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Analyzing effects of climate change on streamflow in a glacier mountain catchment using an ARMA model

Youcun Liu [a], Jing Wu [b], Yan Liu [c], Bill X. Hu [d,e], Yonghong Hao [a,*], Xueli Huo [f], Yonghui Fan [c], Tianchyi J. Yeh [g], Zhong-Liang Wang [a]

[a] Tianjin Key Laboratory of Water Environment and Resources, Tianjin Normal University, No. 393 Binshuixi Road, Xiqing District, Tianjin 300387, PR China
[b] Department of Statistics, Tianjin University of Finance and Economics, No. 25 Zhujiang Road, Hexi District, Tianjin 300222, PR China
[c] College of Mathematical Science, Tianjin Normal University, No. 393 Binshuixi Road, Xiqing District, Tianjin 300387, PR China
[d] Collage of Water Resources and Environmental Sciences, China University of Geosciences, Beijing 100083, PR China
[e] Department of Earth, Ocean & Atmospheric Sciences, 108 Carraway Building, Florida State University, Tallahassee, FL 32306, USA
[f] College of Urban and Environmental Science, Tianjin Normal University, Tianjin 300387, PR China
[g] Department of Hydrology and Water Resources, The University of Arizona, John Harshbarger Building, 1133 E. North Campus Drive, Tucson, AZ 85721, USA

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ABSTRACT

Impacts of the climate change on streamflow have been of great concern over recent decades. The streamflow from a glacier mountain in an arid or semiarid region, in particular, plays a vital role in ecological, social and economic developments of the region. In this study, a long-term climate and runoff data were collected from an upstream glacier mountain area in the Ürümqi River basin, China. An autoregressive-moving-average model (ARMA) was used to quantitatively analyze the influence of the air temperature and the precipitation on the streamflow that originated from mountain glaciers. We used the differences between two consecutive years in the monthly air temperature and the monthly precipitation over a period of 48 years (from January 1959 to December 2006) as our climate change indexes. Similarly, the corresponding differences of monthly runoff were treated in the same way to derive the streamflow response indicator time series. These three new time series (temperature, precipitation, and runoff) were then transformed by removing their seasonal trends to construct three stationary time series. The ARMA model was subsequently applied to analyze the transformed time series. Results of this analysis indicated that the runoff was related to the temperature and the precipitation at any given time and that the precipitation was more important than the temperature in controlling the streamflow. The runoff in the upstream of the Ürümqi River increased approximately 1 m^3/s every 10 years due to the climate change.

1. Introduction

Glacier meltwater plays an important role in the local ecological and economic developments (i.e. irrigation, municipal and industry) of a catchment (Barnett et al., 2005; Stahl et al., 2008; Sorg et al., 2012; Wang et al., 2013), especially in the arid and semi-arid regions of central Asia (Li et al., 2012; Sun et al., 2013). Streamflow in glacier mountain catchments is vulnerable and sensitive to climate change (Kuhn and Batlogg, 1998; Chen and Xu, 2005; L. Liu et al., 2011). Streamflow in any given catchment is generally controlled by air temperature and precipitation. However, the air temperature can be of significant importance in glacier mountain catchments because it can modulate or even control the streamflow through altering the glacier mass balance (Aizen et al., 2006; Li et al., 2010). The climate change has accelerated over the last two to three decades (Motyka et al., 2002; Oerlemans, 2005; Zemp et al., 2006). A sound knowledge on the response of streamflow to climate change is crucial to assessing the water resources availability (Huss et al., 2007; Wang et al., 2012) and also to developing strategies of sustainable water resources management (Ding and Xiao, 2013).

In order to quantitatively analyze and predict the impacts of the climate change on streamflow in a glacier mountain catchment, a mathematical model is often preferred. Most studies of this type have relied on either a hydrological physical models or hydrological mathematical statistical models of glacier mountain catchments (Schaefli et al., 2005; Kampf and Burges, 2007; Versini et al., 2010).

The hydrological physical models are built according to physical mechanisms of hydrological processes in a watershed and are

* Corresponding author.
E-mail addresses: haoyhong@yahoo.com, haoyh@sxu.edu.cn (Y. Hao).

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considered to be the most adequate tools to explore the hydrological characteristics of a watershed (Chen et al., 2003; Kampf and Burges, 2007; Rakovec et al., 2012). However, they are rarely applied to watershed streamflow forecasting (Tesfaye et al., 2006; Anderson et al., 2013) because they require much more detailed information of the watershed that is normally available.

On the other hand, the hydrological statistical models well express the hydrological prototypes by means of statistical relationships between inputs and outputs (Dutta et al., 2012) without explicit consideration of mechanisms of hydrological processes (Box and Jenkins, 1976; Castellano-Méndez et al., 2004; Can et al., 2012). Compared with the physical models, mathematical statistical models require much less hydrological data and parameters (Adamowski et al., 2012). In recent years, many studies outlined the approach of using mathematical statistical models to predict streamflow (e.g., Box and Jenkins, 1976; Claps et al., 1993; Can et al., 2012). More recently, Castellano-Méndez et al. (2004) modeled the daily and the monthly runoff of the Xallas River in Spain using autoregressive integrated moving average (ARIMA) and ANN models. Tesfaye et al. (2006) used periodic autoregressive moving average (PARMA) model to capture the seasonal variations in river flow statistics. Anderson et al. (2013) developed periodic autoregressive moving average (PARMA) models and applied them to predict the monthly runoff.

Ürümqi River, originated from the Tien Shan Glacier No.1 is the only glacier river which has been systematically monitored for nearly 50 years (Wang et al., 2012). Over the past decades, many studies have been conducted to study glacier responses to climate change (e.g., Shi et al., 1992; Immerzee et al., 2010; Lan et al., 2010; Li et al., 2010; Kong and Pang, 2012; Sun et al., 2013), but most were focused on exploring the linear relationships between the climate factors and hydrological parameters by using relatively simple statistical methods. Due to data insufficiency at the upstream of Ürümqi River, physical models are not adequate to analyze and predict the streamflow. Instead, we employed mathematical statistical models to study and predict the streamflow (Liu et al., 2013).

The main objectives of this paper are (1) to apply ARMAX model to the Ürümqi River basin to simulate the hydrological processes in the glacier mountain basin, (2) to quantify the relationships between runoff, air temperature and precipitation during 1958–2006, (3) to analyze the river's sensitivity to climate change, and (4) to predict the runoff in Ürümqi River for the next few years.

