Postprint of Future Climate Change Scenario Projections for the Kaidu-Kongque River Basin in the 21st Century

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Abstract

Utilizing 31 CMIP5 downscaled datasets provided by the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections (DCHP) and CRU monthly temperature and precipitation gridded datasets, this study evaluates the simulation capabilities of three multi-model ensemble mean projection models—PLS (Partial Least Squares regression), RR (Ridge Regression), and EE (Equal Weighting)—for historical climate change, determines the optimal ensemble method, and subsequently projects 21st-century climate change scenarios for the Kaidu-Kongque River basin. The results indicate: The established PLS model demonstrates good simulation capability for both temperature and precipitation in the basin, particularly for temperature, with r-values all reaching above 0.64, which is significantly better than that for precipitation (0.19-0.36), although spatial heterogeneity exists; Temperature in various sub-regions of the Kaidu-Kongque River basin shows a significant increasing trend during the 21st century, with the warming rate under the RCP8.5 scenario [0.58–0.67 ℃ · (10a)-1] being more than twice that under the RCP4.5 scenario [0.25–0.31 ℃ · (10a)-1]; the mid-21st century marks the beginning of obvious differences between the two scenarios. The warming rate across the entire basin gradually increases from the northwest mountainous area to the southeast desert area; The distribution of change rates for future precipitation varies slightly under different emission scenarios, but all show a significant increasing trend, with the increasing rate under the RCP8.5 scenario [1.22%–1.54% · (10a)-1] being generally higher than that under RCP4.5 [0.80%–1.32% · (10a)-1].

Full Text

Projection of Future Climate Change in the Kaidu-Kongqi River Basin in the 21st Century

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Abstract

Climate change assessments on both global and regional scales rely strongly on global climate models (GCMs), predominantly provided by the Coupled Model Intercomparison Project Phase 5 (CMIP5). Based on gridded monthly air temperature and precipitation datasets from CRU (Climate Research Unit) and 31 CMIP5 GCMs from the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections (DCHP), this paper evaluates the performance of three Multi-Model Ensemble Mean methods (PLS, RR, and EE) in simulating historical climate change processes, and determines the optimal ensemble method for predicting future climate change in the Kaidu-Kongqi River Basin during the 21st century. The results indicate that: (1) The established Partial Least Squares (PLS) model performed best in simulating air temperature and precipitation in the study area. The correlation coefficients (r values) of simulated temperature were all higher than 0.64, which were obviously better than those of simulated precipitation (0.19-0.36). However, there was spatial heterogeneity in both temperature and precipitation simulations; (2) In the 21st century, air temperature in the four sub-basins of the Kaidu-Kongqi River Basin would show a significant increasing trend. The increase rates of air temperature [0.58-0.67℃ · (10a) ^{1}] under the RCP8.5 scenario would be double those under the RCP4.5 scenario [0.25-0.31℃ · (10a) ^{1}]. The significant difference between the two scenarios would begin from the mid-21st century. From the perspective of the entire watershed, the warming rate increased gradually from the mountainous area in the northwest to the desert in the southeast; (3) The distribution of change rates of precipitation was slightly different under different discharge scenarios, but both would show a significant increasing trend. The increase rate under the RCP8.5 scenario [1.22%-1.54% · (10a) ^{1}] would be holistically higher than that under the RCP4.5 scenario [0.80%-1.32% · (10a) ^{1}].

Keywords: downscale; CMIP5; air temperature; precipitation; Multi-Model Ensemble; future climate change; Kaidu-Kongqi River Basin

1 Introduction

Climate change research relies heavily on future emission scenarios and climate projections from global climate models. The IPCC Fifth Assessment Report adopted four Representative Concentration Pathways (RCPs) scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP8.5. The Coupled Model Intercomparison Project Phase 5 (CMIP5) provides multi-model ensemble data that serves as an important foundation for climate change impact assessment studies. However, GCM outputs contain systematic biases and have coarse spatial resolutions, making them unsuitable for direct application in regional climate change studies. Downscaling methods, including Bias Correction and Spatial Disaggregation (BCSD), are necessary to correct these biases and refine the spatial resolution.

Multi-model ensemble mean (MME) methods can effectively reduce uncertainties in single-model simulations. Common MME methods include the arithmetic ensemble mean (EE), Partial Least Squares regression (PLS), and Ridge Regression (RR). Previous studies have shown that PLS and RR methods generally outperform the simple arithmetic mean approach. This study evaluates the performance of these three MME methods in simulating historical climate processes and selects the optimal method for projecting future climate change in the Kaidu-Kongqi River Basin.

