LONG-MEMORY IN STREAMFLOW PROCESSES OF THE YELLOW RIVER

W. Wang¹,², P.H.A.J.M. Van Gelder² and J.K. Vrijling²

¹ Faculty of Water Resources and Environment, Hohai University, Nanjing, 210098, China, w.wang@126.com.
² Faculty of Civil Engineering & Geosciences, Section of Hydraulic Engineering, Delft University of Technology, 2600 GA Delft, Netherlands.

Abstract
The long memory property of streamflow processes at different timescales (i.e., daily, 1/3-monthly and monthly) of the headwaters of the Yellow River at Tangnaihai and of the middle reaches at Tongguan is investigated via heuristic methods and statistical test methods. The results show that both daily streamflow processes at Tangnaihai and Tongguan exhibit strong long-memory. With the increase of timescale, the intensity of long memory weakens. 1/3-monthly streamflow processes may still exhibit long memory. But there is less evidence of the presence of long memory in monthly streamflow processes. In addition, the streamflow processes at Tangnaihai show stronger long-memory properties than those at Tongguan, although the drainage area at Tongguan is much larger than that at Tangnaihai.

Keywords: GPH test; Lo’s modified R/S statistic; long memory time series; Streamflow processes.

INTRODUCTION

Since the early work of Hurst (1951), it is has been well recognized that many time series, in diverse fields of application, may exhibit the phenomenon of long-memory or long-range dependence (e.g., Montanari et al., 2000; Ooms and Frances, 2001). Long memory property denotes that a series has a slowly declining correlogram. Mandelbrot and Wallis (1969) were the first to introduce mathematical models with long-range dependence: the Fractional Gaussian Noise model. Then, Hosking (1981) and Granger and Joyeux (1980) proposed the fractional integrated autoregressive and moving average model, denoted by ARFIMA(p,d,q). The parameter d is called long-memory parameter which indicates the intensity of long-range dependence. When 0.5<d<0.5, the ARFIMA (p,d,q) process is stationary and if 0<d<0.5 the process presents long-memory behaviour. For a long memory process, ρ(k) approaches Ck2d-1 as k→∞, where 0<|d|<0.5 and C = Γ(1-d)/Γ(d) (Beran, 1994). Thus, the autocorrelation function of a long memory process decays slowly at a hyperbolic rate. In fact, it decays so slowly that the autocorrelations are not summable.

Many methods for estimating the self-similarity parameter H or the long-memory parameter d are available (Beran, 1994). These techniques can be categorized into two classes: the heuristic and the parametric methods. The heuristic methods are useful to find a first estimate of d or H and to test if there exists a long-range dependence in the data. The parametric methods obtain consistent estimators of d or H via maximum likelihood estimation of parametric long-memory models. They give more accurate estimate of d or H, but generally require knowledge of the true model.

In the hydrology community, many studies have been carried out on the test for long memory in streamflow processes. Montanari et al. (1997) applied fractionally integrated ARFIMA model to the monthly and daily inflows of Lake Maggiore, Italy. Rao and Bhattacharya (1999) explored some
monthly and annual hydrologic time series, including average monthly streamflow, maximum monthly streamflow, average monthly temperature and monthly precipitation, at various stations in the midwestern US. They stated that there is little evidence of long-term memory in monthly hydrologic series, and for annual series the evidence for lack of long-term memory is inconclusive. Montanari et al. (2000) introduced seasonal ARFIMA model and applied it to the Nile River monthly flows at Aswan, to detect whether long memory is present. The resulting model also indicates that nonseasonal long memory is not present in the data. At approximately the same time, Ooms and Franses (2001) documented that monthly river flow data displays long memory, in addition to pronounced seasonality based on simple time series plots and periodic sample autocorrelations. Wang et al. (2002) investigated the long memory property of two daily streamflow of the Yellow River in China and found that both daily streamflow processes exhibit strong long memory.

In this paper we apply three heuristic methods, i.e., autocorrelation function analysis, classical $R/S$ analysis, aggregated variance plot, and two statistical test methods, i.e., Lo’s modified $R/S$ test (Lo, 1991) and GPH Test Geweke and Porter-Hudak (1983), to test for the existence of long memory for daily, 1/3-monthly and monthly streamflow processes of the Yellow River in China at two stations.

