Spatial and temporal characteristics of the daily precipitation concentration index over China from 1979 to 2015
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ABSTRACT
Irregular precipitation has a nontrivial influence on hydrological processes and regional agriculture. The precipitation concentration index provides convenient quantitative characterizations of precipitation variability. To explore the spatial and temporal distribution of the precipitation concentration index, the long-term concentration index (LCI) and the annual concentration index (ACI) during 1979–2015 were calculated based on the China Meteorological Forcing Dataset. The results are as follows: (1) The LCI in China ranged from 0.4571 to 0.9197, and the values between 0.6 and 0.7 accounted for 61.61% of the dataset. The highest and lowest LCI values were both recorded in Northwest China, which features low precipitation levels. Additionally, there are high LCI values (greater than 0.6) in Southeast China, which features high precipitation levels. (2) Application of the Mann-Kendall test (M-K test) and Sen’s slope revealed that more than 88% of the grids exhibited nonsignificant positive or negative ACI trends and that more than 10% of the grid ACI values exhibited positive trends, with approximately 2.8% showing significant changes at the 0.1 significance level. (3) Application of the Pettitt test revealed that approximately 11.9% of the grid ACI values exhibited an abrupt change at the 0.5 significance level, with abrupt changes occurring in 1991, 1992 and 1993, together accounting for 45.89% of all grids with abrupt changes.

Key words | Mann-Kendall trend test, Pettitt test, precipitation concentration index, spatio-temporal characteristics

INTRODUCTION
Climate change is on an upward trend in the context of global warming and has a significant effect on the global natural ecosystem and socioeconomic system (IPCC 2013; Chang et al. 2019). One of the most noticeable consequences of climate change is changes in the water cycle, with precipitation being a key aspect of this process. Changes in precipitation patterns, including intensity, amount, duration, timing and rate, may lead to anomalous weather events, such as floods and droughts (Zhang et al. 2009b, 2013; Parajka et al. 2010; Chang et al. 2017). In this context, the analysis of precipitation concentration is a subject of great interest and can be used to identify irregular temporal patterns of precipitation (Vyshkvarkova et al. 2018; Wang et al. 2019). In general, a higher precipitation concentration, represented by a higher percentage of the yearly total precipitation in a few rainy days, has the potential to cause flood and drought phenomena (Li et al. 2010).

In recent years, the analysis of daily precipitation concentration has been a focus of research. The essence of analyzing precipitation concentration is describing the
percentage of precipitation on very rainy days relative to the total precipitation over a period of time. The precipitation concentration index was presented (Martin-Vide 2004) based on the Gini concentration index, which relates the magnitude of precipitation events to the time period in which they occur (Serrano-Notivoli et al. 2018). Due to its considerable scientific and practical merits, the precipitation concentration index has been widely employed to analyze spatio-temporal patterns in many regions, such as Peninsular Spain (Martin-Vide 2004), Iran (Alijani et al. 2008), Peninsular Malaysia (Suhaila & Jemain 2012), New Zealand (Caloiero 2014), western Turkey (Yeşilorman & Atatanır 2016), India (Chatterjee et al. 2016; Yin et al. 2016), the contiguous United States (Royé & Martin-Vide 2017), southern Russia (Vyshkovskaya et al. 2018), central-southern Chile (Sarricolea et al. 2019) and around the world (Monjo & Martin-Vide 2016). Similarly, studies on precipitation concentration in China have been carried out. Based on the precipitation concentration degree and the precipitation concentration period, the characteristics of the spatial and temporal distribution of precipitation have been analyzed in the Yangtze River Valley (Zhang & Qian 2005), Xinjiang (Zhang et al. 2009a; Li et al. 2010), Guangxi (Qin & Wang 2010) and throughout China (Liu et al. 2016). Based on the precipitation concentration index, the statistical structure of precipitation rates was analyzed in the Pearl River basin (Zhang et al. 2009b; Zheng et al. 2017), Xinjiang Province (Li et al. 2010), the Lancang River basin (Shi et al. 2013) and Northeast China (Wang et al. 2019). On a national scale, the spatio-temporal variability of the monthly precipitation concentration index (Zhang et al. 2019) and the daily concentration index (Huang et al. 2019) have been investigated in China. In previous studies, precipitation concentration indices (including precipitation concentration degree, precipitation concentration period and precipitation concentration index) were investigated based on precipitation data from meteorological stations. The precipitation concentration index in areas without precipitation data was obtained by interpolating the values of the surrounding stations. Changes in the precipitation concentration index appear to be rather complex and possibly related to global atmospheric characteristics (Huang et al. 2019) as well as geographical factors (latitude, longitude and altitude) (Zhang et al. 2019), so the analysis of interpolated results across China may include a considerable error. Considering that the characteristics of precipitation concentration play a key role in watershed management, the purpose of this study is (1) to explore the spatial distribution of the precipitation concentration index and (2) to investigate the temporal variation and abrupt changes in the precipitation concentration index. In this paper, the daily precipitation concentration index in China was analyzed based on a gridded daily precipitation dataset for China with a resolution of 0.1° for the period from 1979 to 2015. Then, the Mann-Kendall test (M-K test) and Sen’s slope estimator were used to determine the trend in the precipitation concentration index. Finally, the nonparametric Pettitt test was employed to identify the change point in the precipitation data.

