Detection and attribution of abrupt shift in minor periods in human-impacted streamflow

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Abstract: Understanding the long-term variability of streamflow and its response to human activities in water-limited areas is essential for socio-hydrologic models' development. In this study, a framework for the detection and attribution of abrupt shift of minor periods in human-impacted streamflow is proposed. First, the most significant abrupt shift in human-impacted streamflow is detected using the Pettitt test and verified based on different statistical characteristics of streamflow series (trend, periodicity, and different quantiles) and main physical causes (main reservoirs operations). According to the breakpoint, the study period was divided into approximately natural sub-period and human-impacted sub-period. Interestingly, we found the "missing" of minor (2-4-year timescale) periods of the runoff records after abrupt shift points in the study cases. To investigate its mechanisms, we proposed an Improved Multivariate Fuzzy Mean Generating Function (IMFMGF) model to simulate the natural runoff in the human-impacted period and decomposed the observed runoff into natural runoff component and human-impacted changing runoff component. Then, the periodicity of these two components was compared based on Morlet wavelet analysis and Ensemble Empirical Mode Decomposition (EEMD). Results showed that the minor periods' wave crests and troughs of the above two components had excellent negative correspondence. The candidate mechanism is that the offsetting effects (i.e., the regular anthropogenic withdrawal or intake of water.) resulted in the disappearance of minor periods of the human-impacted observed, which can give more certain inputs into the prediction of non-stationary streamflow series.

Keywords: Runoff; Minor periods; Abrupt change, Human activities; IMFMGF; Wei River basin

1 Introduction

Climate variability and human activities have some notable impacts on the various components of the hydrological cycle (Ishak et al., 2013; Milly et al., 2002; Li et al., 2019; Chen et al., 2019; Esha & Imteaz, 2019). About 31% of 145 major rivers in the world have exhibited statistically significant variations in annual streamflow in recent decades (Zhai & Tao, 2017). It has been questioned that streamflow records are viewed as a stationary time series. Hence, many researchers have focused on detecting the non-stationary changes in long-term hydrological time series (Deng and Chen, 2017; Wang et al., 2015; Zhai and Tao, 2017). Moreover, understanding the reasons for runoff variation in a changing environment is vital to coping with droughts or floods as well as to avoid unforeseen changes in the future (Cassé et al., 2015). Most of the previous studies focused on the changes in mean or trend of hydrological series (Feng et al., 2016; Gao et al., 2016a; Rougé et al., 2013; Zuo et al., 2012, 2016). There were various techniques that have been applied to detect potential changes, such as the Mann-Kendall test, Bayesian inference, and Pettitt test (Reeves et al., 2007). Wherein significant changes in mean values are defined as abrupt shifts for hydrological time series (Rougé et al., 2013; Verbesselt et al., 2010). The abrupt changes can be related to some anthropogenic activities, such as the construction of reservoirs and dams, streamflow regulation, the rapid increase of water consumption (Cloern et al., 2016; Kam and Sheffield, 2016; Wu et al., 2017a; Zhang et al., 2015). The abrupt change point is usually regarded as a breakpoint. Usually, the hydrological records before the first breakpoint are viewed to undergo little influence from human interference. Conversely, the records after the breakpoint are usually disturbed by intense human activities. A significant gradual trend may also occur in the non-stationary hydrological time series. The relevant candidate human interferences include soil conservation, terrace construction, gradually increasing population, and hydraulic engineering (Cloern et al., 2016; Kam and Sheffield, 2016; Zhang et al., 2015). Similar to mean or trend, streamflow can be characterized by significantly seasonal and annual periodicities (Zhang et al., 2014). Some human activities (such as hydrological regulations of reservoirs) may alter the seasonal or annual periodic properties of streamflow (White et al., 2005). However, the periodic variations of streamflow due to human activities received less attention, even though they play a vital role in regional water supply and hydropower generation (Koch et al., 2011; Stojković et al., 2014).

Some studies have reported the periodicity properties or multi-timescale characteristics in hydrology, meteorology, and other fields (Li et al., 2017; Wei et al., 2016; Wu et al., 2017b; Yuan et al., 2015, 2016; Zhao et al., 2017). For instance, Yuan et al. (2015) found the significant 2-year to 4-year periodicities in precipitation and temperature time series in the Yellow River basin. In addition, an 8-year periodicity of streamflow was significant from the end of the 1960s to the beginning of the 1990s. Wei et al. (2016) applied the Morlet wavelet to analyze the cycles of oscillations occurring in streamflow and suspended sediment discharge series. The cycles of oscillations are mainly due to an alternate change in the wet/dry periods and the high/low sediment discharge periods in the mainstream of the Yellow River. Li et al. (2017) investigated the variations of the trend, inter-annual variability, and periodicity of precipitation and sunspot numbers as well as their interrelationships using Morlet wavelet analysis. Results indicated that, unlike precipitation, the sunspot number reflected a clear periodic variability in the Loess Plateau, China.

Furthermore, some gradual variations of the periodicity of time series have been of increasing concern in hydrological fields. Lv et al. (2012) found that the periodicity of the runoff series presented a gradual attenuation after 1965 at Huayuankou hydrological station in the Yellow River basin, China. Wu et al. (2017b) analyzed the runoff records using continuous wavelet analysis. Results showed that the periodicity of the runoff was weak in the 1980s and strengthened after 1998. Also, this phenomenon was found in Karst hydrology by Wei et al. (2013) who proposed that "the strong periodic signal attenuated and even some smaller time-scale signal disappeared in the transmission process from precipitation to the spring flow through Karst aquifer".

Besides the aforementioned gradual variations of the periodicity of time series, may the periodicity of hydrological series occur abrupt shifts? However, there is hardly any literature discussing the abrupt shift of periodicity of runoff at one or several timescales caused by anthropogenic interference. Thus, the objective of this study is to propose a framework for the detection and attribution of the abrupt shift of periodicity in human-impacted streamflow. What is more, although numerous current reports have concentrated on quantifying the impacts of human activities and climate change on runoff variation (Bennett et al., 2016; Dey and Mishra, 2017; Deng and Chen, 2017;

Feng et al., 2016; Gao et al., 2015, 2016b; Jiang et al., 2015; Wang et al., 2015; Wang, 2014; Wu et al., 2017c, 2012; Zhai and Tao, 2017; Zhan et al., 2014; Zuo et al., 2016), the ways human activities interfere with runoff have not been explored from the perspective of periodicity. Thus, the main contribution of this study is exploring the potential response mechanism for the abrupt shift of periodicity in the long-term runoff. The exploration of the response mechanism is critical to the water resources planning and management but also provides essential information for predicting non-stationary streamflow in complex hydro-social systems.

The primary novelty of this study is as shown in the following: (1) A systematic scheme for detecting and verifying the abrupt shift of streamflow series is developed. (2) A framework for investigating candidate mechanism of abrupt shift of minor periods in human-impacted streamflow is provided. (3) A forecast model is proposed for predicting long-term natural runoff in ungauged basins.

2 Study area and data

The Wei River basin was selected as the study area in this paper (as shown in Figure 1). The Wei River is the largest tributary of the Yellow River basin in China (Huang et al., 2017). With a total length of 818 km, its drainage area is 134,800 km^2. The elevation of Wei River basin range spans from 320 to 3600 m above sea level and its latitude range 33° 50′ N-37° 18′ N. The mean annual runoff is approximately 10.4 billion m^3. The climatic conditions are significantly different over the whole year in the Wei River basin, belonging to continental monsoon. The snowmelt has a little impact on the runoff due to climate warming and winter is a very dry season (Huang et al., 2017). The annual precipitation is approximately 572 mm, which is mainly concentrated in June to October. The multi-year average temperature is approximately 10.6℃ (Zuo et al., 2012). As a leading grain-yielding basin in Northwest China, the Wei River basin is the main source of water supply, which controls the water use of 22 million people. The basin, where the Guangzhong-Tianshui Economic Zone is located, plays a vital role in economic development in the Northwest of China (Huang et al., 2017; Zuo et al., 2015). Over the past five decades, intensive human activities, covering constructing terraces, reservoir construction, sediment-trap dams, river diversion, soil conservation, and other related engineering and management practices, have caused the significant changes in the long-term hydrological time series in the Wei River basin (Chen et al., 2016; Gao et al., 2013; Guo et al., 2013; Zhan et al., 2014; Zuo et al., 2012; Zhao et al., 2013, 2015). Thus, the Wei River basin is appropriate for this study to represent significant human-impacted basins.

Thirty meteorological stations and two representative hydrological gauges (including the Xianyang and Zhangjiashan stations) in the Wei River basin were considered in this study (Figure 1). Precipitation and temperature in each sub-area were calculated using the tessellation polygon method (Okabe et al., 2009). The Xianyang and Zhangjiashan stations are located in the lower areas of the Wei River and downstream of the Jing River, respectively. The datasets used in this study included mean annual precipitation, temperature, and runoff. The annual precipitation and temperature data (including 1952-2009 in the Xianyang basin and 1960-2010 in Zhangjiashan basin) from 30 meteorological stations were collected from the National Climate Center (NCC) of the China Meteorological Administration (CMA). The annual runoff records from 1934-2009 (Xianyang gauge) and 1960-2010 (Zhangjiashan gauge) are provided by the Shaanxi Hydrometric and Water Resource Bureau. The sampling rate of the meteorological stations and Xianyang gauge and Zhangjiashan gauge is 1-Hz and their sampling period is 1 min.

