Hydrology Research

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

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

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Keywords: streamflow time series; wavelet decomposition; R/S analysis; Hurst index; the Poyang Lake basin.
1. 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; IPCC, 2013; Lakshmi et al. 2011; Li et al. 2016). Following the climatic and anthropogenic change stressors, there is an increasing water shortage in most of river basins (Xia et al. 2007). The study by Walling and Fang (2003) reported that about 22% of world rivers have shown statistically significant decreases in annual runoff, and only 9% have statistically significant increases during last decades. Changes of river runoff, especially runoff decrease has 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 eco-environment (Humphries and Baldwin, 2003; Wang et al. 2008; Liu et al. 2016). Therefore, investigation on the evolution characteristics of hydrological variables and assessment of future changes have been the theme of many studies (e.g. Labat et al. 2004; Bekele and Knapp 2010; Ye et al. 2013, 2016; Lai et al. 2016; Yan et al. 2016).

Due to the formation and evolution are influenced by many factors, hydrological series show complex characteristics of randomness, fuzziness, nonstationary and multi-time scale variation, etc. (Li and Liu 1991; Percival and Walden 2002). Identification of these properties is essential for the understanding of 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 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 and Walden 2002). However, wavelet analysis is not competent in trend forecasting, making it difficult to meet the demand of hydrological forecasting under 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 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 facing water resources and ecological problems. A permanent example in this region is that the Poyang Lake, the largest freshwater lake in China which feeds the lower Yangtze River has suffered frequent floods and droughts during the past decades (Shankman et al. 2006; Liu et al. 2013; Yao et al. 2016; Li et al. 2016). Especially, since the earlier 2000s, the shrinking of the wetlands has posed significant threats to the 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. 2016; Tan et al. 2016). In order to help policymakers to 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.

2. 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 km² with 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. For annual precipitation, 55% 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 the five rivers and discharges into the Yangtze River from a narrow outlet (Figure 1). Observed stream flows at six gauging stations that 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 that located at the branches of the Raohe and Xiushui rivers (Figure 1). The average annual runoff varies from 34.8 ×10^8 m^3 at Wanjiabu station to 681.2 ×10^8 m^3 at Waizhou station. The lake discharge is monitored at Hukou gauging station and the average annual discharge is 1,477×10^8 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 on the change of water resources in the catchment. It is reported that a total amount of 9530 reservoirs were built across the catchment until 2007 (Min et al. 2011). In addition, there exists lots of big irrigation areas in the middle-lower reaches of the
inflow tributaries, especially in the Ganjiang and Fuhe sub-basins. Annual water consumption of the Jiangxi Province (which almost equivalent to the whole Poyang Lake catchment) is about 94.38 × 10^8 – 126.95 × 10^8 m^3 during 1997–2007, of which 73% for agriculture irrigation and 21% for domestic and industrial utilization (Ye et al. 2013).

Figure 1 Insert here

Table 1 Insert here

3. Methods

3.1 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 on analyzing local variation characteristics in both time and frequency domains (Nejad and 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 \( L^2(R) \) denotes the square integrable function space defined on the real axis, for any time series \( f(t) \in L^2(R) \), the continuous wavelet transform is defined as the following equation:

\[
W_f(a,b) = |a|^{-1/2} \int_{-\infty}^{\infty} f(t) \overline{\psi} \left( \frac{t-b}{a} \right) dt
\]

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 \( \overline{\psi}(t) \) is conjugate function of \( \psi(t) \).
Wavelet decomposition is usually calculated by a fast discrete wavelet transform (DWT) algorithm, among which the Mallat's 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 (D1) and approximation (A1) representations of the time series data. To further decompose the data, A1 can be passed through a second pair of high and low pass filters to yield a second layer of detail (D2) and approximation (A2). 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 Insert here

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). Among which, 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.

3.2 Rescaled Range analysis (R/S)

The R/S analysis (Rescaled Range Analysis) was first proposed by Hurst et al. (1965) in analyzing the hydrological data of the Nile River. 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 and Turcotte 1997; Sakalauskienë 2003; Tong et al. 2007; Zhang et al. 2010). The main principle of the method is as follows:

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

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

Cumulative deviation is:

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

Range is:
\[ R(\tau) = \max_{t \leq s \leq t+\tau} F(t, \tau) - \min_{t \leq s \leq t+\tau} F(t, \tau) \] (4)

Standard deviation is:
\[ S(\tau) = \left[ \frac{1}{\tau} \sum_{i=1}^{\tau} (x(t) - y(\tau))^2 \right]^{1/2} \quad \tau = 1, 2, 3, ..., n \] (5)

Consider the ratio between \( R(\tau) \) and \( S(\tau) \), then a relationship holds:
\[ R(\tau)/S(\tau) \propto (\tau)^H \] (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 5 levels (Table 2).

