Spatial and Temporal Variability of Precipitation and Dryness/Wetness During 1961–2008 in Sichuan Province, West China

Jin Huang · Shanlei Sun · Yan Xue · Jinjian Li · Jinchi Zhang

Abstract Changes in precipitation exerts a huge impact on human beings and it is of vital importance to study the regular pattern of meteorological and hydrological factors. In order to explore the changing patterns of precipitation in Sichuan province in west China during 1961–2008, several precipitation related indices were analysed by the Mann–Kendall test. For monthly precipitation, significant increasing trends are mainly found during January, March and June, while significant decreasing trends mostly are observed during July, September and October. Most of extreme precipitation indices are decreasing. Especially the annual total precipitation in wet days and maximum number of consecutive wet days show significant negative trends. Furthermore, the spatial and temporal variation of dryness/wetness has been assessed by Standardized Precipitation Index (SPI) and principal component analysis (PCA) on 24-month time scales. The results demonstrated noticeable spatial patterns with several sub-regions characterized by different trends: a remarkable dry tendency prevails in central and east Sichuan, while the other areas are dominated by a wet tendency.

Keywords Sichuan · China · Precipitation · Dryness/wetness

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1 Introduction

Global warming and climate change significantly altering various environmental variables in many countries around the world (Yavuz and Erdoğan 2012). It was believed that projected global climate changes have the potential to alter precipitation patterns. Changes in precipitation patterns directly affect hydrology, agriculture, and ecosystems, water resources management. Temporal and spatial variability of precipitation around the world are receiving increasing attention, for the information about changing patterns of precipitation is the starting point for accurate assessment of water resources, flood and drought control, understanding climate change, and efficient water management (Wang et al. 2011). Recently, the analysis of changes in precipitation amounts, extreme precipitation events and drought/wetness episodes based on historical observations are used by many researchers to investigate the changing patterns of precipitation.

Long-term trends of precipitation amounts have been analysed by many researchers in various regions. The main areas where decreasing trends have been observed are Greece, the Canadian Prairies, Bologna and the island of Sicily in Italy, western and southern Turkey and the Indian Himalayas, while increasing trends in annual precipitation have been observed in the USA, eastern and northeastern Australia, South Africa and the UK (Huang et al. 2013a). In China, detections of trends in precipitation have been widely conducted in different regions, and the results revealed trends in precipitation were uneven both in space and time. Changes in precipitation extremes are likely to have greater immediate impact on human society than any likely changes in precipitation amount. Many studies have shown that the changes in extreme precipitation indices around the globe exhibited strong regional-scale variability. In China, much work has been also done on extreme precipitation indices. In addition, the analysis of changes in drought is also very important. Drought is a natural hazard that results from a deficiency of precipitation from expected or "normal" which is insufficient to meet the demands of human activities and the environment (Tabari et al. 2013). A relatively larger number of meteorological drought indices have been developed to date (Banimahd and Khalili 2013; Bazrafshan et al. 2014). One of the most popular drought indices which has also been widely used, is the Standardized Precipitation Index (SPI) developed by Mckee et al. (1993). In China, the SPI has been applied for accessing spatial and temporal variation of dryness/ wetness in some important regions, since it is simple and commonly used, taking only rainfall into account (Huang et al. 2014).

Sichuan is the most important agricultural province with abundant natural resources in west China, which plays a key role in the sustainable development of the economy and ecology of this region. However, frequent droughts and floods in this province have hindered its economic development and resulted in severe environmental problems. Being affected by the uneven spatial–temporal distribution of precipitation, man-made destruction of the natural environment, complex landform characteristics, and other factors, Sichuan is one of the provinces with the most serious drought-flood disasters in the Yangtze River basin (Hu et al. 2009; Liao et al. 2012). Thus, the study of precipitation changes in this province is increasingly being paid more and more attention (Hu et al. 2009; Chen et al. 2010; Zhang and Ma 2011; Zhou et al. 2011; Liao et al. 2012). However, there is no comprehensive information on precipitation amount, precipitation extremes and drought/wetness episodes in Sichuan province, west China. Therefore the key objectives of this study were to systematically investigate long-term trends of precipitation in both space and time using historical observed daily precipitation from 1961 to 2008 at a monthly time scale, and to detect the trends of extreme precipitation and drought/ wetness patterns using a selection of precipitation-related indices. Such a study may provide a

valuable database for the management and planning of water resources under the backdrop of globe warming in Sichuan province.

2 Study Region and Data

2.1 Study Region

Sichuan province (97° E–109° E, 26° N–35° N), with an area of 48.14×10^4 km^2, is the fifth largest province of China. Sichuan is located in western China and is the important joint of southwest, northwest and central China. Sichuan is strongly impacted by the Southeast Pacific Ocean Monsoon and the Southwest Indian Ocean Monsoon. The average temperature in January is 5–8 °C, the average temperature in July is 25–29 °C and the annual average temperature is 15–19 °C. The average annual precipitation is 500 to 1,200 mm, and the precipitation in the rainy season (from May to October) takes up 70 % to 90 % of the total annual precipitation. This province lies in the transitional zone between Qinghai-Tibet Plateau and the eastern plains and therefore has complex and diverse climates with rather obvious regional differences and vertical changes. There are distinct disparities between east and west Sichuan as well. Sichuan is generally divided into three major climate zones: humid subtropical climate zone of Sichuan Basin, sub-humid and subtropical climate zone of southwest Sichuan's mountainous regions, and alpine climate zone of high mountains and plateaus of northwest Sichuan. The meteorological disasters of Sichuan happen in various forms with a high frequency and large scope, which are mainly droughts, rainstorms, floods and cold weather.

