Trends, change points and spatial variability in extreme precipitation events from 1961 to 2017 in China
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ABSTRACT

Extreme precipitation events vary with different sub-regions, sites and years and show complex characteristics. In this study, the temporal variations, trends with significance and change points in the annual time series of 10 extreme precipitation indices (EPIs) at 552 sites and in seven sub-regions were analyzed using the modified Mann–Kendall test and sequential Mann–Kendall analysis. Three representative (extremely wet, normal and extremely dry) years from 1961 to 2017 were selected by the largest, 50%, and smallest empirical frequency values in China. The spatiotemporal changes in the EPIs during the three representative years were analyzed in detail. The results showed that during 1961–2017, both the consecutive wet or dry days decreased significantly, while the number of heavy precipitation days had no significant trend, and the other seven wet EPIs increased insignificantly. The abrupt change years of the 10 EPIs occurred 32 and 40 times from 1963 to 1978 and from 1990 to 2016, respectively, regardless of sub-region. The extremely dry (or wet) events mainly occurred in western (or southwestern) China, implying a higher extreme event risk. The extremely wet, normal and extremely dry events from 1961 to 2017 occurred in 1961, 1997 and 2011 with empirical frequencies of 1.7%, 50% and 98.3%, respectively. In addition, 1998 was the second-most extremely wet year (empirical frequency was 3.7%). The monthly precipitation values were larger from February to August in 1998, forming a much earlier flood peak than that of 2016. The 10 EPIs had close connections with Normalized Difference Vegetation Indexes during the 12 months of 1998 and 2016. This study provides useful references for disaster prevention in China.

Key words | abrupt change point, empirical frequencies, extreme precipitation index, NDVI, representative year, trend

INTRODUCTION

Climate changes are expected to influence the occurrence of extreme precipitation events, which have attracted considerable attention (Croitoru et al. 2016). Future extreme precipitation events are likely to be more frequent in the context of global warming (Kharin & Zwiers 2005; Shi et al. 2018), which will have substantial impacts on the hydrological cycle, agricultural production (Cammarano & Tian 2018), land use (Pabst et al. 2016; Golroudabary et al.
Human life and natural ecosystems. The study of extreme precipitation events is essential.

Extreme precipitation indices (EPIs) have been extensively used to quantitatively characterize extreme precipitation events. Some frequently used EPIs are the maximum 1-day (Rx1day) or consecutive 5-day (Rx5day) precipitation amounts, simple daily intensity index (SDII), consecutive dry days (CDDs), very (R95p) or extremely wet days (R99p) and annual total wet-day precipitation (PRCPTOT) (Table 1). Each index has an interior meaning. For example, the ‘day-count’ type has fixed thresholds (R10, R20, ..., R100, etc.), while the percentile type (R95p and R99p) is relative to the base period and used among a wide variety of climates, and it overcomes the weakness of a fixed threshold (Li et al. 2010; Zhang et al. 2011). Donat et al. (2016) analyzed the global PRCPTOT and Rx1day indices and concluded that extreme precipitation events have significantly increased in dry regions but have had small changes in wet regions. Tariku & Gan (2018) predicted the extreme precipitation and temperature events for the 2050s and 2080s in the Nile River basin using four general circulation models. The authors suggested that the Nile River basin would experience more severe and frequent extreme precipitation events in the future. Jiang et al. (2016a) analyzed the spatiotemporal variability in 13 EPIs (including CDD, CWD, R10, R20, R25, R50, R100, PRCPTOT, SDII, Rx1day, Rx5day, R95p and R99p) from 1954 to 2013 in the Shaanxi Province of China, indicating that most of the EPIs except CDD and CWD had increasing trends. With the more frequent occurrence of extreme precipitation events, particularly in dry regions, their site- and region-specific characteristics as well as the occurrence mechanisms need to be systematically investigated to provide references for addressing these events.

China has complex topography and landforms with different climatic zones (Peng et al. 2017; Yao et al. 2018a). Correspondingly, extreme precipitation events show complicated characteristics in different regions of China. Wang et al. (2013a) analyzed the change of extreme precipitation in northeastern China over 1960–2011, and the results showed that the change patterns of the studied EPI trend were not spatially clustered and had significant periods of 7, 14 and 17 years. Yuan et al. (2017) analyzed the changes in Rx1day, RX3day, RX15day and RX30day based on the observed daily precipitation data and five general circulation models from 1961 to 2011 and from 2011 to 2050. The authors concluded that the Rx1day, RX5day, RX15day and RX30day indices may increase in the future, with a 50-year return period in southern China and a 10-year return period in northern China. Su et al. (2009) projected daily precipitation (Pr) using the ECHAM5/MPI-OM model from 2001 to 2050 based on observed data from 1960 to 2005 which is used to calibrate the model in the Yangtze River basin, China and concluded that the extreme rainfall at the 50-year return period will be more frequent. Du et al. (2013) analyzed the spatiotemporal characteristics of annual maximum rainfall in the Huai River basin from 1960 to 2011 and showed increasing trends at most stations. Wang et al. (2016) analyzed 11 EPIs from 1951 to 2011 at 12 weather stations along the Yellow Sea western coast in China and concluded that extreme Pr has become more concentrated and intense. There were many studies which have investigated the EPI changes in different parts of China.

