An approach to simulate the climate-driven streamflow in the data-scarce mountain basins of Northwest China

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With global warming, the inland river basin in the arid region of Northwest China is facing a serious water supply situation. The headwater basin of the inland river is located in the high-altitude mountainous region, and there are few meteorological observation sites, so it is difficult to apply distributed hydrological models and other models based on the physical mechanism of runoff generation to evaluate climate change and its impact on streamflow. To simulate the climate-driven streamflow in data-scarce mountain basins of Northwest China, we developed an integrated approach by using downscaled reanalysis data, Mann–Kendall test, ensemble empirical mode decomposition and backpropagation artificial neural networks together with the weights connection method. We validated the approach in the Kaidu River basin located in the Tianshan mountains. The results showed that the streamflow increased 12.9% by $2.5 \times 10^8 \text{ m}^3$ per decade with the warm and wet climate, while the average annual temperature increased 5.2% at a rate of 0.3°C per decade and the precipitation increased 37.3% at a rate of 16.4 mm per decade during the period from 1980 to 2015. The impact of temperature variability on streamflow was $44.21 \pm 2.08\%$ and the impact of precipitation variability on streamflow was $55.79 \pm 2.08\%$.

Keywords. Climate change; impact; streamflow; data-scarce mountainous basins; Northwest China.

1. Introduction

Climate change affects hydrological processes (Yao *et al.* 2018). The trend analysis of climate variables reveals the process of climate change. Temperature and precipitation are climate variables which are mainly affected by global warming. So the key point for hydrological forecasting is to understand

the hydrological processes affected by temperature and precipitation. Research in different countries and regions has shown that the hydroclimatic processes are complex systems and have nonlinear features (Sivakumar 2010; Xu *et al.* 2011).

In recent years, there has been plenty of research in the field of hydroclimatic processes including regression method, fitting by spline or empirical

function, Mann–Kendall trend test, Pettitt's test for single change-point detection (Li *et al.* 2012), singular spectrum analysis (Wang *et al.* 2013), wavelet decomposition and reconstruction method, empirical orthogonal functions and artificial neural networks (Xu *et al.* 2014).

Empirical statistics model is an effective way to simulate hydroclimatic processes. Based on the analysis of runoff and precipitation at various stations and various soil and water conservation measures, Mu *et al.* (2004) established a statistical hydrological model of precipitation soil and water conservation runoff in basins using multiple regression methods. Chen *et al.* (2003) established six empirical models for streamflow simulation in the inland mountainous regions of Northwest China and found that there was a high degree of correlation between climate factors and streamflow. Especially, in mountainous areas, where there were more glaciers and more snow, the temperature was a very important factor.

The soil and water assessment tool (SWAT; Arnold *et al.* 1998; Arnold and Fohrer 2005) is a distributed model widely applied in runoff simulation and hydrologic process analyses (Pereira *et al.* 2016; Ghane *et al.* 2017). SWAT is developed based on the simulator for water resources in rural basins model (USDA Agricultural Research Service contributes to the development of SWAT with modelling experience that spans nearly 30 yr (Yang and Musiak 2003; Lévesque and Ancil 2008; Shope *et al.* 2014). The construction of distributed hydrological model requires sufficient parameters and drive data sets (Yang *et al.* 2015). Especially, in the high mountains, such as the Tianshan mountains, Qilian mountains and the Kunlun mountains, in the vast area of Northwest China, the rare observation sites result in the lack of meteorological and hydrological data with high spatial resolution. All the reasons above make it difficult to simulate the climate-driven streamflow and estimate the impact of climate change on streamflow in data-scarce mountain basins. Therefore, it is necessary to develop an approach further for modelling the hydroclimatic process in the data-scarce mountain basins of Northwest China.

Along with global warming, the water supply situation in the inland mountainous basin has become more and more serious. Since the inland mountainous basin is located in a high-altitude region, there are few meteorological observation sites. It is difficult to create distributed hydrological models to assess climate change and its impact on

streamflow. Therefore, it is necessary to develop a comprehensive model based on downscaled earth data products to simulate the hydroclimatic process and quantitatively assess the impact of climate change on streamflow.

For the purpose of simulating the climate-driven streamflow and for assessing the impact of climate change to streamflow in data-scarce mountain basins of Northwest China, this work developed an integrated approach by using downscaled reanalysis data, Mann–Kendall test, ensemble empirical mode decomposition (EEMD), backpropagation artificial neural networks (BPANN) together with weights connection method. We validated the approach by selecting the Kaidu River basin in the Tianshan mountains of Northwest China. The combined approach can effectively simulate the change of climate and streamflow in the basin lacking observational data, quantitatively identify the impacts of changes in temperature and precipitation on the streamflow in typical valleys on the southern slope of the Tianshan mountains and provide a framework for hydrological simulation and water resources management in inland mountainous regions.

