Quaternary International 311 (2013) 132–139

Contents lists available at ScienceDirect

Quaternary International

journal homepage: www.elsevier.com/locate/quaint

Characterizing cross-scale chaotic behaviors of the runoff time series in an inland river of Central Asia

Zengyun Hu[a,b], Chi Zhang[a,*], Geping Luo[a], Zhidong Teng[b], Chaojun Jia[a]

[a] State Key Laboratory of Desert and Oasis Ecology, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, 818 South Beijing Road, Urumqi, 830011 Xinjiang, China

[b] College of Mathematics and System Sciences, Xinjiang University, Urumqi, Xinjiang 830046, China

ARTICLE INFO

Article history:
Available online 9 August 2013

ABSTRACT

Understanding the multi-scale patterns and uncertainties of inland river runoff is important for runoff management and rational utilization of water resources in arid regions. This study investigates the chaotic behaviors of the runoff processes at four different time scales— daily, 2-day, 7-day and 10-day, in an inland river (Manas River) of the Central Asia dryland. The observed data period is from February 14, 1981 to October 31, 2000. Phase space reconstruction technology and chaos theory are applied to study the chaotic characteristics of runoff at different time scales. According to our analysis, the phase space diagram exhibited strange attractors in a well-defined region at all time scales, suggesting that the runoff processes in Manas River Basin was simple and can possibly be explained by deterministic chaos. All of the maximum Lyapunov exponents were positive, showing the chaotic characteristics in the runoff processes. Further, the finer resolution time series exhibits stronger chaotic characteristics than the coarser resolution time series, corresponding to the normal runoff processes. By quantifying the chaotic characteristics of the runoff time series of a typical inland river in Central Asia, this study helps water resource managers evaluate uncertainty of runoff in the arid regions, and make decisions according to the predicted runoff pattern at different time scales. The findings from this study also provide the theoretical basis and scientific foundation for cross-scale hydrologic climate model simulations and data downscaling in the arid region of Central Asia.

1. Introduction

A chaotic motion refers to an irregular behavior that resembles random motion in a nonlinear deterministic system that is sensitive to initial conditions, a pattern called determined randomness. There are important differences, however, between the chaotic motion and the random motion. The main characteristics of the chaotic motion are non-periodicity, unrepeatability, and high sensitivity to initial conditions. The seemingly irregular-looking behavior of the deterministic chaos could be caused by a few nonlinear interdependent variables in a simple deterministic system. Therefore, the methods and models used in analyzing and constructing time series for chaos systems are different from that for random systems. Chaos theory has been used in solving many scientific problems in various fields, such as meteorology, hydrology, engineering, medicine, psychology and economics.

The hydrological cycle is influenced by various environmental factors, such as precipitation, temperature, topographic conditions and the types of land utilization. It is an open and nonlinear dynamic composite system with huge space and time variability and complex evolution law (Sivakumar, 2000). Despite the complexity and random-looking behavior of the hydrological cycle system, hydrological processes may be governed only by a few factors called low-dimensional chaos in the hydrologic time series (e.g., Ghilardi and Rosso, 1990; Pasternack, 1990; Koutsoyiannis and Pachakis, 1996; Schertzer et al., 2002).

There have been many studies focusing on the chaotic behavior and the underlying mechanism of hydrological process, including rainfall, runoff, floods, and lake reservoir and ground water dynamics in recent decades (e.g. Hense, 1987; Rodriguez-Iturbe et al., 1989; Wilcox et al., 1991; Jayawardena and Lai, 1994; Sangoyomi et al., 1996; Stehlik, 1999; Elshorbagy et al., 2002a,b). In his pioneering work, Hense (1987) introduced the chaos theory to hydrological study. Using the correlation dimension method, he analyzed 1008 monthly rainfall records and found the correlation dimension ranged from 2.5 to 4.5. In addition, his study revealed

* Corresponding author.
E-mail addresses: zc@ms.xjb.ac.cn, zhchbob@gmail.com (C. Zhang).

1040-6182/$ – see front matter © 2013 Elsevier Ltd and INQUA. All rights reserved.
http://dx.doi.org/10.1016/j.quaint.2013.07.031

low dimension chaos in the monthly rainfall time series. Rodriguez-Iturbe et al. (1989) analyzed the rainstorm dynamics of a 148-year rainfall time series in 15s and weekly temporal resolutions. According to their study, the system exhibits chaotic characteristic under the finer resolution, and stochastic process under the coarser resolution. Sangoyomi et al. (1996) analyzed the chaotic characteristics of water dynamics in the Great Salt Lake, United States, and found the water yield can be described with a 4 dimensions phase-space. Zhou et al. (2002) found the attractor dimension of the flood series in Huaihe River Basin for the last 500-year period to be 4.66, with a power spectrum structure similar to that of typical chaotic series. They further reconstructed the chaotic dynamics of the flood series in the Huaihe River Basin according to chaos theory and inverted theorem of differential equations. The chaotic characteristic of the runoff and rainfall-runoff time series have also been studied (Sivakumar et al., 2000, 2003). The simulation and prediction of the hydrological time series using chaos theory were discussed by Jayawardena and Lai (1994).

The above studies highlight the chaotic/nonlinear characteristics of hydrological process. Most of them focused on the chaotic characteristics at single scale. Only a few studies addressed cross-scale chaotic behaviors of hydrological process (Sivakumar, 2001; Wang et al., 2006), and their conclusions were contradictory. Sivakumar (2001) analyzed the patterns of rainfall time series at multiple scales and found weak chaos at finer resolution, and strong chaos at coarser resolution. In contrast, Wang et al. (2006) found that as the times cale increase from a day to a year, the nonlinearity weakens. Many factors can influence the analysis results. For example, the weak chaos at the finer (daily) scale in Sivakumar (2001) could be caused by the large number of zero rainfall in the dry season, while a possible presence of a higher level of noise in the coarse (yearly) resolution rainfall time series might have caused strong chaos. Therefore, Sivakumar (2001) cautioned that the results must be verified using other methods to detect chaos and additional evidence must be provided to prove the existence of chaos in hydrological process.