2.2 Data

There are total 158 surface meteorological stations in Sichuan province. On the basis of record length, 109 stations with 48-year records were selected as candidate stations. The raw data sets of daily precipitation amounts for the period 1961–2008 at the 109 candidate stations were collected from the National Meteorological Information Center of China. We use the RclimDex software package (http://etccdi.pacificclimate.org/software.shtml), to "clean up" the daily precipitation data. The process of "cleaning up" including: (1) identifying errors in the precipitation data, such as precipitation value below 0 mm; (2) searching for outliers, where we choose three standard deviations as the threshold for a finer quality control of the data; (3) using the generalized data plot in RclimDex to visually inspect the data to further identify outliers and a variety of other problems that may cause error or bias in analyzing changes in the seasonal cycle or variance of the data; (4) using RHtestsV3 (Wang and Yang 2010) to detect artificial shifts that could exist in a time series. After rejecting 11 stations with inhomogeneous series, 98 stations were finally selected in this study. The locations of the 98 stations are plotted in Fig. 1.

3 Methodology

In this study, the temporal trends and spatial distributions of monthly precipitation and several extreme precipitation indices in Sichuan province during 1961–2008 are examined by the Mann–Kendall test. Spatial and temporal variation of dryness/wetness has been assessed by means of Standardized Precipitation Index (SPI), and the principal component analysis (PCA) is applied to the SPI series. The detailed principles of calculating indices and methods are described in the following text.
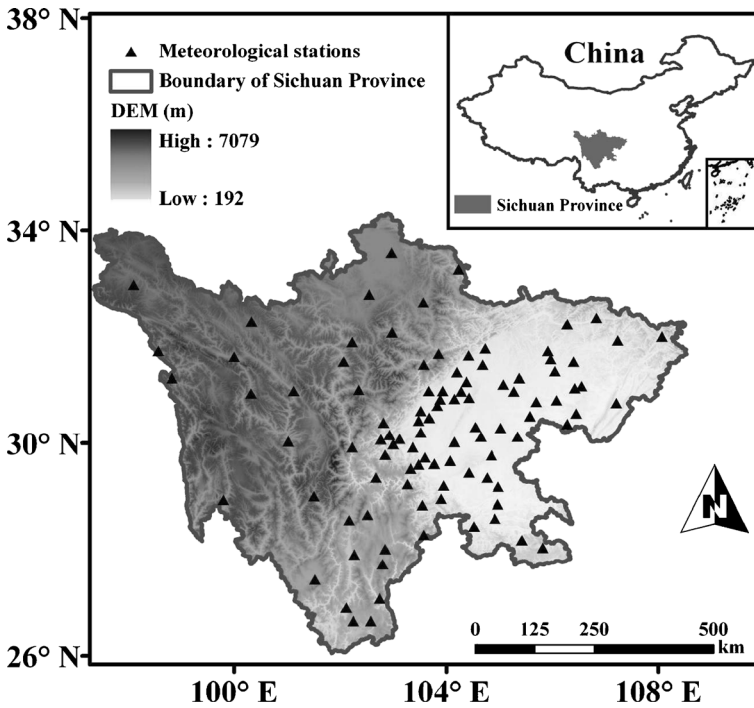
Fig. 1 The meteorological stations used in this study and location of Sichuan province, China

3.1 Extreme Precipitation Indices

The ETCCDI defined 27 core extreme indices based on daily temperature and precipitation amount. Exact definitions of all the indices are available from the ETCCDI website. In this study, only the extreme indices derived from daily precipitation were analysed. Altogether, six extreme indices are listed in Table 1. An R-based program, RClimDexV3 developed at the Climate Research Branch of the Meteorological Service of Canada and available from the ETCCDI Website (http://etccdi.pacificclimate.org/software.shtml), is applied to calculate these six extreme indices.

Table 1 Definitions of the extreme precipitation indices

Indices	Description
Max1d	Annual maximum 1-day precipitation
Max5d	Annual maximum 5-day precipitation
CDD	Maximum number of consecutive dry days
CWD	Maximum number of consecutive wet days
R95pTOT	Annual total precipitation when RR>95th percentile of precipitation on wet days during the study time series (precipitation fraction due to very wet days)
PRCPTOT	Annual total precipitation in wet days

A wet day is defined when daily precipitation amount ≥1 mm and a dry day when daily precipitation amount <1 mm

3.2 Standardized Precipitation Index (SPI)

The standard precipitation index (SPI) was computed by including the long-term monthly precipitation data at a given period (McKee et al. 1993). The SPI can track dry/wet events on different time-scales, i.e. 1-, 3-, 6-, 12-, and 24-months, and is flexible with respect to the period chosen. Among users there is a general consensus about the fact that the SPI on shorter time scales (say 3 and 6 months) describes drought events affecting agricultural practices, while on the longer ones (12 and 24 months) it is more suitable for water resources management purposes (Razlei et al. 2009). In this paper, results concerning the 24-month time scale (SPI-24) are discussed. Zhao et al. (2011) has provided a brief description of the computation of SPI as below. The calculation involves fitting a Gamma probability density function to a given frequency distribution of precipitation totals for a station. The Gamma distribution is formulated as:

$$g(x) = \frac{1}{\beta^\alpha \tau(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad \text{for } x > 0 \tag{1}$$

where α and β are the shape and scale parameters, respectively, x is the monthly precipitation sum ($x>0$) and $\tau(\alpha)$ is the gamma-function. Maximum likelihood solutions are used to estimate the shape parameter α and scale parameter β. And then, the resulting parameters are used to calculate the cumulative probability of an observed precipitation event for the given month. Since the gamma-function $G(x)$ is undefined for x equal 0 and the precipitation record may contain zero values, the cumulative probability becomes:

$$H(x) = q + (1-q)G(x) \tag{2}$$

where q represents the probability of zero precipitation, and $G(x)$ is the incomplete gamma function, representing the cumulative distribution of $g(x)$. The probability $H(x)$ is then transformed to the standard normal random variable Z according to the following approximation.

$$Z = SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), \quad \text{for } 0 < H(x) \leq 0.5, \tag{3}$$

$$Z = SPI = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), \quad \text{for } 0.5 < H(x) \leq 1, \tag{4}$$

where

$$t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)}, \quad \text{for } 0 < H(x) \leq 0.5,$$

$$t = \sqrt{\ln\left(\frac{1}{(1-H(x))^2}\right)}, \quad \text{for } 0.5 < H(x) \leq 1, \tag{6}$$

and $c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$ and $d_3 = 0.001308$

Once the SPI is calculated, the intensities of dry and wet events are classified as shown in Table 2.