3 Methodology

3.1 The framework for detection and attribution of abrupt shift of periodicity in long-term runoff series

From the perspective of hydrological time series, the main statistical properties include mean, variance, trend, periodicity, distribution, autocorrelation, and entropy (Hosking, 1984; Matalas, 1967; Salas, 1980; Yue et al., 2002a). When human perturbation on the hydrological system (or cycle) is intensive, these properties could present varying degrees of changes, and the forms of these changes mainly include abrupt change and gradual change (Machiwal et al., 2017; Rougé et al., 2013). In this study, the form of abrupt change of hydrological time series was focused. In this regard, it is not suggested to conclude that hydrological time series are significantly changed based on the detection of sole property (such as mean or variance) in the attribution of the human disturbances. In this regard, this study took the abrupt change of mean of streamflow series as the breakpoint, the significance of changes of other properties (covering tendency, periodicity, and distribution) was detected before and after the abrupt change point. Also, it is vital to investigate the time when intense human interference occurred to verify the above results. Most importantly, it is interesting to note that the disappearance of the 2-4-year minor periods after the abrupt change point and its candidate mechanisms were further explored.

The developed framework (Figure 2) can be summarized as follows. (1) The abrupt shift in the annual runoff series was detected using the Pettitt test which is usually applied to identify the significant abrupt shift of the mean value of a signal. To avoid the interference from the smooth trend, the trend-free (TF) (Yue et al., 2002a) procedure is performed before the Pettitt test. Based on the detected abrupt shift point, the study period was divided into approximately natural sub-period (period-1) with less anthropogenic interference and human-impacted period (period-2), respectively. (2) Ensuring the effectiveness of the detected abrupt shift point under human-induced hydrological change is a prerequisite for performing the following work. Hence, we applied a systematic verification scheme from two different perspectives. First, the different statistical characteristics of the runoff series before and after the abrupt shift were compared. Wherein, the statistical characteristics include mean, trend, periodicity, and different quantiles (the minimum and maximum range values, the upper and lower quartiles, and the median). The variations of the above-mentioned statistical characteristics were, respectively, detected using the Pettitt test, Trend-free pre-whitening Mann-Kendall test, Morlet wavelet analysis, and boxplots techniques (see Appendix A). Second, from the perspective of physical causes, we pay more attention to large-scale human activities which interfered the streamflow. (3) The candidate mechanisms of abrupt change or extinction of minor periods of runoff time series are investigated. First, the proposed forecast model was used to simulate the natural runoff component in the human-impacted period using precipitation data and temperature data over the whole period and extracting the information on runoff data before the abrupt shift. The human-impacted changing runoff component was the difference between the observed runoff and the simulated natural runoff component. As a result, the observed runoff in the human-impacted period was decomposed into the natural runoff component and the human-impacted changing runoff component. Then, the periodic variations of these two components are compared to identify the causes of the disappearance of minor periods using Morlet wavelet analysis and Ensemble Empirical Mode Decomposition (see Appendix A).

3.2 Improved multivariate fuzzy mean generating function model

The prediction methods of natural runoff mainly include hydrological models (such as SWAT, Soil and Water Assessment Tool) (Zhang et al., 2012), Restoring Water Volume (RWV) via investigating water consumption from different departments, and precipitation-runoff regression model (Blöschl et al., 2013). However, there are some practical limitations to these techniques. For example, the RWV approach is easily influenced by the completeness and accuracy of collected data and could result in larger deviations from real natural runoff. Precipitation-Runoff regression modeling is one of the most classical applications of hydrology. It simulated the river flow induced by describing the relationship between the precipitation and observed runoff. The precipitation-runoff regression model is limited in areas where the precipitation-runoff relationship is weak. The hydrological models, especially spatially distributed hydrological models, have better predictive performance, but these models need to be supported by a large amount of data. Thus, this study developed a simple and practical model, termed as Improved Multivariate Fuzzy Mean Generating Function forecasting model (IMFMGF), to simulate the natural runoff on human impacts and environmental change. The basic time step of the proposed model is a year.

The proposed model addresses the following challenges. (1) This study detected the abrupt shift of the minor (2-4-year scale) periods in streamflow series. Actually, we found that there were no significant 2-4-year scale main periods in the precipitation series and temperature series based on the analysis of peak values of their wavelet variance at both two study sites. Hence it is vital to capture the autocorrelation and period components of streamflow series themselves. In this regard, the model was proposed and it could effectively extract the different periodic components of a signal (as well as its first-order and the second-order difference signals). (2) Second, extracted autocorrelation and periodic information of streamflow series can improve the simulation accuracy of the model. (3) Third, the advantage of the proposed forecast model is more significant when the relationship between precipitation and runoff is weak. (4) Last, the model offers better performances for forecasting extremes due to the extraction of the second-order difference signals. The peak values of the simulated streamflow are critical to periodicity analysis using the Morlet wavelet (Bayazit et al., 2001). Its algorithm is composed of the following steps (see Figure 3).

Step 1. Design exponentially increasing Membership Function:

$$\mu_{\mathrm{A}} = \mathrm{e}^{-\beta(n-t)} (t = 1, \ldots, n) \tag{1}$$

where μ_{A} is the membership degree with time *t*; *n* is the length of the signal *x*; *β* is the fuzzy membership parameter which is usually set to 0.01.

Step 2. Calculate Fuzzy Mean Generating Function (FMGF):

$$\overline{x_l}(i) = \frac{\sum_{j=0}^{n_l-1} \mu_A(X) \cdot x(X)}{n_l} \; (i = 1, \ldots, l;\; 1 \leq l \leq m) \; (X = \mathrm{REM}\,(n, l) + i + jl) \tag{2}$$

$$n_l = \mathrm{INT}(\frac{n}{l});\; m = \mathrm{INT}(\frac{n}{2})$$

where l is the time-interval sequence; $\mathrm{REM}\,(n, l)$ returns the remainder after the division of *n* by *l*; $\mathrm{INT}(n/l)$ returns the signed integer after the division of *n* by *l*.

Step 3. Calculate Extended Fuzzy Mean Generating Function (EFMGF):

$$f_l(t) = \overline{x_l}(i), \mathrm{mod}(t, l) \equiv \mathrm{mod}(i, l) \; (t = 1,2,..,n) \tag{3}$$

where $\mathrm{mod}(t, l)$ returns the modulus after the division of *t* by *l*.

Step 4. Calculate the EFMGFs of the first-order difference signal and second-order difference signal:

$$\Delta x(t) = x(t+1) - x(t) \; (t = 1, \ldots, n-1) \tag{4}$$

$$\Delta^2 x(t) = \Delta x(t+1) - \Delta x(t) \; (t = 1, \ldots, n-2) \tag{5}$$

The EFMGFs of the original signal, the first-order difference signal, and the second-order difference signal are $f_l^{(0)}(t)$, $f_l^{(1)}(t)$, $f_l^{(2)}(t)$, respectively. All the EFMGFs are regarded as predictive factors.

Step 5. Optimize the predictive factors by applying the screening criteria based on the variance analysis.

$$Z = \frac{S(l)}{l} \tag{6}$$

$$S(l) = \sum_{i=0}^{l} n_i(\overline{x_l}(i) - \bar{x})^2 \ (2 \le l \le m) \tag{7}$$

All the predictive factors are sorted according to their corresponding Z values. The first P predictive factors are selected as the final predictive factors. In general, the range of the P-value is 3 to 5.

Step 6: Add K external predictive factors, such as precipitation and temperature. Multiple regression model is estimated as follows:

$$\hat{x}(t) = a_0 + \sum_{i=1}^{P+K} a_i f_i(t) \tag{8}$$

where $\hat{x}(t)$ is the simulations; a_0 and a_i are the regression parameters; $f_i(t)$ is the i^{th} predictive factors.

The classical mean generating function (MGF) was proposed by Cao and Wei (1991). The fuzzy mean generating function (FMGF) was subsequently developed by means of a Membership Function, which can represent the fuzzy behavior of this algorithm. The exponentially increasing Membership Function is designed to maximize the effectiveness of the latest data of the signal because the latest data play a more critical role in long-term prediction. The FMGF can extract the different periodic components of the signal. However, the latest data of the signal are usually not effectively used in the FMGF. Hence, we construct the FMGF based on the reverse-order signal (Zuo and Gao, 2004). The same operations are performed in the first-order and the second-order difference signals to fit the high-frequency components of the signal. The verification of the proposed model is elaborated as follows.

4 Results and discussion

4.1 Detecting and verifying the abrupt change of long-term runoff

The results of the Pettitt test (see Figure 4) are that the most significant abrupt shift point of mean values of the annual runoff time series is at Xianyang gauge in 1972 (Figure 5(a)) and at Zhangjiashan gauge in 1998 (Figure 5(c)). The streamflow series in the period-1 (before the abrupt change point) and period-2 (after the abrupt change point) are redetected using the Pettitt test to reconfirm whether the streamflow in the natural period (period-1) existed the intense human interference. The results showed that there are no significant abrupt change points in the streamflow series in Period-1 at both two study sites. In period-2, there is no significant abrupt change point at Zhangjiashan gauge, and a significant abrupt shift point in 1995 exists in the streamflow series at Xianyang gauge. The results demonstrated that in 1972, it was not only the most significant abrupt change point of the measured runoff at Xianyang gauge but also the first abrupt shift point. This situation at Zhangjiashan gauge was the same as that at Xianyang gauge. The detected abrupt shift points are verified from the following perspectives.

