Dynamic Assessment and Multi-Scenario Projection of Climate Risk in the Chinese Tianshan Mountains under a Warming-Wetting Background

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Abstract

Constructing a sound climate risk assessment system is of great significance for regional climate change assessment and prediction. However, previous studies have mostly focused on climate disasters or climate change, with relatively little attention paid to the comprehensive climate risk index (Climate risk index, CRI). Based on observational data from 26 meteorological stations during 1961–2020 and multi-model mean data from the Sixth Coupled Model Intercomparison Project (Coupled model intercomparison project phose, CMIP6), this study constructed a CRI using four climate risk indicators: drought index, high-temperature index, low-temperature freezing index, and temperature-humidity index, and comprehensively assessed and projected climate risk in the Chinese Tianshan Mountains. The results show that: (1) Over the past 60 a, both temperature and precipitation in the Chinese Tianshan Mountains have shown a continuous upward trend, with a significant warming and humidification tendency. (2) The CRI has increased markedly, indicating a significant rise in climate risk in the Chinese Tianshan Mountains over the past 60 a. Most areas of the Chinese Tianshan Mountains are at medium or lower climate risk levels, with relatively low risk levels in the central and northern parts, while the eastern and southwestern parts exhibit higher climate risk. (3) The CMIP6 multi-model mean data simulate temperature and precipitation in the Chinese Tianshan Mountains well and can be used for climate risk projection analysis in the Tianshan Mountains. Under the SSP2-4.5 and SSP5-8.5 scenarios, the CRI shows a continuous upward trend, indicating that future climate risk in the Chinese Tianshan Mountains will increase, with climate risk in the east significantly higher than that in the west.

Full Text

Dynamic Assessment and Multi-Scenario Projection of Climate Risk in the Chinese Tianshan Mountains under a Warming-Wetting Background

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Abstract: Establishing a sound climate-risk assessment system is of great significance for the assessment and prediction of regional climate change. However, previous studies have mostly focused on climatic disasters or climate change, with relatively little attention paid to an integrated climate risk index (CRI). Based on observational data from 26 meteorological stations during 1961–2020 and multi-model ensemble mean data from Phase 6 of the Coupled Model Intercomparison Project (CMIP6), this study constructs a CRI using four climate-risk indicators—the drought index, high-temperature index, low-temperature freezing index, and warm–humid index—and conducts a comprehensive assessment and projection of climate risk in the Chinese Tianshan Mountains. The results show that: (1) Over the past 60 years, both temperature and precipitation in the Chinese Tianshan Mountains have shown sustained increasing trends, with a significant warming–wetting tendency. (2) The CRI has risen markedly, indicating a significant increase in climate risk in the Chinese Tianshan Mountains over the past 60 years. Most areas of the Chinese Tianshan region are at medium or lower climate-risk levels; risk levels are relatively low in the central and northern parts, whereas higher climate risks are observed in the eastern and southwestern parts. (3) The CMIP6 multi-model ensemble mean data perform well in simulating temperature and precipitation in the Chinese Tianshan Mountains and can be used for climate-risk projection analysis in the region. Under both the SSP2-4.5 and SSP5-8.5 scenarios, the CRI shows a sustained upward trend, indicating that climate risk in the Chinese Tianshan Mountains will increase in the future, with climate risk in the east significantly higher than that in the west.

Keywords: CMIP6; warming–wetting; comprehensive climate risk index; Chinese Tianshan Mountains

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Climate change is a global hot-button issue that has attracted broad attention from governments, the scientific community, and the general public worldwide. Many scientists continue to focus on changes in precipitation and temperature, seeking to anticipate future trends from past and present changes[1–2]. Since 2020, meteorological disasters have intensified; frequent meteorological disasters not only threaten people' s lives and property, but also seriously constrain the sustained and stable development of society and the economy[3]. Under the combined influence of global warming and human activities, the frequency and intensity of extreme climate events have continued to increase, exerting tremendous impacts on grain production, the social economy, water resources, and ecological security[4]. The Working Group I report of the Intergovernmental Panel on Climate Change (IPCC), released in August 2021, pointed out that climate change in all regions of the world will continue to intensify over the coming decades; this view was reiterated and confirmed in the recently released Working Group II and Working Group III reports. Among these issues, climate-risk monitoring and assessment have become major concerns requiring sustained attention because of their complexity and uncertainty[5]. Therefore, studying and revealing the patterns of climate risk from multiple perspectives and projecting future climate risk are of great significance for formulating disaster-prevention plans and sustainable-development strategies.