**CASE STUDY AREAS AND DATA USED**

**Case study areas**

The headwaters of the Yellow River are on the Tibet Plateau. The discharge gauging station Tangnaihai (TNH) on the main course of the Yellow River has a drainage area of 133,650 km², of which 192 km² are permanently snow-covered. Most part of the watershed is 3,000 to 6,000 meters above sea level. Snowmelt water composes about 5% of total runoff. Most rain falls in summer. Because the watershed is partly permanently snow-covered, sparsely populated, and lacking any major hydraulic works, it is fairly pristine.

The middle reaches of the Yellow River differ from the headwaters significantly. The precipitation is highly concentrated in summer, and often in the form of storm-rain. Because of the special geomorphology and poor vegetation-cover, the runoff usually responds fast to rainfall. Because the area along the middle reaches is densely populated, water withdrawal for industry and agriculture is very influential on river flow process. Furthermore, there are many hydraulic works in the main channel and main tributaries. Therefore, the streamflow process is severely intervened by human activities. The streamflow at Tongguan (TG) will be analysed in this study. The drainage area at TG is 682,141 km², 5 times more than that at TNH.

**Data used and data pre-processing**

The daily streamflow data of TNH gauging station for this analysis extend from January 1, 1956 to December 31, 2000, yielding 16,437 mean daily observations. The data of TG station used here extend from January 1, 1962 to December 31, 2000. To aggregate daily data 1/3-monthly series, we take the averages of daily streamflows of the first and the second 10-days to be the 1st and 2nd 1/3-month average discharges of each month, and the average of the daily streamflows of last 8~11 days (depending on the length of the month) to be the 3rd 1/3-month discharge of each month.

To eliminate possible impacts of trend and seasonality present in the streamflow processes on the effectiveness of the long memory analyses, data are pre-processed. Data pre-processing procedures include normalization, detrending, and deseasonalization. They proceed as follows. First, we normalize the river flow series by taking logarithmization. Then, because the streamflow process at TG presents a significant downward trend, the trend is removed by subtracting the trend component calculated with the regression model. Finally, deseasonalization is performed by subtracting the seasonal (daily or monthly) mean values and dividing by seasonal standard deviations. After normalization, detrending and
deseasonalization, we obtain a process without seasonality (in mean value and variance) and trend and then we can analyse long-memory properties for the pre-processed process.

HEURISTIC ANALYSIS OF LONG MEMORY

Autocorrelation function analysis

In the presence of long memory, the autocorrelation function (ACF) of a time series decreases to 0 at a much slower rate than the exponential rate implied by an ARMA model. So, we can compare the ACF of a time series with the theoretical ACF (McLeod, 1975) of the ARIMA model fitted to the time series. If the ACF of fitted ARIMA model decays faster than the ACF of the observed series, then it probably indicates the existence of long memory.

First, we select the best fitting AR models for the streamflow series using AIC, which turns out to be an AR(38), AR(9) and AR(4) model for streamflow series at TNH, and an AR(9), AR(5) and AR(15) model for streamflow series at TG. The high autoregressive order for monthly flow at TG arises from the seasonality in the flow series that remained after deseasonalization. The sample ACF of the streamflow series and the theoretical ACF of the fitted models from lag 1 to lag 100 are plotted in Figures 1 and 2.

![Figure 1](image1.png)

Figure 1. Sample ACF (vertical lines) and the theoretical ACF (curve line) of fitted AR models for (a) daily, (b) 1/3-monthly and (c) monthly streamflow at TNH.

![Figure 2](image2.png)

Figure 2. Sample ACF (vertical lines) and the theoretical ACF (curve line) of fitted AR models for (a) daily, (b) 1/3-monthly and (c) monthly streamflow at TG.

Comparing the theoretical ACF implied by the fitted AR models with the sample autocorrelation function of the observed streamflow series, we can find that:

a. The autocorrelation of daily streamflow is highly persistent and remains very significant at lag 100. The theoretical autocorrelation closely matches the sample autocorrelation at small lags. However, for large lags, the sample autocorrelation decays much more slowly than the theoretical autocorrelation. Thus, daily streamflow processes at both TNH and TG may have long memory.

b. The autocorrelation of 1/3-monthly and monthly streamflow are much less persistent. For 1/3-monthly flow series, the sample autocorrelation is slightly larger than theoretical autocorrelation for large lags. But for monthly flow series, the sample autocorrelation is basically at the same level of theoretical autocorrelation. Thus, 1/3-monthly streamflow processes may still have weak long memory, but there...
is no clear evidence of the existence of long memory for monthly flow series.