2. Materials and methods

2.1 Description of the study area

We selected the Kaidu River basin as the study area because it is a typical data-scarce mountain basin, which is located on the southern slope of the middle Tianshan mountains and the northern edge of the Tarim basin. There is one meteorological and one hydrological station in the study area (figure 1) ($82^{\circ}58'-86^{\circ}55'E$; $41^{\circ}47'-43^{\circ}21'N$). The river originated in the Jacsta Valley and the Hargat Valley in the Sarming mountain and ended at the Bosten Lake. The basin area of the Kaidu River above Dashankou is $18,827 \text{ km}^2$, with an average elevation of 3100 m. The average annual temperature in the basin is 4.6°C , the extreme maximum temperature is 25.27°C and the extreme minimum temperature is -48.1°C . The yearly snow-cover days are 139.3 days, and the largest average yearly snow depth is 12 cm.

2.2 Data sources

The elevation data for downscaled reanalysis data was extracted from the Shuttle Radar Topography Mission (SRTM) 90 m digital elevation model data

Figure 1. Locations of Kaidu River basin, meteorological stations and hydrological stations.

V4.1. International Center for Tropical Agriculture (Reuter *et al.* 2007) preprocessed the SRTM DEM data, and the data can be downloaded from United States Geological Survey/National Aeronautics and Space Administration (<http://srtm.csi.cgiar.org>). The grid cell size of SRTM is 90 m.

To reveal the climate characteristics in data-scarce mountain basins, we chose the reanalysis data for downscaling. Based on the accuracy test of reanalysed data products (MERRA-2 instM.2d_lfo_Nx V5.12.4, ERA-Interim 2m temperature data and China's surface air temperature $0.5^{\circ} \times 0.5^{\circ}$ grid dataset), we chose the MERRA-2 instM.2d_lfo_Nx V5.12.4 data for downscaling. The MERRA-2 data can be downloaded from the web of Global Modeling and Assimilation Office (<http://goldsmr4.gesdisc.eosdis.nasa.gov>). The spatial resolution of the monthly temperature data is $0.5^{\circ} \times 0.625^{\circ}$. Since the most reanalysed data starts in 1980, the date range of this research is all from January 1980 to December 2015.

We chose the China precipitation grid data V2.0 provided by National Meteorological Information Center (NMIC) (<http://data.cma.cn>) for downscaling. The grid size of the monthly precipitation is 0.5° and the date range is from January 1980 to December 2015.

We used the measured meteorological data provided by NMIC (<http://data.cma.cn>) to test the downscaling model effect. The meteorological station for verification is Bayinbuluke, which is the only national base weather station in the Kaidu River basin. The time resolution is monthly, and the date range is from January 1980 to December 2015.

The long-term hydrological station monitoring streamflow data offered by Xinjiang Tarim River Basin Management Bureau was used to verify the stream simulation effect. The monitoring station is Dashankou at the outlet of the Kaidu River basin. The monthly data is in ASCII format and the period is from 1980 to 2015.

2.3 Methods

We used an integrated approach for simulating the climate-driven streamflow in the data-scarce mountain basins (figure 2). The integrated approach contains three processes. The reanalysis data was downscaled and tested at first. Then the Mann–Kendall trend test and EEMD methods were used to detect the trends and decompose the monthly temperature, precipitation and streamflow data into different scales. At last, a BPANN was trained with the downscaled regional climate mean values. The weights of each layer in the BPANN were connected and the impact of climate variation on streamflow was evaluated.

2.3.1 Downscaling the reanalysis data

With the development of technology, the atmospheric reanalysis data and downscaling technique provide the complete fields in space and time of the hydrological variables (Huth *et al.* 2015). Downscaling the reanalysis data could be applied in the research of simulating the impact of climate change on streamflow (Emanuel *et al.* 2010; Strzepek *et al.* 2013; Koster *et al.* 2017).

Figure 2. Framework of an integrated approach to downscale reanalysis data, detect the trends and model the hydroclimatic process.

The Kaidu River basin has just one national long-term observation meteorological station in Bayanbulak, so the climate data is scarce and could not represent the overall climate variation in the complex mountain basin. The variability of temperature and precipitation is related to altitude. With the altitude data, we can downscale the reanalysis data of temperature and precipitation to reveal the regional climate characteristics (Xu *et al.* 2013; Georgakakos *et al.* 2014). An improved downscaling method, which can dynamically adjust the parameter based on terrain feature (Wang *et al.* 2018), was applied to downscale the reanalysis data. The downscaling method includes temperature lapse rates, simulation of precipitation gradients, reanalysis of climate data downscaling and basin's monthly temperature and precipitation calculation.

