Stoch Environ Res Risk Assess (2014) 28:1383–1400
DOI 10.1007/s00477-013-0832-9

ORIGINAL PAPER

Multifractal and long memory of humidity process in the Tarim River Basin

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Published online: 11 December 2013

Abstract Based on the daily data of relative humidity from 23 meteorological stations in the Tarim River Basin of northwest China during the period from 1961 to 2010, this paper analyzed the multifractal and long memory property of humidity process. Main findings are as follows: (1) The processes present scaling and multifractal property. (2) The left-skewed multifractal spectrum $f(\alpha)$ indicates that the time series of relative humidity is predominated by small fluctuations. (3) There exists long memory with the $\delta \in (0, 0.5)$ in the processes, except for Kalpin and Aksu's exhibiting non-stationary long memory with the parameter δ being 0.67 and 0.69 respectively. (4) We found that on the whole, the degree of multifractality exhibits a strengthening trend with the longitude and latitude increasing, but decreasing trend with elevation rising; For length of long memory, we investigated that on the whole, the δ values increased with the longitude and latitude increasing, which indicates that the bigger the longitude and latitude is, the longer the memory of humidity process is, but the higher the elevation is, the shorter the memory of humidity process is.

Keywords Multifractal · Long memory · Fractional difference · Humidity process · The Tarim River Basin

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1 Introduction

Climate change has long been paid close attention to by governments and the public throughout the world. So are there any trends among climate change or long-range correlations within the climate system? It seems that the answer has been positive since global warming was reported by the IPCC in the last few decades (Dai et al. 1998; Zhai and Pan 2003; Zhai et al. 2005; Zou et al. 2005). Numerous studies had been published in the recent years regarding to the global climate change and its corresponding regional response (Khon et al. 2007; Lenderink et al. 2007; Ramanathan and Carmichael 2008). Many case studies conducted in China as well as other countries indicated that the regional climate was a huge and complex system (Shackley et al. 1998; Rial 2004; Dong et al. 2005; Zhao et al. 2007).

In the last 20 years, many studies have been conducted to evaluate climatic change and hydrological processes in the arid and semi-arid regions of northwest China (Chen and Xu 2005; Xu et al. 2010; Zhang et al. 2010; Xu et al. 2011, 2013a). A number of studies have indicated that there was a visible transition of hydro-climatic processes in the past half-century (Chen and Xu 2005; Chen et al. 2006; Shi et al. 2005). This transition was characterized by a continual temperature raise, precipitation, and river runoff increase, lake level lowering, and groundwater dropping. The changes have led to huge fluctuation of water resources, need to provide immediate relief to the local water shortage (Yang and He 2003; Mansuer and Chu 2007). Therefore, the large scale climate change has aroused a widespread concern in the climatic research community in China (Zhang et al. 2004; Chen and Xu 2005; Chen et al. 2006; Deng 2006; Xu et al. 2009a, b). The current researches pay more attention to air temperature, precipitation, evaporation and their influence on ecosystem hydrology (Koscielny-Bunde et al. 1998; Marin et al. 2000; Roderick and Farquhar 2002; Kimoto et al. 1963; Zhai and Pan 2003; Zhai et al. 2005; Merritt et al. 2006; Lenderink et al. 2007; Lin and Fu 2008; Khon et al. 2007; Alexandersson 1986; Feng et al. 2001), but relative humidity research only focused on simple time–space variation tendency. For instance, relative humidity showed downtrend in Changling County, Jilin Province (Han et al. 2003), and a negative (positive) correlation to temperature variation (precipitation change) (Akinbode et al. 2008); it also was downtrend in Akure province, Nigeria and America (Surratt et al. 2004). In addition, there was a negative correlation to water drop evaporation. When the evaporation increases by 40 %, the relative humidity will decrease by 25–45 %, so Surratt et al. (2004) argued that the decrease of humidity was an important factor affecting the aggravating drought degree.

Relative humidity studies on large scale have not been very numerous, but some pioneering studies are worth mentioning. First is a pioneering study by Szava-Kovats (1938), who presented surface maps of mean relative humidity and mean water vapor pressure for January and July conditions. For the upper atmosphere, however, the research on relative humidity has been mainly confined to regional studies with the notable exception of studies. Telegadas and London (1954) presented maps for the Northern Hemisphere at 850, 700 and 500 mb based on a 2-year average using around 150 upper-air stations available at the time. Gaffen et al. (1992) studied various relative humidity regimes around the world based on 56 selected radiosonde stations for the period 1973–1990. Rasmusson (1972) and Rind et al. (1991) have presented cross sections of the seasonal variations of relative humidity. Peixoto and Abraham (1996) regarded that the global distribution of relative humidity at various levels was not zonally uniform with centers of various intensities at all latitudes, and the global maps showed maxima in the equatorial zone and minima in the dry subtropical belts around 30°N and 30°S.

The relative humidity is a very important climatic factor for the precipitation, temperature and evaporation significantly, and thus, it is necessary to study the law of humidity variation, associating with the future drought-wet changes (Gao and Fu 2013). Moreover, relative humidity affects the growth of plants and animals in the ecological system, the comfort level of human living environment and all kinds of industry, such as spinning, light industry, machinery industry, forest fire prevention and so on. The relative humidity is also an important factor affecting shortwave radiation properties of atmospheric aerosol particles (Qiu et al. 1997; Yang and Li 1999; Luo et al. 2002). Recently some meteorologists have deep interest in multifractal and long memory within humidity process in China. By studying three multifractal parameters ($\Delta\alpha$, $\Delta\alpha_{as}$ and α_0) of a singularity spectrum, Gao and Fu (2013) found that multifractal behavior could be checked for relative humidity records at most stations in China, mainly due to the broad distribution of sequence values. For some stations in Yunnan, Guangdong, and Inner Mongolia provinces, the multifractal behaviors are much stronger, which are mainly caused by different long memory between large and small fluctuations. Long memory is also called "long-rang correlation" or "long-rang persistence". Lin et al. (2007) found that the relative humidity fluctuations take different statistical behavior from other meteorological quantities and there exists a stronger persistence in the relative humidity fluctuations. Furthermore, they also held that, in the north of China, especially in Northwest China, random rainfall shuffles the small-scale persistence of humidity process and leads to smaller small-scale scaling exponents than large-scale scaling exponents at some weather stations. So Chen et al. (2007) proposed the product of the scaling exponent and the standard deviation of the same record to form a new climate region classifying index. Overall, it is a slight decreasing trend for the relative humility in China. As for the partition, the relative humidity shows increased significantly in the south of the Yangtze River in summer since 1990s; the relative humidity in North China, however, has decreased greatly during the same period (Wang et al. 2004). Taking account of the change in temperature and precipitation, it can be found that West China is becoming warmer and wetter, especially in Northwest China (Zuo et al. 2005). The Tarim River Basin is the typical representative of Northwest China. And the region belongs to the typical arid climate zone, and exhibits different geophysical distributions and several specific climate regions. Thus, the climate changes over the Tarim River Basin may vary from place to place. So for humidity process, the Tarim River Basin presents more complex than other regions in China, but there are few studies on the fractal characteristic and self-memorial mode for humidity process in the basin. In order to reveal the physical mechanism of humidity process, this paper analyzed their multifractal and long memory properties by using multifractal methods and daily relative humidity data from 23 meteorological stations in the Tarim River Basin. We hope that it can provide certain theory basis for the diagnosis and forecast of local relative humidity change.

2 Study area and data

The Tarim River Basin (34°20′–43°39′N, 71°39′–93°45′E) is the hinterland of the Eurasia, high mountains and hungriness surround basins and oasis in the basin, covering almost the entire southern part of Xingjian, including 42 cities or counties and 55 collective farms managed by Xingjian Production and Construction Corporation. Its area is 1.02×10^6 km^2 and over 97 % of the area belongs to a drainage basin internal to China. This area has a typical desert climate with an average annual temperature of 10.6–11.5 °C. Monthly mean temperature ranges from 20 to 30 °C in July and −10 to −20 °C in January. The highest and lowest temperatures are 43.6 and −27.5 °C, respectively. The accumulative temperature of >10 °C ranges from 4,100 to 4,300 °C. Average annual precipitation is 116.8 mm in the basin, ranging from 200 to 500 mm in the mountainous area, 50 to 80 mm in the edges of the basin, and only 17.4 to 25.0 mm in the central area of the basin. There is greatly uneven distribution of precipitation within any single year. More than 80 % of the total annual precipitation falls between May and September, while less than 20 % from October to next April.

