual precipitation simulated by the WRF model under RCP4.5 and RCP8.5 for the mid-21st century (2040–2059), in terms of the difference from the present annual precipitation. These differences exhibit a general increase in annual precipitation in most areas and slight decrease in others. These findings are consistent with the previously reported result, which states that future amounts of precipitation will increase in China and the largest increase will occur in Northwest China (Gao et al. 2008). The variations in annual precipitation under RCP4.5 and RCP8.5 in Xinjiang suggest that wet conditions will continue. Under RCP4.5 (Fig. 4a), this increase in precipitation has more orographic features than those under RCP8.5, with the largest increases being observed along Tianshan and Altay Mountain. Meanwhile, in the Kunlun Mountains located in the northwestern Tibetan Plateau, the precipitation amounts exhibit a decreasing trend. Under RCP8.5 (Fig. 4f), although the precipitation still shows an increasing trend, the precipitation magnitudes significantly differ from those under the RCP4.5 scenario (Table 2). The areas with the largest increases in precipitation are still the Tianshan and Altay Mountains, whereas the largest difference in precipitation occurs in the Kunlun Mountains where the change in precipitation is exactly the opposite to that observed under RCP4.5.

In addition, the second and third rows of Table 2 show the area-averaged changes in annual precipitation for the three subregions under RCP4.5 and RCP8.5, respectively. Relative to the present (1986–2005) precipitation, area-averaged increases in annual precipitation in Xinjiang in the 21st century are evident. These changes show that annual precipitation increased in all three subregions. Compared to those under RCP4.5, the precipitation amounts under RCP8.5 demonstrated flat or smaller magnitudes of change over the Tianshan Mountains and Northern Xinjiang; the only subregion that exhibits a continuous rise in annual precipitation through the decades is the desert in Southern Xinjiang (Table 2). These changes are also observed in the spatial patterns of precipitation shown in Figs. 4a and f.

In the context of annual precipitation changes in Central Asia since the last 60 years, these results indicate that the current humid conditions in eastern Central Asia started in the mid-1980s, with the most significant occurrence being observed in Tianshan and Northern and Southern Xinjiang (Hu et al. 2002); the findings also predict that these humid conditions will persist until this century.

3.3 Seasonal precipitation

The differences in projected seasonal precipitation in the mid-21st century from the present seasonal precipitation can be observed in Figs. 4b–e and Figs. 4g–j for RCP4.5 and RCP8.5, respectively. Although the magnitude of increase in precipitation under RCP8.5 is smaller than that under RCP4.5, similar changes are observed in both scenarios. The increases in precipitation under RCP4.5 and RCP8.5 in Tianshan primarily occur in spring and summer, and the amount of precipitation in spring and summer as a percentage of the increase in annual precipitation is 78.3% and 88.4%, respectively. Autumn and winter exhibit smaller precipitation increases in Northern Xinjiang under RCP4.5 (Figs. 4d and e), whereas smaller precipitation increases mainly occur in summer and autumn under RCP8.5 (Figs. 4h and i). In Southern Xinjiang, the precipitation amounts tend to decrease relative to the present values under RCP4.5 in summer, and the area with the most significant decrease is located within the Kunlun Mountains (Fig. 4c). This feature is the main reason for the annual precipitation
decrease in all of the Kunlun Mountains. Table 2 summarizes the area-averaged changes in seasonal precipitation relative to the present conditions in all three subregions. Most of the area-averaged changes in seasonal precipitation are positive under RCP4.5 and RCP8.5; however, Northern Xinjiang and Tianshan have negative rates in autumn under RCP8.5 and Southern Xinjiang has a negative rate in summer under RCP4.5.

The changes in seasonal precipitation are mostly statistically significant at the 95% confidence level (based on the two-tailed Student’s t-test), especially in mountainous areas such as the Tianshan, Altay, and Kunlun Mountains. The significance tests of precipitation relative to the present changes indicate that the areas predicted to experience the largest precipitation changes in the future in Xinjiang are likely the mountainous areas.

