A CMIP6-based assessment of regional climate change in the Chinese Tianshan Mountains Postprint

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Abstract

Climate warming profoundly affects hydrological changes, agricultural production, and human society. Arid and semi-arid areas of China are currently displaying a marked trend of warming and wetting. The Chinese Tianshan Mountains (CTM) have a high climate sensitivity, rendering the region particularly vulnerable to the effects of climate warming. In this study, we used monthly average temperature and monthly precipitation data from the CN05.1 gridded dataset (1961-2014) and 24 global climate models (GCMs) of the Coupled Model Intercomparison Project Phase 6 (CMIP6) to assess the applicability of the CMIP6 GCMs in the CTM at the regional scale. Based on this, we conducted a systematic review of the interannual trends, dry-wet transitions (based on the standardized precipitation index (SPI)), and spatial distribution patterns of climate change in the CTM during 1961-2014. We further projected future temperature and precipitation changes over three terms (near-term (2021-2040), mid-term (2041-2060), and long-term (2081-2100)) relative to the historical period (1961-2014) under four shared socio-economic pathway (SSP) scenarios (i.e., SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). It was found that the CTM had experienced significant warming and wetting from 1961 to 2014, and will also experience warming in the future (2021-2100). Substantial warming in 1997 was captured by both the CN05.1 derived from interpolating meteorological station data and the multi-model ensemble (MME) from the CMIP6 GCMs. The MME simulation results indicated an apparent wetting in 2008, which occurred later than the wetting observed from the CN05.1 in 1989. The GCMs generally underestimated spring temperature and overestimated both winter temperature and spring precipitation in the CTM. Warming and wetting are more rapid in the northern part of the CTM. By the end of the 21st century, all the four SSP scenarios project warmer and wetter conditions in the CTM with multiple dry-wet transitions. However, the rise in precipitation fails to counterbalance the drought induced by escalating temperature in the future, so the nature of the drought in the CTM will not change at all. Additionally, the projected summer precipitation shows negative correlation with the radiative forcing. This study holds practical implications for the awareness of climate change and subsequent research in the CTM.

Full Text

Preamble

A CMIP6-based assessment of regional climate change in the Chinese Tianshan Mountains

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Abstract: Climate warming profoundly affects hydrological processes, agricultural production, and human society. Arid and semi-arid regions of China are currently exhibiting marked warming and wetting trends. The Chinese Tianshan Mountains (CTM) exhibit high climate sensitivity, rendering the region particularly vulnerable to climate warming effects. This study employed monthly average temperature and precipitation data from the CN05.1 gridded dataset (1961–2014) and 24 global climate models (GCMs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6) to assess the applicability of CMIP6 GCMs in the CTM at regional scale. Based on this evaluation, we conducted a systematic analysis of interannual trends, dry–wet transitions (based on the standardized precipitation index (SPI)), and spatial distribution patterns of climate change in the CTM during 1961–2014. We further projected future temperature and precipitation changes over three periods (near-term (2021–2040), mid-term (2041–2060), and long-term (2081–2100)) relative to the historical period (1961–2014) under four shared socio-economic pathway (SSP) scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). The results reveal that the CTM experienced significant warming and wetting from 1961 to 2014, a trend that will continue through 2021–2100. Both the CN05.1 dataset (derived from interpolated meteorological station data) and the CMIP6 multi-model ensemble (MME) captured substantial warming in 1997. The MME simulation results indicated apparent wetting in 2008, which occurred later than the wetting observed in CN05.1 (1989). The GCMs generally underestimated spring temperature while overestimating both winter temperature and spring precipitation in the CTM. Warming and wetting are accelerating more rapidly in the northern part of the CTM. By the end of the 21st century, all four SSP scenarios project warmer and wetter conditions with multiple dry–wet transitions. However, the projected precipitation increase fails to counterbalance drought intensification driven by escalating temperatures, meaning the fundamental drought characteristics of the CTM will not change. Additionally, projected summer precipitation shows negative correlation with radiative forcing. These findings have practical implications for climate change awareness and subsequent research in the CTM.

Keywords: climate change; Coupled Model Intercomparison Project Phase 6 (CMIP6); global climate models (GCMs); shared socio-economic pathway (SSP) scenarios; standardized precipitation index (SPI); Chinese Tianshan Mountains

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1 Introduction

Climate change reflects the equilibrium of natural systems \cite{Ghil_{{{Lucarini}}{{2020}}}}. Greenhouse gas-induced warming has become the dominant driver of global temperature rise since the mid-20th century \cite{Tokarska{{{et}}{{al}}}{2020}}. Human activities have increased atmospheric greenhouse gas concentrations (such as carbon dioxide), representing a significant cause of runoff changes \cite{Dey_{{{Mishra}}{{2017}}}, Sun{{{et}}{{al}}}{2022b}}. The Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) provides systematic assessment and reasonable projections of likely changes in multiple climate components and cycles \cite{Zhou_{{{et}}{{al}}}{2021}}. Warming increases atmospheric heat and water vapor content, accelerates the hydrological cycle, and intensifies uneven water resource distribution within regions \cite{Shi_{{{et}}{{al}}}{2020}, Zhang_{{{et}}{{al}}}{2021b}}. Rational perception and evaluation of regional climate change form the basis for determining its influence on regional ecology, production, and livelihoods \cite{Christensen_{{{et}}{{al}}}{2013}}.

The complexity of climate determines its temporal and spatial diversity \cite{Jiang_{{{et}}{{al}}}{2016}}. Numerous studies have recognized and agreed on the occurrence of large-scale climate change in Northwest China, with unique regional characteristics shifting from "warm and dry" to "warm and wet" \cite{Shi_{{{et}}{{al}}}{2007}, Wang_{{{Qin}}{{2017}}}, Wang{{{et}}{{al}}}{2020}, Li_{{{et}}{{al}}}{2022b}, Chen_{{{et}}{{al}}}{2023}}. Global warming and high-intensity human activities not only cause higher temperatures but also disrupt precipitation patterns, resulting in more pronounced regional and seasonal precipitation diversity \cite{Luo_{{{et}}{{al}}}{2019}}. These changes have increased regional drought events and extreme weather occurrences, posing significant threats to agricultural production and severely disrupting ecological balance \cite{Li_{{{et}}{{al}}}{2018}, Jiang_{{{et}}{{al}}}{2022}}. For example, as the climate warms, the frequency and intensity of extreme precipitation are increasing at high altitudes \cite{Xu_{{{et}}{{al}}}{2021}}. This phenomenon contributes to glacier retreat, reduced available water resources, and escalating water supply-demand disparities \cite{Yu_{{{et}}{{al}}}{2019}, Javadinejad_{{{et}}{{al}}}{2020}}. Coupled with detrimental human impacts, these changes have resulted in soil degradation, salinization, desertification, and ecological equilibrium disturbances \cite{Zheng_{{{Wang}}{{2014}}}, Li{{{et}}{{al}}}{2018}, Chen_{{{et}}{{al}}}{2019}, Liu_{{{et}}{{al}}}{2020}, Xu_{{{et}}{{al}}}{2021}, Jiang_{{{et}}{{al}}}{2022}, Yu_{{{et}}{{al}}}{2022}}. Warmer climates influenced by monsoons and atmospheric circulation have accelerated glacial ablation in most mountainous regions while affecting glacier contributions to stream discharge \cite{Wang_{{{et}}{{al}}}{2011}, Shen_{{{et}}{{al}}}{2020}, Li_{{{et}}{{al}}}{2022b}, Tang_{{{et}}{{al}}}{2022}}. The temperature and precipitation in the Chinese Tianshan Mountains (CTM) exhibit unique spatiotemporal characteristics \cite{Wang_{{{et}}{{al}}}{2011}, Li_{{{et}}{{al}}}{2022b}}, and understanding these patterns is essential for determining the applicability of global climate models (GCMs) in this region.