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**Table 1** Descriptions of the selected 10 EPIs and abbreviation in this study

| Type          | Abbreviation of Indices | Definition                                                                 |
|---------------|-------------------------|---------------------------------------------------------------------------|
| EPI           | RX1day (mm)             | Annual maximum 1-day Pr                                                   |
|               | RX5day (mm)             | Annual maximum consecutive 5-day Pr                                       |
|               | R10 (days)              | Count of days for Pr ≥ 10 mm                                              |
|               | R20 (days)              | Count of days for Pr ≥ 20 mm                                              |
|               | CWD (days)              | Maximum consecutive day number for Pr ≥ 1 mm                               |
|               | CDD (days)              | Maximum number of consecutive days when Pr < 1 mm                         |
|               | R95p (mm)               | Annual total Pr from days >95th percentile                                 |
|               | R99p (mm)               | Total Pr from days >99th percentile                                        |
|               | SDII (mm day⁻¹)         | The ratio of total Pr to wet-day number (≥1 mm)                           |
|               | PRCPTOT (mm)            | Total Pr from days ≥1 mm                                                  |
| Other         | Pr                      | Precipitation                                                             |
| abbreviation  | EPI                     | EPI                                                                       |
|               | NDVI                    | NDVI                                                                       |
|               | AO                      | The Arctic Oscillation                                                      |
|               | PDO                     | The Pacific Decadal Oscillation                                            |

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2017;
Several studies associated extreme precipitation with atmospheric circulations (Tu et al. 2010; Gemmer et al. 2011; Ma et al. 2015; Jiang et al. 2016b). The spatial pattern of EPI varied in different years. However, the EPI changes in some of the most representative (extremely dry, normal and extremely wet) years have not been systematically investigated, which limit the further understanding and characterization of extreme precipitation events in the regions of interest in China. Therefore, for clearly showing the spatial pattern of EPI, three representative years were selected.

Our objectives were to (1) investigate the site- and region-specific characteristics of EPIs in mainland China by analyzing the serial trends with significance, the change points, the abrupt change years, the changes in steps and the long-term mean spatial distribution from 1961 to 2017 and (2) select the three representative (extremely dry, normal and extremely wet) years according to the minimum, medium and maximum empirical frequencies of annual PRCPTOT values in China as well as compare the daily precipitation variations and analyze the spatiotemporal variations in the EPI changes during the three representative years selected. This research provides useful information for the prevention and management of extreme precipitation events in China.

DATA AND METHODOLOGY

Data collection and selection of EPIs

The observed daily Pr data at 552 weather stations during the period 1961–2017 were collected from the China Meteorological Data Sharing Network (http://data.cma.cn/). The missing or abnormal data were interpolated from 10 neighboring sites using the inverse distance weight method. We deleted the site with the missing or abnormal data for more than 1 month. The entire mainland China (EMC) is divided into seven different sub-regions with different geological information and meteorological stations according to the temperature, water resources, soil and vegetation conditions (Figure 1) (Zhao 1983). Detailed sub-region information is given in Table 2. Detailed descriptions of multi-year mean climatic variables in each sub-region and China are listed in Table 1 in Yao et al. (2018a). We excluded the site with the missing or abnormal data longer than 1 month in our analysis. In northwestern China and Qinghai-Tibet Plateau, where the density of stations is very sparse, the missing data are interpolated by the nearest site when the data missing ratio is not higher than 1% (data

Figure 1 | Geological map of the location of the national weather stations, elevation (m) and sub-regions in China. Region with blue color means sea. Please refer to the online version of this paper to see this figure in color: http://dx.doi.org/10.2166/nh.2020.095.
missing ratio: the length of missing data/the length of all data). The number of such sites is less than 9. The grid-based maps of EPI were interpolated by 552 sites using inverse distance weight. This interpolation method was used as we found that the range of interpolated values was more appropriate than other methods such as Kriging interpolation which often resulted in many values out of the station data.

A total of 10 EPIs were selected from the Expert Team on Climate Change Detection and Indices (http://etccdi.pacificclimate.org/docs/ETCCDMIndicesComparison1.pdf) to characterize the extreme precipitation events (Table 1). EPIs were computed at the annual time scale. The total precipitation of 95th and 99th percentiles were calculated from data from 1961 to 1990.

### Trend test and change-point analysis

To analyze the trends of EPIs, the modified Mann–Kendall test (Mann 1945; Kendall 1976; Yue & Wang 2002) was used to test the trend and abrupt changes of 10 EPIs for the 552 selected stations in China. This method is a robust, non-parametric procedure. It has been widely used in identifying time series trends and abrupt change in previous studies (Peng et al. 2017; Yao et al. 2018). The modified Mann–Kendall test was proposed by Yue & Wang (2002) based on the original Mann–Kendall test. This test considers time series self-correlation and was utilized here to test the trends and significance in the annual EPI time series. If the EPI series is self-correlated, the Mann–Kendall statistic (Z) has a standard normal distribution under the no trend null hypothesis. If Z is positive (negative), the annual EPI has an upward (downward) trend. The null hypothesis is rejected if |Z| > 1.96 at a confidence level of 0.05; thus, the EPI series has a significant trend. After introducing a correcting factor $n_1$ into Z, the statistic of the modified Mann–Kendall test ($Z_M$) is re-estimated as follows:

\[
Z^* = Z/\sqrt{n_1^*}
\]

where $n_1^* = \begin{cases} 
1 + 2 \sum_{j=1}^{n_1} (n_1 - 1)r_{jj} & \text{for } jj > 1 \\
1 + 2 \sum_{j=1}^{n_1+1} - n_1 r_j^2 + (n_1 - 1) r_j \end{cases}

\frac{1}{n_1 (r_1 - 1)^2} \quad \text{for } jj = 1

(1)

where $r_{jj}$ is the sample self-correlation coefficient.