**R/S analysis**

The R/S statistic is the adjusted range of partial sums of deviations of a times series from its mean, rescaled by its standard deviation. Classical R/S analysis is first introduced by Hurst (1951). Consider a time series \( \{x_t\}, t=1,2,\ldots,N \), and define the \( j \)th partial sum as \( Y_j = \sum_{i=1}^{j} x_t, \quad j = 1, 2, \ldots, N \). Suppose to calculate the storage range of a reservoir between time \( t \) and \( t+k \), and assume that: (a) the storage at time \( t \) and \( t+k \) is the same; (b) the outflow during time \( t \) and \( t+k \) is the same; and (c) there is no any loss of storage. Then the rescaled adjusted range, i.e., \( R/S \) statistic, is defined as (Beran, 1994):

\[
R/S_{(t,k)} = \frac{1}{S_{(t,k)}} \left\{ \max_{0 \leq i < k} \left[ Y_{t+i} - \frac{i}{k} (Y_{t+k} - Y_t) \right] - \min_{0 \leq i < k} \left[ Y_{t+i} - \frac{i}{k} (Y_{t+k} - Y_t) \right] \right\}
\]

(1)

where,

\[
S_{(t,k)} = \sqrt{k^{-1} \sum_{j=t+1}^{t+k} (x_j - \bar{x}_{t,k})^2}, \quad \text{and} \quad \bar{x}_{t,k} = k^{-1} \sum_{j=t+1}^{t+k} x_j.
\]

\( R/S \) varies with the time span \( k \). Hurst (1951) found that the \( R/S \) statistic for many geophysical records is well described by the following empirical relation: \( E[R/S] \sim c_1 k^H \), as \( k \to \infty \), with typical values of the Hurst coefficient \( H \) in the interval (0.5, 1.0), and \( c_1 \) a finite positive constant that does not depend on \( k \). Classical R/S analysis is based on a heuristic graphical approach. Compute the \( R/S \)-statistic in Eq. (1) at many different lags \( k \) and for a number of different points, and plots the resulting estimates versus the lags on log-log scale. The logarithm of \( k \) should scatter along a straight line having a slope equal to \( H \). The value of \( H \) can be estimated by a simple least-squares fit. An \( H \) value equal to 0.5 means absence of long memory. The higher the \( H \), the higher the intensity of long memory. The log-log plots of \( R/S \) versus different lags \( k \) for streamflow processes at both Tangnaihai (TNH) and Tongguan (TG) displayed in Figure 3 and 4. The slopes of the fitted lines are the estimates of values of \( H \).

![Figure 3. R/S plot of (a) daily, (b) 1/3-monthly and (c) monthly flow series at TNH.](image-url)

![Figure 4. R/S plot of (a) daily, (b) 1/3-monthly and (c) monthly flow series at TG.](image-url)
According to the $R/S$ statistics obtained with classical approach, all the streamflow have $H$ values larger than 0.5, indicating the presence of long memory in all these streamflow series. The $H$ values, namely the intensity of long memory, decrease with the increase of timescales. Furthermore, at each timescale, the long memory intensity of streamflow process at TNH is stronger than that at TG.

To check the effectiveness of $R/S$ analysis for detecting long-memory, we generate ten simulations of an AR(1) model \((ar = 0.9)\), and ten simulations of an ARFIMA\((0,d,0)\) model \((d = 0.3)\), and ten simulations of an ARFIMA\((1,d,0)\) model \((ar = 0.9, d = 0.3)\). All of the simulations have standard Gaussian noise. Each of them has a size of 3,000 points. The estimated $H$ values are listed in Table 1.