The CN05.1 gridded dataset offers a valuable data source for regional climate analysis in China and has been widely used in analyzing conventional meteorological factors and extreme climate events \cite{Yang_{{{et}}{{al}}}{2017a}, Zhu_{{{et}}{{al}}}{2019}, Ge_{{{et}}{{al}}}{2023}}. The GCMs in the Coupled Model Intercomparison Project Phase 6 (CMIP6) provide universally accepted models and frameworks applicable across multiple activities \cite{Kim_{{{et}}{{al}}}{2020}, Lei_{{{et}}{{al}}}{2023}}. To some extent, CMIP6 features optimized framework structure and physical parameters, with higher effective radiation intensity, higher resolution, greater climate sensitivity, and a more comprehensive warming response range compared to CMIP5 \cite{Zhou_{{{et}}{{al}}}{2021}}. Shared socio-economic pathways (SSPs), as the primary scenarios for Scenario Model Intercomparison Project (ScenarioMIP) activities in CMIP6, are used to project future changes, compensating for the lack of typical greenhouse gas concentrations in CMIP5 \cite{Arora_{{{et}}{{al}}}{2020}, Chen_{{{et}}{{al}}}{2020}}. CMIP6 provides significant assistance in analyzing and applying multiple climate factors \cite{ONeill_{{{et}}{{al}}}{2016}, Zhu_{{{et}}{{al}}}{2021}} and has improved simulation capabilities for China compared to CMIP5 \cite{Jiang_{{{et}}{{al}}}{2020}}.

Current climate change research in China predominantly concentrates on the country' s northwestern region \cite{Yao_{{{et}}{{al}}}{2022}, Yu_{{{et}}{{al}}}{2022}, Aizizi_{{{et}}{{al}}}{2023}}, necessitating detailed studies on long-term regional climate change in the CTM. Given the challenges posed by global warming to the CTM, comprehensive analyses of temperature and precipitation changes in this region are essential. Such analyses help clarify the actual impacts of temperature and precipitation changes on glaciers, vegetation, and other factors in the context of climate warming. They also reveal crucial relationships among temperature, precipitation, and "warming and wetting" characteristics, all of which have implications for ecologically sustainable development and provide a robust scientific foundation for government policymaking and scientific research. In this study, we assessed the applicability of CMIP6 GCMs in the CTM based on monthly average temperature and precipitation data from the CN05.1 gridded dataset and CMIP6 GCMs. We then analyzed dry–wet transitions from 1961 to 2014 and projected spatiotemporal variation characteristics of temperature and precipitation in the CTM for the future period (2021–2100) under four radiative forcing scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). The results will have crucial implications for the conservation of glacial and snow resources, as well as for regional sustainable development in the CTM.

2.1 Study Area

The CTM (39°03 N–45°23 N, 73°26 E–95°28 E) are located in the arid northwestern part of China and serve as a natural boundary between the northern and southern portions of the Xinjiang Uygur Autonomous Region. The altitude varies greatly from -35 to 7129 m a.s.l., and the region features unique topographical characteristics and abundant glaciers [Figure 1: see original paper]. The region falls within the mesothermal zone and is characterized by a typical arid and semi-arid climate, making it highly susceptible to climate change \cite{Yao_{{{et}}{{al}}}{2022}, Aizizi_{{{et}}{{al}}}{2023}}. The CTM are rich in mineral resources and have complex lithospheric and geomorphologic characteristics \cite{Charvet_{{{et}}{{al}}}{2011}, Muhtar_{{{et}}{{al}}}{2022}}. The ecological environment is particularly sensitive to changes in temperature and precipitation.

[Figure 1: see original paper] Overview of the Chinese Tianshan Mountains (CTM) based on the digital elevation model (DEM) derived from the 90 m resolution Shuttle Radar Topography Mission (SRTM) dataset. The DEM data were downloaded from the Geospatial Data Cloud (http://www.gscloud.cn).

2.2.1 CN05.1 Gridded Dataset

Available meteorological stations within the study area are sparsely distributed along the boundary and cannot sufficiently reflect the spatial distribution of temperature and precipitation. Therefore, this study used monthly average temperature and precipitation data from the CN05.1 gridded dataset for 1961–

2020. This dataset offers high spatial resolution and continuity in both time series and spatial distribution, compensating to some extent for the uneven distribution of meteorological stations. The CN05.1 gridded dataset was provided by the Climate Change Research Center, Chinese Academy of Sciences (https://ccrc.iap.ac.cn/resource/detail?id=228). It was constructed by calculating a gridded climatology and adding daily anomalies interpolated from station observations (approximately 2400 meteorological stations) across China \cite{Xu_{{{et}}{{al}}}{2009}, Wu_{{{Gao}}_{{2013}}}}. Its horizontal resolution is 0.25°$×$0.25°. Since the historical experiment for GCM simulations only extended to 2014, the period 1961–2014 was selected as the historical period for comparison and analysis. Evaluating GCM simulations during the historical period is essential to ensure their applicability for future projections.

2.2.2 CMIP6 GCMs

Table 1 shows the basic details of the 24 CMIP6 GCMs. The period 1961–2014 was taken as the baseline for historical simulations. We compared monthly average temperature and precipitation data from the GCMs with those from the CN05.1 gridded dataset to analyze the regional applicability of CMIP6 GCMs and regional temperature and precipitation changes. The period 2021–2100 was selected as the future time scale to project temperature and precipitation variation characteristics in the CTM under different radiative forcing scenarios. Four scenarios were established: SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 \cite{ONeill_{{{et}}{{al}}}{2016}}. Future social development possibilities were considered without climate impacts or policy disruptions \cite{Jiang_{{{ONeill}}{{2017}}}, Kc{{{Lutz}}_{{2017}}}}. The SSP1-2.6 scenario represents low radiative forcing, simulating relatively optimistic sustainable development that keeps warming targets at 2.0°C. The SSP2-4.5 and SSP3-7.0 scenarios represent medium radiative forcing; however, SSP3-7.0 accounts for greater regional social change inequalities and land use changes than SSP2-4.5. The SSP5-8.5 scenario addresses integrated scientific problems as a high radiative forcing scenario under energy-intensive development and is the only pathway achieving radiative forcing of 8.5 W/m^2 by 2100.