The slope of the trend ($b$) is estimated by Sen (1968) as follows:

\[
b = \text{Median} \left( \frac{x_i - x_j}{i - j} \right) \quad \text{for all } i < j
\]

(2)

where $x_i$ and $x_j$ are the values in the $i$th and $j$th year, respectively.

A sequential Mann–Kendall analysis containing sequential progressive $u(t)$ and backward $u(t)$ analyses was applied for abrupt change point (year) detection (Partal & Kahya 2010; Li et al. 2017) in the studied EPI series. If the two series of $u(t)$ and $u'(t)$ cross each other, the crossing point exhibits the change point. Otherwise, the beginning divergent year shows the abrupt change point. The equations for the sequential progressive $u(t)$ analysis are from Partal & Kahya (2010). Sequential backward serial value $u'(t)$ was calculated in a similar manner with the end of $x_i$ being the starting point.

### Empirical frequencies

The annual PRCPTOT from 1961 to 2017 (a total of 57 years) were ranked in the descending order to compute empirical frequencies (i.e., $m/(n + 1)$, where $m$ is the order...
and \( n \) is 57) for the seven sub-regions and mainland China. The empirical frequencies were used to select represent year of extreme precipitation.

**Wavelet analysis**

A cluster of wavelet functions was used to show signal (Kumar & Foufoula Georgiou 1997; Whitcher et al. 2000). The key function was written as follows:

\[
\int_{-\infty}^{\infty} \psi(t) \, dt = 0
\]

where \( t \) is the time (year), and \( \psi(t) \) is a wavelet function that forms a cluster of functions on the timeline:

\[
\psi_{a,b}(t) = |a|^{-1/2} \psi\left(\frac{t-b}{a}\right), \quad a, b \in R, \quad a \neq 0
\]

where \( \psi_{a,b}(t) \) is a sub-wavelet, \( a \) is a scale factor reflecting the wavelet length, and \( b \) is a translation factor that shows the translation of time. In this study, the multi-Morlet-wavelet was selected as a basic function.

**RESULTS**

**Temporal variations and trends of the 10 selected EPIs**

**Annual variations**

The annual variations of the selected 10 EPIs over 1961–2017 in seven different sub-regions and EMC (averaged from the sites) are illustrated in Figure 2. First, regional variability in all EPIs was observed, and nine EPI curves (except CDD which indicated dry conditions) generally decreased in sub-regions VII to VI, V, IV, II, III and I. The EPI variation pattern was mostly stable for arid or semi-arid sub-regions (I, II and III) but had large ranges for humid and super-humid regions (IV, V, VI and VII). The temporal variations of the 10 EPIs were shown in Figure S1 in Supplementary Materials. Taking Rx1day as an example, it fluctuated similarly in sub-regions II, VI, VII and mainland China but differed in the other four sub-regions (Figure S1a). The values of CDD were high in dry sub-regions (I, II and III) and the values of other nine EPIs were high in wet sub-regions (IV–VII). In the same sub-region, the peak and valley values of the other eight wet EPIs (Rx1day, Rx5day, R10, R20, R95p, R99p, SDII and PRCPTOT) were reasonably similar with that of Rx1day. This result showed that the spatial patterns of the nine EPIs were generally similar but differed with that of CDD. The annual Rx1day ranged between 13.1–25.2, 28–51, 23–31.7, 42.5–81.1, 54.1–92.6, 78.8–110.9 and 101–164 mm corresponding to sub-regions I–VII, respectively, and between 63.9 and 82.3 mm in mainland China. Annual mean values of Rx1day, Rx5day, R10, R20, R95p, R99p, SDII and PRCPTOT ranked in a descending sub-region order from VII, VI, V, IV, II (III) to I. However, the CDD, which denotes dry conditions, varied in a decreasing rank from sub-regions I to II (or III), IV (V or EMC), VII and VI. Note that the annual mean temperatures were 8.0, 5.4, 3.9, 4.4, 11.4, 17.0, 22.4 and 11.7 °C, and the annual mean Pr values were 136, 305, 455, 597, 591, 1,274, 1,604 and 815 mm, corresponding to sub-regions I–VII and mainland China, respectively. The variations in EPIs were not only region-specific but also had random principles. Second, the pairs of R10 vs. R20, Rx1day vs. Rx5day and R95p vs. R99p had similar variation patterns due to their similar attributions. Third, the peak values of the years (Figure S1), for Rx1day, Rx5day and SDII in China mainly occurred in 1983, 1994, 1996, 1998, 2012 and 2016; for R10 and R20 in 1973, 1983, 1998 and 2016; for CWD in 1968, 1973, 1981, 1998 and 2005; for CDD in 1963, 1968, 1983, 1988 and 1999; and for R95p, R99p and PRCPTOT in 1964, 1973, 1983, 1998, 2010 and 2016. In general, the EPI’s temporal variation was regionally specific.

