Hybrid method for assessing the multi-scale periodic characteristics of the precipitation–runoff relationship: a case study in the Weihe River basin, China

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ABSTRACT

Fully elucidating the precipitation–runoff relationship (PRR) is of great significance for better water resources planning and management and understanding hydrological cycle processes. For investigating the multi-scale PRR variability in the Weihe River basin in 1960–2010, a new hybrid method is proposed in which ensemble empirical mode decomposition (EEMD) and cross wavelet transform and wavelet transform coherence are used in combination. With the application of mutual information entropy, monthly precipitation and runoff are decomposed into two parts: high- (HFC) and low-frequency components (LFC). The results show that HFCs are characterized by inter- and intra-annual variations in precipitation and runoff, whereas LFCs display approximately two-year periodicity and contain abundant abnormal information of the raw data. Therefore, the PRR between HFCs exhibited significant correlations at the 95% confidence level over the whole time period. However, the correlations of the PRR between LFCs are not significant for many of the time-frequency domains. Additionally, the phase relations are disordered in these time-frequency domains, and no certain trend in phase angle variations can be identified. Through comparative analysis of the anthropogenic activities and climatic events with PRR variations, it can be concluded that the hybrid method can efficiently capture the PRR in various time-frequency domains.

Key words | cross wavelet transform, ensemble empirical mode decomposition, hydrologic time series analysis, multi-time scale variability, precipitation–runoff relationship, wavelet transform coherence

INTRODUCTION

The precipitation–runoff relationship (PRR) is an important model in engineering hydrology, and has great significance in the operation and management of watersheds (Areerachakul & Junsawang 2014; Kamruzzaman et al. 2014; Wang et al. 2015a, 2015b; Xing et al. 2015). Globally, the environment has undergone drastic changes over the past century (Milliman et al. 2008; Liu et al. 2009; Zhan et al. 2014). The changes in the environment have impacted the already complex hydrological processes, particularly in semi-arid and sub-humid regions (Xia et al. 2011; Zhang et al. 2011). Undoubtedly, the PRR, one of the core links of the hydrological cycle, has changed dramatically in many regions of the globe. The greater complexity of the PRR poses a more substantial challenge for water resources planning and management (Milly et al. 2008; Jiang et al. 2015), reservoir operation, etc. Therefore, revealing the changes in the PRR is still an urgent and significant task to better respond to this challenge under changing environmental conditions.

The motion of the Earth and other planets in the solar system, atmospheric circulation, anthropogenic activities, etc., influence the intra-annual, inter-annual and even inter-decadal variations of precipitation and runoff and therefore

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exhibit close relationships with changes in the PRR (Durocher et al. 2016). The sunspot activity and El Niño-Southern Oscillation (ENSO) phenomenon can be used as examples. Considerable research has inferred that the periodical changes of both have close relationships with changes in precipitation/runoff (Ouarda et al. 2014). Generally, the sunspot activity exhibits an 11-year period. Therefore, natural runoff and precipitation usually exhibit an 11-year feature of fluctuation. Meanwhile, ENSO presents a two- to seven-year period, and correspondingly, runoff and precipitation change with a two- to seven-year feature of fluctuation. Due to the influence of various external factors in addition to solar activity and ENSO, the original precipitation and runoff data have multiple physical interpretations under various periodic oscillatory patterns. Thus, merely considering the original precipitation and runoff data in previous studies is not sufficient to analyse the changes in the PRR (Chen et al. 2007, 2014; Liu et al. 2009). Hence, extracting the modes of oscillation with various periodic characteristics from the original precipitation and runoff is essential and meaningful for fully revealing the multi-scale relationship between precipitation and runoff.