**METHODOLOGY**

**Study area and data**

China is located in East Asia and has a climate dominated by monsoon winds (Yihui & Chan 2005). The remarkable regional diversity of natural conditions results in spatial characteristics in the meteorological factors across China. Precipitation exhibits spatial and temporal variability in China because of differences in climate and complex topography (Xu et al. 2006; Zhang et al. 2011). To clarify the characteristics of precipitation concentration in association with various regional climates and geographical features, the study area is divided into ten major basins, as defined by the Ministry of Water Resources of China (Hu et al. 2018). The ten major basins are the Songhua River (SON) basin, the Liaohe River (LIA) basin, the Haihe River (HAI) basin, the Yellow River (YEL) basin, the Huaihe River (HUA) basin, the Northwestern Rivers (NWR) basin, the Yangtze River (YAN) basin, the Pearl River (PEA) basin, the Southeastern Rivers (SER) basin and the Southwestern Rivers (SWR) basin, and the distribution of these basins is shown in Figure 1.

The climatic data used to calculate the precipitation concentration index are from the China Meteorological Forcing Dataset (CMFD), which was produced by merging a
variety of data sources, including China Meteorological Administration station data, from 1979 to 2015. The applicability and reliability of the CMFD has been verified in other studies (Chen et al. 2014; Xue et al. 2013). The spatial resolution of the climatic data is 0.1°, and the land of China is divided into 97,711 grids. The temporal resolution is 1 day, and there are 13,505 days of precipitation data in each grid.

**Precipitation concentration index**

The precipitation concentration index was proposed to determine the relative importance of the daily precipitation classes to the total amount, especially the influence of heavy precipitation events (Martin-Vide 2004; Shi et al. 2013; Zheng et al. 2017). The precipitation concentration index is calculated based on an exponential relationship between the cumulative percentages of the precipitation amount and the cumulative frequency of rainy days. For the precipitation data in a given period, the steps for calculating the precipitation concentration index can be summarized as follows:

1. The daily precipitation values in a period are classified using intervals of 1 mm ranging from 0 to the maximum. The number of days with the precipitation ranges in each class are calculated as follows: Based on the sum of the precipitation values and the number of rainy days in each class, the cumulative percentages of precipitation values and rainy days are obtained.
2. A positive exponential distribution curve, called the Lorenz curve (Martin-Vide 2004), is employed to describe the relationship between the cumulative percentages of
the precipitation amount \(Y\) and the cumulative percentages of rainy days \(X\). The relationship can be expressed as follows:

\[
Y = ax \exp(bx)
\]  
(1)

where \(a\) and \(b\) are estimated using the least-squares method (Martin-Vide 2004).