### 3.4 Daily precipitation

Daily precipitation events of different intensities comprise the daily precipitation, which is a key aspect of the regional precipitation climate (Higgins et al. 2007). Fig. 5 shows the changes in daily precipitation events in terms of their contribution to the annual precipitation under RCP4.5 and RCP8.5 in the three subregions. Although light rain events (those with intensities less than 10 mm·d$^{-1}$) will remain the main component in the future precipitation increase, the percentage of future heavy precipitation events (those greater than 30 mm·d$^{-1}$) under both RCP4.5 and RCP8.5 is significantly greater than that of the light rain events, especially in Northern Xinjiang and Southern Xinjiang. This result is consistent with the change trend of the precipitation patterns in Xinjiang (Yuan et al. 2017; Zhang et al. 2012). All precipitation changes pass the 95% confidence level test. Note that the Tianshan has a relatively flat curve because this region has a large precipitation base across the entire spectrum, and the precipitation increment in each intensity category accounts for a relatively small part of its base value. Under RCP4.5 and RCP8.5, the increase in strong events and decrease in the contribution of light rain events to the annual precipitation in Xinjiang are similar to the global average trends detected in the GCM results of this century (Fischer and Knutti 2016; Hennessy et al. 1997).

### Table 2

Differences in mean annual and seasonal precipitation between future (2040–2059) and present (1986–2005) conditions under RCP4.5 and RCP8.5 in three subregions (units: mm). The values in parentheses are percent differences from the precipitation amounts in 1986–2005.

| Scenario | Northern Xinjiang | Tianshan | Southern Xinjiang |
|----------|-------------------|----------|------------------|
| ANN      |                   |          |                  |
| RCP4.5   | 29.8 (13)         | 82.8 (15)| 11.4 (11)        |
| RCP8.5   | 23.9 (12)         | 53.7 (11)| 22.9 (22)        |
| MAM      |                   |          |                  |
| RCP4.5   | 16.2 (29)         | 30.6 (17)| 6.5 (16)         |
| RCP8.5   | 8.4 (15)          | 16.2 (9)| 6.7 (17)         |
| JJA      |                   |          |                  |
| RCP4.5   | 9.5 (20)          | 34.3 (21)| –1.5 (–3)        |
| RCP8.5   | 5.7 (9)           | 30.4 (21)| 4.8 (13)         |
| SON      |                   |          |                  |
| RCP4.5   | 2.7 (5)           | 5.1 (6) | 1.6 (10)         |
| RCP8.5   | –0.7 (–1)         | –0.4 (–1)| 3.9 (22)        |
| DJF      |                   |          |                  |
| RCP4.5   | 1.4 (2)           | 12.8 (9)| 4.8 (26)         |
| RCP8.5   | 10.5 (16)         | 6.5 (5) | 7.5 (38)         |
3.5 Possible mechanism

To elucidate the possible mechanism of the future precipitation changes in the WRF simulations, we study several key thermodynamic and dynamic fields including the 500 hPa (which is used instead of 850 hPa because of the elevated orography of Xinjiang) geopotential as well as the relative vorticity, vertically integrated column precipitation (PW), and relative humidity (RH) under the RCP4.5 and RCP8.5 scenarios.

Fig. 6 shows the future seasonal changes in PW and the 500 hPa air temperature under RCP4.5 and RCP8.5 relative to the present. Based on the Clausius–Clapeyron relationship (O’Gorman and Muller 2010; Pall et al. 2007), as the emission scenario increases from RCP4.5 to RCP8.5, the air temperature continues to rise in each season, leading to a continuous increase in PW. In contrast to the absence of continuous increases in annual and seasonal precipitation from RCP4.5 to RCP8.5 (Fig. 4 and Table 2), the continuous rise in PW in the same period suggests that the PW is not a strong factor affecting changes in precipitation. However, Fig. 5 reveals that the increase in strong events in Xinjiang under RCP4.5 is smaller than that under RCP8.5. As previous studies have shown, these differences are related to the PW (Fig. 6) because this has been suggested to affect a rise in the number of extreme rainfall events in warm climates (Fischer and Knutti 2016; Lehmann et al. 2015; Lenderink and Van Meijgaard 2008).