2. Data and methods

2.1. Study area

Originating from the Tien Shan Mountain in Xinjiang, northwest China (Liu et al., 2008; Sorg et al., 2012), the Ürümqi River is a typical inland intermountain river which is recharged by a mixture of glacier-melt water and precipitation (Metivier et al., 2004; Li et al., 2010; Liu et al., 2013). In 1958, the Yingxiongqiao Hydrological Gauging Station (YHGS) was established to gauge the upstream of Ürümqi River (Y. Liu et al., 2011). The upstream of the Ürümqi River was sparsely populated and the human impact (i.e., water resources development) was negligible on the hydrological process prior to 2006. Therefore, we selected the upstream as our study area to investigate the effects of the climate change on the streamflow. The data used include the observed monthly hydrometeorological parameters covering the period from 1959 to 2006.

The source of the Ürümqi River is No. 1 Glacier in Tianger Peak II, the highest peak in the eastern Tien Shan Mountains, with an elevation of 4484 m above mean sea level (AMSL) (Fig. 1). The river flows through the Wulabo Reservoir, and finally ends in the Junggar Basin (Shi et al., 1992). The watershed of the Ürümqi River ranges from 86°45′E to 87°56′E and 43°00′N to 44°07′N, with a drainage area of 4684 km^2 (Liu et al., 2008; Lan et al., 2010; Kong and Pang, 2012). The YHGS, located 5 km upstream of the mountain pass, is the sole hydrological gauging station in the upstream portion of the Ürümqi River. The length of the river above the YHGS is 62.6 km with a drainage area of 924 km^2 and an average altitude of 3483 m AMSL (Fig. 1). The study area (i.e., the area above YHGS) can be divided into three climatic zones: 1) the mountain snow zone (i.e., modern glacier area), where the average snow line altitude is 4050 m AMSL, the average annual air temperature is −6 °C, and more than 75% of annual precipitation occurs in form of snow; 2) the subalpine permafrost zone, where the average annual air temperature is −1.86 °C, and the snowfall accounts for 50% of the annual precipitation; 3) the alpine cold temperature zone, where the average annual air temperature is 2 °C, and the snowfall accounts for 25% of the annual precipitation (Lan et al., 2009). In the upstream area, precipitation occurs most frequently from June to August. The average annual precipitation is 454 mm (from 1958 to 2006) at the Daxigou Meteorological Station (DMS). The observed maximum annual precipitation in the upstream of the Ürümqi River is 632 mm (in 1996). The average annual air temperature in the upstream ranges from −5.2 °C to 0 °C. The average annual runoff of the upstream is 7.71 m^3/s observed in YHGS.

The altitude of the riverbed decreases significantly from 3860 m at the headwater to 1680 m near the mountain pass, over the 68-km route. The river channel slope varies greatly with the maximum gradient of 0.5 and the minimum gradient of 0.0158. Daxigou Reservoir, located 5 km upstream of YHGS, was constructed in 2007. Its construction disturbed the natural hydrological conditions of upstream of the Ürümqi River, and the data of YHGS after 2006 were thus not used in this study.

2.2. Data acquisition

The monthly average runoff and precipitation data from January 1958 to December 2006 and the air temperature data from January 1959 to December 2006 collected from YHGS and DMS respectively, were displayed in Fig. 2 that also included the 12-month running average curves for the three time series (i.e., air temperature, precipitation, and runoff). According to Fig. 2, all three series exhibited a similar pattern.

The data for the average monthly runoff, precipitation and air temperature in the corresponding time intervals were shown in Table 1. According to Table 1, the runoff, precipitation and air temperature series had similar temporal variation patterns with trends of slight decreases before the 1980s and trends of dramatic increases after the 1980s.

Table 1
Monthly precipitation, monthly average temperature and monthly average runoff in different decades.

Average monthly data	1959–1968	1969–1978	1979–1988	1989–1998	1999–2006
Precipitation (mm)	37.07	36.21	33.89	39.72	42.46
Temperature (°C)	−5.29	−5.35	−5.39	−4.75	−4.52
Runoff (m^3/s)	7.55	7.36	7.33	8.45	7.46

2.3. The autoregressive–moving-average model with exogenous inputs (ARMAX)

2.3.1. The ARMA model

Before the introduction of the autoregressive moving average (ARMA) model (Hao et al., 2013), we first defined the autoregressive (AR) and moving average (MA) models.

