

# Comprehensive evaluation of multiple methods for assessing water resources variability of a lake–river system under the changing environment

Xuchun Ye, Chong-Yu Xu, Xianghu Li and Qi Zhang

## ABSTRACT

The inherent regularities of hydrological processes will not be stationary under the changing environment, making the evaluation of hydrological characteristics and trend forecasting face great uncertainty. Based on the observed streamflow series in the Poyang Lake catchment during the period 1960–2013, this study investigated the evolution characteristics and future trend of water resources. The extracted trend component by wavelet decomposition and the reliability of trend forecasting by rescaled range analysis (R/S analysis) were verified and assessed by a non-parametric statistical test. Results indicate a change point at 1995 when the trend of annual streamflows across the catchment changed. Periodic components indicated that the lake basin seems to enter into an increasing process under inter-decadal scale, while decreasing under inter-annual scale in the near future. R/S analysis revealed that annual streamflow series of most stations in Poyang Lake show ‘weaker’ or ‘very weak’ persistence. For the whole study period, Hurst exponents of most stations are less than 0.5 (0.224–0.339), therefore, opposite from the increasing trend of historical series, decreasing trend is forecasted for the basin. However, due to the effect of intensified human activities in the Fuhe sub-basin, the reliability of R/S analysis on trend forecasting is disturbed at Lijiadu station.

**Key words** | Hurst index, Poyang Lake basin, R/S analysis, streamflow time series, wavelet decomposition

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## INTRODUCTION

Within the context of ecological, social, and economic development, water quantity and quality have become increasingly serious issues for water resources management at catchment and/or regional scale (Ren *et al.* 2002; Xia *et al.* 2007; Lakshmi *et al.* 2011; IPCC 2013; Li *et al.* 2016). Following the climatic and anthropogenic change stressors, there is an increasing water shortage in most river basins (Xia *et al.* 2007). A study by Walling & Fang (2003) reported that about 22% of the world's rivers have shown statistically significant decreases in annual runoff, and only 9% have statistically significant increases during the last decades. Changes of river

runoff, especially runoff decrease, have significant impacts on fluvial processes, such as riverine sedimentation in lower reaches (Syvitski *et al.* 2005). In addition, these changes may further produce social and environmental problems, including limiting local socioeconomic development and threatening the health of the eco-environment (Humphries & Baldwin 2003; Wang *et al.* 2008; Liu *et al.* 2016a, 2016b). Therefore, investigation into the evolution characteristics of hydrological variables and assessment of future changes has been the theme of many studies (e.g., Labat *et al.* 2004; Bekele & Knapp 2010; Ye *et al.* 2013, 2016; Lai *et al.* 2016; Yan *et al.* 2016).

Due to formation and evolution being influenced by many factors, hydrological series show complex characteristics of randomness, fuzziness, nonstationarity, and multi-time scale variation, etc. (Li & Liu 1991; Percival & Walden 2002). Identification of these properties is essential for the understanding of the physical mechanism of hydrology changes and future forecasting. Previous studies introduced many time series analysis methods to reveal the complexity of hydrological processes, including serial correlation analysis, hydrological frequency analysis, fuzzy analysis, chaos theory analysis, and wavelet analysis (Sang *et al.* 2013; Gorgij *et al.* 2017; Kim *et al.* 2017). Among these methods, wavelet analysis has a unique application in the field of hydroclimatology. It can reveal the statistical characteristics of hydrological time series from both the time and frequency domains. In addition, multi-resolution analysis (MRA) can decompose hydrological time series into low-frequency and high-frequency components, which can be used to identify the change trend and periodic component of hydrological time series (Percival & Walden 2002). However, wavelet analysis is not competent in trend forecasting, making it difficult to meet the demand of hydrological forecasting within the background of global warming. Developed by Hurst, rescaled range analysis (R/S analysis) provides a powerful tool for studying the long-term correlation of time series (Hurst *et al.* 1965). Due to its advantage in the identification of long-term persistence or anti-persistence of time series, the method can well explain the inherent regularity and fractal characteristics of dynamic changes of hydrological variables, and therefore effectively predicts and controls the change trend (Hurst *et al.* 1965; Tong *et al.* 2007).

The inherent regularities of hydrological processes are determined by natural climate and underlying surface conditions. However, these conditions may be changed under exacerbated global climate change and anthropogenic stresses, making the evaluation of hydrological characteristics and trend forecasting face great uncertainty. For example, magnification of floods has been observed in some regions across the world due to altered precipitation processes (Zolina *et al.* 2010). The assumption of stationarity is often violated and the accuracy of existing flood estimation methods mostly diminishes under this assumption (Singh *et al.* 2005; Xie *et al.* 2013; Gu *et al.* 2016).