Basic details of the 24 global climate models (GCMs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6)

<table>
<tr><th>Model name</th><th>Institution/Country (or region)</th><th>Spatial resolution (longitude×latitude)</th></tr>
<tr><td>ACCESS-CM2</td><td>CSIRO/Australia</td><td>1.875°$×1.250°||ACCESS −
ESM1 −
5|CSIRO/Australia|1.875°×1.250°||AWI−
CM − 1 − 1 −
MR|AWI/Germany|0.974°×0.974°||BCC−
CSM2 −
MR|BCC/China|1.125°×1.125°||CanESM5|CCCma/Canada|2
ESM2 −
0|CAS/China|1.406°×1.406°||CESM2−
FV2|NCAR/America|2.500°×1.875°||CESM2−
WACCM|NCAR/America|2.500°×1.875°||CMCC−
CM2 −
SR5|CMCC/Italy|1.250°×0.974°||EC−
Earth3|EC − Earth −
Consortium/EU|0.703°×0.703°||EC−
Earth3 − Veg|EC − Earth −
Consortium/EU|0.703°×0.703°||FGOALS−
f3 −
L|CAS/China|1.250°×1.000°||FGOALS−
g3|CAS/China|2.000°×2.250°||GFDL−
ESM4|GFDL/America|1.250°×1.000°||INM−
CM4 −
8|INM/Russia|2.000°×1.500°||INM−
CM5 −
0|INM/Russia|2.000°×1.500°||IPSL−
CM6A −
LR|IPSL/France|2.500°×1.259°||KACE−
1 − 0 −
G|NIMS/Korea|1.875°×1.250°||MIROC6|MIROC/Japan|1.40
ESM1 − 2 − HR|MPI −
M/Germany|0.974°×0.974°||NESM3|NUIST/China|1.875°×1.8
MM|NCC/Norway|1.250°×0.974°||SAM0−
UNICON|SUN/Korea|1.250°×0.974°||TaiESM1|RCEC/Chin</td></tr>
</table>

Note: CSIRO, Commonwealth Scientific and Industrial Research Organization; AWI, Alfred Wegener Institute; BCC, Beijing Climate Center; CCCma, Canadian Centre for Climate Modelling and Analysis; CAS, Chinese Academy of Sciences; NCAR, National Center for Atmospheric Research; CMCC, Euro-Mediterranean Centre on Climate Change; EU, European Union; GFDL, Geophysical Fluid Dynamics Laboratory; INM, Institute for Numerical Mathematics; IPSL, Institut Pierre Simon Laplace; NIMS, National Institute of Meteorological Sciences; MIROC, Model for Interdisciplinary Research on Climate; MPI-M, *Max Planck Institute for Meteorology; NUIST, Nanjing University of Information Science and Technology; NCC, National Climate Centre; SUN, Seoul National University; RCEC, Research Center for Environmental Changes. All GCM data used in this study were at monthly scale.*

2.3.1 Downscaling and Bias Correction of the GCMs

The spatial resolutions of CN05.1 and GCM data were divergent, with resolution varying among different GCMs. Low spatial resolution in models may lead to insufficient information collection. Therefore, the bias correction and spatial disaggregation (BCSD) method was used to preprocess GCM data \cite{Wang_{{{Chen}}_{{2014}}}}. GCM spatial resolution was downscaled by resampling to match CN05.1 resolution, unified at 0.25°$×$0.25°. Bias correction established a transfer function between observed (CN05.1 gridded dataset) and simulated (GCM outputs) data based on the historical period (1961-2014), then applied it to future projections. We upscaled observed data resolution to match simulated model data and constructed their functional relationships, subsequently downscaling simulated data to observed data resolution using climate state indices and interpolation factors.

The equidistant cumulative distribution function (EDCDF) mapped the distribution of monthly GCM data onto observed data \cite{Li_{{{et}}*{{al}}*}{2010}}:

$$x_{m-p} = F_{o-c}^{-1}\left(F_{m-p}(x_{m-p})\right)$$

where x_{m-p} is the bias-corrected GCM output for each climate variable in the future period; x_{m-p} is the original GCM output for each climate variable in the future period; F_{o-c} is the transfer function of observed data in the historical period; F_{m-p} is the transfer function of GCM outputs in the future period; and F_{m-c} is the transfer function of GCM outputs in the historical period. The baseline training period was 1961-2000. This functional relationship was assumed applicable for bias correction of GCMs for the future period 2021-2100 \cite{Xu_{{{Wang}}_{{2019}}}}.

2.3.2 Taylor Diagram Quantitative Evaluation Index

The Taylor diagram quantitative evaluation index assessed advantages and disadvantages of single model simulations, based primarily on calculating correlation coefficients and standard deviations between simulated and observed data \cite{Taylor_{2001}, Xiang_{{{et}}*{{al}}*}{2021}}. The calculations are as follows:

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

$$\sigma_f = \frac{\sigma_y}{\sigma_x}$$

$$S = \frac{4(1+R)^4}{(\sigma_f + 1/\sigma_f)^2(1+R_0)^4}$$

where R is the correlation coefficient between simulated and observed values; n is the number of grid cells; x_i and y_i are observed and simulated values of the ith grid cell in the study area, respectively; $\bar{x}$ and $\bar{y}$ are mean observed and simulated values in the study area, respectively; σ_f is the ratio of standard deviation of simulated data (σ_y) to observed data (σ_x); S is the Taylor diagram quantitative evaluation index; and R_0 is the maximum correlation coefficient of all GCMs. The closer the S value is to 1.0, the better the GCM simulation capability.

2.3.3 Interannual Variability Skill Score (IVS)

The IVS quantitatively measures similarity between observed and simulated values in terms of interannual variability \cite{Scherrer_{2011}, Yang_{{{et}}{{al}}}{2021}}. This index was calculated as:

$$IVS = \sqrt{\left(\frac{\sigma_y}{\sigma_x} - 1\right)^2 + (R-1)^2}$$

The lower the IVS value, the better the GCM simulation of interannual variability.

2.3.4 Mann-Kendall Test

The Mann-Kendall test is a widely used non-parametric statistical method for detecting trends in long time series in meteorological and hydrological studies. The samples need not follow a specific distribution and are not disturbed by outliers \cite{Kendall_{{{Stuart}}{{1979}}}}. In the Mann-Kendall test, the trend value can be calculated as \cite{Salehnia{{{Ahn}}_{{2022}}}}:

$$S_t = \sum_{j=1}^{t-1} \sum_{k=j+1}^{t} \mathrm{sgn}(y_k - y_j)$$

where

$$\mathrm{sgn}(y) = \begin{cases} +1 & \text{if } y > 0 \\ 0 & \text{if } y = 0 \\ -1 & \text{if } y < 0 \end{cases}$$

S_t is the trend value at time t; l is the series length; and y_j and y_k are the jth and kth data points in the series, respectively. The variance of S_t was calculated as:

$$\sigma^2 = \frac{1}{18}\left[l(l-1)(2l+5) - \sum_{p=1}^{g} t_p(t_p-1)(2t_p+5)\right]$$

where σ^2 is the variance of S_t; c is the number of data points; g is the number of tied groups in the dataset; and t_p is the number of data points in the pth tied group. Introducing the normalized test statistic Z and significance level α, when $|Z| \geq Z_{1-\alpha/2}$, a significant change trend exists. A positive or negative Z value denotes an increasing or decreasing trend, respectively. If the absolute Z value exceeds 2.32, the trend is significant at $P < 0.01$ level. If it exceeds 1.64, the trend is significant at $P < 0.05$ level \cite{Kim_{{{et}}{{al}}}{2018}}.

