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An analyses of long-term precipitation variability based on entropy over Xinjiang, northwestern China

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Abstract

Precipitation is one of important supply of water resources in arid and semiarid region of northwestern China, ~~plays the~~ vital role to maintain the fragile ecosystem. The entropy method was employed to detect the spatial variability of precipitation over monthly, seasonal and annual timescales in Xinjiang. The spatial distribution of precipitation variability was significantly affected by topography, and was zonal on annual, seasonal and monthly. The non-parametric Mann-kendall test was used to analyze the change point of trend. A precipitation concentration index has been developed categorize the variability of annual precipitation. The summer variability contributed less than that of other seasons to the annual variability. There is a great difference in the contribution of the different monthly variabilities to the annual mean variability in different years. Overall, the variability of precipitation was shown increase north of Xinjiang, especially in mountainous regions where the increase was statistically ($P = 0.05$) significant. South of the Xinjiang, the variability increased only slightly, consistent with the distribution of precipitation.

1 Introduction

Precipitation processes represent the transfer of mass and energy from the atmosphere to the surface components of the hydrological cycle (Brunsell, 2010), and precipitation is one of the most important variables in the global hydrological cycle, for meteorology, climate and for applications (Prigent, 2010; Mehrotra and Sharma, 2007). Understanding the spatial and temporal variability of precipitation is important not only to weather forecasters and climate scientists, but also to a wide range of decision makers, including hydrologists, agriculturalists, emergency managers, and industrialists (Ebert, 2007; Brunsell, 2010). In modern times, estimates of the variability and distribution of daily, monthly and annual precipitation are critical inputs to a variety of ecological and hydrological models, including vegetation models, water balance

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models, water quality models, and crop production models. With the widespread use of modeling as a predictive and investigative tool in a number of fields, the number and complexity of models has increased greatly (Daily, 1994; Adger and Kelly,1999; De Lima, 2002; Mendelsohn et al., 2006; Byg and Salick, 2009).

Precipitation is one of the most important indicators of the availability of water resources in a region. Changes to precipitation due to, for example, climate change, may vary greatly from region to region (Houghton et al., 2001; Symeonalcis et al., 2009). However, the strong spatial and temporal variability of precipitation in a region can directly affect water resources, thereby affecting the amount of river runoff, the supply of drinking water, the generation of water power or waste treatment (Socrates, 2006). Furthermore, variability and distribution of precipitation are affected by topography and its relationship to wind direction. So slope, aspect and geography all play a role in local regions, more so when the region is mountainous, (Barry and Gregory, 2000; Vaes, 2005; Colombo et al., 2007).

The arid area in northwestern China is an agricultural-pastoral transition zone. The variability of precipitation is a central characteristic of this region (Romero et al., 1998; Batisani and Yarnal, 2009). The ecological environment there is sensitive to climate variation, particularly to precipitation change. Because of complex terrain, rain-gauge observations are limited, being sparse in many important regions, and practically nonexistent in remote areas. This makes the assessment and analysis of precipitation variability difficult, particularly if precipitation trends are the potential impacts of climate change. Thus, knowledge of precipitation and its temporal and spatial variation is vital for assessment of the potential availability of water resources in arid regions.

Consistent with the likely local impacts of changes in climate in the local North Carolina area of the USA, Boyles and Raman (2003) used linear regression analysis to study precipitation trends there. The results show that precipitation seems to have increased, especially the fall and winter seasons. They used the non-parametric Mann-Kendall trend analysis test, which is widely used for the assessment of hydrometeorological time series. This method has the advantage that it is not affected by the actual distribution of the time series being analyzed, e.g. temperature and precipitation, (Yue et al., 2002; Cannarozzo et al., 2006; Abdul et al., 2006; Chen et al., 2007 and 2009; Hamed, 2009; Li et al., 2010; Xu et al., 2010).

Other authors have successfully applied geomorphological tools (e.g. "Wavelet") to climate analysis. The climate time series is decomposed into a time-frequency space, and then it is the time-frequency characteristics that are analyzed and forecasts made on that basis, (Daubechies, 1990; Polikar, 1999; Pisoft et al., 2004; Simth et al., 1998; Yan et al., 2004; Özger et al., 2010; Nourani et al., 2009; Partal and Küçük, 2006).