Table 2 The standardized precipitation index (SPI) categories based on the initial classification of SPI values

Category	SPI
Extremely wet	2.00 and above
Severely wet	1.50–1.99
Moderately wet	1.00–1.49
Near normal	−0.99–0.99
Moderate drought	−1.00 to −1.49
Severe drought	−1.50 to −1.99
Extreme drought	−2.00 and less

3.3 Mann–Kendall Test

The World Meteorological Organization (WMO) has suggested using the Mann–Kendall (M–K) test for assessing trends in climatology and hydrology (Wang et al. 2013; Huang et al. 2013b). This test is known as the Kendall's tau statistic, which is a non-parametric test, meaning that it does not assume any priority in the distribution of the data and allows the presence of a tendency over long period of rainfall data to be observed (Yavuz and Erdoğan 2012). To eliminate the effect of serial correlation on M–K results, the "pre-whitened" technique is used to remove effects of serial correlation before M–K analysis. The 10 % significance level was used as a threshold to classify the significance of positive and negative MK trends. Meanwhile, it was important both to identify trends and to determine the magnitude of the trends. The non-parametric Sen's method was used to detect the magnitude of slope changes (Sen 1968).

3.4 Principal Components Analysis

The principal component analysis (PCA) is a popular used method to identify patterns in climatic data and to highlight their similarities and differences (Santos et al. 2010). It is a standard statistical method, often used in meteorological studies, to reduce the original intercorrelated

Table 3 Number of stations with significant positive (SP), insignificant positive (ISP), significant negative (SN), insignificant negative (ISN) and no change (NC) trends for monthly precipitation in this study

	SP	ISP	SN	ISN	NC
Jan	17 (17.3)	63 (64.3)	0 (0)	18 (18.4)	0 (0)
Feb	8 (8.2)	63 (64.3)	0 (0)	21 (21.4)	6 (6.1)
Mar	19 (19.4)	59 (60.2)	1 (1)	19 (19.4)	0 (0)
Apr	9 (9.2)	51 (52)	7 (7.1)	29 (29.6)	2 (2)
May	5 (5.1)	47 (48)	1 (1)	44 (44.9)	1 (1)
Jun	15 (15.3)	42 (42.9)	1 (1)	38 (38.8)	2 (2)
Jul	2 (2)	28 (28.6)	22 (22.4)	46 (46.9)	0 (0)
Aug	0 (0)	26 (26.5)	8 (8.2)	60 (61.2)	4 (4.1)
Sep	0 (0)	10(10.2)	26 (26.5)	60 (61.2)	2 (2.0)
Oct	3 (3.1)	19 (19.4)	31 (31.6)	44 (44.9)	1 (1)
Nov	5 (5.1)	30 (3.6)	5 (5.1)	55 (56.1)	3 (3.1)
Dec	0 (0)	57 (58)	1 (1)	37 (37.8)	3 (3.1)

The value in parentheses represents the percentage of stations relative to the total number of stations
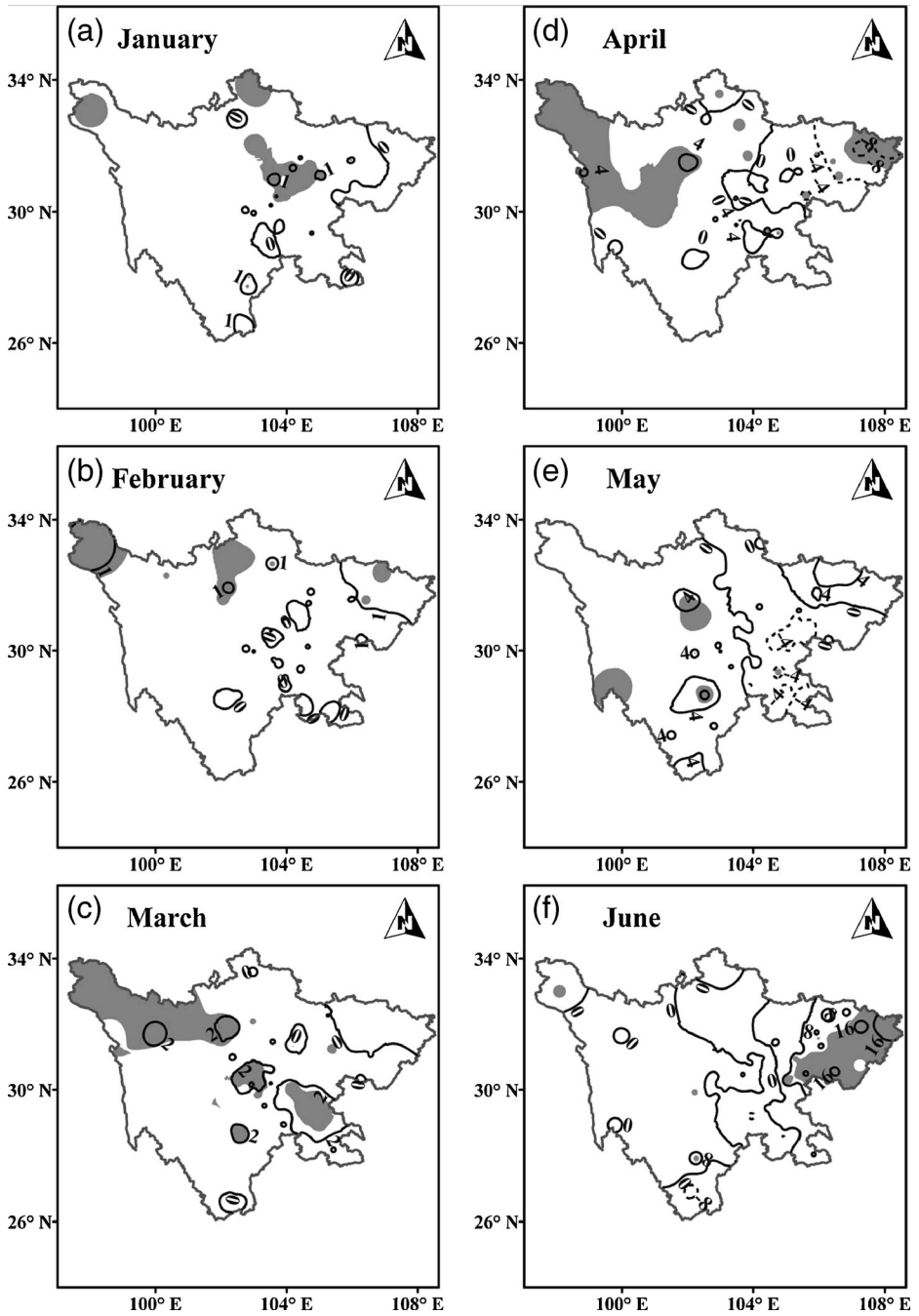
Fig. 2 Spatial distribution for trends of monthly precipitation during 1961–2008 (**a ~ l** mm/decade; the trends of *shaded area* are significant at the 10 % significance level)