2.3.5 Standardized Precipitation Index (SPI)

The SPI is a generic drought indicator measuring standardized precipitation anomalies and calculating multiple precipitation patterns for given time scales \cite{WMO_{2006}, Dogan_{{{et}}{{al}}}{2012}, Zhang_{{{et}}{{al}}}{2014}, Li_{{{et}}{{al}}}{2022a}}. It uses the cumulative probability function to define the gamma distribution:

$$g(X) = \frac{1}{\beta^\gamma \Gamma(\gamma)} X^{\gamma-1} e^{-X/\beta}$$

$$G(X) = \int_0^X g(X)dX$$

where $G(X)$ is the cumulative probability function of precipitation; X is precipitation amount (mm; $X > 0$); $g(X)$ is the probability density function of precipitation; γ and β are shape and scale parameters, respectively; and $\Gamma(\gamma)$ is the gamma function of precipitation. Precipitation may contain zero values, so we defined parameter q as the probability of zero precipitation and $H(X)$ as the cumulative probability of zero and non-zero precipitation:

$$H(X) = q + (1-q)G(X)$$

The result was then transformed into a standardized normal distribution, enabling calculation of cumulative precipitation at multiple time scales and depiction of dry and wet conditions \cite{Salehnia_{{{et}}{{al}}}{2017}}. To define the relationship between precipitation amount and probability, 3, 6, 12, 24, and 60 months were taken as typical average periods \cite{McKee_{{{et}}{{al}}}{1993}}. This study calculated SPI at four time scales (3, 12, 24, and 60 months) to reflect dry-wet transitions in the CTM. We defined climatic moisture categories in the CTM based on SPI by referring to the National Climate Center Drought Scale \cite{General_{{{Administration}}*{{of}}*}{{{Quality}}*{{Supervision}}*}{{{Inspection}}*{{and}}*}{{{Quaran (Table 2).

Climatic moisture categories based on the standardized precipitation index (SPI)

SPI interval	Category	SPI interval	Category
SPI $\leq$ -2.0	Extreme drought	1.0 $\leq$ SPI $<$ 1.5	Moderate wet
-2.0 $<$ SPI $\leq$ -1.5	Severe drought	1.5 $\leq$ SPI $<$ 2.0	Severe wet
-1.5 $<$ SPI $\leq$ -1.0	Moderate drought	SPI $\geq$ 2.0	Extreme wet
-1.0 $<$ SPI $<$ 1.0	Normal		

2.3.6 Multi-Model Ensemble (MME)

Simulations by a single GCM may contain uncertainties in initial conditions, parameters, and structure. The MME assumes errors between GCMs are independent, which can be used to remove errors and improve uncertainty estimation \cite{Tebaldi_{{{Knutti}}*{{2007}}*}, *Zarrin*{Dadashi}-Roudbari_{2021}}. We obtained MME outputs based on:

$$\mathrm{MME}(t,h)=\frac{1}{u}\sum_{a=1}^{u}M_a(t,h)$$

where $\mathrm{MME}(t,h)$ is the MME output of the hth grid cell in the region at time t; $M_a(t,h)$ represents the output of the ath GCM of the hth grid cell in the region at time t; and u is the total number of GCMs. The MME is widely used in projecting climate variables \cite{Weigel_{{{et}}*{{al}}*}{2008}, Kharin_{{{et}}*{{al}}*}{2013}}.

2.3.7 Cumulative Departure (CD) Method

The CD is a concept commonly used for inter-decadal or seasonal analyses of climate variables, where the anomaly represents the offset between a value and the mean of a climate variable \cite{Randall_{{{et}}*{{al}}*}{2007}}. This index often assesses GCM bias by transforming climate variables into a series with zero mean through anomaly calculations, enabling visualization and analysis of simulation and correction performance. In this study, observed values were assumed to have zero mean for measuring GCM bias over different time series. The formula is:

$$\mathrm{CD}(t,h)=\sum_{i=1}^{t}\left[M_a(i,h)-\bar{M}_a(h)\right]-\sum_{i=1}^{t}\left[O_a(i,h)-\bar{O}_a(h)\right]$$

where $\mathrm{CD}(t,h)$ is the cumulative departure value of the hth grid cell in the region at time t; and $\bar{M}_a(t,h)$ and $\bar{O}_a(t,h)$ are the mean simulated and observed CD values of the ath GCM of the hth grid cell in the region at time t, respectively.

3.1 Capability of the CMIP6 GCMs in the CTM

Figure 2 [Figure 2: see original paper] shows the relationship of correlation coefficients between monthly average temperature and monthly precipitation after bias correction for the 24 GCMs and MME. Some variability existed among GCMs due to differences in physical mechanisms. It should be noted that the GCMs mentioned below are bias-corrected models. Most GCMs simulated monthly average temperature well, with correlation coefficients above 0.976, with three GCMs (ACCESS-ESM1-5, EC-Earth3, and CMCC-CM2-SR5) achieving correlation coefficients greater than 0.980. The mean correlation coefficient for monthly precipitation from the GCMs was approximately 0.700, 0.2%–59.0% higher than observations from CN05.1. Among the 24 GCMs, the best simulations were from ACCESS-CM2, INM-CM5-0, AWI-CM-1-1-MR, and EC-Earth3. The MME reduced uncertainty in single GCM simulations, resulting in simulated monthly average temperature and precipitation values close to observed values.

[Figure 2: see original paper] Scatter plot of the relationship of correlation coefficients between monthly average temperature and monthly precipitation after bias correction for the 24 global climate models (GCMs) and multi-model ensemble (MME)

Table 3 presents quantitative evaluation results analyzing bias-corrected effects of the 24 GCMs during the historical period (1961–2014). The comprehensive ranking was calculated using the arithmetic average of rankings obtained through two distinct scoring methods for monthly average temperature and precipitation simulations. Taylor diagram quantitative evaluation index values for monthly average temperature were above 0.9913, while values for monthly precipitation exceeded 0.9270. Notably, for monthly precipitation, Taylor diagram quantitative evaluation index values for four models (ACCESS-CM2, AWI-CM-1-1-MR, EC-Earth3, and INM-CM5-0) were above 0.9700. IVS values for monthly average temperature and precipitation were close to zero, indicating that interannual variability simulations of the 24 GCMs performed well. In summary, INM-CM5-0 (ranking 1st) produced the best simulations of monthly average temperature and precipitation in the CTM, whereas SAM0-UNICON produced the worst simulations (ranking 24th).

