Projections of Temperature Extremes Based on Preferred CMIP5 Models: A Case Study in the Kaidu-Kongqi River Basin in Northwest China Postprint

Authors: Li Chen, XU Changchun, LI Xiaofei, Changchun Xu

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Abstract

Extreme temperature has a more pronounced impact on ecology and water resources in arid regions than average temperature. Using downscaled daily temperature data from 21 Coupled Model Inter-comparison Project (CMIP) models of NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) and observation data, this paper analyzed changes in temporal and spatiotemporal variation of temperature extremes, i.e., maximum temperature (Tmax) and minimum temperature (Tmin), in the Kaidu-Kongqi River basin in Northwest China over the period 2020-2050 based on the evaluation of a preferred Multi-Model Ensemble (MME). Results showed that the Partial Least Square ensemble mean participated by Preferred Models (PM-PLS) better represented temporal change and spatial distribution of temperature extremes during 1961-2005 and was chosen to project future change. In 2020-2050, the increasing rate of Tmax (Tmin) under RCP (Representative Concentration Pathway) 8.5 will be 2.0 (1.6) times that under RCP4.5, and that of Tmin will be larger than that of Tmax under each corresponding RCP. Tmin will continue to contribute more to global warming than Tmax. The spatial distribution characteristics of Tmax and Tmin under the two RCPs will be overall similar; but compared to the baseline period (1986-2005), the increments of Tmax and Tmin in plain areas will be larger than those in mountainous areas. With increasing emission concentrations, however, the response of Tmax in mountainous areas will be more sensitive than that in plain areas, and that of Tmin will be equally sensitive in mountainous and plain areas. The impacts induced by Tmin will be universal and far-reaching. Results of spatiotemporal variation of temperature extremes indicate that large increases in the magnitude of warming may occur in the basin in the future. These projections can provide a scientific basis for water and land planning and management and disaster prevention and mitigation in

inland river basins.

Full Text

Projections of Temperature Extremes Based on Preferred CMIP5 Models: A Case Study in the Kaidu-Kongqi River Basin, Northwest China

CHEN Li[1], XU Changchun[1,2*], LI Xiaofei[1]

[1] MOE Key Laboratory of Oasis Ecology, College of Resource and Environment Sciences, Xinjiang University, Urumqi 830000, China
[2] School of Civil Engineering and Environmental Science, University of Oklahoma, Norman OK 73072, USA

Abstract: Extreme temperature exerts more pronounced impacts on ecology and water resources in arid regions than average temperature. Using downscaled daily temperature data from 21 Coupled Model Intercomparison Project (CMIP) models of NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) together with observational data, this paper analyzes temporal and spatiotemporal variations in temperature extremes—specifically maximum temperature (Tmax) and minimum temperature (Tmin)—in the Kaidu-Kongqi River basin of Northwest China over the period 2020–2050, based on evaluation of a preferred Multi-Model Ensemble (MME). Results show that the Partial Least Squares ensemble mean participated by Preferred Models (PM-PLS) better represents both the temporal changes and spatial distribution of temperature extremes during 1961–2005 and was therefore selected for future projections. During 2020–2050, the increasing rate of Tmax (Tmin) under RCP8.5 will be 2.0 (1.6) times that under RCP4.5, with Tmin showing larger increases than Tmax under each corresponding RCP scenario. Tmin will continue to contribute more to global warming than Tmax. The spatial distribution characteristics of Tmax and Tmin under both RCPs will remain largely similar overall; however, compared to the baseline period (1986–2005), increments in both Tmax and Tmin will be larger in plain areas than in mountainous areas. With increased emission concentrations, Tmax in mountainous areas will become more sensitive than in plain areas, while Tmin will show equivalent sensitivity across both topographic zones. The impacts induced by Tmin will be universal and far-reaching. Spatiotemporal variation results indicate that substantial warming may occur throughout the basin in the future. These projections can provide a scientific basis for water and land resource management and disaster prevention and mitigation in inland river basins.

