Impact of natural climate variability on runoff based on Monte Carlo method

Jie Yang, Jianxia Chang, Jun Yao, Yimin Wang, Qiang Huang and Guoxin Xu

ABSTRACT

Studying the impact of climate variability is important for the rational utilization of water resources, especially in the case of intensified global climate variability. Climate variability can be caused by natural climate variability or human-caused climate variability. The analysis of Jinghe River Basin (JRB) may not be comprehensive because few studies have concentrated on natural climate variability. Therefore, the primary goal is to explore the impact of natural climate variability on runoff. A modified Mann–Kendall test method was adopted to analyze the aberrance point to determine the natural condition period during which runoff was only influenced by natural climate variability. Then, the Monte Carlo method was employed to extract segments of monthly runoff in the natural condition period and combine them to construct a long series to reduce the instability. Results indicate that the percentage of runoff variability affected by natural climate variability is 30.52% at a confidence level of 95%. Next, a topography-based hydrological model and climate elasticity method were used to simulate runoff after the aberrance point without considering the impact caused by local interference. Through a comparison of the measured and simulated runoff, we discovered that local interference has the greatest impact on runoff in the JRB.

Key words | climate elasticity method, Monte Carlo method, natural climate variability, topography-based hydrological model

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INTRODUCTION

Over the past century, the global climate has changed dramatically, which has affected hydrologic circulation (Christensen *et al.* 2004; Graham *et al.* 2007; Xu *et al.* 2013; Croitoru & Minea 2015). Meanwhile, local interference (such as the variability of land use, large number of reservoirs and dams, water and soil conservation engineering, and urbanization) has also changed hydrologic circulation (White & Greer 2006; Astaraie-Imani *et al.* 2012; Zhou *et al.* 2012). Due to the double impacts of climate variability and local interference on runoff, surface runoff has changed significantly (Xu *et al.* 2013; Dong *et al.* 2014). Therefore, quantitative analysis of the impacts of climate variability and local interference on water resources is of great importance to watershed management and highly efficient utilization of water resources.

Climate variability includes natural climate variability and human-caused climate variability. In climate science, natural climate variability means climate driven by natural phenomena, such as variabilities in solar activity or the Earth's orbit. Human-caused climate variability refers to climate affected by local interference, such as increasing greenhouse gas emission, land use change, and deforestation. After the third assessment report of the IPCC, an increased emphasis on the impact of climate variability on runoff was proposed for future study regarding the attribution of natural climate variability. Since then, experts have

doi: 10.2166/wcc.2017.177

conducted considerable research on natural climate variability and have found that hydrological phenomena also have inter-annual variation, even without human-caused climate variability (Marengo 1995; Vogel *et al.* 1997; Chiew *et al.* 1998). Furthermore, experts have tried to analyze the contribution rates of all impacts on runoff. Hulme *et al.* (1999) introduced the signal to noise ratio and global climate models to analyze the contribution rates of natural climate variability. Arnell (2003) employed global climate models to quantitatively analyze the impact of natural climate variability on unchanged greenhouse gas emission scenarios. Milly *et al.* (2005) combined the global climate models with the response model to analyze the impact of natural climate variability.

The Jinghe River, the largest tributary of the Weihe River and second largest tributary of the Yellow River, is an important agricultural base in Shaanxi province (Peng *et al.* 2014). However, in recent decades, due to the impacts of climate variability and local interference, a multitude of problems has arisen, such as serious soil erosion, land degradation, soil desertification, water shortages, vegetation degradation, and many other issues that hinder the sustainable development of the economy and society (Peng *et al.* 2014). Therefore, it is important to analyze the hydrological characteristics and impacts of natural climate variability, human-caused climate variability, and local interference on water resources for sustainable utilization in the Jinghe River Basin (JRB) and water resources planning.

There is a great deal of research on the variability of runoff in the Yellow River Basin including the JRB. Liu & Cui (2011) and Du & Shi (2012) both found that local interference was the dominant reason for runoff variability. Wang *et al.* (2012) estimated that the contribution rates of local interference and climate variability on runoff were 92.07% and 7.93%, respectively. Chang *et al.* (2014) employed a variable infiltration capacity (VIC) to determine the runoff variability and found that local interference had a greater influence on runoff than climate variability, and the percentage of runoff changed by local interference was over 60%. The Budyko framework was used by Zhao *et al.* (2014) in the middle reaches of the Yellow River Basin, and they found that the local interference was the dominant factor responsible for the decline of runoff. Yao *et al.* (2015) identified the effect of climate variability due to local interference on runoff and found a recent increase in the effect of climate variability on runoff. The Budyko framework, a climate elasticity method, was adopted by Gao *et al.* (2016) to analyze the sensibility of local interference and climate variability on hydrological elements.

Experts have conducted numerous studies on the contribution rates of climate variability and local interference on runoff using hydrological models, climate elasticity methods, and many other methods (Chang *et al.* 2014; Yao *et al.* 2015; Gao *et al.* 2016) in the JRB. However, these studies did not focus on making a distinction within climate variability between natural climate variability and human-caused climate variability, which may have led to the results being incomprehensive. Furthermore, few studies have been devoted to using hydrological models together with climate elasticity methods to investigate runoff variability. Therefore, the main goal of this study is to quantitatively analyze the contributions of natural climate variability, both human-caused climate variability and local interference, on runoff in the JRB using hydrological models and climate elasticity methods, which can provide the basis for water resources management and sustainable development.

A simulation of natural climate variability requires long series data that are unaffected or minimally affected by local interference; however, observation data only exist for approximately 100 years worldwide, and only since the 1960s in most parts of China. Given that the hydrological data series in the JRB is too short to analyze the natural climate variability on runoff, the Monte Carlo method, a random sampling method, is employed in this study to extract short time series data and combine them to construct long time series data. The Monte Carlo method is based on probability statistics theory to obtain an approximate solution to a problem by random sampling (Jeremiah *et al.* 2012; Brodie 2013). The Monte Carlo method has advantages that include: a good reflection of statistical law; not being limited by the complexity of the multidimensional system; the ability to solve complex problems; and a simple structure that is flexible in application.

There are two main assumptions in the process of analyzing the effects of natural climate variability on runoff. Assumption 1 is that: hydrological data of each month in the natural condition period (the period before the aberrance point) are unaffected or minimally affected by local interference. It indicates that in this period, the changes in hydrological data are only influenced by natural climate variability, not by human-caused climate variability or local interference. Moreover, during this period, the monthly runoff varies between the maximum and minimum monthly runoff. Random monthly runoff can be combined arbitrarily to construct the random long time series runoff, and the measured monthly runoff series in the natural condition period being only just one of the possible combinations. A long series of all possible combinations can be regarded as the natural climate variability process. Assumption 2 is that: natural climate variability on runoff remains the same whether in the natural condition period or not.