(1) The statistical characteristics from boxplot (including maximum value, first quartile (25%), mean, third quartile (75%), and minimum value of data) between the observed runoff series in period-1 and period-2 were compared, as shown in Figure 5(b). The figures show that these characteristic values of annual runoff in period-2 decreased at Zhangjiashan gauge. Notably, the 25-75% intervals of data could effectively represent the variance of series, which were also significantly narrowed. Furthermore, a more rigorous statistical test, i.e., KS test for the difference between the distribution of the series in period 1 and period 2. The results that the null hypothesis at the

1% significance level is not rejected, which indicated that the distributions of these two series (streamflow series in period 1 and period 2) are significantly different. In addition, the length of data after the abrupt shift point at Zhangjiashan gauge is not applicable to the boxplot.

(2) The significance of the trend of runoff series in period-1and the entire period was detected and compared using TFPW-MK (i.e., Trend-free pre-whitening Mann-Kendall test) at the different significant level (0.001, 0.005, 0.01, 0.05, 0.1, 0.5). The results (see Table 1) showed that the observed runoff series in period-1 at both two study sites have no significant trend. For the entire period, the results manifested that both the runoff series in the whole period at both two study sites significantly decreased at a different significance level. It indicated that the sharp reduction after the abrupt change point leads to the results of the MK test for the whole series, i.e., a significant trend. This further validated the results of Pettitt's test. It is worth noting that the significant trend tested by MK is likely not smooth because non-parametric MK test converts original time series to ranks, which can only be used to illustrate the monotonicity of monotonic series (Hamed, 2008; Hamed and Ramachandra Rao, 1998; Yue et al., 2002a). Also, the results of the TFPW-MK test in period-1 and the entire period were consistent with the results of other relevant literature (Guo et al., 2013; Zhan et al., 2014; Zuo et al., 2012).

(3) For periodicity properties, we apply Morlet wavelet analysis to reveal the changes in frequency components of observed runoff series in different time domains. The modulus and the real part of the wavelet transform coefficients are two important factors. The modulus represents the energy density of the signal because the energy is in direct ratio to the modulus. The real part of wavelet transform coefficients denotes the distribution of the signal phase in the time domain. In the hydrological system, the Morlet wavelet transform coefficients can characterize the multi-scale evolution and the transient properties of hydrological processes. The positive value of the real part corresponds to the wet period, the negative value corresponds to the drought period, and the zero corresponds to the transitional area (Hao et al., 2012; Zhang et al., 2007). In this regard, the real part of the wavelet coefficient contour maps of runoff is used to analyze the variations of periodicity properties of runoff time series in this study. The real parts of the wavelet coefficient contour maps of the observed runoff and their schematics in minor periods at the Xianyang gauge and Zhangjiashan gauge are shown in Figure 6. It can be seen that ① the 25-year main period of runoff was shortened to the 20-year period over time. This phenomenon indicated that the low-frequency runoff exhibited a gradually decreasing trend, which was consistent with the results of the TFPW-MK test at both gauges; ② at Xianyang gauge, the 9-year main period of the observed runoff first reduced and then expanded, next to more irregular after 2000. However, the 9-year main period of the observed runoff was more steady at Zhangjiashan gauge; ③ Most notably, the significant 2-4 year minor periods of the runoff series disappeared after the abrupt shift point at both two gauges, which is further discussed below. The wavelet variance for the observed streamflow is usually used to identify the main periodic components (Jenouvrier et al., 2005; Li et al., 2013; Nakken, 1999). So, we utilize the wavelet variance for after and before abrupt change point of observed streamflow to verify the disappearance of the minor periods of human-impacted observations. As shown in Figure 7, the results showed that the minor periods (2-4-year timescale) disappeared after the significant abrupt change points at both two sites.

(4) Indeed, any method of detecting hydrological change cannot be viewed as convincing evidence (Buishand, 1984). Hence the main human interference (such as the reservoirs regulations) were further investigated. In the Wei River basin, the reservoirs are the largest human disturbance (Zhan et al., 2014). It is important to emphasize the operation mode of the reservoir system. The large-scale surface water withdrawals from the reservoirs are used to irrigation fields, industrial, and domestic water consumption (Zhan et al., 2014). Hence, the construction of reservoirs not only redistributes the seasonal water discharge within any given year but also significantly adjusts inter-annual distribution. The inter-annual distribution is identified by two important indices including the completion time and

storage capacities of the main reservoirs, which are visualized in Figure 8. In the upstream of the Xianyang gauge, the main reservoirs with relatively large reservoir capacity include Jinping reservoir, Xiazhai reservoir, Zhangjiazuitou reservoir, Duanjiaxia reservoir, Fengjiashan reservoir, Shituhe reservoir. Xinyigou reservoir, Yangmaowan reservoir, Dabeigou reservoir, Laoyaju reservoir, and Shibianyu reservoir. According to the colors of the bubble chart, most of them were built simultaneously in the early 1970s. In the Jing River basin, the largest reservoir, Xijiao reservoir, was constructed in 1997. It directly controls the streamflow volume in the downstream of the Zhangjiashan gauge. Besides, some water withdrawal from the river channel for regional agriculture, industry, and human life caused the approximate doubling of a decrease in the early 1970s in the mainstream of the Wei River basin. As a result, the interference time of the main human activities in the study areas is close to the abrupt shift point of runoff, which further verified the above results.

4.2 Natural runoff simulating

To explore the candidate mechanisms of abrupt change or the disappearance of minor periods of the runoff time series in the study areas, we decomposed the observed runoff into the natural runoff component and human-impacted runoff component which mainly reflected water intake or water consumption by human activities. Hence, it is vital for simulating natural runoff.

4.2.1 Verification of the IMFMGF model in the natural period

The annual runoff series at Xianyang gauge was taken as an example to verify the IMFMGF (i.e., Improved Multivariate Fuzzy Mean Generating Function) model. The hydrological data (including annual precipitation, temperature, and runoff data) in 1953-1964 and in 1965-1971 were used for the calibration and verification of the model, respectively. In the proposed model, the optimized predictive factors and their corresponding regression parameters and Z values are listed in Table 2. The simulated natural runoff is shown in Figure 9. The model performance in the calibration and verification periods is evaluated using the Nash Sutcliffe efficiency coefficient (NSE) (Nash and Sutcliffe, 1970), and their NSE values are 0.971 and 0.892, respectively. The result shows that the model performance for simulating natural runoff is good. Furthermore, the model performance in the peaks is evaluated using the Mean Relative Errors (MRE) metric (Islamoglu, 2003). Wherein the peaks are extracted using the built-in findpeaks MATLAB function (Ferraris et al., 2014), which are marked in red in Figure 9. The MRE values of the extreme points in the validation period is 0.153, which indicates that the model has an advantage in simulating extremum.

4.2.2 Verification of the IMFMGF model in the human-impacted period

Considering there is no measured natural runoff in the human-impacted period that can be referred, the simulated natural runoff is verified in three different ways: (1) the different statistical characteristics of the observed natural runoff and the simulated natural runoff are compared, which are represented using the boxplots in Figure 10. The observed natural runoff denotes the observed runoff before the abrupt change point (1933-1971). The simulated natural runoff denotes the simulated runoff after the abrupt change point (1972-2009). As shown in Figure 10, these statistical characteristics and the intervals of these two series are with no significant difference. (2) The precipitation-natural runoff relationship can comprehend the tremendous spatial and temporal watershed characteristics, snowpack or precipitation patterns, as well as other complex hydrological phenomena (Tokar and Johnson, 1999). Hence, it is also used to verify the simulated natural runoff by determining whether the precipitation-runoff relationship was stable before and after the abrupt change point. See Figure 11, the regression lines of the precipitation-natural runoff scatter plot before and after the abrupt change was close. Their correlation coefficients (R^2) are 0.846 and 0.901, respectively, which are also close. (3) The simulation accuracy of hydrological time series is sensitive to its high-frequency components (i.e., minor periods) (Karthikeyan and Nagesh Kumar, 2013). Hence, we analyzed the contour maps of the real part wavelet coefficients of the simulated natural runoff components to further verify the model performance. In Figure 12, the 2-4-year main periods of the simulated natural runoff were restored and their regular distributions were consistent with the distributions of the observed natural runoff in the natural period. Consequently, with the limitation of the absence of the observed natural runoff in the human-impacted period, the three different verification processes suggest that the proposed model for simulating natural runoff is robust.

The predicted results and the observed values at both two study cases are drawn in Figure 13. The Nash-Sutcliffe efficiency coefficient values for the simulated natural streamflow in the natural period at Xianyang gauge and Zhangjiashan gauge are 0.958 and 0.889, respectively. Moreover, in the natural period (period-1), the NSE value for simulated and observed runoff is 0.971 in the calibration period and 0.892 in the verification period. In the human-impacted period (period-2), the NSE for simulated natural runoff and observed runoff is 0.958 in the period-1 and 0.413 in the period-2. As a result, the difference between the calibration and simulation in period-1 and period-2 is large. It indicates that the effect of model errors on simulated runoff is insignificant compared to the interference of human activities on observed runoff.