Keywords: temperature extremes; multi-model ensemble; RCP; projection; Kaidu-Kongqi River basin

1 Introduction

Temperature plays a key role in the climate system. Scientific projection of future temperature change and quantitative assessment of associated uncertainties are not only essential for predicting future climate evolution but also critical for formulating effective climate adaptation policies (IPCC, 2014; Qin, 2014). Climate warming will further accelerate water cycling in river basins and alter the spatial and temporal distribution of water resources (Chen et al., 2017; Yu et al., 2019). Rising temperatures also exert substantial impacts on agriculture, daily life, and socioeconomic development (Barriopedro et al., 2011; Wu and Yan, 2013; Guan et al., 2015). Compared with average temperature, extreme temperature has more pronounced effects on ecology and water resources in arid regions (Yao, 1995; Rosenzweig et al., 2001; Keellings and Waylen, 2012; Ye et al., 2013; Huang et al., 2016; Yu and Sun, 2019). Therefore, investigating temperature extreme characteristics—particularly in arid inland river basins with severe water shortages—is crucial for local agricultural economic development, water resource allocation, and ecological civilization construction.

Global Climate Models (GCMs) have developed rapidly as important tools for climate simulation and projection (Li et al., 2012; Xu and Xu, 2012a, b; Yao et al., 2012; Chen and Sun, 2013; Wang et al., 2018; Li et al., 2020). The Coupled Model Intercomparison Project (CMIP), driven by the World Climate Research Programme (WCRP), has strongly advanced climate model development. Phase 5 of CMIP (CMIP5) adopts new scenarios characterized by Representative Concentration Pathways (RCPs), including RCP2.6, RCP4.5, RCP6.0, and RCP8.5. These RCPs represent integrated concentration and emission scenarios used as input parameters for climate change projection models under anthropogenic influence in the 21st century. RCP8.5 will cause the largest temperature rise, while RCP4.5 represents a climate scenario with government intervention and is the only emission scenario incorporating cultivated land reduction. Given our focus on temperature extremes, we selected RCP4.5 and RCP8.5 for this study. Numerous studies have evaluated CMIP5 model performance in simulating climatic variability (Hu et al., 2014; Chen et al., 2019). Although GCMs have achieved remarkable development, their spatial resolution remains limited, and simulations and projections contain considerable uncertainties and potential biases that can propagate into results (Chen et al., 2012; Su et al., 2016; Sun et al., 2016). Multi-Model Ensemble (MME) approaches can reduce uncertainty in future climate projections (Almazroui et al., 2016, 2017a, b), as ensemble results are typically closer to observations than most single models, and weighted ensemble methods can further reduce estimation uncertainty. Previous studies have also demonstrated that preferred models outperform general models in simulation capacity, with PM-PLS (Partial Least Squares ensemble mean participated by Preferred Models) showing superior projection performance (Xu et al., 2007; Raisanen and Ylhaisi, 2011; Jiang and Wu, 2013; Jiang et al., 2017; Zhang et al., 2017).

High-resolution data can be obtained through appropriate downscaling methods for simulation and projection research (Wang et al., 2017; Yang et al., 2017; Raghavan et al., 2018). Raghavan et al. (2018) simulated and evaluated future climate variation in Southeast Asia using statistically downscaled data and concluded that NEX-GDDP (NASA Earth Exchange Global Daily Downscaled Projections) data showed good consistency with observations. However, questions remain regarding NEX-GDDP performance in China, particularly in data-sparse Northwest China, and what datasets can verify its reliability. The CN05.1 grid dataset, developed and maintained by Chinese scientists, is considered accurate and reliable as it is interpolated from more than 2400 weather stations and strictly constrained by surface observations (Xu et al., 2009; Wu and Gao, 2013). This study uses CN05.1 to evaluate NEX-GDDP accuracy.

The Kaidu-Kongqi River basin is an inland river basin in the arid region of Northwest China that is highly sensitive to climate change, with signals of global warming detected there for decades (Shi et al., 2002). However, future climate conditions in the basin remain unclear, and while a few studies have explored this topic, detailed research on temperature extremes is lacking (He et al., 2018; Li et al., 2019a, b). High-resolution future climate information, including both mean and extreme conditions, is urgently needed to support scientific research and policy-making. This paper takes the Kaidu-Kongqi River basin as the study area, using CN05.1 and NEX-GDDP data to simulate and analyze future temperature extremes (Tmax and Tmin). We first select models with strong simulation capability for basin air temperature from the 21 NEX-GDDP models as preferred models to form the MME. Second, we evaluate the selected single models and MMEs in terms of temporal and spatial variation based on historical data. Third, we analyze future temperature extreme changes using the preferred MME (Partial Least Squares regression non-equal weighted ensemble mean). The objective is to validate the applicability of the NEX-GDDP dataset in the study area and provide projections of temperature extremes to assist basin managers in water, land, and agricultural resource planning and management.