Table 2 Insert here

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 \( V_\tau \).
\[ V_\tau = (R/S)_\tau / \sqrt{\tau} \] (7)
When \((R/S)\tau\) and \(\sqrt{\tau}\) increase synchronously, the scatters of \(V\tau - \ln \tau\) will distribute on one line. If the increase of \((R/S)\tau\) is faster than \(\sqrt{\tau}\), the scatters of \(V\tau - \ln \tau\) present an upward trend, which indicates the persistence of time series. In contrast, the time series is considered to be 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 \(V\tau - \ln \tau\) may indicate the disappearment of the long-term memory (Song and Tian 2004).

3.3 MK test

The non-parametric Mann-Kendall (MK) statistical test was also applied as supplementary estimates 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 \(X (x_1, x_2, x_3 \ldots x_n)\). 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.

4. Results and discussion

4.1 Wavelet decomposition of historical streamflow series

Based on wavelet decomposition theory, when the sample size is \(N\), the number of decomposition cannot exceed the maximum layer of \(\log_2 N\). In this study, the sample size of annual streamflow sequence is 54, so the maximum layer can be decomposed to is five. However, by comparing the deviation of the trend component from linear regression, it is determined that 4-layer decomposition
can meet the needs of the extraction of the trend change and trend components.

Figure 3 shows the 4-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 the figure clearly indicate the trends of long-term evolution of streamflow series. Generally, trends variation of annual streamflow of the six gauging stations show 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 turned to decreasing after the year. In addition, trends evolution of different stations also shows some detailed characteristics in certain periods. For example, Waizhou and Lijiadu show a decreasing trend in the initial several years. The decreasing trends of most 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 give any guiding significance due to short time series.

Figure 3 Insert here

The obtained high frequency parts (d1, d2, d3, d4) 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-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 an 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 hydro–meteorological drought in the Poyang Lake basin exists three primary periodicities: <5.0a, 5.0–10.0a and 20.0–25.0a. Pin et al. (2006) pointed out that the key areas affecting the Yangtze rainfall are the western Pacific warm pool on the inter-annual time scale and the EINO3 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 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), while a decreasing process under inter-annual scale (d2) in the near future.

Table 3 Insert here

4.2 Verification from non-parametric test

The year 1995 was found to be the crucial year that the trend of streamflow series turned to change. 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 period.

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-persistent. In other words, opposite to the increasing trend during the period 1960–1995, decreasing trend should be prevail in the following years after 1995. Analysis from 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. Actually, 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 Insert here

4.3 Streamflow trend prediction

Table 4 lists the result of calculated Hurst exponents of the six gauging stations under different
periods. For the calculation result of whole study period 1960–2013, it can be seen that Hurst exponents of the six gauging stations are less than 0.5 (0.223–0.339), which suggest 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 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 forecasted with reference to former period. This decreasing trend doesn’t contradict to 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 of 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. Question comes out that whether it is true that an increasing trend would be forecasted for this station which is different from the other stations? This result seems not reasonable because all the stations are located in the same climate zone and they would have the same trend variation. Further investigation indicates that 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 large-scale diversion canal of water conservancy project in the lower reaches of Ganjiang-Fuhe plain, which significantly decrease the streamflow of Lijiadu station (Wu et al., 2014). Previous study from Ye et al. (2013) revealed that relative impact of human activities inside the Fuhe sub-basin played a dominant role on streamflow decreasing in 2000s than that of the other stations with comparison to the effect of climate change. The result is also found by Liu et al. (2016), who reported that human activities (massive
agricultural irrigation) is the principle driving factor behind the decreasing of 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, and also the reliability of R/S analysis. However, periodic component of the hydrological time series is mainly controlled by the regional climate condition, which is not easy to be affected by human activities.

Figure 4 depicts the relationship between $V_\tau$ and $l\tau$ 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 disappearment of the long-term memory according to the curves in $V_\tau$–$l\tau$ 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. For the Waizhou, Lijiadu and Hukou stations, the turning points are occurred at about $\tau =10$ ($l\tau=1$), and for Meigang, Hushan and Wanjiabu stations at about $\tau =7$ ($l\tau=0.85$). 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 the most stations show 'weaker' or 'very weak' persistence under a short time scale. The non-periodic cycle components are about 7 or 10 years, and then the long-term memory will be disappeared. However, for a relatively longer time scale, streamflow series of the most stations show 'weaker' or 'stronger' anti-persistence. As one of the basic properties of hydrological series, time scale dependent 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.

Figure 4 Insert here

5. Conclusion remarks

In the current study, evolution characteristics and future trend were evaluated with multiple methods
in a large 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 are 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
in most of 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
the 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 the most stations in the Poyang Lake show 'weaker' or 'very weak' persistence under a short time scale, and then the long-term memory disappeared within about 7 or 10 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 forecasted for the basin.