In recent years, an Entropy Theory approach has been adopted as an attractive way of evaluating disorder based on spatial and temporal precipitation variability patterns. It has been used in a wide range of applications assessing variability in the hydrological variables (Koutsoyiannis, 2005; Delsole and Tippett, 2007; Mishra et al., 2009). The Entropy Theory was developed to assess the flow of information along communications transmissions by Shannon (1948a, b). This approach is employed here to investigate the variability of precipitation in Xinjing, northwestern China. The results of this work will be useful to inform the management of water resources in arid regions generally, and Xinjing in particular.

2 Materials and methods

2.1 Study area

The study area is focused on Xinjiang, which is located between 73–96° E and 34–49° N. It is an arid area of northwestern China. The area is 1.66 × 106 km^2, accounting for about one-six of the national land area (Fig. 1). The terrain is quite complex, with the sierra and the basin systems interacting. North are the Altay Mountains with a maximum elevation of 4373 m, and South the Kunlun Mountains with a maximum elevation of 8611 m. In the middle of the region are the Tianshan Mountains, with a maximum elevation of 7455 m, that divide Xinjiang into two parts: the Tarim basin to the South,

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and the Songorine Basin to the North. Xinjiang has a classic continental type climate being in the Eurasia hinterland, far away from oceans (the source of water vapor), and in the rain shadow of high mountains. In terms of temperature, the northern area is colder than the South, and the West lower than the East. Of course, the plains are warmer than the highlands. Precipitation is scarce and unevenly distributed, with an average annual mean of 150 mm (Fig. 2). This annual mean disguises great variability with that of the North being 206 mm, and that of the South being only 59 mm. The windward slopes of Tianshan Mountains may reach 500–700 mm. The precipitation mainly occurs in summer (June–August) when 50–60% of the annual precipitation falls.

2.2 Data collection

There are 54 meteorological stations in the study area, and they are not distributed particularly well (Fig. 1). There are 23 stations at an elevation below 1000 m, 27 between 1000 m and 2000 m, 4 above 2000 m, and only 2 above 3000 m. The precipitation data records for 1960–2008 were obtained from the China Meteorological Administration (CMA) observation archives. This period represents the longest consistent time-series in those archives. In this work, the entropy approach has been applied to the monthly, seasonal and annual series.

2.3 Entropy approach

Since the development of the Entropy Theory (Shannon, 1948) and the principle of maximum entropy (Jaynes, 1957a, b), it has been widely applied in the hydrological and environmental sciences (Singh, 1997). It provides a measure of dispersion, uncertainty, disorder and diversification of precipitation intensity and/or precipitation amount (Kawachi, 2001). In this study, it is used to investigate the spatial and temporal variability of precipitation, and is defined as follows:

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$$H = -\sum_{i=1}^{n} p_i \log_2 p_i \quad (1)$$

where p_i is regarded relative frequency as an accurrence probability for the precipitation on the ith month, and therefore H measures the temporal variability of monthly precipitation over a year, $(0 = < H < = \log_2 n)$.

If annual precipitation series of n years are available at each rain-gauge, then better estimates of the annual entropy can be obtained by averaging the entropy values as:

$$\overline{H} = \frac{1}{n} \sum_{i=1}^{n} H_i \quad (2)$$

where $\overline{H}$ is the mean entropy.

2.4 Entropy-baed variability

Variability is defined as the difference between maximum possible entropy and the entropy obtained by calculation from individual series. It is expressed by the disorder index:

$$\mathrm{DI} = \log_2 n - H \quad (3)$$

where n is the length of series, H is the entropy obtained by Eq. (1).

The higher the disorder index, the higher the variability. The spatial and temporal variability can be compared based on the mean disorder index, calculated as:

$$\overline{\mathrm{DI}} = \frac{1}{m} \sum_{i=1}^{m} \mathrm{DI}_i \quad (4)$$

2.5 Precipitation concentration index

In order to analyze the heterogeneity of precipitation and the relationship between variability and distribution of monthly precipitation, the precipitation concentration index (PCI) is used in this study, (De Luìs, 1997). The PCI is described as:

$$\mathrm{PCI} = 100 \times \frac{\sum_{i=1}^{12} p_i^2}{\left(\sum_{i=1}^{12} p_i\right)^2} \tag{5}$$

where p_i is the precipitation in the ith month.

