Will the arid and semi-arid regions of Northwest China become warmer and wetter based on CMIP6 models?

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ABSTRACT

Whether there is a transition underway, from a warm-dry climate to a warm-wet climate in Northwest China remains a controversial and scientifically significant issue. Will this trend continue in the future? Another hot issue is whether the climate in Northwest China will continue to be warm and humid over the next few decades. In this paper, eight CMIP6 models were employed to investigate temperature and precipitation changes under five principal Shared Socioeconomic Pathway (SSP) scenarios (from 2015 to 2099) to project the future warming and humidification in Northwest China using the SPEI (standardized precipitation evapotranspiration index) method. The results revealed that (1) the simulated temperature and precipitation of eight CMIP6 models were consistent with that of observed data during 1961–2014, which showed an increase of approximately 28.2 mm, while simulated data revealed an increase of approximately 9.4 mm. The annual precipitation gradually decreased from Eastern Inner Mongolia and the Southern Northwest Mongolia region (>700 mm) to the Central Northwest Mongolia region (<100 mm) from 1961 to 2014; (2) the MME significantly overestimated the temperature and slightly underestimated the precipitation in Northwest Mongolia. The temperature difference between the simulated and observed data was approximately 0.4 °C. The observed data showed an increase of approximately 0.9 °C from 1961 to 2014, whereas the simulated data revealed an increase of approximately 0.7 °C; (3) in the SSP5-8.5 scenario, the percentage of precipitation anomalies at 1.5, 2, 3, and 4 °C were 166.64, 190.58, 226.44, and 274.56\%, respectively; thus, alleviating the drought situation while facilitating the warm-dry to warm-wet climate transition; (4) the water balance between rising temperatures and increased evapotranspiration resulting from increased precipitation suggested that not all sites will be wet in the future. There was still a drying trend in some areas, where drought was more severe under the high emissions scenario than the low emissions scenario.

Key words: climate transition, CMIP6, Northwest China, SPEI, SSPs

HIGHLIGHTS

- The bias-corrected CMIP6 models sufficiently captured the spatial patterns of temperature and precipitation in China from 1961 to 2014, and the transition from warm-dry to warm-wet in Northwest China can be simulated by MME.
- Due to the uncertainty of the model results, the future climate change in Northwest China is quite uncertain and needs further study.
1. INTRODUCTION

In recent years, the issue of global climate change has increasingly drawn the attention of the international community. Over the last 40 years with the intensification of global warming, extreme minimum and mean minimum temperatures have been rising at various high latitudes and in tropical areas, whereas precipitation has also increased (Wang et al. 2018). According to the report of Working Group I of the Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC), when the global temperature rises by 1.5 °C, heat waves will increase, warm seasons will lengthen, and cold seasons will shorten. Critical tolerance thresholds for agricultural production and human health will be reached more frequently.
when the global temperature rises by 2 °C (IPCC 2021). The responses of arid and semi-arid regions to climate change are even more dramatic (Chen & Frauenfeld 2014). China’s arid and semi-arid regions account for approximately 47% of the total land area, which is primarily located in Northwest China, which is one of the most sensitive regions to global climate change (Yao et al. 2018). From 1960 to 2010, the air temperature in Northwest China significantly increased at a rate of 0.34 °C/decade, which was higher than the average for China (0.25 °C/decade), and that of the entire globe (0.15 °C/decade) during the same period (Li et al. 2012). Since Northwest China is deep in the country’s interior, it is situated too far from the moist ocean air. When this is coupled with the dynamic and thermal effects of the Tibetan Plateau, the precipitation in this region is scarce, the evapotranspiration is strong, and the climatic system is extremely fragile (Zhang et al. 2000). Consequently, the shortage of water resources and fragility of the ecological environment has seriously restricted the social and economic development of Northwest China. However, since 1987, the climate in this area has shown strong indications of a transition from warm-dry to warm-wet (Shi et al. 2002).

Many studies have been conducted to explore the climate transition in Northwest China. The changing trends in precipitation and dryness indices for Xinjiang, Gansu, Qinghai, Shaanxi, and Ningxia from 1961 to 2008 based on meteorological observations, and revealed that the temperature and precipitation in portions of Northwest China showed significant increasing trends (Zhang et al. 2010). The water level of Qinghai Lake in the eastern monsoon area of Northwest China was continuously decreasing, whereas the runoff from the Shiyang River in the eastern section of the Qilian Mountains was also decreasing (Shi et al. 2002). Global warming accelerated the water cycle and enhanced precipitation and evaporation. If the precipitation increases at a higher value, it is consistent with the climate transition to warm-wet (Shi et al. 2003). However, if the changes in precipitation are at a lower value, the northwest may become drier after the equilibrium with evaporation. Although the phenomenon of warmth and humidity occurred locally, the warming and drying trend across the entirety of Northwest China was obvious (Zhang et al. 2010). The trends of annual runoff and precipitation in China from 1956 to 2005 revealed that the runoff of inland river regions dropped sharply, as the increase of evapotranspiration surpassed the replenishment of water from precipitation (Zhang et al. 2011). The climate transition over the Boston Lake Basin in Southern Xinjiang and discovered that it became increasingly arid over the last 30 years (Yang et al. 2020). Although many studies have been conducted on historical climate transitions, few papers have endeavored to investigate future climate transitions.

The numerical simulation of the IPCC Fourth Assessment Report provided by the National Climate Center and indicated that it remained uncertain whether the local warm and wet indicators for Northwest China will persist or expand in the future (Zhang et al. 2010). To estimate whether these warming and wetting trends would continue, the changes in temperature and precipitation over eastern Northwest China were explored based on the latest observational data and the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project Phase 6 (CMIP6) collection data, which found that significant warming and humidification began in the late 1990s and were expected to continue until the end of the 21st century under the medium CO₂ emissions scenario (Yang et al. 2021). Based on outputs from 15 CMIP6 climate models under the latest future scenarios, the three drought characteristics (frequency, intensity, and duration) at 1.5 and 2 °C warming levels were analyzed over the poverty-stricken areas of China. The results showed that when global warming increased from 1.5 to 2 °C, the frequency and duration of drought increased in the southern region, but decreased in the northern region, whereas the intensity of drought increased across most areas (Wang et al. 2021). However, as for the climate change caused by global warming, there is insufficient research on future climate transitions for Northwest China, particularly the prediction of future climate transitions using CMIP6.

Due to a clear understanding of the physical processes of the climate system and recent advances in modeling, the use of the general circulation model (GCM) has become a major and vital tool for precipitation change studies (Tian et al. 2021). Today, CMIP has entered its sixth phase, which has higher spatial resolution and a more complete parameterization scheme. A primary difference between CMIP5 and CMIP6 is the set of future scenarios used to project climate evolution (Editorial 2019). The CMIP5 implemented four Representative Concentration Pathways (RCPs). These four RCPs comprised a set of pathways developed for the climate modeling community, which defined the radiative forcing values reached by 2100 (O’Neill et al. 2016). In contrast, the CMIP6 employed a new scenario framework rooted in socioeconomic trajectories: the shared socioeconomic pathways (SSPs), in which RCPs were combined with alternative pathways of socioeconomic development (Editorial 2019). However, the projection of GCMs still has considerable uncertainties (Yang et al. 2021). Since the output of one single global climate model is always biased and uncertain, it cannot accurately predict future climate trends (O’Neill et al. 2016). The methods of the arithmetic mean, the weighted mean, multivariate linear regression, and
singular value decomposition to perform the ensembles for temperature, precipitation, and sea level pressure, and indicated that the model credibility could be improved by using multiple model integrations (Feng et al. 2011). The multi-model ensemble (MME) results of CMIP6 could better capture the spatial patterns of annual mean temperature, maximum daily mean temperature, and minimum daily mean temperature (Zhu et al. 2020). Hence, the future scenarios of CMIP6 appear to be more reasonable in the new archive, particularly the MME results.