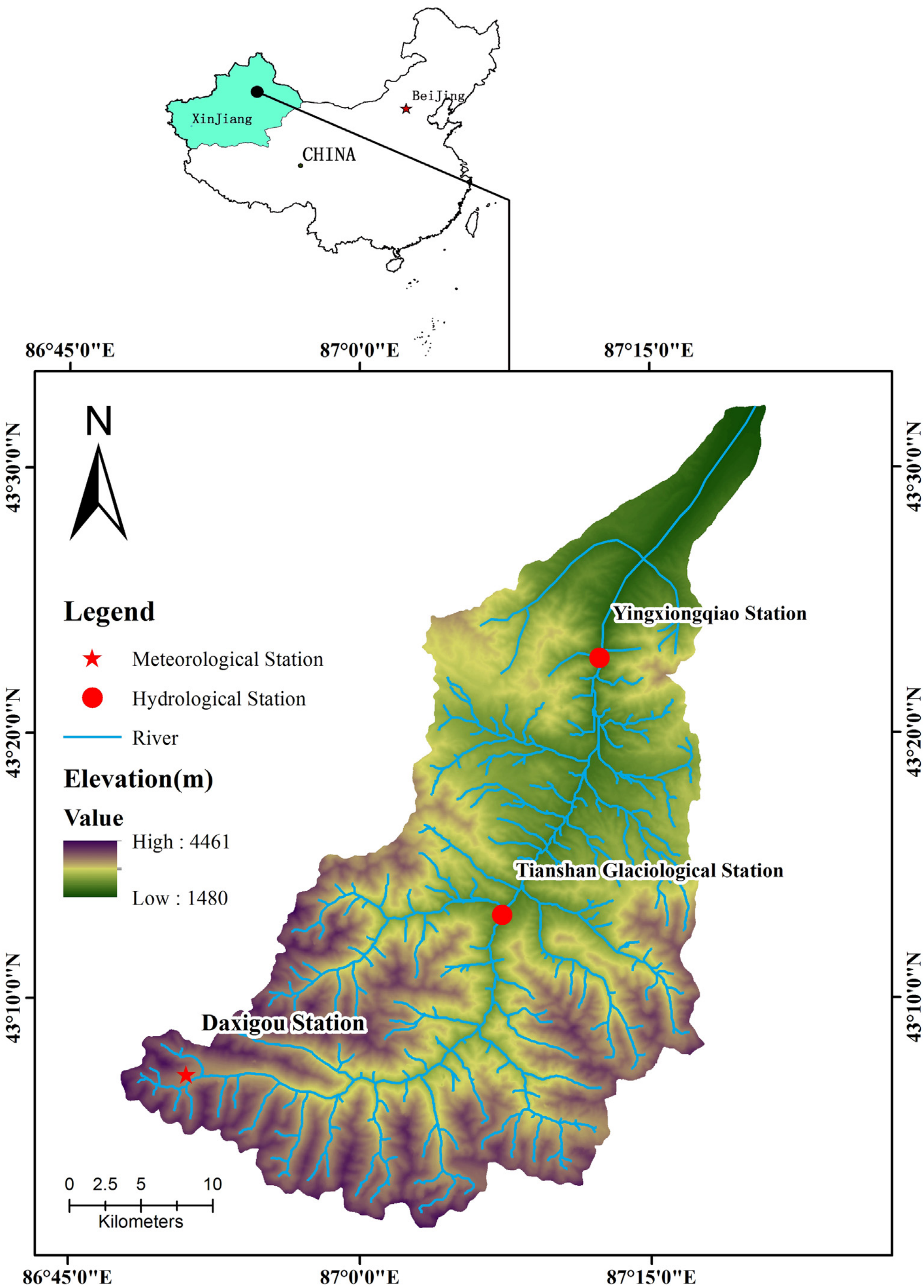

Fig. 1. The position of hydro-meteorological observation sites and digital elevation map (DEM) of the upstream portion of the Ürümqi River, Tianshan Mountains, China.

The autoregressive model of order $p \geq 1$ ($AR(p)$), proposed by Yule (1927), was defined as:

$$Y_t = b_1 Y_{t-1} + b_2 Y_{t-2} + \ldots + b_p Y_{t-p} + \varepsilon_t \quad (1)$$

where $Y_t, Y_{t-1}, \ldots, Y_{t-p}$ denote the values of the time series (e.g., the flow of a river) at the moments $t, t-1, \ldots, t-p$ respectively; $b_1, \ldots, b_p$ are parameters to be estimated; ε_t is the white noise sequence, denoted as $\varepsilon_t \sim WN(0, \sigma^2)$, satisfying $E\varepsilon_t = 0$, $Var(\varepsilon_t) = \sigma^2$, and $Cov(\varepsilon_i, \varepsilon_j) = 0$, for all $i \neq j$. Equation (1) can also be expressed as:

$$\phi(B) Y_t = \varepsilon_t \quad (2)$$

where $\phi(B) = 1 - b_1 B - \cdots - b_p B^p$, represents the autoregressive polynomial of order p, and B denotes the backshift operator.

The moving average process with order $q \geq 1$ ($MA(q)$), first studied by Slutsky (1937) and Wold (1938), is:

$$Y_t = \varepsilon_t + a_1 \varepsilon_{t-1} + a_2 \varepsilon_{t-2} + \cdots + a_q \varepsilon_{t-q} \quad (3)$$

where $a_1, \ldots, a_q$ are parameters and ε_t also represents the white noise sequence. Similarly, Equation (3) can be written as:

$$Y_t = \theta(B) \varepsilon_t \quad (4)$$

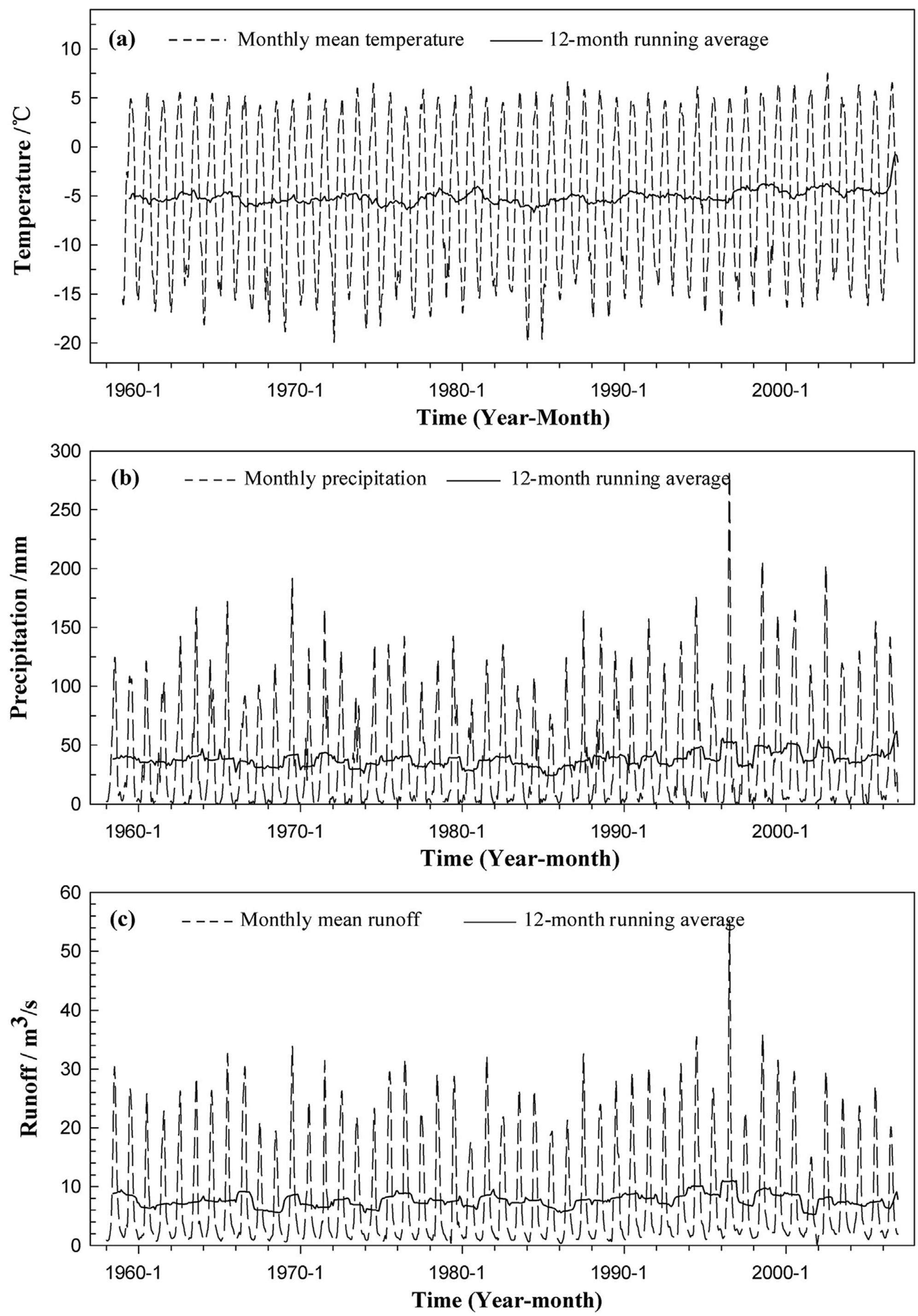

Fig. 2. The variations of average monthly air temperature (a), monthly precipitation (b) and average monthly runoff (c) from 1959 to 2006.

where $\theta(B) = 1 + a_1B + \ldots + a_qB^q$ is the moving average polynomial of order q.