Quantitative evaluation results of monthly average temperature and monthly precipitation simulations after bias correction from the 24 GCMs

Model name	Monthly average temperature	Monthly precipitation	Comprehensive ranking
	S	IVS	S
INM-CM5-0	0.9999	1.026×10^{-5}	0.9999
EC-Earth3-Veg	0.9999	2.628×10^{-5}	0.9999
INM-CM4-8	0.9999	7.841×10^{-8}	0.9999
ACCESS-ESM1-5	0.9999	5.232×10^{-5}	0.9999
EC-Earth3	0.9999	4.450×10^{-5}	0.9999
KACE-1-0-G	0.9999	3.122×10^{-5}	0.9999
NorESM2-MM	0.9999	1.227×10^{-5}	0.9999
CAS-ESM2-0	0.9999	3.563×10^{-5}	0.9999
CMCC-CM2-SR5	0.9999	1.923×10^{-5}	0.9999
MPI-ESM1-2-HR	0.9999	3.956×10^{-5}	0.9999
AWI-CM-1-1-MR	0.9999	1.768×10^{-5}	0.9999
CESM2-FV2	0.9999	1.046×10^{-4}	0.9999
CanESM5	0.9999	3.599×10^{-7}	0.9999
FGOALS-f3-L	0.9999	7.778×10^{-5}	0.9999
FGOALS-g3	0.9999	8.615×10^{-5}	0.9999
ACCESS-CM2	0.9999	2.267×10^{-4}	0.9999
IPSL-CM6A-LR	0.9999	3.167×10^{-5}	0.9999
BCC-CSM2-MR	0.9999	7.256×10^{-5}	0.9999
NESM3	0.9999	6.686×10^{-5}	0.9999

Model name	Monthly average temperature	Monthly precipitation	Comprehensive ranking
CESM2-WACCM	0.9999	1.382$\times10^{-4}$	0.9999
GFDL-ESM4	0.9999	6.719$\times10^{-5}$	0.9999
MIROC6	0.9999	1.316$\times10^{-4}$	0.9999
TaiESM1	0.9999	2.310$\times10^{-4}$	0.9999
SAM0-UNICON	0.9999	1.680$\times10^{-4}$	0.9999

Note: S is the Taylor diagram quantitative evaluation index; IVS is the interannual variability skill score.

3.2 Spatiotemporal Variations in Temperature and Precipitation in the CTM During 1961–2014

During 1961–2014, both observed values and MME results indicated fluctuating rises in annual average temperature and annual precipitation (Fig. 3 [Figure 3: see original paper]). Moving averages of MME outputs were plotted to visualize trends. Annual average temperature increased consistently from 1961 onward. After 1997, annual average temperature from both MME and CN05.1 increased substantially, corresponding with temperature change patterns recorded throughout Northwest China \cite{Yang_{{{et}}{{al}}}{2017b}}. The fitted trend line from CN05.1 indicated rapid warming between 1975 and 1997, followed by slower warming from 1998 to 2014 in the CTM. During 1961–1997 and 1998–2014, MME-simulated rates of change in annual average temperature were 0.016°C/10a and 0.241°C/10a greater than observed values, respectively.

Annual precipitation in the CTM displayed a notable rising trend after 1989. MME-simulated annual precipitation showed a smoother pattern than observed values, with a distinct increase starting from 2008. Notably, simulated annual precipitation demonstrated delayed onset of apparent changes compared to observations. Furthermore, substantial disparities in precipitation simulations were observed among GCMs during the same period (data not shown). Toward the end of the 20th century, the moving average of annual precipitation increased slowly with little change. The rate of change in annual precipitation accelerated from the beginning of the 21st century.

Temperature simulated by the GCMs increased at rates of 0.140°C/10a–0.350°C/10a during 1961–2014, close to the rate from CN05.1 (0.290°C/10a) (Fig. 4 [Figure 4: see original paper]), and substantially higher than the global average (approximately 0.200°C/10a) \cite{Mathew_{2022}}. Five models (CanESM5, CAS-ESM2-0, CESM2-WACCM, EC-Earth3, and NorESM2-MM) simulated temperature increase rates above 0.300°C/10a, exceeding the CN05.1

rate (0.290°C/10a). The MME simulation reduced variability among different GCMs, but its simulated increase rate (0.230°C/10a) was lower than that from CN05.1 (0.290°C/10a).

Precipitation change rates simulated by the GCMs ranged from -3.300 to 9.720 mm/10a, whereas the CN05.1 precipitation change rate was 10.500 mm/10a, greater than the current 50-year growth rate (9.700 mm/10a) across Xinjiang Uygur Autonomous Region, Northwest China \cite{Wang_{{{et}}*{{al}}*}{2020}}. Although most GCMs captured rapid precipitation increases, they consistently underestimated precipitation amounts. The model with outputs closest to observed values was MIROC6, followed by EC-Earth3. Eight GCMs (CAS-ESM2-0, CESM2-FV2, CESM2-WACCM, CMCC-CM2-SR5, FGOALS-f3-L, GFDL-ESM4, INM-CM4-8, and NESM3) simulated negative precipitation increase rates, indicating decreased total precipitation in the CTM at the beginning of the 21st century. Temperature simulated by these eight models displayed an opposite trend to simulated precipitation at the beginning of the 21st century, with obvious temperature increase (warming) accompanied by precipitation decrease (drying). The MME-simulated precipitation increase rate was 2.210 mm/10a, which reduced uncertainty in single model simulations to some extent but still underestimated precipitation amount \cite{Tian_{{{et}}*{{al}}*}{2021}}.

[Figure 3: see original paper] Temporal variations in annual average temperature (a) and annual precipitation (b) from the MME and CN05.1 during 1961–2014

[Figure 4: see original paper] Increase rates of temperature and precipitation simulated from the 24 GCMs, CN05.1, and MME during 1961–2014

Figure 5 [Figure 5: see original paper] shows the intra-annual distribution of CD values for temperature and precipitation between GCMs and CN05.1 during 1961-2014. Based on World Meteorological Organization definitions \cite{Greenwood_{2022}}, we divided the year into four seasons: winter (December–February of the next year), spring (March–May), summer (June–August), and autumn (September–November). Temperature simulated in spring and September, and precipitation simulated in winter and October, were closest to observed values. CD values for monthly average temperature and monthly precipitation ranged from -0.200°C to 0.370°C and from -0.690 to 1.450 mm during 1961-2014, respectively. This indicated that monthly average temperature and precipitation were well simulated by the GCMs, with overall warming and wetting bias. The models underestimated spring temperature while overestimating winter temperature and spring precipitation. Winter and spring temperature profoundly affected spring precipitation \cite{Wang_{{{et}}*{{al}}*}{2011}}. Generally, the GCMs simulated warmer and wetter conditions in the CTM.

[Figure 5: see original paper] Portrait diagrams showing the intra-annual distribution of cumulative departure (CD) values of temperature and precipitation between the GCMs and CN05.1 during 1961–2014 at different time scales

Monthly average temperature simulated by the MME was broadly consistent with that determined from CN05.1 during 1961–2014. CD values of seasonal precipitation between simulated and observed values ranged from 0.010–0.320 mm. The MME captured the concentrated precipitation period (summer) in the CTM. Summer precipitation simulated by the MME accounted for 49.10% of the annual total, which was 8.80% larger than the CN05.1 value. Spring precipitation simulated by the MME was overestimated by 5.20% compared to observed values. The MME accurately reflected regional temperature and precipitation variation trends during the historical period (1961–2014) and can therefore be used to project temperature and precipitation for the future (2021–2100) in the CTM.

Figure 6 [Figure 6: see original paper] shows SPI values calculated at four time scales (3, 12, 24, and 60 months) from 1961 to 2014. Overall SPI trends were similar across time scales, with visible wetting trends in the CTM during 1961–2014. A shift from dry to wet conditions occurred in the 1980s. Over time, the wetting trend simulated by the MME became more obvious, as did differences in SPI between simulated and observed values. Differences were more evident at 24- and 60-month time scales than at 3- and 12-month scales.