<table>
<thead>
<tr>
<th>Simulation</th>
<th>AR(1)</th>
<th>ARFIMA((0,d,0))</th>
<th>ARFIMA((1,d,0))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.83789</td>
<td>0.75434</td>
<td>0.91157</td>
</tr>
<tr>
<td>2</td>
<td>0.79296</td>
<td>0.76044</td>
<td>0.89271</td>
</tr>
<tr>
<td>3</td>
<td>0.78578</td>
<td>0.73048</td>
<td>0.90742</td>
</tr>
<tr>
<td>4</td>
<td>0.78821</td>
<td>0.77499</td>
<td>0.87063</td>
</tr>
<tr>
<td>5</td>
<td>0.82238</td>
<td>0.75269</td>
<td>0.88660</td>
</tr>
<tr>
<td>6</td>
<td>0.82636</td>
<td>0.73367</td>
<td>0.87649</td>
</tr>
<tr>
<td>7</td>
<td>0.77678</td>
<td>0.81083</td>
<td>0.89122</td>
</tr>
<tr>
<td>8</td>
<td>0.83730</td>
<td>0.77748</td>
<td>0.91854</td>
</tr>
<tr>
<td>9</td>
<td>0.77904</td>
<td>0.76316</td>
<td>0.89593</td>
</tr>
<tr>
<td>10</td>
<td>0.83119</td>
<td>0.77612</td>
<td>0.90586</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>0.80779</strong></td>
<td><strong>0.76342</strong></td>
<td><strong>0.89570</strong></td>
</tr>
</tbody>
</table>

The simulation results show that, for a pure fractionally integrated process ARFIMA\((0,d,0)\), the estimate of $H$ is very close to its real value. But when a process is a mixture of short memory and long memory, as the ARFIMA\((1,d,0)\) process, then the estimates of $H$ are biased towards higher values. Furthermore, classical $R/S$ analysis gives estimated $H$ values \((H = d + 0.5)\) higher than 0.5 even for short memory AR(1) processes, which indicates its sensitivity to the presence of explicit short-range dependence.

**Variance plot**

For independent random variables $x_1, \ldots, x_N$, the variance of sample mean is equal to $\text{var}(\bar{x}) = \sigma^2N^{-1}$. But in the presence of long memory, Beran (1994) proved that the variance of the sample mean can be expressed by $\text{var}(\bar{x}) \approx cN^{2H-2}$, where $c>0$ and $H$ is the Hurst coefficient. Correspondingly, Beran (1994) suggested the following method for estimating Hurst coefficient $H$.

- Take a sufficient number (say $m$) of subseries of length $k$ \((2 \leq k \leq N/2)\), calculate the sample means $\bar{x}_i(k), \bar{x}_2(k), \ldots, \bar{x}_m(k)$ and the overall mean $\bar{x}(k) = m^{-1}\sum_{j=1}^{m} \bar{x}_j(k)$;
- For each $k$, calculate the sample variance $s^2(k)$ of the $m$ sample means:
  $$s^2(k) = (m-1)^{-1}\sum_{j=1}^{m} (\bar{x}_j(k) - \bar{x}(k))^2$$
- Plot log $s^2(k)$ against log $k$. For large values of $k$, the points in this plot are expected to be scattered around a straight line with negative slope $2H - 2$. The slope is steeper (more negative) for short-memory processes. In the case of independence, the ultimate slope is $-1$.

Comparing the variance plot for the streamflow processess at TNH and TG, displayed in Figures 5 and
6, respectively, we can find that the slopes of the fitted line get more negative as the timescale increases (from day to month) for the streamflow processes at both TNH and TG, which indicate the \( H \) values, namely the intensity of long memory, decreases with the increase of timescales. Furthermore, at each timescale, the long memory intensity of streamflow process at TNH is stronger than that at TG.

![Figure 5. Variance plot of (a) daily, (b) 1/3-monthly and (c) monthly flow series at TNH.](image)

![Figure 6. Variance plot of (a) daily, (b) 1/3-monthly and (c) monthly flow series at TG.](image)

Similar to \( R/S \) analysis, to assess the effectiveness of variance analysis for detecting long-memory, we apply the variance analysis method to the generated simulations of the AR(1) model, the ARFIMA(0,d,0) and the ARFIMA(1,d,0) to estimate their \( H \) values. The estimated \( H \) values are listed in Table 2. The results show that, variance analysis is also sensitive to the presence of explicit short-range dependence, and generally it gives smaller estimate than \( R/S \) analysis. Because both the \( R/S \) analysis method and variance plot method are sensitive to the presence of explicit short-range dependence, we need some formal test techniques for detecting long memory in the streamflow series.

Table 2. Estimated \( H \) values with variance analysis.