The ecosystems of arid and semiarid regions in Central Asia are sensitive and vulnerable to the change of evapotranspiration, precipitation, snowmelt and others hydrological process. Therefore, investigating the nonlinearity of the hydrological process in this arid and semiarid region can help identify the major controlling factors and mechanisms that govern the nonlinear dynamics of dryland ecosystems. Such a study can also provide valuable information for constructing nonlinear models to simulate and predict hydrological time series that are required as inputs to drive ecological models (Li et al., 2013).

This study attempts to detect the dynamical behaviors of the runoff processes at four different temporal scales, i.e. daily, 2-day, 7-day and 10-day runoff time series using a phase diagram, phase space reconstruction theory and the maximum Lyapunov exponent theory; and to simulate runoff time series based on chaos theory. The data is from an inland river of Central Asia, the Manas River, spanning from February 14, 1981 to October 31, 2000. The Manas River is the largest river in the north Tianshan Mountains with significant inter-annual runoff fluctuation and uneven spatial and temporal distribution. As one of the major water sources to the north Tianshan oases in the Central Asia desert, its runoff dynamics have important impacts on the sustainability of natural ecosystems and socioeconomics in this region (Hu, 2004; Chen, 2010). However, review has indicated that few studies have addressed the nonlinear characteristic of runoff of major rivers in this arid and semiarid region, not to mention cross-scale chaotic analysis. The study can reveal the cross-scale pattern of hydrological processes in a typical inland river in Central Asia and improve understanding of the underlying mechanisms. Finally, the chaotic analysis provided valuable information for adaptive modeling to simulating and predicting runoff time series for inland rivers in arid and semiarid region of Central Asia.

2. Study area and data

The Manas River Basin (Fig. 1) is located in the north slope of Tianshan Mountains of Xinjiang. The river length is 524 km with a drainage area of 1.04×10^4 km^2. Water supply of the Manas River comes from meltwater of ice and snow as well as rainfall (Chen, 2010).

With the help of the local management office of the Manas River, we collected the daily runoff observations of the river from February 14, 1981 to October 31, 2000. The 2-day, 7-day and 10-day runoff time series are obtained from daily data by taking the sums of daily runoff time series. According to Sivakumar (2000), chaotic analysis requires large data/sample size. Nerenberg and Essex (1990) pointed out that the minimum number of points required for dimension estimate is 630–1000 if the dimension size is in the range of 2–3. A higher dimension size will require larger data sets (e.g., a dimension size of 4 will require 3981 data). There are 720 data in the 10-day runoff time series from February 14, 1981 to October 31, 2000. Any further data aggregation (e.g., to monthly or annual scales) will disqualify the dataset as being too small for chaotic analysis. Therefore, the coarsest temporal resolution in this study was set to 10-day. Fig. 2 shows the variation of the daily runoff time series of the Manas River during 1981–2000. The daily runoff time series showed a periodic pattern. However, it is difficult

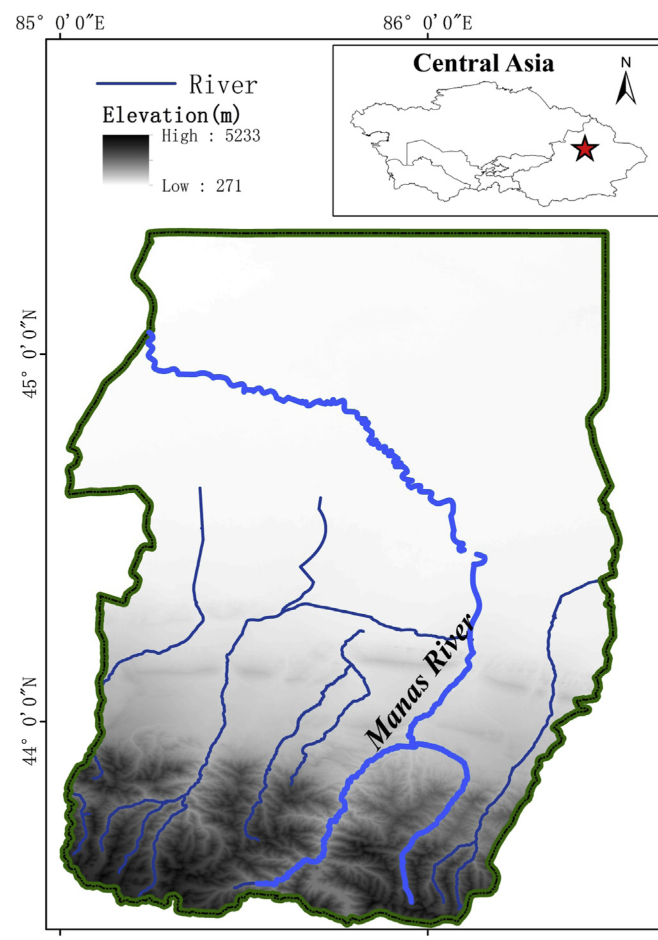

Fig. 1. Study area.

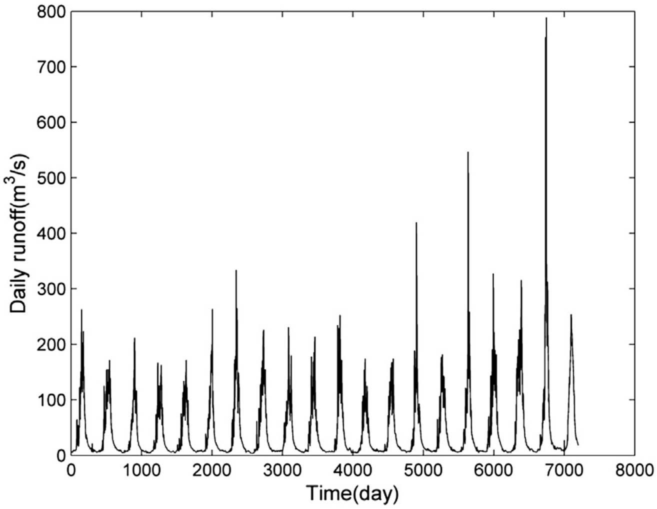

Fig. 2. Daily runoff time series of Manas River Basin during 1981–2000.

to investigate the complex dynamical behaviors of runoff processes from Fig. 2. In addition, the statistical characteristics of the runoff series at different temporal scales are summarized in Table 1. The coefficient of variation for a hydrology time series can indicates the complexity and variability of the time series (Sivakumar, 2001). The coefficient of variations for the daily, 2-day, 7-day and 10-day runoff time series is 1.37, 1.36, 1.33 and 1.32, respectively. This result shows the variation in runoff decrease with temporal scales, and the lowest variability and the weakest complexity are found at the coarsest resolution (10-day) (Table 1).