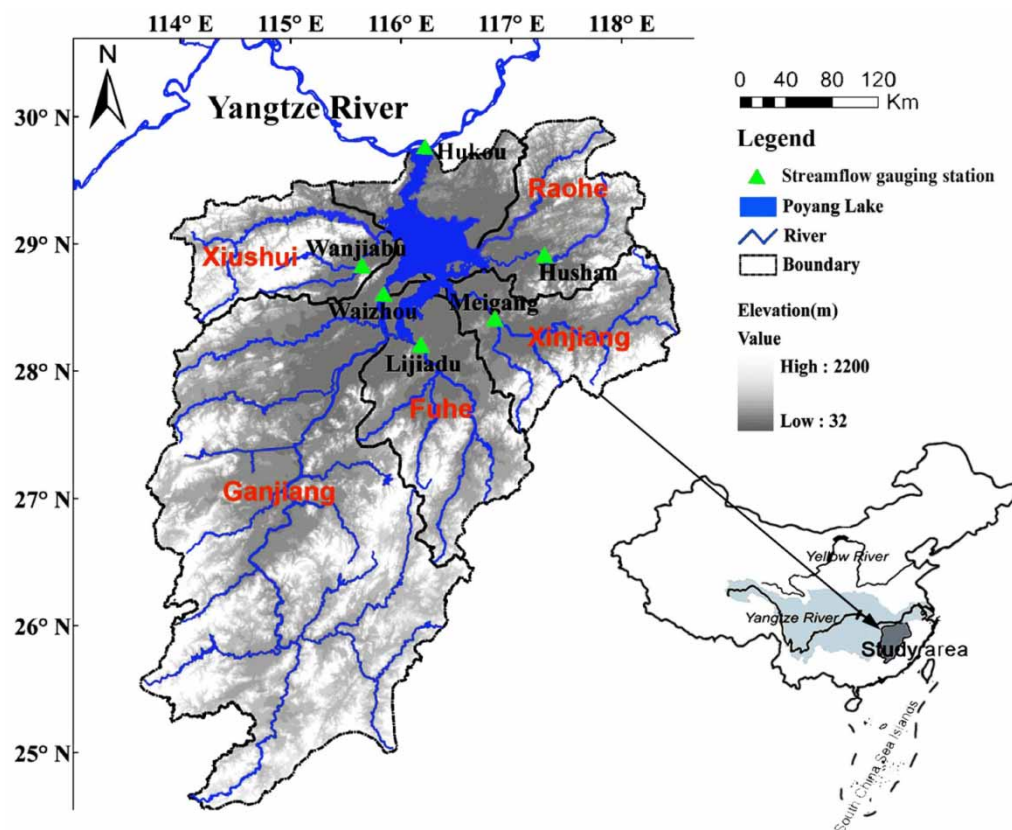
In addition, intensive human activities, such as large-scale land use change and hydrological regulation of water reservoirs may trigger alterations of hydrological processes and introduce nonstationarity in hydrological variables (Hattermann *et al.* 2013; Xie *et al.* 2013). The fractal characteristics and the long-term persistence of hydrological variables can be disturbed (Zhou *et al.* 2014), and uncertainty exists in trend forecasting when applying the R/S analysis. Therefore, comprehensive evaluation of the complex hydrological system under the changing environment needs multiple methods and cross validation because different evaluation methods have their advantages and limitations.

In China, the middle-lower Yangtze River (MLYR) is one of the fastest developing regions. It is also a region that is facing water resource and ecological problems. A permanent example in this region is Poyang Lake, the largest freshwater lake in China which feeds the lower Yangtze River, and that has suffered frequent floods and droughts during the past decades (Shankman *et al.* 2006; Liu *et al.* 2013; Li *et al.* 2016; Yao *et al.* 2016). Especially, since the earlier 2000s, the shrinking of the wetlands has posed significant threats to habitat for many winter birds, and caused various environmental problems and economic hardship (Feng *et al.* 2011; Zhang *et al.* 2012; Jia *et al.* 2013; Liu *et al.* 2016a, 2016b; Tan *et al.* 2016). In order to help policymakers manage the water resource of the lake basin more effectively, the current study was conducted to investigate the evolution characteristics and possible future trend of major tributaries in the Poyang Lake catchment. In this study, we investigated the significance of wavelet and R/S methods in water resources variation assessment. The reliability of these methods was further validated and assessed by a non-parametric statistical test. Most importantly, we examined the time scale of long-term persistence of streamflow series and the potential disturbance of intensive human activities.

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## STUDY REGION AND DATA

The Poyang Lake basin is located on the south bank in the middle reaches of the Yangtze River in southeast China (Figure 1). The lake basin covers an area of 162,225 km<sup>2</sup>



**Figure 1** | Topography and river network of the Poyang Lake basin and its location in the Yangtze River basin, China. The lake basin consists of five sub-basins: Xiushui, Ganjiang, Fuhe, Xinjiang, and Raohe. The downstream river gauging station in each sub-basin is indicated by triangles.

and elevation varies from 2,200 m (above sea level) in mountainous regions to about 30 m in alluvial plains around the lake. The basin belongs to a subtropical monsoon climate zone with an average annual temperature of 17.5 °C and average annual precipitation of 1,665 mm. Of annual precipitation, 55% is concentrated in the period March–June. Also, temperatures are highly seasonal, with June–August average of 27.3 °C and December–February average of 7.1 °C.