To date, the ensemble empirical mode decomposition (EEMD) method has been widely applied to extract various periodic oscillatory patterns through the sifting process (Wu & Huang 2009). The method was proposed to overcome the mode-mix problem of the traditional empirical mode decomposition (EMD) method. It is popular due to its adaptive property and ability to analyse the local properties of the signal. Note that the EEMD can efficiently extract a limited number of physically meaningful components changing from high-frequency to low-frequency from both non-linear and non-stationary data, such as precipitation and runoff. Thus, the multi-scale variations of original signals can be fully exhibited by the various frequency components. Hence, studying the relationship between two specific frequency components is the following core issue that should be urgently addressed. As far as we know, however, previous applications of EEMD primarily focused on the periodic characteristics and trend analysis of the original signal and the prediction of future time series (Kim et al. 2014; Yadav et al. 2014; Yang & Wu 2015; Zhao & Chen 2015). Until now, less attention has been given to investigating the relationship between two specific frequency components (Zolotova & Ponyavin 2007; Durocher et al. 2016). In addition, the research of Zolotova & Ponyavin (2007) and Durocher et al. (2016) neglects the drawback of the mode-mix problem in EMD when decomposing the signals. Therefore, a method that analyses the relationship between two specific frequency components is an outstanding and urgent task that should be considered.

In recent years, to fully elucidate the temporal relationships between non-stationary time series in a time-frequency space, cross wavelet transform (XWT) and wavelet transform coherence (WTC) have been widely used in many studies (Zhang et al. 2007; Miao et al. 2014; Szolgayova et al. 2014; Yu et al. 2015). These methods are adept in capturing coupled oscillations of two time series both in the time and frequency domains (Huang et al. 2015). However, many researchers have also indicated that the XWT and WTC are easily influenced by the wavelet basis (Farge 1992; Tewfik et al. 1992; Gong et al. 2005). The application of a different wavelet basis will obtain different decomposition results. In particular, the aliasing in the frequency domains usually produces errors in terms of the components. However, the EEMD is a self-adaptive process of decomposition and averts the issue mentioned above. Hence, in order to provide a new perspective to study the relationship between the two signals, the hybrid approach combining the EEMD and XWT and WTC is proposed to reveal the relationship between the specific frequency components.

The Weihe River basin, the largest tributary of the Yellow River and one of the most important industrial and agricultural production zones in China, was selected as the study area. The primary aims of this study are: (1) to explore the variations of monthly precipitation and runoff; (2) to reconstruct the intrinsic mode functions (IMFs) of the high-(HFC) and low-frequency components (LFC); and (3) to capture the characteristics of the PRR at high- and low-frequency, respectively.

**STUDY AREA**

The Weihe River (104°–110° E longitude, 33°–37° N latitude) is the largest tributary of the Yellow River, with a total length of 818 km and a drainage area of 134,800 km², and lies in the semi-humid and semi-arid transitional zone (Figure 1) (Zhao et al. 2015). It originates in the mountains of the southern Gansu Province and passes through 502 km in Shaanxi Province. It serves as the primary water supply resource for 0.93 million hm² of fertile fields in the Guanzhong Plain and supports more than 61% of Shaanxi Province’s population (Liu & Li 2006).
The Weihe River basin is dominated by semi-arid hydrological characteristics and belongs to the continental monsoon climate zone. The climate is dry and cool in winter and hot and rainy in summer. The annual precipitation is approximately 610 mm and approximately 80% of precipitation occurs between June and October (Chang et al. 2015). The mean annual natural runoff of the river is 10.4 billion m³, accounting for 17.3% of the Yellow River’s total discharge (Du & Shi 2012). The seasonal variation of runoff is similar to that of precipitation. The sum of runoff in July and October accounts for approximately 65% of the mean annual runoff (Gao et al. 2012).

During the past 50 years, runoff in the Weihe River has decreased dramatically. Especially in the late 1990s, the average runoff was merely 3.60 billion m³, i.e., a reduction of 6.20 billion m³ compared with that in the 1950s (Chang et al. 2015).