We simulated the temperature lapse rates and precipitation gradients with meteorological stations along with the south slope of Tianshan mountains (Baluntai, Yanqi, Korla, Luntai, Bayanbulak, Kuqa, Baicheng, Aksu, Kalpin, Akqi, Torugart, Kashgar and Wuqia) from 1980 to 2015 at first. The average monthly temperature t_i and average monthly precipitation p_i were calculated at first to reduce the impact of parameter error on downscaling.

Existing studies in Northwest China have shown that (Fu *et al.* 2013; Wang *et al.* 2018) the altitude h and temperature t have a linear relationship, while the altitude h and precipitation p have a quadratic polynomial relationship. So, a linear equation $t = mh + n$ and a quadratic polynomial equation $p = ah^2 + bh + c$ were fitted to downscale the reanalysed temperature and precipitation data. The parameters (i.e., m , n , a , b , c) were estimated with meteorological observations. The fitting effect was tested with R^2 (coefficient of determination) and F test. R^2 was calculated with the following equation:

$$R^2 = 1 - \frac{\sum_{i=1}^k (y_i - \hat{y}_i)^2}{\sum_{i=1}^k (y_i - \bar{y}_i)^2}, \quad (1)$$

where y_i , $\hat{y}_i$ and $\bar{y}_i$ are the observed, simulated and average values of meteorological time series, respectively, and k is the length of the meteorological observation series.

Then, we calculated the temperature lapse rate dt/dh and the precipitation gradient dp/dh by

calculating the derivative of fitting functions:

$$\frac{dt}{dh} = m, \quad (2)$$

$$\frac{dp}{dh} = 2ah + b. \quad (3)$$

With equations (4 and 5) and changing values of altitude between reanalysis data and SRTM data, the monthly reanalysis climate data was down-scaled. Firstly, based on the altitude of SRTM h_s and bilinear interpolation resampling method, the elevation of the reanalysis data h_r was calculated. To facilitate the matrix operation among different grid sizes, the reanalysis temperature data t_r , reanalysis precipitation data p_r and h_r were resampled to the grid size same as h_s by bilinear interpolation. Then the downscaled monthly temperature t_d and monthly precipitation p_d with the spatial resolution of 90 m at the elevation h_s were obtained by equations (6 and 7):

$$t_d = t_r + (h_s - h_r) \cdot \left(\frac{dt}{dh_s} + \frac{dt}{dh_r} \right) / 2, \quad (4)$$

$$p_d = p_r + (h_s - h_r) \cdot \left(\frac{dp}{dh_s} + \frac{dp}{dh_r} \right) / 2, \quad (5)$$

where $(h_s - h_r)$ is the change value of elevation, $((dt/dh_s) + (dt/dh_r))/2$ is the average temperature lapse rates between elevation h_s and h_r , $((dp/dh_s) + (dp/dh_r))/2$ is the average precipitation gradients between elevation h_s and h_r .

With equations (4 and 5), the downscaling equations are as follows:

$$t_d = t_r + (h_s - h_r) \cdot m, \quad (6)$$

$$p_d = p_r + (h_s - h_r) \cdot [a(h_s + h_r) + b]. \quad (7)$$

The downscaled time series at the meteorological station Bayanbulak were extracted by the nearest-neighbour method which means selecting the closest cell value from the meteorological station as the extracted value of this point. We measured the performance of the downscaling model by calculating Slope, NSE (Nash–Sutcliffe efficiency coefficient), MAE (mean absolute difference) and RMSE (root-mean-square error) between downscaled time series and observation series.

The basin temperature and precipitation for each month were calculated by the arithmetic average method. Then we can get the average basin

temperature and total basin precipitation each year. Mann–Kendall trend test, Pettitt's test, and Sen's slope were used to detect the trend and change point of the basin annual average temperature and annual total precipitation. Seasonal Mann–Kendall test, seasonal Mann–Kendall test with correlations and seasonal Sen's slope were used to detect the trend of basin's monthly temperature and precipitation.

2.3.2 Non-parametric trend test

The Mann–Kendall trend test, the seasonal Mann–Kendall test, seasonal Mann–Kendall test with correlations, the Sen's slope, the seasonal Sen's slope and Pettitt's test were used to detect linear trends in climate or hydrologic time series (Khaliq *et al.* 2009; Sonali and Kumar 2013). The use of multiple test methods can mutually verify the reliability of the test results.