Based on the above assumptions, the JRB was chosen as the study area. The Monte Carlo method was employed to analyze the natural climate variability on runoff. Then, a topography-based hydrological model (TOPMODEL) and climate elasticity method were employed to quantitatively assess the impact of natural climate variability, human-caused climate variability and local interference. The results of this study can provide a theoretical foundation for the management of water resources and sustainable utilization in the JRB.

DATA AND METHODS

Study area and data

The JRB was chosen as the study area and is shown in Figure 1. The Jinghe River originates from Mountain Liupan in Jingyuan County, Ningxia Hui Autonomous Region and flows for approximately 451 km. It lies in the Loess Plateau (106°E–110°E, 34°N–38°N) with a basin area of 4.54×10^4 km^2. The altitude of the JRB ranges from approximately 352 m to 2,922 m, and the terrain of the northwest region is higher than that of the southeast region. To the north is the loess hilly region; in the central and southern areas, there is a gully region of Loess Plateau; to the west is a soil stone mountain area; and in the east is the Ziwuling Forest area. The vegetation in the JRB is sparse and soil erosion is severe. It is located in a temperate continental climate and in a semi-dry and semi-humid region. The annual average rainfall is approximately 514 mm, mainly concentrated in a 6–8 month period, with rainfall rare in winter (Peng *et al.* 2014).

The measured monthly runoff was collected from the Zhangjiashan hydrological station (108°36′E, 34°38′N), and the monthly precipitation was collected from the Wuqi, Huanxian, Guyuan, Pingliang, Xifengzhen, Changwu, Tongchuan, Baoji, Wugong, and Xi'an meteorological stations, whose data are displayed in Figure 1. Monthly potential evaporation for each meteorological station was calculated by the Penman formula (Penman 1948). Digital elevation model (DEM) data were obtained from USGS. The longest data period is from 1960 to 2010. The measured monthly runoff of the Zhangjiashan hydrological station is presented in Figure 2. It can be observed from Figure 2 that the monthly runoff has a downward trend.

Modified Mann–Kendall test method

The modified Mann–Kendall test method was employed in this study to analyze the aberrance point of the measured runoff to determine the natural condition period. The modified Mann-Kendall test method is a nonparametric statistical method, whose samples do not need to obey a certain distribution and are not interfered with by outliers (Hamed & Rao 1998). With a simple structure and convenient calculation, it has been used to analyze the aberrance point (Tabari *et al.* 2012; Xuan *et al.* 2015), and the test statistic UF can be computed as follows:

$$UF = \frac{[s_k - E(s_k)]}{\sqrt{Var(s_k)}} \quad (k = 2, 3, \cdots, n) \tag{1}$$

$$s_k = \sum_{i=1}^{k} \sum_{j}^{i-1} \alpha_{ij} \tag{2}$$

$$\alpha_{ij} = \begin{cases} 1, x_i > x_j \\ 0, x_i < x_j \end{cases} \quad 1 \le j \le i \tag{3}$$

$$E(s_k) = \frac{\tau(\tau - 1)}{4} \tag{4}$$

$$Var(s_k) = \frac{\tau(\tau - 1)(2\tau + 5)}{72}$$

$$\tau = \frac{4k}{n(n-1)} - 1 \tag{5}$$

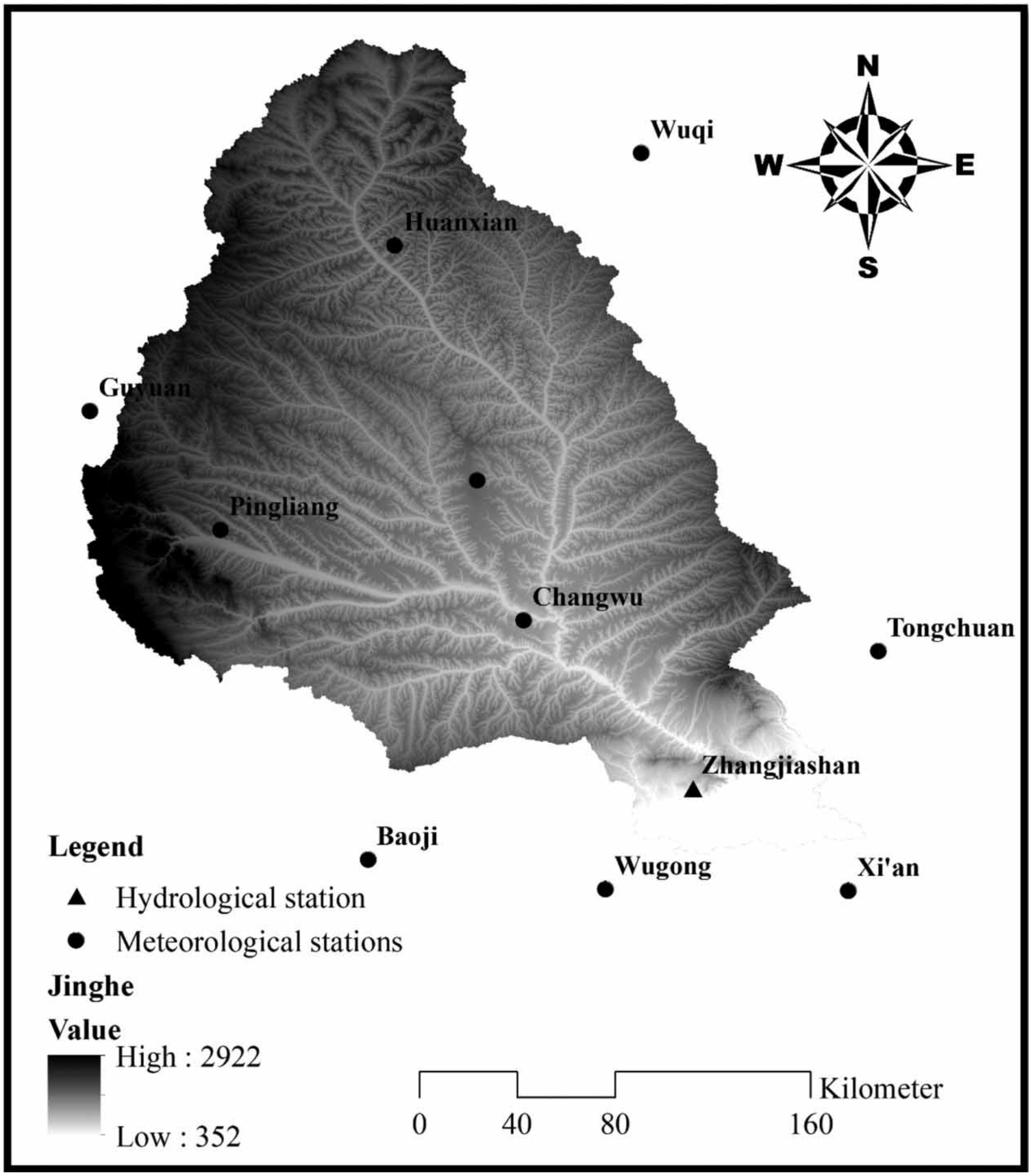

Figure 1 | Locations of the meteorological stations and hydrological station in the JRB.

where $x_1, x_2, \cdots, x_n$ is the runoff series; n is the number of runoff series; k is the total number of the situation $x_i < x_j$.