4.3 Effect of climatic conditions on the streamflow

(1) The precipitation and temperature datasets at two study areas are visualized, as shown in Figure 14. The stationarity of precipitation and temperature is assessed using TFPW-MK. The results (see Table 3) show that the precipitation time series in both study areas have no significant trend, but the temperature time series have a significant upward gradient. It is worth emphasizing that the changes in the temperature time series are gradual rather than abrupt. (2) On the one hand, the main climate factor which controls the runoff generation is precipitation. The MK test results showed that the precipitation time series is stationary. The temperature time series with a gradual upward trend control the regional evapotranspiration. The increase in evaporation is insignificant compared to the variation of runoff caused by human activities in the study areas (Huang et al., 2016; Wu et al., 2017c; Zhan et al., 2014; Zou et al., 2018). (3) On the other hand, the objective of this study is actually the detection and attribution of abrupt shifts in minor periods in human-impacted streamflow. Hence, the form of the abrupt change of the streamflow time series was focused rather than a gradual shift. The large-scale human activities, which may cause the abrupt changes of runoff, were investigated to explore the mechanism of the abrupt shift in minor periods. The reservoir system is the largest human disturbance in the Wei River basin (Zhan et al., 2014). It is important to emphasize the operation mode of the reservoir system. The large-scale surface water withdrawals from the reservoirs are used to irrigation fields, industrial, and domestic water consumption (Zhan et al., 2014). The inter-annual distribution is identified by two important indices including the completion time and storage capacities of the main reservoirs. The volume of stored water along the time is difficult to be collected in this study, which is one of the limitations of this study and the future work needs to be considered. (4) Furthermore, the proposed forecasting model for the natural runoff after the abrupt change point used the precipitation and temperature as two of prediction factors. That is, the forecasted natural runoff involved the variation of climate conditions only. The negative values of measured minus simulated runoff which is human-impacted runoff component reveals the human-impacted changing runoff corresponds to human-induced water withdrawal. (5) Moreover, it was found that there were no significant 2-4-year scale main periods in the precipitation series and temperature series based on the analysis of peak values of their wavelet variance. Excluding the effects of the variations in climatic conditions on the abrupt shift of the minor periods

of the runoff, we focus on exploring the potential mechanism considering the effects of human activities.

4.4 Mechanism of abrupt shift in minor periods in human-impacted streamflow

Here, the periodicity properties of the natural runoff component and the human-impacted runoff component were compared via Morlet wavelet analysis and EEMD (i.e., Ensemble empirical mode decomposition) techniques. The contour maps of the real part wavelet coefficients of the two components at Xianyang and Zhangjiashan gauges are shown in Figure 12. According to the schematics in their minor periods, it is interesting to note that the wave crests and troughs of the two components in 2-4-year minor periods have good negative correspondence. Specifically, when the minor periods of natural component series are in the troughs, the minor periods of human-impacted runoff components are at the peaks, and vice versa. The referred potential mechanism is that the larger the amount of natural water was, correspondingly, the more the anthropogenic water withdrawal was. Indeed, in the wavelet analysis algorithm, selecting a different mother wavelet would affect the outcome (Zhang et al., 2016). Hence, the stability of the results of the wavelet analysis needs to be further verified. In this regard, we further used EEMD (i.e., Ensemble empirical mode decomposition) method to filter out the long-term background change of the runoff time series and extract the high-frequency components (Intrinsic Mode Functions, IMFs) from the natural runoff and human-impacted runoff. The results (see Figure 15) indicated that the relationships between crests and troughs of the IMFs from the natural runoff and the human-impacted runoff were consistent with the above results from Morlet wavelet analysis.

Our preliminary analysis indicates that the response of the abrupt shift of minor periods of long-term runoff to human activities in the human-impacted period was an objective existence in the Wei River basin. The human-impacted runoff component was at the same frequency with the natural runoff in opposite directions. One candidate mechanism for the abrupt shift of minor periods in the Wei River basin, we suggest, is the regular anthropogenic disturbance in the annual runoff, i.e., the regular anthropogenic withdrawal or intake of water (more water was withdrawn in wet years, and the less water was withdrawn in dry years). The offsetting effects in the 2-4-year minor periods resulted in the disappearance of minor periods of observed runoff in the human-impacted period. The effective benefits coming from the discussion of the potential mechanism of abrupt shift in minor periods in human-impacted streamflow are that the abrupt changes of the components in the frequency domain can provide the variable references for the inputs of simulating models. The identified variational periodicity properties as the inputs can significantly increase the prediction accuracy of hydrological models in non-stationary hydrological regime (Yaseen et al., 2016). Also, the attribution can provide vital information for building the coupled human-water systems in socio-hydrologic models (Elshafei et al., 2015; Troy et al., 2015).

5 Conclusions

A framework for the detection and attribution of abrupt shift of minor periods in human-impacted streamflow was proposed and applied at two hydrological gauges in the Wei River basin, China. The framework provides vital information in socio-hydrologic models and gives more certain inputs into the prediction of non-stationary hydrological time series in the changing natural and social environment. The main contributions can be drawn:

1. The most significant abrupt shift in human-impact streamflow in the study areas was detected by the Pettitt test. It was effectively verified by a systematic verification scheme including trend, periodicity, different quantiles, and main physical causes.
2. It is found that the significant 2-4-year minor periods of the runoff series disappeared after the abrupt shift point in the study cases. The candidate mechanism was investigated that the offsetting effects (i.e., the regular

anthropogenic withdrawal or intake of water) resulted in the disappearance of the minor periods of observed runoff in the human-impacted period. The exploration of the mechanism of this phenomenon is implemental to develop socio-hydrologic models and simulate the non-stationary hydrological time series.

3. The proposed model for simulating the long-term natural runoff (i.e., Improved Multivariate Fuzzy Mean Generating Function) addressed the three challenges including the extraction of autocorrelation and periodic information of streamflow series, application for the area where the relationship between precipitation and runoff is weak and data are poor, and robust extreme point predictions. Additionally, the uncertainty in the proposed model needs to be further considered and supplemented.

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Appendix A

Pettitt test

The Pettitt test detects the change points of the mean values of signals against the null hypothesis on the initial distribution. It is based on the Mann and Whitney statistical function ($U_{t,T}$) for comparing two independent samples ($x_1, \ldots, x_t$) and ($x_{t+1}, \ldots, x_T$) and gives the date of change point (Fraedrich et al., 2001; Kam and Sheffield, 2016; Pettitt, 1979; Serinaldi et al., 2018). $U_{t,T}$ is computed by:

$$U_{t,T} = U_{t-1,T} + V_{t,T} \quad (t = 2, \ldots, T) \tag{9}$$

$$V_{t,\mathrm{T}} = \sum_{j=1}^{T} sng(x_t - x_j) \tag{10}$$

$$sng(x) = \begin{cases} -1, & x < 0 \\ 0, & x = 0 \\ +1, & x > 0 \end{cases} \tag{11}$$

The most significant change point is evaluated by:

$$p(t) = max\left|U_{t,T}\right| \tag{12}$$

The significant probability associated with potential change point is approximated by:

$$q(t) \approx 2 \cdot exp\left(\frac{-6{U_{t,T}}^2}{T^3 + T^2}\right) \tag{13}$$

Trend-free pre-whitening Mann-Kendall test

The non-parametric Mann-Kendall (MK) statistical test recommended by WMO (World Meteorological Organization) has been widely used to determine the significance of trend in hydrological time series (Douglas et al., 2000; Hamed and Rao, 1998; Kendall, 1975; Mann, 1945; Yue et al., 2002b; Yue and Wang, 2004). The Mann-Kendall test statistic can be stated as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_k), \text{ and } \operatorname{sng}(\theta) = \begin{cases} +1 & \theta > 0 \\ 0 & \theta = 0 \\ -1 & \theta < 0 \end{cases} \begin{cases} +1, \ \theta > 0 \\ 0, \ \theta = 0 \\ -1, \ \theta < 0 \end{cases} \tag{14}$$

where x_j and x_k are the sequential values at times j and k, respectively, and n is the length of the data set.

With an asymptotically normal distribution, the mean and variance are given by

$$E(S) = 0, \text{ and } Var(S) = [n(n-1)(2n+5)]/18 \tag{15}$$

The standard normal *Z*-test statistic is computed by

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{Var(S)}} & S > 0 \\ 0 & S = 0 \\ \dfrac{S+1}{\sqrt{Var(S)}} & S < 0 \end{cases} \tag{16}$$

When $|Z| \leq Z_{1-\alpha/2}$ at the α level of significance, the null hypothesis is accepted. $Z_{1-\alpha/2}$ is the critical value of *Z* from the standard normal table, the value of $Z_{1-\alpha/2}$ is 1.96 for 5% significant level. Positive Z value means an increasing trend, while negative Z value means a decreasing trend (Douglas et al., 2000).

The autocorrelation of the runoff series has a negative effect on the results of the MK test. Thus, the hydrological time series showing significant serial correlation effects were subjected to trend-free pre-whitening (TFPW) procedures before applying the MK test (Aziz and Burn, 2006; Serinaldi and Kilsby, 2016; Wu et al., 2016; Yue et al., 2003, 2002b). The TFPW procedure first estimated the value of trend slope to remove the trend component in the series, and then estimated $\rho 1$ (the lag-1 data autocorrelation coefficient) so as to reduce or eliminate the serial correlation by removing the AR(1) component from the detrended series, and finally reinstalled the trend component before applying the MK test.