The null hypothesis H_0 of the Mann–Kendall trend test (Mann 1945; Kendall 1948) assumes that the data comes from independent random variables and has the same distribution. The alternative hypothesis H_1 is that the data presents a monotonous trend. For the time series $X_t = (x_1, x_2, K, x_n)$, the statistic S of the Mann–Kendall test is calculated according to the following formula:

$$S = \sum_{i=1}^{n-1} \sum_{k=i+1}^n \text{sgn}(X_k - X_i), \quad (8)$$

where n represents the length of the sample data, X_i represents the i th data of the time series and sgn represents the symbolic function, which is defined as

$$\text{sgn}(\theta) = \begin{cases} 1, & \theta > 0, \\ 0, & \theta = 0, \\ -1, & \theta < 0. \end{cases} \quad (9)$$

For a set whose sample size is greater than or equal to 8, the statistic S is close to a normal distribution, its mean is 0 and the variance is

$$\begin{aligned} \text{Var}(s) &= \frac{n(n-1)(2n+5) - \sum_{i=1}^n t_i(i-1)(2i+5)}{18}, \quad (10) \end{aligned}$$

where t_i is the number of data in the i th group.

The standardised statistic Z_c is calculated as follows:

$$Z_c = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(s)}}, & S > 0, \\ 0, & S = 0, \\ \frac{S+1}{\sqrt{\text{Var}(s)}}, & S < 0, \end{cases} \quad (11)$$

where Z_c is a trend statistic. If Z_c is positive, it means that the tested series shows an increasing trend. If Z_c is negative, it means a decreasing trend. Zero hypothesis H_0 is that there is no significant change in the time series. If the absolute value of Z_c is greater than the statistical value corresponding to the 95% confidence level of 1.96, the null hypothesis is rejected, indicating that the sequence change trend is significant.

For the g th season, the Mann–Kendall test statistic S_g is calculated as follows:

$$S_g = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(X_{jg} - X_{ig}), \quad g = 1, 2, \dots, m. \quad (12)$$

According to the study of [Hirsch et al. \(1982\)](#), the statistics of the seasonal Mann–Kendall test for all seasons $\hat{S}$ is calculated by

$$\hat{S} = \sum_{g=1}^m S_g. \quad (13)$$

For more information on the seasonal Mann–Kendall test can be found in some related literature ([Hirsch et al. 1982](#); [Hipel and Mcleod 1994](#)). If the elements of the time series are related, the correlated seasonal Mann–Kendall test can be applied ([Hipel and Mcleod 1994](#)).

The Sen's slope test calculates the slope (i.e., the linear rate of change) using the Sen method. First, a set of linear slopes is calculated as follows:

$$d_k = \frac{X_j - X_i}{j - i}. \quad (14)$$

For $1 \leq i < j \leq n$, d is the slope, X is the variable, n is the length of the data, and i and j are subscripts.

Sen's slope is calculated by calculating the median of all slopes:

$$b = \text{Median } d_k. \quad (15)$$

A study by [Hirsch et al. \(1982\)](#) shows that the seasonal Sen's slope is calculated by

$$d_{ijk} = \frac{X_{ij} - X_{ik}}{j - k}. \quad (16)$$

For any number of pairs X_{ij} , X_{ik} , $i = 1, 2, \dots, m$, where $1 \leq k < j \leq n_i$, n_i is the number of values in the i th season. The estimate value of seasonal Sen's slope is the median d_{ijk} .

[Pettitt \(1979\)](#) proposed Pettitt's test, a mutation point detection method, which has been widely used for the detection of mutations in meteorological and hydrological time series. The null hypothesis H_0 of Pettitt's test is that the T variable follows the distribution of one or more of the same parameters. The alternative hypothesis is that there is a point of mutation. Non-parametric test statistics are defined as

$$K_T = \max |U_{t,T}|, \quad (17)$$

where

$$U_{t,T} = \sum_{i=1}^t \sum_{j=t+1}^T \text{sgn}(X_i - X_j). \quad (18)$$

The mutation point in the time series is at K_T and the significance level is calculated by the following formula:

$$p \cong 2 \exp \left(\frac{-6K_T^2}{T^3 + T^2} \right). \quad (19)$$

2.3.3 Ensemble empirical mode decomposition

EEMD is a new signal detection method which overcomes the scale-mixing problem and is an improvement of the EMD method ([Huang et al. 1998](#)). We use the EEMD method to decompose temperature, precipitation and streamflow, calculate the intrinsic mode function (IMF) components and reconstruct them to obtain the characteristics on different time scales. We can analyse the relationship among the temperature, precipitation and streamflow on different time scales. The EEMD method decomposes a time series $x(t)$ into adaptively obtained, amplitude–frequency modulated oscillatory components C_i ($i = 1, 2, \dots, n$) ([Wu and Huang 2009](#)) and extracts a residual R_n , a curve either monotonic or containing only one extremum from which no additional oscillatory

components:

$$x(t) = \sum_{i=1}^n C_i(t) + R_n(t). \quad (20)$$

As demonstrated in the previous studies (Qian *et al.* 2011; Qian and Zhou 2014; Bai *et al.* 2015), the extracted trend (R_n) follows no a priori shape and varies with time after the intrinsic variability of multi-decadal and shorter timescales is removed. Unlike traditional methods, EEMD does not need to specify a priori basis function. It adopts natural waveforms (Feng *et al.* 2014) to guarantee the physical interpretation within specified time intervals and does not change with the addition of new data (Ji *et al.* 2014).