The lake basin consists of five sub-basins: Xiushui, Ganjiang, Fuhe, Xinjiang, and Raohe. The largest fresh water lake in China, Poyang Lake, located in the north part of the basin, receives water mainly from five rivers and discharges into the Yangtze River from a narrow outlet (Figure 1). Observed stream flows at six gauging stations used in this study were collected from the Hydrological Bureau of the Yangtze River Water Resources Commission of the Ministry of Water Resources of China, and cover

the period of 1960–2013. Among the six stations, Waizhou, Lijiadu, and Meigang are located at the lower reaches of the Ganjiang, Fuhe, and Xinjiang rivers, while Hushan and Wanjiabu are the two stations located at the branches of the Raohe and Xiushui rivers (Figure 1). The average annual runoff varies from  $34.8 \times 10^8 \text{ m}^3$  at Wanjiabu station to  $681.2 \times 10^8 \text{ m}^3$  at Waizhou station. The lake discharge is monitored at Hukou gauging station and the average annual discharge is  $1,477 \times 10^8 \text{ m}^3$ , which is about 15% of the water resources of the Yangtze River basin. The basic features of these gauging stations are listed in Table 1.

As a typical agriculture catchment, the Poyang Lake catchment serves as an important food base for China. According to the rapid economic development and population explosion, human activities have become increasingly important regarding the change of water resources in the catchment. It is reported that a total of 9,530 reservoirs were built across the catchment up to

**Table 1** | List of hydrological gauging stations used in this study

Gauging station	Location	Coordinates	Gauged area (km <sup>2</sup> )	Average annual runoff (10 <sup>8</sup> m <sup>3</sup> )	Average annual runoff depth (mm)
Waizhou	Ganjiang	(115.83°, 28.63°)	80,948	681.2	841
Lijiadu	Fuhe	(116.17°, 28.22°)	15,811	122.8	777
Meigang	Xinjiang	(116.82°, 28.43°)	15,535	180.1	1,159
Hushan	Le'an tributary of Raohe	(117.27°, 28.92°)	6,374	70.0	1,099
Wanjiabu	Liaohe tributary of Xiushui	(115.65°, 28.85°)	3,548	34.8	981
Hukou	Outlet of Poyang Lake	(116.22°, 29.75°)	162,225	1,477.5	911

2007 (Min et al. 2011). In addition, there exist many large irrigation areas in the middle-lower reaches of the inflow tributaries, especially in the Ganjiang and Fuhe sub-basins. Annual water consumption of Jiangxi Province (which is almost equivalent to the whole Poyang Lake catchment) was about  $94.38 \times 10^8$  to  $126.95 \times 10^8$  m<sup>3</sup> during 1997–2007, of which 73% was for agriculture irrigation and 21% for domestic and industrial utilization (Ye et al. 2013).

## METHODS

### Wavelet decomposition

Wavelet decomposition is a widely used signal processing technique that separates a time series (or signal) into its high-frequency (level of detail) and low-frequency (level of approximation) components (Sabaliauskas et al. 2014). It is applicable in analyzing local variation characteristics in both time and frequency domains (Nejad & Nourani 2012), especially for non-steady hydrological and meteorological time series (e.g., Kisi 2010; Seo et al. 2015).

The wavelet analysis method was derived from Fourier theory, and its basic content is wavelet transform. Let  $L^2(\mathbb{R})$  denote the square integrable function space defined on the real axis, for any time series  $f(t) \in L^2(\mathbb{R})$ , the continuous wavelet transform is defined as the following equation:

$$W_f(a, b) = |a|^{-1/2} \int_{-\infty}^{+\infty} f(t) \bar{\psi}\left(\frac{t-b}{a}\right) dt \quad (1)$$

where  $W_f(a, b)$  is the wavelet transform coefficient under different scale and position;  $\psi(t)$  is the basic wavelet or

mother wavelet;  $a$  is the scale parameter;  $b$  is translation parameter; and  $\bar{\psi}(t)$  is conjugate function of  $\psi(t)$ .

Wavelet decomposition is usually calculated by a fast discrete wavelet transform (DWT) algorithm, among which, the Mallat algorithm (Mallat 1989) is the most famous one. The Mallat algorithm is based on four filters, including decomposition low-pass, decomposition high-pass, reconstruction low-pass, and reconstruction high-pass filters. The low-pass filter, associated with the scaling function, allows the analysis of low-frequency components, while the high-pass filter, associated with the wavelet function, allows the analysis of high-frequency components (Seo et al. 2015). The filters used in Mallat's algorithm are determined according to the selection of mother wavelets (González-Audícana et al. 2005).

Wavelet decomposition in its simplest form involves passing a signal (or a time series) through a high-frequency filter and a low-frequency filter, and obtains 'approximation' and 'details' of the signal. Figure 2 shows a multi-layer decomposition process. The first layer of decomposition creates the first layer of detail ( $D_1$ ) and approximation ( $A_1$ ) representations of the time series data. To further decompose the data,  $A_1$  can be passed through a second pair of high- and low-pass filters to yield a second layer of detail ( $D_2$ ) and approximation ( $A_2$ ). This process can be repeated multiple times until the specified layer of signal decomposition is reached or the signal cannot be further decomposed. An approximation holds the general trend of the original signal, while a detail depicts high-frequency (periodic) components of it (Seo et al. 2015). According to this process, the original data can also be reconstructed by summing each layer of detail and the final layer of approximation.

