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Reconstructing meteorological time series to quantify the uncertainties of runoff simulation in the ungauged Qira River Basin using data from multiple stations

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Abstract The existence and development of oases in arid plain areas depends mainly on the runoff generated from alpine regions. Quantifying the uncertainties of runoff simulation under climatic change is crucial for better utilization of water resources and management of oases in arid areas. In the present study, based on the ungauged Qira River Basin in Xinjiang, China, a modified version of the Delta statistical downscaling method was applied to reconstruct the monthly mean temperature (MMT), monthly accumulated precipitation (MAP), and monthly accumulated evaporation (MAE) of two target stations. Then, the uncertainty in runoff simulation, implemented using the Three-Layered Feedforward Neural Network model with the Back-Propagation learning algorithm, was quantified. The modified Delta method reproduced the MMT, MAP, and MAE time series of the two target stations very well during the calibrated periods, and the reconstructed uncertainty ranges were small among reconstructed datasets using data from 12 observation stations. The monthly accumulated runoff simulated by the reconstructed MMT, MAP, and MAE as input variables of the model possessed unpredictable uncertainty. Although the use of multi-data ensembles in model inputs are considered an effective way to minimize uncertainties, it could be concluded that, in this case, the efficiency of such an approach was limited because of errors in the meteorological data and the deficiency of the model's structure. The uncertainty range in the runoff peak was unable to capture the actual monthly runoff. Nevertheless, this study represents a significant attempt to reproduce historical meteorological data and to evaluate the uncertainties in runoff simulation through multiple input ensembles in an ungauged basin. It can be used as reference meteorological data for researching long-term climate change and producing runoff forecasts for assessing the risk of droughts and/or floods, as well as the existence and management of plain oases in the Qira River Basin.

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1 Introduction

Water resources are crucial for both social and economic sustainable development in all parts of the world, but especially in semiarid and arid regions, whose vulnerable environments and ecology suffer a more severe threat due to the scarcity and unreasonable utilization of water resources (Boehmer et al. 2000; Meng et al. 2009; Ling et al. 2011; Chen 2014). Xinjiang, in Northwest China, as one of the world's largest arid areas, is characterized by seriously fragile water resources and associated eco-environmental challenges (Chen 2014). Over the last few decades, intensive exploitation of water resources, mainly from agricultural activities, especially oases expansion, has changed the temporal and spatial distribution of water resources and led to serious environmental problems.

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In particular, the southern rim of the Tarim Basin in Xinjiang has become a significant challenge for addressing water allocation. The region is highly complex due to its climatic conditions with low precipitation and very high evaporation rates and extremely limited water resources.

The Qira River Basin, a typical inland river watershed in the southern rim of the Tarim Basin, is characterized by a mountain–oasis–desert ecosystem, owing to its different climatic characteristics. The tops of the mountains form the glacier/snowpack area, grassland and shrubland are the main feature at middle altitudes, and oases are found at the mountain foot. Then, adjoining the oases are the desert plain areas (Wu et al. 2011, 2013). In recent years, with increasing industrialization, agricultural irrigation, and, especially, the water needs of oasis extension for combating desertification in the Qira River Basin, the river runoff has gradually decreased in the downstream part of the Qira River. The state of the eco-environmental system has worsened severely (Dai et al. 2009a, b). The government has appealed to the people in Qira County to save water resources through adopting the dripping irrigation technique; however, most of the people prefer to employ flooding irrigation for agricultural irrigation and oasis supply, causing quite a large depletion of the water resource. More worryingly, the unreasonable utilization of water resources in this severely water-deficient basin has led to multiple dry-out episodes in the lower reaches of the Qira River. The Qira oasis, the center of the region's human population, is facing an ever more severe threat, without a stable water supply. These problems can also be found in other basins in the southern rim of the Tarim Basin and even further afield across the whole of Xinjiang.

Climate forcing plays a crucial role in integrated assessments of water resources, as well as in the simulation of hydrological and environmental processes in state-of-the-art models (Ninyerola et al. 2000; Jeffrey et al. 2001; Li et al. 2013). Although the structure of models can be modified depending on data availability, a representatively complete dataset within the research region is a basic requirement (Skirvin et al. 2003; Marquinez et al. 2003; Li et al. 2013). Meteorological data in hydrological models is essential for efficiently simulating and predicting various hydrological and environmental dynamic processes. However, because of difficulties in making observations in high mountain areas, as well as the paucity of meteorological gauge sites, a great challenge exists for hydrological modeling and runoff prediction within ungauged basins in the mountain–basin systems of the world's arid and semiarid regions (Murugesu 2003; Sivapalan et al. 2003; Nataliya et al. 2005). One such region is Northwest China, in which the observed meteorological and/or hydrological data in the majority of its alpine watersheds are insufficient or, in some cases, completely absent (i.e., ungauged) (Huang et al. 2009; Jin et al. 2009). The Qira River Basin is an example of a poorly gauged basin. The resultant data shortages from such basins limit the possibility of a deep understanding of long-term climate variation and its influence on water resources and agro-/ecological environments.

Runoff formation is a complicated meteorological–hydrological process and, as with most river basins, reliable runoff prediction in the Qira River Basin could provide important information for water resources use and oases management, including industrial and agricultural utilization and, especially, choosing a suitable scale for the expansion of oases. Unfortunately, long-term meteorological data in the Qira River Basin are scarce. Indeed, only short-term observational time series (6-year period) at Kartash (2,800 m above sea level), located in the upstream region of the Qira River, were used by Osamu and Wang (2004) to investigate the local meteorological characteristics. In fact, there is only one meteorological station, at Qira, situated among the hydrological stations in the lower reaches of the Qira River Basin, that can provide long-term time series.

To obtain reliable meteorological data, many previous studies have reconstructed local climatic parameters by using relevant reference data, such as ice cores, tree rings, spore pollen, fossil pollen, and isotopes (Shen et al. 2001; Esper et al. 2002; Fang et al. 2011; Li et al. 2013). However, few attempts have been made to reconstruct long-term time series by applying the data of adjoining areas or similar environmental conditions. In Xinjiang, due to the consistent climate of the northern slope of the Kunlun Mountains, an opportunity existed to attempt to use the available data to reproduce historical meteorological data for the Qira River Basin based on correlation theory. The subsequent reconstructed meteorological data could then be used as the input data for the chosen hydrological model to simulate the runoff of the basin.

However, there are considerable uncertainties involved in reconstructing climatic parameters such as temperature, precipitation, and evaporation (Li et al. 2013; Cleridou et al. 2014) and modeling catchment runoff—the latter largely related to model structure and parameter calibration (Krzysztofowic 1999; Cleridou et al. 2014). Since the upstream catchment of the Qira River Basin above the gauging station is not inhabited, the runoff observed in the basin is basically the natural amount of runoff controlled by climatic factors rather than human disturbance. Assuming that the underlying surface is largely unchanged, the errors in runoff simulation would derive mainly from the biases between the observations and the corresponding reconstructed meteorological data and any deficiencies in the model's structure.

In the present study, based on data from 12 stations on the northern slope of the Kunlun Mountains, an attempt was made to apply a modified version of the statistical downscaling Delta method to reconstruct the short-term meteorological time series at two stations in the Qira River Basin, and to reproduce the long-term monthly mean temperature (MMT), monthly accumulated precipitation (MAP), and monthly accumulated evaporation (MAE) time series from 1961 to 2010. To simulate the hydrometeorological characteristics of the

Qira River Basin, the Three-Layered Feedforward Neural Network model with the Back-Propagation learning algorithm (TL-FNN-BP) was run with reconstructed and observed MMT, MAP, MAE, and monthly accumulated runoff (MAR) data during 1961–2010. In addition, the uncertainties of the reconstructed meteorological time series, and of the runoff simulation, were quantified and analyzed. The ultimate aim of the work was to provide useful supporting data for the study of long-term climate variation, for assessments of sustainable water resources use, and in the management of oases in the Qira River Basin.

2 Materials and methods

2.1 Research area and data

The Qira River Basin is situated on the northern slope of the Kunlun Mountains in Xinjiang, China (36° 02′ N–37° 16′ N, 80° 07′ E–81° 00′ E) and covers a basin area of approximately 3,328.51 km^2 (Fig. 1). The Qira River, which originates in the high-altitude valley of the Kunlun Mountains, flows through the plain oasis, and finally discharges into the desert, is approximately 136.2-km long. Surface runoff is mainly generated by glacier- and/or snow-melt, as well as rainfall, in the high altitudes of the mountains (Dai et al. 2009a, b). This is because the precipitation there, which exists as snowfall, is temporarily stored as snow pack and/or ice cover, while precipitation over oasis and desert zones is unable to form effective streamflow. The mountains have abundant precipitation, and the temperature in these regions is very low. However, the plain areas are quite hot and dry (Wu et al. 2011, 2013).