The energy distribution was examined to determine the scales of IMF components. The energy density of the i th IMF components (E_i) was defined as equation (11):

$$E_i = \frac{1}{N} \sum_{j=1}^N |I_i(j)|^2, \quad (21)$$

where N is the length of the IMF component and $I_i(j)$ denotes the i th IMF component. The white noise sequence is tested by the Monte Carlo method (Wu and Huang 2004); then, a simple equation that relates the energy density ($\bar{E}_l$) and the averaged period ($\bar{T}_l$) is obtained:

$$\lg \bar{E}_l + \lg (\bar{T}_l)_a = 0. \quad (22)$$

With $\lg(\bar{T}_l)_a$ and $\lg \bar{E}_l$ as X -axis and Y -axis, the relationship between the averaged period and the energy density was linear and the slope of the fitting line was -1 . In theory, the IMF component of the white noise series should distribute on the line, while deviation exists in actual application. So the confidence interval for the energy spectrum distribution of white noise was calculated as follows:

$$\lg \bar{E}_l = -\lg(\bar{T}_l)_a \pm a\sqrt{2/N}e^{\lg[(\bar{T}_l)_a/2]}, \quad (23)$$

where a is the significance level.

The standard deviation of white noise is used to eliminate the noise in the original signal. It is determined by the noise interference in the original signal. The standard deviation of Gaussian white noise is generally set to 0.01–0.4 which is determined based on the signal; the ensemble number is used to set the number of times the noise is added, which usually takes 50 or 100. In this research, with

downscaled meteorological data and hydrological series in a mountain basin, the climate and stream-flow variability in different scales were abstracted with the EEMD method. In the EEMD method, the ensemble number was set as 100 and added white noise was set to 0.2 times of standard deviation (Feng *et al.* 2012). Also, the decomposed IMFs have been tested for the significance. To reduce the impact of edge effects in EEMD decomposition, mirror-symmetric extension (Huang and Shen 2005) was adopted to pre-process the input time series.

2.3.4 Backpropagation artificial neural network

BPANN was constructed to simulate the nonlinear relationship of streamflow driven by climate change with the downscaled temperature and precipitation series. BPANN is a useful tool to simulate the complex climate and hydrological relationships (Xu *et al.* 2013, 2016; Loukas and Vasiliades 2014). In this research, we constructed a network that contained two nodes in the input layer, 5×5 nodes in the hidden layers and one node in the output layer (figure 3). In the network, t_m and p_m were the input time series, s_m was the target time series to train the network, w_{ij} was the weight from the i th node in the input layer to the j th node in the hidden layer, w_{jk} was the weight from the j th node in the hidden layer 1 to the k th node in the hidden layer 2, and w_{kl} was the weight from the k th node in the hidden layer to the l th node in the output layer.

Figure 3. Input layer, hidden layer, an output layer, nodes and weights of the BPANN.

The nodes in the same layer did not connect to each other and just connected to the node in the next layer. In training, the information was transmitted forward and the error was propagated back. In total, 70% of the input and target series was selected as the training group, 15% were selected as the calibration group, and 15% were selected as the validation group. The information from one layer to another was transmitted by an activation function. This study chose the sigmoid function as the activation function. If the simulated series does not equal to the observed sequence, the error would be backpropagated. The connection weights were optimised by gradient descent algorithm with the backpropagated error from the output nodes to the input node. The Levenberg–Marquardt algorithm was used to accelerate the convergence. The neural network with the minimum square error was selected as the optimal fitting result of one BPANN fitting after 1000 pieces of training.

To reduce the impact of the initial randomised parameters in training, we trained the BPANN many times. Then the mean of the simulated streamflow was calculated as the final output. In this research, the mean value of the outputs was relatively stable after 10 fittings after testing. The Slope, R^2 , MAE and RMSE were calculated to test the performance of BPANN.

2.3.5 Impact of climate change on streamflow

BPANN could fit the non-linear relationship with high precision, while its ability to explain the relationship among variables remains to be explored further. Therefore, an improved weight connection method was used based on previous research studies (Olden and Jackson 2002; Olden *et al.* 2004; Fischer 2015; Wang *et al.* 2018) to evaluate the impact of climate change on streamflow quantitatively. We obtain the total weight by adding the absolute value of the positive weights and the negative weights avoiding the offsetting of the weights.