Fig. 7 shows the future seasonal changes in RH at 500 hPa relative to the present. In contrast to PW, the seasonal changes in RH exhibit many characteristics that are consistent with the seasonal changes in precipitation (Fig. 4). For example, the decrease in RH in the northwest of Tianshan is consistent with the changes in precipitation, especially in spring, summer, and autumn under
Fig. 6 Differences in PW (color scale, units: kg·m$^{-2}$) and 500-hPa air temperature (contour line, line interval 0.1 K) averaged under RCP4.5 and RCP8.5 in the future relative to the present day.
RCP8.5; meanwhile, the reduction in summer precipitation in the Kunlun Mountains in southern Xinjiang under RCP4.5 is consistent with the decrease in RH. Moreover, the increases in future precipitation in Northern and Southern Xinjiang correlate with the increases in RH (observed by comparing Figs. 4 and 7). The difference between the relationships between precipitation and RH, and that between precipitation and PW may originate because PW is a strong function of atmospheric temperature, as observed in the Clausius–Clapeyron relationship. The warm temperatures over the next few decades will determine the increases in atmospheric moisture content (Panthou et al. 2014), which will lead to a rise in PW. However, the atmospheric RH is relatively stable (i.e., given a sufficient time after the air temperature rises); thus, the RH will return to its previous value (Ivancic and Shaw 2016; Manabe and Wetherald 1967). This characteristic of the atmospheric RH and its strong relationship with precipitation are consistent with our results, which indicate that the scale of future precipitation changes is limited (Figs. 4 and 5). However, a considerable increase in atmospheric PW results in more intense precipitation during rainfall (Fig. 5).

Future spatial variations in precipitation and RH largely depend on the potential for vertical motion in the circulation. From the perspective of vorticity, positive relative vorticity is conducive to vertical upward movement and precipitation (Dodla and Ratna 2010). Fig. 8 shows the changes in relative vorticity ($\zeta$) and geopotential height ($\phi$) in the lower troposphere. $\phi$ has an upward trend in the future decades, and its spatial variations reveal the dynamic processes and $\zeta$ ($-\nabla^2\phi$). Focusing on the summer, Fig. 8b shows slightly more positive vorticity associated with low geopotential in most of Xinjiang, where less precipitation is expected in summer under RCP4.5 (Fig. 6b). In contrast, under RCP8.5, Fig. 8f shows more positive vorticity and low geopotential over Xinjiang, which corresponds to strong increases in precipitation magnitude across the region (Fig. 6f). Compared with the present, the change in relative vorticity under RCP4.5 is significantly larger than that under RCP8.5. This difference will likely cause the amount of precipitation to be lower under RCP8.5 than that under RCP4.5. Moreover, the geopotential of Xinjiang will continue to increase under RCP4.5 and RCP8.5. Compared to RCP4.5, the increase in geopotential will be more obvious under RCP8.5, which may suppress the occurrence of precipitation. In summer, the changes in geopotential height are smaller than those in winter and the changes in water vapor are generally larger (Figs. 6 and 8), which explains why there are more areas where precipitation increases in summer and decreases in winter. The suppression of precipitation by the positive geopotential is evident, particularly over the Kunlun Mountains in summers when the precipitation decreases. The positive anomalous geopotential heights are strengthened in each season under RCP8.5, which explains why the precipitation decreases are much larger under the RCP8.5 than under RCP4.5, although there is abundant water vapor in the atmosphere. Similar relationships between precipitation and $\phi$ and $\zeta$ are also identified in the transition seasons.

These variations in large-scale dynamic processes provide a mechanism for configuring instabilities and vertical motion for the projected changes in seasonal and annual precipitation in Xinjiang, in addition to a moisture advection effect suggested by Huang et al. (2014) based on their analysis of GCM outputs.

4 Discussion

Previous studies have suggested that when compared with common datasets such as the Global Precipitation Climatology Center (Schneider et al. 2018), the Climatic Research Unit Timeseries (Harris et al. 2014), and Asian Precipitation-Highly-Resolved Observational Data
Fig. 7 Differences in 700 hPa RH (units: %) averaged under RCP4.5 and RCP8.5 in the future relative to the present day.
Fig. 8 Differences in relative vorticity (color scale, unit: $10^{-5}$ s$^{-1}$) and 500-hPa geopotential (contour line, line interval 98 gpm) averaged under RCP4.5 and RCP8.5 relative to the present day. The white area is underneath the ground.
Integration Towards Evaluation (Yatagai et al. 2012), the MERRA dataset is more suitable for reanalyzing the precipitation in Central Asia (Hu et al. 2016). This is due to the advantageous characteristics of the MERRA dataset such as better performance and minimal uncertainty; it benefits from the integration of satellite observations during the development of the dataset (Rienecker et al. 2011; Xu et al. 2020). In addition, although some remotely sensed datasets, such as the Tropical Rainfall Measurement Mission (Kummerow et al. 1998), Global Precipitation Measurement (Hou et al. 2014), and the Climate Prediction Center Morphing Technology dataset (Joyce et al. 2004), have a higher accuracy than that of the reanalysis dataset, remotely sensed datasets exhibit inaccuracies when applied to describe the precipitation during the winter months (Ferraro et al. 1998; Zhang et al. 2018). Based on these considerations, we choose the MERRA dataset in our experiments to verify the effectiveness of the downscaling of the WRF model.