Although some scholars have analyzed past and future temperature and precipitation changes in Northwest China, only a few papers have comprehensively discussed future climate transitions in Northwest China based on CMIP6 outputs. Consequently, the goals of this paper were to (1) evaluate the performance of CMIP6 MME in simulating historical temperature and precipitation from 1961 to 2014 in Northwest China; (2) evaluate and analyze the historical climate transition in Northwest China based on the SPEI drought index and three drought characteristics simulated by CMIP6; and (3) explore future climate transitions over different periods under various SSP scenarios. The conclusions of this study may be used as a supplement for research on climate transitions in Northwest China to assist decision-makers toward the development of disaster reduction and ecological construction plans in arid and semi-arid areas.

2. MATERIALS AND METHODS

2.1. Study area

The northwest region of China is located at 73°40'E–126°04'E longitude, and 31°36'N–53°23'N latitude and spans an area of 4.06 million km². The study area encompasses Qinghai Province, Gansu Province, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region, and Inner Mongolia Autonomous Region (Figure 1).

The observed data employed in this study comprised the monthly gridded temperature and precipitation interpolated from 2,472 meteorological stations in China (1961–2014) at a spatial resolution of 0.5°×0.5° (http://data.cma.cn/site/index.html). In the paper, data on the precipitation, maximum temperature, minimum temperature, relative humidity, wind speed, and sunlight duration were derived from the daily datasets of basic meteorological elements of China's national surface weather station (V3.0) and the monthly data of China's surface climate (http://data.cma.cn/).

The stations with missing meteorological data, which accounted for more than 5% of the time series were removed, and missing meteorological data were supplemented by linear interpolation. To ensure the scientific accuracy of the calculation results, we selected 0.5°×0.5° spatial resolution global SPEI monthly datasets from the ecological institution of Spanish Pyrenees (http://spei.csic.es/database.html) and compared the results with historical periods to support the climate change predictions. The modeled temperature and precipitation were from eight CMIP6 models with r1i1p1f1 operators under five major future launch scenarios (https://esgf-node.llnl.gov/search/cmip6) (Table 1).

![Figure 1](http://iwaponline.com/hr/article-pdf/doi/10.2166/nh.2021.069/978138/nh2021069.pdf)
To maintain consistency, the CMIP data was corrected and downscaled to a spatial resolution of 0.5° × 0.5° (Su et al. 2018). The correction effects of the eight models were variable; however, the simulation was improved overall following the correction treatment, and the accuracy of the simulation was improved. All of the models were closer to the observed values in the order of magnitude. The five future scenarios were SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. The SSP1-1.9 scenario corresponded to a very low forcing level, with a probability of warming being below 1.5 °C in 2100. The emission curve of the SSP1-1.9 scenario revealed the characteristics of a rapid decline to zero and long-term negative emissions.

The SSP1-2.6 scenario represented the low ending range of future scenarios observed by its radiative forcing pathway. This scenario produced a multi-model mean of significantly less than 2.0 °C warming by 2100; thus, supporting the 2 °C temperature rise target study. The SSP2-4.5 scenario was considered to be moderately stable, whereas the SSP3-7.0 scenario corresponded to the medium to high-end future forcing path range. The SSP5-8.5 scenario was considered to be a high radiation forcing scenario (O’Neill et al. 2016).

2.2. Methodology

Based on the bias between the modeled and observed precipitation and temperature at each percentile, the Equidistant Cumulative Distribution Functions (EDCDFs) were used for the bias correction of raw CMIP6 outputs (Su et al. 2018; Tian et al. 2021). The EDCDF approach could be written as in Equations (1) and (2):

\[ \Delta = F_{oc}^{-1}(F_{ms}(x)) - F_{mc}^{-1}(F_{ms}(x)) \]  
\[ x_{\text{correct}} = x + \Delta \]

where \( x \) is the precipitation and temperature; \( F \) refers to the cumulative distribution function (CDF), and \( F^{-1} \) refers to the inverse CDF; \( oc \) is the observations during the training period; \( mc \) is the model outputs during the training period; and \( ms \) is the model outputs in a correction period.

A simplified longitude and latitude grid of 0.5° × 0.5° was used through spatial decomposition (SD; Wang & Chen 2014). A bilinear interpolation method based on the multi-year mean value was employed to interpolate the precipitation and temperature observed on a 0.5° grid in Northwest China with CMIP6 coarse resolution (Su et al. 2018). Anomaly fields between the observed and bias-corrected model outputs were defined as the ratio of CMIP6 output to observation. The coarse resolution anomalous field was interpolated to 0.5° × 0.5° via the bilinear method to obtain simplified CMIP6 outputs (Katiraei Boroujerdy et al. 2019). It could elevate the veracity of CMIP6 in climate prediction; however, the models had different responses following bias correction due to the various internal structures and initial conditions of the models (Taylor 2001). Accordingly, the CMIP6 model data shown hereafter were all bias-corrected.

### Table 1 | List of model details

<table>
<thead>
<tr>
<th>Code</th>
<th>Model</th>
<th>Modeling center</th>
<th>Horizontal resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CanESM5</td>
<td>Canadian Centre for Climate Modelling and Analysis, Canada</td>
<td>128 × 64</td>
</tr>
<tr>
<td>2</td>
<td>GFDL-ESM4</td>
<td>Geophysical Fluid Dynamics Laboratory, USA</td>
<td>288 × 180</td>
</tr>
<tr>
<td>3</td>
<td>IPSL-CM6A-LR</td>
<td>Institut Pierre-Simon Laplace, France</td>
<td>144 × 143</td>
</tr>
<tr>
<td>4</td>
<td>MIROC6</td>
<td>Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan</td>
<td>256 × 128</td>
</tr>
<tr>
<td>5</td>
<td>MIROC-ES2 L</td>
<td>Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies, Japan</td>
<td>128 × 64</td>
</tr>
<tr>
<td>6</td>
<td>MRI-ESM2-0</td>
<td>Meteorological Research Institute, Japan</td>
<td>320 × 160</td>
</tr>
<tr>
<td>7</td>
<td>UKESM1-0-LL</td>
<td>UK Natural Environment Research Council centers and the Met Office Hadley Centre, UK</td>
<td>192 × 144</td>
</tr>
<tr>
<td>8</td>
<td>CAMS-CSM1-0</td>
<td>Chinese Academy of Meteorological Sciences</td>
<td>320 × 160</td>
</tr>
</tbody>
</table>

Horizontal resolution means the number of longitudinal grids and the number of latitudinal grids.
A Taylor diagram was adopted to assess the simulation of all the bias-corrected CMIP6 climate patterns to provide a reference. The standard deviations $\sigma$ of the observed data and models were calculated as follows:

$$\sigma_{\text{obs}} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (X_{\text{obs}} - \bar{X}_{\text{obs}})^2}$$  \hspace{1cm} (3)$$

$$\sigma_{\text{model}} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (X_n - \bar{X})^2}$$  \hspace{1cm} (4)$$

where $\sigma_{\text{obs}}$ and $\sigma_{\text{model}}$ denote the mean values of observation and models, respectively.