Combining the models AR and MA together, we obtained the autoregressive moving average (ARMA) model, denoted by *ARMA*(p, q), which was written as:

$$Y_t = b_1Y_{t-1} + b_2Y_{t-2} + \cdots + b_pY_{t-p} + \varepsilon_t + a_1\varepsilon_{t-1} + a_2\varepsilon_{t-2} + \cdots + a_q\varepsilon_{t-q} \tag{5}$$

or

$$\phi(B)Y_t = \theta(B)\varepsilon_t \tag{6}$$

where p and q are the orders of the model.

2.3.2. Seasonal difference

The time series required for an ARMA model must be stationary. The stationary condition reflects certain time-invariant properties of time series and is a necessary condition for making a statistical inference. However, real time series data often exhibit seasonality which violates the stationary assumption embedded in ARMA models. Removing the seasonal difference is a convenient and effective way to eliminate the non-stationary. The seasonal difference is defined as a difference between Y_t and $Y_{t\text{-}s}$ (where t denotes any given time, and s is the length of the seasonal period of the sequence). The seasonal difference can be written as:

$$\nabla_s Y_t = Y_t - Y_{t-s} = (1 - B^s)Y_t \tag{7}$$

If the time series (or sequence) presents stationary after removing the seasonal periodicity, we can use the ARMA model to simulate it.

2.3.3. The ARMAX model: an autoregressive–moving-average model with exogenous inputs

Besides using the past values and residuals of the response sequence Y_t, one can also model Y_t through the current and past values of other series, called input series or exogenous variables, which were originally introduced in the time series theory by Box and Jenkins (1976). The ARMA model with input series, call the ARMAX model, is generally written as:

$$\phi(B)(Y_t - \mu - \sum_i \psi_i(B)X_{i,t}) = \theta(B)\varepsilon_t \tag{8}$$

where Y_t is the response series or a difference sequence of the response sequence Y_t; μ is the mean term; $\psi_i(B)$ is the transfer function with the form $\psi_i(B) = 1 - c_{i1}B - \ldots - c_{is}B^s$; $X_{i,t}$ denotes ith input series. In this study, the precipitation and air temperature will be the two input series involved in Equation (8) to estimate the flow rate of Ürümqi River. The forecast of the ARMAX model can be implemented through the recursive property of Equation (8).

3. Results and discussion

The average monthly runoff, air temperature, and precipitation of the upstream of the Ürümqi River exhibited obvious seasonality (Fig. 2), which indicated non-stationary. The data seasonality was removed by taking difference in the average monthly runoff, air temperature, and precipitation between two consecutive years over a period of 48 years (i.e., January, 1959 to December, 2006).

$$\begin{aligned}
\nabla_{12}Q_t &= Q_t - Q_{t-12} = \left(1 - B^{12}\right)Q_t \\
\nabla_{12}T_t &= T_t - T_{t-12} = \left(1 - B^{12}\right)T_t \\
\nabla_{12}P_t &= P_t - P_{t-12} = \left(1 - B^{12}\right)P_t
\end{aligned} \tag{10}$$

where Q_t, T_t, and P_t are the tth month's river flow, air temperature and precipitation respectively; Q_{t-12}, T_{t-12}, and P_{t-12} are $(t-12)$th month's river flow, air temperature and precipitation respectively (i.e., the corresponding monthly runoff, air temperature, and precipitation of last year respectively); $\nabla_{12}Q_t$, $\nabla_{12}T_t$, and $\nabla_{12}P_t$ are the difference in monthly runoff, air temperature, and precipitation between two consecutive years.

The data of the runoff, air temperature, and precipitation after removing the seasonality were presented in Fig. 3. The 12-month increments of air temperature (i.e., $\nabla_{12}T_t$) and precipitation (i.e., $\nabla_{12}P_t$) were used as indicators for climate change; while the 12 month increments of runoff (i.e., $\nabla_{12}Q_t$) were considered as the streamflow response indicator to climate change. The transformed resultant time series are assumed to be stationary to satisfy the condition of ARMA method. Then the resultant time series were analyzed by ARMA method (SAS Institute Inc., 2008) to acquire effects of climate change on streamflow based on the observed data from January 1959 to December 2006.

It was shown in Fig. 3 that the data exhibited stationary after deseasonalization. Then we used the AR, MA, ARMA, ARMAX models to fit the increment sequence in the runoff rate of 12 months (i.e., $\nabla_{12}Q_t$) based on the corresponding increment sequences of air temperature and precipitation (i.e., $\nabla_{12}T_t$, and $\nabla_{12}P_t$).

In the process of searching for the optimal model of $\nabla_{12}Q_t$, first the AR and MA models were tried. Because both normality tests of residuals showed that the p-values were less than 0.05 (i.e., the general significance level), the AR and MA models were thus rejected. Then the ARMA and ARMAX models were tried. Table 2 showed that the coefficient estimates of model 1 (i.e., the ARMA model) were significant. An autocorrelation check of residuals of model 1 indicated that the residuals were white noise, because the p-value was not small enough to reject the null hypothesis that the series was white noise (Table 3). Based on model 1, an ARMAX model was set up (i.e., model 2), using the air temperature and precipitation data in the ARMA model to find the best forecasting model (Table 2). The values of Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) of model 2 were less than those in model 1. The smaller values of AIC and BIC mean that model 2 was a better model (Wooldridge, 2003). However, an autocorrelation check of residuals of model 2 indicated that the residuals were not white noise, because most of the p-values were less than 0.1 (Table 3). Accordingly, we improved model 2 by introducing a 2nd-order autoregressive polynomial $\phi(B) = 1 - b_1B - b_2B^2$ in Equation (8) and denoted the improved model 2 as the model 3. The autocorrelation check of residuals of model 3 indicated that the residuals were white noise, because all of the p-values were larger than 0.1 (Table 3). From Table 2 illustrated that the coefficients of AIC and SBC of model 3 were the smallest among the three models, which meant that model 3 was the best choice for the series. Model 3 can be expressed by the following equation:

$$\begin{aligned}
&\left(1 - 0.203B - 0.149B^2\right)\left(\nabla_{12}Q_t - 0.191\nabla_{12}T_t - 0.093\nabla_{12}P_t\right) \\
&\quad = \left(1 - 0.881B^{12}\right)\varepsilon_t
\end{aligned} \tag{11}$$

where $\varepsilon_t \sim N(0,4.92)$. The accuracy of Equation (11) can be described by the coefficients' standard errors, which was listed in Table 4. According to Table 4, each coefficient in (11) had very small standard error compared with the value itself, meaning that the model was accurate and the forecast values via this model would not have larger errors.

Table 2
Results of ARMAX Regressions for Ürümqi River flow.