Table 1
Statistics of Manas River runoff data (m^3/s).

Parameter	Daily	2-day	7-day	10-day
Number	7200	3600	1028	720
Mean	40.76	81.51	285.38	407.57
Minimum value	3.43	6.87	24.67	36.35
Maximum value	788.97	1205.94	3058.77	4291.66
Standard deviation	56.07	111.17	378.60	537.58
Variance	3143.50	12358.26	143336.59	288992.29
Coefficient of variation	1.38	1.36	1.33	1.32

3. Method and technology

3.1. Reconstruction of phase space

The method first reconstructs the single-dimensional (or variable) runoff series in a multi-dimensional phase space to represent its dynamics, then detects chaos characteristics in the runoff, and finally uses the Volterra adaptive model to make chaos simulation (Sivakumar et al., 2001). For a scalar time series $x(1), x(2), \cdots, x(n)$, n is the length of time series. When the delay time τ is known, the correlation dimension d is calculated for the time series $x(1), x(2), \cdots, x(n)$with the G–P (Grassberger–Procaccia) algorithm (Grassberger and Procaccia, 1983). Then, the optimal embedding dimension m with $m \geq 2d+1$ is selected according to the Takens theory (Takens, 1981). The phase space is

$$Y(i) = (x(i), x(i+\tau), \cdots, x(i+(m-1)\tau)) \quad i = 1, 2, \cdots, M, \qquad (1)$$

where $M = N-(m-1)\tau$.

Hence, the single dimensional time series is reconstructed in a multi-dimension phase space. The determinations of delay time τ and embedding dimension m are important for the phase space reconstruction. In this paper, the delay time parameter τ is determined by the mutual information method, and the embedding dimension m is obtained by the Cao method.

3.1.1. The delay time τ

For the delay time τ, if τ is too small, then there is little new information contained in each subsequent datum and this will lead to the underestimate of the correlation dimension (Havstad and Ehlers, 1989; Sivakumar, 2000; Dhanya and Kumar, 2011). On the contrary, if τ is too large, and the system is chaotic, all relevant information for phase-space reconstruction is lost since neighboring trajectories diverge, and averaging in time and/or space is no longer useful (Sangoyomi et al., 1996; Sivakumar, 2000; Dhanya and Kumar, 2011). This may result in an overestimation of the correlation dimension (Havstad and Ehlers, 1989; Sivakumar, 2000; Dhanya and Kumar, 2011). There are several approaches for computing τ, such as the autocorrelation function method, average displacement method, complex correlation method and mutual information method. Frazer and Swinney (1986) pointed out that the autocorrelation function method only indicates the linear relationship of the time series, but it is not useful when analyzing nonlinear systems. However, the mutual information method is not only useful to the linear system but also to the nonlinear system. Then, the delay time τ is determined by the mutual information method. The mutual information method is based on the Shannon comentropy theory; that is used to compute the correlation of two variables and measure the whole dependence of two variables at the same time. When the mutual information reaches the local minimum value firstly, the value of delay time is the delay time of the phase-space reconstruction. The recursive algorithm of the mutual information is calculated following Frazer and Swinney (1986). Considering the following variables

$$x = (x_1, x_2, \cdots, x_n), \quad y = (y_1, y_2, \cdots, y_m),$$

the mutual information is

$$\begin{aligned} I(x,y) &= H(x) + H(y) - H(x,y) \\ &= -\sum_{i=1}^{n} P(x_i)\ln P(x_i) - \sum_{j=1}^{m} P(y_j)\ln P(y_j) \\ &\quad + \sum_{i=1}^{n}\sum_{j=1}^{m} P(x_i,y_j)\ln P(x_i,y_j) \end{aligned} \qquad (2)$$

where $P(x_i)$, $P(y_j)$ are appear probabilities of the two variables x_i, y_j and $P(x_i, y_j)$ is the joint probability distribution of x_i, y_j. Then, for any time series $x = (x_1, x_2, \cdots, x_N)$adding delay time we obtain $x_\tau = (x_{1+\tau}, x_{2+\tau}, \cdots, x_{(N-\tau)+\tau})$. From equation (2), the mutual information $I(x,x_\tau)$ of x and x_τ is obtained. $I(x,x_\tau)$ is the function of τ. Then, $I(x,x_\tau)$ is noted as $I(\tau)$. When $I(\tau)$ reaches the local minimum value for the first time, the corresponding delay time is the delay time (τ_{min}). If $I(\tau_0-1) > I(\tau_0)$ and $I(\tau_0) < I(\tau_0+1)$, then $I(\tau_0)$ is the local minimum value and the first τ_0 is τ_{min}.

3.1.2. Determination of m

The optimal embedding dimension (m) can be determined with several different methods, such as the G–P (Grassberger–Procaccia) algorithm (Grassberger and Procaccia, 1983), the FNN (False Nearest Neighbors) method (Kennel et al., 1992) and the Cao method (Cao, 1997). Compared with other methods, the Cao (1997) method has the following advantages: (1) not containing any subjective parameters except for the time-delay for the embedding; (2) not strongly depending on how many data points are available; (3) clearly distinguishing deterministic signals from stochastic signals; (4) working well for time series from high-dimensional attractors; (5) having high computational efficiency. Therefore, in this study the Cao method is used to determine the optimal embedding dimension m.