3. Based on estimates of \(a\) and \(b\), the area \(S\) under the Lorenz curve is the definite integral of the exponential curve between 0 and 1:

\[
S = \int_0^1 ax \exp(bx)dx
\]  
(2)

4. The precipitation concentration index (CI in the following equation) can be calculated as follows:

\[
CI = \frac{0.5 - S}{0.5}
\]  
(3)

If the period is 1 year, the final calculated result is called the annual concentration index (ACI). If the period is 1979–2015, the final calculated result is called the long-term concentration index (LCI) in this study.

**Mann-Kendall test and Sen’s slope estimator**

The M-K test is a nonparametric trend test that is applicable for analyzing nonnormally distributed data, and the sample data are not necessarily compliant with a specific distribution (Hirsch & Slack 1984). Using the M-K test, the concentration trends can be quantified, and the comparison of trends among regions is more intuitive. According to this test, the null hypothesis \(H_0\) states that the deseasonalized data \(\{x_1, x_2, \ldots, x_n\}\) is a sample of \(n\) independent and identically distributed random variables (Partal & Kahya 2006). The procedures to calculate the test statistics, the variance of the test statistics, and the standardized test statistics are as follows:

\[
S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i)
\]

\[
S = \frac{n(n - 1)(2n + 5) - \sum_i n_i(t_i - 1)(2t_i + 5)}{18}
\]

\[
Z = \begin{cases} 
\frac{S - 1}{\sqrt{\text{VAR}(S)}} & S > 0 \\
0 & S = 0 \\
\frac{S + 1}{\sqrt{\text{VAR}(S)}} & S < 0 
\end{cases}
\]  
(6)

where \(S\) is the test statistic, \(\text{VAR}\) is the variance of \(S\), \(Z\) is the standardized test statistic, \(n\) is the total number of sample data, \(x_j\) and \(x_i\) are the yearly mean values of years \(i\) and \(j\), and \(t\) is the extent at any given time. If \(|Z| > Z_{1-a/2}\), the null hypothesis is rejected with a given confidence level \(\alpha\); namely, there is a significant trend in the time series data \(\{X\}\). When \(\alpha\) is equal to 0.05 and 0.01, \(Z_{1-a}\) is equal to 1.960 and 2.576, respectively. If \(Z > 0\), there is an increasing trend of \(S\), which means that the sample data \(\{X\}\) exhibit the same trend. In contrast, if \(Z < 0\), \(\{X\}\) exhibits a decreasing trend.

The slope of the trend of the data is evaluated by the nonparametric Sen's slope estimator (Sen 1968) and is calculated as follows:

\[
\beta = \text{Median}\left(\frac{x_j - x_i}{j - i}\right), \forall j > i
\]  
(7)

where \(x_j\) and \(x_i\) are data values at times \(j\) and \(i\). The median of the ascending sequence of values \(\{(x_j - x_i)/(j - i)\}\) reflects Sen's slope estimator, and the confidence interval of the slope can be calculated as follows:

\[
C_a = Z_{1-a/2} \sqrt{\text{VAR}(S)}
\]

\[
M_{1,2} = (N \pm C_a)/2
\]

\[
P(\{X_{(M)} < \beta < X_{(M+1)}\} | \beta) = 1 - \alpha
\]

where \(Z_{1-a}\) and \(\text{VAR}(S)\) are defined as mentioned above. \(N\) is the length of the ascending series \(\{(x_j - x_i)/(j - i)\}\), written as \(X\), and \(X_{(M)}\) represents the \(M\)th values in series \(X\). Sen's slope estimator has been widely used in trend analysis of...
hydrometeorological data (Partal & Kahya 2006; Gocic & Trajkovic 2013).