2.1 Study Area

The Kaidu-Kongqi River basin is located on the southern slope of the Tianshan Mountains in Xinjiang, Northwest China [Figure 1: see original paper]. The region has a typical temperate continental arid climate characterized by drought, sparse rainfall, strong evapotranspiration, large diurnal temperature ranges, and abundant sunlight and heat. The terrain slopes from northwest to southeast, with elevations gradually decreasing from 4294 m to 767 m.

2.2 Data

2.2.1 Observation Data

Observational data are derived from the CN05.1 dataset (Xu et al., 2009; Wu and Gao, 2013), which includes daily precipitation, mean temperature, Tmax, and Tmin at a spatial resolution of 0.25°$\times$0.25° (25 km by 25 km). The dataset is established using anomaly approximation methods based on measurements from more than 2400 weather stations across China. This study uses the Tmax and Tmin data covering the period 1961–2005.

2.2.2 Simulation Data

The NEX-GDDP dataset (https://cds.nccs.nasa.gov/nex-gddp/) includes downscaled projections for RCP4.5 and RCP8.5 from 21 models and scenarios for which daily outputs were produced and distributed under CMIP5. Each climate projection includes daily Tmax, Tmin, and precipitation for the period 1950–2100 at 0.25°$×$0.25° spatial resolution. This study uses daily Tmax and Tmin data, with historical data from 1961–2005 used for simulation evaluation and projected data from 2020–2050 used to analyze temperature extremes.

2.3 Historical Climate Simulation Performance Metrics

To facilitate validation of GCMs against observational data, we averaged temperature values to define regionally averaged monthly and annual time series and spatial patterns for both GCM simulations and observations. Annual Tmax and Tmin were calculated as deviations from the climatology during 1961–2005. To quantify agreement between observations and model simulations, we constructed Taylor diagrams (Taylor, 2001), calculating correlation coefficients, standard deviations (STD), and root mean square errors (RMSE) between CMIP5 model datasets and observational datasets. Trends were calculated using linear trend estimation. Partial Least Squares ensemble mean was employed to address unsatisfactory projection results caused by multicollinearity among independent variables, yielding more in-depth and comprehensive information (Zhi et al., 2016).

3.1.1 Preferred Model Selection

In this paper, the two ensemble means participated by all models are designated as EE (equal-weight ensemble mean) and PLS (Partial Least Squares), respectively, according to their different weight determination methods. The two ensemble means participated by preferred models are called PM-EE (equal-weight ensemble mean participated by preferred models) and PM-PLS, respectively. The screening criteria for preferred models are: (1) simulated air temperature shows an increasing trend passing the 1% significance test; and (2) the correlation coefficient between simulated and observed annual mean Tmax and Tmin time series passes the 1% significance test.

Based on these criteria, 4 and 17 preferred models are selected for Tmax and Tmin, respectively . The models BCC-CSM1-1 and MPI-ESM-LR have linear trend values closest to observations with increasing rates (both 0.17°C/decade) slightly higher than observed (0.16°C/decade), but they did not pass the significance test. The models ACCESS1-0, CSIRO-MK3-6-0, GFDL-ESM2M, and NorESM1-M have higher correlation coefficients than others, with both linear trends and correlation coefficients passing significance tests. Therefore, these four models are used in the preferred MME (PM-EE and PM-PLS) for Tmax. Model performance in simulating Tmin is obviously better than for Tmax in both trend magnitude and correlation coefficient. In addition to the four selected models, 13 other models—BCC-CSM1-1, BNU-ESM, CanESM2, CCSM4, CESM1-BGC, CNRM-CM5, GFDL-CM3, GFDL-ESM2G, IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC5, MIROC-ESM, and MPI-ESM-MR—are used for Tmin.