The records used in this paper were obtained from a high-quality daily relative humidity data sets spanning from January 1st 1961 to December 31st 2010, processed by Information Center of Meteorological Office in Xinjiang Uygur Autonomous Region, of 23 meteorological stations in the Tarim River Basin. The definition of relative humidity can be seen in the reference offered by Vattay and Harnos (1994). Figure 1 shows the daily relative humidity of Yanqi station. Locations of the 23 stations can be referred to Fig. 2 and more detailed information can be referred to Table 1. According to Chen et al. (2002), scaling of correlated data series was not affected by randomly cutting out segments and stitching together the remaining parts, even when 50 % of the points are removed. Therefore, we remove the missing values from the raw data over some stations, since they are only a little part of series. Furthermore, to overcome the natural nonstationarity of the data due to season trends, we remove the annual cycle from the raw data e by computing the anomaly series $e' = e - \langle e \rangle_d$ for relative humidity, where $\langle \rangle_d$ denotes the long-time average value for the given calendar day. And we apply the Standard normal homogeneity test (SNHT), Buishand and Pettit homogeneity test method to check these data (Pettit 1979; Buishand 1982; Alexandersson 1986). The stepwise multiple linear regression method was employed to revise the inhomogeneity of time series.

3 Methodology

3.1 Spectrum analysis

Spectrum analysis is a way of evaluating and the scaling regime is to calculate the power spectrum density (PSD), $S(f)$, of the data (Priestley 1981; Baselli et al. 1986; Van der Schaaf et al. 2002). It has been used in several investigations to examine the scaling behavior of some time series (Lu et al. 2012; Malamud and Turcotte 1999; Lennartz and Bunde 2011). If the spectrum obeys a power-law form $S(f) \propto f^{-\beta}$, where f is frequency and β is the spectral exponent, it reveals the scale-free memory effect as a power law dependence of the frequency distribution (often displaying a "1/f" distribution (Kobayashi and Musha 1982), and methods that plot fluctuations of a signal around a trend line when the data are aggregated over different time windows [e.g., fluctuation analysis (Peng et al. 1993), detrended fluctuation analysis (Goldberger et al. 2002), or relative dispersion analysis (West et al. 1999)]. The potential importance of identifying these nontrivial correlations in complex physiological functions is in disease conditions, it has been shown that the fractal character of the system can break down (Aon et al. 2006). Furthermore, the spectrum with $\beta > 0$ represent long memory up to the time scale considered (Blender et al. 2006; Lu et al. 2012). This is the temporal analogy to spatial fractal scaling observed in, for example, the branching patterns of a tree, the pulmonary bronchioles, or the arterial system. Thus, fluctuations at all scales within the range are related to each other and a fractal and long memory behavior may be assumed.

3.2 Multifractal analysis

Multifractal analysis was first introduced for the study of turbulence by Mandelbrot (1972, 1974) and Halsey et al. (1986) and was then much developed in a mathematical

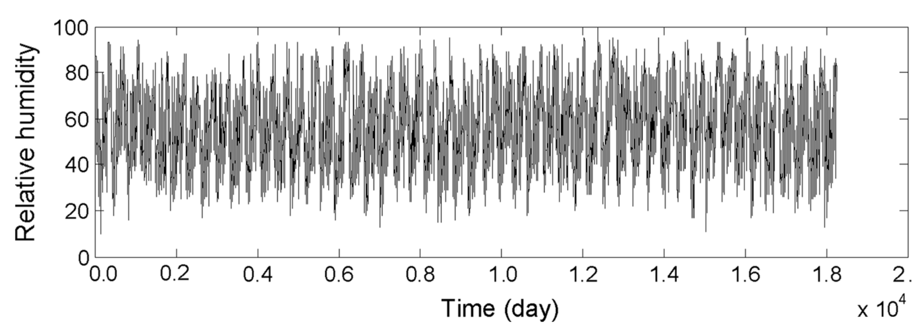

Fig. 1 The relative humidity of Yanqi station from Jan-1961 to Dec-2010 [The data lengths all are 18,262 (days)]

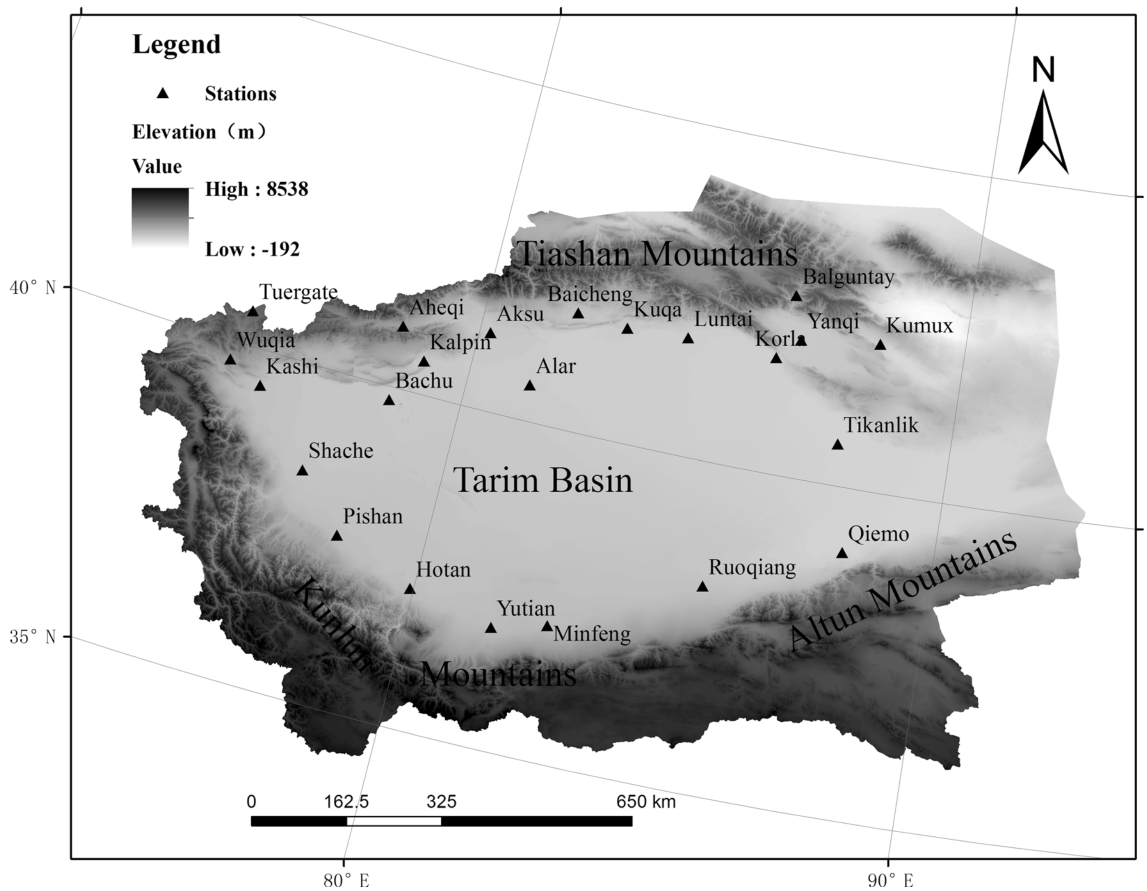

Fig. 2 Location of meteorological station in the Tarim River Basin

framework, for instance, many scholars extended multifractal analysis to point functions (Bacry et al. 1993; Jaffard 1992, 1997a, b; Ivanov et al. 1999; Kravtsov et al. 2012), obtaining quite complete descriptions. A multifractal analysis is defined for sequences of Choquet capacities with respect to a general class of measures, and some preliminary results are presented concerning the usual spectra. In particular, we show how to construct a sequence of capacities whose Hölder spectrum is, under mild conditions, prescribed (Véhel and Vojak 1998).

We further investigate the possibility that time series generated by certain climatic system may be members of a special class of complex process, termed multifractal, which require a large number of exponents to characterize its long memory property. The related literatures can be seen in the further detail computation (Ivanov et al. 1999; Lee et al. 2006; Böttcher et al. 2007; Ruiz-Medina et al. 2008; Yuan et al. 2012).