When realigning the runoff series $x_n, x_{n-1}, \cdots, x_1$, repeated, and the new test statistic UB can be calculated.

When $UF = UB$, that is, when the curves of UF and UB intersect under a certain confidence level, the aberrance point may be interpreted to have occurred in that period (Xuan *et al.* 2015). In general, the confidence level is always 95% (Gerstengarbe & Werner 1999).

Monte Carlo method

As the hydrological data series in the JRB is too short to analyze the impact of natural climate variability on runoff, in this study,

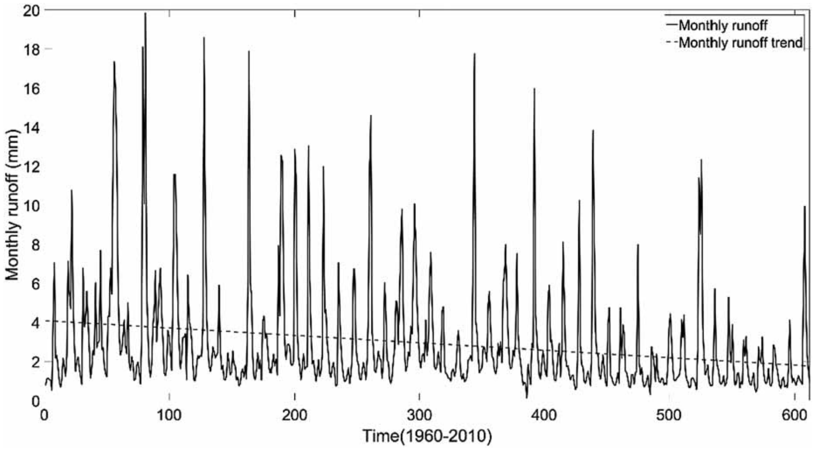

Figure 2 | Measured monthly runoff of the Zhangjiashan hydrological station from 1960 to 2010.

the Monte Carlo method was employed to extract the monthly runoff between the maximum and minimum values to construct long time series runoff data regarding the natural climate variability process. The method was proposed in the 1940s and has been widely used in the field of water resources (Jeremiah *et al.* 2012; Brodie 2013). Due to the advantages mentioned above, it was adopted in this study. A brief introduction of how to use the Monte Carlo method to determine the effect of natural climate variability on runoff is expressed below.

The theory of the Monte Carlo method is described as follows:

$$Y = f(X); X = (x_1, x_2, x_3, \cdots, a_n) \tag{6}$$

where Y is the function, X is a random variable of monthly runoff obeying a certain probability distribution, and $f(X)$ is an unknown or a complex function.

It is difficult to obtain the probability distribution of Y by analytical methods. The approach of the Monte Carlo method is that it can directly or indirectly sample from each random variable X, and then bring the sample into Equation (6) to calculate Y and repeat this cycle multiple times, thus obtaining a batch of functions $Y_1, Y_2, \cdots, Y_n$. If the number of simulations is large enough, the probabilistic characteristics of Y can be determined, and the sample mean and sample variance of Y can be expressed as follows:

$$\bar{Y} = \frac{1}{N}\sum_{i=1}^{N} Y_i \tag{7}$$

$$S_y^2 = \frac{1}{N}\sum_{i=1}^{N} (Y_i - \bar{Y})^2 \tag{8}$$

where $\bar{Y}$ represents the approximate expected value of Y, S_y^2 represents the sample variance of Y, N represents the number of sampling times, and Y_i represents the value of simulation of Y in each time, $i = 1, 2, \cdots, N$.

Based on assumption 1 and the Monte Carlo method, if the number of samples of monthly runoff in the natural condition period are large enough, the expected value of monthly runoff in the natural condition period will be obtained. Then, the natural climate variability on runoff can be obtained by analyzing the change of the long time series monthly extracted runoff compared to the expected value of monthly runoff.

Brief introduction of the TOPMODEL

A TOPMODEL is used to simulate monthly runoff after the aberrance point without considering the impact of local interference on runoff. TOPMODEL was proposed by Beven & Kirkby (1979). It is a semi-distributed hydrological model that uses a mathematical method to represent the hydrological circulation process. It has a simple concept and fewer parameters, making it easy to operate. In recent years, TOPMODEL has been modified by combining with the DEM, therefore, it has been widely used by scholars all over the world (Vincendon *et al.* 2010; Gao *et al.* 2014). In this study, a brief presentation about how to adopt TOPMODEL to analyze the impacts of natural climate and human-caused climate variability and local interference follows.

It is assumed that the variation of the monthly average runoff ΔQ is affected by natural climate variability $\Delta Q_{natural}$, human-caused climate variability ΔQ_{human} and local interference ΔQ_H (Bao *et al*. 2012). Runoff in the natural condition period is only affected by natural climate variability or is less influenced by local interference. Therefore, if the parameters in the natural condition are determined to simulate runoff $\Delta Q_{simulated}$ after the aberrance point, the variation ΔQ_H, i.e., the variation between the measured runoff $\Delta Q_{obs,2}$ after the aberrance point and the simulated runoff $\Delta Q_{simulated}$, is only affected by local interference.

$$\Delta Q = \Delta Q_C + \Delta Q_H \tag{9}$$

$$\Delta Q = \Delta Q_{obs,2} - \Delta Q_{obs,1} \tag{10}$$

$$\Delta Q_C = \Delta Q_{natural} + \Delta Q_{human} \tag{11}$$

$$\Delta Q_H = \Delta Q_{obs,2} - \Delta Q_{simulated} \tag{12}$$

where ΔQ_C (mm) and ΔQ_H (mm) represents the variability of runoff by climate variability and local interference, respectively; $\Delta Q_{obs,1}$ is the monthly average runoff before the aberrance point (mm).