3.1.2 Simulation Evaluation Based on Taylor Diagram

Agreement between model-simulated and observed temperature is further evaluated through Taylor diagrams. Figure 2 shows results for climatology differences across the entire historical period. Based on comparison of Taylor diagrams for temporal variability, most models show similar ability to simulate temperature time series, though some differences exist among models. Most models can simulate Tmax variability well, with RMSE > 0.61 and close matches to CN05.1 observations. For Tmin, differences among simulations appear in correlation coefficients ranging from 0.42 to 0.69, indicating that some models have better simulation capability. Generally, CSIRO-MK3-6-0, GFDL-ESM2M, and NorESM1-M perform somewhat better for both Tmax and Tmin.

For MMEs, temperature simulation results are close to observed values: Tmax correlation coefficients range from 0.47 to 0.61, RMSE is 0.44–0.48, and STD is larger than observed values (0.31–0.44); Tmin correlation coefficients range from 0.80 to 0.83, RMSE is 0.42–0.46, with STD ranges similar to Tmax. Tmax results show large deviations from observed values. Overall, MME simulation performance is better than that of single models.

3.2 Simulation and Evaluation in Temporal Variation

Table 2 and Figure 3 show that Tmax and Tmin in the basin have exhibited significant increasing trends over the past 45 years, with all single models and MMEs capturing this trend.

For Tmax, simulated increasing rates for most models and the four MMEs (0.17°C–0.30°C/decade) are higher than observed (0.16°C/decade) [TABLE:2; FIGURE:3], indicating that most models overestimate historical Tmax changes [Figure 3a: see original paper]. The primary reason is that most models cannot simulate the downward trend before the mid-1980s, instead replacing it with an upward or short downward trend, which magnifies the overall growth trend. The selected preferred models cannot overcome this limitation either [Figure 3b: see original paper], but applying the MME mean method greatly improves results [Figure 3c: see original paper]. The four MMEs show very similar variations from 1961 to 2005. However, EE and PM-EE significantly overestimate Tmax, while PLS and PM-PLS are close to the observation curve. PM-PLS outperforms PLS in better simulating peaks and valleys.

For Tmin in the basin, increasing rates for all models (0.12°C/decade-0.36°C/decade), including single models and MMEs, are lower than observed (0.41°C/decade) , meaning all models underestimate the historical change rate of Tmin. However, simulated values are greater than observed values [Figure 3d: see original paper] because large gaps between early simulation and observation values result in an overall gentle increasing rate. Thus, increasing rate alone cannot indicate whether temperature is overestimated or underestimated. Compared to Tmax, Tmin shows larger increasing rates , indicating stronger Tmin increases consistent with most studies (Zhao et al., 2014; Sun et al., 2016; Shang et al., 2018). Similarly, EE and PM-EE significantly overestimate Tmin, while both PLS and PM-PLS are close to the observation curve, though they cannot well depict changes in peaks and valleys due to smoothing effects from too many preferred models.

3.3 Simulation and Evaluation in Spatial Variation

According to observed results [Figure 4a: see original paper], annual mean Tmax ranges from -0.9°C to 21.5°C, showing a gradually increasing trend from northwest to southeast as altitude decreases. All models capture these spatial distribution characteristics. For MMEs, both PM-EE and PM-PLS can well reproduce the Tmax distribution range [FIGURE:4c and e], but PM-PLS produces spatial distribution patterns closer to observations.

Annual average Tmin ranges from -13.5°C to 6.5°C [Figure 4b: see original paper], which most models can simulate, showing similar spatial distribution characteristics as Tmax. Notably, a small area in the basin' s middle is colder than adjacent areas, likely resulting from the cold island effect of Bosten Lake [Figure 1: see original paper]. For MMEs, PM-EE can simulate Tmin' s overall characteristics but poorly represents specific distributions in plain and mountainous areas—for example, large high-value areas in the south do not accurately depict characteristics around Bosten Lake [Figure 4d: see original paper]. In contrast, PM-PLS shows better simulation results with spatial correlation coefficients approaching 1.0.

Figure 5 shows the spatial correlation coefficient distribution of Tmax and Tmin between PM-EE, PM-PLS, and observations. Generally, simulation performance is better in flatter, simpler regions. High-resolution models can better reflect steep topographic features in high-altitude areas and eliminate existing high deviations, thus improving simulation capability (Jiang et al., 2016). Based on spatial simulation results [Figure 5: see original paper], Tmin shows better simulation performance than Tmax, and PM-PLS outperforms PM-EE in exhibiting temperature extreme spatial distributions.