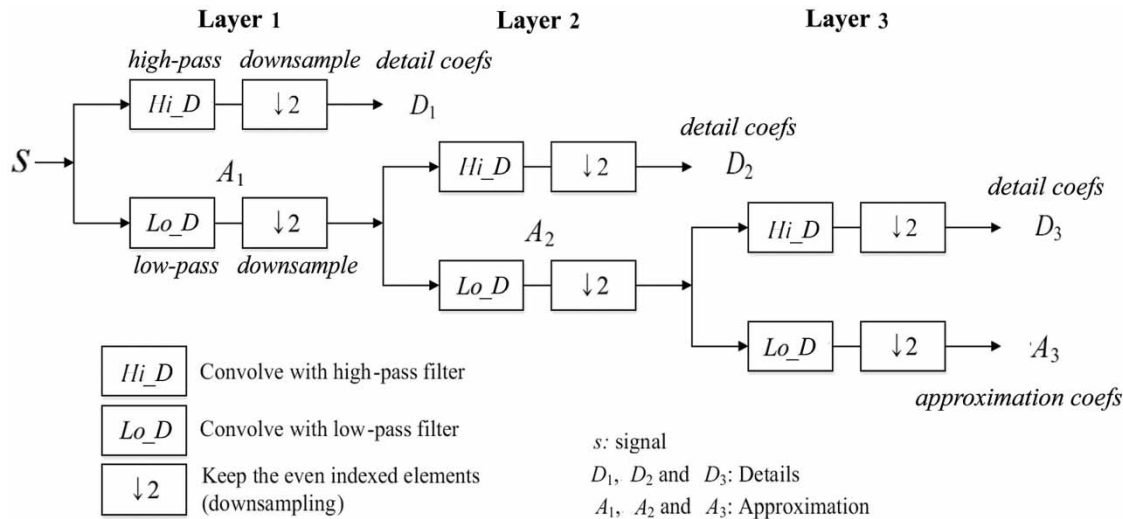


Figure 2 | Algorithm for three-layer decomposition of a signal.

The selection of mother wavelets is necessary when applying the wavelet decomposition. There are many types of wavelets that can be used for wavelet-based time series analysis, including Daubechies, Symmlet, Meyer, Mexican hat, Morlet, and so on (Minu *et al.* 2010). Of these, Daubechies wavelets are one of the most widely used wavelets for discrete wavelet analysis. They represent a collection of orthogonal mother wavelets with compact support, characterized by a maximal number of vanishing moments for some given length of the support (Seo *et al.* 2015). With consideration of the characteristics of streamflow time series and wavelet function, and also the existing application in the study area (e.g., Liu *et al.* 2009), db3 (Daubechies wavelet that has three vanishing moments) was selected for wavelet decomposition in this study.

### R/S analysis

The R/S analysis (rescaled range analysis) was first proposed by Hurst *et al.* (1965) in analyzing the hydrological data of the River Nile. The method is also known as the extreme difference method. It provides a good property to quantitatively characterize the persistence or long-term dependence of time series. In recent years the R/S analysis has been widely applied in the field of environmental changes, geographical science, and so on (e.g., Pelletier & Turcotte 1997; Sakalauskiene 2003; Tong *et al.* 2007; Zhang *et al.* 2010). The main principle of the method is as follows.

For a time series  $x(t)$ ,  $t = 1, 2, 3, \dots$ , the mean sequence can be defined as:

$$y(\tau) = \frac{1}{\tau} \sum_{t=1}^{\tau} x(t) \quad \tau = 1, 2, 3, \dots, n \quad (2)$$

Cumulative deviation is:

$$F(t, \tau) = \sum_{\mu=1}^t x(\mu) - y(\tau) \quad 1 \leq t \leq \tau \quad (3)$$

Range is:

$$R(\tau) = \max_{1 \leq t \leq \tau} F(t, \tau) - \min_{1 \leq t \leq \tau} F(t, \tau) \quad (4)$$

Standard deviation is:

$$S(\tau) = \left[ \frac{1}{\tau} \sum_{t=1}^{\tau} (x(t) - y(\tau))^2 \right]^{1/2} \quad \tau = 1, 2, 3, \dots, n \quad (5)$$

Consider the ratio between  $R(\tau)$  and  $S(\tau)$ , then a relationship holds:

$$\frac{R(\tau)}{S(\tau)} \propto (\tau)^H \quad (6)$$



where  $H$  parameter is called the Hurst exponent.  $H$  values can be simulated according to linear regression analysis using the least squares method under double logarithmic coordinate system ( $\lg\tau$ ,  $\lg R/S$ ). In dynamical systems, the Hurst exponent characterizes the stochastic memory in time of a random process. Different  $H$  values ( $0 < H < 1$ ) indicate different trend variations. A process is said to be persistent when  $H > 0.5$ , while an exponent  $0 < H < 0.5$  indicates short memory or anti-persistence. In the particular case  $H = 0.5$ , the time series show a random uncorrelated behavior with no stochastic memory in time (Zhang et al. 2010). The more  $H$  values approach 1 or 0, the stronger the positive correlation or negative correlation. In order to better understand the meaning of  $H$  value, we divide the persistence and anti-persistence of hydrological series from weak to strong into five levels (Table 2). However, the long-term memory of a time series is bounded. Theoretically, the length of long-term memory can be determined through finding the turning points in  $\lg\tau$ – $\lg R/S$  plots. The average length of periodic can be identified by the statistics  $V_\tau$ .

$$V_\tau = \frac{(R/S)_\tau}{\sqrt{\tau}} \quad (7)$$

when  $(R/S)_\tau$  and  $\sqrt{\tau}$  increase synchronously, the scatters of  $V_\tau - \lg\tau$  will distribute on one line. If the increase of  $(R/S)_\tau$  is faster than  $\sqrt{\tau}$ , the scatters of  $V_\tau - \lg\tau$  present an upward trend, which indicates the persistence of the time series. In contrast, the time series is considered anti-persistence when the scatters present a downward trend. A horizontal trend of the scatters indicates a random property of the time series. A step change in the plot of  $V_\tau - \lg\tau$  may indicate the disappearance of the long-term memory (Song & Tian 2004).