The Cao method is based on the FNN. Let Y_n be one point of the reconstruction phase space and $Y_{\eta(n)}$ be the nearest neighbor point of Y_n. We define

$$a(i,m) = \frac{\left\|Y_{\eta(n)} - Y_n\right\|_{\infty}^{(m+1)}}{\left\|Y_{\eta(n)} - Y_n\right\|_{\infty}^{m}}, \tag{3}$$

where $\|\|_\infty$ is L_∞ norm. The average value of $a(i, m)$ with i is noted as

$$E(m) = \frac{1}{N - m\tau} \sum_{i=1}^{N-m\tau} a(i,m). \tag{4}$$

$E(m)$ is a function of the embedding dimension m and delay time τ. To analyze the change in the phase space with the embedding dimension from m to m+1, the following equations are defined

$$E_1(m) = \frac{E(m)}{E(m+1)} \tag{5}$$

and

$$E_2(m) = \frac{E^*(m)}{E^*(m+1)}, \tag{6}$$

where

$$E^*(m) = \frac{1}{N - m\tau} \sum_{i=1}^{N-m\tau} \left\|Y_{\eta(i)+m\tau} - Y_{i+m\tau}\right\|. \tag{7}$$

If $E_1(m)$ stops changing when m is greater than a threshold m_0, m_0+1 is the optimal embedding dimension we look for.

In general, for random time series, $E_1(m)$ in principle will never attain a saturation value as m increases. However, in practical computations, it is difficult to distinguish whether $E_1(m)$ is slowly increasing or has stopped changing if m is sufficiently large. Because the available observed data samples are limited, it may happen that $E_1(m)$ stop changing at some m although the time series is random. To solve this problem, $E_2(m)$ is needed. For random time series, since the future values are independent of the past values, then $E_2(m) \equiv 1$ for any m in this case. However, for deterministic data, $E_2(m)$ is related to m. As a result, it cannot be a constant for all m, that is, there must exist some m values such that $E_2(m) \neq 1$. Therefore, we calculated both $E_1(m)$ and $E_2(m)$ to determine the minimum embedding dimension of a scalar time series.

3.2. The chaos discriminant

There are many methods to distinguish the chaotic time series, including phase space diagram, power spectrum method, Poincare section method, correlation dimension method, K entropy method, and Lyapunov exponent. The phase space diagram, power spectrum method, and the Poincare section method analyze the chaotic time series from the qualitative point, while the correlation dimension method, K entropy method, and Lyapunov exponent method analyze the chaotic time series from the quantitative point.

In this study, the phase space diagram method is used to analyze the chaotic time series from the qualitative point and the Lyapunov exponent method is used to analyze the chaotic time series from the quantitative point. Finally, the simulation of the daily time series in Manas River Basin will be given by the Volterra adaptive model theory.

3.2.1. Lyapunov exponent λ

The Lyapunov exponent λ indicates the average speed of the track separation in the phase space, and it can reflect the changing of variables with time and the sensitivity of the initial conditions in the chaos dynamical system effectively. If the track is shrinking in the direction $\lambda < 0$ and the movement is stable, the system is not sensitivity to the initial conditions. If the track is separating rapidly in the direction $\lambda > 0$, the system is sensitive to the initial conditions. For the discrete system or the nonlinear time series, we only calculate the maximum Lyapunov exponent λ_{max}, which is an important indicator of the existence of chaos and the chaotic characteristic in dynamical systems. If $\lambda_{max} > 0$, there exists chaos in the system. A big λ_{max} indicates strong chaotic characteristic of the system.

There are many approaches to computing the λ, such as, p-norm method (Barana and Tsuda, 1993), Wolf method (Wolf et al., 1985), Jacobian method (Sano and Sawada, 1985), and small data sets method (Rosenstein et al., 1993). Because the small data sets method has relatively high computational efficiency and accuracy, it is used to compute the maximum Lyapunov exponent in this study.

3.3. Volterra adaptive model

The adaptive model is a recently developed chaotic-time-series simulation method (Zhang and Xiao, 2000). It uses the immediate preceding observed data and the immediate preceding simulation error to adjust the model parameters error to continuously adjust the model. This simulation model is suitable for incomplete data and physical system with time varying characteristic. Furthermore, this model can track the chaotic trajectory and obtain high simulation accuracy. As the output of the Volterra filter is the nuclear linear combination and the filter function can be easily analyzed, the Volterra filter has been widely used as one of the nonlinear adaptive simulation model. This study used the Volterra adaptive model to simulate the runoff time series. Following Jiang (2011), the simulation results are evaluated by CC (correlation coefficient), AMAE (absolute value of mean relative error) and RMSE (root mean square error).

4. Results and discussion

4.1. Phase space reconstruction

Fig. 3A shows that when delay time $\tau = 54$, the mutual information $I(\tau)$ reach the local minimum value for the first time. Therefore, the delay time τ is 54 for the daily time scale of Manas River. Similarly, the delay time τ for the 2-day, 7-day and 10-day time scales is 25, 9 and 6, respectively. Based on τ values, the optimal embedding dimension of phase space reconstruction for daily, 2-day, 7-day and 10-day runoff time series are 22, 17, 13 and 13, respectively (Fig. 4). Following Sivakumar et al. (2001), Islam and Sivakumar (2002), and Jiang (2011), we used a two-dimensional figure (Fig. 5) to show the reconstructed phase space where τ = 54, 25, 9 and 6. The phase space diagram exhibited strange attractors in well-defined region which suggested that the runoff properties in Manas River Basin were simple and can possibly be explained by deterministic chaos.