2 Data and Methods

2.1 Study Area and Data Sources

The Kaidu-Kongqi River Basin is located in Xinjiang, China, and was divided into four sub-basins (SB1–SB4) based on a 1:4,000,000 digital geomorphology database [Figure 1: see original paper]. The basin exhibits significant spatial heterogeneity, with elevations ranging from 770 m to over 4,666 m.

Observational data from 1961–2005 were obtained from the CRU TS3.23 dataset. Future climate projections were derived from 31 CMIP5 GCMs downscaled using the BCSD method to a 0.5° (approximately 50 km) resolution . The correlation coefficients between CRU data and observed temperature and precipitation ranged from 0.983 to 0.998 for temperature and 0.168 to 0.890 for precipitation, with all correlations significant at the 95% confidence level .

2.2 Multi-Model Ensemble Methods

Three MME methods were employed: (1) Partial Least Squares regression (PLS), (2) Ridge Regression (RR), and (3) Equal Weight ensemble (EE). The PLS method constructs predictive models by maximizing the covariance between independent variables (GCM outputs) and dependent variables (observations), making it particularly suitable for climate data with multicollinearity. The RR method addresses overfitting through L2 regularization, while the EE method applies equal weights to all models.

Model weights were determined based on historical performance during the 1950–2005 calibration period [Figure 2: see original paper]. The PLS method demonstrated superior performance, with temperature simulation r values exceeding 0.64 across all sub-basins. Precipitation simulation showed lower but acceptable correlations (0.19–0.36), reflecting the inherent difficulty in modeling precipitation variability .

3 Results

3.1 Model Performance Evaluation

The PLS method exhibited the best overall performance in simulating both temperature and precipitation. For temperature, the lowest RMSE values were achieved with PLS (16.34–23.12), followed by RR (16.49–23.22) and EE (17.13–29.10). The performance advantage of PLS was particularly evident in sub-basin SB4, where complex terrain creates significant climate heterogeneity.

Spatial analysis revealed that model performance varied across sub-basins. In the mountainous SB1, all three methods performed well due to strong topographic forcing. In the intermediate SB2 and SB3, performance was moderate, while in the desert-influenced SB4, the PLS method' s ability to capture nonlinear relationships provided clear advantages.

3.2 Future Climate Projections

Projections for 2006–2099 indicate significant warming trends across all sub-basins under both RCP4.5 and RCP8.5 scenarios [Figure 3: see original paper]. Under RCP8.5, temperature increase rates range from 0.58 to 0.67℃ · (10a) ^{1}, approximately double the rates under RCP4.5 (0.25–0.31℃ · (10a) ^{1}). The divergence between scenarios becomes pronounced from the mid-21st century onward.

Spatially, warming rates increase from northwest to southeast, with the highest rates in the desert regions of SB4. This gradient reflects the combined effects of elevation and continental climate influences.

Precipitation also shows significant increasing trends, though with greater inter-model uncertainty. Under RCP8.5, precipitation increase rates range from 1.22% to 1.54% · (10a) ^{1}, while under RCP4.5 they range from 0.80% to 1.32% · (10a) ^{1}. The PLS method projects more reliable precipitation changes by effectively weighting models based on their historical performance in capturing regional precipitation patterns.

4 Discussion

The superior performance of the PLS method aligns with previous studies demonstrating that regression-based ensemble methods outperform simple averaging. The spatial heterogeneity in model performance highlights the importance of using region-specific evaluation metrics when selecting ensemble methods for climate projection.

The projected temperature increases are consistent with CMIP5-based studies for arid regions of Northwest China. The pronounced northwest-southeast warming gradient has important implications for water resource management, as higher temperatures in downstream desert areas will exacerbate evapotranspiration rates.

While precipitation projections show increasing trends, the lower correlation coefficients and higher RMSE values compared to temperature simulations indicate substantial uncertainty. This uncertainty must be considered in adaptation planning, particularly for agricultural and ecological water use in the basin.

5 Conclusion

This study demonstrates that the PLS-based multi-model ensemble method provides the most reliable climate projections for the Kaidu-Kongqi River Basin. The 21st century will experience significant warming and precipitation increases, with the magnitude dependent on emission scenarios. The spatial patterns of change suggest that adaptation strategies should be tailored to sub-basin characteristics, with particular attention to the vulnerable desert regions in the southeast.

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