<table>
<thead>
<tr>
<th>Simulation</th>
<th>AR(1)</th>
<th>ARFIMA(0,d,0)</th>
<th>ARFIMA(1,d,0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.69158</td>
<td>0.78782</td>
<td>0.83284</td>
</tr>
<tr>
<td>2</td>
<td>0.64412</td>
<td>0.71964</td>
<td>0.77195</td>
</tr>
<tr>
<td>3</td>
<td>0.66903</td>
<td>0.67128</td>
<td>0.84894</td>
</tr>
<tr>
<td>4</td>
<td>0.64130</td>
<td>0.80683</td>
<td>0.79878</td>
</tr>
<tr>
<td>5</td>
<td>0.65846</td>
<td>0.78597</td>
<td>0.87033</td>
</tr>
<tr>
<td>6</td>
<td>0.71512</td>
<td>0.71407</td>
<td>0.87689</td>
</tr>
<tr>
<td>7</td>
<td>0.68218</td>
<td>0.80170</td>
<td>0.80999</td>
</tr>
<tr>
<td>8</td>
<td>0.69148</td>
<td>0.72700</td>
<td>0.80335</td>
</tr>
<tr>
<td>9</td>
<td>0.59842</td>
<td>0.64447</td>
<td>0.82691</td>
</tr>
<tr>
<td>10</td>
<td>0.71557</td>
<td>0.72315</td>
<td>0.78931</td>
</tr>
<tr>
<td>Average</td>
<td>0.67073</td>
<td>0.73819</td>
<td>0.82293</td>
</tr>
</tbody>
</table>
TEST FOR LONG MEMORY

Lo’s modified R/S analysis

The classical R/S analysis is sensitive to the presence of explicit short-range dependence structures, and lacks of a distribution theory for the underlying statistic. To overcome these shortcomings, Lo (1991) proposed a modified R/S statistic that is obtained by replacing the denominator $S_t(k)$ in Equation (1), i.e., the sample standard deviation, by a modified standard deviation $S_q$ which takes into account the autocovariances of the first $q$ lags, so as to discount the influence of the short-range dependence structure that might be present in the data. Instead of considering multiple lags as in Equation 1, only focus on lag $k = N$. The $S_q$ is defined as

$$S_q = \left( \frac{1}{N} \sum_{j=1}^{N} (x_j - \bar{x}_N)^2 + \frac{2}{N} \sum_{j=1}^{q} \omega_j(q) \left[ \sum_{i=j+1}^{N} (x_i - \bar{x}_N)(x_{i-j} - \bar{x}_N) \right] \right)^{1/2} \quad (2)$$

where,

$\bar{x}_N$: denotes the sample mean of the time series, and the weights $\omega_j(q)$: are given by $w_j(q) = 1 - j/(q+1)$, $q < N$.

Then the Lo’s modified R/S statistic is defined by:

$$Q_{N,q} = \frac{1}{S_q} \left[ \max_{0 \leq r \leq N} \sum_{j=1}^{N} (x_j - \bar{x}_N) - \min_{0 \leq r \leq N} \sum_{j=1}^{N} (x_j - \bar{x}_N) \right] \quad (3)$$

If a series has no long-range dependence, Lo (1991) showed that given the right choice of $q$, the distribution of $N^{-1/2}Q_{N,q}$ is asymptotic to that of $W = \max_{0 \leq r \leq 1} V(r) - \min_{0 \leq r \leq 1} V(r)$, where $V$ is a standard Brownian bridge, that is, $V(r) = B(r) - rB(1)$, where $B$ denotes standard Brownian motion. The distribution of the random variable $W$ is known as:

$$P(W \leq x) = 1 + 2 \sum_{j=1}^{n/2} (1 - 4x^2 j^2) e^{-2x^2 j^2} \quad (4)$$

Lo gave the critical values of $x$ for hypothesis testing at sixteen significance levels using Equation 4, which can be used for testing the null hypothesis $H_0$ that there is only short-term memory in a time series at a significance level $\alpha$.

GPH test

Geweke and Porter-Hudak (1983) proposed a semi-nonparametric approach to testing for long memory. Given a fractionally integrated process $\{x_t\}$, its spectral density is given by:

$$f(\omega) = \left[ 2 \sin(\omega/2) \right]^{-2d} f_u(\omega)$$

where,$$
\omega: \text{ is the Fourier frequency,}
\omega: f_u(\omega): \text{is the spectral density corresponding to } u_t, \text{ and}
u_t: \text{is a stationary short memory disturbance with zero mean.}