The centered pattern RMS difference $E$ was defined by:

$$E = \sqrt{\frac{1}{N} \sum_{n=1}^{N} [(X_n - \bar{X}) - (X_{\text{obs}} - \bar{X}_{\text{obs}})^2]}$$  \hspace{1cm} (5)$$

The correlation coefficient $r$ between observed data and models was defined as:

$$r = \frac{\sqrt{\frac{1}{N} \sum_{n=1}^{N} (X_n - \bar{X})(X_{\text{obs}} - \bar{X}_{\text{obs}})}}{\sigma_{\text{model}}\sigma_{\text{obs}}}$$  \hspace{1cm} (6)$$

The key to constructing such a diagram was to recognize the relationships between the four statistical quantities of interest here (Taylor 2001):

$$E^2 = \sigma_{\text{obs}}^2 + \sigma_{\text{model}}^2 - 2\sigma_{\text{obs}}\sigma_{\text{model}}r$$  \hspace{1cm} (7)$$

The drought characteristics included drought frequency, drought duration, and drought intensity. Drought frequency refers to the number of drought events occurring each year. Drought duration is defined as the number of months between the start and end of the drought. The drought intensity of an event is the average of the monthly index values between its beginning and end. The basic steps of extracting drought intensity and the duration of drought events based on Runs theory were divided into three steps.

Firstly, the threshold value was determined, followed by the determination of the potential drought events, and finally, the drought events were screened from the potential events. In the study area, drought was the main natural feature, whereas the continuous process with $\text{SPEI}_i \leq -0.5$ and $\text{SPEI}_{i+1} > -0.5$ were selected as a drought event, where $i$ represents the number of months. The drought index division based on the classification level GB/T20481-2017 only considers a drought event with $\text{SPEI} \leq -1$ (Table 2).

<table>
<thead>
<tr>
<th>Category</th>
<th>Range of SPEI drought index values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme wetness</td>
<td>$2 \leq \text{SPEI}$</td>
</tr>
<tr>
<td>Severe wetness</td>
<td>$1.5 &lt; \text{SPEI} \leq 2$</td>
</tr>
<tr>
<td>Moderate wetness</td>
<td>$1 &lt; \text{SPEI} \leq 1.5$</td>
</tr>
<tr>
<td>No drought</td>
<td>$-0.5 &lt; \text{SPEI} \leq 0.5$</td>
</tr>
<tr>
<td>Moderate drought</td>
<td>$-1.5 &lt; \text{SPEI} \leq -1$</td>
</tr>
<tr>
<td>Severe drought</td>
<td>$-2 &lt; \text{SPEI} \leq -1.5$</td>
</tr>
<tr>
<td>Extreme drought</td>
<td>$\text{SPEI} \leq -2$</td>
</tr>
</tbody>
</table>
Drought frequency describes the rate of drought occurring at a site or grid point during the study period. The higher this value is, the higher the frequency of drought. The calculation formula is as follows:

\[ P = \frac{n}{N} \times 100\% \]  

(8)

where \( n \) is the total time, months, or years of drought occurring at a station and grid point, and \( N \) is the total length of data series of a station and grid point; namely the total time.

Therefore, this study selected the SPEI drought index to simulate the drought situation and future prediction in Northwest China under CMIP6 multi-model conditions. We described a multiscale drought index (the standardized precipitation evapotranspiration index; SPEI) that used precipitation and temperature data, which was based on a normalization of the simple water balance developed by Thornthwaite (1948). Here, two different potential evapotranspiration formulae were used to analyze the drought issues in the study area. Among them, in the study of future climate change, PET was calculated based on the Thornthwaite formula (Thornthwaite 1948), which was used to calculate the future SPEI drought index. Furthermore, the PET calculated based on the Penman formula was used to determine the SPEI drought index of historical periods (Vicente-Serrano et al. 2010).

The SPEI introduced potential evapotranspiration, which when combined with the PDSI index can accurately describe the geographic center, influence range, and drought intensity to provide a more precise and convenient drought description (Wang & Chen 2014). The Penman-Monteith (PM) formula belongs to the synthesis method, which is one of the formulas with the most common application and the highest accuracy. The disadvantage is that it requires detailed meteorological data, while the Thornthwaite (Tho) method belongs to the temperature method, which has low requirements for data, and is a flexible and convenient application that has been extensively applied worldwide. The calculation steps of the Tho method, the PM method, and the SPEI drought index are as follows:

Firstly, different formulas were used to calculate potential evapotranspiration (Table 3).

Secondly, the difference between monthly precipitation and potential evapotranspiration was denoted as \( D_i \):

\[ D_i = P_i - (ET_0)_i \]  

(9)

where \( i \) represents the precipitation on a certain day, \( P_i \) is the precipitation on a certain day (mm), and \( ET_i \) is the calculated potential evapotranspiration on a certain day, in bulk quantity (mm).

<table>
<thead>
<tr>
<th>Method</th>
<th>Calculation formula of potential evapotranspiration ( ET_0 )</th>
<th>Explain</th>
</tr>
</thead>
</table>
| PM    | \[ ET_0 = \frac{0.408s(R_n - G) + \gamma \frac{900}{T + 273} U_2(e_s - e_a)}{\Delta} \] | \( R_n \) – net surface radiation: MJ \( \cdot \) m\(^{-2} \cdot \) d\(^{-1}\)  
\( G \) – Soil heat flux: MJ \( \cdot \) m\(^{-2} \cdot \) d\(^{-1}\)  
\( \gamma \) – hygrometer constant: kPa/°C  
\( T \) – Daily average temperature: °C  
\( U_2 \) – two meters high wind speed: m/s  
\( e_s \) – saturated vapor pressure: kPa  
\( e_a \) – actual vapor pressure: kPa  
\( \Delta \) – the slope of water vapor pressure curve: kPa/°C |
| Tho   | \[ ET_0 = k(10T/I)^s \times uN/360 \] \[ I = \sum \frac{i_j}{4} \] \[ i_j = 0.09 \times T^{1.5} \] | \( T \) – mean monthly temperature: °C  
\( u \) – the number of days per month  
\( N \) – month average sunshine time: h/d  
The empirical coefficient \( k = 16 \) |
The cumulative sequence of water surpluses and deficits at different time scales was constructed:

\[ D^n_k = \sum_{i=0}^{k-1} [P_{n-i} - (ET_{0})_{n-i}] \quad (n \geq k) \]  

(10)

where \( k \) represents the time scale, and \( n \) represents a certain day.

Finally, the value of SPEI could be obtained by normalizing the data sequence \( D^n_k \).