The percentage of runoff changed by natural climate variability (*PN*) can be calculated by the Monte Carlo method; the percentages attributed by human-caused climate variability (*PC*) and local interference (*PH*) are computed as follows:

$$PC = 1 - PN - PH \tag{13}$$

$$PH = \frac{\Delta Q_H}{\Delta Q} \tag{14}$$

Evaluation indexes

The Nash–Sutcliffe efficiency coefficient (R^2) (Nash & Sutcliffe 1970), mean relative error (*MRE*) and root mean square errors (*RMSE*) were chosen as the evaluation indexes to estimate the accuracy of the simulation results of TOPMODEL. The best simulation results are those with a higher R^2 and lower *MRE* and *RMSE*. R^2 and *MRE* and *RMSE* are defined as follows:

$$R^2 = \left[1 - \frac{\sum_i (Q_i - Q_s)^2}{\sum_i (Q_i - \overline{Q_c})^2}\right] * 100\% \tag{15}$$

$$MRE = \frac{1}{N} \frac{\sum_i |Q_i - Q_s|}{Q_i} * 100\% \tag{16}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (Q_i - Q_s)^2} \tag{17}$$

where Q_i represents the measured runoff, Q_s represents the simulated runoff, $\overline{Q_c}$ is the mean measured runoff, and N denotes the number of the data set.

Climate elasticity method

The climate elasticity method was proposed by Schaake (1990) and is widely used to quantitatively analyze the hydrological response affected by climate variability after the aberrance point (Sankarasubramanian *et al*. 2001). The impact of climate variability, including natural climate variability and human-caused climate variability, on runoff after the aberrance point is calculated as follows:

$$\Delta Q_C = \left(\varepsilon_P \frac{\Delta P}{P} + \varepsilon_{E_0} \frac{\Delta E_0}{E_0}\right) Q \tag{18}$$

$$\Delta P = P_2 - P_1 \tag{19}$$

$$\Delta E_0 = E_2 - E_1 \tag{20}$$

$$\varepsilon_P = 1 + \frac{\phi F'(\phi)}{1 - F(\phi)} \tag{21}$$

$$\varepsilon_P + \varepsilon_{E_0} = 1 \tag{22}$$

$$\phi = \frac{E_0}{P} \tag{23}$$

where E_0, P, and Q are the monthly average potential evaporation (mm), monthly average precipitation (mm), and monthly average runoff in the whole period, respectively. P_2 and P_1 are the precipitation after and before the aberrance point, respectively. ΔP represents the variation of precipitation (mm) between P_2 and P_1; E_2 and E_1 denote the potential evaporation after and before the aberrance point, respectively. ΔE_0 represents the variation of potential evaporation (mm) between E_2 and E_1. ε_p and ε_{E_0} are dimensionless coefficients. ϕ is the aridity index. There are some climate elasticity methods to calculate $F(\varphi)$ listed in Table 1.

Table 1 | Formula of the climate elasticity method

References	Formula
Schreiber (1904)	$F(\phi) = 1 - E^{-\phi}$
Ol'dekop (1911)	$F(\phi) = \phi \tanh(1/\phi)$
Budyko (1961)	$F(\phi) = [\phi \tan(1/\phi)(1 - e^{-\phi})]^{1/2}$
Turc (1954) and Pike (1964)	$F(\phi) = 1/\sqrt{1 + \phi^{-2}}$
Fu (1981)	$F(\phi) = 1 + \phi - (1 + \phi^m)^{(1/m)}$
Zhang *et al.* (2001)	$F(\phi) = (1 + w^\phi)/(1 + w^\phi + 1/\phi)$

PN, PC, PH can be computed as follows:

$$PC + PN = \frac{\Delta Q_C}{\Delta Q} \tag{24}$$

$$PH = 1 - PN - PC \tag{25}$$

A detailed flowchart showing how the data were processed and analyzed is presented in Figure 3.

RESULTS

Aberrance point analysis

To analyze the impact of natural climate variability on runoff, the natural condition that is considered to be unaffected or minimally affected by local interference must be selected. In this study, the modified Mann–Kendall test method was chosen to analyze the aberrance point of the runoff, displayed in Figure 4 at a significance level of 95%.

Figure 4 shows that the curves of UF and UB intersected in 1996. Therefore, it can be concluded that the

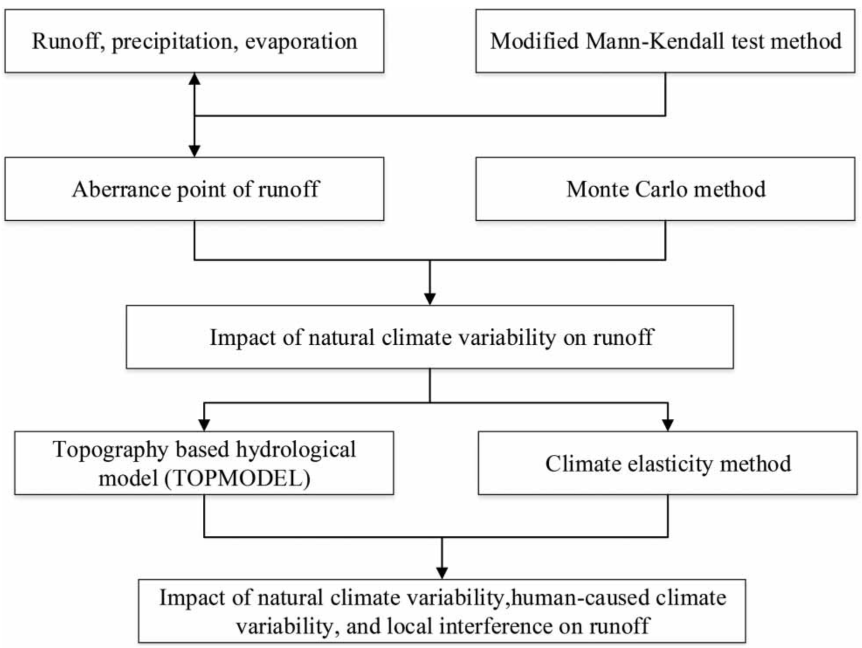

Figure 3 | Flowchart to analyze impacts on runoff.