The purpose of climate-risk management is to reduce the negative impacts of climate on the natural environment, human society, and the economy[6]. To reduce climate risk, it is necessary to coordinate disaster-risk management with adaptation to climate change, and to closely link the drivers of climate risk, policy measures, and actors[7]. The climate risk index (CRI) is a scientific tool that, based on historical climate data, quantitatively assesses single or integrated climate risks by identifying disaster-causing thresholds for extreme weather and climate events, and analyzes actual disaster losses[8]. Previously, scholars carried out a series of studies on climate risk and achieved substantial results. After considering extreme temperature, precipitation, and other indicators, Karl et al.[9] defined the U.S. extreme climate index in 1996 in order to facilitate the summarization and presentation of complex multivariable and multidimensional climate change; Gleason et al.[10] revised it in 2008; Hansen et al.[11] comprehensively considered indicators such as the number of warming days and the frequency of heavy-rainfall events, which have practical application val—

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indices, and in 1998 proposed a Climate Change Index. These indices have, to a certain extent, analyzed the causes of climate change, but they are all based on the calculation and analysis of one or more climatic factors and indices, and rarely consider the losses or impacts that climate disasters impose on society. Burck et al. [12], a German non-governmental organization, used data from Munich Re as the basis and, according to the number of deaths caused by climate disasters, the mortality rate per 1×10^5 people, direct economic losses, and the ratio of economic losses to regional gross domestic product, calculated the CRI with weights to quantify the impacts of extreme weather and climate events, thereby providing a reference for global climate-risk management.

China has experienced some of the world' s most diverse, influential, frequent, and destructive climate disasters. Since the beginning of the 21st century, direct economic losses caused by extreme weather and climate events have exceeded 2.0×10^{11} yuan annually and have shown an increasing trend year by year [13]. Previous studies on climate risk in China have generally had the following shortcomings: in terms of content, they have mostly focused on a single climate disaster [14] or climate change [15-16], with insufficient systematic examination of overall climate risk; spatially, they have mostly concentrated on densely populated eastern coastal areas, while paying inadequate attention to the arid and semi-arid regions of western China. The Chinese Tianshan Mountains are located in the arid–semi-arid region of northwestern China. With diverse ecosystem types, they constitute an important mountain system linking oases, deserts, and grasslands, and they are also an important ecological barrier in Northwest China and a key region of the Silk Road Economic Belt. Some studies [17-18] have revealed trends such as climate warming, glacier retreat, and changes in water resources in the Chinese Tianshan Mountains, and have pointed out that this region is highly prone to climate extremes under the background of global warming. However, at the regional scale, most existing studies on the Tianshan Mountains [19-20] have focused on a single climatic factor or natural process. Comprehensive risk assessments of multiple climate disasters remain relatively lacking, and a climate-risk assessment framework suited to the regional characteristics of the Tianshan Mountains has not yet been established, limiting a comprehensive understanding of the dynamic processes of risk change. Therefore, based on daily observational data from 26 meteorological stations in the Chinese Tianshan Mountains from 1961 to 2020 and multi-model climate simulation data from the Coupled Model Intercomparison Project Phase 6 (CMIP6), this study constructs a climate-risk assessment system applicable to regional characteristics, explores the spatiotemporal distribution characteristics of climate risk, and provides scientific evidence and decision-making support for responding to regional climate change, formulating risk-response policies, and promoting sustainable development.

1 Data and Methods

1.1 Overview of the Study Area

The Tianshan Mountains are located in the hinterland of the Eurasian continent, extending approximately 2,500 km from Hami City in Xinjiang, China, to the Kyzylkum Desert in Uzbekistan, and spanning four countries: China, Kyrgyzstan, Kazakhstan, and Uzbekistan [21]. The portion of the Tianshan Mountains located in China is referred to as the Chinese Tianshan Mountains [22]. The Chinese Tianshan Mountains are 1,760 km long, accounting for more than two-thirds of the total length of the Tianshan range (Fig. 1). The Chinese Tianshan region covers about one-third of the total area of Xinjiang and is usually divided into three parts: the eastern Tianshan, northern Tianshan, and southern Tianshan. The Chinese Tianshan Mountains lie in a mid-latitude, extremely continental arid climate zone. Precipitation is unevenly distributed, and short-duration heavy rainfall is prone to occur in summer. Precipitation gradually decreases from west to east, and is greater on the windward slope (northern slope) than on the leeward slope (southern slope). The mean annual

Fig. 1 Schematic diagram of the study area. The map shows meteorological stations including Wenquan, Jinghe, Wusu, Caijiahu, Qitai, Barkol, Yiwu, Yining, Urumqi, Dabancheng, Shisanjianfang, Hami, Zhaosu, Bayinbuluk, Baluntai, Turpan, Baicheng, Yanqi, Kumishi, Korla, Kuqa, Aksu, Keping, Torugart, Wuqia, and Kashi. Legend: boundary of the Chinese Tianshan Mountains; meteorological stations; elevation/m, ranging from 7385 to −187. Scale: 0–100 km.