The calculation steps of the statistical method are briefly described as follows Halsey et al. (1986) and Chen et al. (2004). The multifractal analysis is applied to operate on the relative humidity time series $\{X_t\}$, where $t = 1, 2,\ldots, N$ and N is the length of the series.

Step 1 The normalized the relative humidity series is determined by

$$M_t = X_t / \sum_{i=1}^{N} X_t \tag{1}$$

Step 2 M_t is divided into v non-overlapping intervals of a certain time resolution, s. Each interval is characterized by a time resolutions s. Then for each s, we compute the sum of normalized the relative humidity series M_t in each interval. And we obtain the box probability of each interval

$$Pv(s) = \sum_{t=(v-1)+1}^{vs} M_t, v = 1, 2, \ldots, 2Ns \tag{2}$$

where $Ns = [N/s]$ ([] represents the integral zed Gauss mark.).

Step 3 The so-called partition function $Z(q, s)$ (Ivanov et al. 1999; Kantelhardt et al. 2002) has to be defined by

Table 1 The main multifractal parameters for humidity process

ID	Station	Longitude (E)	Latitude (N)	Elevation (m)	β_1	β_2	$\Delta\alpha$	$f_{\max}$	Δf	θ	δ
51705	Wuqia	75.25	39.72	2,176	1.5249	2.359	0.0214	0.9025	−0.0743	−0.0091	0.12
51701	Tuergate	75.40	40.52	3,504	1.6473	2.3671	0.0305	0.9499	−0.0833	−0.0148	0.19
51709	Kashi	75.98	39.47	1,289	1.7672	2.2784	0.0331	0.9385	−0.0764	−0.0078	0.23
51811	Shache	77.27	38.43	1,231	1.8351	2.3346	0.0332	0.9042	−0.0326	−0.0082	0.22
51818	Pishan	78.28	37.62	1,375	1.7946	2.1975	0.0334	0.9553	−0.0384	−0.0163	0.19
51711	Aheqi	78.45	40.93	1,985	1.8317	2.3469	0.0354	0.9179	−0.0347	−0.0087	0.21
51716	Bachu	78.57	39.80	1,117	1.8015	2.2683	0.0368	0.9238	−0.0101	−0.0109	0.23
51720	Kalpin	79.05	40.50	1,162	1.9667	2.491	0.0391	0.8934	−0.0542	−0.0099	0.67
51828	Hotan	79.93	37.13	1,375	1.859	2.3858	0.0397	0.6968	−0.0581	−0.0078	0.25
51628	Aksu	80.23	41.17	1,106	1.8843	2.4949	0.0402	0.9221	−0.0347	−0.0125	0.69
51730	Alar	81.27	40.55	1,012	1.9966	2.6664	0.0405	0.9792	−0.0842	−0.0046	0.27
51931	Yutian	81.65	36.85	1,422	1.7621	2.3227	0.0408	0.9721	−0.0321	−0.0103	0.3
51633	Baicheng	81.90	41.78	1,230	1.5901	2.1942	0.0414	0.9585	−0.0426	−0.0069	0.31
51839	Minfeng	82.72	37.07	1,410	1.6457	2.3168	0.0424	0.9569	−0.0465	−0.0102	0.33
51644	Kuqa	82.97	41.72	1,082	1.8906	2.4046	0.0428	0.9632	−0.0747	−0.0009	0.36
51642	Luntai	84.25	41.78	976	1.8932	2.4178	0.0431	0.9564	−0.0568	−0.0114	0.41
51777	Ruoqiang	85.55	38.15	888	1.8642	2.3743	0.0431	0.9937	−0.0432	−0.0175	0.39
51656	Korla	86.13	41.75	932	1.1377	2.0075	0.0433	0.9935	−0.0337	−0.007	0.43
51467	Balguntay	86.30	42.73	1,739	1.9557	2.4191	0.0447	0.9273	−0.0015	−0.0033	0.42
51567	Yanqi	86.57	42.08	1,015	1.9982	2.4742	0.0453	0.9905	−0.0432	−0.0016	0.47
51765	Tikanlik	87.70	40.63	846	1.5881	2.3594	0.0464	0.9719	−0.0583	−0.0045	0.49
51855	Qiemo	88.17	39.03	1,247	1.7014	2.2255	0.0482	0.9465	−0.0783	−0.0142	0.48
51526	Kumux	88.22	42.23	922	1.9867	2.5258	0.0585	0.9988	−0.0357	−0.0087	0.49

$$Z(q,s) = \sum_{v=1}^{vs} |p_v(s)|^q \tag{3}$$

where q is a real number ranging from $-\infty$ to ∞. For multifractal distributed measures, the partition function scales with the resolution as

$$Z(q,s) \propto s^{\tau(q)} \tag{4}$$

where $\tau(q)$ is the mass exponent of order q (namely qth-order moment structure partition function) (Kravchenko et al. 1999; Lee et al. 2003). The mass exponent for each q-value can be obtained by plotting log$Z(q, s)$ vs. log$s$. The obtained $\tau(q)$ may be regarded as a characteristic function of the fractal behavior. If $\tau(q)$ against q is a straight line (convex function), the data set is monofractal (multifractal) (Sivakumar 2001; Shang and Kamae 2005; Shi et al. 2009, 2010). In addition, it is important to describe the strong or weak characteristics of the degree of multifractality for the three parameters of multifractal spectrum (Sun et al. 2001; Shimizu et al. 2002; Shi et al. 2009).

Another way to characterize a multifractal series is the singularity spectrum $f(\alpha)$, that is related to $\alpha(q)$ via a Legendre transform (Feder 1988; Peitgen et al. 1999),

$$\alpha(q) = \frac{d\tau(q)}{dq} \quad \text{and} \quad f(\alpha) = q\alpha(q) - \tau(q) \tag{5}$$

where α called Holder singular index, which is also called singular strength or the singularity of the subset of probabilities (Shang et al. 2012), reflecting the degree of singular interval measures. And $f(\alpha)$ is the multifractal spectrum, denoting the dimension of the subset of the series that is characterized by α. The curve $\alpha \sim f(\alpha)$ is a single-humped function for multifractal, which reduces to a point for monofractal. The shape and the extension of $f(\alpha)$ curve contain significant information about the distribution characteristics of the examined data set.

Two conventional multifractal parameters of them are used to be deduced from the approximated $f(\alpha)$ (Yonaiguchi et al. 2007). The spectrum width is defined as $\Delta\alpha = \alpha_{\max} - \alpha_{\min}$, where $\alpha_{\max}$ and $\alpha_{\min}$ are obtained from the relation $f(\alpha) = 0$. The parameter $\Delta\alpha$ describes the inhomogeneity of the distribution of probability measured on the overall fractal structure, which has been identified as the degree of multifractality and intermittency (Macek 2007; Macek and Wawrzaszek 2009; Macek et al. 2011). $f(\alpha)$ takes a maximum value $f_{\max}$ ($f_{\max} = f(\alpha_0)$) at a specific α_0, which corresponds to the peak of the multifractal spectrum (Telesca et al. 2003).To be specific, the bigger the $\Delta\alpha$ and the larger $f_{\max}$, the stronger is the degree of multifractality. Moreover, the difference of the fractal dimensions between the minimum probability and maximum probability subsets Δf ($\Delta f = f(\alpha_{\min}) - f(\alpha_{\max})$) describes the proportion of the number of elements at the maximum and minimum in the subset, which refers to the proportion of the large and small peaks of vibration signals.

We can make a quantitative characterization of the spectra by least square, fitting it to a quadratic function (Shimizu et al. 2002) around the position of maximum α_0 (Dutta 2010; Ghosh et al. 2012; Samadder et al. 2013)

$$f(\alpha) = \theta_1(\alpha - \alpha_0)^2 + \theta(\alpha - \alpha_0) + \theta_2 \tag{6}$$

where θ_2 is an additive constant $\theta_2 = f(\alpha_0) = 1$ and θ indicates the asymmetry of the spectrum. It is zero for a symmetric spectrum. The better symmetry (namely the closer to 0), the stronger is the degree of multifractality. A larger θ value (positive) for a process indicates a left-skewed shape of multifractal spectrum and a relative dominance of lower fractal exponents corresponding to more smooth-looking structures, which is ascribed to the time series with long memory (Shimizu et al. 2002).