**Table 2** | Classification of Hurst exponent

Hurst exponent	Persistence strength	Hurst exponent	Anti-persistence
$0.50 < H \leq 0.55$	Very weak	$0.45 < H \leq 0.50$	Very weak
$0.55 < H \leq 0.65$	Weaker	$0.35 < H \leq 0.45$	Weaker
$0.65 < H \leq 0.75$	Stronger	$0.25 < H \leq 0.35$	Stronger
$0.75 < H \leq 0.80$	Strong	$0.20 < H \leq 0.25$	Strong
$0.80 < H \leq 1.00$	Very strong	$0.00 < H \leq 0.20$	Very strong

## MK test

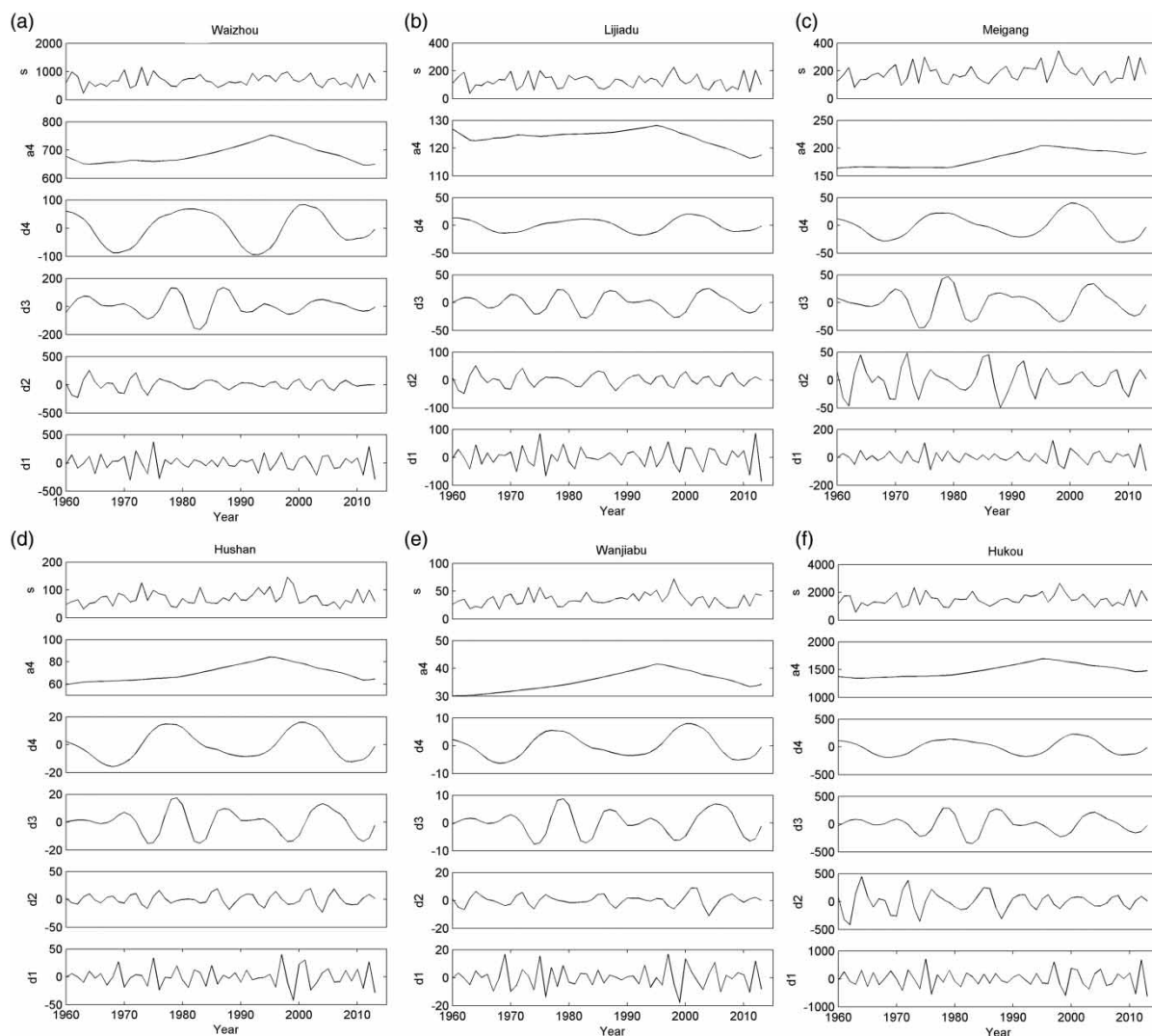
The non-parametric Mann–Kendall (MK) statistical test was also applied as supplementary estimate of the change trend. The method is widely used for trend detection in hydrological and meteorological series (e.g., Ye et al. 2013; Zhang et al. 2014). According to the method, the null hypothesis  $H_0$  of the test is that there is no trend of the data set  $X(x_1, x_2, x_3 \dots x_n)$ . The null hypothesis  $H_0$  should be rejected if  $|Z| \geq 1.96$  at 5% significance level, and  $|Z| \geq 2.32$  at 1% significance level. The  $Z$  value is a standard normal variable that represents the significance level of a specific trend. A positive value of  $Z$  indicates an increasing trend, and a negative value of  $Z$  indicates a decreasing trend.