Generally, the lower the annual precipitation, the more variable is the monthly precipitation – i.e. a greater proportion of the annual precipitation is delivered in any one discrete event. Therefore, the greater the value of the PCI, the more variable is the monthly precipitation, Olive (1980).

2.6 Change point analysis

The non-parametric approach proposed by Mann (1945) and Kendall (1975) derived the test statistic distribution. This approach allowed analysis of the time series, identifying significant trends and the location of change point(s) in the mean of a time series when the exact time of the change is unknown. This approach is unaffected by the actual distribution of the data and is robust to missing data.

For a sequence $x_1, x_2, \ldots x_n$ of an annual mean time series, the number of $x_j > x_k$ (j=1, 2...n; k = 1, 2...(j-1)) is counted and denoted by n_j at each comparison. The test statistic t_j is given by:

$$t_j = \sum_{1}^{j} n_j. \tag{6}$$

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The mean and variance of test statistic are

$$E(t) = \frac{n(n-1)}{4}, \tag{7}$$

and

$$Var(t_j) = \frac{j(j-1)(2j+5)}{72} \tag{8}$$

The sequential values of the statistic $u(t)$ are then calculated as

$$u(t) = \frac{t_j - E(t)}{\sqrt{Var(t_j)}} \tag{9}$$

Using the same method, the values of $u(t)$ are calculated from the end of the series. Hence, the sequential version of the Mann-Kendall statistic can be considered an effective way of detecting the change point.

2.7 Approach

The variability of precipitation is measured using the mean entropy and disorder index. The analysis is performed for all available annual precipitation sequences. Then, the mean entropy obtained over the years of interest is considered the mean annual entropy at the observation station. The mean annual entropy, thus obtained, for the observation stations densely scattered throughout the study area are employed to construct map with iso-entropy contours that delineates precipitation characteristics.

In order to investigate the variability of annual, seasonal and monthly precipitation, the mean entropy is calculated for individual stations respectively for each time series. The deviation of individual entropy represents the variability associated with the each station.

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3 Results and discussions

3.1 Variability of annual precipitation

The spatial distribution of mean entropy [inverse distance weighted, (IDW)], is shown in Fig. 3. The value of the mean entropy ranges between 1.96 and 3.32. It is noteworthy that the distribution of the annual precipitation over Xinjiang has regional characteristics with zones showing an increasing pattern from south to north. Mountainous regions such as Tianshan Mountains and Altai Mountains are clearly visible. It is clear that the distribution of the variability of mean entropy is consistent with the provenance of precipitation. Overall, the variability is high in southern relative to northern Xinjiang. The Tarim basin has the highest variability, coincident with the lowest precipitation. Both the Turpan Basin and Hami Basin also have very variable mean entropy, again consistent with the very low precipitation provenance in these areas. Areas with low variability are in northern Xinjiang, where there are few mountainous regions.

The analysis of the relationship between the disorder index and elevation, longitude, and latitude is shown in Fig. 4. The correlation between the disorder index and latitude is significant ($P = 0.05$), with a correlation coefficient of 0.8. However, the correlation with either elevation or longitude is not significant. There is a weak trend of variability diminishing with the increasing elevation when the elevation is less than 1500 m. These results are consistent with the distribution of annual mean precipitation, and the pattern of spatial variability of precipitation increasing from south to north. In summary, the variability of precipitation is mainly determined by topography.

3.2 Variability of seasonal precipitation

To examine seasonal variability, the mean disorder index was also calculated for all stations shown as Fig. 5. For eighty percent of stations, consistent with precipitation, the variability is greater for winter than for the other seasons. In contrast, for the twenty percent of stations that lie on the northern slopes of the Kunlun Mountains, the variability

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is greatest for that in the fall. Thus winter and fall variability (and precipitation) is the greatest contributor to annual variability (and precipitation). This pattern of the winter variability contributing more to the annual variability holds for most regions, except for the Tarim Basin, where it is the fall variability that contributes most. The Tianshan Mountains form dividing line – the seasonal variability of areas north of this range is smaller than those to the south. Although the variability of annual precipitation is consistent for all seasons, it is perhaps better described in Xinjiang by a model that reflects the division of North and South.