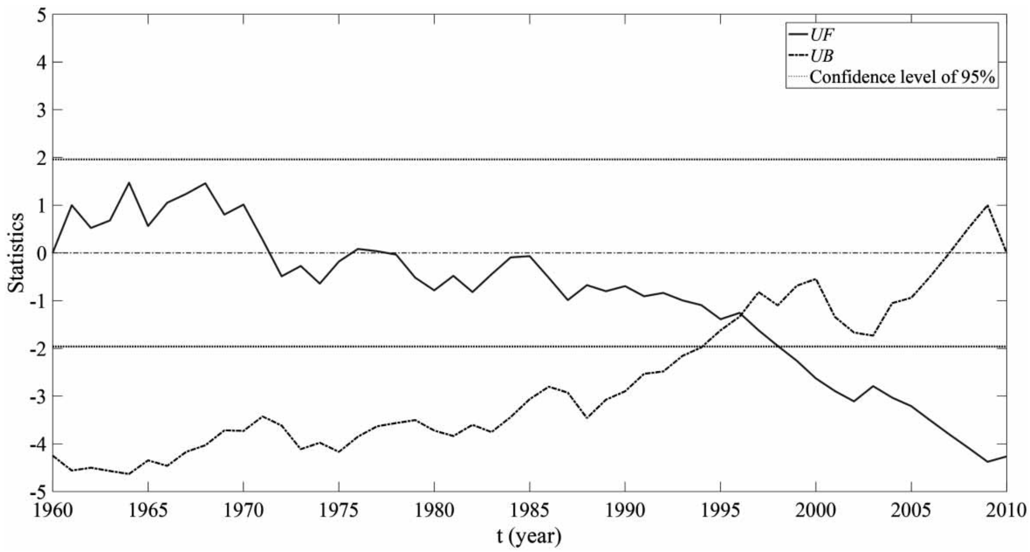

Figure 4 | Aberrance point of runoff tested by the modified Mann–Kendall method in the JRB.

aberrance point occurred in 1996, and that runoff from 1960 to 1995 was in the natural condition. This means that during this period, runoff was in a natural state of fluctuation and the variability of runoff was only affected by climate variability without local interference. More importantly, in this study, it can be concluded that the impact of natural climate variability was significantly greater than the impact of human-caused climate variability during this period. The monthly average runoff, precipitation, and potential evaporation in each period are listed in Table 2.

Table 2 shows that the monthly average runoff and monthly average precipitation from 1996 to 2010 decreased by 1.35 mm and 2.12 mm compared with that from 1960 to 1995, respectively. By contrast, the monthly average potential evaporation climbed by 2.97 mm from 1996 to 2010 compared to that from 1960 to 1995.

Table 2 | Monthly average data in the JRB

Periods	Q (mm)	P (mm)	E_0 (mm)	ΔQ (mm)	ΔP (mm)	ΔE_0 (mm)
1960–1995	3.34	43.46	71.64			
1996–2010	1.99	41.34	74.61	−1.35	−2.12	2.97
1960–2010	2.94	42.84	72.51			

Quantifying the impact of natural climate variability on runoff

To analyze the impact of natural climate variability on runoff, a long time series of hydrological data unaffected or minimally affected by local interference is needed. The short series of the runoff data from the Zhangjiashan hydrological station may lead to less reliability in the process of analyzing the impact of natural climate variability. Based on assumption 1, the Monte Carlo method is adopted in this study because it can randomly extract a short series of monthly runoff data between the maximum and minimum measured monthly runoff in the natural condition period, i.e., from 1960 to 1995, and combine them to construct long time series monthly runoff data. Therefore, we can also obtain a mass of monthly runoff data with a data period from 1960 to 1995 by combining monthly runoff data.

It is believed that the more sampling times available, the higher the accuracy of the extracted runoff close to the natural runoff in the natural condition period. However, there are limitations to the number of samples that can be taken. To reduce the workload, reasonable sampling times must be determined. In this study, extracted runoffs of 1,000 times, 5,000 times, 10,000 times, 15,000 times, 20,000 times, and 25,000 times are shown in Figure 5. In

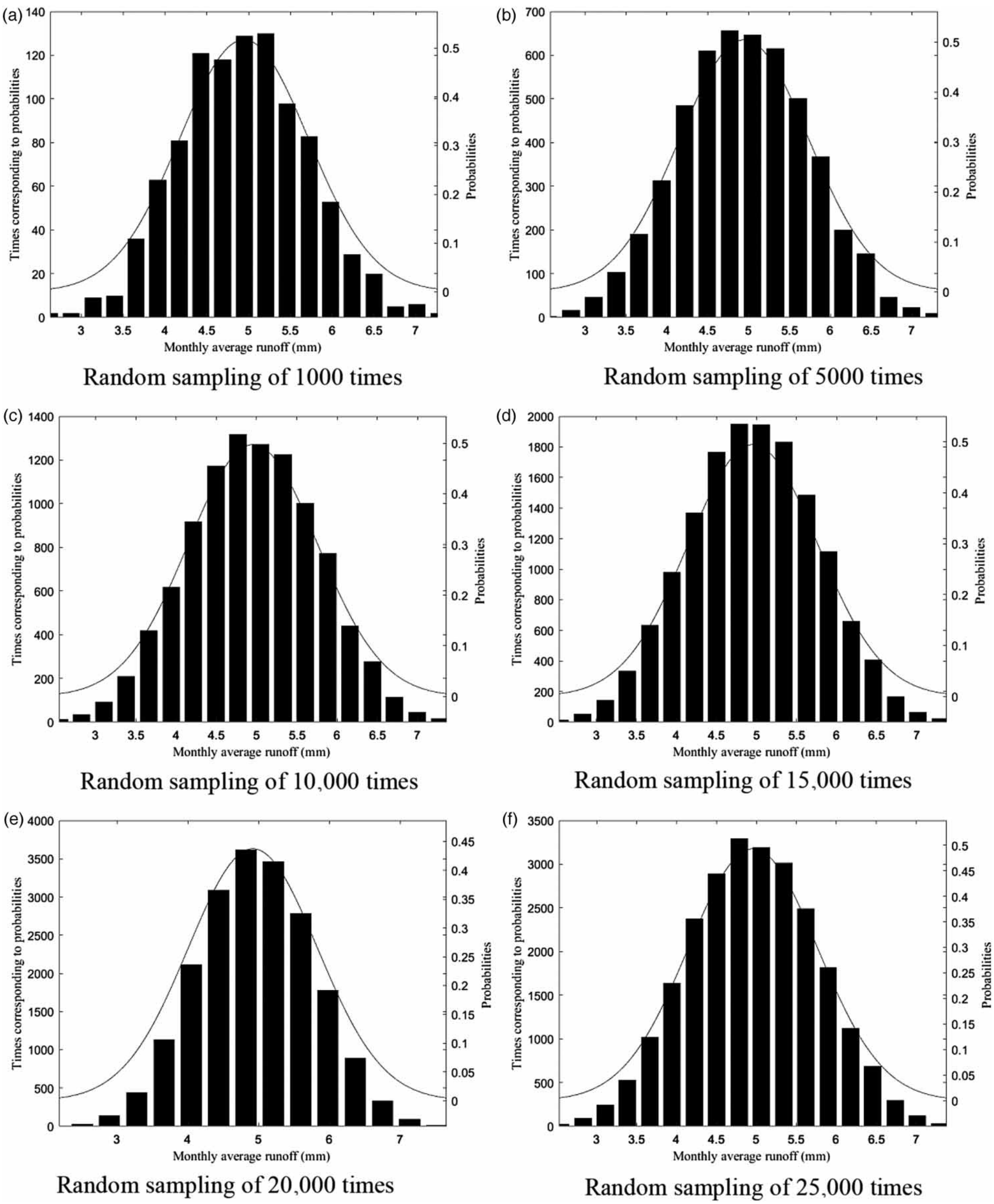

Figure 5 | Random sampling results of the measured runoff.