**Trends and significance**

Six out of nine wet EPIs in sub-region I had significantly increasing trends, indicating strong wetter signals (Table 3). Meanwhile, in sub-region I, the slope \( b \) values of nine wet EPIs were positive, which consistently implied the increased occurrence of wet extremes. EPIs in sub-region III had similar trends to those of sub-region I, but the signal was slightly weaker. Generally, similar but even weaker trends and slopes of EPIs (compared to those of sub-region VII) in sub-regions I, III and VI were also observed, except that CWD and CDD had nonsignificant
trends. Different from sub-regions I, VI, III and VII, the trends of most EPIs in sub-regions II, IV and V were decreasing, of which sub-region II had stronger signals (4 out of 10 EPIs had significant decreasing trends), indicating drier extreme signals. Specifically, SDII in most sub-regions (except IV) and mainland China showed increasing trends and implied larger Pr intensities in China. CWD in most sub-regions (except I) and CDD in most sub-regions (except V and VII) had decreasing trends and implied longer CWDs and longer CDDs in China. For the EMC, the Rx1day, Rx5day, SDII, R20, R95p, R99p and PRCPTOT significantly increased from 1961 to 2017, the CWD and CDD significantly decreased, and R10 showed no trend. Due to the complexity of climatic systems, variations or

Figure 2 | Annual variations of the 10 EPIs in seven sub-regions and mainland China during 1961–2017. On each box, the central mark indicates the median, the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The whiskers extend to the most extreme data points not considered outliers, and the outliers are plotted individually using the ‘+’ symbol.
trends in different EPIs should be combined to comprehensively explain the characteristics of extreme precipitation events.

**Abrupt change points**

The results of the modified Mann–Kendall test showed the overall trends in the EPIs during the period 1961–2017. The abrupt change years possibly existed in the studied EPIs when further comparing the $\nu(t)$ and $\nu'(t)$ curves using the sequential Mann–Kendall test. As described in section 'Trends and significance', sub-region I showed significant trends in 6 out of 10 EPIs; correspondingly, the abrupt change years of EPIs for this sub-region were also clearly shown (Figure 3). Similar pairs of indices (Rx1day vs. Rx5day, R10 vs. R20 and R95p vs. R99p) had close $\nu(t)$ and $\nu'(t)$ curves and therefore close change points. All EPIs in each sub-region had change points from 1961 to 2017, and the abrupt change years varied with different EPIs and different sub-regions (Table 4). This result occurred 32 times from 1965 to 1978 and 40 times from 1990 to 2016, regardless of sub-regions. In 1998, abrupt change years occurred six times (the highest among all the abrupt change years) but mainly occurred in sub-regions VI, III and VII for different EPIs. To our knowledge, in 1998, a whole-basin type flooding event occurred in the Yangtze, Nenjiang and Songhuajiang basins and affected 29 provinces of China (Hu et al. 1999; Guo et al. 2005). It is reasonable that the year 1998 changed the precipitation and hydrological trends. The abrupt change years of 1993, 1995 and 2005 occurred four times. Specifically, the abrupt change years of indicators CDD and CWD occurred once for sub-region I in 1988, when a historical drought event occurred in China. The abrupt change years of CDD occurred from 1967 to 1977 for the other sub-regions or China when drought more frequently occurred (Yao et al. 2018a). There was largely heavy flooding (or drought) during the abrupt change years of the wet EPIs (or CDD).

Since the abrupt change years occurred, there were steps before and after the change points in the 10 EPIs from 1961 to 2017 in sub-region I (Figure 4), which was similar for the other sub-regions and China. Except for the

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**Table 3** | Modified Mann-Kendall statistics ($Z^*$) and Sen's slope ($b$) for the 10 EPIs in different sub-regions of China

| EPI    | Index | II     | III    | IV     | V      | VI     | VII    | Mainland China |
|--------|-------|--------|--------|--------|--------|--------|--------|----------------|
| RX1day | $Z^*$ | 1.94   | –      | 1.9    | 0.18   | –      | –2.09* | 1.83          | 1.01           | 0.94          |
|        | $b$   | –      | 2.21*  | –      | 2.07   | –      | –0.14  | –0.07         | 0.12           | 0.01          |
| RX5day | $Z^*$ | 0.06   | –      | 0.03   | 0.01   | –      | –0.14  | –0.07         | 0.15           | 0.07          |
|        | $b$   | –      | 0.06   | –      | 0.03   | –      | –0.14  | –0.07         | 0.15           | 0.07          |
| SDII   | $Z^*$ | 0.09   | –      | 0.07   | –      | –0.21  | –      | –0.19         | 0.16           | 0.04          |
|        | $b$   | –      | 0.07   | –      | 0.07   | –      | –0.21  | –0.19         | 0.16           | 0.04          |
| R10    | $Z^*$ | 0.03   | –      | –0.39  | –      | –1.37  | –      | –0.87         | –0.02          | 0.02          |
|        | $b$   | 0.02   | –      | –0.39  | –      | –1.37  | –      | –0.87         | –0.02          | 0.02          |
| R20    | $Z^*$ | 0.02   | –      | –0.39  | –      | –1.37  | –      | –0.87         | –0.02          | 0.02          |
|        | $b$   | 0.02   | –      | –0.39  | –      | –1.37  | –      | –0.87         | –0.02          | 0.02          |
| CDD    | $Z^*$ | 0.01   | –      | –0.39  | –      | –1.37  | –      | –0.87         | –0.02          | 0.02          |
|        | $b$   | 0.01   | –      | –0.39  | –      | –1.37  | –      | –0.87         | –0.02          | 0.02          |
| R95p   | $Z^*$ | 0.01   | –      | –0.39  | –      | –1.37  | –      | –0.87         | –0.02          | 0.02          |
|        | $b$   | 0.01   | –      | –0.39  | –      | –1.37  | –      | –0.87         | –0.02          | 0.02          |
| R99p   | $Z^*$ | 0.11   | –      | –0.39  | –      | –1.37  | –      | –0.87         | –0.02          | 0.02          |
|        | $b$   | 0.11   | –      | –0.39  | –      | –1.37  | –      | –0.87         | –0.02          | 0.02          |
| PRCPTOT| $Z^*$ | 0.74   | –      | –0.39  | –      | –1.37  | –      | –0.87         | –0.02          | 0.02          |
|        | $b$   | 0.74   | –      | –0.39  | –      | –1.37  | –      | –0.87         | –0.02          | 0.02          |