3.3 Variability of monthly precipitation

The basic statistics (minimum, maximum, mean and standard deviation (S.D.)) selected for the calculation of the disorder index are summarized in Table 1. The minimum value of disorder index is 0.057 in June and maximum value is 3.398 in October. It is clear that from May to September, the precipitation contributes less variability over the year than in the other months, whereas precipitation in March, October and November contributes much. As shown in Fig. 6a, for high altitude stations, the variability of December and February dominated in winter, January seems to contribute less to the variability of winter. For most of the high altitude stations, the variability of spring is dominated by March compared to April or May (Fig. 6b). It is obvious that the variability of summer is the least of all the seasons (Fig. 6). August seems to be contributing more to the variability of summer than the other months (Fig. 6c). The variability of fall significantly affects the annual variability, and October and November are dominant, though no particular month dominates all stations as shown in Fig. 6d.

3.4 Correlation between mean disorder index (DI) and the PCI

The PCI shows the relationship between variability and distribution of monthly precipitation. The distribution of the PCI shows distinct zones over the whole study area (Fig. 7). The range of the PCI in this work is between 12 and 34. Values below 20 (e.g.

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North of Tianshan Mountains) indicates significant seasonality in precipitation distribution. Whereas a value of the PCI greater than 20, (e.g. South of Tianshan Mountains and the Tarim Basin), indicates extraordinary monthly variability in precipitation amount. Overall, the distribution of the PCI is basically consistent with a mean entropy for annual precipitation, and a correlation coefficient of 0.99 shown in Fig. 8.

3.5 Change point test

The change point of annual precipitation is tested using the Mann-Kendall method. For clarity, only one station (of the total 54 stations), is represented in detail (Fig. 9). Horizontal dashed lines correspond to confidence limits at the 5% significance level. It can be seen that two functions begin to diverge in 1984, indicating the change point occurred then. Consistent with this, it should also be noted that meaningful long term trends begin to be increasingly apparent from the late 1980s. In summary, a significant trend change occurred in the early 1980s at 22 stations that are mainly located along Tianshan Mountains. Then, in the late 1980s the same trend occurred at a further 19 stations located along the two basins on each side of the Tianshan Mountains. However, for 13 stations located along northern slopes of Kunlun Mountains no trend is apparent.

4 Conclusions

In this paper, an entropy-based method is discussed for precipitation over Xinjiang, northwest China. This method has been used to investigate the variability of precipitation on the annual, seasonal and monthly timescales. The following conclusions are drawn from this study: (1) The distribution of annual precipitation is obvious zonal with the increasing pattern from south to north, significantly dependent on topography. (2) The variability of annual precipitation based on mean entropy seems to be less than seasonal. The variability of winter and fall contributes more to the annual variability than

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spring or summer. Summer contributes least to the annual variability. (3) Overall, the seasonal distributions of variability based on the disorder index are similar, and show the same trend with a decrease from south to north over Xinjiang. (4) Although the PCI has a good relationship with the annual variability overall, the annual variability is particularly affected by that of the individual months (especially February, March, November and December). (5) A significant trend change occurred in the early 1980s in mountainous regions, and in basin regions in the late 1980s.

The results of this study could be used as a reference for sustainable development in northwest China, providing a basis for the planning and management of water resources, and for the protection of eco-environment system of arid regions in Xinjang.

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Table 1. Statistical of disorder index for monthly.