At the 12-month time scale, more wet and drought events were identified according to SPI (Fig. 6). At the end of the 1980s, a clear difference in SPI (maximum of 2.5) existed between simulated and observed values. At the 60-month time scale, the MME simulated a shorter drought period, with dry–wet transitions occurring earlier than those derived from CN05.1. At the 24- and 60-month time scales, the MME preferred continued wetting trends in the 2010s. SPI confirmed that the most frequent droughts occurred in the late 1960s, late 1970s, and 1980s. In the 2000s, conditions converted to a wetter period.

[Figure 6: see original paper] Temporal variations of standardized precipitation index (SPI) based on the CN05.1 (a1, b1, c1, and d1) and MME (a2, b2, c2, and d2) during 1961-2014 at the 3-, 12-, 24-, and 60-month time scales. CN05.1_{SPI3}, CN05.1_{SPI12}, CN05.1_{SPI24}, and CN05.1_{SPI60} denote SPI values at the 3-, 12-, 24-, and 60-month time scales, respectively, based on CN05.1. MME_{SPI3}, MME_{SPI12}, MME_{SPI24}, and MME_{SPI60} denote SPI values at the 3-, 12-, 24-, and 60-month time scales, respectively, based on the MME. SPI values between -1.0 (red dotted line) and 1.0 (blue dotted line) indicate normal dry and wet conditions in the region.

Figure 7 [Figure 7: see original paper] shows the spatial distribution of rates of change in annual average temperature and annual precipitation in the CTM from 1961 to 2014. Divergent rates of change were apparent in northern and southern parts of the CTM \cite{Li_{{{et}}{{al}}}{2012}}. Warming and wetting have accelerated in the northern CTM. The MME captured geographical variability and simulated spatial distributions of temperature and precipitation consistent with CN05.1. MME-simulated warming rates were almost consistent with CN05.1-derived rates. Specifically, values were higher than CN05.1-derived rates by 0.030°C/10a–0.083°C/10a in the southwestern CTM but slightly lower in the northern CTM. MME-simulated wetting rates were lower than CN05.1-derived rates throughout the region, whereas simulated precipitation centers were consistent with observed results. MME simulation results reduced spatial variability of wetting rates in eastern and western CTM and underestimated wetting change rates in the western CTM from 1961 to 2014.

[Figure 7: see original paper] Spatial distribution of rates of change in annual average temperature (a1 and b1) and annual precipitation (a2 and b2) based on CN05.1 and MME during 1961–2014. Dotted areas indicate temperature and precipitation change trends significant at $P < 0.05$ level, and lined areas indicate trends significant at $P < 0.01$ level.

3.3 Spatiotemporal Variations in Future Temperature and Precipitation Patterns During 2021–2100

After validation and analysis during the historical period (1961–2014), bias-corrected GCMs could be applied to project future temperature and precipitation in the CTM. However, not all models had access to all four future scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). Therefore, the MME used to characterize future temperature and precipitation under the four SSP scenarios differed from that used for the historical period. After excluding models with incomplete time series and those not including all four SSP scenarios, the MME consisted of 12 GCMs: ACCESS-CM2, BCC-CSM2-MR, CAS-ESM2-0, CESM2-WACCM, CMCC-CM2-SR5, EC-Earth3, EC-Earth3-Veg, FGOALS-f3-L, FGOALS-g3, KACE-1-0-G, MIROC6, and TaiESM. After downscaling and bias correction, MME averaging was performed on data from the 12 GCMs, reducing uncertainty in single model projections.

Annual average temperature and annual precipitation will increase with increasing radiative forcing in the future (Fig. 8 [Figure 8: see original paper]). Annual average temperature presents a significant upward trend, while annual precipitation shows a volatile growing trend (Table 4). As radiative forcing increases, annual average temperature increases at faster rates, with the largest increase rate under the SSP5-8.5 scenario. By the end of the 21st century, MME-simulated annual average temperature will reach up to 4.100°C under SSP1-2.6 scenario, with an increase rate of 0.090°C/10a. Under SSP5-8.5 scenario, the corresponding value is 8.900°C, with an increase rate of 0.730°C/10a, much higher than the rate during 1961–2014 (0.290°C/10a). Annual precipitation projected by individual models fluctuates widely, whereas the MME indicates a slowly increasing trend. By the end of the 21st century, annual precipitation will increase by 3.09% under SSP1-2.6 scenario and by 16.19% under SSP5-8.5 scenario, compared to the historical period (1961–2014).

[Figure 8: see original paper] Temporal variations in annual average temperature (a) and annual precipitation (b) during 2021–2100 under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios compared to CN05.1 values in the historical period (1961–2014). Colored shaded areas indicate the range of simulated fluctuations for individual models under a given scenario, and solid lines indicate the simulated mean value after averaging multiple models under a given scenario.

Rates of change in annual average temperature and annual precipitation during 2021–2100 under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios

Rate of change	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
Annual average temperature (°C/10a)	0.091**	0.283**	0.553**	0.726**
Annual precipitation (mm/10a)	0.681*	2.429**	3.897**	4.929**

Note: and ** indicate that change trends are statistically significant at $P < 0.05$ level and $P < 0.01$ level, respectively.*

Monthly average temperature shows general increasing variability during 2021–2100 under the four SSP scenarios relative to the historical period (Fig. 9 [Figure 9: see original paper]). As with annual average temperature, its rate of increase also rises with increasing radiative forcing. The magnitude of temperature increase in some months exhibits symmetrical characteristics, with the largest amplitude increases under SSP5-8.5 scenario in March and October (102.23% and 126.87%, respectively). Winter and spring temperature shows a maximum increase magnitude of 126.00%. Despite slight summer temperature increases, temperatures will continue rising in the future relative to the historical period. Against this backdrop of sustained warming, implications for the CTM, which contains abundant glacial snow resources, are self-evident.

[Figure 9: see original paper] Magnitude of increase in monthly average temperature (a) and monthly precipitation (b) during 2021–2100 under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios relative to the historical period

Monthly precipitation variation is distinct from monthly average temperature variation; monthly precipitation is no longer synchronous during May–October with increasing radiative forcing. The magnitude of monthly precipitation increase is most prominent (52.23%) in January under SSP5-8.5 scenario. Under all four scenarios, the magnitude of monthly precipitation increase continuously rises from October to January of the following year and gradually decreases from January to July. Precipitation in July will decrease under both SSP3-7.0 and SSP5-8.5 scenarios compared to the historical period. Winter and spring precipitation values during 2021–2100 are higher than those during the historical period.

We divided the future period 2021–2100 into three terms: near-term (2021–2040), mid-term (2041–2060), and long-term (2081–2100). Overall trends and distributional characteristics of annual average temperature and precipitation in the three future terms are consistent with those during the entire future period (2021–2100), displaying increasing trends over time (Fig. 10 [Figure 10: see original paper]). However, in each term, annual average temperature values are more focused than annual precipitation values. Annual precipitation varies over a wider range in each term. Under SSP1-2.6 scenario, both annual average temperature and precipitation increase rapidly in near-term and mid-term, while increasing slowly in long-term. Compared with mid-term, some years show decreases in annual average temperature and precipitation in long-term under SSP1-2.6 scenario. Annual average temperature reaches up to 4.180°C, and annual precipitation increases to 283.770 mm in long-term under SSP2-4.5 scenario. Under SSP2-4.5 and SSP3-7.0 scenarios, increasing trends from near-term to long-term occur in both annual average temperature and precipitation. Under SSP5-8.5 scenario, annual average temperature reaches up to 8.100°C in long-term, representing a 116.00% increase compared to near-term. Annual precipitation under SSP5-8.5 scenario in long-term will increase by 10.41% compared to near-term. By the end of the 21st century, the CTM may display warming and wetting characteristics under SSP5-8.5 scenario.