In the above normalization process, Vicente-Serrano et al. (2010) compared the log-logistic distribution, the Pearson III distribution, the log-normal distribution, the generalized extreme value distribution, and the fitting effect of sequence \( D^n_k \).

The results showed that the logarithmic distribution and sequence \( D^n_k \) had the best fitting effect. The logarithmic logical distribution \( F(x) \) was used to normalize sequence \( D^n_k \) as follows:

\[ F(x) = \left[ 1 + \left( \frac{\alpha}{x - \gamma} \right)^\beta \right]^{-1} \]  

(11)

where \( \alpha \), \( \beta \), and \( \gamma \) are the parameters, which are obtained using linear moment fitting, as follows:

\[ \alpha = \frac{(w_0 - 2w_1)\beta}{r(1 + 1/\beta)r(1 - 1/\beta)} \]  

(12)

\[ \beta = \frac{2w_1 - w_0}{6w_1 - w_0 - 6w_2} \]  

(13)

\[ \gamma = w_0 - \alpha \Gamma(1 + 1/\beta)\Gamma(1 - 1/\beta) \]  

(14)

where \( \Gamma \) is a factorial function, and \( w_0, w_1, w_2 \) are the probabilistic weighted moments of the original data sequence \( D^n_k \). The calculation formula is as follows:

\[ W_s = \frac{1}{N} \sum_{i=0}^{N} (1 - F_i)^s D_i \]  

(15)

\[ F_i = \frac{i - 0.35}{N} \]  

(16)

where \( N \) is the number of days.

Then, the cumulative probability density was standardized:

\[ P = 1 - F(X) \]  

(17)

when \( P \leq 0.5 \),

\[ \text{SPEI} = W - \frac{c_0 + c_1w + c_2w^2}{1 + d_1w + d_2w^2 + d_3w^3} \]  

(18)

\[ W = \sqrt{-2\ln(P)} \]  

(19)

when \( P > 0.5 \),

\[ \text{SPEI} = \frac{c_0 + c_1w + c_2w^2}{1 + d_1w + d_2w^2 + d_3w^3} - W \]  

(20)

\[ W = \sqrt{-2\ln(1 - P)} \]  

(21)

In the formula: \( c_0 = 2.515517, c_1 = 0.802853, c_2 = 0.010328, d_1 = 1.432788, d_2 = 0.189269, d_3 = 0.001308 \).
Figure 2 | Spatial distribution of annual mean temperature and precipitation from 1961 to 2014, and the difference ratio of annual mean temperature and precipitation between the MME and observed values. The dots indicate that the difference was estimated at the 95% confidence level based on the T-test. (a) Temperature (Obs.), (b) temperature (MME), (c) precipitation (Obs.), (d) precipitation (MME), (e) temperature D-value, and (f) precipitation D-value.
3. RESULTS

3.1. Evaluation of CMIP6 simulated temperature and precipitation with the observed data

The temperature difference between the simulated and observed data was about 0.4 °C. The observed data showed an increase of approximately 0.9 °C from 1961 to 2014, whereas the simulated data showed an increase of approximately 0.7 °C (Figure 2(a) and 2(b)). The bias-corrected MME significantly overestimated the temperature in the western portion of the northwest (Figure 2(b)). This may be influenced by the complex topography in Northwest China; however, the observed values and the simulated values in other locations have high consistency. The precipitation in the eastern portion of Northwest China is higher than that in the western portion. The mean annual precipitation in the historical period indicated that the difference between MME and the observed value was only 27.6 mm.

The observed data showed an increase of approximately 28.2 mm from 1961 to 2014, whereas the simulated data revealed an increase of approximately 9.4 mm (Figure 2(c) and 2(d)). There may be a certain deviation between the simulated and observed data. The observed value of precipitation was slightly higher than the simulated value, and the MME simulated data underestimated the precipitation in Northwest China to a certain extent. The annual precipitation decreased gradually from Eastern Inner Mongolia and the Southern Northwest region (>700 mm) to the Central Northwestern region (<100 mm) from 1961 to 2014 (Figure 2(c)). The MME was consistent with the observed value on the whole, which could simulate the distribution and changes in temperature and precipitation of Northwest China.

The differences between the simulated and observed temperature (temperature D-value) and precipitation (precipitation D-value) were less than ±10% (Figure 2(e) and 2(f)). In terms of temperature, there was a certain deviation in Northwest China as a whole, and the deviation was larger in the central part of Northwest China (exceeded 50%) (Figure 2(c)). In terms of precipitation, the difference ratios were even less than ±5% in many places in Northern Inner Mongolia, which could be ignored. The bias at the high elevations of Xinjiang exceeded ~60%. Meanwhile, there was a larger positive bias in the middle of the northwest region (exceeded 50%) (Figure 3(f)).

The annual average precipitation and temperature differences of MME were small (±5%). Among them, the differences between MME and the observed values of temperature and precipitation were 20.87 and 25.67%, respectively. The temperature (difference ratio < –50%: 12.27%; difference ratio >50%: 11.20%), and precipitation (difference ratio < –50%: 9.31%;

![Figure 3](image)

**Figure 3** | Taylor diagrams for mean temperature and precipitation between observation, MME value, and eight bias-corrected CMIP6 models (indicated by the head of each arrow) from 1961 to 2014 in Northwest China dashed lines are for centered RMS differences, dot-dashed lines corresponded to correlations.

<table>
<thead>
<tr>
<th>D-value</th>
<th>≤ –50</th>
<th>–50 to –10</th>
<th>–10 to –5</th>
<th>–5 to 5</th>
<th>5 to 10</th>
<th>10 to 50</th>
<th>≥ 50</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>12.27</td>
<td>17.78</td>
<td>6.76</td>
<td>20.87</td>
<td>9.25</td>
<td>21.87</td>
<td>11.20</td>
</tr>
<tr>
<td>Precipitation</td>
<td>9.01</td>
<td>24.18</td>
<td>7.47</td>
<td>25.67</td>
<td>9.48</td>
<td>18.32</td>
<td>5.87</td>
</tr>
</tbody>
</table>

**Table 4** | Comparison of the percentage of grids for various difference ratios between the simulated and observed annual mean temperature and precipitation in Northwest China (unit: %)
difference ratio >50%: 5.69%) are shown in Table 4. The temperature bias was more pronounced than that for the precipitation. The overall simulation showed a good simulation effect and the spatial distribution was at a high confidence level.

A Taylor diagram is a proposed evaluation method for comparing the performance of different models (Taylor 2001). Firstly, the Correlation Coefficient (CC), Root Mean Square (RMS), and Standard Deviation (SD) of two sets of data, or two fields, are calculated, after which the four indices are plotted into the same polar coordinates. The best model simulation can then be determined by comparing the distance between each model in terms of polar coordinates and observed data. As shown in the CC in Taylor’s diagram, the CC of precipitation was 0.94, and the CC of temperature was 0.99 (Figure 3(a) and 3(b)). The central RMS dissimilarity of temperature was lower than 1.2, and the precipitation was higher than 7.1. Among them, GFDL-ESM4 and UKESM1-0-LL were better at describing the temperature situation in the study area (Figure 3(a)). Bias-corrected GFDL-ESM4 and MIROC6 exhibited the best performance between eight bias-corrected CMIP6 outputs in terms of describing the temporal variability of precipitation in the northwest region (Figure 3(b)). However, the MME indicated the highest similarity with observation, with a temperature of 0.99 and 0.97 precipitation in the northwest region. The MME presented the lowest centered RMS differences in all the models. Thus, the MME better simulated historical periods. Some researchers hold the same view; future scenarios of CMIP6 appear to be more reasonable in the new archive, particularly the MME results (Feng et al. 2011). Numerous studies have emphasized that the MME technique is an effective way to reduce the uncertainty of independent models, thereby improving predictions and their credibility (Knutti & Sedláček 2013).