Figure 1: Fig. 1 Schematic diagram of the study area. The map shows meteorological stations including Wenquan, Jinghe, Wusu, Caijiahu, Qitai, Barkol, Yiwu, Yining, Urumqi, Dabancheng, Shisanjianfang, Hami, Zhaosu, Bayinbuluk, Baluntai, Turpan, Baicheng, Yanqi, Kumishi, Korla, Kuqa, Aksu, Keping, Torugart, Wuqia, and Kashi. Legend: boundary of the Chinese Tianshan Mountains; meteorological stations; elevation/m, ranging from 7385 to −187. Scale: 0–100 km.

precipitation on the northern slope exceeds 500 mm, making it a "wet island" in China' s arid region [23]. The southern slope of the Tianshan Mountains has experienced the greatest increase in precipitation; the increase in mountainous areas is larger than that in plain areas, and the increase in western areas is larger than that in eastern areas. Vegetation varies markedly with elevation, with desert, grassland, forest, and alpine meadow distributed successively from the mountain foothills to the summits; at higher elevations, the surface is mainly covered by bare rock or ice and snow. The Chinese Tianshan Mountains are the source regions of important rivers such as the Ili River, Manas River, and Tarim River, and the existence of numerous glaciers provides these rivers—

Fig. 1 Schematic diagram of the study area

runoff provided a stable and sufficient supply. The coefficient of variation of annual runoff is 0.1–0.2, the mean annual runoff depth is 271 mm, and the changes are relatively stable.

1.2 Data sources

The data used in this study mainly include historical meteorological-station observations and CMIP6 global climate model data under future climate-change scenarios. The observational data cover daily mean temperature, daily mean precipitation, and daily mean relative humidity from 26 meteorological stations in the Chinese Tianshan Mountains during 1961–2020, obtained from the National Meteorological Information Center (http://data.cma.cn/). To compensate for missing data at individual stations, a multiple-regression difference method[24] was used, with observations from neighboring stations employed for interpolation. Based on an applicability analysis of CMIP6 models in the Chinese Tianshan Mountains and considering the completeness of CMIP6 climate model data, this study selected daily temperature and precipitation data for the historical period (1961–2014) and projection period (2015–2100) from five global climate models in the CMIP6 Scenario Model Intercomparison Project (Table 1). The CMIP6 global climate model data include four scenarios—SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5—which represent a low-forcing scenario, a medium-forcing scenario, a medium-to-high-forcing scenario, and a high-forcing scenario, respectively[25]. The CMIP6 data are divided into a baseline period and a projection period; the baseline period is 1961–2014, and the projection period is 2015–2100. In general, 2021–2040, 2041–2060, and 2081–2100 are taken as the near-term, mid-term, and long-term future periods, respectively. Therefore, this study selected the two scenarios with relatively complete outputs at the present stage, SSP2-4.5 and SSP5-8.5, to simulate and project climate risks in different future periods. To correct systematic errors between climate-model outputs and observational data, this study used statistical downscaling and bias-correction methods[26–27] to downscale and adjust the data, with the spatial resolution unified to 0.5° × 0.5°. In addition, bilinear interpolation was used to interpolate directly to the 26 meteorological observation stations in the Chinese Tianshan Mountains[28], so as to evaluate the ability of CMIP6 multi-model mean data to simulate temperature and precipitation.

Table 1 Overview of CMIP6 climate models

Tab. 1 Overview of CMIP6 climate models

<table>
<tr><th>No.</th><th>Model name</th><th>Country</th><th>Resolution /(°)</th></tr>
<tr><td>1</td><td>ACCESS-ESM1-5</td><td>Australia</td><td>1.875$×1.250||2|CanESM5|Canada|2.8×2.8||3
MM|Norway|2.5×1.9||4|CNRM−
CM5|France|1.4×1.4||5|BCC_CSM1.1|China|2</td></tr>
</table>

1.3 Research methods

1.3.1 Climate risk assessment framework

To comprehensively assess the increasingly prominent climate risks under the background of climate change, this study constructed a climate-risk assessment indicator system (Fig. 2). Starting from dimensions such as the frequency and intensity of extreme climate events and their spatial extent of influence, the system selects four key climatic factors—the drought index, high-temperature index, low-temperature freezing index, and temperature–humidity index—to comprehensively reflect the level of risk under different climate scenarios. Among them, the drought index not only reflects the pressure of insufficient precipitation on the urban water-supply system, but also characterizes the water-deficit conditions generated in ecosystems due to inadequate water supply; the high-temperature index measures the impacts of extreme high temperatures on human health and energy systems; the low-temperature freezing index characterizes the pressure exerted by extreme low temperatures on residents' quality of life; and the temperature–humidity index integrates the effects of temperature and humidity on human comfort and health risks. Based on the above indicator system, identifying and quantifying the spatial heterogeneity of climate risk within the region can improve perception and early-warning capability regarding the impacts of climate change in the Tianshan region, and can also provide decision-making support for regional ecological security and sustainable development.