[Figure 10: see original paper] Violin plot showing trends and distribution of annual average temperature (a) and annual precipitation (b) in near-term (2021–2040), mid-term (2041–2060), and long-term (2081–2100) under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios. The violin shape indicates distributional characteristics, with width representing degree of concentration. Black dots indicate data points of annual average temperature and precipitation in different years. Box boundaries indicate 25th and 75th percentiles across years, and whiskers below and above the box indicate 10th and 90th percentiles, respectively. The horizontal line within each box indicates the median of data points.

The rate of change in annual average temperature over time under the four scenarios is significantly spatially heterogeneous (Fig. 11 [Figure 11: see original paper]). Most regions in the CTM display significant warming trends. In all three future terms, warming rates change smoothly under SSP1-2.6 and SSP2-4.5 scenarios, while increasing substantially over time under SSP3-7.0 and SSP5-8.5 scenarios. The rate of change in annual average temperature gradually decreases from near-term to long-term under both SSP1-2.6 and SSP2-4.5 scenarios. It is negative in long-term under SSP1-2.6 scenario (Fig. 11a3) and increases slowly from near-term to mid-term under SSP2-4.5 scenario (Fig. 11b1–b3). Under SSP2-4.5 scenario, the fastest warming appears in the western CTM in long-term (Fig. 11b3), while under the other three scenarios, the fastest warming occurs in the eastern part (Fig. 11a3, 11c3, and 11d3). For all three future terms, the overall temperature increase rate is fastest under SSP5-8.5 scenario, even reaching 0.090°C/a in the eastern CTM in long-term (Fig. 11d1–d3).

[Figure 11: see original paper] Spatial distribution of the rate of change in annual average temperature increase (warming) in near-term (2021–2040), mid-term (2041–2060), and long-term (2081–2100) under SSP1-2.6 (a1–a3), SSP2-4.5 (b1–b3), SSP3-7.0 (c1–c3), and SSP5-8.5 (d1–d3) scenarios. SSP1-2.6_{Near}, SSP2-4.5_{Near}, SSP3-7.0_{Near}, and SSP5-8.5_{Near} mean SSPs in near-term; SSP1-2.6_{Mid}, SSP2-4.5_{Mid}, SSP3-7.0_{Mid}, and SSP5-8.5_{Mid} mean SSPs in mid-term; SSP1-2.6_{Long}, SSP2-4.5_{Long}, SSP3-7.0_{Long}, and SSP5-8.5_{Long} mean SSPs in long-term. Dotted areas indicate temperature change trends significant at $P < 0.05$ level, and lined areas indicate trends significant at $P < 0.01$ level.

Generally, spatial variability of annual precipitation is diversified (Fig. 12 [Figure 12: see original paper]). The center of annual precipitation changes over time in the CTM. Under SSP1-2.6 scenario, the rate of change in annual precipitation increases significantly in the western CTM in long-term compared to near-term and mid-term (Fig. 12a1–a3). The region showing significant wetting in long-term shrinks compared to near-term under SSP2-4.5 scenario (Fig. 12b1 and b3). Under SSP3-7.0 scenario, the rate of change in annual precipitation decreases in the western CTM, whereas it initially decreases then increases in the central region across the three terms, compared to SSP2-4.5 scenario (Fig. 12b1–c3). Under SSP5-8.5 scenario, the fastest increase in the rate of annual precipitation occurs in long-term (Fig. 12d3), and the average rate of change in annual precipitation in the northern CTM reaches up to 2.500 mm/a in long-term.

[Figure 12: see original paper] Spatial distribution of the rate of change in annual precipitation in near-term (2021–2040), mid-term (2041–2060), and long-term (2081–2100) under SSP1-2.6 (a1–a3), SSP2-4.5 (b1–b3), SSP3-7.0 (c1–c3), and SSP5-8.5 (d1–d3) scenarios. Red dotted areas indicate precipitation change trends significant at $P < 0.05$ level, and lined areas indicate trends significant at $P < 0.01$ level.

Figure 13 [Figure 13: see original paper] shows variations in SPI values from the MME during 2021–2100 under the four SSP scenarios. Generally, a trend from dry to wet occurs in the CTM under all scenarios, with obvious wetting at the end of the 21st century. The CTM will become wetter with increasing radiative forcing in the future. SPI at the 12-month time scale shows larger interannual fluctuation than at the 60-month scale. At the 12-month scale, the number of dry years (with SPI $\leq$ -1.0) would reduce with increasing radiative forcing. At the 60-month scale, the moment when non-drought state begins is almost the same under all scenarios.

Under SSP1-2.6 scenario, drought conditions are captured in the late 2080s and early 2090s, lasting about 5 years, after which SPI rebounds rapidly and wet conditions occur (Fig. 13a1 and a2). SPI values will decline under SSP2-4.5 scenario in the 2070s (Fig. 13b1 and b2), with moderate drought conditions occurring. However, SPI values will exceed 2.0 in the 2080s under SSP2-4.5 scenario, exhibiting extreme wet conditions. Values continue increasing without apparent drought conditions under SSP3-7.0 and SSP5-8.5 scenarios in the future (Fig. 13c1–d2). Notably, an extreme wet level would be reached under SSP5-8.5 scenario by the end of the 21st century.

[Figure 13: see original paper] Temporal variations of SPI values based on the MME during 2021–2100 at the 12- and 60-month time scales under SSP1-2.6 (a1 and a2), SSP2-4.5 (b1 and b2), SSP3-7.0 (c1 and c2), and SSP5-8.5 (d1 and d2) scenarios. SSP1-2.6_{SPI12}, SSP2-4.5_{SPI12}, SSP3-7.0_{SPI12}, and SSP5-8.5_{SPI12} denote SPI values at the 12-month time scale under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios, respectively. SSP1-2.6_{SPI60}, SSP2-4.5_{SPI60}, SSP3-7.0_{SPI60}, and SSP5-8.5_{SPI60} denote SPI values at the 60-month time scale under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios, respectively. SPI values between -1.0 (red dotted line) and 1.0 (blue dotted line) indicate normal drought and wet conditions in the region.

4.1 Capability of the CMIP6 GCMs in the CTM

This study combined CN05.1 with CMIP6 GCMs during 1961–2014 to construct a probability function. The accuracy of bias-corrected GCMs for both temperature and precipitation simulations improved considerably, and bias-corrected GCMs were considered suitable for small-scale studies in regions such as the CTM \cite{Du_{{{et}}{{al}}}{2022}}. We used the MME to reduce uncertainty in single models and project spatiotemporal variations in temperature and precipitation from 2021 to 2100 under four SSP scenarios. The GCMs demonstrated strong performance in simulating and projecting temperature but tended to underestimate precipitation, consistent with findings of \cite{Lafon_{{{et}}{{al}}}{2013}} and \cite{Hu_{{{et}}{{al}}}{2021}}. Notably, significant differences exist in precipitation simulation performance among individual GCMs over the same period \cite{Lei_{{{et}}{{al}}}{2023}}.