3.3 Long memory process

There are several possible definitions of the property of long memory. Given a discrete time series, X_t with an autocorrelation function ρ_j at lag j. McLeod and Hippel (1978) described X_t as having long memory if

$$\lim_{n\to\infty} \sum_{j=-n}^{n} |\rho_j| = \infty \tag{7}$$

Equivalently, the spectral density function (SDF) denoted by $S_X(\cdot)$ will be unbounded at low frequencies.

Furthermore, if there exist constant a and C_S satisfying $-1 < a < 0$ and $C_S > 0$ such that

$$\lim_{f\to 0} \frac{S_X(f)}{C_S|f|^{\alpha}} = 1 \tag{8}$$

Then, we say that X_t is a stationary long memory process. In other words, a stationary long memory process has an SDF $S_X(\cdot)$ such that $S_X(f) \approx C_S|f|^{a}$, with a approximation improving as f approaches zero. In colorful terms, so called stationary long memory process, the current observations retain some 'memory' of distant past. In the case of long memory within the climate system, a cold day is usually followed by a cold day, and a warm day is more likely to be followed by a warm day.

The Fractional Differenced (FD) process was introduced independently by Granger and Joyeux (1980) and Hosking (1984). The model is expressed as the following FD equation:

$$(1-B)^{\delta} X_t = \varepsilon_t \tag{9}$$

where $\{_t\}$ is related to a (typically Gaussian) white noise process with mean zero (Akaike 1974). And B is the backward shift operator, δ is the "long memory parameter", and satisfies $-1/2 < \delta < 1/2$; and $(1 - B)$ is interpreted as

$$(1-B)^{\delta} X_t = \sum_{k=0}^{\infty} \binom{\delta}{k} (-1)^k B^k \tag{10}$$

it can be re-expressed as:

$$\sum_{k=0}^{\infty} \binom{\delta}{k} (-1)^k B^k = \varepsilon_t \tag{11}$$

where

$$\binom{\delta}{k} \equiv \frac{\delta!}{k!(\delta-k)!} \equiv \frac{\Gamma(\delta+1)}{\Gamma(k+1)\Gamma(\delta-k+1)} \tag{12}$$

Beran (1994) gave the SDF a FD process:

$$S_X(f) = \frac{\delta_\varepsilon^2}{\left|4\sin^2(\pi f)\right|^{\delta}}, \quad -\frac{1}{2} \le f \le \frac{1}{2} \tag{13}$$

For small f, we have $S_X(f) \propto |f|^{-2\delta}$ approximately, so a FD process is a stationary long memory process when $-1 < -2\delta < 0$, i.e. when $0 < \delta < 0.5$. We use shorthand notation "FD(δ)" to denote a FD process with parameter δ. Moreover, the larger of δ value, the stronger is long memory process.

When $\delta > 0$, we sometimes call δ the "long memory parameter" for a FD process (Percival and Walden 2000); when $\delta = 0$, the FD process becomes White noise process; when $-0.5 < \delta < 0$, the FD process is deficient in power at low frequencies, and we have $S_X(0) = 0$. In this case, the correlation coefficient of X_t is also negative, and it is a stationary short memory process. While for $\delta \ge 0.5$, a FD process is a non-stationary long memory process (Taqqu et al. 1995; Kantelhardt et al. 2001, 2002; Hu et al. 2001; Chen et al. 2002), but while for $\delta \le -0.5$, the process is non-invertible; while for $0 < \delta < 0.5$, the FD process exhibits stationary long memory or long-range positive interdependence. But at this time, the autocorrelation coefficient of X_t decay very slowly and is positive, and the sum of correlation coefficient will diverge to infinity, or call continuing existence. Time series presents persistence or enhanced trend, and with δ gradually approach 0.5, the persistent state gradually increased. Furthermore, δ is the parameter that determines the degree of long memory (the higher the δ is, the longer the memory becomes) and so testing the null hypothesis of weak dependence against the alternative of long memory is equivalent to testing $\delta = 0.5$ against $\delta \neq 0.5$. For further detail computation, see Lobato and Savin (1998) and Baillie (1996).

For a continuous time series in state, it displays long memory characteristics (Comte and Renault 1998). Theoretically, what happened today will always affect the future. In chaotic dynamics terms, there is sensitivity to initial conditions. No matter what time scale to scale, the long memory always exists. The monograph by Beran (1994) and the reviewing article by Robinson (1994) provided two updated surveys of recent developments of long memory processes in statistics and economics, respectively. A distinctive feature of a long memory process is that its spectral density f is unbounded at the frequency zero. In fact, some empirical evidence seems to long memory. For instance, the stock price series of financial markets from the US and the UK (Jegadeesh 1991), the macroeconomic series of the food prices (Granger and Joyeux 1980) and the time series of Ethernet traffic (Leland and Wilson 1993) seem to exhibit a slowly decaying serial correlation. This corresponds to the fact that the autocorrelation function at large lags decays to zero at a slower rate than independent data or data following an ARMA(p, q) model (Granger and Joyeux 1980; Apergis and Tsoumas 2012), which is one of the most common models for non-stationary long memory process. While for stationary long memory process, the FD process is very popular.

3.4 Kriging and cokriging method

Cokriging is a multivariate spatial method to estimate spatial correlated variables and wildly used in soil science (Vauclin et al. 1983; Webster 1985; Webster and Burgess 1980), which is an extension of the Kriging method and can incorporate secondary information, such as values of gradients in addition to primary function values of the sample points has been utilized for constructing approximation models in a realistic design optimization process (Chung and Alonso 2002). The estimation precision may be improved by accounting simultaneously for spatial autocorrelation in population density and impervious surface fraction and the cross-correlation between these spatial variables. Moreover, it is suitable when the variable to be estimated (e.g. population density) is under-sampled while other supplementary variables are abundant (e.g. impervious surface fraction) (Wu and Murray 2005). Ordinary Kriging can mathematically be defined as given in the following:

$$Z_X^* = \sum_{i=1}^{n} \lambda_i Z(X_i) \tag{14}$$

where Z_X^* is the estimated value, λ_i is the corresponding weight of each observation $Z(X_i)$ on the estimation. The weights are calculated to ensure that the estimator is unbiased and the estimation variance is a minimum. The nonbias condition requires that:

$$\begin{cases} \sum_{i=1}^{n} \lambda_i \gamma(X_i, X_j) - \mu = \gamma(X_i, X^*) \\ \sum_{i=1}^{n} \lambda_i = 1 \end{cases} \tag{15}$$

where $\gamma(X_i, X_j)$ is the variogram between sampled point i and point j, $\gamma(X_i, X^*)$ is the variogram between sampled point and estimated point, μ is the Lagrange multiplier of minimum condition.

The general form of cokriging equations are:

$$\begin{cases} \sum_{l=1}^{v} \sum_{i=1}^{n_l} \lambda_{il} \gamma_{lv}(X_i, X_j) - \mu_v = \gamma_{uv}(X_i, X^*) \\ \sum_{i=1}^{n_l} \lambda_{il} = \begin{cases} 1, & l = u \\ 0, & l \neq u \end{cases} \end{cases} \tag{16}$$

where u and v are the primary and covariate (secondary) variables, respectively. In the cokriging method, the u and v are cross-correlated and the covariate contributes to the estimation of the primary variable. Generally, measuring the covariate is simpler than measuring the primary variable (Xu et al. 2013b). For cokriging analysis, the cross variogram (or cross-variogram) should be determined in prior. Provided that there are points where both u and v have been measured, the cross-variogram is estimated by

$$\gamma_{uv}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z_u(X_i) - Z_u(X_i + h)][Z_v(X_i) - Z_v(X_i + h)] \tag{17}$$

4 Results and discussion

4.1 Scale-free property of humidity process

Figure 3 shows the power spectrum of Yanqi station's humidity process, it is easy to find that the power spectral density obeys two different power laws in the high-frequency and low-frequency regimes, namely $\beta_1 = 1.9982$ (>0) for 100 day$^{-1} < f <$ 1 day^{-1} and $\beta_2 = 2.4742$ for $f <$ 100 day^{-1}. In shorter period, spectral analysis shows that the humidity process is well characterized by 1/f noise and self-affine type fractal behaviors (Malamud and Turcotte 1999; Shi et al. 2013). That is to say, in the time quantum, the humidity process exhibits scale-free property and long memory.