Visible text in Fig. 2, translated:

- Climate risk assessment indicators
  - High-temperature index
    - Extreme temperature
    - Measures the frequency and intensity of extreme high-temperature events ···
    - Intensifies drought; strengthens the heat island
  - Low-temperature freezing index
    - Focuses on freezing damage caused by extreme cold events ···
    - Intensifies freezing damage; triggers cold waves
  - Drought index
    - Evaluates drought occurrence frequency and duration ···
    - Intensifies evaporation; accelerates drying
  - Temperature–humidity index
    - Compound heat–humidity
    - Considers combined heat–humidity stress from temperature and humidity ···
    - Intensifies disasters; damages ecosystems
- Synergistic enhancement
- Coupling effect
- Construct a comprehensive climate risk index to assess and predict climate risk

Fig. 2 Climate risk assessment framework

1.3.2 Drought Index

This study uses the standardized precipitation index (SPI) [29] to characterize drought conditions. This index takes only readily available precipitation data as input and determines the occurrence and severity of drought by measuring the degree to which precipitation deviates from the normal state. It is simple to calculate and has strong spatiotemporal adaptability, and is widely used in drought monitoring and assessment [30]. The specific calculation formula for SPI is as follows:

$$\mathrm{SPI} = \frac{t - (c_2 t + c_1) + c_0}{[(d_3 t + d_2)\, t + d_1]\, t + 1.0} \tag{1}$$

$$t = \sqrt{\ln \frac{1}{F(x)^2}} \tag{2}$$

$$F(x) = \frac{2}{\beta^{\gamma}\Gamma(\gamma)} \int_0^x x^{\gamma-1} \varepsilon^{-\frac{x}{\beta}} \, \mathrm{d}x, \quad x > 0 \tag{3}$$

where t is an auxiliary variable that maps the cumulative probability $F(x)$ to the standard normal distribution; c_0, c_1, c_2, and d_1, d_2, d_3 are calculation parameters of the simplified approximate solution formula used when the γ-distribution function is transformed into cumulative probability, with values $c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$; $F(x)$ is the precipitation distribution probability calculated from the γ distribution; x is the precipitation amount in a given period; β and γ are the shape and scale parameters of the Γ-distribution function; $\mathrm{d}x$ is the integration differential; and ε is the natural base.

1.3.3 High-Temperature Index

Research on high temperature is generally based on absolute temperature thresholds, relative humidity thresholds, and statistical thresholds based on probability distributions for quantitative analysis [31]. However, the degree of high temperature is not determined solely by daily maximum air temperature; it is also affected by daily minimum air temperature and duration. Therefore, this study comprehensively considers daily maximum air temperature, daily minimum air temperature, and duration to define the high-temperature index.

According to the classification criteria (Table 2), the daily maximum air temperature ($T_{\max}$) and daily minimum air temperature ($T_{\min}$) at a station are divided into three grades [32], and the corresponding daily maximum air temperature index (T_g) and daily minimum air temperature index (T_d) are calculated.

Table 2. Classification criteria of T_g and T_d

$T_{\max}$/°C	T_g	$T_{\min}$/°C	T_d
$35 \leq T_{\max} < 37$	Grade 1	$25 \leq T_{\min} < 28$	Grade 1
$37 \leq T_{\max} < 40$	Grade 2	$28 \leq T_{\min} < 30$	Grade 2
$40 \leq T_{\max}$	Grade 3	$30 \leq T_{\min}$	Grade 3

Note: $T_{\max}$ and $T_{\min}$ are the daily maximum air temperature and daily minimum air temperature, respectively; T_g and T_d are the daily maximum air temperature index and daily minimum air temperature index, respectively.

Based on the calculated T_g and T_d, the monthly high-temperature index (MT) is constructed. The calculation formula is as follows:

$$\mathrm{MT} = \frac{\sum_{i=1}^{\mathrm{Day}} T_{gi} \times \left(D_{gi}\right)^{0.5} + \sum_{j=1}^{\mathrm{Day}} T_{dj} \times \left(D_{dj}\right)^{0.5}}{\mathrm{Day}} \tag{4}$$

where Day is the number of days in the month; T_g is the daily maximum air temperature index at a meteorological station; T_d is the daily minimum air temperature index at a meteorological station; D_g is the number of days during which the daily maximum temperature at a station continuously remains at 35 °C; D_d is the number of days during which the daily minimum temperature at a station continuously remains at 25 °C; and i and j are the i-th and j-th days of the current month, respectively.

1.3.4 Temperature-Humidity Index

This study uses the temperature humidity index (THI) to characterize heat-risk conditions. This index comprehensively considers two meteorological factors—air temperature and relative humidity—and reflects the heat-exchange conditions of the human body in a specific environment, thereby assessing the level of heat stress and its potential impacts [33]. The specific formula for THI is as follows:

$$\mathrm{THI} = (1.8z + 32) - 1.55 \times (1 - f)(1.8z - 26) \tag{5}$$

where z is temperature in degrees Celsius (°C), and f is relative humidity (%).

1.3.5 Low-Temperature Freezing Index

Based on previous studies [34], this study defines the low-temperature index as the total number of days within 1 a, or within a certain period, during which the minimum temperature is at least 5 °C lower than the multi-year mean daily minimum temperature for at least 5 d. It is used to reflect the potential threats posed by extreme low-temperature events to the human settlement environment, infrastructure, and energy-security systems.