variables in a small number of new linearly uncorrelated ones that explain most of the total variance. The new (uncorrelated) variables are called principal components (or principal
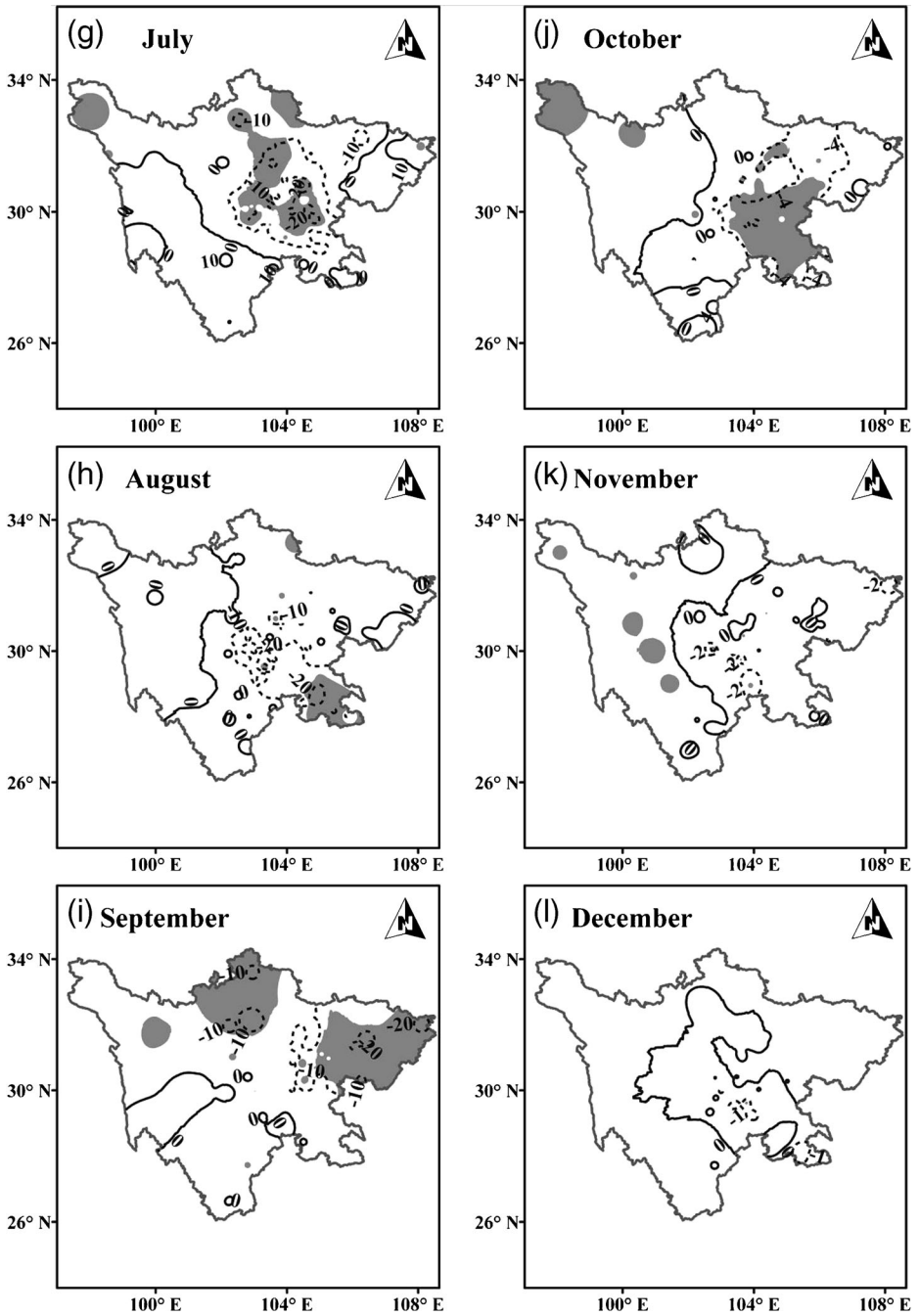
Fig. 2 (continued)

component scores) and consist of linear combinations of the original variables. In this study, the PCA is used to capture the spatial patterns of co-variability of dryness/wetness according to SPI

Table 4 Number of stations with significant positive (SP), insignificant positive (ISP), significant negative (SN), insignificant negative (ISN) and no change (NC) trends for extreme precipitation indices used in this study

	SP	ISP	SN	ISN	NC
Max1d	6 (6.1)	44 (44.9)	6 (6.1)	42 (42.9)	0 (0)
Max5d	3 (3.1)	32 (32.7)	13 (13.3)	50 (51)	0 (0)
CDD	6 (6.1)	39 (39.8)	8 (8.2)	44 (44.9)	1 (1)
CWD	2 (2)	15 (15.3)	22 (22.4)	57 (58.2)	2 (2)
R95pTOT	6 (6.1)	27 (27.6)	11 (11.2)	54 (55.1)	0 (0)
PRCPTOT	5 (5.1)	26 (26.5)	34 (34.7)	33 (33.7)	0 (0)