The availability of meteorological data in the basin is very poor, and there is only one long-term meteorological station in Qira County, which is located in the downstream region of the river (1,337 m above sea level). However, there are two short-term meteorological stations at Kartash (2,800 m above sea level) and Qira (1,318.6 above sea level), which provide only 5- and 8-year time series, respectively. Fortunately, long-term runoff data are available from a hydrological station (1,557 m above sea level), which is 27 km from the mountainous region. Therefore, to reconstruct long-term time series of meteorological parameters at Kartash and Qira stations, this study, based on climatic similarity, used the MMT, MAP, and MAE from 1961 to 2010 at 12 meteorological stations. Information on all of the meteorological stations and the hydrological station is listed in Table 1. Before using the data, some outliers and abnormal values were deleted and substituted using interpolation, such that a complete and reliable data source would be available.

2.2 Methods

2.2.1 Reconstructing the meteorological data: the modified Delta approach

Statistical downscaling approaches are generally applied to estimate point-scale meteorological parameters (such as temperature and precipitation) by transforming large-scale climate scenarios of general circulation models to local- and/or regional-scale variables. These methods require a wide variety of transfer functions and available data (Wilby et al. 1999; Hay et al. 2000; Tripathi et al. 2006). The Delta method is a relatively popular and straightforward downscaling approach that is more efficient and can more easily deal with large samples of data in comparison with other methods. Indeed, the method has already been extended to reconstruct climatic variables and has drawn some satisfying conclusions (Li et al. 2013). From the statistical perspective, the baseline time series for the region or site of interest typically needs a long-term average of variables, such as 30 years or more. In fact, according to the law of large numbers, the mean of large samples converges to the expectation of the population distribution. However, the Delta method is unadaptable and defective for limited samples or smaller samples. Fortunately, the Bayesian paradigm provides an optimal method for updating a person's beliefs about a parameter of interest given new information. The updated parameter distribution (i.e., the posterior distribution) is a very useful means of providing robust estimation and inference for cases in which the sample size is very small (Hoff 2009).

Supposing the time series $X_1, X_2, \cdots X_n$ are independent and identically distributed, and follow normal distribution with mean θ and variance $\sigma^2>0$, the joint sampling density (likelihood function) is expressed by

$$p\left(x_1, x_2, \cdots x_n \middle| \theta, \sigma^2\right) = \prod_{i=1}^{n} p\left(x_i \middle| \theta, \sigma^2\right)$$

$$= \left(2\pi\sigma^2\right)^{-n/2} \exp\left\{-\frac{1}{2}\sum_{i=1}^{n}\left(\frac{x_i-\theta}{\sigma}\right)^2\right\}. \tag{1}$$

If the prior parameter θ follows a normal distribution ($\theta \sim N(\mu_0, \tau_0^2)$), then the posterior distribution also obeys the normal distribution $p(\theta | x_1, x_2, \cdots, x_n, \sigma^2) \sim N(\mu_n, \tau_n^2)$ given $\sigma^2>0$, where $\mu_n = \frac{\mu_0/\tau_0^2 + n\bar{x}/\sigma^2}{1/\tau_0^2 + n/\sigma^2}$ and $\tau_n^2 = \frac{1}{1/\tau_0^2 + n/\sigma^2}$. According to existing short-term meteorological data, the population mean θ can be estimated and inferred. The hyper-parameters of the normal prior distribution are set to $\mu_0 = \bar{x} + s/2$ and $\tau_0 = \mu_0/2$ (for any normal distribution, most of the probability lies between two standard deviations of the mean, i.e., $\mu_0 - 2\tau_0 \geq 0$ or, equivalently, $\tau_0 \leq \mu_0/2$ (Grogan and Wirth 1981; Hoff 2009).

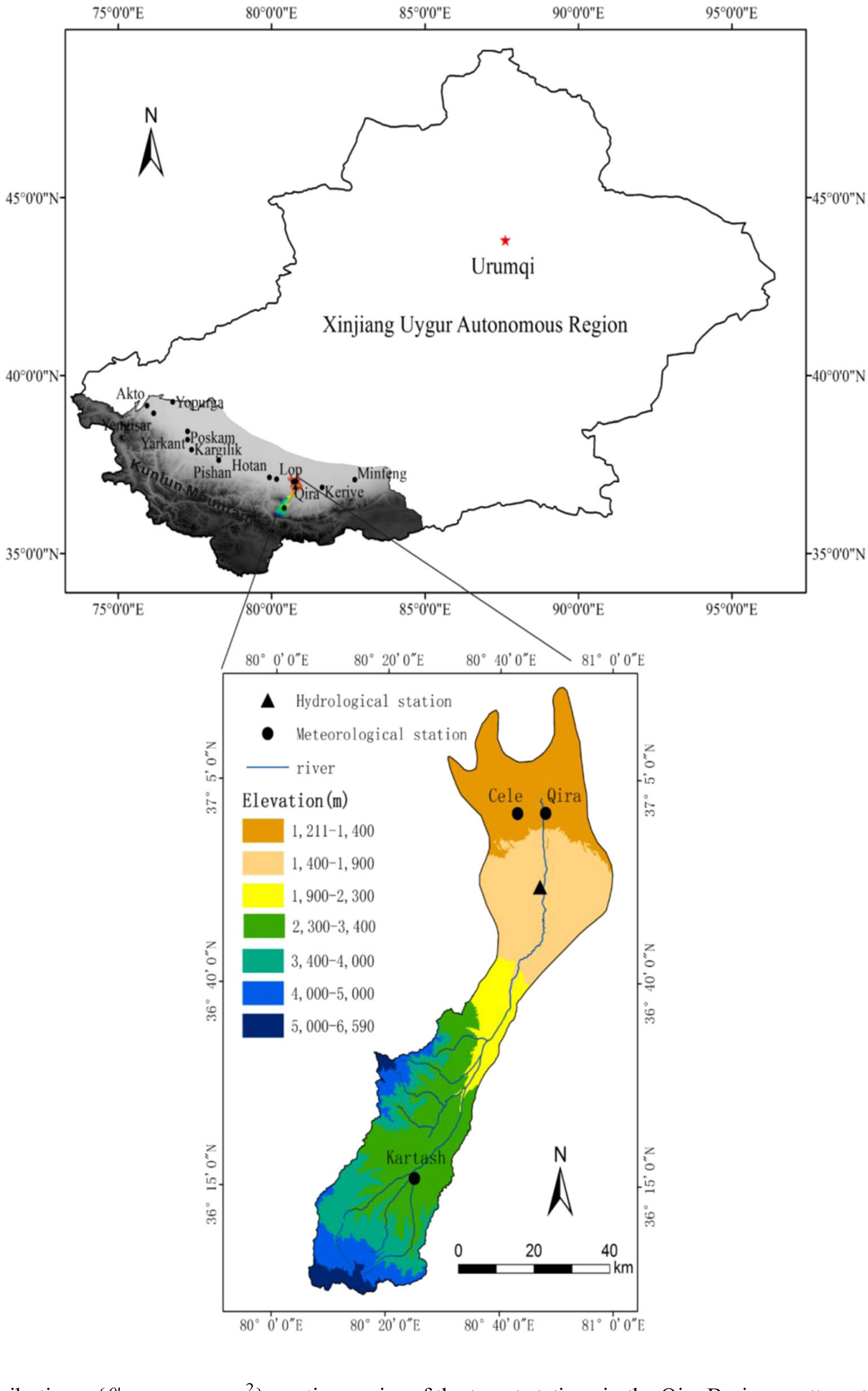

Fig. 1 Location and topography of the study area

Given σ^2=s^2, the posterior distribution $p\{\theta|x_1,x_2,\cdots,x_n,\sigma^2\}$ then follows the normal distribution, with mean $\mu_n = \frac{\mu_0/\tau_0^2+n\overline{x}/\sigma^2}{1/\tau_0^2+n/\sigma^2}$ and variance $\tau_n^2 = \frac{1}{1/\tau_0^2+n/\sigma^2}$.