## RESULTS AND DISCUSSION

### Wavelet decomposition of historical streamflow series

Based on wavelet decomposition theory, when the sample size is  $N$ , the numbers of decomposition cannot exceed the maximum layer of  $\text{Log}_2 N$ . In this study, the sample size of annual streamflow sequence is 54, so the maximum layer that can be decomposed to is five. However, by comparing the deviation of the trend component from linear regression, it is determined that four-layer decomposition can meet the needs of the extraction of the trend change and trend components.

Figure 3 shows the four-layer wavelet decomposition of streamflow series of the six gauging stations during the period 1960–2013. As the approximation through low-frequency filter holds the general trend of the original signal, the low-frequency parts ( $a4$  in Figure 3) clearly indicate the trends of long-term evolution of streamflow series. Generally, the trends' variation of annual streamflow of the six gauging stations shows good regional consistency. All the gauging stations show almost the same trends' evolution during the study period: an increasing trend was observed before 1995, and then changed to decreasing after that year. In addition, trends' evolution of different stations also show some detailed characteristics in certain periods. For example, Waizhou and Lijiadu show a decreasing trend in the initial years. The decreasing trends of most



**Figure 3** | Wavelet decomposition of streamflow series of the six gauging stations.

stations seem to turn to increasing in the last two years, which may imply a remarkable change of streamflow in recent years. However, this result does not provide any guiding significance due to the short time series.

The obtained high-frequency parts ( $d1$ ,  $d2$ ,  $d3$ ,  $d4$  in Figure 3) from wavelet decomposition, to a large extent, reflect the characteristics of periodicity at different levels. According to the high-frequency parts of the six gauging stations, average periodicity was extracted. It is seen from Table 3 that the average periodicities of the six gauging stations are 3.0–4.0a, 5.0–7.0a, 9.0–14.0a, 21.0–22.0a, respectively, for the decomposed high-frequency components. This result reflects the inter-annual and inter-

**Table 3** | Average periodicity of high-frequency components of the six gauging stations

Station	$d1$	$d2$	$d3$	$d4$
Waizhou	3.0	5.0/7.0	9.0	22.0
Lijiadu	4.0	7.0	9.0/14.0	21.0
Meigang	3.0	6.0	12.0	22.0
Hushan	4.0	5.0	9.0/13.0	22.0
Wanjiabu	4.0	7.0	9.0/13.0	22.0
Hukou	4.0	7.0	9.0/14.0	21.0

decadal cycles of streamflow change in the study area, which is comparable with some previous studies in the Yangtze River basin (e.g., Yan et al. 2004; Shao et al. 2016;

Ye et al. 2016). For example, Yan et al. (2004) pointed out obvious <3.5a, 3.5–7.0a, 7.0–14.0a, and 14.0–28.0a periodicities of precipitation in China. Ye et al. (2016) revealed that for hydro-meteorological drought in the Poyang Lake basin three primary periodicities exist: <5.0a, 5.0–10.0a, and 20.0–25.0a. Ping et al. (2006) pointed out that the key areas affecting the Yangtze's rainfall are the western Pacific warm pool on the inter-annual time scale and the EINO<sub>3</sub> area on the decadal time scale, respectively. Also, Shao et al. (2016) investigated the potential correlation of large-scale climate oscillations like ENSO, NAO, IOD, and PDO on the variability of precipitation distribution in the Poyang Lake basin. This may be the background mechanism influence of the two different variations. In this study, in consideration of the variation of high-frequency parts in Figure 3, streamflows of all the gauging stations seem to enter into an increasing process under inter-decadal scale (*d4*), and a decreasing process under inter-annual scale (*d2*) in the near future.

### Verification from non-parametric test

The year 1995 was found to be the crucial year when the trend of streamflow series changed. In order to test the effectiveness of wavelet decomposition in trend extraction and R/S analysis in trend predicting, trend detection by MK test and Hurst exponents were calculated under different time periods.

The calculated *Z* value from MK test in Table 4 indicates that streamflows of all the six gauging stations show an increasing trend during the period 1960–1995, among

which, the increasing trends of Hushan and Wanjiabu are significant. This result is consistent with the obtained trend components by wavelet decomposition that is visible in Figure 3. In other words, the extracted trend component by wavelet decomposition sounds reasonable, and the year 1995 can be considered as a turning point. The result in the table also shows an increasing trend for all the gauging stations except for Lijiadu during the whole study period. This further indicates a time scale based trend analysis as well as different responses of streamflows at the six gauging stations under the changing environment during different periods.