Month	Min	Max	Mean	Std Dec
Jan	0.133	1.751	0.708	0.47
Feb	0.171	2.435	0.891	0.649
Mar	0.147	2.664	1.012	0.754
Apr	0.151	2.51	0.852	0.608
May	0.071	1.386	0.546	0.351
Jun	0.057	0.836	0.413	0.182
Jul	0.083	0.85	0.386	0.177
Aug	0.086	1.484	0.484	0.27
Sep	0.125	2.169	0.698	0.511
Oct	0.142	3.398	1.064	0.832
Nov	0.145	3.117	1.221	0.958
Dec	0.168	2.058	0.903	0.657

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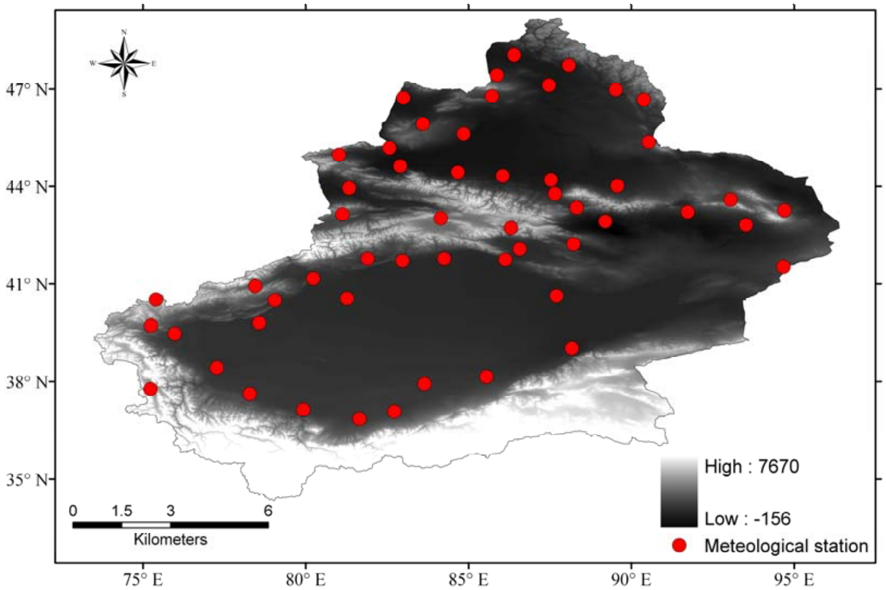

Fig. 1. Location of study area and the distribution of meteorological stations.

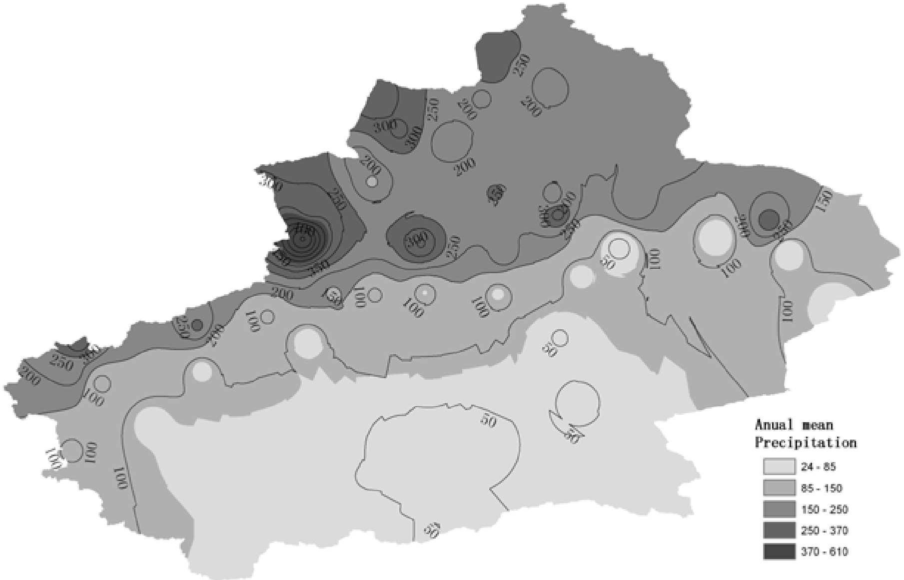

Fig. 2. The distribution of annual mean precipitation.