Morlet wavelet analysis

Wavelet analysis is a time-frequency decomposition technique. Comparing simple frequency analysis (e.g. Fourier analysis), wavelets transform can extract the dominant modes of variability from time series and reveal the localized time and frequency information at different timescales. The Fourier transform assumes that the signal is stationary and that the signals in the sample continue into infinity. However, it performs poorly when this is not the case. Wavelets perform better for non-stationary and non-smooth time series (Labat, 2005; Labat et al., 2000; Morlet et al., 1982; Partovian et al., 2016; Torrence and Webster, 1998; Werner, 2008). Hence, wavelet analysis is used to detect the variations of the frequency distribution of non-stationary series. The continuous wavelet transform $C_X(a, \tau)$ of $x(t)$ is defined as follows:

$$C_X(a, \tau) = \int_{-\infty}^{\infty} x(t) \Psi_{a,\tau}(t) dt = \langle x(t) \Psi_{a,\tau}(t) \rangle \tag{17}$$

$$\Psi_{a,\tau}(t) = |a|^{-0.5}\Psi\left(\frac{t-\tau}{a}\right), a, \tau \in R, a \neq 0 \tag{18}$$

Where a and τ are scale and time variables, respectively; $\Psi_{a,\tau}(t)$ denotes the wavelet family generated by continuous translation and dilation of the mother wavelet $\Psi(t)$.

Because Morlet wavelet provides a good balance between time and frequency localization (Hao et al., 2012), Here, Morlet wavelet is applied as mother wavelet and its definition as follows:

$$\Psi(t) = e^{iw_0 t}e^{-t^2/2} \tag{19}$$

Where w_0 is a constant. For $w_0 \geq 5$, the Morlet wavelet can approach the admissible condition.

The wavelet spectrum $W_X(a,\tau)$ of $x(t)$ is defined as the modulus of its wavelet coefficients:

$$W_X(a,\tau) = C_X(a,\tau)C_X^*(a,\tau) = |C_X(a,\tau)|^2 \tag{20}$$

Where $C_X(a,\tau)$ and $C_X^*(a,\tau)$ are the conjugate of the wavelet coefficient of X (Labat, 2010).

Ensemble empirical mode decomposition

The ensemble empirical mode decomposition (EEMD) is the extension of EMD (Empirical Mode Decomposition) (Huang et al., 1998). EEMD combines a noise-assisted adaptive data analysis algorithm. In the process of implementing EEMD, white noise is added to the original noise to eliminate the mode mixing problem (Antico, Schlotthauer, & Torres, 2014; Torres, Colominas, Schlotthauer, & Flandrin, 2011; Z. Wu & Huang, 2009). The trial is that the modified signal inputs EMD, which is repeated *m* times to obtain the final mode. The theoretical frame of the EEMD method is:

$$x_m(t) = x(t) + w_m(t), m = 1,2, \ldots N \tag{21}$$

$$x_m(t) = \sum_{i=1}^{l} + r_{m,l}(t), m = 1,2, \ldots N \tag{22}$$

$$x(t) = \frac{1}{N}\sum_{i=1}^{l}\sum_{m=1}^{N} c_{m,i}(t) + \frac{1}{N}\sum_{m=1}^{N} r_{m,l}(t) \tag{23}$$

where $x(t)$ is the original signal, $w_m(t)$ is the *m*th adding white Gaussian noise, $c_{m,i}(t)$ is the *i*th IMF of the *m*th trial, *l* is the number of IMFs based on the EMD method, and *N* is the ensemble number of the EEMD method.

Appendix B

Dataset size for the statistical tests

The feasibility of dataset size for the statistical tests is discussed. (1) The length of datasets for precipitation, temperature, and runoff in the study areas is emphasized in the revision, as shown in Table 4. (2) The Pettitt test based on the Mann and Whitney statistical function requires large enough sample sizes (> 30) (Pettitt, 1979). In this study, the length of annual streamflow time series is 76 years in Xianyang gauge and 79 years in Zhangjiashan gauge which is feasible for Pettitt test. (3) The minimum number of samples that can be analyzed using the Mann-Kendall test is

17 (Mann, 1945; Pettitt, 1979; Yue and Wang, 2004). In this study, the length of whole streamflow time series is 76 years in Xianyang gauge and 79 years in Zhangjiashan gauge. The length of streamflow time series before the abrupt change point at both gauges is 38 years. Hence, it is feasible to the application of Mann-Kendall test. (4) The applications of Morlet wavelet analysis with continuous wavelet transform and Ensemble Empirical Mode Decomposition (EEMD) are not limited by the sample size (Flandrin et al., 2004; Grossmann et al., 1990; Lin and Qu, 2000; Wu and Huang, 2009). Moreover, the significant 2-4-year minor periods of the runoff series were focused in this study. Hence, the length of the whole streamflow time series and the streamflow after the abrupt change point at both gauges is workable for Morlet wavelet analysis and EEMD. (5) Moreover, the boundary effects in Morlet wavelet analysis and EEMD are eliminated to overcome the limitation of definite sample size. Padding, one of the simplest and effective methods for ameliorating the edge effect of continuous wavelet transform (Boltežar and Slavič, 2004), was applied for Morlet wavelet analysis in the revision. The wave extension method proposed by (Coughlin and Tung, 2004) was utilized to handle the edge effects of EEMD. (6) The proposed statistical hydrological model based on fuzzy mean generating function is designed by extracting the effective periodic components from streamflow time series. Its basic structure is multiple regression model which requires a minimum sample size of 30 (Kutner et al., 2005). Accordingly, the 70 points are sufficient to assess the proposed model.

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Figure

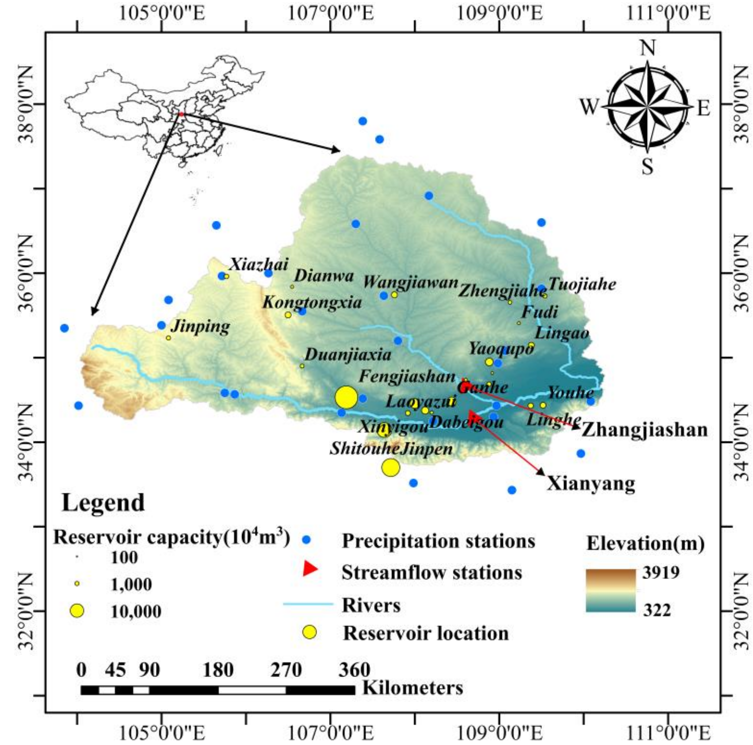


Figure 1. Locations of precipitation stations, hydrological gauges and main reservoirs in the Wei River baisn, China.

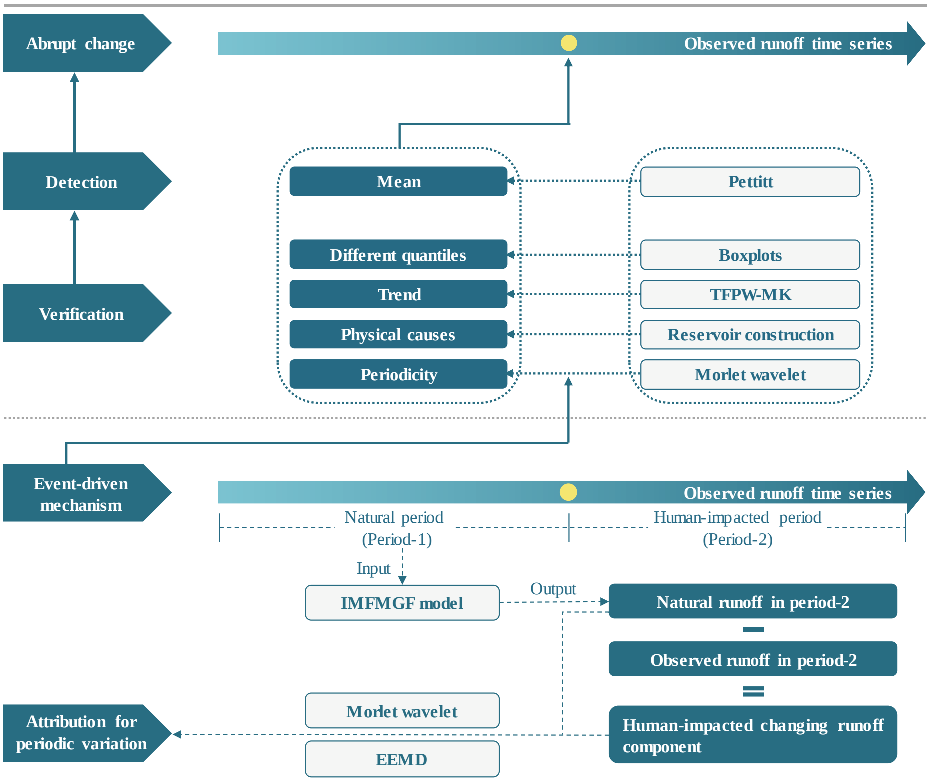


Figure 2. Flowchart for methodologies of detection and attribution of abrupt shift of periodicity in long-term runoff series.