Consider the set of harmonic frequencies $\omega_j = (2\pi j/n)$, $j = 0, 1, \ldots, n/2$, where $n$ is the sample size. By taking the logarithm of the spectral density $f(\omega)$, we have

$$\ln f(\omega_j) = \ln f_u(\omega_j) - d \ln \left[ 4 \sin^2 \left( \omega_j/2 \right) \right]$$

which may be written in the alternative form
\[
\ln f(\omega_j) = \ln f_u(0) - d \ln \left[ 4 \sin^2 \left( \frac{\omega_j}{2} \right) \right] + \ln f_u(\omega_j) / f_u(0)
\] (5)

The fractional difference parameter \( d \) can be estimated by the regression equations constructed from Equation 5. Geweke and Porter-Hudak (1983) showed that using a periodogram estimate of \( f(\omega_j) \), if the number of frequencies used in the regression Equation 5 is a function \( g(n) \) (a positive integer) of the sample size \( n \) where \( g(n) = n^\alpha \) with \( 0 < \alpha < 1 \), the least squares estimate \( \hat{d} \) using the above regression is asymptotically normally distributed in large samples:

\[
\hat{d} \sim N(d, \frac{\pi^2}{6 \sum_{j=1}^{g(n)} (\bar{U}_j - \bar{U})^2})
\]

where,

\( U_j = \ln[4 \sin^2(\omega_j/2)] \) and \( \bar{U} \) is the sample mean of \( U_j, j = 1, \cdots, g(n) \).

Under the null hypothesis of no long memory \( (d = 0) \), the \( t \)-statistic \( t_{d=0} = \hat{d} \left( \frac{\pi^2}{6 \sum_{j=1}^{g(n)} (U_j - \bar{U})^2} \right)^{-1/2} \) has a limiting standard normal distribution.

**Test results**

The Lo's modified R/S test and the GPH test are carried out with S+FinMetrics module of statistical software S-plus (Zivot and Wang, 2003). The null hypothesis is tested at the 5% level of significance. For Lo's modified R/S test, the right choice of \( q \) in Lo's method is essential. It must be chosen with some consideration of the data at hand. Some simulation studies performed in Lo (1991) used series of length 100 to 1000 and \( q \)'s ranging up to 50. For any of these series, the probability of accepting the null hypothesis varied significantly with \( q \). In general, for the larger sample lengths, the larger the \( q \), the less likely was the null hypothesis to be rejected (Teverovsky et al., 1999). Because the essence of Lo’s modification is to discount the influence of short-range dependence in the data, in this study, we choose the values of \( q \) as the orders of fitted AR models for the streamflow at TNH. For making a fair comparison between the streamflow at TNH and the streamflow at TG, we choose the same lag \( q \) for testing the long memory in the streamflow at TG at each timescale. The null hypothesis of no long-term dependence is rejected if \( Q_{N,q} \) is not contained in the interval \([0.809, 1.862]\) (Lo, 1991).

For GPH test, an important practical problem in the implementation is the choice of the number of frequencies, \( g(n) \), to be used in the regression of Equation 5. This choice entails a bias-variance tradeoff. For a given sample size, as \( g(n) \) is increased from 1, the variance of the \( d \) estimate decreases, but this decrease is typically offset by increase in bias due to non-constancy of \( f_u(\omega) \). Geweke and Porter-Hudak (1983) found that choosing \( g(n) = n^{0.5} \) gave good results in simulation. We adopt such a criterion in this study. The periodogram used for calculating GPH test statistic is smoothed with a modified Daniell smoother of length 5. The null hypothesis of no long memory \( (d = 0) \) is rejected if \( t \)-statistic is not contained in the interval \([-1.960, 1.960]\).

The test results for all streamflow series are listed in Table 3. While the Lo's method only indicates whether long-range dependence is present or not, GPH test provides an estimate of the fractional integration parameter \( d \). The estimated \( d \)'s are also listed in Table 3. The results show that, the intensity of long memory decreases with the increase of timescale. Daily and 1/3-monthly streamflow at both TNH and TG exhibit strong long memory. But the evidence of the presence of long memory in monthly streamflow is not clear because while the results from Lo’s test show that monthly flows at both TNH and TG have long memory, GPH test tells that the null hypothesis of no long memory is accepted.
Table 3. Lo’s modified R/S test and GPH test for streamflow series at TNH and TG.