DATASET AND METHODOLOGY

Dataset

Monthly runoff series (1960–2010) from gauging stations, including the Huaxian and Zhuangtou stations, are provided by the Hydrology Bureau of the Yellow River Conservancy Commission (Figure 1). The observed runoff at the Huaxian and Zhuangtou stations is considered as the runoff generated in the mainstream basin of the Weihe River (MWRB) and Beiluohe River basin (BRB), respectively.

Monthly precipitation series (1960–2010) of 21 meteorological stations (Figure 1) within and outside the Weihe River basin are provided by the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn). Based on the monthly precipitation of individual sections, the monthly precipitation of the MWRB and BRB is calculated by the Thiessen polygon method on the ArcGIS platform.

Methodology

EEMD

Through a procedure called ‘sifting’, EMD has been widely applied to decompose the time series into several finite IMFs and a trend (Residue) (Huang et al. 1998). However, the mode-mixing problem is the drawback that the EMD
suffers, which inhibits its ability to reveal the variation characteristics of the time series. To eliminate this drawback, the EEMD is proposed by adding white noise-assisted data (Wu & Huang 2009). The EEMD method is highly effective in analysing the time series as compared to EMD and has been used by many researchers (Cao et al. 2015; Sun & Ma 2015; Wang et al. 2015a, 2015b). The specific decomposition steps of the EEMD method can be described as follows.

**Step 1:** Set the number of ensemble M, the amplitude of the added white noise k, and the interactions m = 1.

**Step 2:** Implement the mth trial on the signal with the added white noise:
(a) Add the mth random Gauss white noise (n_m(t)) to the investigated signal (x(t)), and obtain a new mth noise-added series (x_m(t)) (Equation (1)):

\[ x_m(t) = x(t) + n_m(t) \]  

(b) Decompose the new obtained noise-added series (x_m(t)), and acquire several series (I, number of the IMFs of each trial) of finite IMFs \( i = 1, 2, \ldots, I \) and a trend (Residue, \( r_n \)) (Equation (2)):

\[ x_m(t) = \sum_{i=1}^{I} c_i + r_n \]  

(c) If \( m < M \), then \( m = m + 1 \) and return to Step (a), and if not, proceed to Step (3).

**Step 3:** Average the \( c_i \) of the M trials corresponding to each IMF in the decompositions (Equation (3)):

\[ c_i = \frac{1}{M} \sum_{m=1}^{M} c_{im} \quad i = 1, 2, \ldots, I, \quad m = 1, 2, \ldots, M \]  

**Step 4:** Export \( c_i \) and \( r_n \) as the final ith IMF and Residue.

It is worth noting that in this study, the amplitude of the added white noise and the ensemble number are set to 0.2 and 200, respectively (refer to Wu & Huang 2009).

**Mutual information**

The mutual information (MI), originating from the probability and information theory, is generally used to measure the dependency between two random variables (Massmann & Holzmann 2012). The greater relevance there is between the two random variables, the greater the MI, and vice versa. In this study, the MI is applied to measure the dependency between the raw data (i.e., monthly precipitation and runoff) and IMF_i (i = 1, \ldots, n). If a sudden change of \( M_i, (i = 1, \ldots, n) \) occurs in the position of \( k \) (i.e., \( i = k \)), \( \sum_{i=1}^{k} IMF_i \) and \( \sum_{i=k+1}^{n} IMF_i \) represent the HFC and LFC, respectively. The primary reason to study the PRR at high- and low-frequency is to avoid the inconsistent periodicity between the specific pair of IMFs as much as possible.