1.3.6 Comprehensive CRI

The comprehensive CRI is calculated from the drought index, high-temperature index, low-temperature freezing index, temperature-humidity index, and their corresponding weights. First, all indicators are normalized to eliminate dimensional differences among different indicators. The above four indicators are all positive indicators; a positive indicator means that the larger its value is, the greater the climate risk. Then, the AHP-entropy weight method combining subjective and objective approaches [35–36] is used to determine the weights of each indicator (Table 3). Finally, the weighted comprehensive scoring method is used to calculate the comprehensive CRI. The formula is as follows:

Table 3. Results of the evaluation indicator weight calculation

Target layer	Evaluation indicator	Weight
Climate risk assessment and prediction for the Chinese Tianshan Mountains	Drought index	0.42
Climate risk assessment and prediction for the Chinese Tianshan Mountains	High-temperature index	0.30
Climate risk assessment and prediction for the Chinese Tianshan Mountains	Low-temperature freezing index	0.16
Climate risk assessment and prediction for the Chinese Tianshan Mountains	Temperature-humidity index	0.12

$$\mathrm{CRI} = \sum_{m=1}^{n} (D_m \times T_m) \tag{6}$$

where CRI is the climate risk index; n is the total number of climate risk evaluation indicators; m is the indicator sequence number; D_m is the normalized single risk index; and T_m is the weight value calculated by the entropy weight method.

1.3.7 Trend Analysis of Climate Risk Change

To reflect the changing trend of the comprehensive CRI, linear trend estimation is adopted:

$$y = b + k \times t_h \tag{7}$$

In the formula, y is the CRI; t_h is the corresponding time; h is the climate risk index series; and k and b are estimated by the least-squares method. The regression coefficient k can reflect the changing trend of the CRI: $k > 0$ indicates an increasing trend, whereas $k < 0$ indicates a decreasing trend.

1.3.8 Evaluation of the simulation capability of CMIP6 data

Based on observed data from 26 meteorological stations in the Chinese Tianshan Mountains and CMIP6 multi-model ensemble mean data for 1961–2014, radar charts of the correlation coefficients between the observed data and the CMIP6 multi-model ensemble mean data at the 26 meteorological stations were plotted (Fig. 3). The correlation coefficients between observed temperature data and multi-model ensemble mean data were all between 0.96 and 0.99, showing an extremely strong correlation between the two. This indicates that the multi-model ensemble mean data have a strong capability to simulate temperature and can accurately reproduce the characteristics of temperature change in the Tianshan region. By comparison, although the correlation coefficients between the CMIP6 multi-model ensemble mean data and the observed precipitation data were all above 0.6, showing a certain degree of correlation, the overall simulation accuracy for precipitation was lower than that for temperature. Considering that precipitation exhibits large fluctuations and significant differences in both time and space, climate models have greater difficulty in simulating precipitation, resulting in relatively lower simulation accuracy. Although biases exist in the CMIP6 multi-model ensemble mean data, they still have a certain degree of reliability at the regional scale and therefore can be used for predicting and assessing future climate risk in the Chinese Tianshan region.

(a) Correlation coefficients for CMIP6 temperature simulation

(b) Correlation coefficients for CMIP6 precipitation simulation

Fig. 3 Correlation coefficients between CMIP6-simulated temperature and precipitation

2 Results and Analysis

2.1 Spatiotemporal characteristics of warming and humidification

2.1.1 Spatiotemporal variation characteristics of precipitation The linear trend method and moving-average method were used to analyze the temporal variability characteristics of mean temperature and precipitation at 26 meteorological observation stations in the Chinese Tianshan Mountains during 1961–2020. The trend in annual mean precipitation during 1961–2020 varied considerably (Fig. 4), with obvious fluctuations, but overall showed an increasing trend, with a linear trend rate of 8.61 mm $\cdot (10a)^{-1}$ at the 95% confidence level. According to the 5 a moving-average curve, annual precipitation in the Chinese Tianshan Mountains exhibited several distinct cycles, and the interannual precipitation change followed an "increase–decrease–increase" pattern. In the multi-year variation, annual mean precipitation was highest in 2016, at 228 mm, and lowest in 1985, at 104 mm. Spatially, the multi-year mean precipitation at the stations in the Chinese Tianshan Mountains ranged from 14.84 to 507.37 mm, overall showing a distribution pattern of gradual decrease from north to south.

2.1.2 Spatiotemporal variation characteristics of temperature Annual mean temperature during 1961–2020 showed an increasing trend amid fluctuations, with a linear trend rate of 0.30 °C $\cdot$ $(10a)^{-1}$ at the 95% confidence level (Fig. 5). Over the past nearly 60 a, the mean temperature increased by about 2.63 °C; the lowest temperature was 5.93 °C in 1984, and the highest was 8.97 °C in 2019. According to the 5 a moving-average curve, the annual mean temperature of the Chinese Tianshan Mountains showed a wave-like rising trend over 60 a, with no obvious long-term downward trend. Spatially, with increasing latitude, temperature gradually increased from north to south. In most areas of the Chinese Tianshan Mountains, mean temperature ranged from -1.2 to 9.2 °C. Temperatures were relatively high in Kuqa, Keping, Korla, Kashgar, and Turpan, where the multi-year mean temperature was about 11.50 °C. Hami, Shisanjianfang, and Aksu followed, with multi-year mean temperature around 10.50 °C.