Parameter	Model 1 (ARMA)	Model 2 (ARMAX)	Model 3 (ARMAX)
b_1	0.28343** (0.04006)	0.24131*** (0.0413)	0.20309*** (0.04222)
b_2			0.14910*** (0.0419)
a_{12}	0.91227*** (0.0176)	0.87828*** (0.02256)	0.88141*** (0.02235)
c_2		0.20218*** (0.06182)	0.19069*** (0.06041)
c_3		0.09121*** (0.00463)	0.09255*** (0.00449)
Akaike Information Criterion	2856.967	2514.545	2504.054
Schwarz Bayesian Criterion	2865.679	2531.885	2525.729

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Table 3
Diagnosis of Residuals for Model 1–3.

Autocorrelation check of residuals										
	To Lag	χ^2	DF	$p > \chi^2$	Autocorrelations					
Model 1	6	1.05	4	0.9028	−0.006	0.012	0.019	0.026	0.021	0.012
	12	6.46	10	0.7752	0.01	0.02	0.022	0.073	0.051	−0.016
	18	8.26	16	0.9408	−0.026	0.039	0.026	−0.001	−0.011	−0.007
	24	14.64	22	0.8771	0.007	0.007	−0.021	0.067	−0.043	0.061
Model 2	6	14.41	4	0.0061	−0.035	0.146	−0.009	0.048	0.018	0.008
	12	24.19	10	0.0071	0.036	−0.025	0.025	0.091	0.079	0.001
	18	24.78	16	0.0737	0.009	−0.012	0.019	−0.009	−0.018	−0.006
	24	28.66	22	0.1549	0.012	−0.014	−0.025	−0.049	0.044	−0.036
Model 3	6	1.01	3	0.7997	0.004	0.002	−0.035	0.019	0.012	0.004
	12	12.3	9	0.1971	0.024	−0.041	0.011	0.102	0.082	−0.005
	18	12.96	15	0.6053	−0.006	−0.013	0.019	−0.007	−0.023	−0.004
	24	16.32	21	0.7516	0.02	−0.008	−0.036	−0.049	0.032	−0.024

Table 4
The standard errors and P values of the coefficients in Eq. (11).

Coefficient	0.881	0.203	0.149	0.191	0.093
Standard error	0.024	0.043	0.042	0.061	0.004
P value	<0.0001	<0.0001	0.0003	0.0057	<0.0001

By expanding Equation (11), we acquired the following form:

$$\begin{aligned}\nabla_{12}Q_t = {} & 0.203\nabla_{12}Q_{t-1} + 0.149\nabla_{12}Q_{t-2} + 0.191\nabla_{12}T_t \\ & - 0.039\nabla_{12}T_{t-1} - 0.028\nabla_{12}T_{t-2} + 0.093\nabla_{12}P_t \\ & - 0.019\nabla_{12}P_{t-1} - 0.014\nabla_{12}P_{t-2} + \varepsilon_t - 0.881\varepsilon_{t-12}\end{aligned} \quad (12)$$

Because the dimensions of the runoff, the air temperature and the precipitation were different, the coefficients were not comparable in Equation (12). To eliminate the dimensions of Equation (12), we conducted standardized transformations to the series.

$$\begin{aligned} Q_t &= SQ_t\sigma_Q + \mu_Q \\ T_t &= ST_t\sigma_T + \mu_T \\ P_t &= SP_t\sigma_P + \mu_P \end{aligned} \quad (13)$$

where SQ_t, ST_t, and SP_t denote the standardized sequences of Q_t, T_t, and P_t respectively; σ_Q, σ_T, and σ_P represent the standard derivations of Q_t, T_t, and P_t respectively; μ_Q, μ_T, and μ_Q are the mean values of Q_t, T_t, and P_t respectively. The standard derivations and the mean values of Q_t, T_t, and P_t were listed in Table 5.

Table 5
The standard derivations and the mean values of Q_t, T_t, and P_t.

Average monthly data	Runoff (m^3/s)	Temperature (°C)	Precipitation (mm)
Mean value	7.635	−5.107	37.798
Standard derivation	8.742	7.446	44.711

Based on the study results, we obtained the follow equation.

$$\begin{aligned}\nabla_{12}SQ_t = {} & 0.203\nabla_{12}SQ_{t-1} + 0.149\nabla_{12}SQ_{t-2} + 0.163\nabla_{12}ST_t \\ & - 0.033\nabla_{12}ST_{t-1} - 0.024\nabla_{12}ST_{t-2} + 0.476\nabla_{12}SP_t \\ & - 0.097\nabla_{12}SP_{t-1} - 0.072\nabla_{12}SP_{t-2} + \varepsilon_t - 0.881\varepsilon_{t-12}\end{aligned} \quad (14)$$

Equation (14) showed that the tth deseasonalized, standardized runoff rate (DSQ) was positively related to $(t-1)$th and DSQ, the tth deseasonalized standardized temperatures (DST) and precipitations (DSP), while it had a negative correlation with the $(t-1)$th, $(t-2)$th DST and DSP. Moreover, the tth DSQ greatly depended on the tth DSP since the coefficient was 0.476, the largest among all coefficients. Equation (14) quantitatively demonstrated the relation between runoff rate and climate indicators, i.e., air temperature and precipitation.

A complete set of hydrological processes includes streamflow generation, confluence, discharge, and regression. Equation (14) suggested that current streamflow was related to the air temperature and the precipitation of the two previous months in the upstream of the Ürümqi River. Because the time step of our observed data was a month, the relations at shorter time scales (i.e. day or hour) cannot be detected by Equation (14). At the time scale of month, the regression streamflow that originated from hydrological events within the two prior months were a part of the subsequent month's runoff in the upstream of the Ürümqi River. The streamflow was definitely dominated by both the air temperature and the precipitation in the upstream, but the landform and topography regulated the convergence process and complicated the influence of the climate on the streamflow. The drainage area in the upstream of the Ürümqi River is the mountain terrain and the slopes are steep. The mountainous drainage area with the slope of larger than 60% is 15%; the area with the slope of 60%–30% is 75%; and the area with the slope less than 30% is 10% (Wu, 1992). Due to steep slopes, the streamflow convergence time is short and the storage capacity of floodwater in the catchment is low.

Equation (14) also illustrated that the contribution coefficient of the air temperature was 0.163 while the contribution coefficient of precipitation was 0.476, revealing that the contribution of the precipitation to streamflow was larger than the temperature-dictated glacier melting. This result was consistent with that by Li (Li et al., 2010). In Equation (14), the coefficients of the air temperature and the precipitation in the previous two months (i.e., the coefficients of $\nabla_{12}T_{t-1}$, $\nabla_{12}T_{t-2}$, $\nabla_{12}P_{t-1}$, and $\nabla_{12}P_{t-2}$) were very small and negligible, because the main contribution of the air temperature and the precipitation to the streamflow occurred in the same month.