**Pettitt test**

The nonparametric Pettitt test (Pettitt 1979) was employed to identify the change point in the precipitation data. It is a rank-based and distribution-free test used to detect significant changes in the mean of a time series when the exact timing of the changes is unknown (Zhang & Lu 2009; He et al. 2008). Compared to the M-K test, the Pettitt test is more applicable for calculating abrupt changes in nonnormally distributed data (Wijngaard et al. 2005; Villarini et al. 2009; Jaiswal et al. 2008).

A time series of $X_n = (x_1, x_2, \ldots, x_n)$ is divided into two groups: $x_1, x_2, \ldots, x_\tau$ and $x_\tau+1, x_\tau+2, \ldots, x_n$. The statistical index $U_\tau$ is defined as follows:

$$U_\tau = \sum_{i=1}^{\tau} \sum_{j=\tau+1}^{n} \text{sgn}(x_i - x_j) \quad 1 \leq \tau < n \quad (9)$$

The most likely change point can be found as follows:

$$K_\tau = \max |U_\tau| \quad (10)$$

The significance probability $p$ associated with $K_\tau$ can be calculated as follows:

$$p = 2 \exp \left( \frac{-6K_\tau^2}{n^2 + n^2} \right) \quad (11)$$

If $p < \alpha$, $x_\tau$ is accepted as a significant change point at the significance level $\alpha$. The Pettitt test has been widely used to detect change points in the climatic and hydrological time series (Mu et al. 2007; Tekleab et al. 2013).

**RESULTS**

**Spatial distribution of annual precipitation**

Based on the daily precipitation dataset, the spatial distribution of the mean annual precipitation in China during the period of 1979–2015 is shown in Figure 2. The regional average annual precipitation indices of the ten major basins were calculated from all grids, and the statistical results are shown in Table 1. The results indicated that the spatial difference in annual precipitation is large, ranging from 21.2 to 3,433.0 mm and that the annual precipitation decreased from southeast to northwest in China. The difference values between the maximum and minimum annual precipitation were 336.5, 316.7, 323.3, 257.1, 676.2, 369.6, 1,053.6, 771.6, 150.7 and 359.4 mm in SON, LIA, HAI, YEL, HUA, YAN, SER, PEA, NWR and SWR, respectively. The greater the annual precipitation, the greater the difference value between the maximum and minimum annual precipitation.

Based on the 1979–2015 precipitation dataset, the distributions of the statistical parameter $Z$ of annual precipitation derived by the M-K test and Sen’s slope estimator were calculated in each grid. The distribution of annual precipitation trends at various significance levels as determined by Sen’s slope is presented in Figure 3, and the results indicate that there is no obvious increasing or decreasing trend in annual precipitation across most of China. The areas with increasing annual precipitation trends were concentrated in the northwest region of China and Taiwan Island. The areas with decreasing annual precipitation trends were located in the southwest region of China. Contrasting the spatial distribution of annual precipitation (Figure 2) with the spatial distribution of the annual precipitation trend (Figure 3), the regions with increasing trends of annual precipitation are in Northwest China, which features low precipitation levels (<400 mm).

**Spatial distribution of LCI values**

The data with daily precipitation values of $\geq$0.1 mm were selected from the 13,505-day precipitation data in each grid over China. The LCI was calculated by calculating the precipitation concentration index for each grid. The precipitation concentration index can be effectively used to estimate the extent of precipitation variations across China. The spatial distribution and histogram of the LCI values for all grids are shown in Figure 4. The results...
indicated that the LCI in China ranged from 0.4571 to 0.9197 and was mainly between 0.6 and 0.7, with this range accounting for 61.61% of the total grids. On a national scale, the LCI during 1979–2015 showed a decreasing trend from east to west but no obvious trend from north to south. A daily precipitation concentration