The Delta method has been described at length in previous studies (Li et al. 2013). Due to the short-term meteorological time series of the target stations in the Qira Basin, an attempt was made in the present study to reconstruct meteorological parameters by modifying the Delta method. The detailed formula is given by

$$T(x,i) = \hat{\theta}_{n,T} + \left(Tr(y,i) - \hat{\upsilon}_{n,T}\right), \tag{2}$$

Table 1 Information on the meteorological stations (the two target stations are highlighted using bold font), and the hydrological station, used in this study

Station type	Name	Coordinates		Elevation (m)	Period of data availability
		Latitude	Longitude		
Meteorological	Yopurga	76° 47′	39° 15′	1,208	1961–2010
	Poskam	77° 16′	38° 12′	1,275	1961–2010
	Yengisar	76° 10′	38° 56′	1,299	1961–2010
	Qira	80° 48′	37° 01′	1,337	1961–2010
	Lop	80° 10′	37° 05′	1,349	1961–2010
	Kargilik	77° 24′	37° 55′	1,360	1961–2010
	Yarkant	77° 16′	38° 26′	1,232	1961–2010
	Akto	75° 57′	39° 09′	1,325	1961–2010
	Hotan	79° 56′	37° 08′	1,375	1961–2010
	Pishan	78° 17′	37° 37′	1,376	1961–2010
	Minfeng	82° 43′	37° 04′	1,411	1961–2010
	Keriye	81° 39′	36° 51′	1,423	1961–2010
	Kartash	80° 25′	36° 16′	2,800	1992–1996
	Cele	80° 44′	37° 01′	1,319	2005–2010
Hydrological	–	80° 48′	36° 52′	1,557	1961–2008

$$P(x,i) = Pr(y,i) \times \left(\hat{\theta}_{n,P}/\hat{\upsilon}_{n,P}\right), \tag{3}$$

$$E(x,i) = \hat{\theta}_{n,E} + \left(Er(y,i) - \hat{\upsilon}_{n,E}\right), \tag{4}$$

where i refers to the month (i=1, 2,$\cdots$, 12); $T(x, i)$,$P(x, i)$ and $E(x,i)$ are the reconstructed mean temperature, accumulated precipitation, and evaporation at the target station x in the ith month during the reconstruction period, respectively; $Tr(x, i)$, $Pr(x, i)$ and $Er(x,i)$ are the mean temperature, accumulated precipitation, and evaporation at the reference station y in

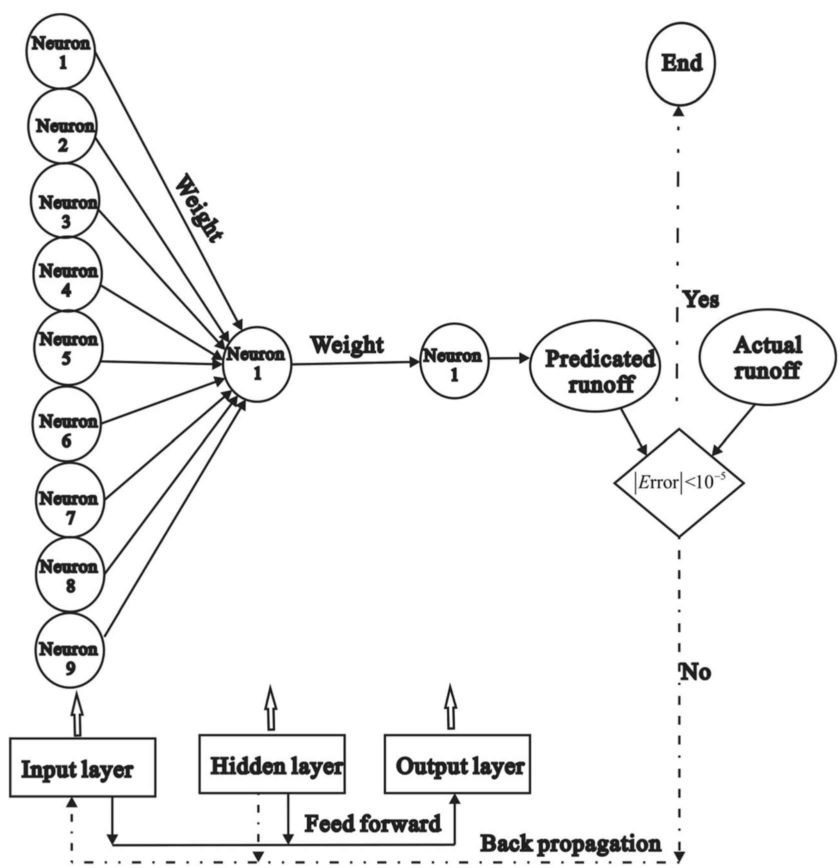

Fig. 2 Schematic diagram of the TL-FNN-BP model with structure (9,1,1)

Table 2 Range of performance rating (adapted from Moriasi et al. 2007; Li et al. 2013)

NSCE	%PBIAS		Grade	Performance rating
	MAT, MAP, MAE	MAR		
(0.75, 1.00]	(−15, 15]	(−10, 10]	A	Very good
(0.65, 0.75]	(−20, −15] ∪ (15, 20]	(−15, −10] ∪ (10, 15]	B	Good
(0.50, 0.65]	(−30, −20] ∪ (20, 30]	(−25, −15] ∪ (15, 25]	C	Satisfactory
(−∞, 0.50]	(−∞, −30] ∪ [30, +∞)	(−∞, −25] ∪ [25, +∞)	D	Unsatisfactory

the ith month during the reconstruction period, respectively; $\hat{\theta}_{n,T}$, $\hat{\theta}_{n,P}$ and $\hat{\theta}_{n,E}$ are the posterior means of temperature, precipitation, and evaporation for the target station x in the ith month, respectively; and $\hat{\upsilon}_{n,T}$, $\hat{\upsilon}_{n,P}$ and $\hat{\upsilon}_{n,E}$ are the posterior means of the temperature, precipitation, and evaporation for the reference station y in the ith month, respectively.

2.2.2 Runoff simulation: the TL-FNN-BP model

Among the available artificial neural network (ANN) models, multilayer feedforward models with the BP learning algorithm are currently the most popular type. In particular, a three-layered nonlinear network can approximate any continuous function with arbitrary precision (Rumelhart and McCelland 1986). Thus, nonlinear functional mapping and forecasting between a series of input and output variables have been widely applied in many fields, such as economics, meteorology, hydrology, amongst others. The BP neural network model is composed of an input layer, a hidden layer, and an output layer and has very strong learning, associations, and fault-tolerant capabilities. In this study, the TL-FNN-BP model was used to simulate monthly runoff. The Tan-sigmoid and linear function

Table 3 Performance of estimated MMT in the Qira River Basin at the target stations of Kartash and Cele during the calibration period using the modified Delta approach

Reconstructed station	Reference station	Verification period	NSCE	%PBIAS	Grade	Performance rating
Kartash	Akto	1992–1996	0.950	0	A	Very good
	Yopurga	1992–1996	0.938	0	A	Very good
	Yengisar	1992–1996	0.913	0	A	Very good
	Yarkant	1992–1996	0.938	0	A	Very good
	Kargilik	1992–1996	0.932	0	A	Very good
	Poskam	1992–1996	0.949	0	A	Very good
	Pishan	1992–1996	0.920	0	A	Very good
	Qira	1992–1996	0.908	0	A	Very good
	Hotan	1992–1996	0.894	0	A	Very good
	Lop	1992–1996	0.937	0	A	Very good
	Minfeng	1992–1996	0.930	0	A	Very good
	Keriye	1992–1996	0.944	0	A	Very good
	Average	1992–1996	0.953	−3.74	A	Very good
Cele	Akto	2005–2010	0.993	0	A	Very good
	Yopurga	2005–2010	0.992	0	A	Very good
	Yengisar	2005–2010	0.992	0	A	Very good
	Yarkant	2005–2010	0.993	0	A	Very good
	Kargilik	2005–2010	0.992	0	A	Very good
	Poskam	2005–2010	0.992	0	A	Very good
	Pishan	2005–2010	0.992	0	A	Very good
	Qira	2005–2010	0.992	0	A	Very good
	Hotan	2005–2010	0.991	0	A	Very good
	Lop	2005–2010	0.992	0	A	Very good
	Minfeng	2005–2010	0.992	0	A	Very good
	Keriye	2005–2010	0.993	0	A	Very good
	Average	2005–2010	0.994	0	A	Very good

were selected as the activation function in the hidden layer and in the output layer, respectively, and the TL-FNN-BP was trained using the Levenberg–Marquardt (LM) algorithm (Levenberg 1944; Marquardt 1963). Two activation functions are given as

$$f_h(x) = \tanh h\left(\frac{e^{\lambda x} - e^{-\lambda x}}{e^{\lambda x} + e^{-\lambda x}}\right), \tag{5}$$

$$f_o(x) = x, \tag{6}$$

where λ is a positive constant and x ranges between $-\infty$ and $+\infty$. In addition, the LM algorithm is expressed by

$$Se(\theta) = \sum_{i=1}^{n} \left[y_i - M(x_i, \theta)\right]^2, \tag{7}$$

where x and y are input and output variables, respectively; $M(X,\theta)$ refers to the TL-FNN-BP model; and θ represents the parameters of the model structure. This algorithm aims to make the sum of the squares of error approach towards minimal values. Li et al. (2013) showed that the forecasting results were similar for an ANN model with the specified input and output structures using different numbers of hidden neurons. Therefore, to simplify the model structure, the number of hidden layer neurons was assigned to 1 in this study. Input variables were selected from the available meteorological data in the Qira River Basin. Specifically, the MMT, MAP, and MAE between 1960 and 2010 from Qira, reconstructed for the Cele and Kartash stations (nine input variables), were applied in the model. Due to being an output variable, the MAR was simulated using TL-FNN-BP with the structure (9, 1, 1) (Fig. 2). The model structure can be written as

$$y = f_0\left[w \cdot f_h\left(\sum_{i=1}^{9} w_i x_i + w_0\right) + w_0'\right], \tag{8}$$