addition, whether the sampled runoff remains invariant is also analyzed based on the mean value and variance displayed in Table 3.

Figure 5 shows that the sampled runoff is basically stable when the number of sampling times reaches 20,000. Table 3 shows that the mean value or variance of the sampled runoff basically remains invariant when the number of sampling times reaches 20,000. Therefore, runoff data sampled 20,000 times are used to analyze the impact of natural climate variability on runoff.

After sampling the monthly runoff from 1960 to 1995 for 20,000 times, the impact of natural climate variability on runoff is analyzed by the Monte Carlo method at a confidence level of 95%, shown in Figure 6. The calculated results show that the percentage of variability of runoff caused by natural climate variability ranges from −30.34% to 30.70% at a confidence level of 95%. Therefore, the average percentage of variability of runoff due to natural climate variability is 30.52%, i.e., $PN = 30.52\%$ at a confidence level of 95%.

Model calibration and verification

TOPMODEL, which is widely used to describe and explain the runoff trend and movement of runoff along the slope due to gravity drainage by means of a topographic index $\ln(\alpha/\tan\beta)$ was chosen to simulate runoff in this study. To better simulate runoff, the accuracy of the topographic index must be improved. In this study, JRB is divided into 19 sub-watersheds, as shown in Figure 7, to obtain the topographic index and to boost the precision of the simulated runoff.

In this study, the natural condition period was from 1960 to 1995, and this period was divided into two smaller periods, the calibration period (1960–1980) and validation period (1981–1995). First, TOPMODEL was employed to simulate monthly runoff in the calibration period according to the monthly precipitation, monthly evaporation, and topographic index $\ln(\alpha/\tan\beta)$ in 19 sub-watersheds. The optimal evaluation indexes in the calibration period were: a Nash–Sutcliffe efficiency coefficient (R^2) of 0.70, *MRE* of

Table 3 | Analysis of the sampled average monthly runoff

Sampling times	1,000	5,000	10,000	15,000	20,000	25,000
Mean value (mm)	4.95	4.94	4.95	4.95	4.96	4.96
Variance (mm^2)	0.5927	0.6257	0.6435	0.6505	0.6544	0.6544

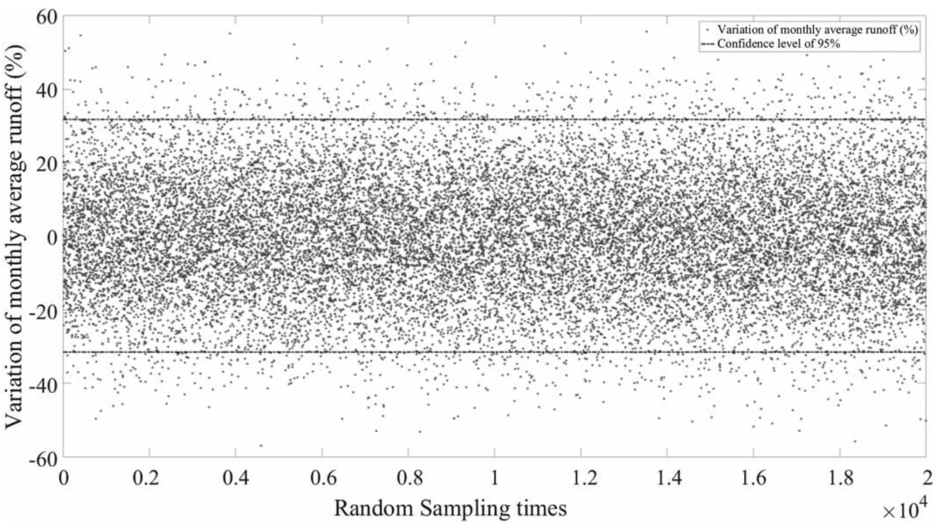

Figure 6 | Impact of natural climate variability on runoff in the JRB at a confidence level of 95%.