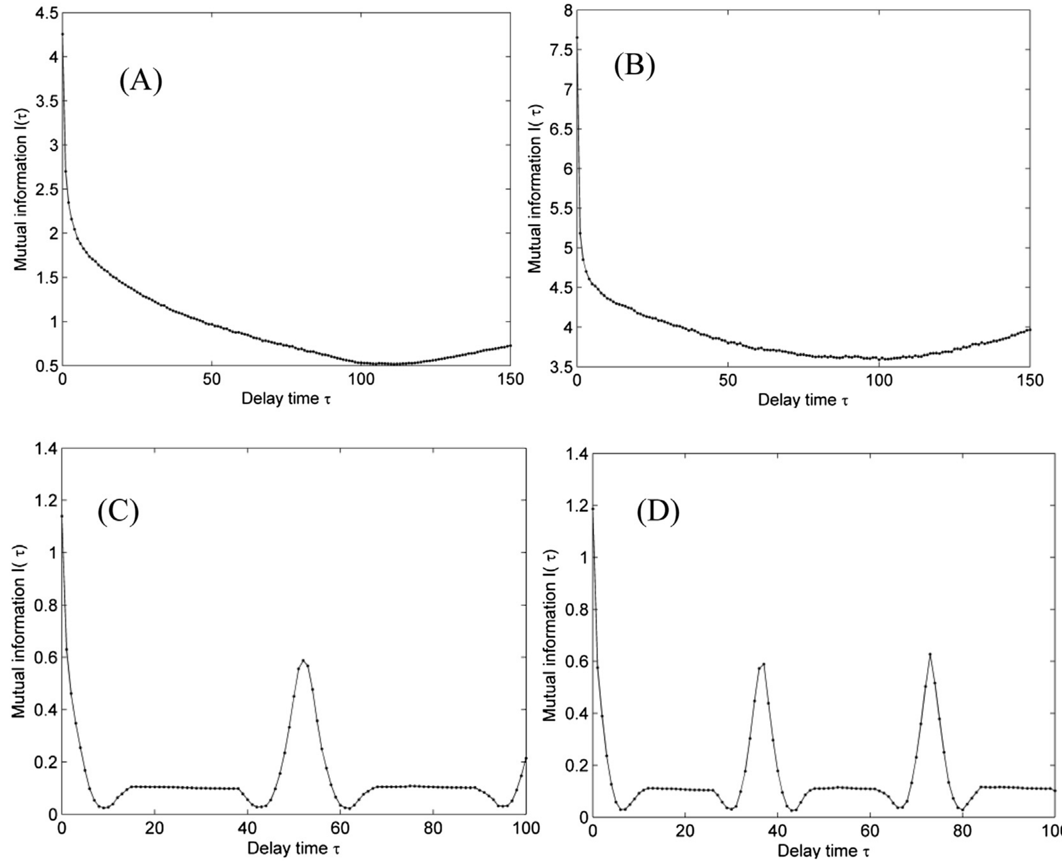

Fig. 3. The mutual information of runoff time series, where (A), (B), (C) and (D) are daily, 2-day, 7-day and 10-day runoff time series, respectively.

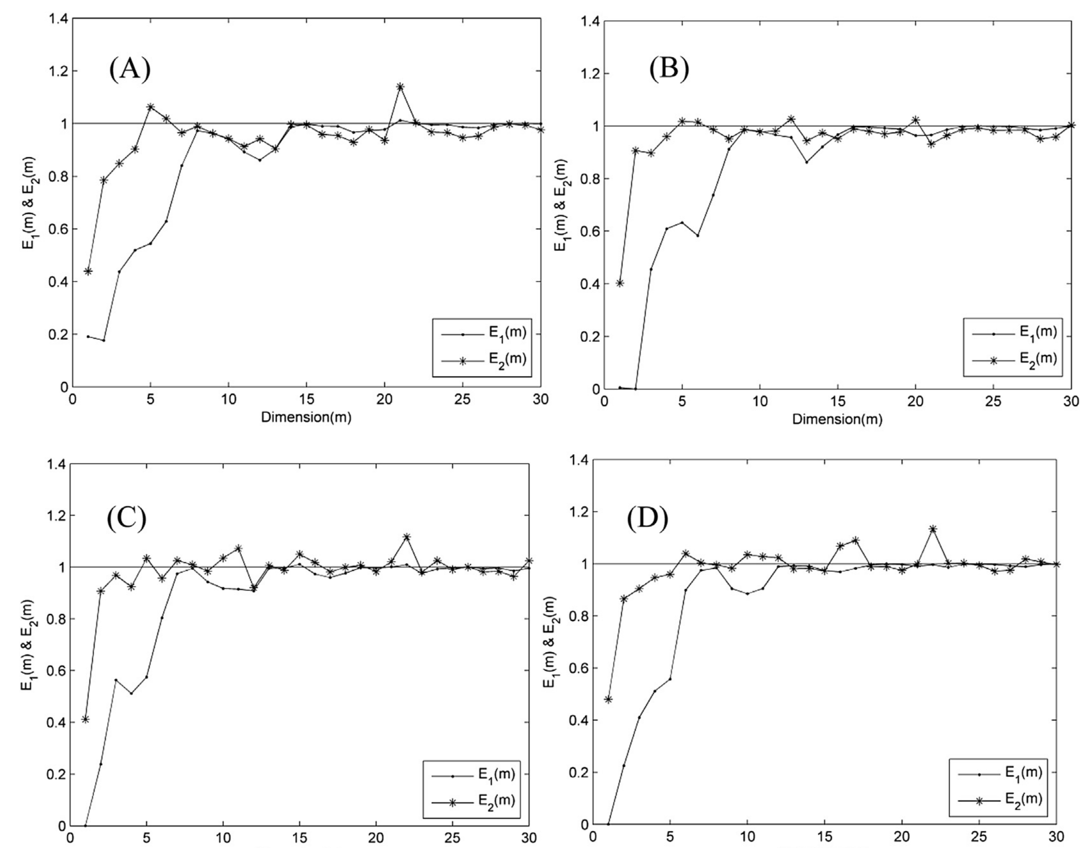

Fig. 4. The relation between $E_1(m)$,$E_2(m)\sim m$, where (A), (B), (C) and (D) are daily, 2-day, 7-day and 10-day runoff time series, respectively.