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Ye, X, Li, X., Xu, C-Y. & Zhang, Q. 2016 Similarity, difference and correlation of meteorological and hydrological drought indices in a humid climate region—the Poyang Lake catchment in


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 green triangles.
Figure 2 Algorithm for three-layer decomposition of a signal.
Figure 3 Wavelet decomposition of streamflow series of the six gauging stations.
Figure 4 Relationship between $V_\tau$ and $lgt$ of the six gauging stations.
Table 1 List of hydrological gauging stations used in this study

<table>
<thead>
<tr>
<th>Gauging Station</th>
<th>Location</th>
<th>Coordinates</th>
<th>Gauged Area (km²)</th>
<th>Average annual runoff (10⁸ m³)</th>
<th>Average annual runoff depth (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waizhou</td>
<td>Ganjiang</td>
<td>(115.83°, 28.63°)</td>
<td>80,948</td>
<td>681.2</td>
<td>841</td>
</tr>
<tr>
<td>Lijiadu</td>
<td>Fuhe</td>
<td>(116.17°, 28.22°)</td>
<td>15,811</td>
<td>122.8</td>
<td>777</td>
</tr>
<tr>
<td>Meigang</td>
<td>Xinjiang</td>
<td>(116.82°, 28.43°)</td>
<td>15,535</td>
<td>180.1</td>
<td>1,159</td>
</tr>
<tr>
<td></td>
<td>Le’an tributary</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hushan of Raohe</td>
<td>(117.27°, 28.92°)</td>
<td>6,374</td>
<td>70.0</td>
<td>1,099</td>
</tr>
<tr>
<td></td>
<td>Liaohe tributary</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wanjiabu</td>
<td>of Xiushui</td>
<td>(115.65°, 28.85°)</td>
<td>3,548</td>
<td>34.8</td>
<td>981</td>
</tr>
<tr>
<td></td>
<td>Outlet of the</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hukou</td>
<td>Poyang Lake</td>
<td>(116.22°, 29.75°)</td>
<td>162,225</td>
<td>1,477.5</td>
<td>911</td>
</tr>
<tr>
<td>Hurst exponent</td>
<td>persistence strength</td>
<td>Hurst exponent</td>
<td>Anti-persistence</td>
<td></td>
<td></td>
</tr>
<tr>
<td>----------------</td>
<td>----------------------</td>
<td>----------------</td>
<td>-----------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.50&lt;H≤0.55</td>
<td>very weak</td>
<td>0.45&lt;H≤0.50</td>
<td>very weak</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.55&lt;H≤0.65</td>
<td>weaker</td>
<td>0.35&lt;H≤0.45</td>
<td>weaker</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.65&lt;H≤0.75</td>
<td>stronger</td>
<td>0.25&lt;H≤0.35</td>
<td>stronger</td>
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<tr>
<td>0.75&lt;H≤0.80</td>
<td>strong</td>
<td>0.20&lt;H≤0.25</td>
<td>strong</td>
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<td></td>
</tr>
<tr>
<td>0.80&lt;H≤1.00</td>
<td>very strong</td>
<td>0.00&lt;H≤0.20</td>
<td>very strong</td>
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<td></td>
</tr>
<tr>
<td>Station</td>
<td>d1</td>
<td>d2</td>
<td>d3</td>
<td>d4</td>
<td></td>
</tr>
<tr>
<td>----------</td>
<td>-----</td>
<td>--------</td>
<td>--------</td>
<td>-----</td>
<td></td>
</tr>
<tr>
<td>Waizhou</td>
<td>3.0</td>
<td>5.0/7.0</td>
<td>9.0</td>
<td>22.0</td>
<td></td>
</tr>
<tr>
<td>Lijiadu</td>
<td>4.0</td>
<td>7.0</td>
<td>9.0/14.0</td>
<td>21.0</td>
<td></td>
</tr>
<tr>
<td>Meigang</td>
<td>3.0</td>
<td>6.0</td>
<td>12.0</td>
<td>22.0</td>
<td></td>
</tr>
<tr>
<td>Hushan</td>
<td>4.0</td>
<td>5.0</td>
<td>9.0/13.0</td>
<td>22.0</td>
<td></td>
</tr>
<tr>
<td>Wanjiabu</td>
<td>4.0</td>
<td>7.0</td>
<td>9.0/13.0</td>
<td>22.0</td>
<td></td>
</tr>
<tr>
<td>Hukou</td>
<td>4.0</td>
<td>7.0</td>
<td>9.0/14.0</td>
<td>21.0</td>
<td></td>
</tr>
</tbody>
</table>
Table 4 The result of MK test and Hurst exponents under different periods

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Z</td>
<td>H</td>
<td>Z</td>
</tr>
<tr>
<td>Waizhou</td>
<td>0.804</td>
<td>0.271</td>
<td>–1.212</td>
</tr>
<tr>
<td>Lijiadu</td>
<td>0.014</td>
<td>0.174</td>
<td>–0.985</td>
</tr>
<tr>
<td>Meigang</td>
<td>1.485</td>
<td>0.238</td>
<td>–0.606</td>
</tr>
<tr>
<td>Hushan</td>
<td>2.139*</td>
<td>0.360</td>
<td>–0.530</td>
</tr>
<tr>
<td>Wanjiabu</td>
<td>2.547**</td>
<td>0.260</td>
<td>–0.909</td>
</tr>
<tr>
<td>Hukou</td>
<td>1.403</td>
<td>0.296</td>
<td>–0.985</td>
</tr>
</tbody>
</table>

Note: *Delineate significance at 0.05 level; **Delineate significance at 0.01 level.