Table 1 also shows spectral exponents of other 22 station's humidity process in the Tarim River Basin. Obviously, similar to Yanqi station, the relative humidity processes of other stations exhibit self-affine type fractal behaviors and scaling properties in the time scale (1–

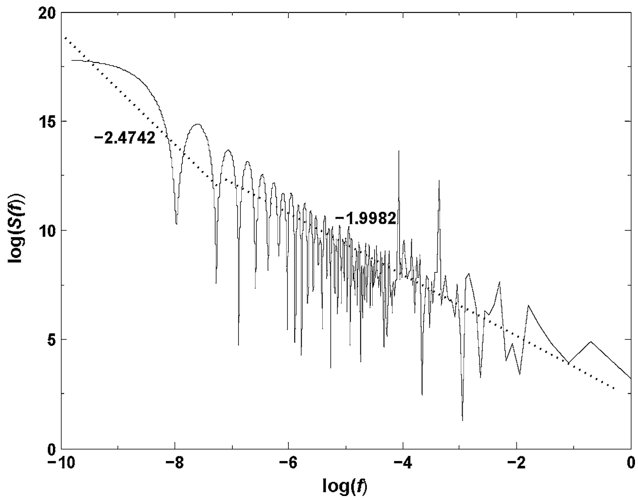

Fig. 3 The power spectra plot of humidity process

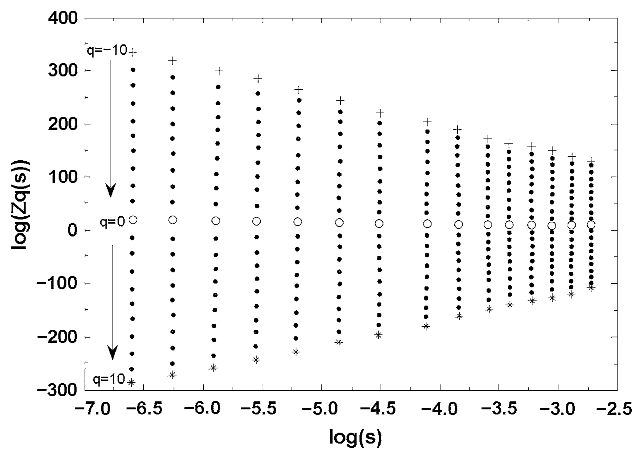

Fig. 4 Partition functions varying the parameter q

100 days), so there is universal fractal and scaling behaviors for humidity processes in the Tarim River Basin. Therefore, the following humidity process analyses are in the time scale of below 100 days. These findings are similar to the Lin et al. (2007), Vattay and Harnos (1994) and Bellon et al. (2006). Moreover, there are appreciable differences among the stations, which reflects that there exists different mechanisms for multifractal and long memory of humidity process in different regions.

4.2 Multifractal behavior of humidity process

Here we will check whether the fluctuations of humidity processes are multifractal or not. If they were, we could measure the degree of multifractality and seek how the multifractality depends on geographical position of meteorological stations. Figure 4 shows plots of the partition function $Z_q(s)$ versus the time scale s in a log–log scale for

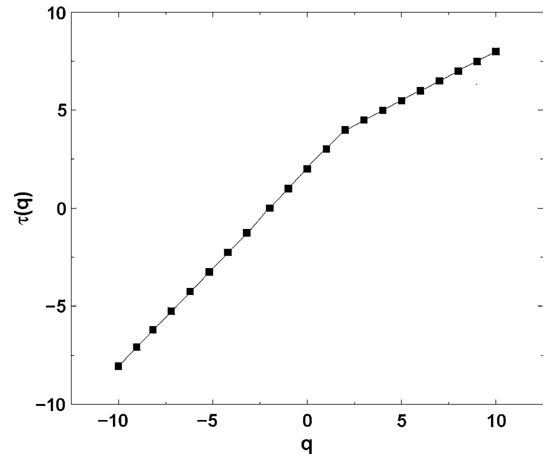

Fig. 5 The $\tau(q)$ curves varying the parameter q

Yanqi station's humidity process. All of these plots are mostly close to being straight for $-10 \leq q \leq 10$. According to the evaluation of the slopes from Fig. 4, we can establish the $\tau(q) \sim q$ plots which are shown in Fig. 5. As shown in Fig. 5, none of the $\tau(q)$ versus q are straight lines, indicating that Yanqi station's humidity process has multifractal structures.

The multifractal spectrum of humidity process is calculated as shown in Fig. 6. $\Delta\alpha$ is an indicator of measuring the degree of multifractality. When the process occurs sharp fluctuations, $\Delta\alpha$ values can increase correspondingly, and also reach a local peak. Moreover, the width of the multifractal spectrum indicates a nonuniform clustering structure for humidity processes. The bigger $\Delta\alpha$ in the humidity process reveals the larger variation of humidity values. The bigger the $\Delta\alpha$ is, the stronger the degree of multifractality gets and the richer structure of the humidity process becomes. Furthermore, the shape of $f(\alpha)$ curve obviously likes a hook to the right with $\Delta f = -0.0432 < 0$, which indicates that the frequency of humidity values at the lower values is more than higher values in the whole 50 years. The larger θ value (positive) of the humidity process indicates that its multifractal spectrum is a relative dominance of lower fractal exponents corresponding more smooth-looking structures. This indicates that small amplitude fluctuations of time series play a leading role in the relative humidity fluctuation, mainly due to the humidity process with long memory. Therefore, we can conclude that the complexity of the changes in the spatial and temporal distribution of abnormal seismic activity is related to the enhanced degree of the distribution of non-uniform stress field within the structural system of the Tarim River Basin region. Our conclusion is extremely similar to the opinion proposed by Yu et al. (2008).

The three parameters over the remaining 22 stations exhibit a roughly normal distribution, with $\Delta f < 0$, $\theta < 0$, and $f_{\max}$ abysmally close to 0, as shown in Table 1, which indicates that the fluctuations of the humidity processes are multifractal. Therefore, every specified status of Δf, θ, and $f_{\max}$ reflects the characteristics of the corresponding records' structure, and these parameters are useful to study the future evolution features in specific processes. In order to study the relations between the degree of multifractality and meteorological station's geographical position (latitude, longitude and elevation, i.e.), the cokriging interpolation technique is applied directly to $\Delta\alpha$, $f_{\max}$, and $|\theta|$ (Figs. 7, 8, 9), and then we fit their slopes ordered by longitude, latitude and elevation respectively (Table 2).

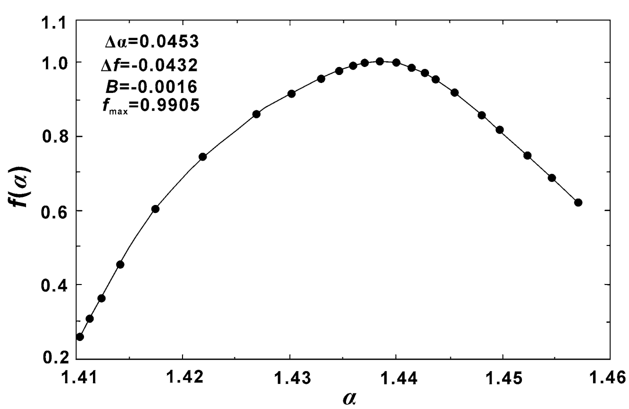

Fig. 6 Multifractal spectra $f(\alpha)$ of humidity process

Figures 7–9 and Table 2 indicate that the degree of multifractality of humidity process exhibits an increasing trend with the increase of longitude and latitude and decreasing trend with the elevation rising. Obviously, the degrees of influence are different among regions. The most obvious factor is longitude, next is elevation and latitude is the last. This difference of humidity processes multifractal behavior is probably caused by the different climatic conditions around the different weather stations and reflects the role of climate dynamic processes on the multifractal behavior of humidity processes and the distinctiveness of physical processes in those regions. Similar results were obtained by Chen et al. (2007), who constructed a new index with the product of the scaling exponent and adopted the standard deviation of the same relative humidity record to classify climate regions. This transitional behavior can be still found in this letter but from the multifractal behaviors, so it can be considered that the transitional behavior is robust and deserves to be studied deeply (Lin and Fu 2008).