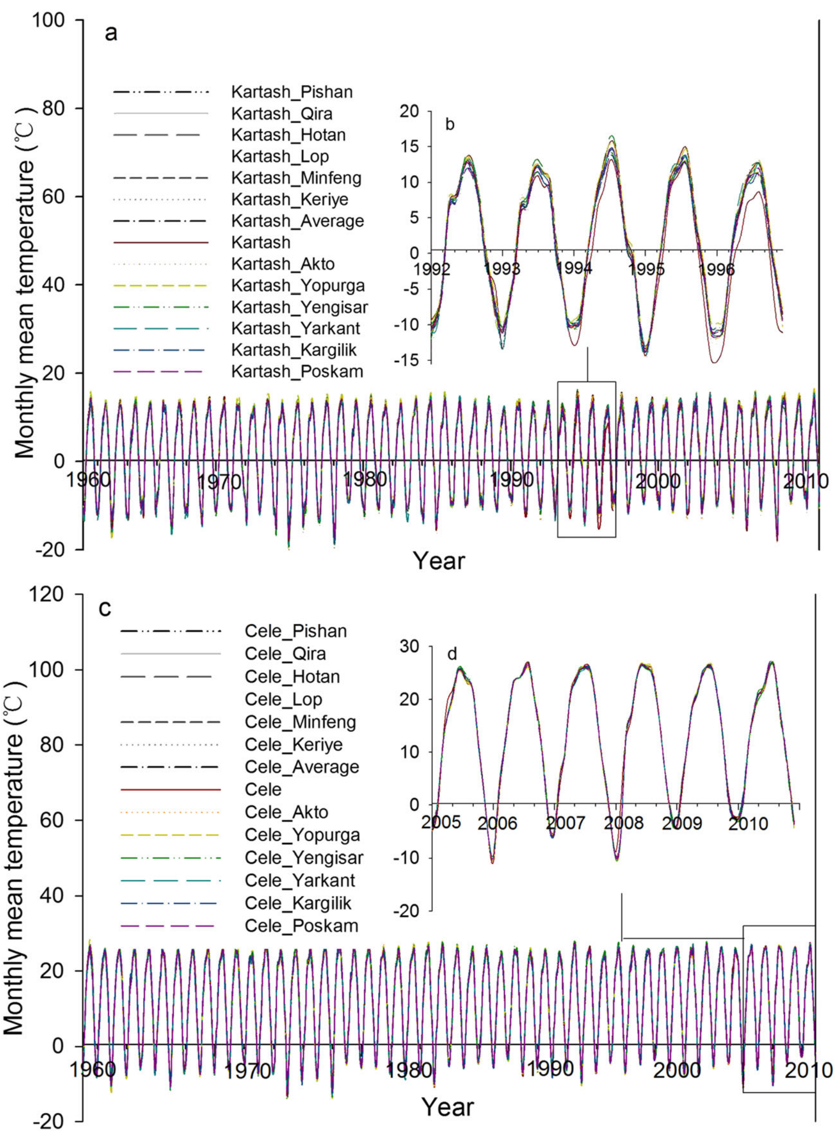

Fig. 3 MMT time series reconstructed in the Qira River Basin at (*a*, *b*) Kartash and (*c*, *d*) Cele using the modified Delta method during (*a*, *c*) 1961–2010 and (*b*, *d*) the calibration period 1992–1996

where w refers to weight linking the neurons between the hidden layer and the output layer, w_i is weights between the neuron in the hidden layer and the ith neuron in the input layer; w_0 and $w_0^{'}$ donate biases for the neuron in the hidden and output layer, respectively; x_i and y are the ith input values in the input layer and output value in the output layer, respectively; and f_h and f_0 represent activation functions in the hidden layer and in the output layer, respectively.

2.2.3 Performance indices for evaluating the reconstructed meteorological data and simulated runoff

The Nash–Sutcliffe Efficiency Coefficient (NSEC) is widely accepted and frequently used to evaluate the objective function of model performance. It is expressed as follows:

$$\mathrm{NSEC} = 1 - \frac{\sum_{i=1}^{n} \left(y_{\mathrm{obs},i} - y_{\mathrm{sim},i}\right)^2}{\sum_{i=1}^{n} \left(y_{\mathrm{obs},i} - \overline{y}\right)^2}, \quad (9)$$

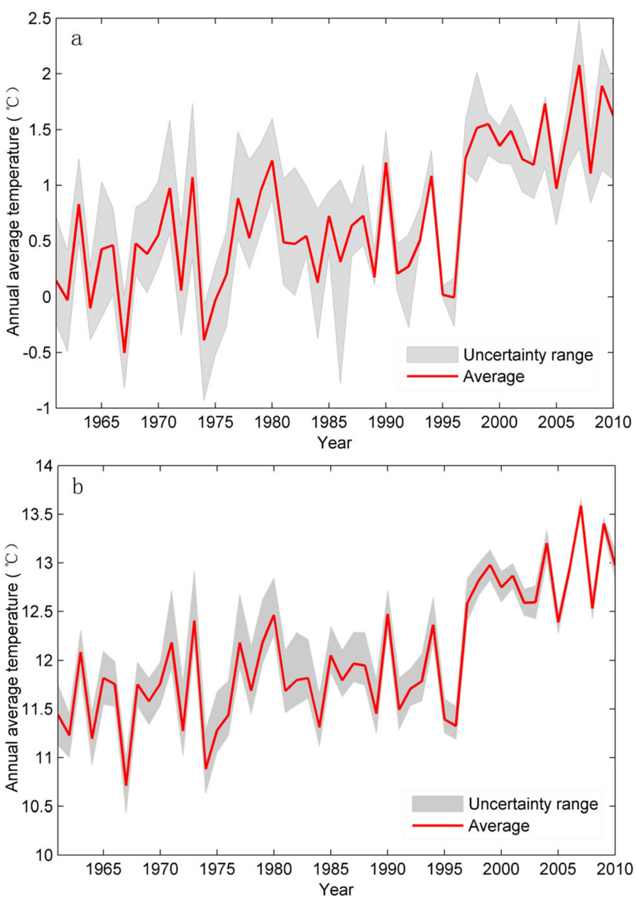

Fig. 4 Annual average temperature and uncertainty range of 95 % confidence intervals during 1961–2010 at the target stations of (**a**) Kartash and (**b**) Cele

where $y_{\mathrm{obs},\,i}$, $y_{\mathrm{sim},\,i}$, $\overline{y}$, and n are the observed value, simulated value, average value of the observed value, and number of observations and/or simulations, respectively. The value range of NSEC is between $-\infty$ and 1. When the NSEC value is equal to 1, the model reproduces completely the observation time series. The smaller the value of NSEC is, the worse the differences are between the observed and simulated values. Moreover, percentage bias (%PBIAS) is also used as an index to assess model performance, given by

$$\%\mathrm{PBIAS} = \frac{\sum_{i=1}^{n} \left(y_{\mathrm{obs},i} - y_{\mathrm{sim},i}\right)}{\sum_{i=1}^{n} y_{\mathrm{obs},i}} \times 100. \quad (10)$$

%PBIAS reflects the rate of deviation between the model output and the corresponding observed values. Positive and negative %PBIAS values show that the model is underestimating and overestimating, respectively (Gupta et al. 1999; Li et al. 2013). Different ranges of NSEC and %PBIAS values indicate the corresponding model performance rating (Moriasi et al. 2007) (Table 2).

3 Results

3.1 Reconstruction of temperature and its uncertainty based on the modified Delta approach and using data from multiple stations

The MMT results for Kartash and Cele stations in the Qira River Basin, estimated using the modified Delta approach, were calibrated (Table 3). From the perspective of the performance indices, the values of NSCE and %PBIAS indicated that the MMT at Kartash station, calculated based on the 12 sets of reference data during the calibration period (1992–1996), reproduced the target data very well. All 12 reference MMT sets yielded identical performance ratings—judged as “very good.” Moreover, the MMT at Cele station, again using the 12 sets of reference data, but during the calibration period of 2005–2010, produced similar results, i.e., all the MMT sets during the calibration period were also identified as “very good” according to the performance ratings. However, according to the NSCE values, the performance of the reconstruction at Cele station during the calibration period was better than that at Kartash station. This reveals that, due to the impact of complex conditions such as airflow dynamics and topographic characteristics, the MMT reconstruction performance can vary at different stations, even when based on the same available data. Although there were differences in the calibration, the reconstructed MMT results at the two target stations, obtained during the calibration period using the modified Delta method, could be classed as “very good” in terms of an estimate of the corresponding observed data. In addition, a better calibration performance was achieved when applying the average of the 12 estimated MMT sets at the two target stations, as compared to estimation based on any single MMT set. Clearly, use of the average of all the reference data provided more reliable estimated MMT results.