3.2. Evaluation of CMIP6 simulated climate transition in Northwest China

The Mann-Kendall (MK) test is a type of climate diagnosis and prediction technology, which can be used to judge whether there is a mutation in a climate series and determine the time of the mutation. Using the observed temperature data from 1961 to 2014 to conduct the MK mutation point test, it could be seen that the UF curves in 1962 and 1978 intersected with the critical line at two points. This indicated that the temperature decreased significantly from 1962 to 1978, which slowed after 1978. The UF and UB had an intersection point in 1990, which could be considered as the temperature mutation point in 1990, after which the temperature began to rise significantly (Figure 4(a)).

The UF curves for 1989 and 2001 intersected the critical line, which indicated a significant increase in precipitation during this period. The increasing precipitation began to slow after 2001 but started to significantly rise again in 2008. The UF and UB curves intersected at several points in 1986, 1997, 1998, 2002, and 2005, respectively. It could be seen from the MK test for precipitation that the first mutation point was in 1986, with 95% significance within the confidence interval (Figure 4(b)).

Here, 1990 and 1986 were considered to be the mutation points of temperature and precipitation, respectively. Through the MK mutation point test, the historical temperature and precipitation were selected for study to analyze the changes in temperature and precipitation following the emergence of the mutation point.

The historical period (1961–2014) was divided into two segments, with 1990 and 1986 as the segmentation points, respectively, after which the historical changes of temperature and precipitation were compared. Temperature observations revealed that the temperatures in Northern Xinjiang, parts of Northern Qinghai, and Central Inner Mongolia rose by more than 40% from 1991 to 2014 compared with the 1961–1990 period (Figure 5(a) and 5(b)). The MME underestimated the temperature
increase in Northwest China during the historical period, but overall, it was in good agreement with the observed data. In addition, temperatures in Northern Mongolia dropped by more than 10–20%, which was reflected in both the observational and simulated data.

Precipitation observation data revealed that precipitation increased by more than 40% from 1987 to 2014 compared with 1961–1986 in most areas of Southern Xinjiang (Figure 5(c) and 5(d)). Moreover, the simulated data also significantly underestimated the increase of precipitation in Northwest China during the historical period, and the simulated precipitation was in good agreement with the observed data in the eastern part of Northwest China. However, there was a large deviation in the simulation of the historical precipitation increase in Xinjiang, which may have been due to the unique terrain in Northwest China (Figure 5(c)). It was found that the temperature in Northwest China increased significantly, most of which was between 10 and 30%. There was an obvious spatial difference in the increase of precipitation in Northwest China, where the change in precipitation in most areas was between ±10%.

According to the SPEI_1 monthly scale data, the occurrence frequency of different degrees of dry and wet conditions during 1961–2014 was statistically calculated. The observed and simulated moderate drought differed by 0.01%, whereas the observed and simulated moderate wetness differed by 0.38%, with the simulated value higher than the observed value.

Figure 5 | The historical periods (1961–2014) were separated according to the years of anomalous changes in temperature and precipitation, and the percentage of temperature and precipitation anomalies for the two periods were compared. (a) Temperature (Obs.), (b) temperature (MME), (c) precipitation (Obs.) and (d) precipitation (MME).
The observed and simulated severe drought differed by 0.11%, with the simulated value being slightly higher than the observed value. The observed and simulated severe wetness differed by 0.07% (Table 5). The observed and simulated extreme drought differed by 0.08%, whereas the observed and simulated extreme wetness differed by 0.15%, with the observed value being slightly higher than the simulated value (Table 5). To summarize, the MME could well simulate the different degrees of drought for historical periods, where the differences between the observed and simulated data were negligible.

From 1961 to 2014, there were 46 drought events, with an average duration of 2.67 months and average severity of –1.16, which indicated that the drought duration was prolonged and the drought intensity was high in the study area. Among the observed results, the most serious drought event occurred from May to October 2006, which lasted for 6 months. The most serious drought event in the MME occurred from March to November 2010, which lasted 9 months (Table 6; Figure 6).

3.3. Forecasting climate transitions in Northwest China

An integrated assessment report comprised of more than 20 global climate model outputs concluded that the currently massive increases in greenhouse gases will increase the global average temperature from between 1.4 and 5.8 °C by the end of the 21st century (Shi et al. 2003). The global average temperature from 1986 to 2005 (benchmark period) increased by 0.61 °C in contrast to before the Industrial Revolution (1850–1900) (Su et al. 2018). With a progressive temperature increase of 2 and 4 °C, droughts will increase in magnitude and duration toward the end of the century (Vicente-Serrano et al. 2010). The MME average results indicated that under RCP2.6, RCP4.5, RCP6.0, and RCP8.5 scenarios, the average global temperature will rise by 1.5 °C relative to pre-industrial temperatures by 2056, 2028, 2033, and 2025, respectively. Under the RCP4.5, RCP6.0, and RCP8.5 scenarios, the average global temperature will rise by 2 °C relative to pre-industrial temperatures by 2049, 2056, and 2039, respectively, while the RCP2.6 scenario did not reach 2 °C by 2100 (although some individual model tests can be achieved) (Wang et al. 2021). The MME exceeded 2 °C under both the RCP4.5 and RCP8.5 emissions scenarios, occurring in 2046 and 2038, respectively. The year that reached the 3 °C warming threshold under the RCP8.5 emissions scenario was 2060, while the increase exceeded 4 °C in 2080 (Chen et al. 2015).

In this paper, the 20 years encompassing 1.5, 2, 3, and 4 °C were estimated under different SSPs scenarios and compared with the base period (1995–2014). The low SSP1-1.9 scenario was not considered for temperature increases of 1.5 °C and above. The low SSP1-2.6 scenario did not reach 2 °C in the temperature forecast for the 21st century, and the percentage difference of precipitation anomalies was low. When the SSP1-2.6 temperature increased by 1.5 °C, the precipitation was elevated to a certain extent; however, the overall precipitation did not change significantly. When SSP2-4.5 temperature increased by 1.5 and 2 °C, the overall precipitation increased significantly; however, there was minimal variation between temperatures (Figure 7(b) and 7(c)). When the SSP3-7.0 temperature increased by 1.5 and 2 °C, the precipitation was significantly altered and increased significantly in many areas. The percentage of precipitation anomalies was high, and the study area was supplemented by substantial precipitation (Figure 7(d) and 7(e)). The high emissions scenario produced a fast warming rate, and SSP5-8.5 was the only scenario where the warming reached 3 and 4 °C within the 21st century. In the SSP1-2.6 scenario, the