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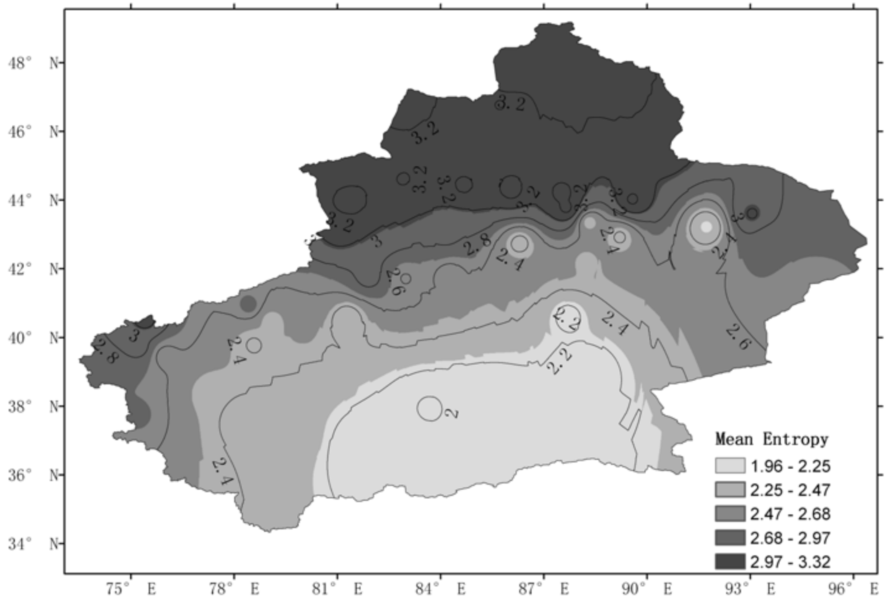

Fig. 3. The distribution of variability of annual precipitation baed on the mean entropy.

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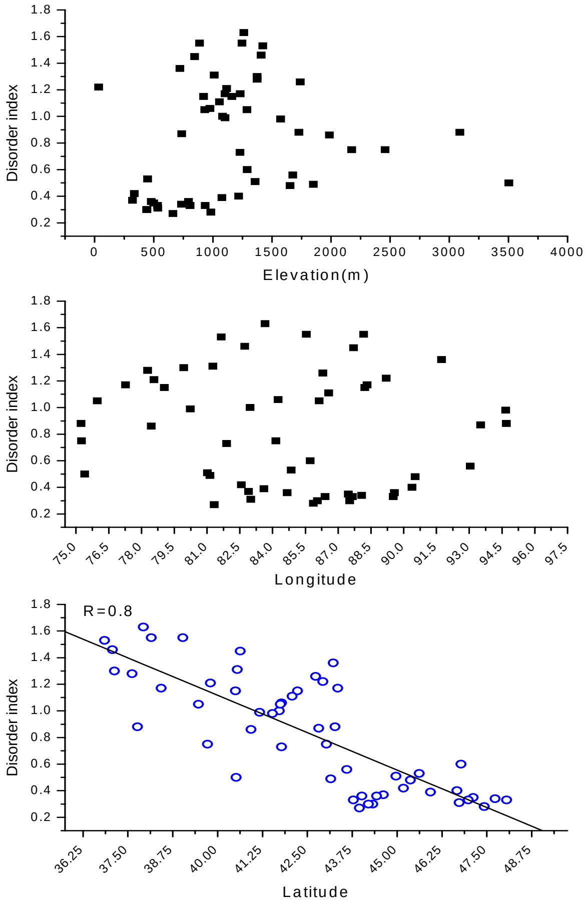

Fig. 4. Relationship between disorder index and elevation, disorder index and longitude, disorder index and latitude.