The value in parentheses represents the percentage of stations relative to the total number of stations

series at different stations. The original SPI variables at different meteorological stations are $X_{i,1}$, $X_{i,2, …}, X_{i,k}$, k is the number of the precipitation stations (equal to 98 in this study) and i represent the length of SPI series at each rainfall station (552 for SPI-24). The principal components are produced for the same time period by using linear combinations according to:

$$
\begin{bmatrix} X_{i,1} \\ X_{i,2} \\ \times \\ \times \\ X_{i,k} \end{bmatrix} \cdot \begin{bmatrix} a_{11} & a_{12} & \times & a_{1k} \\ a_{21} & a_{22} & \times & a_{2k} \\ \times & \times & \times & \times \\ \times & \times & \times & \times \\ a_{k1} & a_{k2} & \times & a_{kk} \end{bmatrix} = \begin{bmatrix} Y_{i,1} \\ Y_{i,2} \\ \times \\ \times \\ Y_{i,k} \end{bmatrix} \tag{7}
$$

where Y values are the orthogonal and new linearly uncorrelated variables which explain most of the total variance. The coefficients of the linear combinations are called "loadings" and represent correlation between the original data and the corresponding principal component scores (PCS) time series. To achieve more stable spatial patterns, a rotation of the principal components with the Varimax procedure was applied. The procedure simplifies the spatial patterns by isolating regions with similar temporal variations, and was proved to be the most common orthogonal method to improve the creation of regions of maximum correlation between the variables and the components (Bordi et al. 2004a, b).

4 Results and Discussion

4.1 Trends of Monthly Precipitation and Extreme Precipitation During 1961–2008

To assess precipitation trends, the Mann–Kendall test were applied to monthly precipitation time series at each station. Our results indicate remarkable differences among the stations with negative and positive precipitation trends for different months (Table 3). In January, March, and June, more than half of stations show increasing trends, of which 15–19 stations show positive trends at the 10 % significance level. In contrast, more than 60 % stations show decreasing trends in July, September and October, of which 22–31 stations show negative trends at the 10 % significance level. For other months, the number of stations with significant positive and negative trends is less. Furthermore, the changing trend presented an apparent spatial variation (Fig. 2). For example, the significant increasing trends for March are mainly found in northwest and southeast areas of Sichuan. For July, the significant downward trends are observed in the middle areas (Fig. 2g). In September, the northern and eastern areas display significant decreasing trends (Fig. 2i). As for October, the significant decrease in precipitation
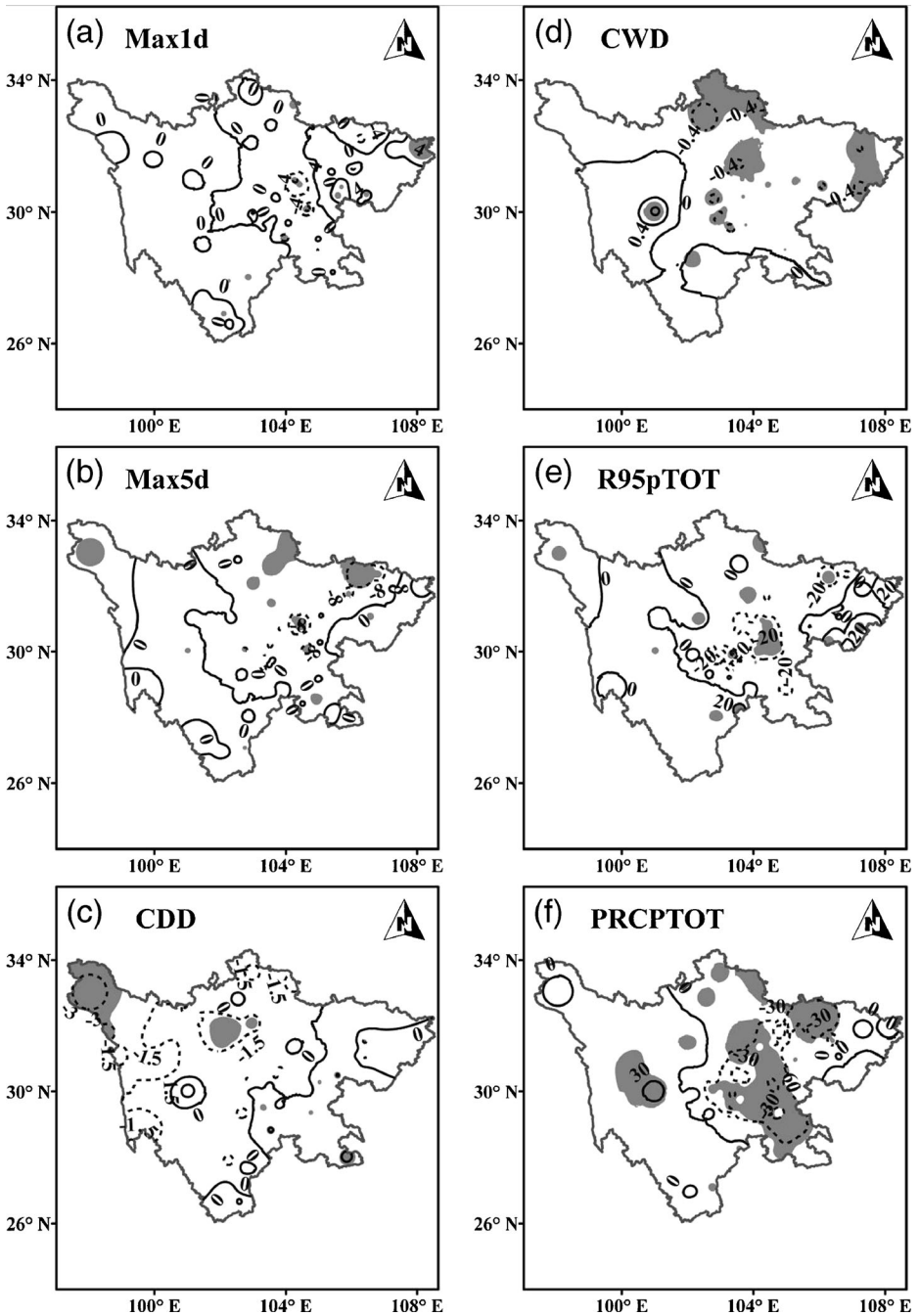
Fig. 3 Spatial distribution for trends of extreme precipitation indices during 1961–2008 (**a, b, e, f** mm/decade; **c, d** days/decade; the trends of *shaded area* are significant at the 10 % significance level)

mostly occurred in southeast Sichuan (Fig. 2j). The precipitation change during wet season (May–October) is an important factor for flood hazards in provinces located in the Yangtze