The MI is expressed as (Press et al. 2007; Xu et al. 2015):

\[ I(X, Y) = H(Y) - H(Y|X) = H(X) + H(Y) - H(X, Y) \]  

where \( I(X, Y) \) is the MI of X and Y, \( H(Y|X) \) is the conditional entropy of event Y under given event X, \( H(X) \) and \( H(Y) \) are the marginal entropies, respectively, and \( H(X, Y) \) is the joint entropy. In our study, X and Y are the raw data (i.e., monthly precipitation and runoff) and IMF_i, respectively. These entropies are defined as:

\[ H(X) = -\sum_{x \in X} p(x) \log p(x) \]  

\[ H(Y) = -\sum_{y \in Y} p(y) \log p(y) \]  

\[ H(X, Y) = -\sum_{x \in X} \sum_{y \in Y} p(x,y) \log p(x,y) \]  

where \( p(x) \) and \( p(y) \) are the marginal probability distribution functions of X and Y, respectively, and \( p(x,y) \) is the joint probability distribution function of X and Y. Therefore, \( I(X, Y) \) can be expressed as:

\[ I(X, Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \]

**XWT and WTC**

XWT can preferably reveal areas with a high common power in time-frequency space (Torrence & Compo 1998). As for the covariance of two time series \( (X_t \text{ and } Y_t) \), XWT can be expressed as:

\[ W_{X,Y}(s, u) = W_X(s, u)W_Y(s, u) \]
where $W_X(s, u)$ is the continuous wavelet transform of $X$, $(^*)$ is the complex conjugation, and $s$ and $u$ are the dilation parameter and translation parameter, respectively. The cross wavelet power can be obtained as $|W_{X,Y}|$. Meanwhile, the phase shift between the time series is obtained by the angle of the complex part of the XWT $\text{arg}(W_{X,Y})$. The theoretical distribution of the cross wavelet power of two time series with background power spectrum $P_X^2$ and $P_Y^2$ can be expressed as:

$$D\left(\frac{|W_{X,Y}(s, u)|^2}{\sigma_X \sigma_Y} < p\right) = \frac{Z_v(p)}{\nu} \sqrt{P_X^2 P_Y^2}$$

(10)

where $Z_v(p)$ is the confidence level associated with the probability $p$ for a probability density function defined by the square root of the product of two chi-square distributions. For a detailed description of calculation processes, the reader is referred to the research of Torrence & Compo (1998). Furthermore, the phase shift between the time series is estimated as the angle of $\text{arg}(W_{X,Y})$.

WTC is another useful tool to reveal regions where the two time series co-vary in time-frequency space. Unlike the XWT, WTC is a measure of the common power. It is defined by Torrence & Webster (1999) as:

$$R^2(s, u) = \frac{|S(a^{-1}W_{X,Y}(s, u))^2}{S(a^{-1}|W_X(s, u)|^2) \cdot S(a^{-1}|W_Y(s, u)|^2)}$$

(11)

where $S$ is a smooth operator. The Monte Carlo simulation is used to determine the 95% confidence level of the WTC (Grinsted et al. 2004).

**Hybrid approach combining EEMD and cross wavelet analysis**

The hybrid method in this paper is proposed by addressing EEMD and cross wavelet analysis together, thereby fully capturing the evolution characteristics of the relationship between monthly precipitation and runoff under different frequencies. Additionally, it can be extended to reveal the evolution characteristics of the relationship between other time series, such as the hydrological factors, meteorological factors, etc. The process of the method (Figure 2) can be briefly described as follows:

1. Apply the EEMD to the monthly runoff and precipitation, and obtain several IMFs and a trend (Residue).
2. Calculate the MI entropy between the raw data and IMFi to find the turning point $k$ of MI $i$ ($i = 1, \ldots, k, \ldots n$).
3. Reconstruct the IMFs to the HFC ($\sum_{i=1}^{k} IMFi$) and LFC ($\sum_{i=k+1}^{n} IMFi$) of the raw data by the turning point $k$ of MI. Obviously, IMF1 is the highest frequency and most nonlinear and unsystematic part of the raw data, which mainly contain a large quantity of noisy signals (Guo et al. 2012). Hence, IMF1 is not taken into account in this paper. Part of the Residue is mainly adopted to reveal the trend of monthly precipitation and runoff.
4. Apply XWT and WTC to the HFC and LFC of the monthly precipitation and runoff, respectively.