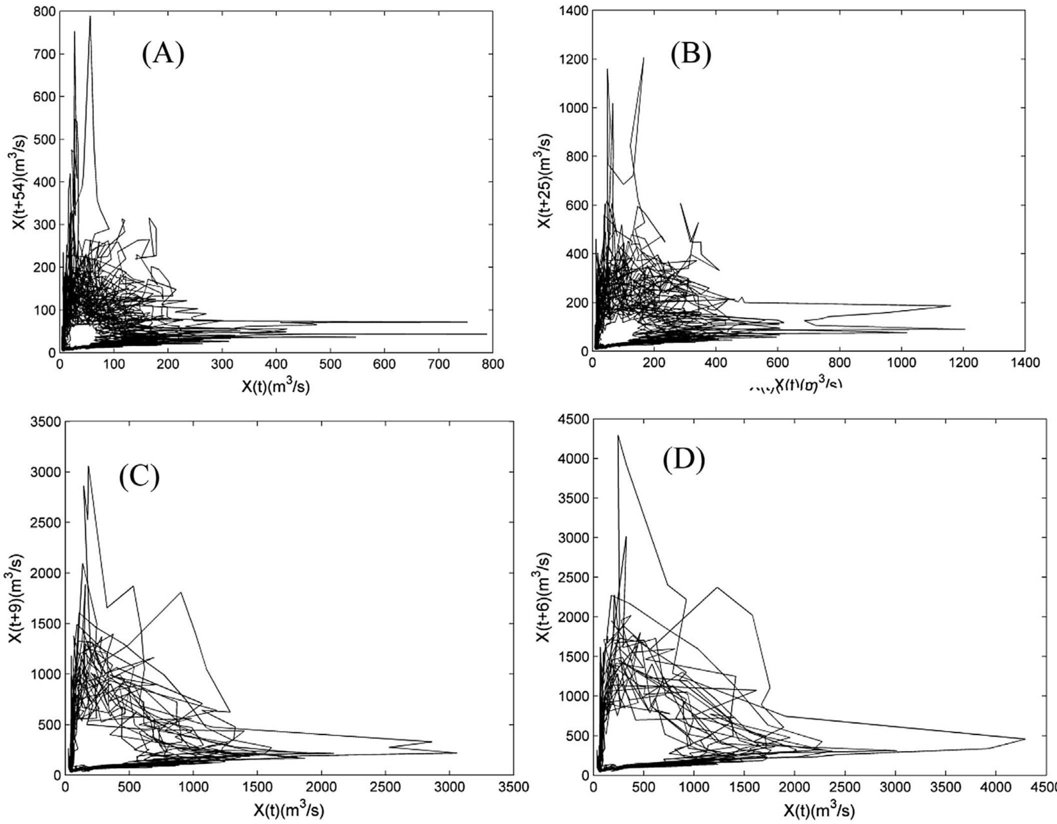

Fig. 5. Phase diagrams of four different temporal scales, where (A), (B), (C) and (D) are daily, 2-day, 7-day and 10-day runoff time series, respectively.

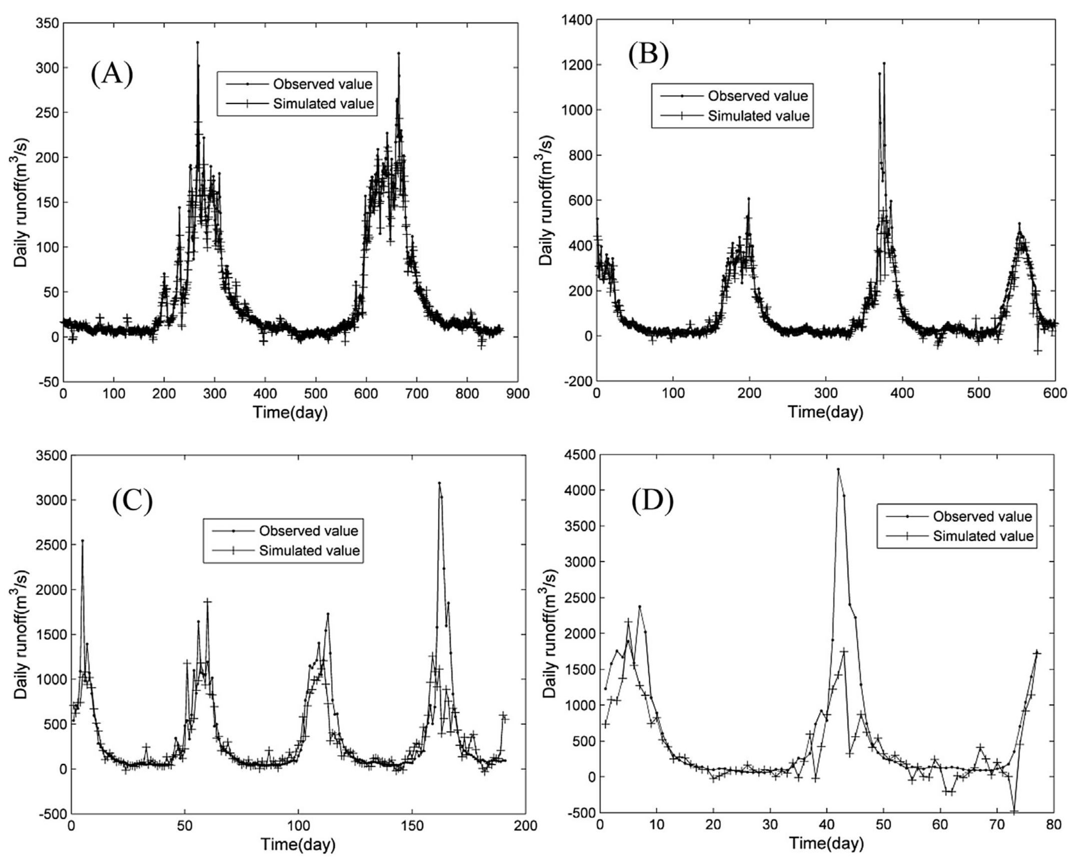

Fig. 6. The simulation results by Volterra adaptive model for the four time scales, where (A), (B), (C) and (D) are daily, 2-day, 7-day and 10-day runoff time series, respectively.

4.2. The maximum Lyapunov exponent λ_{max}

For further investigating the chaos characteristic of the runoff processes of Manas River, the maximum Lyapunov exponents of the four different time scales, i.e. daily, 2-day, 7-day and 10-day are calculated using the small data sets method. The maximum Lyapunov exponent is $\lambda_{\max} = 0.1062, 0.05371, 0.0332, 0.0067 > 0$ for daily, 2-day, 7-day and 10-day runoff time series, respectively. The result indicated the existence of chaotic characteristic at all of the four temporal scales in Manas River runoff processes. Moreover, our analysis found weaker chaos characteristics at coarser resolution and stronger chaos characteristics at finer resolution, being consistent with the findings by Wang et al. (2006). The values of the coefficient variation (Table 1) which can explain the complexity also lend support to these findings.