Table 5 | Frequency of drought events and wetness events of different degrees during 1961–2014 (unit: %)

<table>
<thead>
<tr>
<th></th>
<th>Moderate drought</th>
<th>Severe drought</th>
<th>Extreme drought</th>
<th>Total drought</th>
<th>Moderate wetness</th>
<th>Severe wetness</th>
<th>Extreme wetness</th>
<th>Total wetness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed droughts</td>
<td>11.04</td>
<td>4.86</td>
<td>1.16</td>
<td>17.06</td>
<td>10.16</td>
<td>5.39</td>
<td>1.71</td>
<td>17.26</td>
</tr>
<tr>
<td>Simulated droughts</td>
<td>11.03</td>
<td>4.97</td>
<td>1.24</td>
<td>17.23</td>
<td>10.54</td>
<td>5.32</td>
<td>1.56</td>
<td>17.43</td>
</tr>
</tbody>
</table>

Table 6 | Drought characteristics of different SSPs scenarios in history

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Drought events (Times)</th>
<th>Mean duration (Months)</th>
<th>Mean severity</th>
<th>Mean drought intensity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed droughts</td>
<td>46</td>
<td>2.67</td>
<td>–3.13</td>
<td>–1.16</td>
</tr>
<tr>
<td>Simulated droughts</td>
<td>45</td>
<td>3.27</td>
<td>–3.74</td>
<td>–1.14</td>
</tr>
</tbody>
</table>
The percentage of precipitation anomalies was 121.92% when the temperature increased by 1.5 °C (Figure 7(a)). In the SSP2-4.5 scenario, the percentage of precipitation anomalies was 163.03%, when the temperature increased by 1.5 °C, and 177.45% when the temperature increased by 2 °C (Figure 7(b) and 7(c)). In the SSP3-7.0 scenario, the percentage of precipitation anomalies was 171.26% when the temperature increased by 1.5 °C, and 218.45% when the temperature increased by 2 °C (Figure 7(d) and 7(e)).

We found that under the background of global warming, the precipitation was greatly increased. In the SSP5-8.5 scenario, the percentage of precipitation anomalies at 1.5, 2, 3, and 4 °C were 166.64, 190.58, 226.44, and 274.56%, respectively (Figure 7(f)–7(i)). The substantial amount of precipitation brought by temperature rising can supplement the evaporation consumption in Northwest China; thus, alleviating the drought situation and providing the opportunity to complete the climate transition from warm-dry to warm-wet.

Uncertainty ranges of temperature, precipitation, and SPEI from 1961 to 2099 relative to the historical average (1961–2014) in Northwest China. The uncertainty ranges of projected precipitation fluctuations calculated by the arithmetic ensemble mean method were similar under the five SSPs scenarios. The gray bars on the right of the figures represent the uncertainty range of MME for all five scenarios. According to the MME and observed data, the temperature and precipitation demonstrated significant increasing trends in Northwest China under all five scenarios from 1961 to 2014. According to the historical observation data, the temperature in Northwest China has increased significantly since 1990, with the maximum increase rate reaching more than 30% (Figure 8(a)). The precipitation in Northwest China fluctuated obviously during the year 2000, which mainly showed that the precipitation increased by approximately 20% (Figure 8(b)). The SPEI generally varied at ±2% across the entire historical period. It can be seen from the simulation of MME to SPEI that the simulated data had a smaller fluctuation range than the observed data for the historical period (Figure 8(c)). In conclusion, the MME provided a good simulation of the temperature, precipitation, and SPEI in Northwest China. Uncertainty ranges in temperature, precipitation, and SPEI from 2015 to 2099 in Northwest China. Under the five SSPs scenarios, the uncertainty ranges of projected temperature and precipitation fluctuations were significantly increased. The temperature and precipitation fluctuations are projected to increase from 2015 to 2099 in Northwest China, with some differences between the low SSPs (SSP1-1.9 and SSP1-2.6) and high SSPs (SSP3-7.0 and SSP5-8.5) scenarios. The increase in temperature in

![Figure 6](http://iwaponline.com/hr/article-pdf/doi/10.2166/nh.2021.069/978138/nh2021069.pdf)
Figure 7 | Compared with the base period (1995–2014), percentage of precipitation anomalies under different SSPs scenarios when they reached temperatures of 1.5, 2, 3, and 4 °C. (a) 2021–2040, (b) 2019–2038, (c) 2037–2056, (d) 2024–2043, (e) 2047–2066, (f) 2016–2035, (g) 2029–2048, (h) 2051–2070, and (i) 2071–2090.

Figure 8 | Annual mean temperature, precipitation, and SPEI anomalies (%) from 1961 to 2099 for Northwest China. Shaded areas and gray bars represent the mean ± 1 standard deviation ranges for the mean simulation estimation ranges for the eight models. (a) Temperature MME, (b) precipitation MME, and (c) SPEI MME.
Northwest China might even reach >176% in the 2090s under the SSP5-8.5 scenario (Figure 8(a)). In terms of precipitation, all five scenarios exhibited a certain increase, where the precipitation increase under the SSP5-8.5 scenario was >40%. For the SSP1-1.9 scenario, the increase in precipitation was not obvious, and there was a slight decrease for some years. The differences between the SSP3-7.0 and SSP5-8.5 scenarios and histories were the largest. Under the SSP1-1.9 and SSP1-2.6 scenarios, the differences between future climate change and the historical data were small. Drought in Northwest China was estimated to be greatly alleviated by the abundant rainfall brought by rising temperatures. The percentage of SPEI anomalies in the future was forecast to fluctuate between −1 and 2%, which for the most part alleviated the drought conditions in Northwest China. The high SSP5-8.5 emissions scenario estimated the wettest environment in the northwest soon, although evaporation is forecast to increase significantly as temperatures rise. Precipitation was shown to compensate for the evaporation consumption caused by temperature, and the drought conditions improved in Northwest China (Figure 8(c)). Although the MME has a good predictive capacity, some future SPEI changes in Northwest China remain uncertain. Research on drought prediction revealed that the MME can accurately simulate historical SPEI and predict future SPEI drought indices.

At a global warming rate of 2 °C, the actual evapotranspiration in China increased by 7.8% compared with that from 1986 to 2005, with the most obvious increase being 8.3% in the spring and winter. Compared with the 1.5 °C global warming scenario, an additional 0.5 °C increase in global average temperature may lead to an increase of 3.4% in China’s actual evapotranspiration (Su et al. 2018). According to the SSP1-1.9 scenario, the total drought frequency was between 15.43 and 25.01% in Northwest China, and the total frequency of drought from 2061 to 2090 was between 12.17 and 20.78% (Figure 9(a) and 9(b)). Under the low scenario, with the increase of temperature and precipitation, the frequency of total drought in Northwest China decreased significantly. Under the SSP1-2.6 scenario, the total drought frequency was between 12.2 and 24.73% in Northwest China, and the total frequency of drought from 2061 to 2090 was between 14.08 and 26.47% (Figure 9(c) and 9(d)). There was little difference in the frequency range of total drought. Under the SSP2-4.5 scenario, the total drought frequency was between 6.57 and 23.37% in Northwest China, and the total frequency of drought from 2061 to 2090 was between 14.59 and 33.28%. The total drought frequency fluctuated the most under the SSP2-4.5 scenario (Figure 9(e) and 9(f)). Under different CO2 emissions scenarios, the high concentration scenario had an obvious influence on future dry-wet changes in Northwest China. Under the SSP3-7.0 scenario, the total drought frequency ranged from 6.14 to 22.59% from 2021 to 2050 and ranged from 14.54 to 29.65% during 2061–2090 (Figure 9(g) and 9(h)).