**RESULTS**

**Variations of precipitation and runoff**

Figures 3 and 4 show the changes in monthly precipitation and runoff in the MWRB and BRB, respectively. It can be obviously seen that in both basins, the precipitation changed less than runoff. The runoff presents an overall downward trend. Note that after 1990, the reduction of runoff in the two basins is more obvious than before. In particular, the reduction is notable in the flood season of both basins, i.e., June to September. To better investigate the trend of precipitation and runoff in the two basins, the Residues are extracted from the EEMD method (Figures 5 and 6). It can be observed that in the MWRB, the precipitation increases before approximately 1993 and then decreases with time, whereas the runoff decreases significantly over the whole time scale. As for the BRB, the precipitation increases in the period of 1960–2010, whereas the runoff slightly increases before approximately 1981 and then decreases significantly.

**Decomposition of the monthly precipitation and runoff**

By applying the EEMD method, the monthly runoff and precipitation series are all decomposed into eight independent IMFs in the MWRB and BRB. The illustrations of the
decomposition are shown in Figures 5 and 6. IMF$_1$ has the smallest period and largest amplitude. It is also the most nonlinear and disordered component of monthly runoff and precipitation. As the IMFs increase to IMF$_8$, the periods increase and the amplitudes decrease.

IMF$_1$ of monthly precipitation and runoff shows an approximately four-month period in the two basins. IMF$_2$ and IMF$_3$ mainly reveal 10–15-month periods. The rest of the IMFs (IMF$_4$ to IMF$_8$) of monthly precipitation in the MWRB primarily show 36-month, 63-month, 158-month, 333-month and 582-month periods and have 32-month, 69-month, 105-month, 216-month and 609-month periods for monthly runoff, respectively. The precipitation periods of IMF$_7$ and IMF$_8$ are inconsistent with those of runoff in the BRB.

**IMF reconstruction**

Figure 7 displays the changes in MI entropy between the raw data (i.e., monthly precipitation and runoff) and IMFs in the two basins. As shown in Figure 7, it can be obviously observed that when IMF is IMF$_1$, IMF$_2$ and IMF$_3$, the MIs are all greater than the others in the two basins. Whether the raw data are monthly precipitation or runoff, the MI presents the same change from IMF$_1$ to IMF$_8$. Hence, according to the change in MI, the IMFs are sorted into...
two parts, i.e., $\sum_{i=2}^{3} IMF_i$ and $\sum_{i=4}^{8} IMF_i$. $\sum_{i=2}^{3} IMF_i$ and $\sum_{i=4}^{8} IMF_i$ characterize the HFC and LFC of the raw data, respectively.

The reconstructed HFC and LFC of the raw data in the MWRB and BRB are shown in Figures 8 and 9, respectively. Corresponding to the period of IMF$_2$ and IMF$_3$, the HFC is primarily characterized by an approximately 10- to 15-month periodic variation of the raw data in the two basins. Similarly, the LFC is primarily characterized by an approximately 32- to 609-month periodic variation of the raw data in the MWRB and an approximately 29- to 611-month periodic variation of the raw data in the BRB.
Interaction of runoff and precipitation in HFC and LFC

Interaction of runoff and precipitation in the HFC

XWT and WTC were employed to reveal the variation of the relationship between HFC of monthly runoff and precipitation in both the MWRB and BRB. The results are presented in Figure 10. The upper row of Figure 10 displays the cross wavelet (upper left graph of Figure 10) and wavelet coherence (upper right graph of Figure 10) spectra between HFCs of monthly precipitation and runoff in the MWRB, respectively. Similarly, the lower row of Figure 10 shows the changes in the BRB.

The upper left graph of Figure 10 highlights regions with a significant common power at the 95% confidence level on
Figure 7 | The change in MI entropy between IMF, and the original signal (i.e., monthly precipitation and runoff) in the MWRB (left panel) and BRB (right panel).