2.2 Spatiotemporal variation characteristics of CRI

2.2.1 Temporal variation characteristics of CRI The CRI of the Chinese Tianshan Mountains showed relatively high values in 2010 (8.01), 2015 (7.53), and 2016 (8.12), and climate risk reached its maximum value in 2016 (Fig. 6). Over the long term

(a) Spatial distribution of precipitation

Legend: China Tianshan boundary; mean annual precipitation/mm.
Range: 14.84–507.37 mm.
Scale: 0–100 km. North arrow indicated.

(b) Interannual variation in precipitation

Legend: precipitation; 5-year moving average; linear fit.
Y-axis: mean annual precipitation/mm. X-axis: year.

$$y = 0.861x - 1555.51$$

$$R^2 = 0.132$$

Fig. 4 Spatiotemporal distribution of precipitation

(a) Spatial distribution of temperature

Legend: China Tianshan boundary; mean annual temperature/°C.
Range: -4.28–14.82 °C.
Scale: 0–100 km. North arrow indicated.

(b) Interannual variation in temperature

Legend: temperature; 5-year moving average; linear fit.
Y-axis: mean annual temperature/°C. X-axis: year.

$$y = 0.032x - 56.81$$

$$R^2 = 0.562$$

Fig. 5 Spatiotemporal distribution of temperature

Legend: CRI; linear trend.
Y-axis: CRI. X-axis: year.

$$y = 0.068x - 130.24$$

$$R^2 = 0.502$$

Note: CRI is the climate risk index. The same applies below.

Fig. 6 Interannual fluctuation and trend analysis of CRI

In terms of the trend, from 1961 to 2020 the CRI of the Chinese Tianshan Mountains increased at a rate of $0.68 \cdot (10a)^{-1}$ at the 95% confidence level. The mean CRI was 2.99 during 1961–1980, 4.07 during 1981–1998, and 5.69 during 1999–2020. The mean CRI shows a clear staged increasing pattern, indicating that climate risk in the Chinese Tianshan Mountains has increased year by year in recent years.

2.2.2 Spatial variation characteristics of CRI

The spatial range of CRI values in the Chinese Tianshan Mountains is 3.70–17.44. This study used the natural breaks method to classify CRI, dividing it into 3.70–6.44 (relatively low-risk zone), 6.44–9.18 (low-risk zone), 9.18–11.92 (medium-risk zone), 11.92–14.66 (high-risk zone), and 14.66–17.44 (relatively high-risk zone). In the Chinese Tianshan Mountains, 2 stations belong to the relatively low-risk zone, 9 stations belong to the low-risk zone, and 7 stations belong to medium risk.

area; 3 stations belong to the high-risk zone, and 5 stations belong to the relatively high-risk zone (Fig. 7). Most areas of the China Tianshan Mountains are below the medium-risk zone. Climatic risk is relatively low in the central and northern Tianshan Mountains, whereas it is relatively high in the eastern and southwestern parts. Kashgar has the highest climatic risk, and Zhaosu has the lowest.

2.3 CMIP6 Future-Scenario CRI Projection

2.3.1 Projection Analysis of Temporal Changes in CRI

Under all scenarios, CRI shows an increasing trend (Fig. 8). Under the SSP2-4.5 scenario, the mean rate of increase in CRI is $0.53 \cdot (10a)^{-1}$. The changes in CRI can be divided into two stages: from the near term (2021-2040) to the mid-term (2041-2060), CRI will be in a stage of decelerating increase, with the rate of increase declining from $1.05 \cdot (10a)^{-1}$ to $0.36 \cdot (10a)^{-1}$; from the mid-term (2041-2060) to the long term (2081-2100), CRI will be in a stage of accelerating increase, rising to $1.56 \cdot (10a)^{-1}$ by 2100. CRI is expected to reach its maximum value in 2098. Under the SSP5-8.5 scenario, the mean rate of increase in CRI is $0.77 \cdot (10a)^{-1}$. From the near term to the long term, CRI shows a continuously accelerating upward trend, with the rate of increase rising from $0.61 \cdot (10a)^{-1}$ to $1.47 \cdot (10a)^{-1}$, and it is projected to reach the peak level within the scenario simulation period in the long term.

2.3.2 Projection Analysis of Spatial Changes in CRI

Based on the CMIP6 multi-model mean data obtained under the SSP2-4.5 and SSP5-8.5 scenarios, the CRI of the China Tianshan Mountains for 2021-2100 was constructed (Fig. 9). Under the SSP2-4.5 scenario, CRI exhibits a spatial distribution characterized by higher values in the east and south and lower values in the west and north. The east-west difference is relatively large, whereas the north-south difference is relatively small. Overall, CRI ranges from 0.47 to 8.29. Relative to the baseline-period CRI, CRI increases in the eastern Tianshan Mountains and decreases in the central part; from west to east, it shows a "high-low-high-low-high" pattern of change. Among the climatic zones, the Hami climatic risk is the highest, and the Jinghe climatic risk is the lowest. Under the SSP5-8.5 scenario, the spatial change characteristics of CRI differ more markedly from those under the SSP2-4.5 scenario, showing a spatial distribution of "lower in the south and higher in the north, lower in the west and higher in the east"

(a) Spatial statistics of CRI stations

Axis labels: Station; CRI.