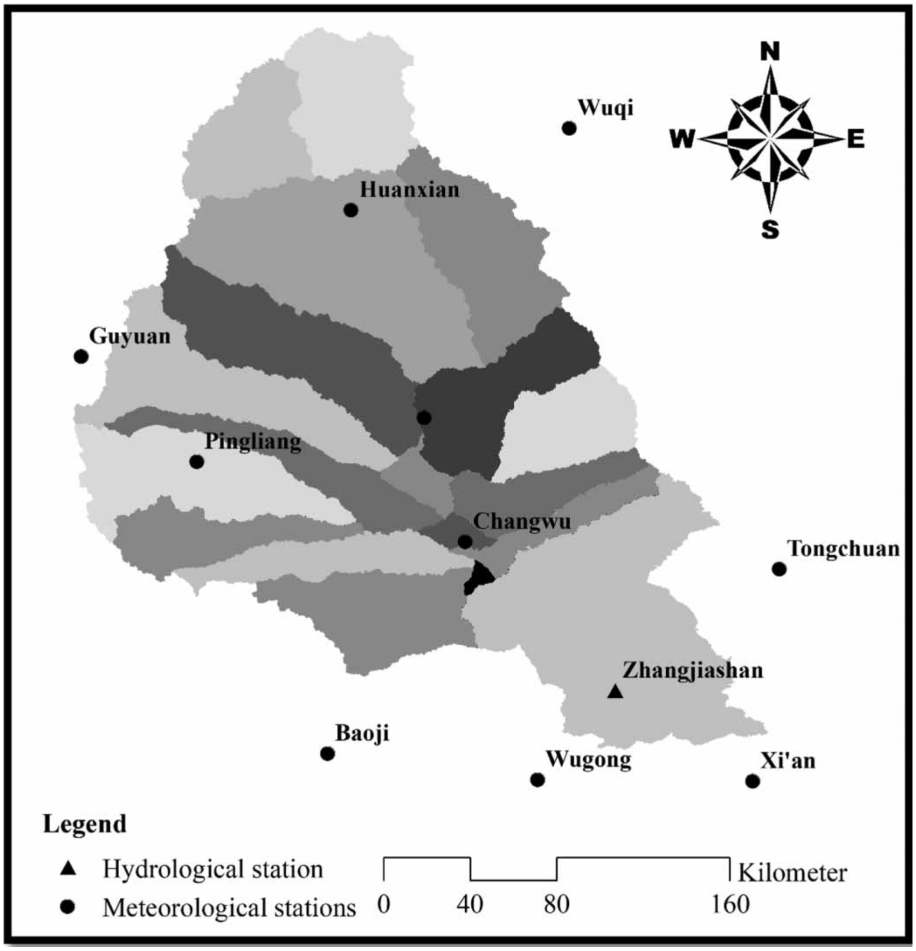

Figure 7 | Sub-watersheds of the JRB.

1.5822, and RMSE of 59.49. Then, TOPMODEL was used to simulate monthly runoff in the validation period according to the determined model parameters in the calibration period. The evaluation indexes in the validation period were: a Nash–Sutcliffe efficiency coefficient (R^2) of 0.76, *MRE* of 0.28, and RMSE of 46.34. Overall, the calibration and validation accuracies of the model are accepted for monthly runoff analysis.

Quantification of the impacts

Runoff from the Zhangjiashan hydrological station exhibits a downward trend. Studying the impact of climate variability has important scientific significance and value for water resources planning. To analyze why runoff varies after the aberrance point, first, runoff after the aberrance point must be simulated according to the determined model parameters, monthly precipitation, monthly evaporation, and topographic index $\ln(\alpha/\tan\beta)$ in 19 sub-watersheds. The simulated runoff from 1996 to 2010 based on TOPMODEL is shown in Figure 8. The difference is only affected by climate variability without local interference. The average simulated monthly runoff from 1996 to 2010 was 2.92 mm, i.e., $\Delta Q_{simulated} = 2.92$. According to Table 2, it can be calculated that $\Delta Q_{obs,2} = 1.99$, $\Delta Q = -1.35$, so $\Delta Q_H = 1.99 - 2.92 = -0.93$. Then, according to the section's brief introduction of the TOPMODEL, the impact of natural climate variability, human-caused climate variability, and local interference are analyzed, and the results are shown in Table 4.

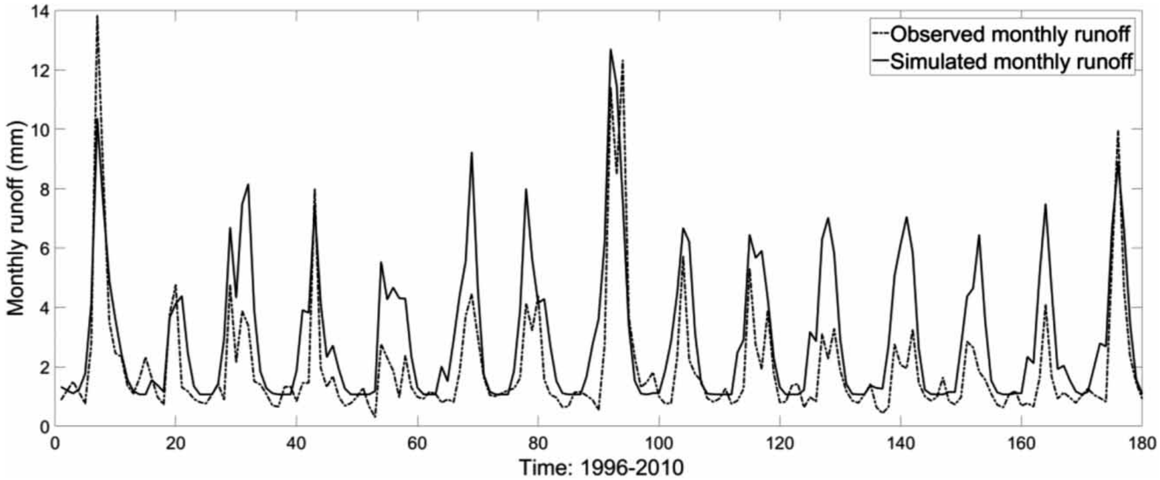

Figure 8 | Monthly runoff simulation from 1996 to 2010 in the JRB.

Table 4 shows the $PN = 30.52\%$, $PC = 0.59\%$, and $PH = 68.89\%$ at a confidence level of 95%. Therefore, the percentage of variability of runoff due to natural climate variability, human-caused climate variability, and local interference is 30.52%, 0.59% and 68.89% at a confidence level of 95%, respectively.

To verify the reliability of the results simulated by TOPMODEL, the climate elasticity method was employed in this study. According to Table 2, we know that $\Delta P = -2.12$, $\Delta E_0 = 2.97$, $Q = 2.94$, $P = 42.84$, and $E_0 = 72.51$. Based on these results and the climate elasticity method formulas, the results calculated at a confidence level of 95% are displayed in Table 5.

Table 5 demonstrates that the percentage of variability of runoff influenced by natural climate variability is 30.52%, by human-caused climate variability varies from

Table 4 | Impacts on runoff in the JRB based on TOPMODEL at a confidence level of 95%

			Impacts of human activities			Impacts of climate change		
Periods	***Q*** **(mm)**	**ΔQ (mm)**	**ΔQ_H (mm)**	***PH*** **(%)**	**ΔQ_{human} (mm)**	***PC*** **(%)**	**$\Delta Q_{natural}$ (mm)**	***PN*** **(%)**
1960–1995	3.34							
1996–2010	1.99	−1.35	−0.93	68.89	−0.01	0.59	−0.41	30.52

Table 5 | Impacts on runoff in the JRB based on the climate elasticity method at a confidence level of 95%

				Impacts of human activities			Impacts of climate change		
Methods	**ε_P**	**ε_{E_0}**	**ΔQ (mm)**	**ΔQ_H (mm)**	***PH*** **(%)**	**ΔQ_{human} (mm)**	***PC*** **(%)**	**$\Delta Q_{natural}$ (mm)**	***PN*** **(%)**
Schreiber	2.69	−1.69	−1.35	−0.76	55.93	−0.18	13.55	−0.41	30.52
Ol'dekop	2.76	−1.76	−1.35	−0.74	54.59	−0.20	14.89	−0.41	30.52
Budyko	2.73	−1.73	−1.35	−0.75	55.18	−0.19	14.30	−0.41	30.52
Turc and Pike	2.6	−1.6	−1.35	−0.78	57.70	−0.16	11.78	−0.41	30.52
Fu	2.33	−1.33	−1.35	−0.85	63.04	−0.09	6.44	−0.41	30.52
Zhang *et al.*	2.68	−1.68	−1.35	−0.76	56.15	−0.18	13.33	−0.41	30.52

6.44% to 14.89%, and by local interference varies from 54.59% to 63.04% at the confidence level of 95%.