The *‘* and significant at the 95% confidence level ($Z_{95} \geq 1.96$).
CDD, the average values of EPI before the change points were less than the values after the change points, and they consistently indicated the intensified EPI values of the recent two or three decades. This non-stationary feature in the EPIs intensified the complexity of extreme precipitation event identification.

Spatial variations in the 10 EPIs

Spatial distributions of long-term mean EPIs

Figure 5 shows the spatial distribution of long-term mean values of the 10 EPIs from 1961 to 2017 in China. All of
Rx1day, Rx5day, CDD, CWD, R10, R20, R95p, R99p, SDII and PRCPTOT had large ranges in China, which were 5.7–218.0 mm, 6.4–393.0 mm, 0.2–67.4 days, 0–36.7 days, 6.0–173.0 days, 2.0–856.0 mm, 0.4–280.4 mm, 3.7–21.4 mm day$^{-1}$ and 13.0–2,581.0 mm, respectively. There were regional differences in the EPIs. The spatial distribution of 8 out of 10 EPIs (except CDD and CWD) had similar patterns, which agreed with the general decreasing elevation (three-level-catena landform) in China from the northwest to the southeast. There were much smaller Rx1day, Rx5day, SDII, R10, R20, R95p, R99p and PRCPTOT values in northwestern China (sub-regions I and III) and larger values in southeastern China (partially in sub-regions VI and VII), implying less (or more) flooding-related extreme precipitation events in western (or southeastern) China. There were transitional regions from southwestern to northeastern China (sub-regions II, IV and V), where extreme dry (or wet) events occurred less frequently than in western (or southeastern) China. The CDD was of a much longer duration in middle-western China but of much shorter duration in eastern China, which also indicated more or less dry weather conditions in the regions of interest in China. Although generally small Rx1day, Rx5day, SDII, R10, R20, R95p, R99p and PRCPTOT values were shown for sub-regions I, II and III, the CDD was much smaller only in the middle-western area of these regions. This finding is beneficial for crop growing since, in arid and semi-arid zones, long-lasting dry conditions are harmful to crop growth and harvesting. Overall, the extreme dry events mainly occurred in western China (sub-regions I, II and III) and the extreme wet events in southwestern China (sub-regions VI and VII).

Trends and significance

From the trend test results of the 10 EPIs (Figure 6 and Table 5), the number of sites with nonsignificant trends was usually greater than that with significant trends. As shown in Figure 6, along the geographical belt from northwestern to southeastern China, more sites showed significant increasing trends in Rx1day, Rx5day, SDII, R10, R20, R95p, R99p and PRCPTOT, particularly in northwestern China (sub-regions I and III) and southeastern China (sub-regions VI and VII). R20 in western China had more nonsignificant (either increasing or decreasing) than significant trends compared to eastern China. CWD in eastern China and CDD in northern China showed more significant decreasing than increasing trends. The sites where Rx1day, Rx5day, SDII, R10 and PRCPTOT significantly increased (showing generally wetter weather conditions as shown in Figures 6(a)–6(d) and 6(i)), and the sites where CDD and CWD significantly decreased (indicating drier weather in the eastern and southern regions as shown in Figure 6(e) and wetter weather in the northern half China as shown in Figure 6(f))) were distributed in more than half of mainland China; this finding implied a generally wetter
background from 1961 to 2017 in China but did not lead to less disasters. Both the northeastern part of sub-regions III (Qinghai-Tibetan plateau) and VI (within the belt from northwest to southeast China where the eight wet EPIs increased but CDD decreased) tended to be wetter. However, considering the larger PRCPTOT (Figure 5(j)), sub-region VI may have a much higher risk of extreme wet events than sub-region III.

In general, the spatial distribution of trends in the 10 EPIs implied that sub-regions I and VII as well as the eastern part of sub-region VI would receive more Prs, be subject to larger Pr intensities, and have longer Pr days,
particularly for extremely large \( Pr \) than prior. However, in sub-regions II, IV and VII as well as the western part of sub-region VI, the EPI trends were nearly reversed. Therefore, extreme precipitation events could be more frequent in sub-regions I, VI and VII but less frequent in sub-regions II, IV, V and III. This result showed the complex nature of extreme precipitation events whose impacts would differ for wet and dry regions. Sub-region I is in an arid and
this condition could transfer to a risk of flooding and other hydro-geographical disasters, provided that extreme precipitation is received over very short durations (days).
Overall, the advantages outweigh the disadvantages, with the increasing seven EPIs in sub-region I. However, increasing trends in the seven wet EPIs for sub-regions VI and VII may imply high risks of flooding and waterlogging because these regions belonged to humid or severely humid climatic types. Detailed implications of disaster risks can be further shown by analyzing EPIs in some representative years as follows.