Firstly, we calculated the cumulative weight from the input layer to the output layer as follows:

$$w_{io} = \begin{bmatrix} w_{ts} \\ w_{ps} \end{bmatrix} = w_{ih_1} \times w_{h_1 h_2} \times w_{h_2 o}, \quad (24)$$

where w_{io} is the cumulative weight matrix from the input layer to the output layer, w_{ts} is the cumulative weight matrix from temperature to streamflow, w_{ps} is the cumulative weight matrix from precipitation to streamflow, w_{ih_1} is the weight matrix (2×5) between the input layer and the hidden layer 1, $w_{h_1 h_2}$ is the weight matrix (5×5) between the hidden layer 1 and the hidden layer 2, $w_{h_2 o}$ is the weight matrix (5×1) between the hidden layer 2 and the output layer,

The impact could be calculated as equations (15 and 16):

$$C_{ts} = \frac{|w_{ts}|}{|w_{ts}| + |w_{ps}|} \times 100\%, \quad (25)$$

$$C_{ps} = \frac{|w_{ps}|}{|w_{ts}| + |w_{ps}|} \times 100\%, \quad (26)$$

where C_{ts} is the impact of temperature variability on streamflow and C_{ps} is the impact of precipitation variability on streamflow.

3. Results and discussion

3.1 Downscaling verification

To provide parameters for the downscaling method, we first fitted functions between the meteorological factors and altitude (table 1). Based on limited observed data, the temperature and altitude have a strong linear relationship ($R^2 = 0.77$) which is significant ($F = 678.7, a = 0.001$). It can be seen from the slope of a linear function that when the altitude increases 1000 m, the temperature drops 6.3°C. The precipitation and altitude have a strong quadratic polynomial relationship ($R^2 = 0.799$) which is significant ($F = 179.4, a = 0.001$). With increasing of the altitude, the precipitation increases first and then decreases at about 3000 m which is consistent with the study in the Tianshan mountains (Chen *et al.* 2013).

Table 1. Functional relationship between the temperature and precipitation changes with altitude.

N	Temperature			Precipitation		
	Function	R^2	F	Function	R^2	F
468	$t = -0.0063 \times h + 17.847$	0.77	678.7*	$p = -5 \times 10^{-5} \times h^2 + 0.3089 \times h - 189.09$	0.66	179.4*

Note: F test indicates the significance of the functions. *Indicates the significance of $a = 0.001$.

With the verified parameters, we downscaled the reanalysed temperature and precipitation data and then reconstruct the mountainous high-resolution climate distribution data. The downscaled temperature and precipitation are consistent with the observed values in the Bayanbulak meteorological station (figure 4). The slope of trend line between the observed and downscaled scatter plots is close to 1, which represents the high fitting accuracy of downscaled data to the observed data. The R^2 of the trend line is also close to 1. Above all, the downscaling method can reconstruct the climate change in the data-scarce mountain basins.

3.2 Climate and streamflow variability and multi-scale features

The descriptive statistics and trend test of average annual temperature, annual precipitation and

annual streamflow are shown in table 2. The average annual temperature from 1980 to 2015 shows an increasing trend ($Z = 1.87$) at a rate of 0.3°C per decade by using the Mann–Kendall trend test. The annual precipitation shows a significant increasing trend ($Z = 1.98, a = 0.05$) at the rate of 16.4 mm per decade. The annual streamflow increases significantly ($Z = 2.71, a = 0.01$) at a rate of $2.5 \times 10^8 \text{ m}^3$ per decade with the rising temperature and precipitation. The Sen's slope is consistent with the linear slope and also shows the increasing trend of temperature, precipitation and streamflow. The Pettitt's test detects mutation year of temperature, precipitation and streamflow in 1997 ($a = 0.02$), 1994 ($a = 0.05$) and 2000 ($a = 0.001$).

The seasonal Mann–Kendall test (table 3) shows that the monthly temperature, precipitation and

Figure 4. Scatter plot and trend line of the downscaled and observed monthly temperature and precipitation series in the verification station.

Table 2. Descriptive statistics and trend test of the annual temperature, precipitation and streamflow from 1980 to 2015.

Factors	Descriptive statistics					Mann–Kendall trend test	Pettitt's test		Sen's slope
	N	Mean	SD	CV	Slope	Z	p	Mutation year	
Temperature ($^\circ\text{C}$)	36	−8.79	0.84	0.10	0.03	1.87	0.02	1997	0.03
Precipitation (mm)	36	336.23	48.45	0.14	1.64	1.98*	0.05	1994	1.85
Streamflow (10^8 m^3)	36	36.14	6.68	0.18	0.25	2.71**	0.001	2000	0.26

Note: *Indicates the significance of $a = 0.05$. **Indicates the significance of $a = 0.01$.