Figure 8 | The HFC and LFC of monthly precipitation and runoff in the MWRB.

Figure 9 | The HFC and LFC of monthly precipitation and runoff in the BRB.
the 10- to 14-month band in 1960–2010 in the MWRB. Note that in this period, precipitation leads runoff by approximately 45° during 1960/1 to 1986/9 and 2000/3 to 2010/12. The phase angle indicates that precipitation leads runoff with an approximately one- to two-month lead time, while the phase relation during 1986/10 to 2000/2 on the 10- to 14-month band exhibits clear in-phase relations (corresponding to a zero-month lead time) between precipitation and runoff.

Similarly, the lower left graph of Figure 10 highlights regions with a significant common power at the 95% confidence level on the 10- to 14-month band in 1960–2010 in the BRB. In this case, precipitation leads runoff by approximately 30° (corresponding to an approximately one-month lead time) during 1960/12 to 1970/12, 1975/2 to 1995/3 and 2001/10 to 2010/12. The in-phase relations between precipitation and runoff of the 10- to 14-month band are mainly presented during 1970/3 to 1975/1 and 1995/4 to 2001/9.

The right graph of Figure 10 reveals that the regions with remarkable 10- to 14-month periodicity are characterized by high coherence, peaking in the 10- to 14-month band in 1960–2010 of the two basins. This finding suggests that precipitation is closely associated with runoff in the 10- to 14-month band over the whole time period. Note that the 10- to 14-month periodicity can be considered as one year (i.e., 12 months). Therefore, it can be concluded that the strong one-year synchronicity of the precipitation and runoff is the principal reason for the high coherence peaking on the 10- to 14-month scale.

Interaction of runoff and precipitation in the LFC

Figure 11 shows the variation of the cross wavelet (the left graph of Figure 11) and wavelet coherence (the right graph of Figure 11) spectra between the LFC of monthly runoff and precipitation in both the MWRB and BRB.

The upper left graph of Figure 11 primarily highlights regions in the 24- to 112-month band with significant common power at the 95% confidence level in 1960–2010 in the MWRB. The regions passing the 95% confidence level account for approximately 80% of the 20- to 112-month band, where the phase relations primarily exhibit an in-phase relation, or with precipitation leading runoff by approximately 45°. Fewer regions fail to pass the 95% confidence level, mainly in 1960/1 to 1975/2 in the 48- to 64-month band and 1960/1 to 1970/12, 1978/6 to 1984/1, 1988/11 to 1997/8 in the 64- to 112-month band. It is worth mentioning that the phase relations are disordered in these regions and that no certain trend of phase angle variations can be easily identified.

The lower left graph of Figure 11 primarily highlights regions in the 24- to 44-month band in 1960–2010, in the 44- to 56-month band in the periods of 1972/8 to 1993/6 and 2002/2 to 2012/12, and in the 64- to 112-month band in 1968/6 to 1987/8, respectively, with a significant common power at the 95% confidence level in the BRB. In these regions, precipitation leads runoff by approximately 45°. Note, however, that the in-phase relations between precipitation and runoff primarily occur in the 24- to 32-month band in the period of 1972/3 to 1989/4.

The upper right graph of Figure 11 shows the wavelet coherence spectra between the LFCs in the MWRB. It can be observed that the correlation is not significant at the 95% confidence level on the 36- to 60-month scale (i.e., three to five years) in the period of 1971/2 to 1984/6 and 2005/12 to 2010/12. Note that at other times on the 36- to 60-month scale, the runoff has a statically positive correlation with precipitation at the 95% confidence level. On the 60- to 84-month scale (i.e., five to seven years), there is a statistically significant correlation at the 95% confidence level over the whole time period, except in 1974/6 to 1998/6. Similarly, on the 84- to 108-month scale (i.e., seven to nine years), the correlation is significant over the whole time period, except in 1984/6 to 2010/12. In particular, the correlation is not significant at the 95% confidence level on the above 112-month scale over the whole time period. Additionally, the phase relations are irregular in the regions failing to pass the 95% confidence level.