The variability of multifractal parameters can provide some information about the temporal evolution dynamics of humidity process (Shi et al. 2005). The evolution of multifractal characteristics ($\Delta\alpha$, Δf, θ, $f_{\max}$) also contains some information about the temporal evolution dynamics of humidity processes. This shows that multifractal spectrum parameters can be another quantitative index

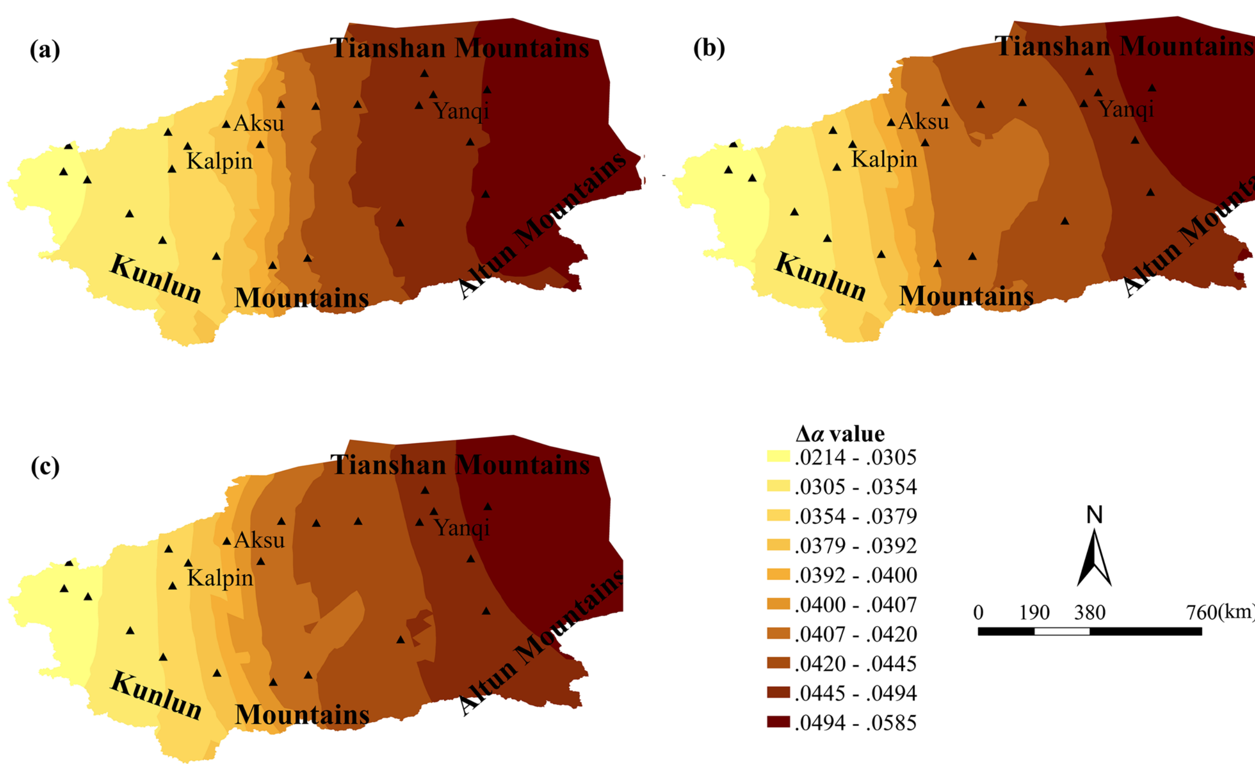

Fig. 7 The change of $\Delta\alpha$ with longitude (**a**), latitude (**b**) and elevation (**c**)

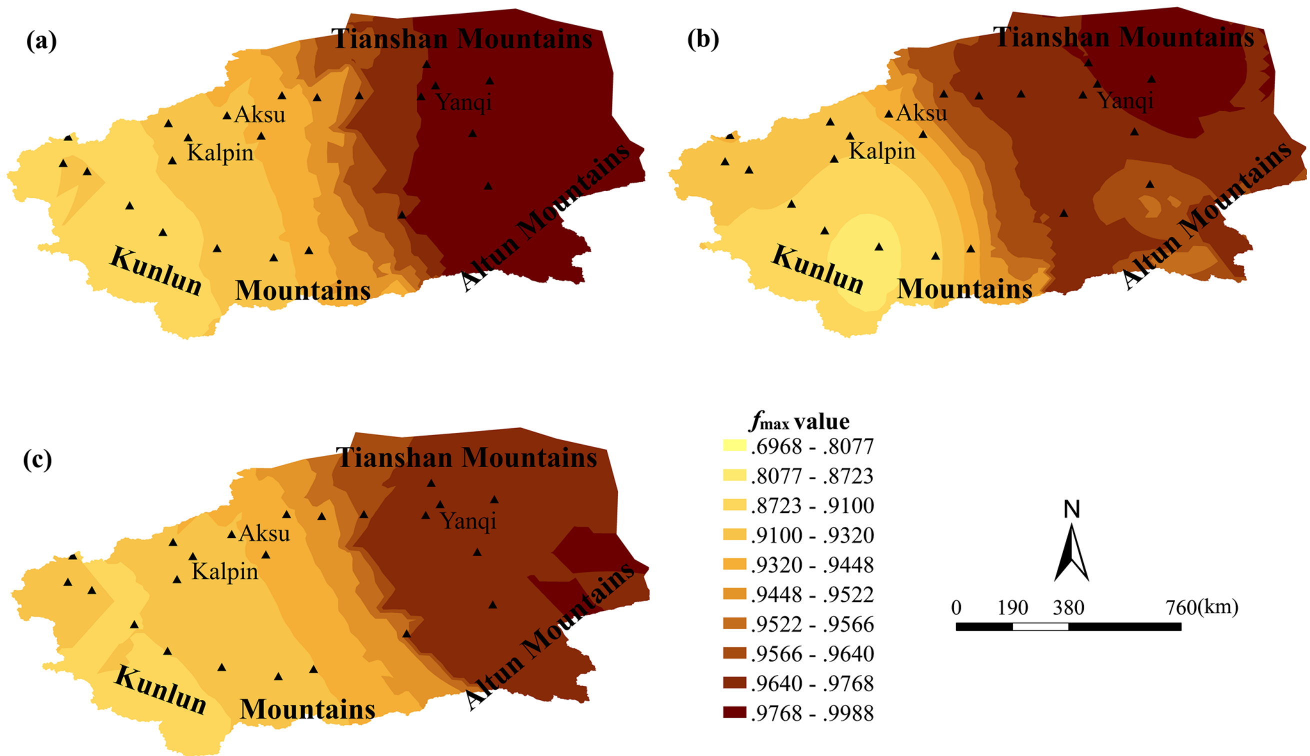

Fig. 8 The change of f_{max} with longitude (**a**), latitude (**b**) and elevation (**c**)

reflecting the buffered capability of climatic change of atmospheric body. The result also indicates that a multifractal approach can provide a much deeper insight into data structure.

4.3 Long memory of humidity process

Gao and Fu (2013) argued that multifractal behavior of humidity process was mainly caused by different long memory of the small and large humidity fluctuations or the complexity of physical processes that determined the variation of relative humidity in nature. So the investigation of long memory behavior for humidity process in the Tarim River Basin is also worth further researching.

Long memory process has been receiving considerable attention among researchers from various disciplines, ranging from econometrics (Cheung and Diebold 1994; Kruse and Sibbertsen 2012) to meteorology (Bloomfield 1992). These studies related to long range dependence include detection of long memory, statistical estimation of parameters of long range dependence, limit theorems under long range dependence, simulation of long memory processes, and many others (Beran 1994; Baillie 1996). The most famous time series with stationary long memory are the fractional Gaussian noises (FGN) with Hurst parameter H (Hurst 1951; Koutsoyiannis 2002) and FARIMA (p, d, q) processes (Box and Jenkins 1970; Baillie 1996). Both these time series used the Fourier transform to estimate the self-similarity parameter of an FGN model, for example, Graf (1983) had reported estimates of $H = d + 0.5$ from 0.83 to 0.85 and Beran (1994) reported estimates of $H = 0.84$ for FGN and $H = 0.90$ for an ARFIMA model with 95 % confidence intervals of (0.79, 0.89) and (0.84, 0.96), respectively. We also implement a version of Gil-Alana (2008) method of estimating the FD parameters under the assumption that the series contains a single structural break. This method is based on minimizing the sum of the squared residuals for a grid of values of the FD parameters with the break date being endogenously determined by the model (Gil-Alana et al. 2010).