Under the SSP5-8.5 scenario, the total drought frequency ranged from 5.87 to 19.47% from 2021 to 2050 and ranged from 14.27 to 28.50% from 2061 to 2090 (Figure 9(i) and 9(j)). With increased temperature and precipitation, the range of drought frequency was reduced, and the drought situation in Northwest China will relieve. However, due to the influence of the original climatic factors in the eastern and western regions, the occurrence frequency of drought in the western part of Northwest China was increased obviously. The atmospheric humidity in the eastern part of Northwest China increased during the 1980 and 1990s; however, due to differences in the weather situation, the main drought in the eastern part of Northwest China and the main humidity in the western part of Northwest China were inversely altered (Shi et al. 2003). Moreover, the water balance between the increased evapotranspiration caused by higher temperatures and precipitation indicated that not all locations were wet. Rather, some locations continued to show a drying trend (Zhang et al. 2010). The study of five near-term (2021–2050) and long-term (2061–2090) emissions scenarios revealed that high emissions scenarios were drier than low ones, and the drought frequency in the high emissions scenario was higher than that in the low emissions scenario. The researchers also believed that the bias of the low SSPs scenario was minimal (Lehner et al. 2019).

Under the low emissions scenario, the mean durations of drought events were shorter, at approximately 2.8 months. It was observed that the average drought intensity will decrease, and extreme drought events will rarely occur in the future. Under the high emissions scenario, the average drought duration increased to more than 4 months, as the number of disaster events decreased. The average severity of drought events was the highest under the SSP3-7.0 scenario, reaching −5.94 (Table 7; Figure 10(g) and 10(h)). In terms of changing trends, the drought intensity values of the five scenarios showed a downward tendency overall, which was aligned with the warming and humidification trends in Northwest China. The CV (coefficient of variation) of each drought duration curve was >0.5 under the five scenarios, with large fluctuations. The drought duration decreased under the SSP1-1.9 and SSP2-4.5 scenarios and increased under the SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios. According to the forecast of future drought events, it was estimated that from the middle to late 21st-century drought events will decrease in the study area with reduced intensities, and the drought duration will shorten. Although drought events will still occur, they will be less severe overall.
Figure 9 | Total drought frequency distribution under five SSPs scenarios during 2021–2050 and 2061–2090.
Xinjiang, the precipitation increased by more than 40% from 1987 to 2014 compared with 1961. It was found that the temperature in Northwest China increased significantly, which was from between 10 and 30%. There was an obvious spatial difference in the increase of precipitation in Northwest China, where the correlation coefficients of temperature and precipitation in Northwest China were 0.99 and 0.97, respectively. Meanwhile, the MME presented the lowest centered RMS differences in all the models. The difference between the simulated and observed temperature was approximately 0.4 °C. The observed temperature showed an increase of approximately 0.9 °C from 1961 to 2014, whereas the CMIP6 MME showed an increase of approximately 0.7 °C.

The MME significantly overestimated the temperature in the western part of the northwest. The bias of West China was likely due to the coarse resolution of models, and the difficulty of fully reproducing processes like localized circulation patterns in complex topographies (Sun et al. 2015). The SD method is dependent on the observed data (Wang & Chen 2014); thus, the lack of meteorological stations in Western China might cause some bias there. The annual precipitation decreased gradually from the East of Inner Mongolia and the Southern Northwest region (>700 mm) to the Central Northwest region (<100 mm) from 1961 to 2014. The mean annual precipitation during the historical period indicated that the difference between the MME and the observed value was only 27.6 mm. The precipitation in the eastern part of Northwest China was greater than that in the western part. The observed value of precipitation was slightly higher than the simulated value, and the MME simulated data underestimated the precipitation in Northwest China to a certain extent. This underestimation presented a disagreement with the results of other researchers, which might have been due to the revision of CMIP6 (Wang & Chen 2014). The annual average precipitation and temperature difference of the MME was small, mainly ±5%. Between them, the difference between the MME and the observed value of temperature and precipitation was 20.87 and 25.67%, respectively. The temperature (difference ratio < −50%: 12.27%; difference ratio >50%: 11.20%), and precipitation (difference ratio < −50%: 9.31%; difference ratio >50%: 5.69%). The drought in Northwest China was forecast to be significantly eased by the abundant rainfall brought by rising temperatures. It was observed that the MME simulation had a smaller fluctuation range than the observed data for the historical period. Furthermore, the MME had a good simulation capacity for temperature, precipitation, and SPEI in Northwest China during the historical period.

Observations indicated that temperatures in Northern Xinjiang, parts of Northern Qinghai, and Central Inner Mongolia rose by more than 40% from 1991 to 2014, compared with the 1961–1990 period. The MME significantly underestimated the temperature increase in Northwest China during the historical period, but on the whole, it was in good agreement with the observed data. In addition, temperatures in Northern Mongolia have dropped by more than 10–20%, which was reflected in both the observational and simulated data. Precipitation observation data showed that in most areas of Southern Xinjiang, the precipitation increased by more than 40% from 1987 to 2014 compared with 1961–1986. Moreover, the simulated data significantly underestimated the increase in precipitation for Northwest China during the historical period, and the simulated precipitation in the eastern part of Northwest China was in good agreement with the observed data. However, there was a large deviation in the simulation of the historical precipitation increase in Xinjiang, which may have been impacted by the unusual terrain in Northwest China. It was found that the temperature in Northwest China increased significantly, most of which was from between 10 and 30%. There was an obvious spatial difference in the increase of precipitation in Northwest China, and the change in precipitation for most areas was between ±10%. From 1961 to 2014, there were 46 drought events,
Figure 10 | Drought intensity and drought duration of five SSPs scenarios during 2015–2099.
with an average duration of 2.67 months and average severity of −1.16, which indicated that the duration of droughts was prolonged and their intensity was high in the study area.

When the SSP1-2.6 temperature was increased by 1.5 °C, the precipitation increased to a certain extent; however, the overall precipitation did not change much. When the SSP2-4.5 temperature was increased by 1.5 and 2 °C, the precipitation increased significantly; however, there was little difference between different temperatures. When the SSP3-7.0 temperature increased by 1.5 and 2 °C, the precipitation changed and increased considerably in many areas. For the SSP5-8.5 scenario, the percentage of precipitation anomalies at 1.5, 2, 3, and 4 °C were 166.64, 190.58, 226.44, and 274.56%, respectively. Thus, the percentage of precipitation anomalies was high, and the study area was supplemented by substantial precipitation. The country-scale precipitation projection studies based on CMIP5 revealed that the precipitation increased significantly over most regions of China, with the increase in Northern China being greater than that in Southern China (Wang & Chen 2014; O’Neill et al. 2016). Under the five SSPs scenarios, the uncertainty ranges of the estimated temperature and precipitation fluctuations were significantly increased from 2015 to 2099. There were some differences between the low SSPs (SSP1-1.9 and SSP1-2.6) and high SSPs (SSP3-7.0 and SSP5-8.5) scenarios. The increase of temperature in Northwest China would even reach over 176% in the 2090s under SSP5-8.5. In terms of precipitation, all five scenarios exhibited certain degrees of increased precipitation, and the precipitation increase under the SSP5-8.5 scenario was >40%. For the SSP1-1.9 scenario, the increase of precipitation was not obvious, and there was a slight decrease for some years. According to the SSP1-1.9 scenario, the total drought frequency was between 15.43 and 25.01% in Northwest China, whereas the total frequency of drought from 2061 to 2090 was estimated to be between 12.17 and 20.78%. Under the low emissions scenario, with the increased temperature and precipitation, the overall frequency of drought in Northwest China decreased significantly.