In this study, there is a relatively large difference in the simulated results achieved by the WRF and CCSM4 models when applied to Northern and Southern Xinjiang (Fig. 3). These differences are due to the different internal physical parameterization schemes used in the WRF and CCSM4 models. This type of discrepancy is also identified during the dynamic downscaling process, which indicates that physical parameterization scheme employed for dynamical downscaling can affect the biases that are intrinsic to the models (Zou et al. 2016). With an increase in the spatial resolution of 10 km, more details about the small-scale local climate can be obtained using the WRF model; however, the same cannot be said for the CCSM4 model. For instance, the current version of the WRF model can simulate spatial precipitation pattern. Owing to this improvement, the boundaries of the high rainfall areas in the Tianshan Mountains and Altai Mountains are well simulated in our experiments (Figs. 2 and 4) (Chen et al. 2019; Qiu et al. 2017). Therefore, although the WRF model overestimates the precipitation in Northern and Southern Xinjiang and underestimates the precipitation in Tianshan, it can estimate the precipitation tendency more accurately than the CCSM4 data (Fig. 3) (Chen et al. 2019; Qiu et al. 2017).

The unique spatial shape of the mountain basin in Xinjiang has greatly affected the water vapor transport and spatial distribution (Yu et al. 2003). Specifically, the Tianshan Mountains block the moisture present in the northwesterly or northerly winds blowing from the Aral, Caspian, Black, and Mediterranean Seas as well as the Arctic Ocean. Similarly, the Himalayas and Tibetan Plateau block most of the moisture coming from the south (Baldwin and Vecchi 2016; Chen et al. 2019). Therefore, the geographical distribution of precipitable water vapor in Xinjiang (Fig. 4) differs from that of actual precipitation (Fig. 6). This further indicates that the precipitation in Xinjiang may be closely related to the water vapor transported by atmospheric circulation (Shi and Sun 2008). This can be explained by the increasing elevation that causes the amounts of precipitation in the Tianshan and Altay Mountains to increase; however, it decreases along the north border of the Tibetan Plateau (Aizen et al. 2006; Baldwin and Vecchi 2016; Guan et al. 2019).

5 Conclusions

This study is primarily focused on investigating the changes in the intensity and frequency of precipitation at Xinjiang in the near future. A regional climate model called the WRF model was used to downscale the CCSM4 model in Xinjiang for the present (1986–2005) and near future (2040–2059) under the RCP4.5 and RCP8.5 scenarios. The following conclusions can be obtained from the results:
The annual precipitation will continue to increase under the RCP4.5 and RCP8.5 scenarios, and Tianshan has the largest increment among the three experimental regions. The increasing precipitation in the experimental regions, excluding Southern Xinjiang, is much smaller under RCP8.5 than that under RCP4.5. The projected annual precipitation in Xinjiang under both RCP4.5 and RCP8.5 suggests that the present wet and warm conditions will likely persist in the future, especially in the Tarim Basin. The largest increase in annual precipitation will be observed in the mountainous areas from the Tianshan to Altay Mountains. These values range from 50 to 150 mm, which are greater than the present levels.

The seasonal precipitation in Xinjiang has remarkable characteristics of increased summer rainfall and decreased winter precipitation under both RCP4.5 and RCP8.5 when compared to present levels. Moreover, the difference in the amount of precipitation between summer and winter is much larger under RCP4.5 than that under RCP8.5. In addition, the largest increase in the amount of seasonal precipitation in the future will likely occur during spring and summer in Tianshan and Northern Xinjiang, whereas this phenomenon will occur during spring and winter in Southern Xinjiang.

The more frequent heavy precipitation events (30–40 mm·d−1) are expected to occur in various subregions of Xinjiang. This change in the intensity of precipitation may result in more events with heavy precipitation in a warming climate. The events with small amounts of precipitation will account for a large proportion of seasonal and annual precipitation events, reducing the impact of the increase in the number of strong precipitation events on the amounts of seasonal and annual precipitation.

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