Long memory effects imply the possibility to predict conditions in the future based on historical records (Pedron 2010). According to the FD process, that the parameter δ value is 0.47(<0.5) indicates Yanqi station's humidity process with a characteristic of stationary long memory. We also calculate δ values of other 22 stations' humidity processes as shown in Table 1, which reveals that the humidity processes also exhibit stationary long memory dynamics similarly to Yanqi station's, except for Kalpin and Aksu station showing non-stationary long memory. As it is, humidity processes in the Tarim River Basin exhibit a long-lasting persistence in the past 50 years. The background should be considered (Chen et al. 2007; Lack et al.

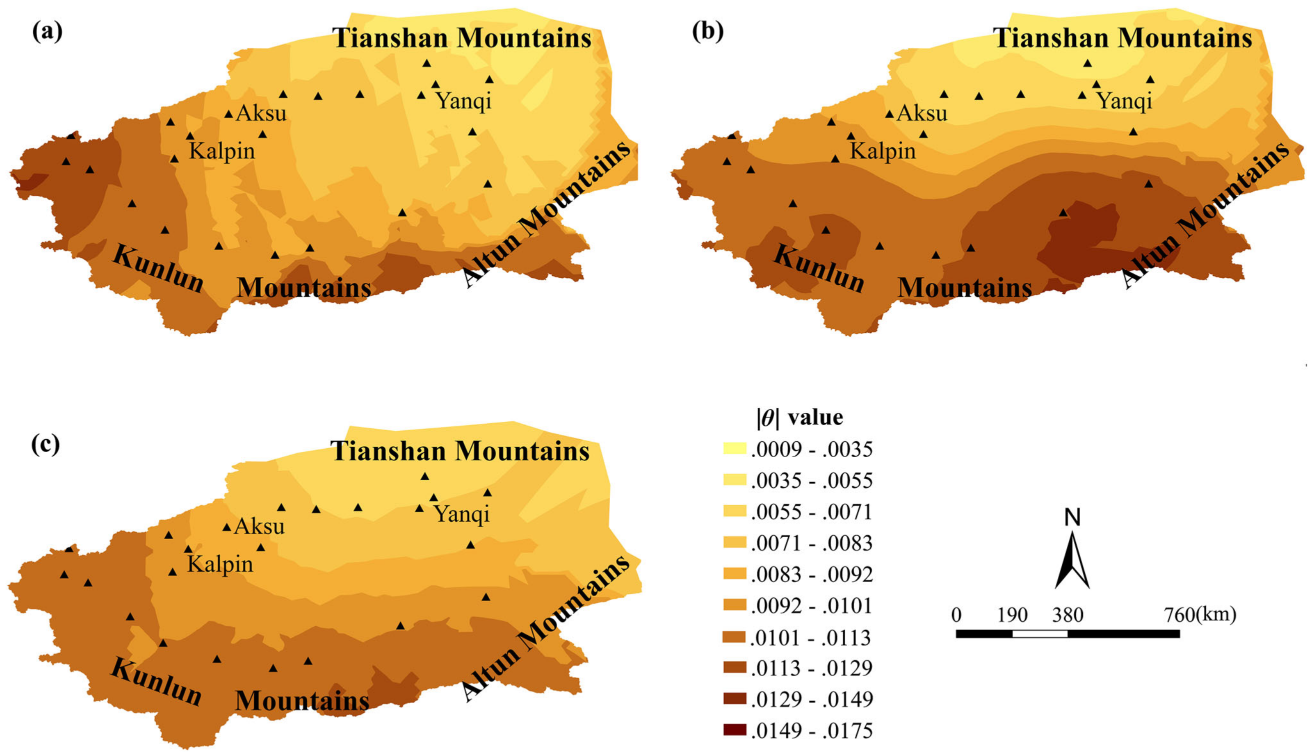

Fig. 9 The change of $|\theta|$ with longitude (**a**), latitude (**b**) and elevation (**c**)

Table 2 The slops of multifractal parameters for humidity process

	$\Delta\alpha$	$f_{\max}$	$\lvert\theta\rvert$	δ
$\text{Slope}_{\text{Longitud}}$	0.018	0.0033	−0.00036	0.017
$\text{Slope}_{\text{Latitude}}$	0.007	0.0029	−0.00017	0.008
$\text{Slope}_{\text{Elvation}}$	−0.009	−0.0031	0.00022	−0.012

2009), whereas we cannot determine the environmental situation of a certain area simply by persistence of the processes.

Figure 10 shows the spatial distribution and variation trend of δ with longitude, latitude and elevation using the kriging and cokriging methods, and calculate the slopes of δ ordered by longitude, latitude and elevation increasing as shown in Table 2, which are 0.017, 0.008 and −0.012, respectively. Figure 10 and Table 2 display generally that the longer of long memory is strengthening trend with the increase of longitude and latitude, especially for longitude, but weakening trend with the elevation rising. Similar to multifractal property of the humidity processes, the most obvious factor is longitude, next is elevation and latitude is the last.

Why do the humidity processes present multifractal and long memory in the Tarim River Basin? Until now, no one can give an accuracy answer, not just in the region. Because these meteorological time series should also be considered by the basis of physical mechanisms and their scales, for example, how they are controlled by circulation systems, how the data are compromised by the process of averaging and how the static nonlinearity is affected by the measurement devices (Lu et al. 2012). Here, authors make some probing explanations. As we all know, the atmospheric motion is a nonlinear and complex system with self-memorial mode and scale property (Atmanspacher et al. 1988; Liu 1990; Liu et al. 2000; Feng et al. 2001; Gao et al. 2003; Diao et al. 2004; Dong et al. 2005; Ren and Chou 2007; Fraedrich and Blender 2003). Therefore, the humidity processes in the Tarim River Basin also have long memory and scale-free properties (Xu et al. 2009b, 2013a; Li et al. 2011; Lu et al. 2012), whereas the multifractal behaviors are mainly caused by them between large and small amplitude fluctuations (Feng et al. 2010). This leads to more complicated predictability in the Tarim River Basin. In addition, many case studies in different countries and regions had suggested that humidity process exhibited multifractal and long memory, whether small or large scales (Chen et al. 2007; Gao and Fu 2013; Lin et al. 2007; Millán et al. 2010; Liu et al. 2004, 2012), which showed that the properties are of the universality for humidity process.

Moreover, it is common knowledge that the climatic system exists energy and material exchange with other systems and its subsystems (Liu 1990; Liu et al. 2000). However, the humidity process is just a subsystem of