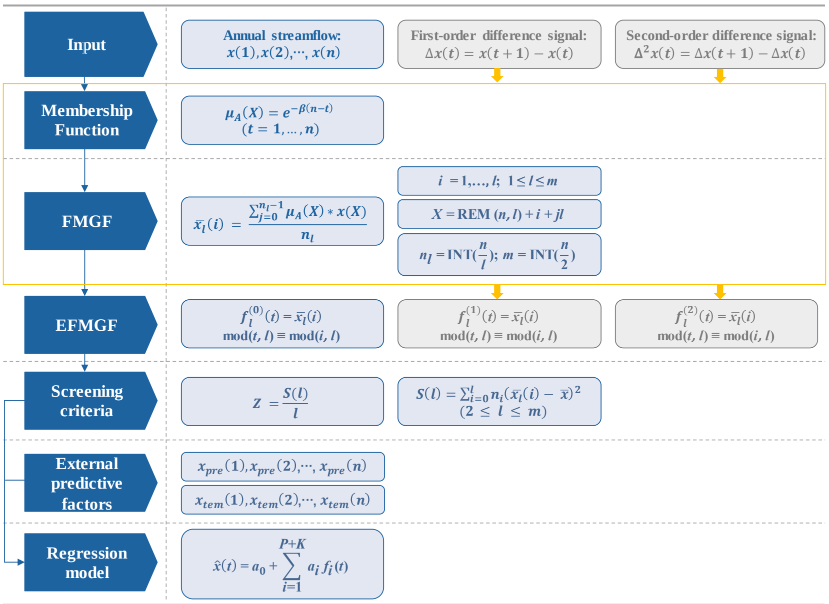
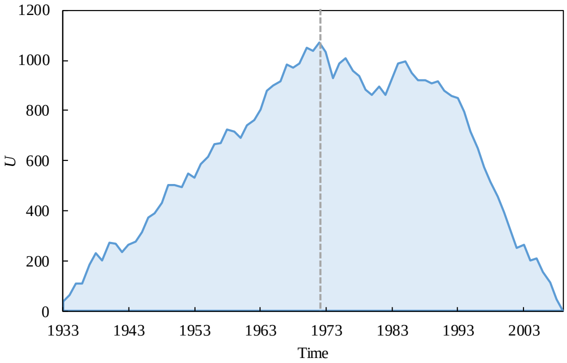
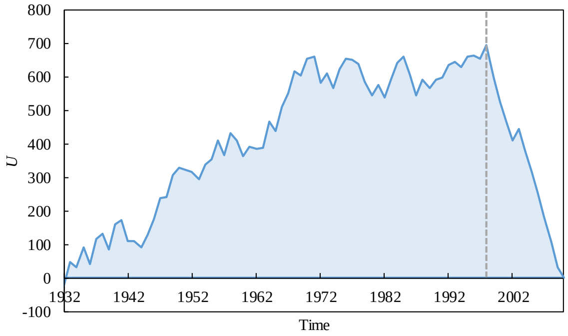


Figure 3. Calculation by the Improved Multivariate Fuzzy Mean Generating Function (IMFMGF) forecast model.



(a)



(b)

Figure 4. The results of Pettitt test at Xianyang gauge **(a)** and Zhangjiashan gauge **(b)**. *U* denotes the Mann and Whitney statistical value. The most significantly abrupt point is where *U* is the largest values.

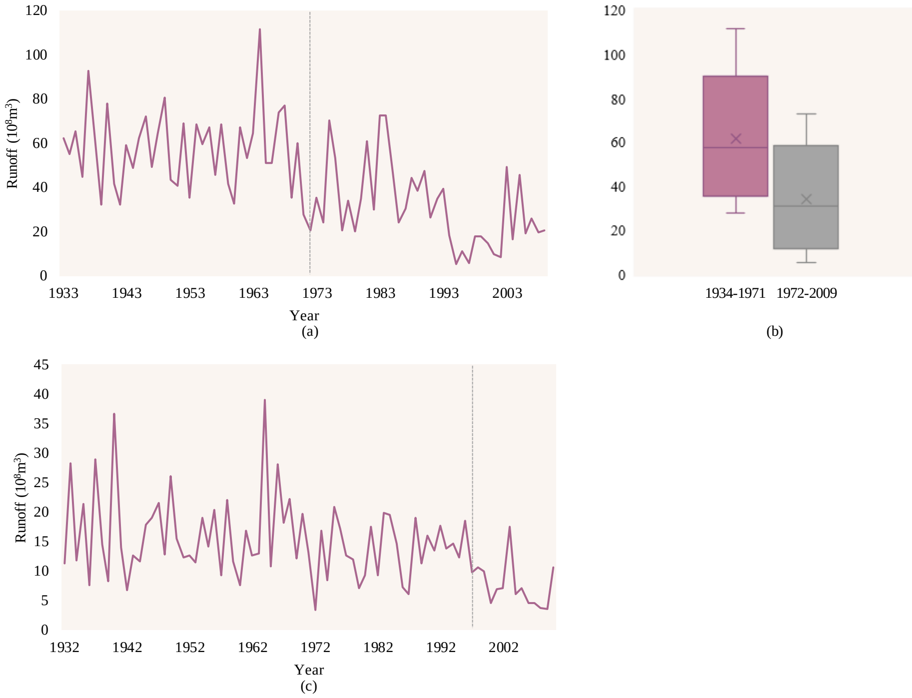


Figure 5. The annual runoff at Xianyang gauge in 1933-2009 **(a)** and the boxplots for the characteristics of its sub-sections **(b)**; the annual runoff at Zhangjiashan gauge in 1932-2010 **(c)**.

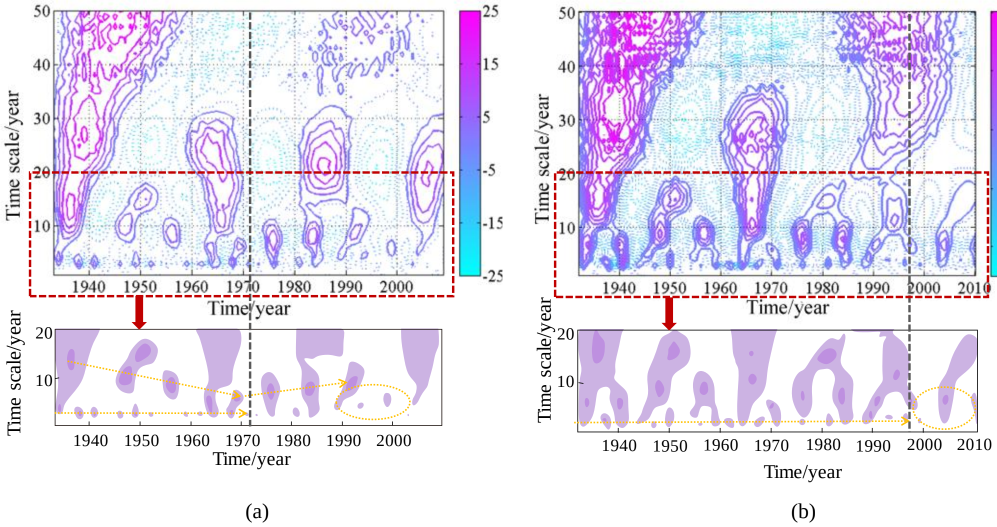


Figure 6. Real part of the wavelet coefficient contour maps of the observed runoff and their schematics in minor periods at Xianyang gauge **(a)** and Zhangjiashan gauge **(b)**.

