remote sensing

Supplemental Materials

Impact of Climate Change on the Hydrological Regime of the Yarkant River basin, China: An Assessment Using Three SSP Scenarios of CMIP6 GCMs

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Supplemental methods

Model performance evaluation

The Nash–Sutcliffe efficiency (NSE) and Coefficient of Determination (R^2) were used to measure the goodness of fit, and Percent Bias (PBIAS) was used to assess the offset of simulated flow against measured flow. The formula is as follows.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_i - Q_i^{'})^2}{\sum_{i=1}^{n}(Q_i - \bar{Q})^2} \tag{S1}$$

where Q_i is the measured flow on day i, $Q_i^{'}$ is the flow on day i of the simulation, $\bar{Q}$ is the average flow during the simulated snowmelt period, and n is the number of days in the simulation period. The value of Nash-Sutcliffe coefficient NS is between 0 and 1, the closer it is to 1, the more accurate the simulation results are.

$$PBIAS = \frac{\sum_{i=1}^{n}(Q_i - Q_i^{'})}{\sum_{i=1}^{n} Q_i^{'}} \tag{S2}$$

PBIAS measures the offset of the simulated flow from the measured flow, with positive values indicating overestimation and negative values indicating underestimation; the smaller the absolute PBIAS, the smaller the deviation of the simulated volume from the observed volume.

The decision coefficient R^2 is also an important metric for evaluating the model, describing the correlation between simulated and measured flows.

Bias correction approaches

(1) Linear scaling（LS）

Linear scaling corrects for deviations from the simulated multi-year monthly averages of precipitation/air temperature. It corrects for the monthly average deviation between the simulated and observed variables, with precipitation corrected by a multiplier and temperature corrected by an additive (plus or minus a value).

$$P_{cor,m,d} = P_{raw,m,d} \times \frac{\mu(P_{obs,m})}{\mu(P_{raw,m})} \tag{S3}$$

$$T_{cor,m,d} = T_{raw,m,d} + \mu(T_{obs,m}) - \mu(T_{raw,m}) \tag{S4}$$

where $P_{cor,m,d}$ and $T_{cor,m,d}$ are the precipitation and temperature values on day d of the corrected month m, respectively, and $P_{raw,m,d}$ and $T_{cor,m,d}$ are the precipitation and temperature values on day d of the simulated month m. μ(.) represents averaging, for example, $\mu(P_{obs,m})$ is the observed precipitation for month m.

(2) Local intensity scaling (LOCI)

The LOCI method corrects for wet day frequency and wet day precipitation intensity, thus improving the correction [75]. In general, the LOCI method is divided into two steps: first, a wet day threshold Pthres_m is defined for month m (m is the month from 1-12), and when $P_{raw,m,d} < P_{thres,m}$, the precipitation for that day is set to 0 to ensure that the number of precipitation days in the simulated series is equal to the observed precipitation days; second, a scaling factor $s_m = \frac{\mu(P_{obs,m,d}|P_{obs,m,d} > 0)}{\mu(P_{raw,m,d}|P_{raw,m,d} > P_{thres,m})}$ to ensure that the corrected total precipitation is equal to the observed total precipitation. With these two correction parameters, the following equation can be used for the correction:

$$P_{cor,m,d} = \begin{cases} 0, & if\ P_{raw,m,d} < P_{thres,m} \\ P_{raw,m,d} \times S_m, & \text{otherwise} \end{cases} \quad (S5)$$

(3) Distribution mapping (DM) of precipitation and temperature

Gamma distribution mapping and Gaussian distribution mapping (DM) methods can adjust the distribution of climate variables simulated by GCMs so that it is the same as the distribution of observed climate variables [76]. Theoretically, DM methods can correct for mean, standard deviation, and deciles, and, importantly, DM methods can preserve the extremes in climate change. However, there are some limitations to the DM method, the most notable of which is that it assumes that the simulated and observed temperature and precipitation obey assumed distributions.