In this study, the maximum Lyapunov exponent of daily runoff time series is 0.1062, showing a more complex and uncertain low-dimensional behavior than other reports (Islam and Sivakumar, 2002; Ghorbani et al., 2010). This may be caused by the complex climate change (temperature, precipitation, evaporation and wind velocity) and the catchment characteristics (basin area, multiple water supplies, land use and irrigation) in the arid region of Central Asia (Chamizo, 2012).

Cross-scale chaotic analysis, as recommended by Sivakumar (2009), is a useful nonlinear downscaling approach in hydrologic and climate modeling (besides the statistical and dynamic downscaling techniques). The results can provide theoretical basis and scientific foundation for hydrologic and climate downscaling in the arid region of Central Asia. The hydrological phase space reconstructed in this study also provides valuable information that can help understand the characteristics of and the mechanisms underlying the hydrological dynamics of a typical river basin (the Manas river basin) in Central Asia. Chaos analysis in combination with modeling approaches (e.g., Volterra adaptive model, support vector machine SVM, artificial neural network ANN et al.) has the ability to make prediction and construct stream flow time series.

4.3. Simulation

Based on the chaotic characteristic of the stream flow as revealed by the above analysis, we used the Volterra adaptive model to simulate the runoff time series of the Manas River. For each time scale, the previous parameters delay times τ and optimal embedding dimensions m were used to reconstruct the phase spaces, and the suitable numbers of training samples and testing samples were chosen for the simulation (Table 2). Fig. 6 shows that the simulation results match the trend and variation of the measured runoff, except for a few peak points (see Fig. 6A–D). Statistical analysis shows that the AMAE values of daily, 2-day, 7-day and 10-day are 0.27, 0.33, 0.53 and 0.59, respectively, suggesting that the Volterra adaptive model can accurately simulate the runoff pattern (Table 3). Furthermore, the model simulation performs better for the daily and 2-day time scales than the 7-day and 10-day time scales (Fig. 6).

Table 2
Parameters in phase space reconstruction and Volterra adaptive model for daily, 2-day, 7-day and 10-day runoff time series, respectively.

Time scale	τ	m	Training samples	Testing samples
Daily	54	22	5000	2000
2-day	25	17	2800	1000
7-day	9	13	750	300
10-day	6	13	600	150

Table 3
Statistical measures of the simulation result at four different time scales.

Time scale	CC	AMAE	RMSE
Daily	0.97	0.27	15.21
2-day	0.92	0.33	72.51
7-day	0.75	0.53	375.01
10-day	0.81	0.59	589.87

5. Concluding remarks

The chaotic characteristic of the Manas River runoff processes at four different time scales (daily, 2-day, 7-day and 10-day) is investigated by the phase space reconstruction technology and chaos theory in this study. Based on the chaotic analysis, the Volterra adaptive model was used to simulate runoff time series at four different time scales. The results from these methods provide convincing cross-verification and confirmation of the existence of a chaos characteristic at the four time scales in the Manas River runoff processes. Clear and well-defined attractors in the phase diagram are observed and the largest Lyapunov exponents are all positive. Our Volterra adaptive model simulation well reflected the variation and trend of the Manas River runoff processes at multiple scales. Our analysis reveals more complex chaotic characteristics in river flow at finer scales than at coarser scales, being consistent with the findings by Sivakumar and Chen (2007). The presence of chaotic characteristic could provide helpful insight for a better understanding of the nonlinear runoff behavior and the underlying mechanisms that control the hydrological process of the rivers in the Central Asia dryland. In addition, this study provides valuable information for constructing the nonlinear model to simulate and predict the hydrological time series for rivers in Central Asia and helping water resources management in this arid and semiarid region.

Finally, we want to caution that the measured time series usually contain some noise due to random influence and inaccuracies, which can never be completely eliminated (Schouten et al., 1994). Some studies tried to suppress the noises using statistical techniques (Kostelich and Schreiber, 1993; Davies, 1994). However, Elshorbagy et al. (2002a, b) suggested that smoothing the original data by noise reduction for further analysis is a questionable approach and therefore should be discouraged. There are two types of noise, measurement noise and dynamical noise in chaotic hydrologic time series. The noise reduction-removed component might contain the noise, but noise reduction in hydrologic data might also remove a significant part of the original signal and introduce an artificial chaoticity to the data. Admittedly, there is no effective way to separate “useful” noise from real noise. For this reason, we did not try noise reduction in this study and future investigations into this issue are needed.

Acknowledgements

This work was supported by the International Science & Technology Cooperation Program of China (Grant No. 2010DFA92720-10), the National Basic Research Programs of China (Grant No. 2009CB825105), the National Natural Science Foundation of P.R. China (11271312) and Xinjiang and Central Asian scientific data sharing platform. We thank the editor and reviewers for their comments and helps in improving this manuscript.

References

Barana, G., Tsuda, I., 1993. A new method for computing Lyapunov exponents. Physics Letters A 175, 421–427.

Cao, L.Y., 1997. Practical method for determining the minimum embedding dimension of a scalar time series. Physica D 110, 43–50.

Chamizo, S., 2012. Runoff at contrasting scales in a semiarid ecosystem: a complex balance between biological soil crust features and rainfall characteristics. Journal of Hydrology 452–453, 130–138.

Chen, X., 2010. Physical Geography of Arid Land in China. Science Press, Beijing, pp. 241–242.

Davies, M., 1994. Noise reduction schemes for chaotic time series. Physica D 79, 174–192.

Dhanya, C.T., Kumar, D.N., 2011. Multivariate nonlinear ensemble prediction of daily chaotic rainfall with climate inputs. Journal of Hydrology 403, 292–306.

Elshorbagy, A., Simonovic, S.P., Panu, U.S., 2002a. Estimation of missing streamflow data using principles of chaos theory. Journal of Hydrology 255, 123–133.

Elshorbagy, A., Simonovic, S.P., Panu, U.S., 2002b. Noise reduction in chaotic hydrologic time series: facts and doubts. Journal of Hydrology 256, 147–165.

Frazer, A.M., Swinney, H.L., 1986. Independent coordinates for strange attractors from mutual information. Physical Review A 33, 1134–1140.

Ghilardi, P., Rosso, R., 1990. Comments on chaos in rainfall by I. Rodriguez-Iturbe. Water Resources Research 26, 1837–1839.