River Basin, which has drawn great attention from researchers (Becker et al. 2006; Gemmer et al. 2008). In this study, it is concluded from Fig. 2 and Table 4 that the precipitation of Sichuan during summer and autumn month display strong decreasing trends. On the one hand, the decreasing trends of precipitation amounts in summer might be mitigating the possibility of flood risk in this province. On the other hand, Sichuan is one of major agricultural production bases of China, and the deceasing trend of precipitation in autumn may bring about adverse effect on autumn grain crops in this region.

In this study, six extreme indices are calculated for the 98 meteorological stations in Sichuan province. The Mann–Kendall test is also used to test any trend in these indices, and the results are given in Table 4. In a majority of cases, most precipitation indices suggest that both the amount and the intensity of precipitation are decreasing. For annual maximum 1-day precipitation (Max1d), annual maximum 5-day precipitation, (Max5d), maximum number of consecutive dry days (CDD), maximum number of consecutive wet days (CWD), very wet day precipitation (R95pTOT), annual total precipitation in wet days (PRCPTOT), the proportion of stations with negative trends for these indices is 49, 64.3, 53.1, 80.6, 66.3, and 68.4 %, respectively, and the proportion of stations with positive trends for these indices is 51, 35.7, 46.9, 17.3, 33.7, and 31.6 %, respectively. Thus, there is a tendency towards negative trends dominating, consistent with the wreaking intensity of hydrological cycle in Sichuan. Figure 3 gives the spatial distribution of trends in extreme precipitation indices in this province. Strong trends can be mainly found for CWD and PRCPTOT. For CWD, the 22 stations in north and east Sichuan show significant decreasing trends (Fig. 3d). As for PRCPTOT, the significant downward trends are mainly found in the 34 stations of middle Sichuan (Fig. 3f). As we know, the changes of intensity and days for extreme precipitation have potential to result in the variability of flood risk in some region. Research results of this paper indicate that decreasing flood may risk the Sichuan province.

4.2 Spatial and Temporal Variability of Dryness/Wetness During 1961–2008

The Principal components analysis (PCA) was applied to the time series of the SPI at 24-month (SPI-24) at each station in Sichuan province. In almost all cases six components are
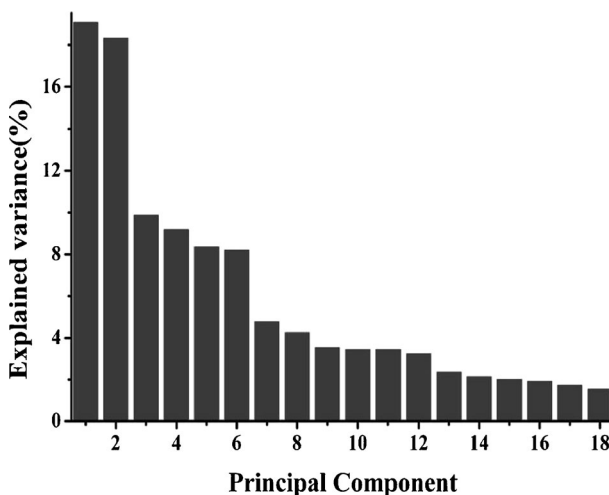

Fig. 4 Percentage of variance explained by rotated principle components
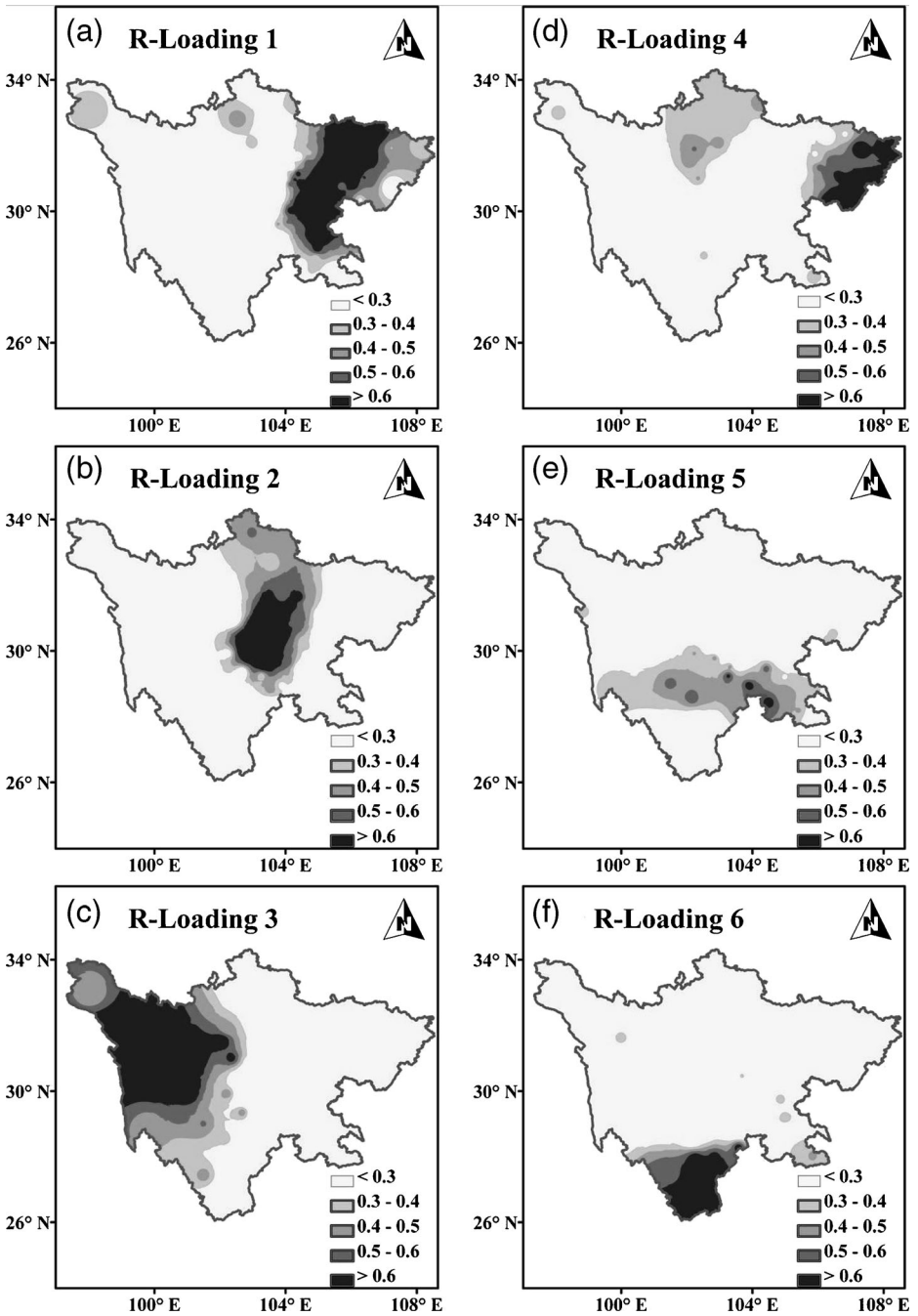
Fig. 5 First six rotated loading patterns (R-Loading) of SPI on 24-month time scale in Sichuan Province