Values shown in the station bar chart: Zhaosu 3.70; Yiwu 16.01; Yanqi 10.30; Yining 8.50; Wuqia 15.82; Wenquan 8.49; Wusu 8.76; Urumqi 6.18; Turpan 10.65; Torugart 6.98; Shisanjianfang 9.10; Qitai 8.56; Kuqa 14.51; Kumishi 10.58; Korla 14.10; Kashgar 17.44; Keping 10.84; Jinghe 13.48; Hami 14.96; Dabancheng 10.64; Caijiahu 11.10; Bayanbulak 8.94; Balikun 8.67; Baluntai 7.68; Baicheng 15.35; Aksu 10.99.

(b) Spatial distribution of CRI

Map labels and legend: N; 0–100 km; Legend; China Tianshan boundary; CRI; relatively low; low; medium; high; relatively high.

Fig. 7 Spatiotemporal evolution of historical CRI

Figure 8 panels

(a) Interannual variation
Legend: SSP2-4.5; SSP5-8.5; SSP2-4.5 linear fitted trend line; SSP5-8.5 linear fitted trend line.
Axes: CRI; Year.

$$y = 0.053x - 104.87$$

$$y = 0.077x - 156.61$$

(b) Near-term variation
Legend: SSP2-4.5; SSP5-8.5; SSP2-4.5 linear fitted trend line; SSP5-8.5 linear fitted trend line.
Axes: CRI; Year.

$$y = 0.106x - 212.03$$

$$y = 0.061x - 121.80$$

(c) Mid-term variation
Legend: SSP2-4.5; SSP5-8.5; SSP2-4.5 linear fitted trend line; SSP5-8.5 linear fitted trend line.
Axes: CRI; Year.

$$y = 0.036x - 69.67$$

$$y = 0.114x - 231.06$$

(d) Long-term variation
Legend: SSP2-4.5; SSP5-8.5; SSP2-4.5 linear fitted trend line; SSP5-8.5 linear fitted trend line.
Axes: CRI; Year.

$$y = 0.147x - 299.98$$

$$y = 0.157x - 321.76$$

Fig. 8 Prediction analysis of CRI under the SSP2-4.5 and SSP5-8.5 scenarios

Figure 9 panels

(a) SSP2-4.5
Legend: China Tianshan boundary; CRI; relatively low; low; medium; high; relatively high.
Scale: 0–100 km. North arrow shown.

(b) SSP5-8.5
Legend: China Tianshan boundary; CRI; relatively low; low; medium; high; relatively high.
Scale: 0–100 km. North arrow shown.

Fig. 9 Spatial distributions of CRI under the SSP2-4.5 and SSP5-8.5 scenarios

The characteristics show large east–west and north–south differences. Overall, CRI ranges from 0.41 to 7.40. Relative to the baseline period, medium-risk areas increase in the central Tianshan, and low-risk areas increase in the southwestern Tianshan; among them, Turpan has the highest climate risk, while Kashgar has the lowest climate risk. Comparing the spatial distribution of climate risk under the two scenarios shows that medium- and high-risk areas in the Chinese Tianshan both increase. Relative to the baseline period, CRI in the eastern region shows an increasing trend. In the northern Tianshan, low-risk areas increase under the SSP2-4.5 scenario, while high-risk areas increase under the SSP5-8.5 scenario; climate low-risk areas in the southwestern Tianshan also increase.

3 Discussion

Under different scenarios, differences in future climate-risk changes in the Chinese Tianshan essentially reflect the non-

linear characteristics and differences in the sensitivity of the internal regional environment to risk-driving factors[37]. Under the SSP2-4.5 scenario, the CRI shows a phased increase, indicating that under a certain emissions-reduction scenario, the slowed rise in greenhouse-gas concentrations causes the frequency and intensity of extreme climatic events such as regional warming and drought to become temporarily stable in the mid-term[38-39], thereby slowing the rate of risk accumulation. However, in the later period, cumulative effects and lagged responses still drive risks to rise again. This is consistent with the conclusion in the IPCC report that "risks rise over the long term under a medium-emissions pathway"[5], indicating that even under a "medium-emissions pathway," regional ecosystems and social systems still find it difficult to escape the long-term influence of high-risk trends. By contrast, under the SSP5-8.5 scenario, climate risk continues to rise at an accelerating rate, highlighting that under sustained high emissions, the combined effects of warming and hydrothermal imbalance become more pronounced[40-41], leading to more frequent compound high-temperature and drought events, and causing the risk-response mechanism to exhibit an "acceleration" effect. This finding echoes results from existing studies in other arid and semi-arid regions of China[17-18], but further reveals the high sensitivity of risks in the Tianshan region to extreme-climate drivers and the abruptness of spatial patterns, underscoring regional specificity. At the spatial level, the differences under the two scenarios reveal the complexity of regional responses to climate change. The "higher in the east and lower in the west" pattern under the SSP2-4.5 scenario is more strongly controlled by baseline differences in climatic factors and the terrain' s moderating capacity, whereas under the SSP5-8.5 scenario, the risk pattern is controlled to a greater extent by the concentrated outbreak of extreme events and the expansion of heat-anomaly areas, thereby breaking the original stable distribution structure[38]. This differs from previous studies that focused only on a single climatic factor[19-20], further highlighting the importance of multi-hazard integrated risk assessment in revealing regional climate-risk patterns. By constructing a regionalized CRI assessment system, this study reveals the suddenness and unpredictability of climate risks under high-emissions scenarios, demonstrating methodological innovation and regional application value, and providing a new reference for climate-risk management in the Tianshan region and similar arid and semi-arid regions.