Equation (12) performed well under the AIC and SBC criteria, so it can be used to forecast the subsequent flow. However, Equation (12) involved the input series $\nabla_{12}T_t$ and $\nabla_{12}P_t$, which should be modeled first. Through analyzing the functions of autocorrelation and partial autocorrelation, the following model was selected to fit and predict the air temperature sequence:

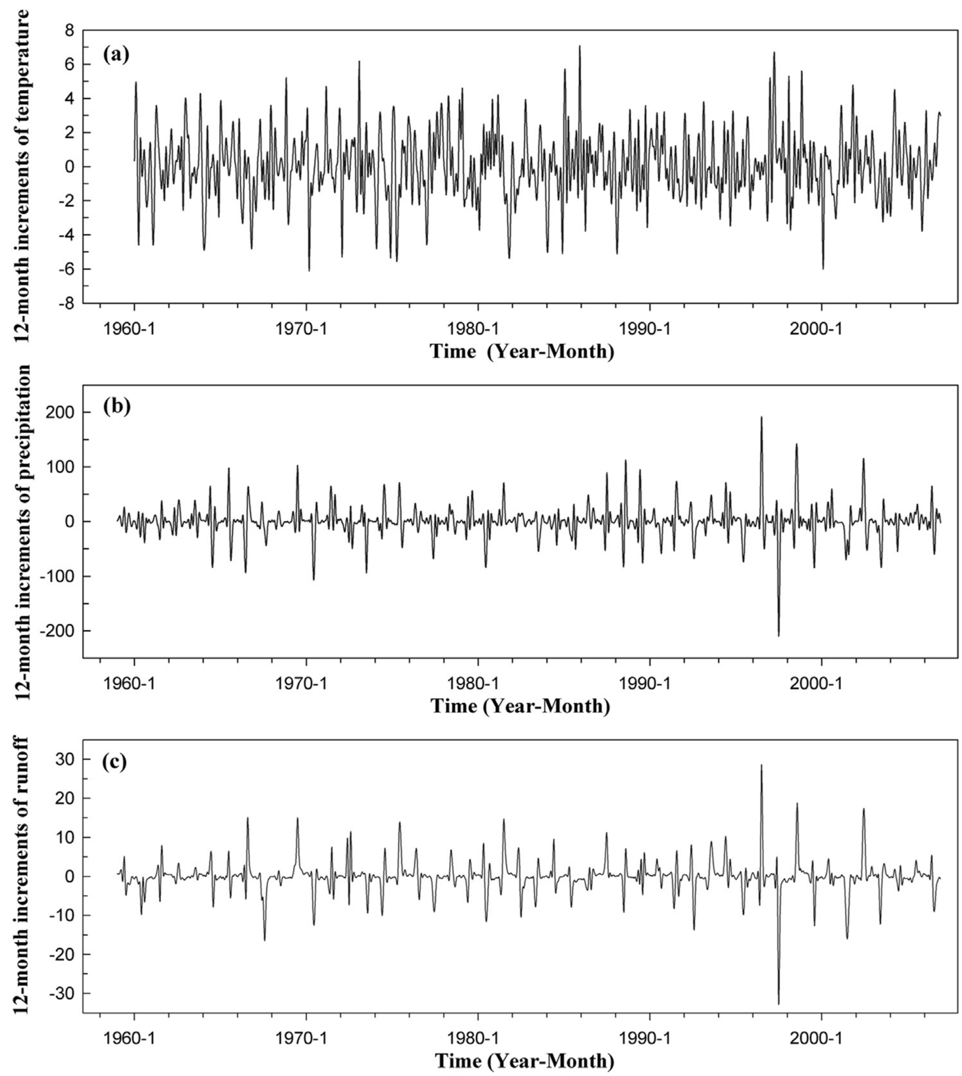

Fig. 3. The 12-month increments of average monthly air temperature (a), monthly precipitation (b) and average monthly runoff (c) between two consecutive years from 1959 to 2006.

$$\left(1-0.092B\right)\nabla_{12}T_t=\left(1-0.846B^{12}\right)\varepsilon_t \tag{15}$$

Similarly, the model:

$$\left(1+0.117B^2\right)\nabla_{12}P_t=\left(1-0.913B^{12}\right)\varepsilon_t \tag{16}$$

was used to forecast the future precipitation.

Introducing the Equations (15) and (16) into Equation (12), we obtained the improved Equation (12) to predict the runoff rate at time t in future. Fig. 4a shows the observed river flow rates and the fitted values, which coincided well with each other (Fig. 4a), 95% confidence intervals were narrow (Fig. 4b), and the residuals were small (Fig. 4c), which meant the improved Equation (12) properly describes the runoff rate. Then, we used it to predict the monthly runoff rates from January 2007 to December 2017. Besides the observed, fitted, and predicted data, Fig. 4b also showed the corresponding 95% confidence intervals of predicted streamflow. The obtained results suggested that the effects of the climate change on the streamflow can be well simulated by the ARMA model. Equation (12) also revealed that monthly runoff was slowly increasing at a rate of approximately 1 m^3/s every 10 years, being consistent with Li's result (Li et al., 2010). In Fig. 4b, the confidence interval became wider in the predicted stage (i.e., after 2006) because the longer the time elapsed from the data-covering period, the less observed data could be used.

4. Conclusions

The differences between two consecutive years in the runoff, the air temperature, and the precipitation data were calculated to remove the seasonality of the data to satisfy the expected stationary status of the data for running the models. The differences of the air temperature and the precipitation were taken as the climate change indicators and the differences of runoff as the hydrological response indicator to model the effects of climate change on hydrological processes.

An ARMA model was then used to investigate the effects of the climate change on the streamflow in a glacier mountain catchment. The ARMA model was applied to the upstream of the Ürümqi River. The results showed that the current streamflow response indicator was closely related to the climate change indicator of the previous two months. The regression coefficients of the air temperature and the precipitation to steamflow rate were 0.163 and 0.476, respectively. Therefore, the precipitation contributed more to the streamflow than did the air temperature.