Due to the “very good” performance during the calibration period, the time series of MMT at the two target stations from 1961 to 2010 were reconstructed based on the modified Delta method. Figure 3 shows the reconstructed MMT at Kartash and Cele stations during 1960–2010, based on the data from the 12 reference stations as well as their average. It can be seen that the reconstructed MMT based on the 12 reference stations, and their average, demonstrated similar results (Fig. 3a, c). However, there were common defects within all the reconstructed MMT results, in that they featured slight differences in maximum and minimum values. Figure 3b, d illustrates the performances of the reconstructions by comparing the estimation results with observed MMT at Kartash and Cele during the calibration period. As can be seen, the reconstructed MMT at Cele performed better than that at Kartash, which was overestimated at times during the calibration period.

An MMT time series reconstructed using the modified Delta method will inevitably involve uncertainty because of the variability in the meteorological time series and limitations of the method. Figure 4a, b shows the reconstructed annual average temperature and uncertainty intervals during 1961–2010 at the two target stations, Kartash and Cele. The gray-shaded region represents the 95 % confidence intervals, and the red line indicates the annual average temperature based on the average data of the 12 reconstructed MMT sets. The uncertainty range differed substantially during different periods. Moreover, there was greater uncertainty for the reconstructed temperature at Kartash than at Cele during the reconstruction period. Nevertheless, since the spatiotemporal field of temperature was continuous, the total uncertainty was modest; the reconstructed temperature at the two target stations reproduced the historical data very well.

Table 4 Performance of estimated MAP in the Qira River Basin at the target stations of Kartash and Cele during the calibration period using the modified Delta approach

Reconstructed station	Reference station	Verification period	NSCE	%PBIAS	Grade	Performance rating
Kartash	Akto	1992–1996	−0.06	0	D	Unsatisfactory
	Yopurga	1992–1996	−0.15	0	D	Unsatisfactory
	Yengisar	1992–1996	−0.48	0	D	Unsatisfactory
	Yarkant	1992–1996	−0.11	0	D	Unsatisfactory
	Kargilik	1992–1996	0.05	0	D	Unsatisfactory
	Poskam	1992–1996	0.19	0	D	Unsatisfactory
	Pishan	1992–1996	0.30	0	D	Unsatisfactory
	Qira	1992–1996	−0.25	0	D	Unsatisfactory
	Hotan	1992–1996	0.26	0	D	Unsatisfactory
	Lop	1992–1996	0.55	0	C	Satisfactory
	Minfeng	1992–1996	0.05	−0.07	D	Unsatisfactory
	Keriye	1992–1996	0.05	−0.07	D	Unsatisfactory
	Average	1992–1996	0.68	−0.14	B	Good
Cele	Akto	2005–2010	0.71	0	B	Good
	Yopurga	2005–2010	0.75	0	B	Good
	Yengisar	2005–2010	0.77	0	A	Very good
	Yarkant	2005–2010	0.80	0	A	Very good
	Kargilik	2005–2010	0.75	−0.13	B	Good
	Poskam	2005–2010	0.79	0	A	Very good
	Pishan	2005–2010	0.76	0	A	Very good
	Qira	2005–2010	0.89	0	A	Very good
	Hotan	2005–2010	0.81	0	A	Very good
	Lop	2005–2010	0.84	0	A	Very good
	Minfeng	2005–2010	0.80	0	A	Very good
	Keriye	2005–2010	0.72	0	B	Good
	Average	2005–2010	0.83	−0.01	A	Very good

3.2 Reconstruction of precipitation and its uncertainty based on the modified Delta approach and using data from multiple stations

The performance of MAP at the target stations within the Qira River Basin (Kartash and Cele), calibrated by the modified Delta method, was assessed and the results are listed in Table 4. At Kartash station, only the MAP estimated based on the average of the 12 reference station MAP sets, and that based on data from Lop station, performed well during the calibration period (1992–1996); according to the NSCE and %PBIAS values, the other MAP reconstructions were relatively poor, rated as "unsatisfactory." In contrast, the calibrated MAP results at Cele station during 2005–2010, estimated based on the data from each of the 12 reference stations, and their average, performed very well. Specifically, the MAP at Cele estimated based on the data from Qira station performed the best, according to the NSCE value. Clearly, the performance at Cele during 2005–2010 was superior to that at Kartash during 1992–1996, demonstrating that it is harder to capture the MAP in alpine areas (i.e., where Kartash is located) than plain areas (i.e., where Cele is located), despite using the same source data for the estimation. However, although the MAP estimations at Kartash based on the data from individual stations were largely "unsatisfactory," the result based on the average was "good." Combined with the fact that the MAP estimations at Cele based on the average were "very good," overall, the reconstruction of precipitation at both target stations based on the average data from the 12 reference stations is a viable approach.

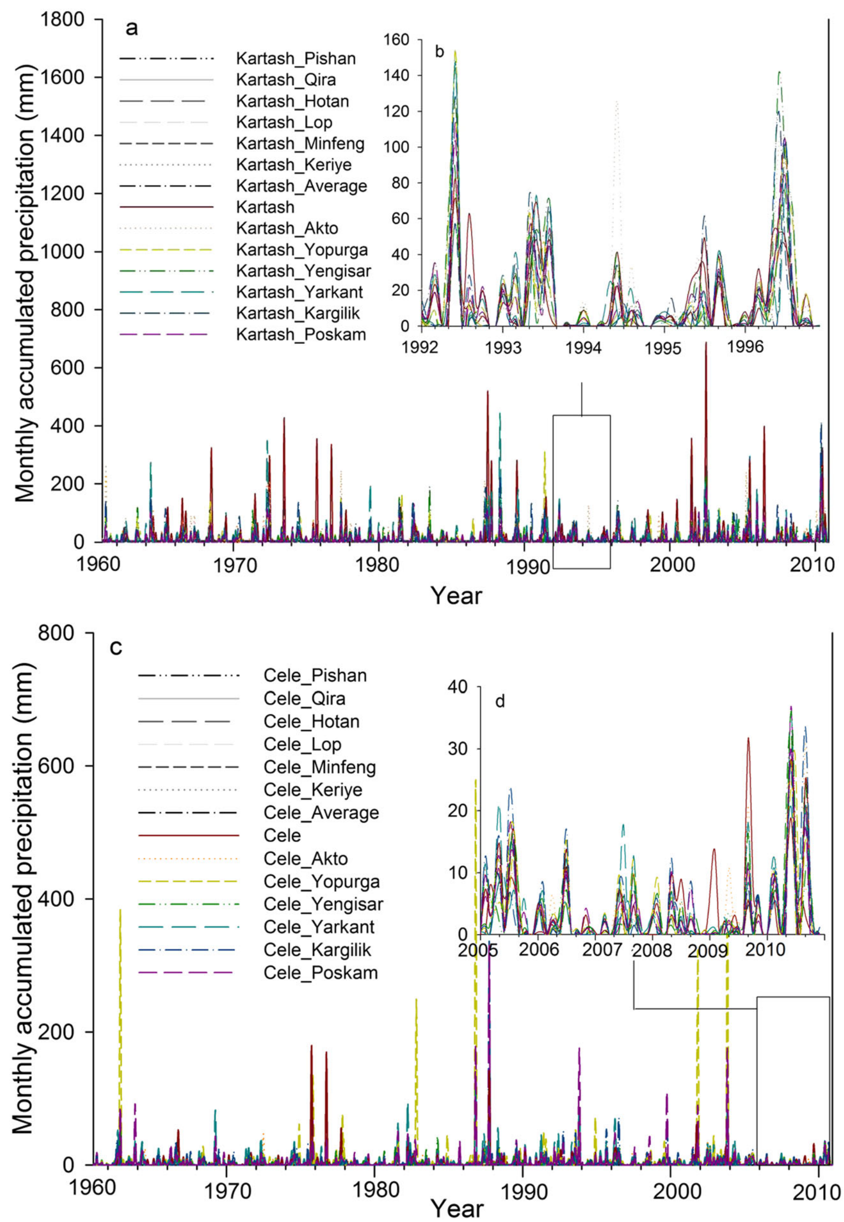

Fig. 5 MAP time series reconstructed in the Qira River Basin at (*a*, *b*) Kartash and (*c*, *d*) Cele using the modified Delta method during (*a*, *c*) 1961–2010 and (*b*, *d*) the calibration period 2005–2010

The MAP time series at the two target stations during 1961–2010 were reconstructed using the modified Delta method (Fig. 5). As can be seen, the ability to reconstruct the MAP during the reconstruction period and calibration period differed depending on the reference station data used for the estimation (Fig. 5a, c). All the reconstructed MAP time series were characterized by non-stationarity and periodicity. Moreover, clear differences could be seen between the observed and calibrated MAP results at Kartash and Cele during the calibration periods of 1992–1996 and 2005–2010 (Fig. 5b, d). The same sources of data yielded different performances of the estimations at the two target stations.