enough to explain at least a 70 % of the variance (Fig. 4). By using the inverse distance weighted (IDW) spatial interpolation method, the rotated loadings are shown in Fig. 5. Since

by construction the rotated loading values represent the correlations between the SPI series and the corresponding rotated PCS, a threshold value of 0.5–0.6 on the rotated loading is reasonable for spatially delimiting the sub-regions that experienced similar drought variability in the study period. As shown in Fig. 5, six sub-regions are identified (most of east Sichuan, central Sichuan, western plateau area, eastern border area of Sichuan, southeastern corner of Sichuan, and southernmost area of Sichuan). Similar to these results, the existing studies also divided this province into 6–8 sub-regions according to different reaches (Hu et al. 2009; Zhang and Ma 2011). These regional patterns in precipitation are likely to be associated with the complex topography and spatial configuration of large-scale circulation systems in Sichuan. Meanwhile, to better understand temporal variability of dryness/wetness for sub-regions, the corresponding rotated principle components scores (PCS) are investigated in Fig. 6. Obviously the dry tendency prevails in central and east Sichuan, and the decreasing liner trends are significant at >95 % confidence level. When it comes to other areas, a wet tendency can be observed. In summary, the PCA seems to well localize in space six distinct sub-regions characterized by different dryness/wetness patterns. Thus, for an efficient water resources management under the back-drop of climate change, these sub-regions should be separately considered.

Furthermore, some further investigations were made in this study base on the standardized precipitation index (SPI) categories of Table 2. The number of months fell in each category (frequency of wet and dry months), i.e. from extreme dry to extreme wet of each year is a useful indicator for the dryness s/wetness (Zhang et al. 2009). The trends of these numbers are calculated via the following steps: (1) adopt the SPI-24 series to count the number of months
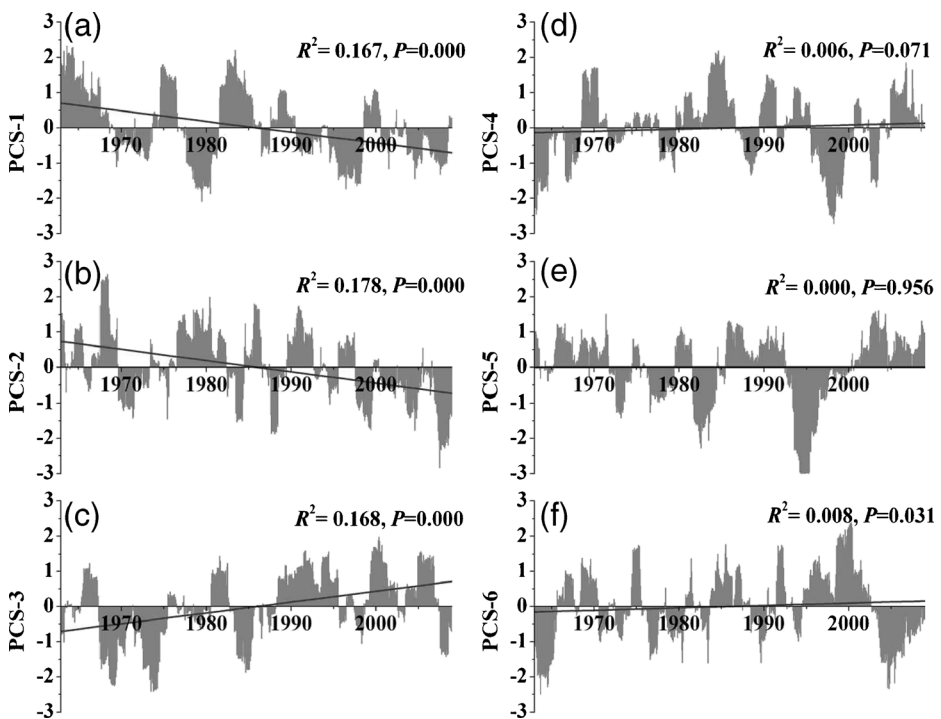