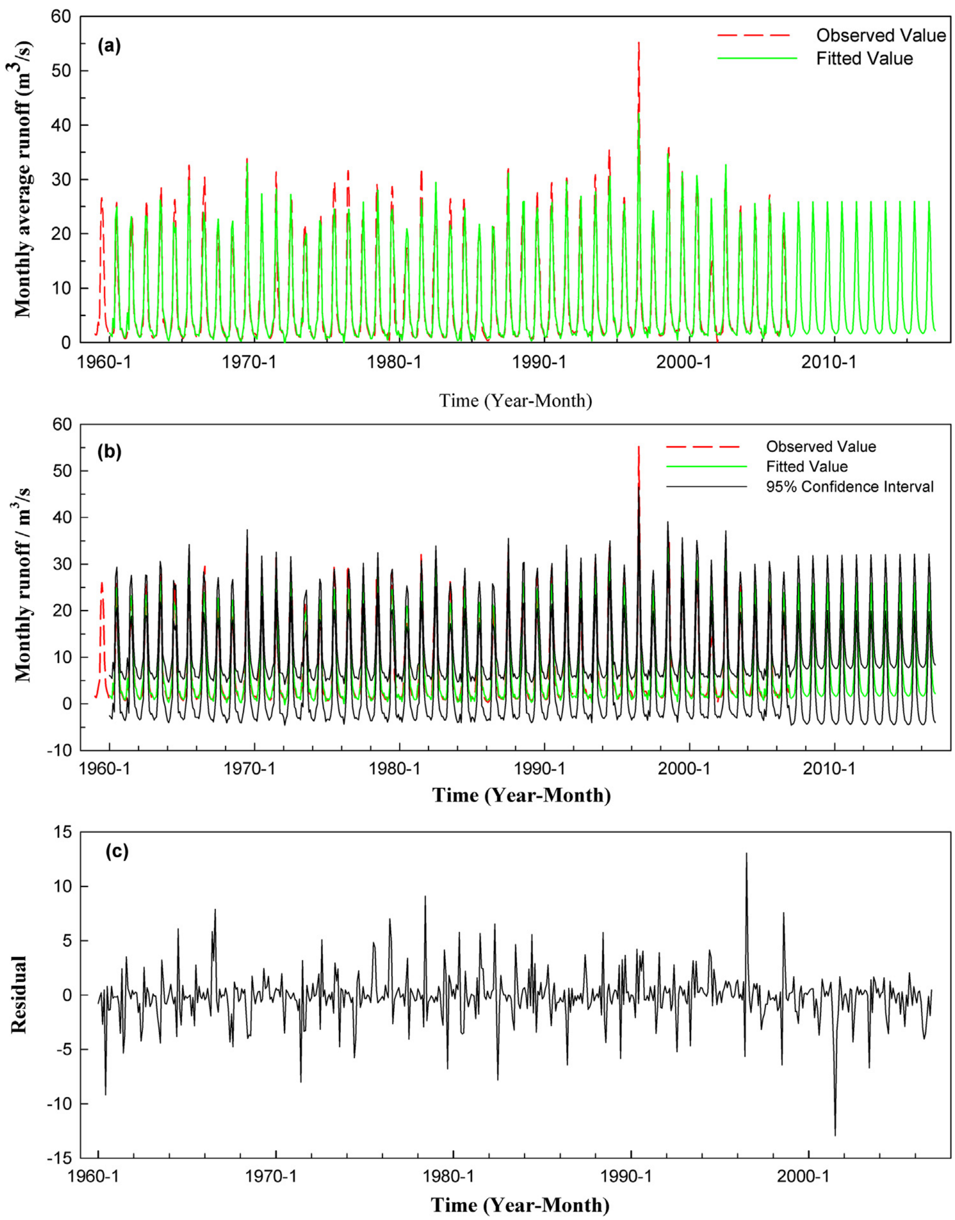

Fig. 4. Change of upstream discharge in the Ürümqi River with different scenarios in 21st century: (a) average annual runoff, (b) average annual runoff growth rate.

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References

Adamowski, J., Fung Chan, H., Prasher, S.O., Ozga-Zielinski, B., Sliusarieva, A., 2012. Comparison of multiple linear and nonlinear regression, autoregressive integrated moving average, artificial neural network, and wavelet artificial neural network methods for urban water demand forecasting in Montreal, Canada. Water Resources Research 48 (1), W01528. http://dx.doi.org/10.1029/2010WR009945.

Aizen, V.B., Kuzmichenok, V.A., Surazakov, A.B., Aizen, E.M., 2006. Glacier changes in the central and northern Tien Shan during the last 140 years based on surface and remote-sensing data. Annals of Glaciology 43 (1), 202–213.

Anderson, P.L., Meerschaert, M.M., Zhang, K., 2013. Forecasting with prediction intervals for periodic autoregressive moving average models. Journal of Time Series Analysis 34 (2), 187–193.

Barnett, T.P., Adam, J.C., Lettenmaier, D.P., 2005. Potential impacts of a warming climate on water availability in snow-dominated regions. Nature 438, 303–309.

Box, G.E.P., Jenkins, G.M., 1976. Time Series Analysis: Forecasting and Control. Holden-Day, San Francisco, CA.

Can, İ., Tosunoğlu, F., Kahya, E., 2012. Daily streamflow modelling using autoregressive moving average and artificial neural networks models: case study of Çoruh basin, Turkey. Water and Environment Journal 26 (4), 567–576.

Castellano-Méndez, M., González-Nanteiga, W., Febrero-Bande, M., Prada-Sánchez, J.M., Lozano-Calderón, 2004. Modeling the monthly and daily behavior of the runoff of the Xallas River using Box–Jenkins and neural networks methods. Journal of Hydrology 296, 38–58.

Chen, R., Kang, E., Yang, J., Zhang, J., 2003. Research review of hydrological modeling. Journal of Desert Research 23 (3), 221–229.

Chen, Y., Xu, Z., 2005. Plausible impact of global climate change on water resources in the Tarim River Basin. Science in China (D): Earth Sciences 48 (1), 65–73.