For the BRB, the lower right graph of Figure 11 shows that there are statically significant correlations on the 36- to 60-month scale (i.e., three to five years) over the whole time period, except for 1964/6 to 1985/12 and 1989/6 to 2010/12. On the 60- to 84-month scale (i.e., five to seven years), the correlation is not significant at the 95% confidence level in 2000/12 to 2010/12. Note that on the above 84-month scale, there are statically significant correlations over the whole time period at the 95% confidence level.
Similarly, the phase relations are also disordered in the regions failing to pass the 95% confidence level.

Overall, it can be summarized from the above discussion that the PRR is not significant during 1971/2 to 1984/6 and 2005/12 to 2010/12 on the three- to five-year scale, 1974/6 to 1998/6 on the five- to seven-year scale, and 1984/6 to 2010/12 on the seven- to nine-year scale in the MWRB. Similarly, the PRR is not significant during 1964/6 to 1985/12 and 1989/6 to 2010/12 on the three- to five-year scale and 2000/12 to 2010/12 on the five- to seven-year scale in the BRB. What is responsible for the changes in the PRR? What are the factors influencing the relation during periods of non-significance? These issues are discussed in the following section.
DISCUSSION

In general, the external factors influencing the PRR mainly contain the anthropogenic activities and atmospheric circulation characteristics. Anthropogenic activities, primarily water projects, soil conservation practices, etc., usually play a dominant role in causing the changes in the PRR, particularly regarding the runoff reduction in the Weihe River basin (Du & Shi 2012; Zhao et al. 2013; Chang et al. 2015; Guo et al. 2016). Atmospheric circulation should chiefly be responsible for the changes in precipitation, such as the ENSO phenomenon in the Weihe River basin (Wang et al. 2017).
Following is a discussion about the association between the PRR variations and these influencing factors.

**Response to anthropogenic activities**

With regard to anthropogenic activities, first, the changes due to water projects are analysed. Figure 12 exhibits the reservoir volume change since 1960 in Shannxi Province of the Weihe River basin accounting for 53% of the total area of the Weihe River basin. It can be easily observed from Figure 12 that the volume increased rapidly from 1970 to 1983. Note that there were no large- or middle-sized reservoirs constructed in the period of 1984 to 2000. Numerous water projects have been undertaken since 2000. The construction of water projects experienced a course of rapid (1970–1983) to gradual (1984–2000) to rapid (2001–2012) increases. In particular, the period broadly corresponds to the period with a non-significant PRR during 1971/2 to 1984/6 and in the 2000s in the two basins on the three- to five-year scale.

Second, soil conservation practices (including grassing, terracing, afforestation, etc.) have been widely implemented to control the severe soil loss in the Weihe River basin since 1970 with government support. Zhao *et al.* (2015) categorized the whole period of soil and water conservation practices into five phases, i.e., 1950s–1963 (preparation), 1964–1978 (erosion control in key areas), 1979–1989 (comprehensive management of small watersheds), 1990–1999 (integrated treatment) and 2000–present (ecological rehabilitation). Xu & Niu (2000) found that the runoff reduction efficiency coefficients of terracing, afforestation and grassing are 65%, 33% and 20%, respectively. Figure 13 presents the change in the soil conservation area in the study area. It can be observed from Figure 13 that the growth rate of the three soil conservation practices in 1989–2006 are all considerably more significant than those in 1959–1979. Considering the runoff reduction efficiency coefficients and areas of different soil conservation practices, it can be concluded that the impacts from soil conservation practices to runoff reduction are significant in the period of 1989–2006. Note that the period probably has close relations with the periods of the non-significant PRR in the two basins in terms of the five- to seven-year cycle and the seven- to nine-year cycle.