3.4.1 Temperature in Temporal Change

Based on evaluation results, PM-PLS is adopted to estimate future changes in basin temperature extremes. Figure 6 shows that Tmax under RCP4.5 will increase overall during 2020-2050 at a rate of 0.24°C/decade [Figure 6a: see original paper], higher than the historical period (0.16°C/decade) and half that under RCP8.5 (0.48°C/decade) [Figure 6c: see original paper]. The fluctuation range (14.5°C-16.5°C) and annual mean (approximately 15.5°C) of Tmax under RCP4.5 closely approximate those under RCP8.5, indicating that large RCP differences do not necessarily cause marked differences in Tmax basic characteristics in the short term. They differ in two aspects: (1) fluctuation period—the former fluctuates violently after 2030, while the latter does so before 2040; and (2) increasing trend—the former does not increase continuously but jumps between stages with no obvious growth within each stage, while the latter increases almost continuously.

For Tmin, increasing rates under RCP4.5 [Figure 6b: see original paper] and RCP8.5 [Figure 6d: see original paper] are 0.36°C/decade and 0.56°C/decade, respectively—higher than corresponding Tmax rates, indicating that Tmin will continue contributing more to global warming than Tmax. However, the Tmin increasing rate under RCP4.5 is lower than the historical period (0.41°C/decade), with a ten-year warming hiatus since 2035, indicating that moderate emission scenarios can relieve warming to some extent. In contrast, Tmin under RCP8.5 will show continuous increase, approaching 2.4°C by mid-21st century.

3.4.2 Analysis of Temperature in Spatial Change

Tmax under both RCP4.5 and RCP8.5 reveals identical spatial distribution characteristics: low temperatures in the northwest (0.9°C to 9.3°C) and high temperatures in the southeast (14.9°C to 23.3°C) [FIGURE:7a and b]. No obvious differences appear between the two scenarios in the short term. Compared to the baseline period, however, they behave differently. Temperature increments are 1.1°C-1.7°C for mountainous areas and 1.6°C-2.0°C for plain areas under RCP4.5 [Figure 7c: see original paper], and 1.2°C-2.1°C and 1.6°C-2.1°C, respectively, under RCP8.5 [Figure 7d: see original paper]. Tmax will increase across the entire basin under both RCPs. Notably, temperature increments are larger in mountainous areas and smaller in plain areas as emission concentrations increase, indicating that Tmax in mountainous areas is more susceptible to increased emission concentrations.

For Tmin, spatial distribution characteristics are almost identical to Tmax [FIGURE:8a and b], with no differences between the two RCPs. Tmin ranges from -9.4°C to -3.4°C in northwest mountainous areas and from 0.6°C to 6.6°C in southeast plain areas. Compared to the baseline period, temperature increments are 1.0°C-1.8°C for mountainous areas and 1.4°C-2.2°C for plain areas under RCP4.5 [Figure 8c: see original paper], and 1.3°C-1.9°C and 1.6°C-2.2°C, respectively, under RCP8.5 [Figure 8d: see original paper]. Tmin will increase across the entire basin under both RCPs. Temperature increments are large in both mountainous and plain areas as emission concentrations increase, indicating that the impact of increased emission concentrations on Tmin is universal throughout the basin.

4 Conclusions

This paper analyzed temperature extremes in the Kaidu-Kongqi River basin during 2020–2050. Both Tmax and Tmin will increase under RCP4.5 and RCP8.5, with Tmin increasing at larger rates than Tmax under each corresponding RCP. Spatial distribution characteristics of Tmax and Tmin under both RCPs will remain largely similar in the short term: low temperatures in the northwest and high temperatures in the southeast. Increments in both Tmax and Tmin will be larger in plain areas than in mountainous areas.

Temperature extremes are important indicators of global warming, and analyzing them enhances our understanding of climate change. This study used observational datasets to verify the accuracy of selected models and the reliability of ensemble means. However, the MMEs employed only two simple methods (PM-EE and PM-PLS), and no optimal method currently exists for scientifically determining weight distributions—this requires further study. Additionally, while CMIP6 has updated numerous climate model datasets, this study primarily used statistically downscaled data with relatively coarse spatial resolution, which restricts simulation and projection accuracy and reliability. Future work should combine dynamic and statistical downscaling approaches.

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