Table 3. Seasonal Mann–Kendall test of the monthly temperature, precipitation and streamflow from 1980 to 2015.

Factors	N	Seasonal Mann–Kendall test	Seasonal Mann–Kendall test with correlations	Seasonal Sen's slope
		Z	Z	
Temperature ($^\circ\text{C}$)	432	2.6**	2.2*	0.03
Precipitation (mm)	432	1.0	0.9	0.01
Streamflow ($\text{m}^3 \text{ s}^{-1}$)	432	3.9***	1.5	0.41

Note: *Indicates the significance of $a = 0.05$. **Indicates the significance of $a = 0.01$. ***Indicates the significance of $a = 0.001$.

streamflow are all increasing ($Z > 0$; slope > 0). The increasing trends of temperature and streamflow are both significant ($\alpha = 0.01$; $\alpha = 0.001$). The Kaidu River basin has become warmer and wetter in the recent 40 yr, which confirms Xu's *et al* (2008) research. The increasing streamflow indicates the positive trends in recycling ratio with global warming trends (Dirmeyer and Brubaker 2006).

The average and the slope of the downscaled grid annual temperature before and after the mutation year show the spatial and temporal variability of temperature (figure 5). The spatial distributions of temperature are consistent before and after the mutation year. The temperature in valleys is generally above 0°C while in mountainous areas it is usually below 0°C . However, the trends of temperature are different before and after the mutation year. From 1980 to 1997, the temperature is continuously rising. The rising trend is high in some northeast mountains. From 1998 to 2015, the temperature decreases. During the 36 years from 1980 to 2015, the temperature increases slowly.

The average and the slope of downscaled grid annual precipitation before and after the mutation

year show the spatial and temporal variability of precipitation (figure 6). The precipitation decreases from the west and north to the middle and south in all the periods. The precipitation is the most abundant in the west and north mountains and the least in the southern valleys and mountains. However, the precipitation trends are different before and after the mutation year. From 1980 to 1994, the trend of precipitation rises from west to east. From 1995 to 2015, the precipitation in the whole basin reduces. From 1980 to 2015, the precipitation is increasing, and the trend in the eastern basin is higher than the west basin.

The EEMD method was used to decompose downscaled climate and streamflow series in the Kaidu River basin from 1980 to 2015. Figure 7 shows IMF components of temperature (a), precipitation (b) and streamflow (c). For each time series, seven IMF components and one RES component (trend) were calculated. IMF components at different frequencies indicate the fluctuation characteristics at corresponding time scales, and the RES component shows the tendency of the original time series. The physical meaning of IMF components is the oscillation at different scales

Figure 5. (a) Shows the average annual temperature from 1980 to 1997; (b) shows the average annual temperature from 1998 to 2015; (c) shows the average annual temperature from 1980 to 2015; (d) shows the slope of annual temperature from 1980 to 1997; (e) shows the slope of annual temperature from 1998 to 2015; and (f) shows the slope of annual temperature from 1980 to 2015.

Figure 6. (a) Shows the average annual precipitation from 1980 to 1994; (b) shows the average annual precipitation from 1995 to 2015; (c) shows the average annual precipitation from 1980 to 2015; (d) shows the slope of annual precipitation from 1980 to 1994; (e) shows the slope of annual precipitation from 1995 to 2015; (f) shows the slope of annual precipitation from 1980 to 2015.

in the original time series. The significance test and confidence levels can indicate oscillation intensity.

It shows that the IMF1 and IMF2 of monthly temperature series, the IMF1, IMF2 and IMF3 of monthly precipitation series and all the IMF components of monthly streamflow series fell above 95% confidence level (figure 8). The significance tests indicate that these IMF components contain more oscillation information and have more actual physical meaning.

Table 4 shows the variance contribution rate of IMF components on the original series. It can be found that the contribution of the 3-month cycle (IMF1) towards temperature, precipitation and streamflow variance is largest, reaching 67.63%, 35.24%, and 57.09%, respectively. The variance contribution of RES component can be up to 31.32%, 49.57% and 29.13%. So, the increasing trend of temperature and the first increasing

and then decreasing trend of precipitation and streamflow are all significant.