Hence, the anthropogenic activities in the Weihe River basin can be summarized as follows from the above analysis. Water projects were mainly focused in the period of 1970–1984, whereas the anthropogenic activities in 1989–2006 were mainly dominated by the implementation of large-scale soil conservation practices.

**Response to climate changes**

According to the research of Wang *et al.* (2007), regional precipitation is remarkably influenced by the frequent and strengthening ENSO events. ENSO events are characterized by two- to seven-year periodicity. Zhou *et al.* (2015) and Zhang & Zhao (2010) found that the probability of ENSO events is higher during 1990–2011 than that before 1990.
Note that the ENSO events have occurred 16 times during 1990–2011, including 11 ENSO warming events (El Niño) and six ENSO cold events (La Niña). In particular, the intensity of the El Niño events in 1997 and 1998 was significantly high. Similarly, the intensities of La Niña events were remarkable in 2000 and 2007. In conclusion, the probability and intensity of ENSO events have both shown significant changes in 1990–2011, leading to changes in precipitation. Hence, it can be concluded that the abnormal ENSO events during 1990–2011 may be responsible for the changes in the PRR of the corresponding time period in the Weihe River basin.

Overall, it can be concluded from the above sections that the variation of the PRR has a close association with anthropogenic activities and climate change. As the major objective of this study is to reveal the multi-scale periodic characteristics of the PRR using the new proposed method combining the EEMD with the XWT and WTC, the quantitative contribution from specific anthropogenic activities and weather events to the PRR variations in various time-frequency domains is expected to do in future study.

CONCLUSIONS

In this study, a new hybrid method, combining the EEMD with XWT and WTC, was proposed for studying the detailed multi-scale periodic characteristics of the PRR in the MWRB and BRB. The EEMD can fully and efficiently extract a limited number of physically meaningful components changing from high- to low-frequency. Meanwhile, the XWT and WTC are adept at capturing coupled oscillations of two time series, both in the time and frequency domains. The hybrid method combines the advantages of the methods mentioned above.

In the two basins, the runoff reductions are both more significant than precipitation changes during the entire time period (Figures 3 and 4). With the application of the EEMD method, the observed monthly runoff and precipitation were all decomposed into eight independent IMFs and one residue (Figures 5 and 6) in the MWRB and BRB, respectively. Employing the MI entropy method, we reconstructed the IMFs of runoff and precipitation into two parts, i.e., the HFC and LFC (Figures 8 and 9).

Adopting the XWT and WTC spectra, the relationships between the HFCs of precipitation and runoff are remarkably significant on the 10- to 14-month band cycle (i.e., one year) at the 95% confidence level over the whole time period in the two basins (Figure 10). Additionally, precipitation leads runoff by approximately one- to two-month lead time most of the time in the BRB and MWRB, respectively. In particular, the relationship between the LFCs is not significant on the 24- to 112-month band cycle (i.e., two to nine years) at the 95% confidence level for many of the time and frequency domains in the two basins (Figure 11). In the MWRB, the PRR is not significant during 1971/2 to 1984/6 and 2005/12 to 2010/12 on the three- to five-year scale, 1974/6 to 1998/6 on the five- to seven-year scale, and 1984/6 to 2010/12 on the seven- to nine-year scale. Similarly, the PRR in the BRB is not significant during 1964/6 to 1985/12 and 1989/6 to 2010/12 on the three- to five-year scale and 2000/12 to 2010/12 on the five- to seven-year scale. In addition, the phase relations are disordered in these regions and no certain trend of the phase angle variations can be identified.

The specific anthropogenic activities and climatic events over time exhibited close relations with the PRR variations, which verifies the validity of the hybrid method to a certain extent. It is worth mentioning that the hybrid approach can be applied to reveal the relationship not only between precipitation and runoff of the HFC and LFC, respectively, but also between any pair of IMFs. Certainly, it can also be extended to any time series, not only those of precipitation and runoff.
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