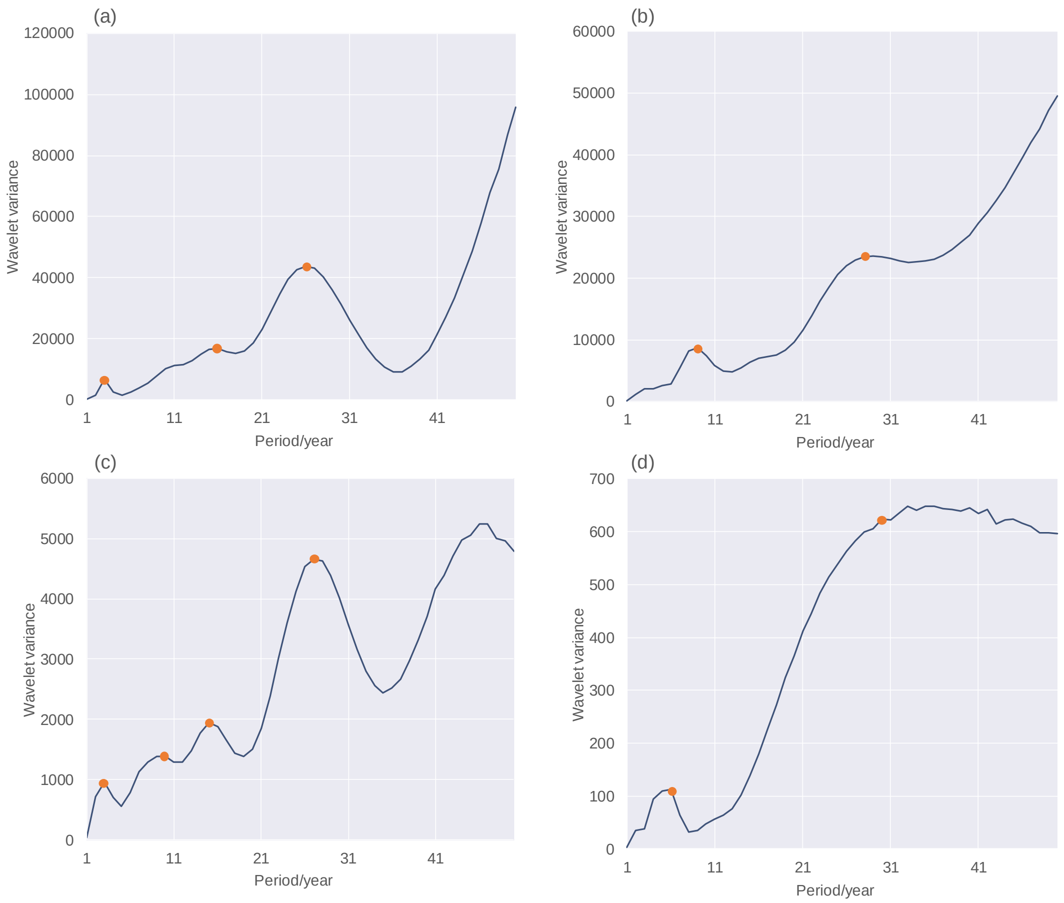


Figure 7. (a): Wavelet variance for the observed runoff before the abrupt change point at Xianyang gauge; **(b):** Wavelet variance for the observed runoff after the abrupt change point at Xianyang gauge; **(c):** Wavelet variance for the observed runoff before the abrupt change point at Zhangjiashan gauge; **(d):** Wavelet variance for the observed runoff after the abrupt change point at Zhangjiashan gauge. The red points denote the major periods of the runoff time series which were identified by Morlet wavelet analysis.

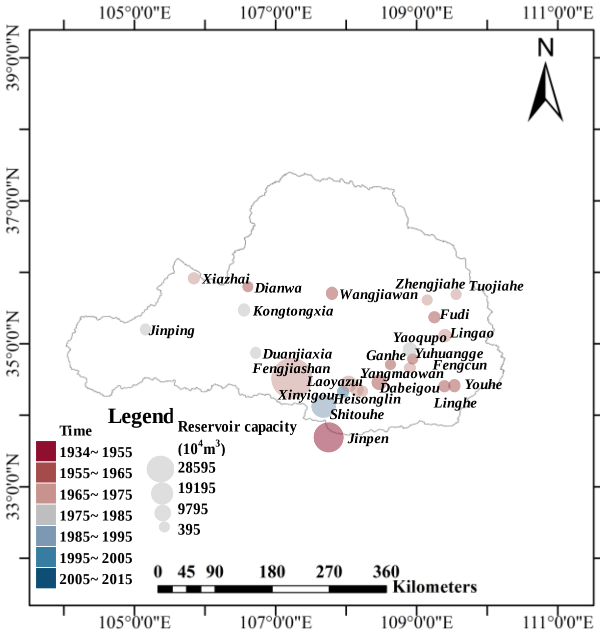


Figure 8. Completion time and storage capacities of main reservoirs in the Wei River basin, China.

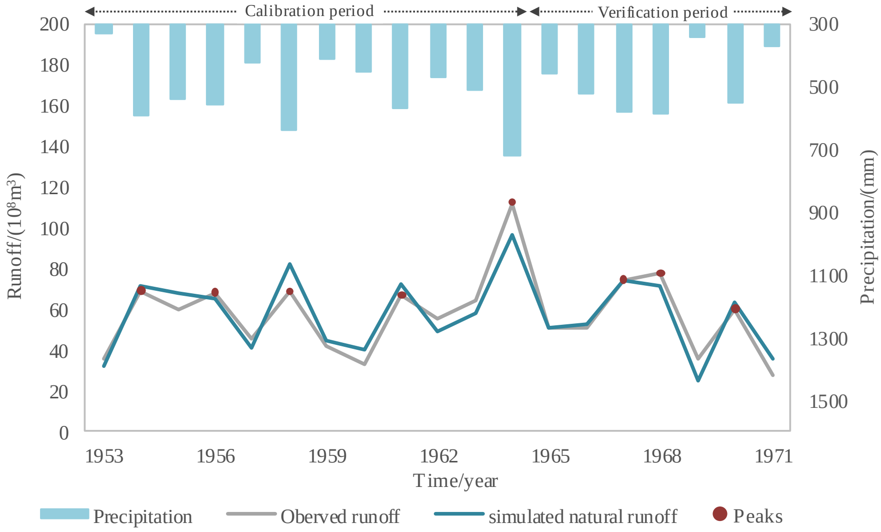


Figure 9. The observed runoff and simulated natural runoff in 1953-1971 at Xianyang gauge.

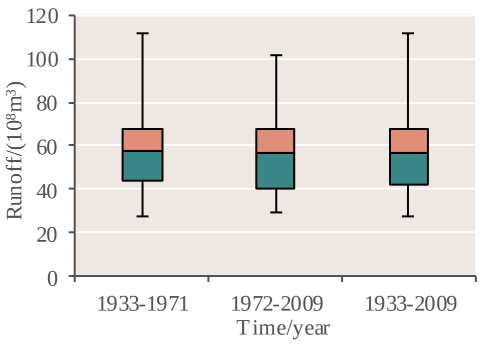


Figure 10. The boxplots of the natural runoff in 1933-1971, 1972-2009 and 1933-2009 at Xianyang gauge. The natural runoff is the observed natural runoff in 1933-1971 and the simulated natural runoff in 1972-2009.

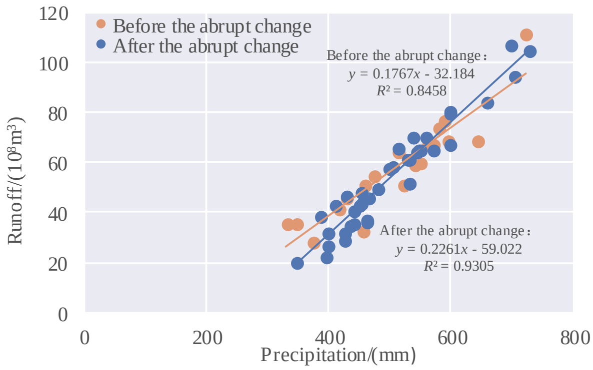


Figure 11. The precipitation-measured runoff relationships before the abrupt change (1971) and the precipitation-simulated natural runoff relationships after the abrupt change at Xianyang gauge.

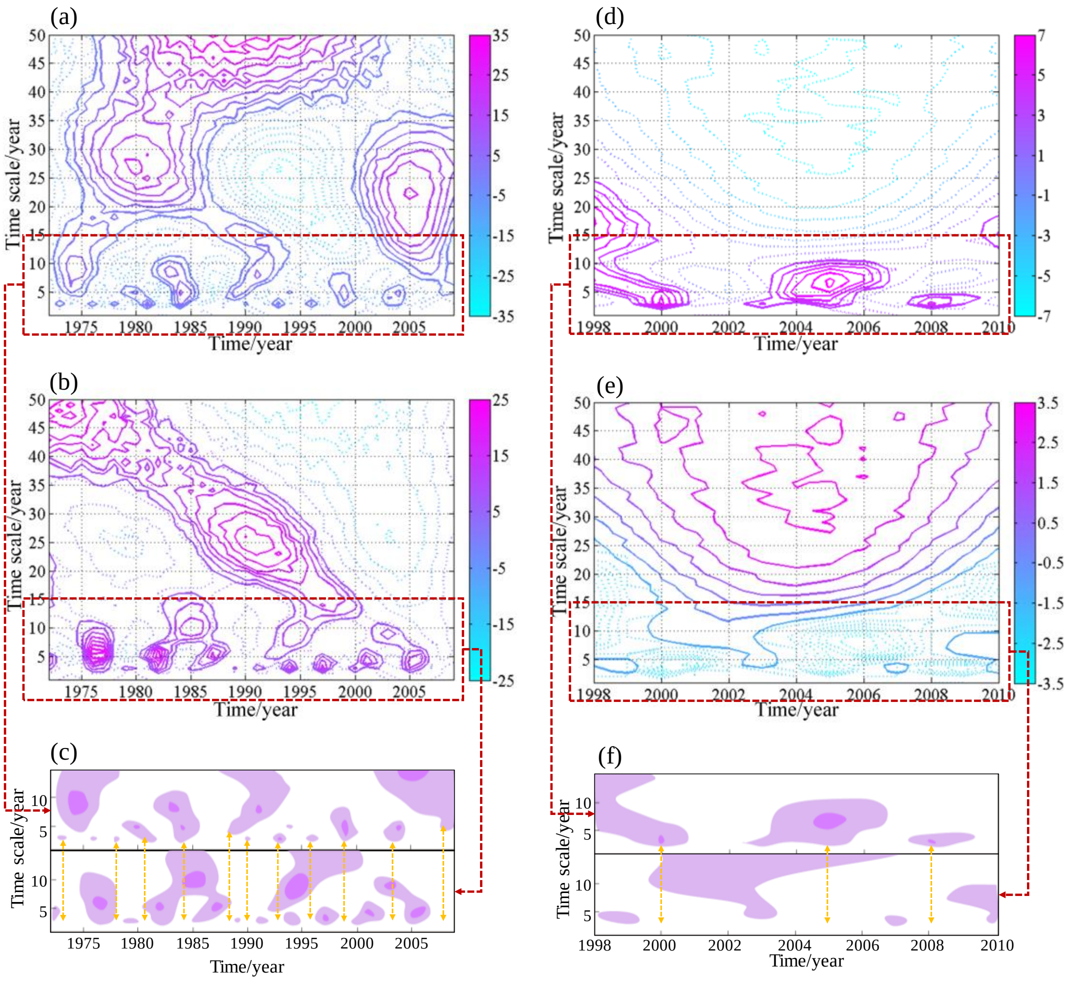
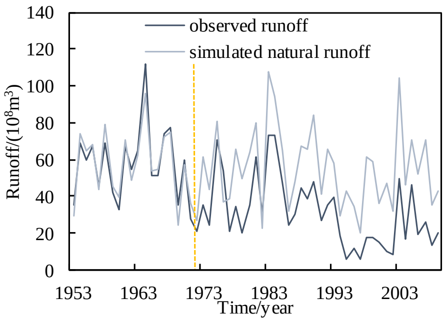
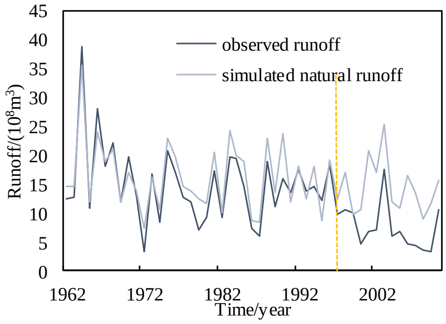