The reconstructed annual accumulated precipitation and uncertainty ranges during the period 1961–2010 at Kartash and Cele are shown in subpanels a and b of Fig. 6, respectively. Compared with the reconstructed MMT results, the uncertainties in the reconstructed MAP at the two target stations are larger, owing to the variability in the meteorological time series and poor performance of the estimations. The annual average precipitation "overflowed" the uncertainty range in some periods at Kartash station. In general, the uncertainty at Kartash was greater than at Cele during the entire reconstruction period. This large uncertainty may be a result of the discreteness of the precipitation in the spatiotemporal field. Nevertheless, the reconstructed annual accumulated precipitation at Kartash and Cele could still capture the original data.

3.3 Reconstruction of evaporation and its uncertainty based on an empirical model and the modified Delta approach

The evapotranspiration in inland river basins in arid zones is crucial to the hydrological cycle and acts as a dissipation quantity in hydrological models. Unfortunately, evaporation data are difficult to obtain quantitatively in high-altitude mountainous areas. Kartash station, situated in the alpine region of the Qira River Basin, is no exception to the rule. To combat the problem, a number of empirical models have been developed to forecast evaporation, yielding good results. In the present study, the empirical evaporation model for alpine areas proposed by Chen et al. (2002) was adopted:

$$E(M) = \frac{104.1\exp\left(\frac{3.545T(M)}{47.281+T(M)}\right)}{1+0.009558P(M)\exp\left(-\frac{3.545T(M)}{47.281+T(M)}\right)}, \quad (11)$$

where $T(M)$, $P(M)$, and $E(M)$ denote the monthly mean temperature, monthly accumulated precipitation, and evaporation, respectively.

The estimated MAE using the above empirical model based on the 12 reference station MMT and MAP results, and their averages, are displayed in Fig. 7a. It can be seen that large differences existed between the reconstructions based on different data sources. The average of the 12 estimated MAE sets was presumed to be the best reconstructed MAE under the circumstances due to no verification data. In terms of the evaporation at Cele station, because 11 (i.e., apart from Qira station) of the reference evaporation datasets were seriously lacking, the MAE at Qira station was used to reconstruct the MAE at Cele based on the modified Delta method. Figure 7b, c illustrates the reconstructed MAE time series during the reconstruction period (1961–2010) and the calibration period (2006–2010). According to the NSCE and %PBIAS values, which were 0.94 and 0 during the period 2006–2010, respectively, the MAE at Cele, estimated based on the MAE at Qira station, achieved "very good" performance. Therefore, the reconstructed MAE at Cele was used in the estimation of runoff, as reported in the next section.

The reconstructed annual accumulated evaporation and uncertainty ranges at Kartash station during the period 1961–2010 are shown in Fig. 8c. The uncertainty at this target station was moderate for the reconstructed MAE. It was similar to the uncertainty for the MMT at Kartash station. Because of the connectivity of the evaporation in the spatiotemporal field,

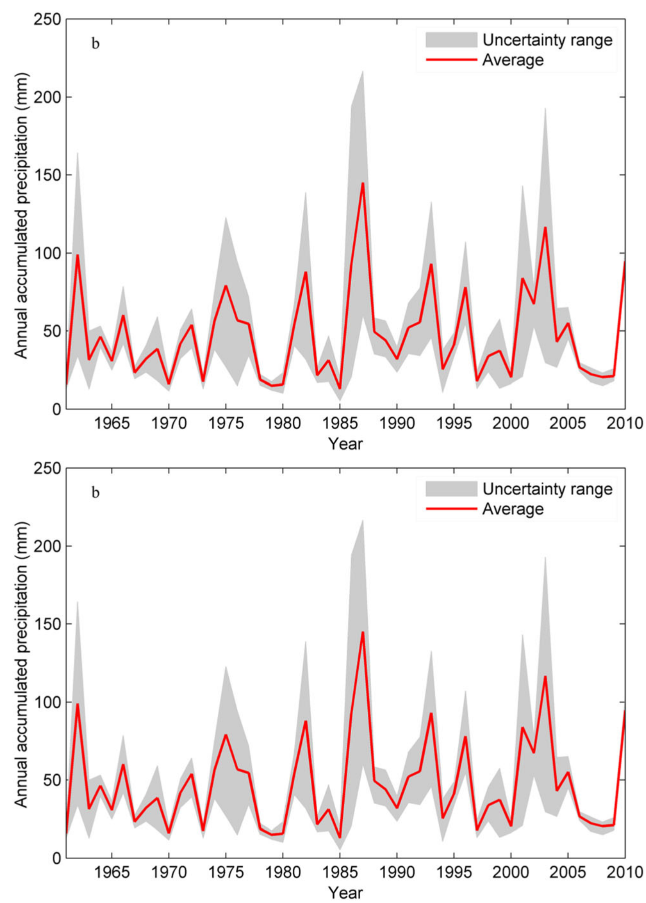

Fig. 6 Annual accumulated precipitation and uncertainty range of 95 % confidence intervals during 1961–2010 at the target stations of (**a**) Kartash and (**b**) Cele

the reconstructed annual accumulated evaporation at Kartash station captured the historical data well.

3.4 Runoff simulation and its uncertainty based on the TL-FNN-BP model

The monthly runoff simulation was divided into three parts: calibration (learning and training), verification, and simulation. Although the meteorological stations within the Qira River Basin, including Qira and Cele, are situated downstream of the hydrological station, the correlation coefficients between the MMT, MAP, and MAE results at the two stations and the MAR at the hydrological station were all statistically significant at the 0.01 significance level (Table 5), and thus

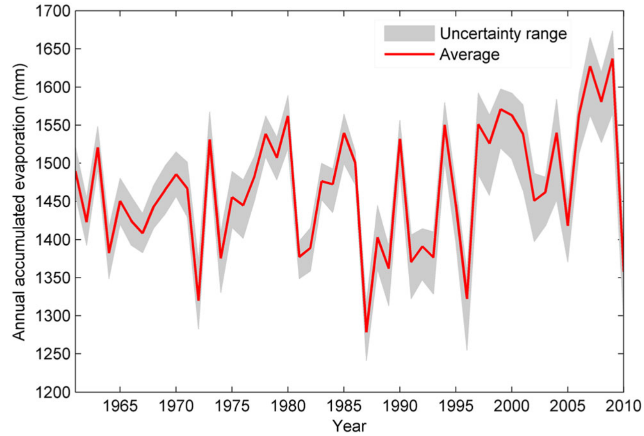

Fig. 8 Annual accumulated evaporation and uncertainty range of 95 % confidence intervals for Kartash station during 1961–2010

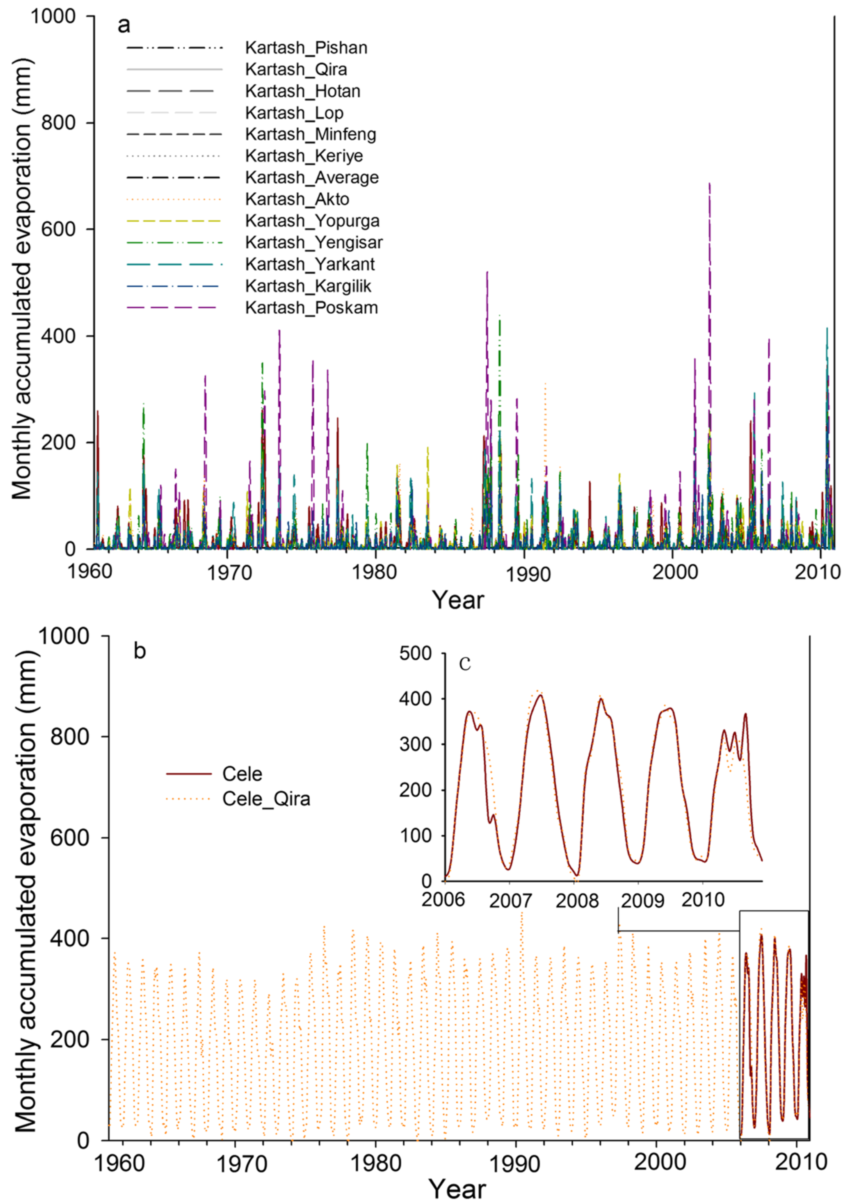

Fig. 7 MAE time series reconstructed using an empirical model and the modified Delta method during 1961–2010 in the Qira River Basin: (*a*) based on the 12 reference stations and at Cele station during (*b*) the entire reconstruction period (1961–2010) and (*c*) the calibration period (2006–2010)