Fig. 6 Time series of the rotated principle components scores (PCS) of the SPI on 24-month time scale for Sichuan (corresponding to the loadings presented in Fig. 5)
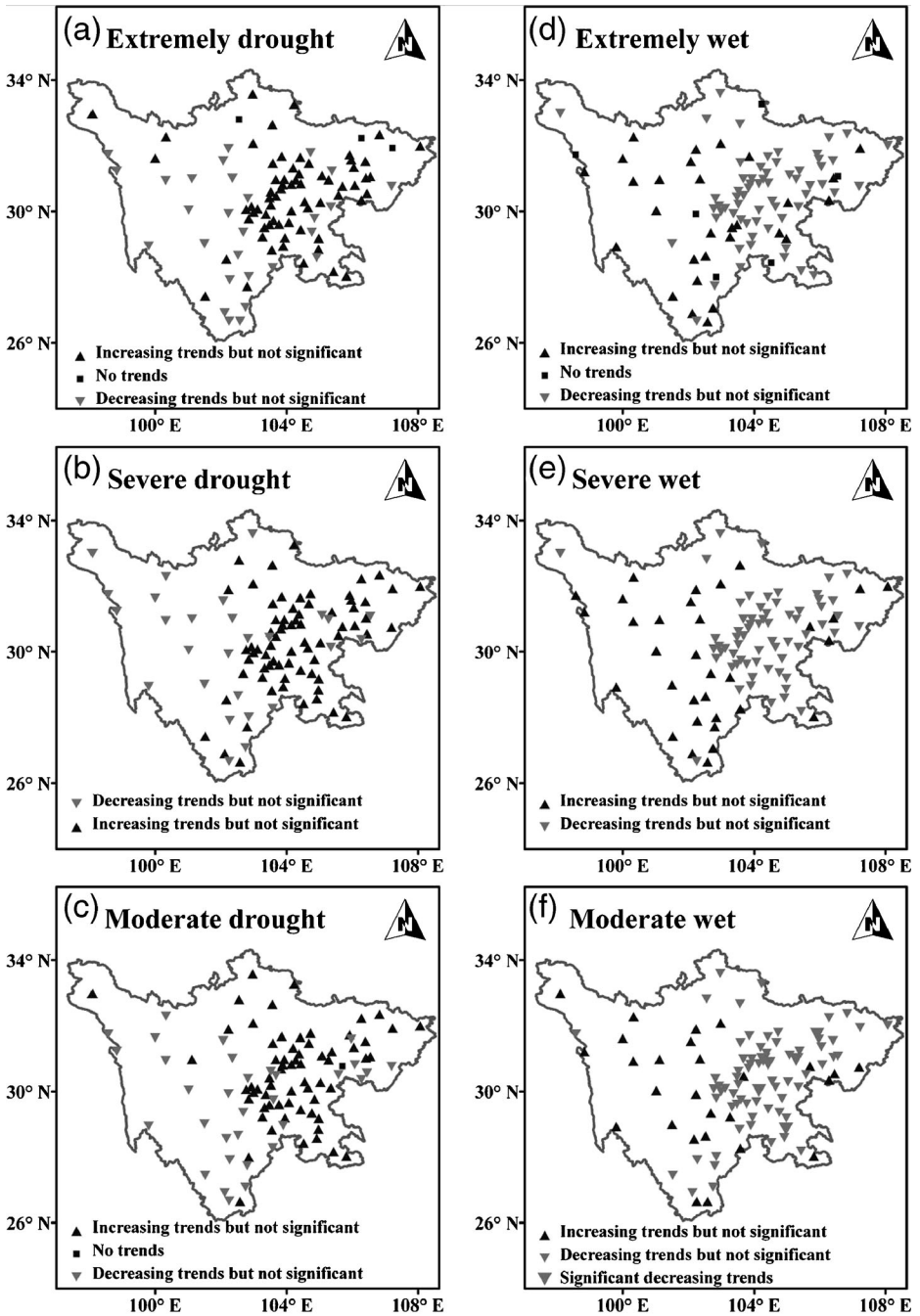
Fig. 7 Spatial distribution for trends of the number of wet and dry months of different categories

falling in each category within each year, (2) take the numbers in each categories of each year as a time series and calculate the trend of the time series with Mann–Kendall test. Figure 7

demonstrates the spatial patterns of trends in the number of dry or wet months during study period. In general, the numbers of extremely, severe and moderate dry months display increasing trends in the most of central and east Sichuan. While the most of west Sichuan are dominated by the increasing trends in the number of extremely, severe and moderate wet months. These results further indicate that central and east Sichuan is dominated by dry tendency, and the drought hazards may become increasingly serious. This was also confirmed by other studies (Chen et al. 2010; Liao et al. 2012), which found increasing trends of dry conditions associated with weaken precipitation. It is hard to ignore that regional water shortage is very serious in Sichuan, especially the 92 % of population and the 90 % of water consumption concentrate in this area (Zhou et al. 2011). Worryingly, the dry tendency may bring in great negative impact on water resource of this region. In this case, the water resources management in Sichuan should be well organized based on the new phenomenon in the changing climate.

5 Conclusions

In this study, the spatial and temporal characteristics of changes in precipitation and dryness/ wetness during 1961–2008 in Sichuan province were explored. The main findings are summarized as follows.

(1) The trends of precipitation were detected by the M–K test. Our results indicate that both the precipitation of wet season and the extreme precipitation indices were decreasing. Precipitation changes in the Yangtze River basin are controlled mainly by the East Asian Monsoons. The northeasterly wind tendency over central-east China is weakening the southwesterly summer monsoon in the region, limiting the northward extension of the summer monsoon and causing a longer Meiyu season in the mid-lower Yangtze River basin (Zhang et al. 2008). As a result, the precipitation decreased in such province as Sichuan in the upper Yangtze River basin.

(2) Dryness/wetness patterns were assessed through the SPI series computed on 24-month time scales, and their variability was analyzed by applying the PCA to the index time series. In terms of the first six loadings, spatial division was conducted into six sub-regions with different climatic variability: a remarkable dry tendency prevails in the central and east areas, while the other areas are dominated by a wet tendency.

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