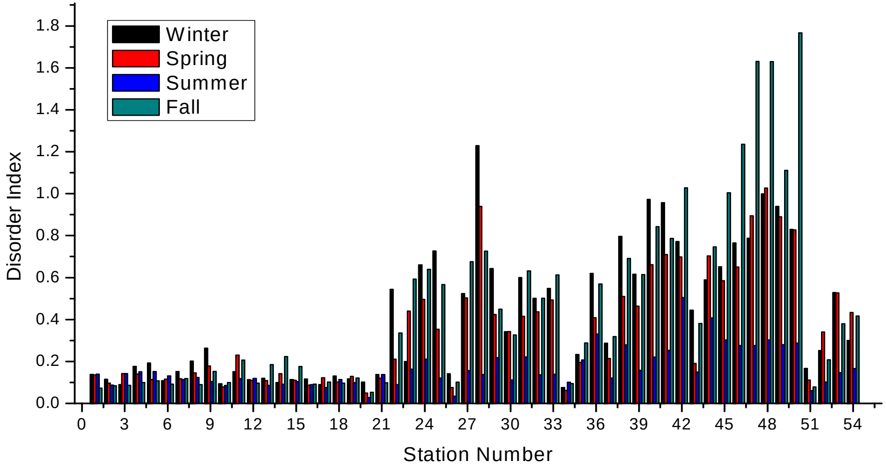

Fig. 5. The distribution of variability of seasonal precipitation based on mean disorder index.

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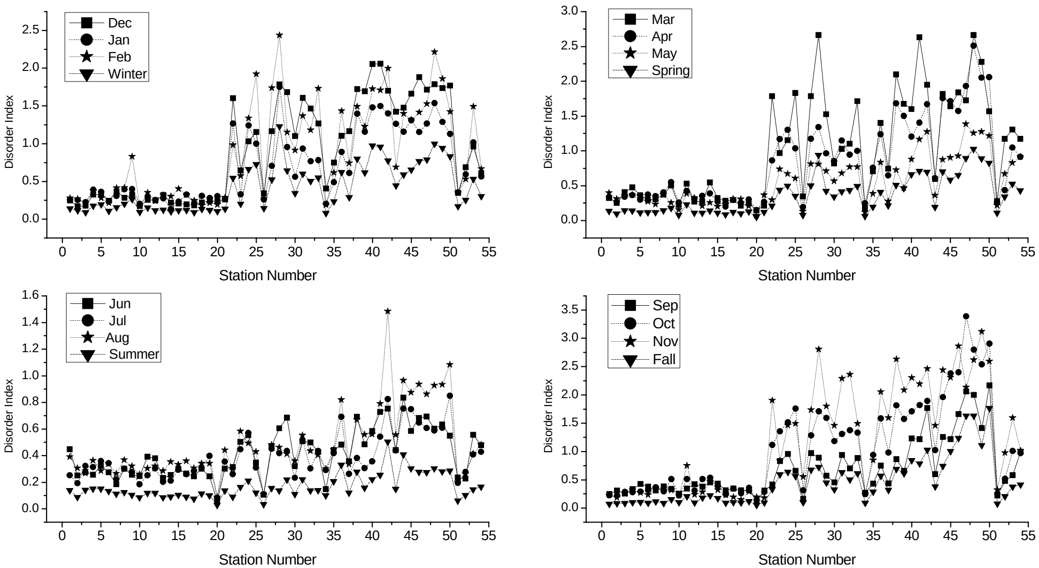

Fig. 6. The distribution of variability of monthly precipitation based on disorder index.

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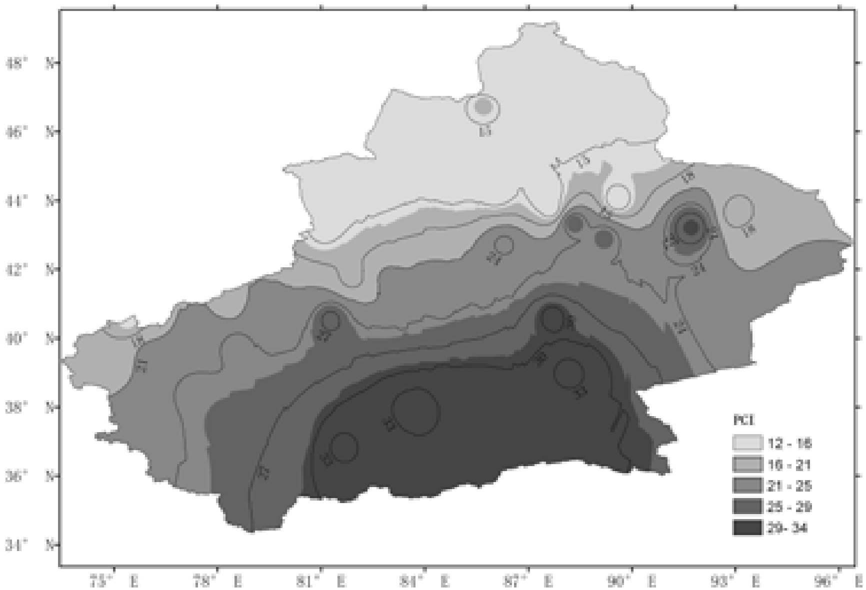

Fig. 7. The distribution of PCI.