DISCUSSION

This paper describes how TOPMODEL and the climate elasticity method were implemented to analyze their impacts on runoff. Tables 4 and 5 show that local interference is the dominant cause of the variability of runoff in the JRB, which agrees with some of the other research for this region. Chang *et al.* (2014) used the VIC hydrological model to analyze the impact of climate variability on runoff in the Weihe River Basin. The results showed that local interference had a greater impact on runoff than climate variability. Zhan *et al.* (2014) used an improved climate elasticity method to assess the impact on runoff in the Weihe River Basin and found that local interference made a greater contribution to the decrease in runoff than climate variability.

Local interference includes land use, soil and water conservation, and urbanization. The reduction on runoff influenced by local interference in the JRB is mainly influenced by soil and water conservation (Shi *et al.* 2013; Zhao *et al.* 2013). Figure 9 shows that the area of grass planting, check dam, afforestation and level terrace continuously increased in all periods, particularly since the 1990s. Since the beginning of the 1990s, the state strongly advocated returning farmland to forest and grassland; thus, forest lands and grasslands grew significantly, while interception also rose, and led to the reduction of runoff. At the same time, soil conservation such as dams and terraces led to significant scarring, which slowed or retained the runoff. Additionally, the rapid growth of population and irrigation areas increased the amount of water consumption, further reducing runoff. Finally, because of the development of urbanization, the developed and urban areas increased, also affecting the distribution of runoff and the water cycle in time and space.

Another important issue is the difference in the results calculated by the two methods. Compared to the results based on TOPMODEL, the impacts caused by local interference by the climate elasticity method are smaller. In addition, from Table 5, we can conclude that ε_p varies with different formulas, and the causes of the differences and how to choose the best formula still require further study.

One additional issue is that observation data are generally no more than 100 years worldwide. However, in most parts of China, data have only been recorded since the 1960s. The modified Mann–Kendall test method was employed in this study to analyze the aberrance point, and

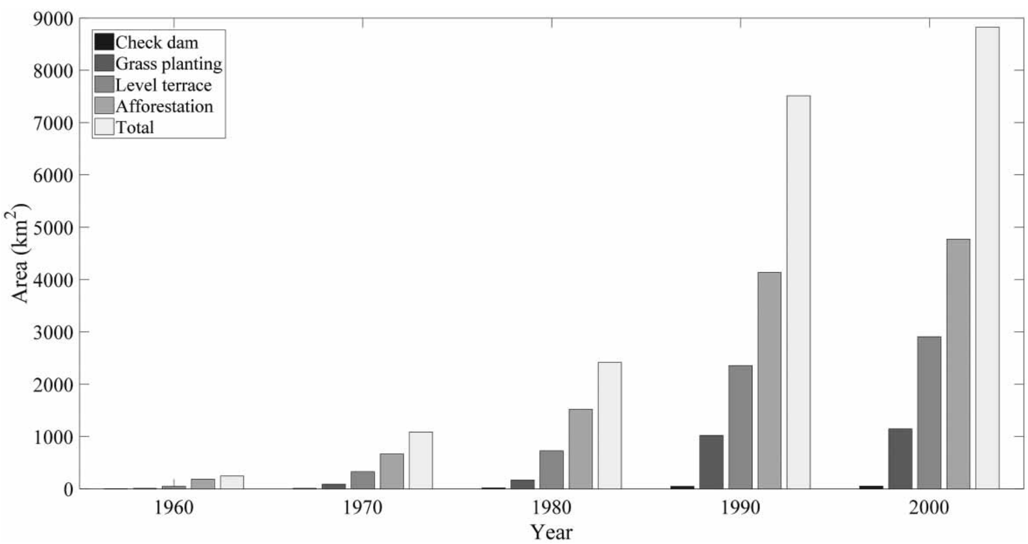

Figure 9 | Cumulative area of soil and water conservation measures in the JRB.

we determined that the natural condition period was from 1960 to 1995, which agrees with the findings of Prudhomme & Davies (2009a). It is generally believed that this period was affected by minimal greenhouse gas emissions in China (Prudhomme & Davies 2009b).

CONCLUSIONS

Although previous studies have investigated the impacts of climate variability and local interference on runoff, this study makes a distinction between natural climate variability and human-caused climate variability. To establish the effects of natural climate variability on runoff, the natural condition period from 1960 to 1995 was used because it is considered to be unaffected or minimally affected by local interference, as determined by the modified Mann–Kendall method.

The Monte Carlo method was employed to extract monthly runoff data during the natural condition period. After that, the extracted monthly runoff data were combined to construct a long time series of runoff data, with the goal of reducing the instability and reliability of the short runoff series, while analyzing the natural climate variability impact on runoff. It was discovered that the sampled runoff remained essentially invariant when the number of samples reached 20,000, and the results sampled 20,000 times showed that the impact on runoff due to natural climate variability was 30.52% at a confidence level of 95%.

To analyze the impact of natural climate variability, human-caused climate variability, and local interference, TOPMODEL and the climate elasticity method were adopted. The results based on TOPMODEL showed that the percentage of runoff variability was 30.52%, 0.59% and 68.89% at a confidence level of 95% due to natural climate variability, human-caused climate variability, and local interference, respectively.

The results based on the climate elasticity method showed that the impact on runoff due to natural climate variability was 30.52%, the impact due to human-caused climate variability changed from 6.44% to 14.89, and the impact due to local interference varied from 54.59% to 63.04% at a confidence level of 95%. The results by both methods indicate that local interference is the dominant cause for the variability of runoff in the JRB. More importantly, the impact of natural climate variability on runoff cannot be ignored in future studies. Although the JRB was selected as the study area in this study, the methods employed here can be applied in other regions as well.

ACKNOWLEDGEMENTS

This research is supported by The National Key Research and Development Program of China (2016YFC0400906), National Natural Science Foundation of China (51190093, 51309188), and Key Innovation Group of Science and Technology of Shaanxi (2012KCT-10). Sincere gratitude is extended to the editor and many reviewers for their help.

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First received 13 December 2016; accepted in revised form 17 May 2017. Available online 4 August 2017