Figure 12. (a): Real part contour maps of wavelet coefficients of natural runoff components in period-2 (human-impacted period) at Xianyang gauge; **(b):** real part contour maps of wavelet coefficients of human-impacted runoff components in period-2 at Xianyang gauge; **(c):** the schematics of Figure 12 (a) and Figure 12 (b) in minor periods at Xianyang gauge; **(d):** Real part contour maps of wavelet coefficients of natural runoff components in period-2 at Zhangjiashan gauge; **(e):** real part contour maps of wavelet coefficients of human-impacted runoff components in period-2 at Zhangjiashan gauge; **(f):** the schematics of Figure 12 (d) and Figure 12 (e) in minor periods at Zhangjiashan gauge. According to the schematics in their minor periods, it is interesting to note that the wave crests and troughs of the two components in 3-4-year minor periods have good negative correspondence. Specifically, when the minor periods of natural component series are in the troughs, the minor periods of human-impacted runoff component series are at the peaks, and vice versa.



(a)



(b)

Figure 13. Observed runoff and simulated natural runoff at Xianyang **(a)** and Zhangjiashan **(b)** gauges.

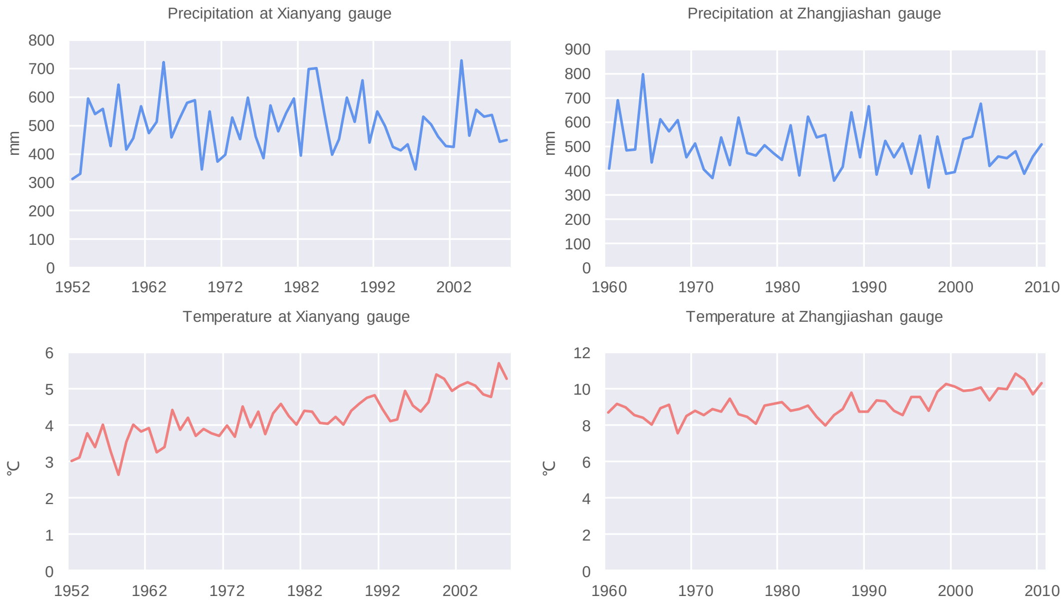


Figure 14. The precipitation and temperature datasets at Xianyang gauge and the Zhangjiashan gauge.

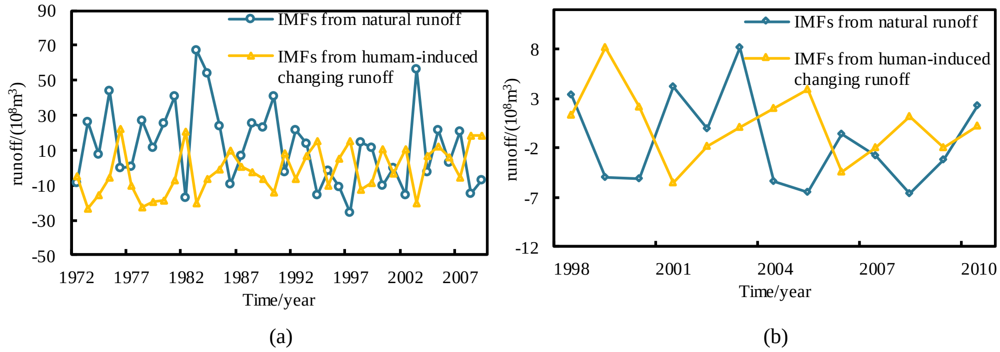


Figure 15. Relationship between crests and troughs of the IMFs from natural runoff and the human-impacted runoff at Xianyang gauge **(a)** and Zhangjiashan gauge **(b)**.

Table 1. Results of TFPW-MK tests

Gauge	Time (year)	α	P value (two-tailed test)	H_0
Xianyang	1934-1971 (period-1)	0.001	0.76	0
		0.005	0.76	0
		0.01	0.76	0
		0.05	0.76	0
		0.1	0.76	0
		0.5	0.76	0
	1934-2009 (whole series)	0.001	3.7×10^{-8}	1
		0.005	3.7×10^{-8}	1
		0.01	3.7×10^{-8}	1
		0.05	3.7×10^{-8}	1
		0.1	3.7×10^{-8}	1
		0.5	3.7×10^{-8}	1
Zhangjiashan	1932-1997 (period-1)	0.001	0.50	0
		0.005	0.50	0
		0.01	0.50	0
		0.05	0.50	0
		0.1	0.50	0
		0.5	0.50	0
	1932-2010 (whole series)	0.001	3.1×10^{-4}	1
		0.005	3.1×10^{-4}	1
		0.01	3.1×10^{-4}	1
		0.05	3.1×10^{-4}	1
		0.1	3.1×10^{-4}	1
		0.5	3.1×10^{-4}	1

Note: The result of the test is returned in H_0 = 1 (denoting significant trend) indicates a rejection of the null hypothesis (No monotonic trend) at the α significance level. H_0 = 0 (denoting no significant trend) indicates a failure to reject the null hypothesis at the α significance level.

Table 2. Optimized predictive factors and their regression parameters in the IMFMGF model

Predictive factors	Regression parameters	Z
$f_2^{(0)}$	-1.392	437873.12
$f_4^{(2)}$	-1.267	434260.76
$f_{19}^{(0)}$	-0.552	385609.55
$f_3^{(1)}$	0.079	203286.13
Precipitation	0.194	
Temperature	0	
a_0	0	

Table 3. Results of TFPW-MK tests for precipitation and temperature at Xianyang gauge and Zhangjiashan gauge.

Gauge	Time series	Z	H_0	
Xianyang	Precipitation	-0.12	0	No significant trend
	Temperature	7.34	1	Upward trend detected
Zhangjiashan	Precipitation	-1.74	0	No significant trend
	Temperature	4.73	1	Upward trend detected

Note: The result of the test is returned in H_0 = 1 (denoting significant trend) indicates a rejection of the null hypothesis (No monotonic trend) at the α significance level. H_0 = 0 (denoting no significant trend) indicates a failure to reject the null hypothesis at the α significance level.

Table 4. Length of streamflow, precipitation and temperature datasets in the study areas.

Dataset	Xianyang gauge	Zhangjiashan gauge
Streamflow	1934-2009 (76 years)	1932-2010 (79 years)
Streamflow before the abrupt change point (period-1)	1934-1971 (38 years)	1932-1997 (66 years)
Streamflow after the abrupt change point (period-2)	1972-2009 (38 years)	1998-2010 (13 years)
Precipitation	1952-2009 (58 years)	1960-2010 (51 years)
Temperature	1952-2009 (58 years)	1960-2010 (51 years)

***Declaration of Interest Statement**

We confirm that this work is original and has not been published elsewhere, nor is it currently under consideration for publication elsewhere. All authors have read and approved the manuscript being submitted, and agree to its submittal to this journal, and have no conflicts of interest to disclose.

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**Author Contributions Section

Detection and attribution of abrupt shift in minor periods in human-impacted streamflow

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Tian Lan and Hongbo Zhang conceived of the presented idea and developed the theory and performed the computations. Kairong Lin verified the analytical methods. Chong-yu Xu and Vijay P. Singh supervised the findings of this work. All authors discussed the results and contributed to the final manuscript.