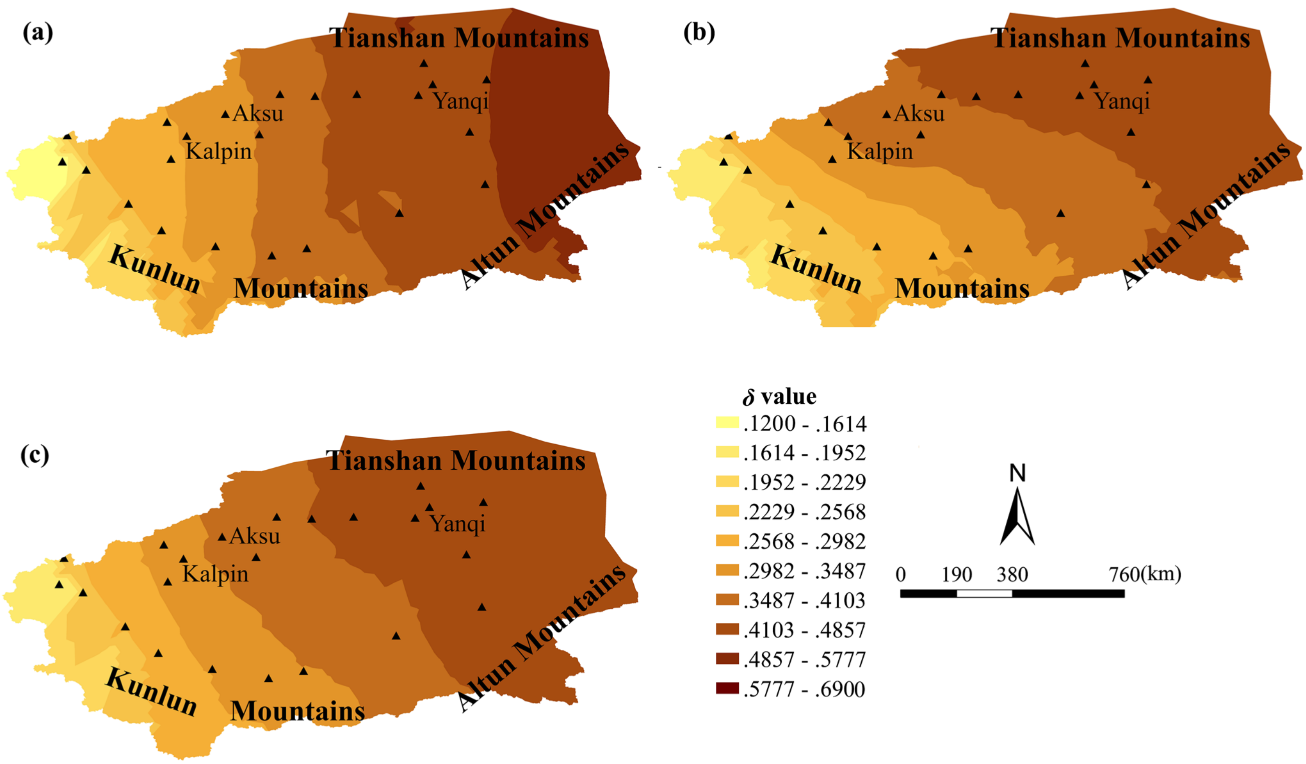

Fig. 10 The change of δ with longitude (**a**), latitude (**b**) and elevation (**c**)

climatic system with nonequilibrium state and layering, which complies with the main features of the dissipation structure (Sobal et al. 1998; Ma and Guan 2003; Liu et al. 2011; Feng et al. 2010). And the climatic system is a dissipative system with dissipative property and usually considered as a chaotic nonlinear dynamical system (Millán et al. 2010). Furthermore, for the atmospheric motion, it is impossible to use linear kinetic equation to make description, the reason is that the climatic system is nonlinear, dominated by the deterministic laws (Palmer 2006; Ashkenazy et al. 2003; Wunsch 2003). But there has an inherent correlation behind the variation of these features for the humidity processes with multifractal and long memory, which are not simply caused by the external random factors. And the variation itself also have a complex nonlinear, which may be a progressional process from some factors of influencing humidity process (Schumm and Lichty 1965; Griggs and Noguer 2002; Peñuelas and Boada 2003), such as the geographical distribution of the Tarim River Basin, deserts with enlarging trend, air movement path, rainfall distributed no-proportionally and thermal variation that caused by seasonal effect of the subtropical high of Western Pacific and the westerlies over East Asia. The lasting existence of these elements may play a leading role. In addition, there are small and large amplitude fluctuations in the humidity processes, but the small are more than the large, which are originated from the same mechanism. They are all concrete manifestation of self-organized criticality (SOC) (Bak et al. 1987, 1988; Bak and Paczuski 1993; Dessai and Walter 2000). Liu et al. (2013) had proved that the temporal variation of humidity process in the Tarim River Basin is a very obvious example of a SOC process, and Vattay and Harnos (1994) also showed the same results in studying humidity process of Hungary during the period 1963–1988. And using a cell dynamical system model for atmospheric flows, Selvam (1990) showed that it exhibits long-range spatial and temporal correlations, signatures of SOC. Thus, dissipation, SOC, nonlinearity, randomness and the factors of influencing humidity process consist of the conditions of forming the multifractal structure (Glisson and James 2002; Little et al. 2007; Yu et al. 2011; Liu et al. 2011). From which we can draw the conclusion that the dissipation, nonlinearity and randomness of climatic system are just the root causes of humidity processes exiting multifractal and long memory.

The climate system often exhibit a hierarchical structure with self-similar behavior in each level, which presents characteristics of chaos and good memory (Payne and Mansfield 1973; Nicolis and Nicolis 1991; Bodri 1994; Atmanspacher et al. 1988). Moreover, the complexity for the change of atmospheric motion depends on its various spatial and temporal scales, and the observed humidity processes also may be the result from superposition of spatial and temporal scale changes (Feng 2001). It is difficult to forecast the occurrence of outbursts and emergence precisely (Xu et al. 2009a, Xu et al. 2009b).

The multifractal and long memory for the humidity processes are closely related to the geographical location of the Tarim River Basin. Due to the special geographical environment and climate feature of the Tarim River Basin, the relative humidity is influenced by many factors, such as geographical factors, climatic factors, topographic factors and soil factors (Wang et al. 1997; Yang et al. 2012; Yeşilırmak 2013), which become increasingly complex from west (north, low) to east (south, high). Some special related properties will become more stable for humidity process. Thus, the multifractal characteristics is more complicated and stronger, and long memory becomes remarkable for the processes. To be specific, latitude (longitude) span is about 9° (13°) for 23 meteorological stations over the Tarim River Basin; therefore, latitude effect is not significant compared with longitude. While for elevation, influencing factors, especially for climatic factors such as temperature, solar radiation, and precipitation, would change obviously as the elevation increasing. In other words, elevation effect is likely to appear an butterfly-effect, which means that a small variation for influencing factors could result in the great humidity changes. This also may be the main causes of multifractal and long memory, which exhibits a strengthening trend with the increase of longitude and latitude, and decreasing trend with elevation rising. However, the mechanism of spatial variation still needs further study.

5 Conclusions

In this work the spectrum analysis, multifractal analysis and cokriging method were applied to detect multifractal and long memory of humidity processes in the time scale of below 100 days for 23 meteorological stations in the Tarim River Basin. The main results may be summarized as following:

(1) Spectrum analysis reveals that humidity processes are well characterized by $1/f$ noise and self-affine type fractal behaviors. In the time scale of below 100 days, humidity processes present multifractal and long memory. By using multifractal method, we calculated three parameters of multifractal spectrum $\Delta\alpha$, $f_{\max}$, and θ. According to the slopes of $\Delta\alpha, f_{\max}$ and $|\theta|$, we found that the degree of multifractality of humidity process shows an increasing trend with the increase of longitude and latitude of 23 stations, but decreasing trend with the elevation rising via kriging and cokriging method. While for the three factors, there are differences in degree of influence on the degree of multifractality. The most obvious factor is longitude, next is elevation and latitude is the last.

(2) A larger positive θ value for each station's humidity process indicates a left-skewed multifractal spectrum and a relative dominance of lower fractal exponents corresponding to more smooth-looking structures. This shows that small amplitude fluctuations of time series play a leading role in humidity processes, which is mostly ascribed to the humidity process with long memory.

(3) There has an inherent correlation behind the variation of dissipation, nonlinearity for the humidity processes with multifractal and long memory, therefore, they are not simply caused by the external random factors. And the variation itself also have a complex nonlinear, which may be a progressional process from some factors of influencing humidity process. In addition, there are small and large amplitude fluctuations in the humidity processes, but the small are more than the large, which are originated from the same mechanism. They are all concrete manifestation of self-organized criticality (SOC). Thus, we can draw the conclusion that the dissipation, nonlinearity and randomness of climatic system are just the root causes of humidity processes exiting multifractal and long memory.

(4) According to the FD process, the estimated scaling parameter δ values of humidity processes range from 0 to 0.5, and their FD processes exhibit stationary long memory dynamics, except for Kalpin and Aksu station showing non-stationary long memory. Adopting kriging and cokriging methods, we investigated that on the whole, the δ values increased with the longitude and latitude increasing, which indicates that the bigger the longitude and latitude is, the longer the memory of humidity process is, but the higher the elevation is, the shorter the memory of humidity process is.

Finally, we pointed out the following caveats. Although we don't expect that it can influence the conclusions of this study, the unequal time period of the relative humidity data sets might affect the accuracy of the parameter estimates. There are also other climate and landscape factors besides geographical factors, which affect multifractal and long memory properties of humidity process; however, much more work remains to be done to fully understand and characterize their impacts. We do not want to overemphasize this discussion on the transitional areas because the number of stations in these areas is too limited. Of course, deeper research is possible, and highly desired on subsequent studies.

Acknowledgments This work was supported by National Basic Research Program of China (973 Program; No: 2010CB951003), and the Director Fund of the Key Lab of GIScience of the Education Ministry PRC.

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