<table>
<thead>
<tr>
<th>Station</th>
<th>Timescale</th>
<th>data size</th>
<th>Lo's test</th>
<th>GPH test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Q</td>
<td>$Q_{N,d}$</td>
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<tr>
<td>TNH</td>
<td>daily</td>
<td>16437</td>
<td>38</td>
<td>3.5458 *</td>
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<tr>
<td></td>
<td>1/3-monthly</td>
<td>1620</td>
<td>9</td>
<td>2.4529 *</td>
</tr>
<tr>
<td></td>
<td>monthly</td>
<td>540</td>
<td>4</td>
<td>2.098 *</td>
</tr>
<tr>
<td></td>
<td>daily</td>
<td>14245</td>
<td>38</td>
<td>3.0958 *</td>
</tr>
<tr>
<td>TG</td>
<td>1/3-monthly</td>
<td>1404</td>
<td>9</td>
<td>2.3107 *</td>
</tr>
<tr>
<td></td>
<td>monthly</td>
<td>468</td>
<td>4</td>
<td>2.027 *</td>
</tr>
</tbody>
</table>

An asterisk indicates that long memory is significant at 5%.

Furthermore, comparing the test statistics for the streamflow processes at TNH and TG, we find that the long memory intensity of daily and 1/3-monthly streamflow process at TNH is stronger than that at TG.

We list in Table 4 the minimum values of truncation lag $q$ that are large enough to accept the null hypothesis of no long memory in Lo’s test at significance level 1%. These values may be interpreted as the memory length. It is shown in Table 4 that the lag needed to exclude short-range dependence for the streamflow at TNH is longer than that for the streamflow at TG at each timescale, which also indicates that the memory length of the streamflow at TNH is longer than that of the streamflow at TG.

Table 4. Minimum lags needed to accept the null hypothesis in Lo’s test (at 1% level).

<table>
<thead>
<tr>
<th></th>
<th>Daily</th>
<th>1/3-monthly</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>TNH</td>
<td>153</td>
<td>15</td>
<td>5</td>
</tr>
<tr>
<td>TG</td>
<td>142</td>
<td>14</td>
<td>4</td>
</tr>
</tbody>
</table>

The reasons that the memory length of the streamflow at TNH is longer than that of the streamflow at TG may be two-folded. Firstly, physical reasons. The drainage area at TNH is partly snow-covered and has lots of lakes and wetlands, which provide stable and smooth sources of runoff supply. In addition, rainfall process in the watershed of TNH is smoother than that in most parts of the watershed of TG. Secondly, man-related reasons. The drainage area at TNH is sparsely populated and lacks of major hydraulic works, whereas most parts of the drainage area at TG are heavily populated and there are lots of dams in major tributaries and the main channel. Therefore the streamflow process at TG is highly affected by human activities. These two reasons make the streamflow at TNH less variable than that at TG, although the drainage area at TG is much larger than that at TNH. Consequently, the streamflow at TNH has longer memory than that at TG.

Notice that while the GPH test results indicate that both monthly streamflow processes at TNH and TG are short-memory processes, the estimate of long memory parameter $d$ given by the GPH test are larger than 0. Agiakloglou et al. (1993) found that GPH estimators performed poorly in certain ordinary AR(1) models. One possible solution may be choosing the number of frequencies used in the regression Equation 5 more carefully (see for example, Hurvich and Deo, 1999).

CONCLUSIONS

In this paper, we investigate the long-memory phenomena in streamflow processes of the Yellow River at different timescales with heuristic and statistical test methods. It is shown that, with the increase of timescale, the intensity of long memory decreases. Daily and 1/3-monthly streamflow at both TNH and TG exhibit strong long memory. But the evidence of the presence of long memory in monthly streamflow is not clear because, while the results from Lo’s test show that monthly flows at both TNH
and TG have long memory, GPH test tells that the null hypothesis of no long memory is accepted. The memory at TNH is longer than that at TG at each timescale. The change of the intensity of long memory with the timescale of streamflow processes is consistent with the change of the intensity of nonlinearity (Wang et al., 2005). Because long memory may be considered as a type of nonlinearity of the first moments (mean values), therefore, this study substantiates the results of Wang et al. (2005), which show that there are stronger and more complicated nonlinear mechanisms acting at small timescales than at larger timescales.

To establish the generality, it would be interesting to investigate the variation of the intensity of long memory with the change of timescale by using more than 3 different timescales and investigate more streamflow processes of watersheds in different regions and of different sizes in the future.

REFFERENCES