Table 5 Pearson correlation analysis between observed MMT, MAP, and MAE at Qira and Cele stations and observed MAR at the hydrological station in the Qira River Basin

Variable	Qira*_MMT	Qira_MAP	Qira_MAE	Cele&_MMT	Cele_MAP	Cele_MAE
MAR	0.678[a]	0.295[a]	0.453[a]	0.641[a]	0.640[a]	0.616[a]

*Qira** observed monthly data from 1961 to 2008, *Cele*& observed monthly data during 2005–2008

[a] Correlation is significant at the 0.01 confidence level (two-tailed)

these variables could be used as the inputted layer neurons in the runoff simulation using the TL-FNN-BP model. Therefore, the MMT, MAP, and MAE at Kartash, Cele, and Qira stations were inputted into the neurons to output the estimated runoff using the TL-FNN-BP model during the calibration period of 1961–1990, the verification period of 1991–1998, and the simulation period of 1999–2008. Table 6 lists the results of MAR simulated by the TL-FNN-BP model with the structure (9,1,1). The resultant values of NSCE of between 0.82 and 0.88, as well as all the 0 %PBIAS values, demonstrated that the simulated results were, on the whole, comparable with observations during the calibration and verification periods, being regarded as "very good" in terms of estimating the actual runoff. However, remarkable differences existed in the model's performance during the simulation period. The meteorological data reconstructed by Yopurga and Hortan's reference data as the inputted data resulted in the worst simulation performance. The runoff simulated by the inputted data reconstructed based on Pishan's reference data achieved the best performance during the simulated period, while the remaining sources showed moderate performance.

Figure 9 illustrates the runoff simulation based on the inputted meteorological data reconstructed based on Pishan's station data. It can be seen that the TL-FNN-BP model with structure (9,1,1) reproduced the MAR very well during the calibration period (Fig. 9a). Similarly, the model captured the runoff's periods of fluctuation and relative smoothness effectively during the verification and simulation periods. However, peak runoff could not be captured in the simulation, with runoff peaks underestimated throughout the whole period. The runoff simulated based on the other inputted datasets showed similar results to that based on Pishan.

Due to bias between the reconstructed meteorological time series and the actual variable series, as well as the reasonability and limitations of the model structure, the monthly accumulated runoff simulated by the TL-FNN-BP model with structure (9,1,1) inevitably possessed uncertainty. Figure 10 shows the MAR and uncertainty range of 95 % confidence intervals during the simulation period (1999–2008). The gray-shaded band refers to the 95 % confidence interval based on the 12 simulated source datasets, and the red line denotes the MAR time series. It can be seen that the uncertainty range was quite small and nearly overlapped in most parts, except for the peak of runoff, which escaped from the gray-shaded band, i.e., it did not fall between the 95 % confidence intervals. All of the uncertainty ranges in the peaks of runoff demonstrated that the TL-FNN-BP model structure (9,1,1) overestimated/underestimated the actual monthly runoff, suggesting that the multi-data ensembles in the model input still could not capture the monthly runoff peaks. However, the total

Table 6 Performance of the estimated MAR in the Qira River Basin based on TL-FNN-BP model with the structure (9,1,1)

Inputted data	NSCE (C/V/S)	%PBIAS (C/V/S)	Grades (C/V/S)	Performance rating (C/V/S)
Kartash_Akto,Cele_Akto,Qira	(0.84/0.83/0.54)	(0/0/−0.25)	(A/A/C)	(V*/V*/S*)
Kartash_Yopurga,Cele_Yopurga,Qira	(0.83/0.82/0.46)	(0/0/−0.22)	(A/A/D)	(V*/V*/U*)
Kartash_Yengisar,Cele_Yengisar,Qira	(0.86/0.82/0.54)	(0/0/−0.27)	(A/A/C)	(V*/V*/S*)
Kartash_Yarkant,Cele_Yarkant,Qira	(0.83/0.88/0.51)	(0/0/−0.46)	(A/A/C)	(V*/V*/S*)
Kartash_Kargilik,Cele_Yarkant,Qira	(0.83/0.87/0.71)	(0/0/−0.20)	(A/A/B)	(V*/V*/G*)
Kartash_Poskam,Cele_Poskam,Qira	(0.84/0.87/0.66)	(0/0/−0.16)	(A/A/B)	(V*/V*/G*)
Kartash_Pishan,Cele_Pishan,Qira	(0.84/0.86/0.83)	(0/0/−0.07)	(A/A/A)	(V*/V*/V*)
Kartash_Qira,Cele_Qira,Qira	(0.83/0.85/0.63)	(0/0/−0.32)	(A/A/B)	(V*/V*/G*)
Kartash_Hotan,Cele_Hotan,Qira	(0.82/0.86/0.45)	(0/0/−0.21)	(A/A/D)	(V*/V*/U*)
Kartash_Lop,Cele_Lop,Qira	(0.83/0.82/0.67)	(0/0/0.14)	(A/A/B)	(V*/V*/G*)
Kartash_Minfeng,Cele_Minfeng,Qira	(0.86/0.87/0.62)	(0/0/−0.21)	(A/A/B)	(V*/V*/G*)
Kartash_Keriye,Cele_Keriye,Qira	(0.82/0.86/0.70)	(0/0/−0.25)	(A/A/B)	(V*/V*/G*)
Kartash_Average,Cele_Average,Qira	(0.85/0.86/0.67)	(0/0/−0.32)	(A/A/B)	(V*/V*/G*)

C/V/S calibration/verification/simulation, *V*/G*/S*/U** very good/good/satisfactory/unsatisfactory uncertainty was small, and could be accepted, meaning the monthly runoff simulated based on the reconstructed meteorological data reproduced the hydrological response in the Qira River Basin.

4 Discussion

The accurate forecasting or prediction of hydrological responses, such as runoff, ground water, etc., has posed great challenges within ungauged or poorly gauged basins, owing to the inadequate records of climatic variables (e.g., precipitation, temperature, evaporation) and hydrological observations in the researched watershed (Murugesu 2003; Sivapalan et al. 2003). The Qira River Basin is a typical poorly gauged basin and is characterized by short meteorological time series within the basin. The scarcity and inadequacy of climate parameter records in the Qira River Basin has limited the ability to analyze long-term climatic variation, simulate the hydrological response, and, more importantly, provide evidence for oasis management in the lower reaches.

In order to overcome the problem of a lack of data, previous studies have attempted to reconstruct meteorological parameters through the use of climate proxy data such as tree rings, ice cores, fossil pollen, and so on (Shen et al. 2001; Esper et al. 2002; Yang et al. 2002; Fang et al. 2011). These proxy data provide quite high precision in reconstructing meteorological parameters, but it is difficult to obtain these data in the Qira River Basin. In addition, remote sensing or satellite data (products) have been applied to assess climatic variability and the climatic forcing of the hydrological response. However, such data need to be coupled with ground-observed data, because their precision and resolution are generally quite coarse or worse (Yang and Luo 2014). This requires complicated downscaling technology and an abundant availability of data. As an alternative, Li et al. (2013) reconstructed hydrometeorological time series in the Kaidu River Basin using neighboring data from Central Asia, based on climate comparability theory. The results showed that the reconstructed variables were reproduced well and satisfactorily estimated the actual hydrometeorological time series. The present study, in which meteorological time series were reconstructed in the Qira River Basin to assess the associated uncertainty in runoff simulation, was inspired by those findings.

However, to apply the Delta method, the baseline time series for the region or site of interest typically need long-term averages of variables, such as 30 years or more; the method is otherwise unadaptable and defective for limited or smaller time series. In this study, the Bayesian paradigm was adopted to modify the conventional Delta method. Such an approach can provide robust estimation and inference with respect to parameters under circumstances where the sample is very limited (Hoff 2009). To compare the modified Delta method based on the Bayesian paradigm, the Delta method was used to reconstruct meteorological time series, and the results showed that the modified method provided superior estimation. In fact, the Delta method implies that it should ensure stationarity for reconstructed variables. Based on the performance of the reconstruction during the calibration period, the modified Delta method can perform very well.