Figure 9 shows the inter-seasonal, inter-annual, inter-decadal variations and the trend of the temperature, precipitation and streamflow series. IMF1 reconstructs the inter-seasonal sequence of temperature and streamflow. IMF1 and IMF2 reconstruct the inter-seasonal sequence of precipitation. Summation of IMF2, IMF3, IMF4 and IMF5 reconstructs the inter-annual set of temperature and streamflow. Summation of IMF3, IMF4 and IMF5 reconstructs the inter-annual set of precipitation. Summation of IMF6 and IMF7 reconstructs the inter-annual sequence of temperature, precipitation and streamflow. From table 4 and figure 9, it can be found that the reconstructed inter-seasonal variation and inter-annual variation are the significant fluctuations of the original monthly climate and streamflow series. Inter-decadal variability is a complicated and long-term process. It can be found

Figure 7. IMF components of temperature (a), precipitation (b) and streamflow (c) by the EEMD method.

Figure 8. Significance test for the IMFs of temperature (a), precipitation (b), and streamflow (c) during the period of 1980–2015.

Table 4. Contribution rates of EEMD decomposition for temperature anomaly, precipitation anomaly and streamflow anomaly.

IMF components	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	RES
Period (month)								
Temperature	3	12	22	48	100	246	435	
Precipitation	3	9	12	28	62	123	282	
Streamflow	3	12	14	33	72	188	242	
Contribution (%)								
Temperature	67.63	0.23	0.12	0.10	0.12	0.06	0.41	31.32
Precipitation	35.24	12.12	1.33	0.66	0.30	0.17	0.61	49.57
Streamflow	57.09	6.66	1.75	1.10	1.10	1.26	1.90	29.13

that the streamflow is affected by both temperature and precipitation. The streamflow fluctuates from 1980 to 2015. According to the last decadal fluctuation, the streamflow in the Kaidu River will present an apparent increasing trend over the next decade with the increasing temperature. By comparing the trend series, with the rising temperature, the streamflow presents a firstly increasing and then decreasing trend and is consistent with the precipitation trend. The increasing streamflow in the next decade may be due to an increase in temperature and snowmelt water. However, in the long term, rising temperatures may lead to reduced winter snowfall. If the precipitation reduces in the future, streamflow will decrease as the combined effects of temperature and precipitation.

3.3 Impact of temperature and precipitation on streamflow

With the downscaled monthly climate data, the BPANN simulates the monthly streamflow

(figure 10). As a river supplied by precipitation and snow meltwater, the maximum of streamflow occurs in summer with large inter-annual change and the minimum of streamflow appears in winter with stable inter-annual change. The BPANN-simulated streamflow can show the non-linear variation of monthly streamflow and need to be improved to simulate the maximum of streamflow. Table 5 shows the performance of BPANN. The slope is near 1 and shows that the simulated and observed streamflow is consistent. The NSE is close to 1 illustrating that the BPANN we contrasted can simulate the streamflow in the mountainous basins well. Compared to observed streamflow, the MAE and the RMSE are relatively small which indicate simulation results are of high precision. The impact of the temperature and precipitation on the streamflow is $44.21 \pm 2.08\%$ and $55.79 \pm 2.08\%$ in the Kaidu basin.

In summary, the BPANN model can well simulate the complex and nonlinear relationship between the monthly meteorological series and streamflow. The integrated approach with good

Figure 9. Inter-seasonal, inter-annual, inter-decadal variations and trend of temperature (a), precipitation (b), and streamflow (c).

Figure 10. Monthly observed and BPANN-simulated streamflows during 1980–2015.

Table 5. Performance of BPANN and the contribution of climate change on streamflow.

Rivers	Accuracy test					Contribution (%)	
	N	Slope	NSE	MAE	RMSE	Temperature	Precipitation
Kaidu River	432	0.81	0.83	19.70	28.07	44.21 ± 2.08	55.79 ± 2.08

performance guarantees the realisation of the weight connection method to quantitatively assess the impact of climate change on streamflow.

4. Conclusions

To simulate the climate-driven streamflow and assess the impact of climate change to streamflow in data-scarce mountain basins of Northwest China, we developed an integrated approach by downscaling reanalysis data and multi-methods. It has been proved that the approach presents a good performance, which can be used to simulate the climate-driven streamflow and assess the impact of climate change to streamflow in data-scarce mountain basins in Northwest China. Using the approach to investigate the Kaidu River basin in the Tianshan mountains of Northwest China, we obtained the following results: (i) the average annual temperature increased 5.2% by 0.3°C per decade and the precipitation increased 37.3% by 16.4 mm per decade during the period from 1980 to 2015. (ii) With the warming and wetting climate, the streamflow increased 12.9% by $2.5 \times 10^8 \text{ m}^3$ per decade in the Kaidu River basin. (iii) The impact of the temperature and precipitation to streamflow is $44.21 \pm 2.08\%$ and $55.79 \pm 2.08\%$.

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