The calculated Hurst exponents (*H* value) of the six gauging stations during the period 1960–1995 are between 0.174 and 0.360, all of which are less than 0.5 (Table 4). According to the theory of R/S analysis, the streamflow series of the six gauging stations are characterized by short memory or anti-persistence. In other words, opposite to the increasing trend during the period 1960–1995, decreasing trend should prevail in the years following 1995. Analysis from the MK test confirmed the decreasing trends of all the six gauging stations during the period 1996–2013, although the trends are not significant (Table 3). Therefore, based on the above analysis, R/S method is verified to be effective in trend predicting of annual streamflow series in the study area. In addition, because there is no data series after 2013, the verification of R/S analysis cannot be checked by this short time series. In fact, the estimated *H* values of all the gauging stations during 1996–2013 are close to 0.5, which may indicate a white noise series and the forecasting significance is much limited.

**Table 4** | The result of MK test and Hurst exponents under different periods

Station	1960–1995		1996–2013		1960–2013	
	<i>Z</i>	<i>H</i>	<i>Z</i>	<i>H</i>	<i>Z</i>	<i>H</i>
Waizhou	0.804	0.271	−1.212	0.385	0.463	0.263
Lijiadu	0.014	0.174	−0.985	0.415	−0.462	0.223
Meigang	1.485	0.238	−0.606	0.549	1.104	0.248
Hushan	2.139*	0.360	−0.530	0.588	0.806	0.339
Wanjiabu	2.547**	0.260	−0.909	0.540	1.164	0.333
Hukou	1.403	0.296	−0.985	0.513	1.059	0.309

\*Delineates significance at 0.05 level; \*\*delineates significance at 0.01 level.



## Streamflow trend prediction

Table 4 lists the results of calculated Hurst exponents of the six gauging stations under different periods. For the calculation result of the whole study period of 1960–2013, it can be seen that Hurst exponents of the six gauging stations are less than 0.5 (0.223–0.339), which suggests a ‘stronger’ to ‘strong’ anti-persistence of the streamflow series. MK test indicates that most of the gauging stations show an increasing trend during the study period, except for Lijiadu station. These values deviate from the increasing trend of the long-distance correlativity of streamflow of most stations, and therefore a decreasing trend is forecast with reference to the former period. This decreasing trend does not contradict the increasing process from the perspective of inter-decadal periodicity as both results are focused on long time scale and short time scale, respectively. This increasing process of inter-decadal variation is included in the long-term decreasing trend.

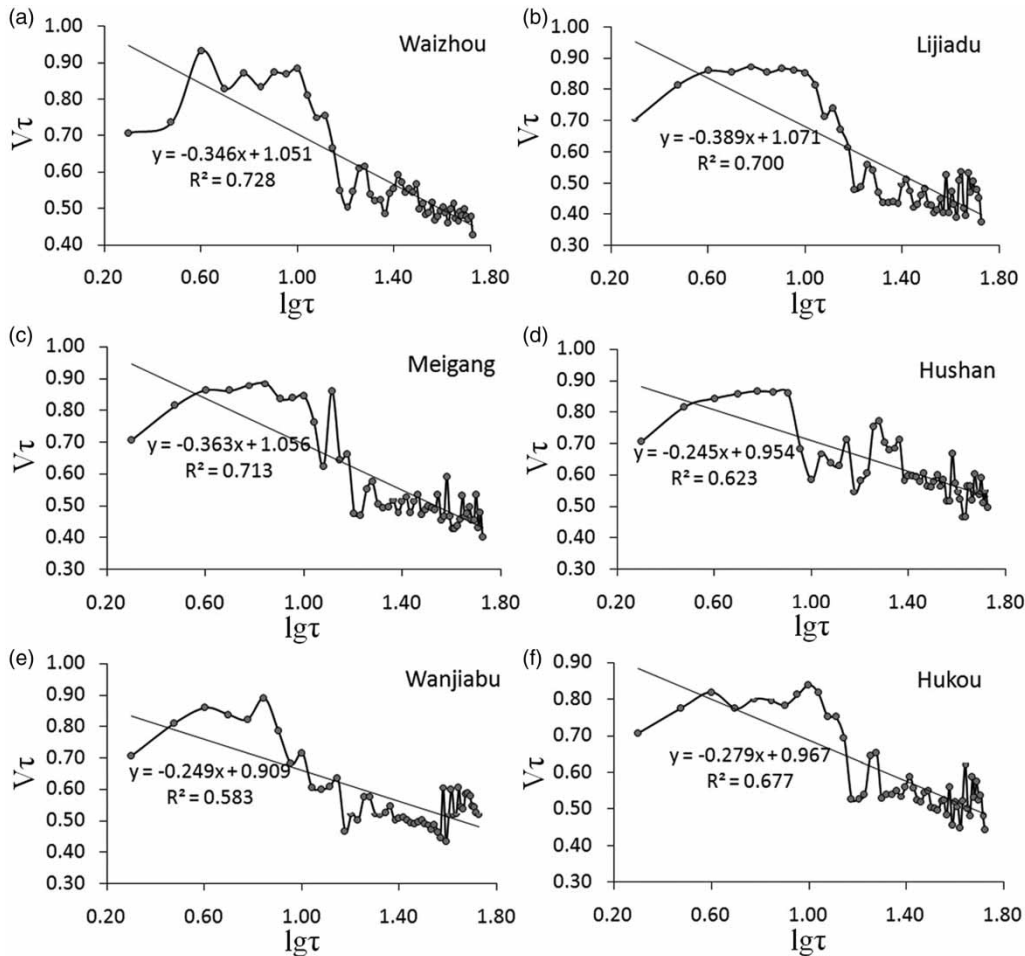
However, it is worth noting that the same anti-persistence of the streamflow series of Lijiadu station was observed, but a decreasing trend was tested during the study period. The question arises whether it is true that an increasing trend would be forecast for this station which is different from the other stations? This result seems not to be reasonable because all the stations are located in the same climate zone and they would have the same trend variation. Further investigation indicates that the streamflow series of Lijiadu station is much more strongly affected by intense human activities in the river sub-basin. It has been reported that Fuhe sub-basin has the biggest irrigation area of the Poyang Lake catchment as well as the large-scale diversion canal of a water conservancy project in the lower reaches of Ganjiang-Fuhe plain, which significantly decreases the streamflow of Lijiadu station (Wu *et al.* 2014). A previous study from Ye *et al.* (2013) revealed that the relative impact of human activities inside the Fuhe sub-basin played a dominant role on streamflow decreasing in the 2000s than that of the other stations with comparison to the effect of climate change. The result is also found by Liu *et al.* (2016a), who reported that human activities (massive agricultural irrigation) is the principal driving factor behind the decrease in streamflow of Lijiadu station. Therefore, due to the strong effect of human activities, the trend and long-term dependence of streamflow variations may