Claps, P., Rossi, F., Vitale, C., 1993. Conceptual-stochastic modeling of seasonal runoff using autoregressive moving average models and different scales of aggregation. Water Resources Research 29 (8), 2545–2559.
Ding, Y., Xiao, C., 2013. Challenges in the study of cryospheric changes and their impacts. Advances in Earth Science 28 (10), 1067–1076 (in Chinese with English abstract).
Dutta, D., Welsh, W.D., Vaze, J., Kim, S.S.H., Nicholls, D., 2012. A comparative evaluation of short-term streamflow forecasting using time series analysis and rainfall-runoff models in Water Source. Water Resources Management 26, 4397–4415.
Hao, Y., Wu, J., Sun, Q., Zhu, Y., Liu, Y., Li, Z., Yeh, T.C.J., 2013. Simulating effect of anthropogenic activities and climate variation on Liulin Springs discharge depletion by using the ARIMAX model. Hydrological Processes 27, 2605–2613.
Huss, M., Sugiyama, S., Bauder, A., Funk, M., 2007. Retreat scenarios of Unteraargletscher, Switzerland, using a combined ice-flow mass balance model. Arctic, Antarctic and Alpine Research 39, 422–431.
Immerzee, W.W., Beek, L.P.H., Bierkens, M.F.P., 2010. Climate change will affect the Asian Water Towers. Science 328, 1382–1385.
Institute Inc SAS, 2008. SAS/ETS®9.2: User's Guide. SAS Institute Inc., Cary, NC.
Kampf, S.K., Burges, S.J., 2007. A framework for classifying and comparing distributed hillslope and catchment hydrologic models. Water Resources Research 43 (W05), 423. http://dx.doi.org/10.1029/2006WR005370.
Kong, Y., Pang, Z., 2012. Evaluating the sensitivity of glacier rivers to climate change based on hydrograph separation of discharge. Journal of Hydrology 434–435, 121–129.
Kuhn, M., Batlogg, N., 1998. Glacier runoff in Alpine headwaters in a changing climate. In: Kovar, K.U., Tappeiner, N., Peters, E., Craig, R.G. (Eds.), Hydrology, Water Resources and Ecology in Headwaters, vol. 248. International Association of Hydrological Sciences Publication, pp. 78–88.
Lan, Y., Shen, Y., Zhong, Y., Wu, S., Wang, G., 2010. Sensitivity of the mountain runoff of Ürümqi River to the climate changes. Journal of Arid Land Resources and Environment 24 (11), 50–55 (in Chinese with English abstract).
Lan, Y., Zhong, Y., Wu, S., Shen, Y., Wang, G., 2009. Sensitivity of mounta in runoff of rivers originated from the South slope and the North slope of the Tianshan Mountain to Climate Change — taking mountain runoff of Urümqi River and Kaidu River for example. Journal of Mountain Science 27 (6), 712–718 (in Chinese with English abstract).
Li, B., Chen, Y., Chen, Z., Li, W., 2012. Trends in runoff versus climate change in typical rivers in the arid region of northwest China. Quaternary International 282, 87–95.
Li, Z., Wang, W., Zhang, M., Wang, F., Li, H., 2010. Observed changes in streamflow at the headwaters of the Ürümqi River, eastern Tianshan, central Asia. Hydrological Processes 24 (2), 217–224.
Liu, L., Liu, Z., Huang, H., Liu, G., Wu, S., 2011. Hydrological impacts of climate change in the Yellow River Basin for the 21st century using hydrological model and statistical downscaling model. Quaternary International 244, 211–220.
Liu, Y., Metivier, F., Lajeunesse, É., Lancien, P., Narteau, C., Ye, B., Meunier, P., 2008. Measuring bedload in gravel-bed mountain rivers: averaging methods and sampling strategies. Geodinamica Acta 21 (1–2), 81–92.
Liu, Y., Metivier, F., Gaillardet, J., Ye, B., Meunier, P., Narteau, C., Lajeunesse, É., 2011. Erosion rates deduced from seasonal mass balance along the upper Ürümqi River in Tianshan. Solid Earth 2 (2), 283–301.
Liu, Y., Huo, X., Hao, Y., Jiao, K., Han, T., Liu, Y., Liu, Z., Liu, C., 2013. A study of the variation of extreme runoff in the upstream of the Ürümqi River, Tianshan Mountains. Journal of Glaciology and Geocryology 35 (5), 1248–1258 (in Chinese with English abstract).
Metivier, F., Meunier, P., Moreira, M., Crave, A., Chaduteau, C., Ye, B., Liu, G., 2004. Transport dynamics and morphology of a high mountain stream during the peak flow season: the Ürümqi River (Chinese Tianshan). River Flow 1, 761–777.
Motyka, R.J., O'Neel, S., Connor, C.L., Echelmeyer, K.A., 2002. Twentieth century thinning of Mendenhall Glacier, Alaska, and its relationship to climate, lake calving, and glacier run-off. Global and Planetary Change 35, 93–112.
Oerlemans, J., 2005. Extracting a climate signal from 169 glacier records. Science 308, 675–677.
Rakovec, O., Weerts, A.H., Hazenberg, P., Torfs, J.J.F., Uijlenhoet, R., 2012. State updating of a distributed hydrological model with Ensemble Kalman Filtering: effects of updating frequency and observation network density on forecast accuracy. Hydrology and Earth System Sciences 16, 3435–3449.
Schaefli, B., Hingray, B., Niggli, M., Musy, A., 2005. A conceptual glacio-hydrological model for high mountainous catchments. Hydrology and Earth System Sciences 9, 95–109.
Shi, Y., Qu, Y., Ma, S., Chen, L., Yuan, Z., Tang, Y., Huang, W., 1992. Bearing Capacity and Rational Utilization of Water Resources of Ürumqi River Basin. Science Press, Beijing, China (in Chinese with English abstract).
Slutsky, E., 1937. The summation of random causes as the source of cyclic processes. Econometrica 5 (2), 105–146.
Sorg, A., Bolch, T., Stoffel, M., Solomina, O., Beniston, M., 2012. Climate change impacts on glaciers and runoff in Tien Shan (Central Asia). Nature Climate Change 2, 725–731.
Stahl, K., Moore, R.D., Shea, J.M., Hutchinson, D., Cannon, A.J., 2008. Coupled modelling of glacier and streamflow response to future climate scenarios. Water Resources Research 44 (W02), 422. http://dx.doi.org/10.1029/2007WR005956.
Sun, M., Li, Z., Yao, X., Jin, S., 2013. Rapid shrinkage and hydrological response of a typical continental glacier in the arid region of northwest China — taking Urumqi Glacier No.1 as an example. Ecohydrology 6 (6), 909–916.
Tesfaye, Y.G., Meerschaert, M.M., Anderson, P.L., 2006. Identification of periodic autoregressive moving average models and their application to the modeling of river flows. Water Resources Research 42 (1), W01419. http://dx.doi.org/10.1029/2004WR003772.
Versini1, P.A., Gaume, E., Andrieu, H., 2010. Application of a distributed hydrological model to the design of a road inundation warning system for flash flood prone areas. Natural Hazards and Earth System Sciences 10, 805–817.
Wang, P., Li, Z., Li, H., Cao, M., Wang, W., Wang, F., 2012. Glacier No.4 of Sigong River over Mt. Bogda of eastern Tianshan, central Asia: thinning and retreat during the period 1962–2009. Environmental Earth Sciences 66, 265–273.
Wang, P., Li, Z., Wang, W., Li, H., Zhou, P., Jin, S., 2013. Changes of six selected glaciers in the Tomor region, Tian Shan, Central Asia, over the past ~50 years, using high-resolution remote sensing images and field surveying. Quaternary International 311, 123–131.
Wold, H.O., 1938. A Study in the Analysis of Stationary Time Series. Almqvist and Wiksell, Stockholm.
Wooldridge, J.M., 2003. Cluster-sample methods in applied econometrics. American Economic Review XCIII, 133–138.
Wu, Y. (Ed.), 1992. Formation and Estimation of Mountain Water Resources in the Ürümqi River Basin. Science Press, Beijing, China, pp. 2–6 (in Chinese with English abstract).
Yule, G.U., 1927. On a method of investigating periodicities in disturbed series with special reference to Wolfer's sunspot numbers. Philosophical Transactions of the Royal Society of London Series A 226, 267–298.
Zemp, M., Haeberli, W., Hoelzle, M., Paul, F., 2006. Alpine glaciers to disappear within decades? Geophysical Research Letters 33 (L13), 504.