Variations in EPIs during the selected three representative years

Selection of the three representative years

Three typical samples, namely, extremely dry, normal and extremely wet years, were selected for the seven sub-regions and mainland China considering the smallest, near 50%, and the largest empirical frequency values (Table S1). Although the values varied for each sub-region, the three representative years in sub-region VI had nearly similar patterns to those of the entire mainland of China, except that the 50% empirical frequency of sub-region 5 was in 1991 and that of mainland China was in 1997. The normal years for different sub-regions were all later than 2004, and one-half of the extremely dry years occurred before 1966, while most of the extremely wet years occurred after 2000. These results implied more frequent wet extremes during the 2010s for China. Considering EMC, the years 2011, 1997 and 2016 (with empirical frequencies of 98.3%, 50.0% and 1.7% over the past 57 years, respectively) represented the extreme dry, normal and extreme wet conditions and were selected for further analysis.

Variations in daily precipitation during the three representative years

Figure S5 indicates the daily and cumulative $Pr$ changes within the three representative years for each sub-region and China. Detailed region-specific representative year information is listed in Table S1. Regardless of sub-region, $Pr$ values were high during the summer and autumn (April to September), and the maximum values of daily $Pr$ mostly occurred during the extremely wet years. Exceptional cases also occurred, e.g., the maximum values of daily $Pr$ occurred during the normal year of 1995 for sub-regions I and VII (Figures S5a and S5f) and during August of the extremely dry year of 1997 for sub-region V (Figures S5a, S5d and S5f). The distributions of daily and cumulative $Pr$ within different representative years not only had large variability for each sub-region and China but also considerably varied between arid and semi-arid areas (sub-regions I, II and III) and humid or super-humid areas (sub-regions IV, V, VI and VII). The ranges in daily $Pr$ had upper limitations for certain sub-regions. During the extremely wet year of 2016, considering EMC, the maximum daily $Pr$ for sub-regions I–VII and China was 4.8, 13.3, 8.6, 26.2, 44.8, 25.1, 46.8 and 11.9 mm, respectively, showing large differences. Therefore, the feature of $Pr$ was regionally specific and should be considered in the later analysis of EPI changes.

Spatial distribution of EPIs during the three representative years

The spatial distributions of each EPI during the extremely wet year of 2016, the extremely wet year 2011 and the normal year 1997 for mainland China are shown in Figure S6. The ranges of each EPI were manually adjusted to be as similar as possible; therefore, the comparison during different years is clearly shown. The ranges of Rx1day, Rx5day, R10, R20, CWD, CDD, R95p, R99p, SDII
and PRCPTOT were 4–450 mm, 6–644 mm, 0–81 days, 0–48 days, 1–22 days, 0–190 days, 0–836 mm, 3–27 mm day$^{-1}$ and 13–2,951 mm, respectively, with maximum values changing during different representative years. The arid and semi-arid areas (sub-regions I and III) always had smaller values of eight EPIs, except CDD, and vice versa for the long-term humid areas (sub-regions V, VI and VII). The main differences between the three representative years were the areas that a certain range of EPI occupied. During the extremely wet year of 2016, the area of large EPI was the largest, followed by the normal years. Thus, there was the largest area coverage of 1- or 5-day maximum Pr, Pr intensity, heavy Pr days, CWDs, >99th percentile and total Pr in 2016. The area changes of CDD in 2016, 1997 and 2011 at certain ranges did not follow a consistent decreasing or increasing rank, for example, the areas of CDD at 134–207 days during the normal year 1997 were the largest, followed by the extremely dry year 2011 but were the smallest during the extremely wet year 2016. This outcome occurred because precipitation events are both spatially and temporally uneven distributed. During the extremely wet year, part of China was still dry; for the extremely dry year, some local regions were much wetter. Although spatial distribution of the EPIs was complex and could not always be generalized with universal features, the EPIs during wet years were larger and occupied most areas of China.

The area percentages of the 10 EPIs within certain ranges of the three representative years are provided in Table S2. The ranges for Rx1day, Rx5day, R10, R20, SDII, R95p, R99p and PRCPTOT were 116–450 mm, 176–644 mm, 14–27 mm day$^{-1}$, 39–81 days, 20–48 days, 12–22 days, 134–190 mm, 392–1,501 mm, 172–863 mm and 1,227–2,951 mm, respectively. The area percentage of EPIs did not follow very consistent orders from the extremely dry to normal and then to extremely wet year but still showed general increasing areas of EPIs, which implied a higher risk of flooding in 2016.

The relationship between EPIs and atmospheric circulation indices

We analyzed the correlations between EPIs and three atmospheric circulation indices, i.e., Pacific Decadal Oscillation (PDO), Arctic Oscillation (AO) and NINO3. Figure 7 shows the spatial distribution of correlation coefficients between 10 EPIs and NINO3. The range of correlation coefficients was from −0.09 to 0.36. The correlation coefficients had a significant spatial pattern and decreased from southern to northern China for nine EPIs except CDD which showed generally reverse pattern. Although the correlation coefficients of 10 EPIs and other two climate indices were lower than NINO3, the spatial pattern had significant regional differences (Figures S7 and S8).