4.2 Performance in Simulating Temperature and Precipitation in the Historical Period (1961–2014)

Generally, trends in annual average temperature and precipitation during 1961–2014 simulated by GCMs in the CTM are consistent with those in Northwest China \cite{Qin_{{{et}}{{al}}}{2021}}. Warming and wetting trends in the CTM were apparent in monthly average temperature and precipitation simulated by the bias-corrected MME during 1961–2014. The MME slightly underestimated spring temperature and overestimated winter temperature, which impacted precipitation phase in winter and spring \cite{Xu_{{{et}}{{al}}}{2016}}. The GCMs overestimated spring and summer precipitation by 75.40% in the CTM \cite{Yang_{{{et}}{{al}}}{2023}}.

During 1961–2014, the CTM climate first experienced rapid warming, followed by a slower warming phase. The MME simulated a slower warming rate than observed. From 1998 to 2013, most GCMs consistently simulated accelerated warming in the CTM, failing to adequately capture warming mitigation \cite{Zhang_{{{et}}{{al}}}{2021a}}. Unlike the change trend of annual precipitation in Northwest China \cite{Deng_{{{et}}*{{al}}*}{2014}}, an increasing trend existed before 1997 in the CTM. Precipitation simulated by the MME increased slowly toward the end of the 20th century, then proliferated rapidly at the beginning of the 21st century. Interannual precipitation variation exhibited cyclical oscillatory characteristics in the range of 4-7 years \cite{Wang_{{{et}}*{{al}}*}{2012}, Li_{{{et}}*{{al}}*}{2016}}. The timing of apparent precipitation changes was delayed in simulations compared with observations. The northwestern CTM displayed a distinctive spatial pattern of accelerated warming coupled with enhanced precipitation between 1961 and 2014 (Fig. 7). The MME-simulated rate of change in precipitation lagged behind the observed rate, particularly in the western CTM. Moreover, previously drought conditions shifted to a wetter environment during the 1980s in the CTM.

4.3 Performance in Projecting Temperature and Precipitation in the Future (2021-2100)

During 2021-2100, annual average temperature displays a significant upward trend, while annual precipitation shows a fluctuating increase trend (Fig. 8). Transitions from dry to wet occur in the CTM in the 21st century under the four SSP scenarios (Fig. 13) \cite{Chen_{{{et}}*{{al}}*}{2022}}. Under SSP1-2.6 scenario, annual average temperature exhibits a trend of increasing then decreasing, and annual precipitation shows a decreasing trend in some years by the end of the 21st century. Warming and drying become more pronounced in the eastern part of the region \cite{Li_{{{et}}*{{al}}*}{2022b}}. Moderate drought will emerge in the 2070s while extreme wet may occur in the 2080s under SSP2-4.5 scenario. Under SSP3-7.0 scenario, significant warming and wetting will exist in the central part of the region. In long-term, annual average temperature and precipitation were projected to increase at rates of 0.090°C/a and 2.500 mm/a, respectively, in the eastern part of the region under SSP5-8.5 scenario. Ultimately, an extreme wet level will be achieved by the end of the 21st century.

The MME-simulated annual average temperature under SSP1-2.6 scenario reaches up to 4.170°C with an increase rate of 0.090°C/10a, while under SSP5-8.5 scenario it is expected to peak at 8.900°C with an increase rate of 0.730°C/10a by the end of the 21st century. During 2021-2100, MME-simulated annual precipitation under SSP1-2.6 scenario reaches 286.000 mm, with an increase rate of 0.680 mm/10a, while under SSP5-8.5 scenario it peaks at 316.710 mm with an increase rate of 4.930 mm/10a. The magnitude of temperature increase in some months exhibits symmetrical characteristics, with the largest increases occurring in spring and autumn. Precipitation increases most in winter, and there is no positive correlation between summer precipitation and radiative forcing (Fig. 9) \cite{Yang_{{{et}}*{{al}}*}{2023}}. Although precipitation increases in near-term and mid-term would alleviate drought conditions to some extent, the "warm and dry" pattern in the CTM will not change at all \cite{Wang_{{{et}}{{al}}}{2020}}.

4.4 Limitations and Prospects

Regional warming and wetting, as a response to global warming, can lead to increased water vapor \cite{Tu_{{{Lu}}{{2021}}}}. *Precipitation, a component of the water cycle, has increased in the CTM in recent decades due to northward moisture transport from the tropical Indian Ocean and intensified southerly currents \cite{Shi*{{{et}}{{al}}}{2007}, Sun_{{{et}}{{al}}}{2022a}}. Due to the nature of the CTM and complex climatic influences, it is difficult to ascertain whether long-term changes in the water cycle stem from changes in water vapor transport, westerly circulation, evapotranspiration, or other factors \cite{Pi_{{{et}}{{al}}}{2020}}. Changes in temperature and precipitation, acceleration of glacial ablation and shrinkage, variations in glacier mass balances, and reduction in potential snowfall season length are indicators of transitions from warm and dry to warm and wet conditions in the CTM \cite{Tang_{{{et}}{{al}}}{2013}, Javadinejad_{{{et}}{{al}}}{2020}, Li_{{{et}}{{al}}}{2023}}.

Significant uncertainty surrounds the intricacies of future climate change \cite{Visser_{{{et}}{{al}}}{2000}, Kundzewicz_{{{et}}{{al}}}{2018}}. The resolution, physical characteristics, and other variables of GCMs generate inaccuracies and uncertainties in future projections \cite{Knutti_{2008}, Schaller_{{{et}}{{al}}}{2011}, Collins_{{{et}}{{al}}}{2012}}. Further experimental and observational data are therefore required for continuous improvement of predictive models. Additionally, multi-factor physical effects, policy decisions, international community responses, and anthropogenic influences will necessitate ongoing discussion and optimization in the future \cite{Hawkins_{{{Sutton}}_{{2011}}}}.

5 Conclusions

The climate in the CTM has notably transitioned from warm and dry to warm and wet (1961–2014). Therefore, this study evaluated CMIP6 GCM simulation performance in the CTM and investigated unique regional climate change at different time scales. We also projected future temperature and precipitation changes during 2021–2100 and applied SPI to analyze dry–wet transitions in the CTM during 1961–2014 and 2021–2100 at different time scales. This enables a detailed overview of temporal trends and spatial distribution of temperature and precipitation in the region. Generally, GCMs can capture climatological features of temperature and precipitation in the CTM very well, with warming and wetting trends occurring by the end of the 21st century under the four SSP scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). Spatial and temporal variations exist in rates of temperature and precipitation change in the region. The central and western parts of the CTM will display significant warming and wetting by the end of the 21st century under SSP5-8.5 scenario.

Climate change poses a multifaceted challenge to the CTM because its impacts not only negatively affect ecosystems and environment but also threaten social and economic stability. The findings of this study could inform government decision-making and development of regional ecological protection and production activities in the CTM, which will be useful for further analyses of meteorological drought in this region.

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Note: Figure translations are in progress. See original paper for figures.