This study still has certain limitations. On the one hand, because of missing observational data and the relatively sparse distribution of meteorological stations, the spatial interpolation accuracy of precipitation and temperature may have been affected to some extent, which limits a comprehensive reflection of actual regional climate-change trends and leads to uncertainty in depicting the distribution of actual climate risk. On the other hand, climate-risk assessment itself is a highly integrated systemic process. Its results are driven not only by climatic factors but are also closely related to multidimensional factors such as physical-geographical conditions, socioeconomic structure, technological development level, and management capacity. Therefore, the current assessment results, to a certain extent, cannot fully and accurately reflect their complexity and uncertainty. Future research should further expand the indicator system, integrate multi-source data, and incorporate complex adaptive systems theory to build a more scientific, dynamic, and integrated climate-risk assessment framework, thereby improving response capacity to the impacts of climate change and the adaptability of policies.

4 Conclusion

(1) During 1960–2020, the Tianshan Mountains of China showed significant warming and wetting. The annual mean temperature exhibited an upward trend amid fluctuations, with an increasing rate of 0.30 ℃ $\cdot$ $(10a)^{-1}$. Temperature showed a latitudinal pattern of decreasing from north to south. Annual mean precipitation fluctuated substantially but generally exhibited an upward trend, with an increasing rate of 8.61 mm $\cdot$ $(10a)^{-1}$. Annual mean precipitation showed a decreasing trend from east to west and from north to south.

(2) Over the past nearly 60 a, climate risk in the Tianshan Mountains of

China has continued to intensify. Temporally, the overall trend of CRI change was relatively stable, but interannual fluctuations were relatively pronounced. Spatially, climate risk was relatively low in the central and northern Tianshan areas, while it was higher in the eastern and southwestern areas.

(3) The CMIP6 multi-model mean data have good capability for simulating precipitation and temperature and can be used for future climate-risk assessment in the Tianshan Mountains of China. Under the SSP2-4.5 and SSP5-8.5 scenarios, CRI shows an upward trend, and under both scenarios CRI reaches its maximum in the far future period (2081–2100). Spatially, under the SSP2-4.5 scenario, CRI exhibits a distribution pattern of being higher in the east and lower in the west, and higher in the south and lower in the north, with relatively large east–west differences and smaller north–south differences. Under the SSP5-8.5 scenario, CRI exhibits a distribution pattern of being lower in the south and higher in the north, and lower in the west and higher in the east, with relatively large east-west and north–south differences.

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Dynamic assessment and multi-scenario projection of climate risk in the Tianshan Mountains of China under the background of warming and humidification

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Abstract: Establishing a comprehensive climate risk assessment framework is essential for evaluating and predicting regional climate change. However, previous studies have primarily focused on climate disasters or climate change in isolation, with limited attention given to the comprehensive climate risk index (CRI). To address this gap, this study examines the Tianshan Mountains of China and develops a CRI based on four climate risk indicators: Drought, high temperature, low temperature, and temperature-humidity. This analysis utilizes observational data from 26 meteorological stations from 1961 to 2020, along with multi-model ensemble data from CMIP6, to conduct an integrated assessment and provide future projections of climate risks in the area. The results show that (1) Over the past 60 years, both temperature and precipitation in the Tianshan Mountains have steadily increased, demonstrating a significant warming and wetting trend. (2) The CRI has risen substantially, reflecting an increased climate risk in the Tianshan Mountains over the last six decades. Most areas in the Tianshan Mountains are categorized as having medium or lower climate risk, with the central and northern parts exhibiting relatively low risk levels, whereas the eastern and southwestern areas exhibit higher climate risks. (3) The CMIP6 multi-model ensemble data accurately simulate temperature and precipitation patterns in the Tianshan Mountains, making it suitable for future climate risk projection analysis. Under the SSP2-4.5 and SSP5-8.5 scenarios, the CRI is expected to continue to rise, indicating that climate risk in the Tianshan Mountains will increase, with the eastern part facing significantly greater risks than the western part.

Keywords: CMIP6; warming and humidification; comprehensive climate risk index; Tianshan Mountains of China

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