The wavelet coherence relationships between 10 EPIs and NINO3 were analyzed using the cross-wavelet for EMC (Figure 8). For Rx1day, there were positive correlations between nine EPIs and NINO3, mainly concentrated in 12 months at all the time intervals and a positive correlation between Rx1day and NINO3 (phase angle of around 45°) with 28–36 months during 1970–1990. The wavelet coherence spectra of other eight EPIs (Rx5day, R10, R20, CWD, SDII, R95p, R99p and PRCPTOT) were similar. The correlation between CDD and NINO3 was negative in 12 months at all time intervals, while the correlations between other nine EPIs and NINO3 were all positive. The wavelet coherence relationships between 10 EPIs and other two climate indices (PDO and AO) were weaker than NINO3 and are described in detail (Figures S9 and S10).

**DISCUSSION**

Most of the previous research has shown the trends in EPIs in different regions of China (Wang et al. 2013b; Ren et al. 2014) or in the world (Donat et al. 2016). Donat et al. (2016) showed that extreme daily Pr showed robust increases in both observations and climate models from 1951 to 2010. This research also verified the overall wetter climates and consistently increasing nine EPIs except CDD in northwestern China and Qinghai-Tibetan Plateau (sub-regions I and III). Our results agreed very well with Wang et al. (2013b) who investigated spatiotemporal variations in EPIs in northwestern China very well and with Donat et al. (2016) who conducted studies for dry regions. However, sub-region II is also a dry region, and the EPIs did not show similar trends to those of sub-regions I and III. In addition, the EPIs in the wet region (sub-region V) did not follow this
Figure 7 | Spatial distribution of the correlation coefficient between 10 EPIs and NINO3.
rule. This result indicated the complexity and region-specific characteristics of EPI changes. In addition, Donat et al. (2016) indicated obvious step changes based on the historical and the projected Pr data; however, their abrupt change year was fixed at 1980. This research tested the abrupt change years in 10 EPIs for each sub-region and mainland China, and the results showed that the abrupt change years varied for each sub-region and EPI. Therefore, when analyzing...
the step changes in climatic variables, \( Pr \) data or EPIs, a robust statistical test is recommended. The change point may appear with abnormality climate. For example, the change point of PRCPTOT in mainland China is 1998, which was a wet year and many people affected by the great flood resulting from the extreme precipitation event.

From the empirical frequency values, 2011 and 2016 were found to be the driest and wettest years, respectively, over the last 57 years in China. Extreme precipitation events not only have intensified during the recent several decades but also have tended to develop in two opposite directions. Thus, human beings are facing more challenges of climatic extremes. Concerning the wet extreme events, to date, only a few researchers have included the wettest year 2016 as the main study subject due to data availability difficulty or data updating issues. For example, Shao et al. (2018) suggested that Madden-Julian oscillation affected summer rainfall in 2016 in China by conducting observational analyses and diagnostic linear baroclinic model experiments. Ma et al. (2018) related a strong El Niño to the 2015–2016 floods and droughts in China and emphasized that different zones had different hydro-climate anomalies. In addition, the extremely dry weather in 2011 has not been clearly studied. This research showed the spatiotemporal change in \( Pr \) and EPIs in 2016 in China in detail. The empirical frequency of annual \( Pr \) in 2016 was 1.7\%, and there was a second extremely wet year, 2018, which had an empirical frequency of 3.5\% in China. However, it seemed more difficult for China to prevent the 1998 flooding than that which occurred during 2016.

The selected representative years were similar by different methods. In this study, we also calculated the low (10\%) and high percentiles (90\%) of 57 years’ EPIs as the extreme dry/wet years and then selected the years when the EPIs were below and above thresholds (Table S2). Figure S4 also showed that the extreme wet and dry EPI values can clearly reflect the differences between wet and dry years.

In 2016, the area of agricultural land covered by floods and direct economic damage was larger than those in 1998, but the number of deaths from floods, the number of people affected and the number of houses destroyed were much less than during 1998 (Table 6) (Duan et al. 2016; Yang et al. 2017). The reason could be the improvements in science and technology and flood control, the application of artificial intelligence, etc. The variation pattern in \( Pr \) differed (Figure 9), which may have resulted in different flood peaks during different periods in 2016. The daily \( Pr \) peak of 7.2 mm started in January of 2016 but started later in 1998, and many peaks occurred later in October of both years. The daily maximum \( Pr \) occurred on 30 April 1998 and 19 July 2016. The monthly \( Pr \) from February to August in 1998 was larger than that in 2016, forming a much earlier flood peak than in 2016, which may have contributed to the higher flood risk and greater damage to human safety in 1998.