be interfered with, and also the reliability of R/S analysis. However, the periodic component of the hydrological time series is mainly controlled by the regional climate condition, which is not easily affected by human activities.

Figure 4 depicts the relationship between  $V\tau$  and  $\lg\tau$  of the six gauging stations. The fitted linear regression equations show obvious downward trends of all the stations. These downward trends indicate the anti-persistent properties of the streamflow series, which are consistent with the result calculated from Hurst exponents. In addition, there exists step change that may reflect the disappearance of the long-term memory according to the curves in  $V\tau$ – $\lg\tau$  plots. For all the stations, a slight increase is observed during the initial intervals, and then turns to a sharp decrease followed by a stable downward trend. For the Waizhou, Lijiadu, and Hukou stations, the turning points occurred at about  $\tau=10$  ( $\lg\tau=1$ ), and for Meigang, Hushan, and Wanjiabu stations at about  $\tau=7$  ( $\lg\tau=0.85$ ). Hurst exponents before and after the change points are 0.622, 0.597, 0.570, 0.628, 0.630, 0.593 and 0.246, 0.246, 0.298, 0.214, 0.350, 0.416 for Waizhou, Lijiadu, Hukou, Meigang, Hushan, Wanjiabu, respectively. This result indicates that persistence of streamflow series of the six gauging stations in the Poyang Lake basin is time scale based. Streamflow series of most stations show ‘weaker’ or ‘very weak’ persistence under a short time scale. The non-periodic cycle components are about seven or ten years, and then the long-term memory will have disappeared. However, for a relatively longer time scale, streamflow series of most stations show ‘weaker’ or ‘stronger’ anti-persistence. As one of the basic properties of hydrological series, the time scale dependence of persistence, to a large extent, is influenced by different factors, such as watershed area and corresponding underlying conditions as well as regional climate condition. Furthermore, preliminary estimation from Figure 4 indicates that the anti-persistence of annual streamflow series is relatively reliable within the time scale  $20 < t < 36$  years as the fluctuations are small and decrease steadily for most of the stations.

## CONCLUSION

In the current study, evolution characteristics and future trend were evaluated with multiple methods in a large



**Figure 4** | Relationship between  $V_r$  and  $\lg\tau$  of the six gauging stations.

lake–river system in China. The effectiveness of wavelet decomposition in trend extraction and R/S analysis in trend predicting was validated and assessed by a non-parametric statistical test. Some conclusions were achieved as follows:

1. Multiple methods' assessment and cross validation are proven to be a useful and efficient tool for studying the hydrological processes evolution of a complex lake–river system. Wavelet decomposition provided an efficient way to identify the change trend and periodic component of hydrological time series. The persistence of streamflow series shows obvious time scale dependence. Although the effectiveness of R/S analysis in trend predicting of streamflow series was confirmed

most of the time, the persistence of streamflow series based on natural climate and underlying surface conditions may be disturbed by intensive human activities. This result deserves special attention when evaluating water resources variations in those areas under strong anthropogenic stresses.

2. In our case study, increasing trends of streamflow series of the six gauging stations across Poyang Lake were found before 1995, and turned to decreasing after that year. Periodic components indicate that the lake basin seems to enter into an increasing process under inter-decadal scale, while decreasing under inter-annual scale in the near future. Annual streamflow series of most stations in Poyang Lake show 'weaker' or 'very weak' persistence under a short time scale, and then the long-term

memory disappeared within about seven or ten years. However, preliminary estimation indicates that the anti-persistence of annual streamflow series is relatively reliable within the time scale  $20 < t < 36$  years. For the whole study period, the calculated Hurst exponents of most stations are less than 0.5 (0.224–0.339), therefore, opposite from the increasing trend of historical series, decreasing trend is forecast for the basin.

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