For precipitation, it is assumed that precipitation obeys the Gamma distribution, which is given by the following formula.

$$f_r(x|\alpha,\beta) = x^{\alpha-1} \times \frac{1}{\beta^{\alpha} \times \Gamma(\alpha)} \times e^{\frac{-x}{\beta}}; x \geq 0, \alpha, \beta > 0 \quad (S6)$$

For air temperature, it is assumed that the air temperature follows a Gaussian distribution, i.e., a general normal distribution, with the following equation.

$$f_N(x|\mu,\sigma) = \frac{1}{\sigma \times \sqrt{2\pi}} \times e^{\frac{-(x-\mu)^2}{2\sigma^2}}; x \in \mathrm{R} \quad (S7)$$

Similarly, the corrected air temperature can be obtained from the following equation.

$$T_{cor,m,d} = F_N^{-1}\left(F_N\left(T_{raw,m,d}\middle|\mu_{raw,m}, \sigma_{raw,m}\right)\middle|\mu_{obs,m}, \sigma_{obs,m}\right) \quad (S8)$$

where μ and σ denote the mean and standard deviation of the temperature, respectively. $F_N(.)$ and $F_N^{-1}(.)$are cumulative distribution functions of the Gaussian distribution and their inverse functions, $\mu_{raw,m}$ and $\mu_{obs,m}$ are the mean values of the simulated and observed air temperature for month m, and $\sigma_{raw,m}$ and $\sigma_{obs,m}$are the standard deviations for the corresponding months.

(4) Power transformation (PT)

The power transformation (PT) method corrects for the standard deviation of precipitation using a power function [77]. the PT method also consists of two steps, first, estimating the power exponent bm such that $\mathrm{f}(b_m)$ obtains a minimum.

$$\mathrm{f}(b_m) = \frac{\sigma(P_{obs,m})}{\mu(P_{obs,m})} - \frac{\sigma(P_{LOCI,m}^{b_m})}{\mu(P_{LOCI,m}^{b_m})} \quad (S9)$$

where bm is the exponent of month m, $\sigma(.)$ represents the calculated standard deviation, and $P_{LOCI,m}$ is the average precipitation for month m after LOCI correction. If bm > 1, the simulated precipitation underestimates the standard deviation of the mth month, and vice versa.

Second, after calculating bm, the coefficient $s_m = \frac{\mu(P_{obs,m})}{\mu(P_{LOCI,m}^{b_m})}$ is calculated to ensure that the corrected precipitation and the observed precipitation in month m are equal. This yields the PT-corrected precipitation series $P_{cor,m,d}$:

$$P_{cor,m,d} = s_m \times P_{LOCI,m,d}^{b_m} \tag{S10}$$

Supplemental tables

Table S1. Precipitation lapse rate of each month in Yarkant River basin.

Month	1	2	3	4	5	6	7	8	9	10	11	12
Pre lapse rate (mm)	0.42	0.49	0.42	0.78	1.64	2.64	2.07	1.56	1.07	0.27	0.10	0.32

Table S2. Estimated and calibrated Parameters for the calibration and validation of streamflow, for the six sub-basins of Yarkant River basin.

Parameter	Optimized Values	Source of Initial Values
	Simple Canopy	
Initial Storage (%)	10	HEC-HMS Help manual (Trial and Error)
Max Storage (%)	10	HEC-HMS Help manual (Trial and Error)
	Simple Surface	
Initial Storage (%)	20	HEC-HMS Help manual (Trial and Error)
Max Storage (%)	20	HEC-HMS Help manual (Trial and Error)
	Soil Moisture Accounting (SMA) Loss Method	
Max Infiltration (mm/h)		FAO soil data
Impervious (%)	20	FAO soil data
Soil Storage (mm)	100	FAO soil data
Tension Storage (mm)	20	HEC-HMS Help manual
Soil Percolation (mm/h)	1	FAO soil data
Ground Water 1 Storage (mm)	100	Calibration trial and error
Ground Water 1 Percolation (mm/h)	10	Calibration trial and error
Ground Water 1 Coefficient (h)	30	Calibration trial and error
Ground Water 2 Storage (mm)	190	Calibration trial and error
Ground Water 2 Percolation (mm/h)	1	Calibration trial and error
Ground Water 2 Coefficient (h)	80	Calibration trial and error
	Clark Unit Hydrograph	
Time of Concentration (h)	90	Optimization Trial
Storage Coefficient (h)	30	Optimization Trial
	Recession	
Recession Constant	0.95	Optimization Trial
Ratio to Peak	0.95	Optimization Trial
	Temperature Index	
Px Temperature (℃)	3	HEC-HMS help
Base Temperature (℃)	-1.6	HEC-HMS help
Lapse Rate (℃/100 m)	-0.65	[33]
Degree Day Factor (DDF) (mm/℃-day)	3.4	Optimization Trial
Evapotranspiration (mm/month)	88.58	Obsecrated data
ATI-Meltrate Function (mm/℃-day)	0.025-0.04	Calculation and Calibration
ATI-Coldrate Function (mm/℃-day)	1.32	Calculation and Calibration