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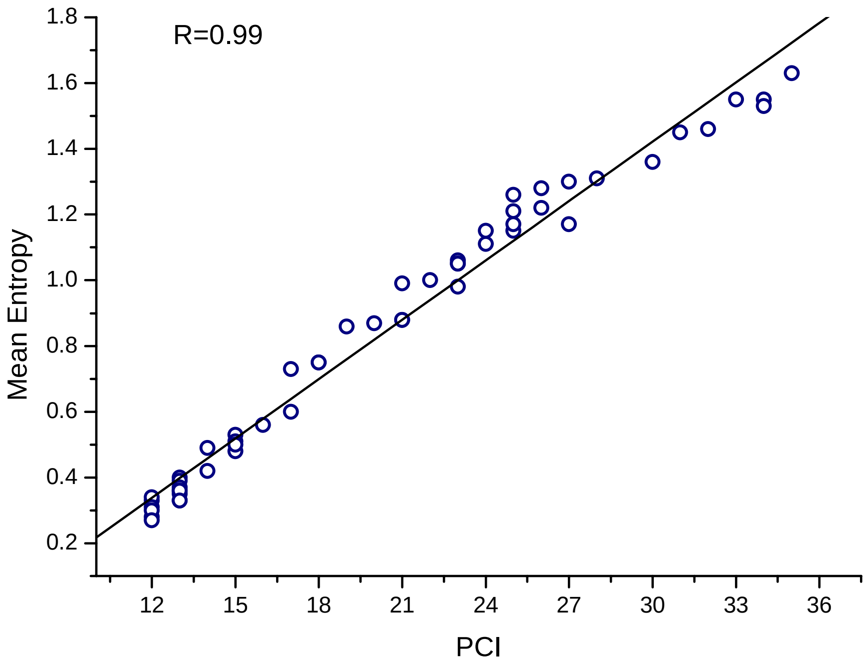

Fig. 8. Relationship between mean entropy and prcipitation concentration index.

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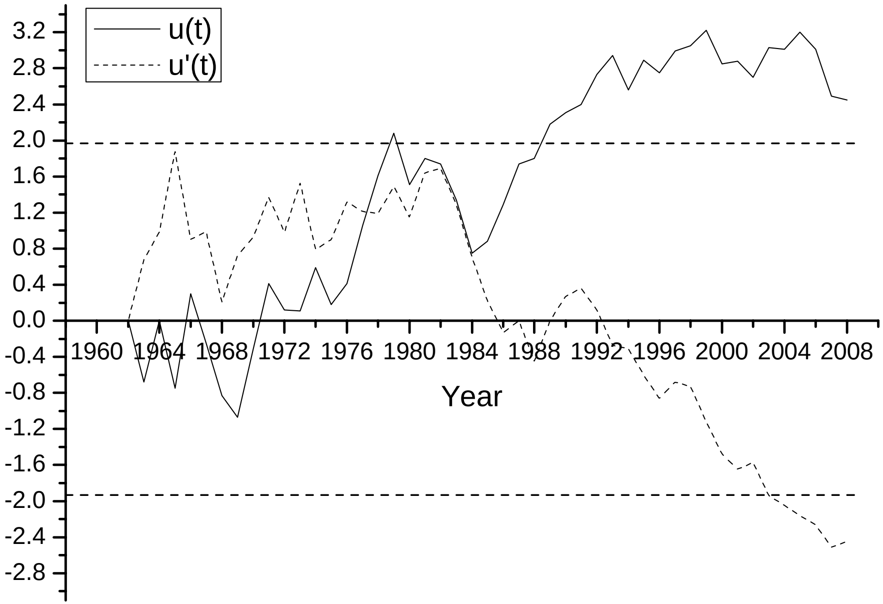

Fig. 9. Mann-Kendall test for detecting the change point in the annual precipitation.

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