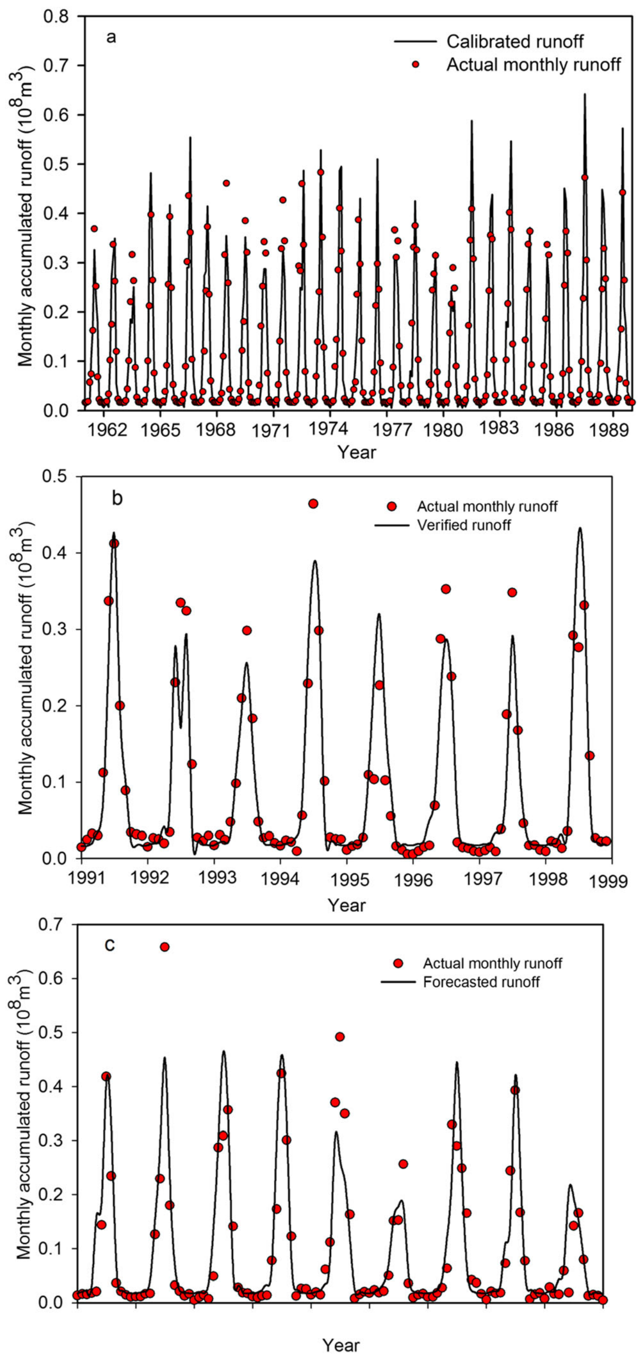

Fig. 9 MAR time series of MAR produced by the TL-FNN-BP model for the period 1961–2008 in the Qira River Basin: (**a**) MAR calibrated by the model based on the reference data from Pishan station; (**b**) verified MAR during 1991–1998; (**c**) simulated MAR during 1999–2008

The MMT and MAE estimations at the Qira River Basin target stations (Kartash and Cele) performed better than that of MAP during the calibration period. A possible reason for this is that the temperature and evaporation, due to being continuous spatiotemporal fields, were affected mainly by the radiation balance and so were easily captured and reconstructed. However, precipitation is influenced by a combination of factors including local climatic changes, geographical location, and moisture sources, and thus there is greater uncertainty in its reconstruction. It is possible that precipitation is a variable with discreteness on certain spatiotemporal scales. In particular, it was found that reliable estimation of precipitation in the mountainous areas, where runoff is generated, remains a significant challenge. In future work, it is necessary to use remote sensing or satellite data (products), coupled with ground-observed data, to improve the precision and resolution of precipitation data in the ungauged Qira River Basin.

Runoff generation is a quite complicated hydrometeorological process. In this study, based on the assumption that the underlying surface is largely unchanged due to the uninhabited nature of the basin, the errors in runoff simulation derived mainly from the biases between the observations and the corresponding reconstructed meteorological data and the defectiveness of the model structure. Therefore, a black-box model, i.e., an ANN model, was used to simulate runoff in the Qira River Basin. The TL-FNN-BP model with structure (9,1,1) was run to estimate the MAR, and satisfactory results were obtained. However, the modeling of catchment runoff and reconstructing the climatic parameters that affect it inevitably involve uncertainties.

A multi-meteorological ensemble in the model input is considered to be an effective way to reduce uncertainties. However, the results in this study showed that the ability of such an approach was limited in predicting runoff, owing to errors in the reconstructed meteorological time series and the reasonability and limitations of the model's structure. The uncertainty ranges of the runoff simulation by the TL-FNN-BP model with structure (9,1,1) were quite small and nearly overlapped in most parts, except for the runoff peaks, which generally escaped the 95 % confidence intervals. It was found that the ability of the TL-FNN-BP model with structure (9,1,1) to simulate runoff by was insufficient. It is possible that this is because an ANN is unable to capture the peak of a variable, and the uncertainty of the input parameters (meteorological time series) jointly lead to uncertainty in the runoff simulation. In fact, this study only attempted to reproduce historical meteorological data and to quantify the uncertainties in runoff simulation via multiple input ensembles in the ungauged Qira River Basin. Further work should focus on improving the accuracy of meteorological time series and developing a sound hydrological model structure, such as hydrological models with physical mechanisms, to minimize the uncertainty in the Qira River Basin.

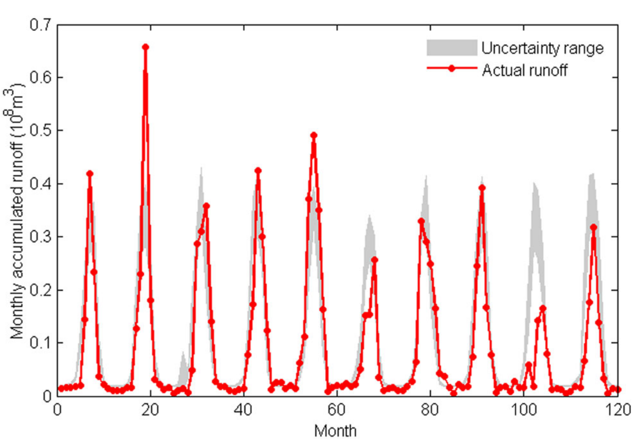

Fig. 10 MAR and uncertainty range of 95 % confidence intervals during the simulation period (1999–2008)

5 Conclusion

Based on available neighboring station data around the northern slope of the Kunlun Mountains, the MMT, MAP, and MAE time series from 1961 to 2010 at Kartash and Cele stations within the Qira River Basin were reconstructed by applying a modified version of the Delta method. In addition, the level of uncertainty for these reconstructed meteorological parameters was analyzed on the basis of the 95 % confidence intervals among 12 reference data sources. Then, the MAR was simulated using the TL-FNN-BP model with the structure (9,1,1), using the reconstructed MMT, MAP, and MAE results at Kartash and Cele, and observed MMT, MAP, and MAE data from Qira station as the model's inputted variables. Finally, the uncertainty of the runoff simulation was quantified and discussed.

The MMT at Kartash and Cele, estimated using the modified Delta method based on the 12 sets of reference station data, achieved "very good" and similar performances during the calibration periods but that the MMT estimations at the two target stations based on the average data of the 12 reference stations showed the best performance, as determined by the values of NSCE and %PBIAS. The calibration of the MAP results at the two target stations performed relatively poorly in comparison with that for MMT. Similarly, the estimated MAP at Kartash and Cele, obtained via the average data of the 12 reference stations, yielded "satisfactory" performance. The MAE at Kartash and Cele was reconstructed based on an empirical model for alpine areas and the modified Delta method, respectively. The MAE at Cele, estimated based on the data from Qira station only, showed good performance during the calibration period, comparable to that of MMT. In addition, the uncertainties for these reconstructed meteorological parameters were also analyzed. It was found that the uncertainty ranges were small, on the basis of the 95 % confidence intervals among the 12 reconstructed datasets.

The MAR simulated by the TL-FNN-BP model with structure (9,1,1) showed that there is inevitable uncertainty in MAR simulation. The results also revealed that the efficiency in runoff simulation is limited because of the errors in meteorological data and the deficiency of the model's structure. In particular, runoff peaks could not be captured in the uncertainty range. However, the total uncertainty of the runoff simulation was small and moderate based on the reconstructed meteorological data, especially based on the data at Pishan station. Therefore, the result provides a useful reference for assessing the risk of droughts and/or floods in the Qira River Basin, as well as for decision-making as part of water resources planning and management.

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