Ghorbani, M.A., Kisi, O., Aalinezhad, M., 2010. A probe into the chaotic nature of daily streamflow time series by correlation dimension and largest Lyapunov methods. Applied Mathematical Modelling 34, 4050–4057.

Grassberger, P., Procaccia, I., 1983. Measuring the strangeness of strange attractors. Physics D 9, 189–208.

Havstad, J.W., Ehlers, C.L., 1989. Attractor dimension of nonstationary dynamical systems from small data sets. Physical Review A 39, 845–853.

Hense, A., 1987. On the possible existence of a strange attractor for the southern oscillation. Beitraige Physik Atmosphere 60, 34–47.

Hu, R.J., 2004. Physical Geography of the Tianshan Mountains in China. China Environmental Science Press, Beijing, pp. 241–246.

Islam, M.N., Sivakumar, B., 2002. Characterization and prediction of runoff dynamics: a nonlinear dynamical view. Advances in Water Resources 25, 179–190.

Jayawardena, A.W., Lai, F., 1994. Analysis and prediction of chaos in rainfall and streamflow time series. Journal of Hydrology 153, 23–52.

Jiang, X., 2011. The Chaotic Characteristic and Prediction Method in Hydrological Time Series. China Water Conservancy and Hydropower Press.

Kennel, M.B., Brown, R., Abarbanel, H.D.L., 1992. Determining embedding dimension for phase space reconstruction using a geometrical construction. Physical Review A 45, 3403–3411.

Kostelich, E.J., Schreiber, T., 1993. Noise reduction in chaotic time-series data: a survey of common methods. Physics Review E 48 (3), 1752–1763.

Koutsoyiannis, D., Pachakis, D., 1996. Deterministic chaos versus stochasticity in analysis and modeling of point rainfall series. Journal of Geophysical Research 101 (D21), 26441–26451.

Li, C., Zhang, C., Luo, G., Chen, X., Li, X., 2013. Modelling the carbon dynamics of the dryland ecosystems in Xinjiang, China from 1981 to 2007-The spatiotemporal patterns and climate controls. Ecological Modelling. http://dx.doi.org/10.1016/j.ecolmodel.2013.06.007.

Nerenberg, M.A.H., Essex, C., 1990. Correlation dimension and systematic geometric effects. Physics Reviews A 42 (12), 7065–7074.

Pasternack, G.B., 1990. Does the river run wild? Assessing chaos in hydrological systems. Advances in Water Resources 23, 253–260.

Rodriguez-Iturbe, I., De Power, F.B., Sharifi, M.B., Georgakakos, K.P., 1989. Chaos in rainfall. Water Resources Research 25, 1667–1675.

Rosenstein, M.T., Collins, J.J., De luca, C.J., 1993. A practical method for calculating largest Lyapunov exponents from small data sets. Physica D 65, 117–134.

Sangoyomi, T.B., Lall, U., Abarbanel, H.I., 1996. Nonlinear dynamics of the Great Salt Lake: dimension estimation. Water Resources Research 32, 149–159.

Sano, M., Sawada, Y., 1985. Measurement of Lyapunov spectrum from a chaotic time series. Physical Review Letters 55 (10), 1082–1085.

Schertzer, D., Tchiguirinskaia, I., Lovejoy, S., et al., 2002. Which chaos in the rainfall-runoff processes? A discussion on evidence of chaos in the rainfall-runoff processes by Sivakumar. Hydrological Sciences Journal 47, 139–147.

Schouten, J.C., Takens, F., Van den Bleek, C.M., 1994. Estimation of the dimension of a noisy attractor. Physical Review E 50 (3), 1851–1861.

Sivakumar, B., 2000. Chaos theory in hydrology: important issues and interpretations. Journal of Hydrology 227, 1–20.

Sivakumar, B., 2001. Rainfall dynamics at different temporal scales: a chaotic perspective. Hydrology and Earth System Sciences 5 (4), 645–651.

Sivakumar, B., 2003. Forecasting monthly streamflow dynamics in the western United States: a nonlinear dynamical approach. Environmental Modelling and Software 18, 721–728.

Sivakumar, B., 2009. Nonlinear dynamics and chaos in hydrologic systems: latest developments and a look forward. Stochiometric Environmental Resource Assessment 23, 1027–1036.

Sivakumar, B., Berndtsson, R., Olsson, J., Jinno, K., Kawamura, A., 2000. Dynamics of monthly rainfall-runoff processes at the Göta basin: a search for chaos. Hydrology and Earth System Science 4, 407–417.

Sivakumar, B., Berndtsson, R., Persson, M., 2001. Monthly runoff prediction using phase space reconstruction. Hydrological Sciences-Journal-des Sciences Hydrologiques 46, 377–387.

Sivakumar, B., Chen, J., 2007. Suspended sediment load transport in the Mississippi River basin at St. Louis: temporal scaling and nonlinear determinism. Earth Surface Processes and Landforms 32 (2), 269–280.

Stehlik, J., 1999. Deterministic chaos in runoff series. Journal of Hydrology and Hydromechanics 47, 271–287.

Takens, F., 1981. Detecting strange attractors in turbulence. In: Rand, D.A., Yong, L.S. (Eds.), Dynamical Systems and Turbulence, Lecture Notes in Mathematics, 898. Springer-Verlag, Berlin, pp. 366–381.

Wang, W., Vrijling, J.K., Pieter, H., 2006. Testing for nonlinearity of streamflow processes at different timescales. Journal of Hydrology 322, 247–268.

Wilcox, B.P., Seyfried, M.S., Matison, T.H., 1991. Searching for chaotic dynamics in snowmelt runoff. Water Resources Research 27 (6), 1005–1010.

Wolf, A., Swift, J.B., Wwinney, Hl, 1985. Determining Lyapunov exponents from a time series. Physica D 16, 285–317.

Zhang, J.S., Xiao, X.C., 2000. Predicting low-dimensional chaotic time series using Volterra adaptive filers (in Chinese). Acta Physica Sinica 49, 403–408.

Zhou, Y.K., Ma, Z.Y., Wang, L.C., 2002. Chaotic dynamics of the flood series in the Huaihe River Basin for the last 500 years. Journal of Hydrology 258, 100–110.