Under the SSP1-2.6 scenario, the total drought frequency was between 12.2 and 24.73% in Northwest China, whereas the total frequency of drought from 2061 to 2090 was projected to be between 14.08 and 26.47%. There was little difference in the overall drought frequency range. Under the SSP2-4.5 scenario, the total drought frequency was between 6.57 and 23.37% in Northwest China, whereas the total drought frequency from 2061 to 2090 was estimated to be between 14.59 and 33.28%. The total drought frequency fluctuated the most under the SSP2-4.5 scenario. Under different emissions concentration scenarios, the high concentration scenario had an obvious influence on future dry-wet changes in Northwest China. Under the SSP3-7.0 scenario, the total drought frequency was estimated to range from 6.14 to 22.39% from 2021 to 2050 and from 14.54 to 29.65% from 2061 to 2090. Under the SSP5-8.5 scenario, the total drought frequency was estimated to range from 5.87 to 19.47% from 2021 to 2050 and from 14.27 to 28.50% from 2061 to 2090. With increased temperature and precipitation, the range of drought frequency will reduce, and the drought situation in Northwest China will relieve. However, due to the influence of the original climatic factors in the eastern and western regions, the occurrence frequency of drought in the western part of Northwest China will still increase. Under the low emissions scenario, the mean durations of drought events were shorter, at approximately 2.8 months. It was found that the average drought intensity will decrease and extreme drought events will rarely occur in the future. Under the high emissions scenario, the average drought duration increased to more than 4 months as the number of disastrous events decreased, and the average severity of drought events was the highest under the SSP3-7.0 scenario, reaching −5.94. Overall, the drought intensity values of the five scenarios showed a downward trend, which was in line with the trend of warming and humidification in Northwest China. The CV (coefficient of variation) of each drought duration curve was >0.5 under the five scenarios, with large fluctuations. The duration of drought decreased under the SSP1-1.9 and SSP2-4.5 scenarios and increased under the SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios. According to the forecast of future drought events, it was found that since the middle and late 21st century, drought events will decrease in the study area, their intensity will decrease, and duration will shorten. The droughts in Northwest China will be greatly eased by the abundant rainfall brought by rising temperatures. In conclusion, the large quantity of precipitation brought by rising temperatures can supplement the evaporation consumption in Northwest China, thus improving the drought situation, which provides the opportunity to complete the climate transition from warm-dry to warm-wet.

5. CONCLUSION

For this study, we investigated changes in temperature and precipitation in Northwest China from 1961 to 2099 under different scenarios (using CMIP6 models and the SPEI drought index) to learn whether the transition from a warm-dry to warm-wet climate might be possible. The major conclusions may be summarized as follows:
(1) All the bias-corrected CMIP6 models sufficiently captured the spatial patterns of temperature and precipitation in China from 1961 to 2014, and MME had a better simulation capacity. The MME significantly overestimated the temperature in the western part of the northwest. The precipitation in the eastern portion of Northwest China was greater than in the western portion. The observed precipitation value was slightly higher than the simulated value, and the MME simulated data underestimated the precipitation in Northwest China to a certain extent.

(2) When the SSP1-2.6 temperature increased by 1.5 °C, precipitation began to increase to a certain extent; however, the overall precipitation did not change much. When the SSP2-4.5 temperature increased by 1.5 and 2 °C, the precipitation increased significantly, but there was little variation between different temperatures. When the SSP3-7.0 temperature increased by 1.5 and 2 °C, the precipitation changed significantly, and precipitation increased considerably in many areas. For the SSP5-8.5 scenario, the percentage of precipitation anomalies at 1.5, 2, 3, and 4 °C were 166.64, 190.58, 226.44, and 274.56%, respectively.

(3) The drought intensity decreased under the five scenarios between 2015 and 2099, whereas the drought duration fluctuated greatly, with a decreasing trend under the lower emissions scenarios than that of the higher emissions scenario. Under the low emissions scenarios, the mean durations of drought events were shorter (approximately 2.8 months). The drought duration will decrease under the SSP1-1.9 and SSP2-4.5 scenarios, whereas it will increase under the SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios.

(4) The frequency of droughts in Northwest China will decrease significantly under the low scenarios. The drought frequency ranged from 6.14 to 22.39% during 2021–2050 and it ranged from 14.54 to 29.65% during 2061–2090 under the SSP3-7.0 scenario. The rising temperatures and increasing precipitation suggested that not all sites will be wet in the future. There was still a drying trend in some areas, where drought was more severe under the higher emissions scenarios than the lower emissions scenarios.

Although the CMIP6 results suggest that Northwest China will continue to get warmer and wetter during 2015–2099, especially in the next 30 years, the projected climate transition is also likely to be highly uncertain because climate models are highly uncertain. Therefore, further research in this area is needed.

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**AUTHOR CONTRIBUTIONS**

Liu Yang: Writing – Original draft preparation, Software, Data Curation; Zengxin Zhang and JiaXi Tian: Conceptualization, Writing – Review & Editing; Michael Tetteh Odamtten, Xu He and Rui Kong: Writing – Review & Editing; Yuanhai Fu: Resources, Data curation; MingKong Gao and Bin Zhu: Methodology. All authors have read and approved the final manuscript.

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**CONFLICTS OF INTEREST**

The authors declare no conflict of interest.

**DATA AVAILABILITY STATEMENT**

All relevant data are included in the paper or its Supplementary Information.

**REFERENCES**


IPCC 2021 Climate Change 2021.


Shi, Y. et al. 2003 Discussion on the present climate change from warm-dry to warm-wet in Northwest China. Quaternary Sciences 23 (02), 152–164.

Su, B. et al. 2018 Drought losses in China might double between the 1.5 °C and 2.0 °C warming. Proceedings of the National Academy of Sciences 115 (42), 10600–10605.


Wang, Y. et al. 2018 Assessment of future climate change impacts on nonpoint source pollution in snowmelt period for a cold area using SWAT. Scientific Reports 8 (1), 2402–2415.


Yang, H. et al. 2020 Has the Bosten Lake Basin been dry or wet during the climate transition in Northwest China in the past 30 years? Theoretical and Applied Climatology 141 (1–2), 627–644.


Zhu, H. et al. 2020 Does CMIP6 inspire more confidence in simulating climate extremes over China? Advances in Atmospheric Sciences 37 (10), 1119–1132.

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