The changes in monthly \( Pr \) were found to be closely connected to the Normalized Difference Vegetation Index (NDVI) in both 1998 and 2016 (Figures S2 and S3). First, the \( Pr \) distribution during the two years was different. Combined with Figure 9, a much smaller \( Pr \) in February, March, July and August but a much larger \( Pr \) in September, October and November were observed in 2016 compared to 1998. In February and March of 1998, heavy \( Pr \) was concentrated in large areas of China, but \( Pr \) in 2016 spread to even more areas; this result also partially explained the reason that damage in 1998 was much greater. From September to December, more areas in 2016 had a larger \( Pr \) than in 1998. Second, \( Pr \) was connected with NDVI for both years. From January to April and from October to December, western and northern China had a \( Pr \) of less than 50 mm and an NDVI of less than 0.4, while southeastern China had much larger monthly \( Pr \) (>100 mm) and NDVI values (even near 1.0). Third, the correlation coefficients between NDVI and precipitation in 1998 and 2016 are listed in Table S1. The correlation coefficients ranged in 1998 from 0.13 to 0.41 and from 0.11 to 0.57 in 2016, and the upper values in 2016 were higher than those in 1998. Finally, more vegetation cover was observed in 2016,

| Flood damage | 1998 | 2016 |
|--------------|------|------|
| Area of agriculture covered by floods (\( \times 10^6 \) ha) | 22.29 | 26.21 |
| Number of deaths from floods | 3656 | 684 |
| Number of people affected by flood (\( \times 10^5 \)) | 2.3 | 1.02 |
| Direct economic damage (Billion RMB) | 2484 | 3661 |
| Number of houses destroyed (\( \times 10^5 \)) | 566 | 43 |
which may have been a result of the Chinese government’s policy of reforestation of marginal arable land. Bryan et al. (2018) also review 16 sustainability programs in China, which invested US$378.5 billion, covered 623.9 million hectares of land, and these programs have greatly increased forest cover through reforestation and afforestation. Several studies showed strong correlations between precipitation and NDVI in the Tibetan Plateau (Lei et al. 2010) and China (Piao et al. 2005). This finding could be an important topic with detailed research in the future.

The EPIs in the driest year, 2011, in China from 1961 to 2017 showed regional differences, considering the long-term mean Pr and climatic differences. Lu et al. (2013) analyzed the weighted averages of Pr and its standard values to monitor the 2011 severe drought in China. In the selected 10 EPIs, only CDD denotes dry conditions; therefore, special attention needs to be paid when considering extreme drought conditions. For example, Yao et al. (2018b) and Li et al. (2016) investigated drought evolutionary characteristics in Xinjiang and mainland China using several drought indices. Further research is necessary to study extremely dry events by using more dry EPIs. Some extensively applied drought indices are promising to be specifically used during extremely dry event research, such as the multi-scalar standardized precipitation index (McKee et al. 1993) and the standardized precipitation evapotranspiration index (Vicente-Serrano et al. 2010).

The spatial pattern of EPI was similar with Figure 7, which implied that EPI was influenced by NINO3, especially in wet regions. The correlation between 10 EPIs and other two climate indices also have regional differences (Figures S7 and S8), but the value of the correlation
coefficient was lower than NINO3 (Figure 7). It implied that the NINO3 is the main factor influencing extreme precipitation events among the three selected atmospheric circulation indices. The wavelet coherence relationships between EPI and NINO3 were also stronger than between EPI and PDO/AO (Figures S9 and S10).

Trend and abrupt change tests are useful tools in the time series analysis. In this study, a large number of time series were analyzed by the modified Mann–Kendall (MMK) test. Although this method considers the influences of self-correlation, it is still insufficient or is applied only to some tests (Serinaldi et al. 2018; Serinaldi & Kilsby 2018). Therefore, the limited power of the trend test used for the data analysis should be taken into account in the future study.

CONCLUSIONS

The temporal variations in 10 selected EPIs (Rx1day, Rx5day, SDII, R10, R20, CWD, CDD, R95p, R99p and PRCPTOT) were investigated by comparing their annual changes, trends and abrupt changes. The annual variations in the 10 selected EPIs (Rx1day, Rx5day, SDII, R10, R20, CWD, CDD, R95p, R99p and PRCPTOT) were mostly stable for arid or semi-arid sub-regions (I, II and III) but had large ranges for humid and super-humid regions (IV, V, VI and VII). The nine wet EPIs for sub-region I increased, and CDD decreased in sub-regions I, VI, III and VII. Most EPIs in sub-regions II, IV and V decreased. Abrupt change years occurred 32 and 40 times from 1963 to 1978 and from 1990 to 2016, respectively, regardless of sub-region differences.

The spatial variations in the 10 EPIs were investigated to obtain long-term mean values and trends. More sites showed significantly increasing trends than significantly decreasing trends in the long-term mean values of Rx1day, Rx5day, SDII, R10, R95p, R99p and PRCPTOT, particularly in northwestern China (sub-regions I and III) and larger values in southeastern China (part of sub-region VI and VII), implying less (or more) flooding-related extreme precipitation events in western (or southeastern) China.

The spatiotemporal variations in the 10 EPIs were analyzed during the three representative years (taking the smallest, medium and largest empirical frequency values), which occurred in 2016, 1997 and 2011, respectively. The daily and monthly precipitation events had large spatial and temporal variability during the three representative years in China, resulting in correspondingly large spatial variability in the 10 EPIs.

The year 1998 was the second-most extreme wet year, but the precipitation distribution within the year was much different than that during 2016, causing even more severe flood damage to society in China. The monthly precipitation was greater from February to August in 1998, forming much earlier flood peaks than those in 2016. Furthermore, the precipitation had close connections with NDVIs during the 12 months of 1998 and 2016.

In general, NINO3 was the major factor influencing extreme precipitation events among PDO, AO and NINO3. The NINO3 impacted EPI especially in southern China (sub-regions VI and VII). This study provided important references for the prevention of extreme precipitation events and heavy rains in China.

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SUPPLEMENTARY MATERIAL

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