| Basin | Mean (mm) | Maximum (mm/year) | Minimum (mm/year) | Standard deviation (mm) | Skewness |
|-------|-----------|-------------------|-------------------|-------------------------|----------|
| SON   | 535.6     | 735.5/2015        | 398.9/1979        | 74.2                    | 0.6526   |
| LIA   | 559.2     | 751.5/2010        | 434.8/2000        | 92.3                    | 0.3231   |
| HAI   | 521.6     | 681.2/1996        | 357.9/1997        | 73.8                    | 0.0182   |
| YEL   | 472.8     | 619.6/2003        | 362.5/1997        | 54.6                    | 0.1018   |
| HUA   | 913.5     | 1,324.2/2003      | 648.0/1988        | 153.7                   | 0.3783   |
| YAN   | 1,069.7   | 1,292.8/2015      | 923.2/2011        | 85.2                    | 0.4835   |
| SER   | 1,817.4   | 2,408.8/2015      | 1,355.2/1991      | 248.2                   | 0.2781   |
| PEA   | 1,540.3   | 1,975.3/2015      | 1,205.7/1989      | 188.6                   | 0.1819   |
| NWR   | 193.4     | 293.3/2015        | 142.6/1984        | 41.6                    | 0.4149   |
| SWR   | 767.5     | 999.3/2015        | 639.9/2009        | 67.6                    | 0.8283   |

Figure 2 | Spatial distribution of annual precipitation during 1979–2015.
greater than 0.61 is considered to be high, which means that 70% of the total precipitation falls on 25% of the rainiest days (Martin-Vide 2004). There were 82,426 grids with LCI values larger than 0.61, accounting for 84.36% of the total grids. The highest and lowest LCI values were both recorded in Northwest China, which features low precipitation levels (<400 mm). There were high LCI values of more than 0.6 in Southeast China, which features high precipitation levels. In particular, LCI values greater than 0.7 were located in the north of the SON and YEL basins, the middle of the YAN basin, the east of the HUA basin, the west PEA basin and most of Taiwan Island.

The LCI values in the ten major basins were calculated by averaging the values of the grids in each basin, and the statistical results are shown in Table 2. The difference values between the maximum and minimum LCI were 0.2352, 0.2186, 0.1987, 0.2426, 0.1573, 0.3057, 0.3057, 0.2356, 0.1643, 0.2356 and 0.4626 in SON, LIA, HAI, YEL, HUA, YAN, SER, PEA, NWR and SWR, respectively. The maximum and minimum LCI values in China during 1979–2015 appeared in the NWR basin. The largest difference value between the maximum and minimum also occurred in the NWR basin, and the smallest difference occurred in the HUA basin.

### Spatial distribution of trends in ACI values

Based on the same data selection and calculation steps, the ACI was calculated in each grid from 1979 to 2015. The M-K test and Sen’s slope techniques were applied to
Figure 4  | Spatial distribution and histogram of LCI values during 1979–2015. (a) Spatial distribution of LCI values. (b) Histogram of LCI values.
the 37-year ACI to analyze the trends of daily precipitation concentration. The distributions of the statistical parameter $Z$ of ACI derived from the M-K test and Sen’s slope results were calculated in each grid, and the distribution of ACI trends at various significance levels, as determined by Sen’s slope, is presented in Figure 5. On a national scale, the distribution of ACI trends indicated that there was no obvious trend in the ACI in most parts of China during 1979–2015. The areas with increasing ACI trends are located in the middle latitudes of China and Northeast China. The areas with decreasing ACI trends are located in Northwest China.

Based on the ACI trend in each grid, the numbers of grids with different trends are shown in Figure 6. The results show that there are more grids with positive ACI trends than negative ones. More than 88% of the grids exhibited non-significant positive or negative ACI trends. More than 10% of the grid ACI values exhibited positive trends, and approximately 2.8% showed significant changes at the 0.1

### Table 2 | Statistical results for the LCI during 1979–2015 in different basins

| Basin | Mean   | Minimum | Maximum |
|-------|--------|---------|---------|
| SON   | 0.6841 | 0.5712  | 0.8064  |
| LIA   | 0.6721 | 0.5488  | 0.7674  |
| HAI   | 0.6683 | 0.5636  | 0.7623  |
| YEL   | 0.6707 | 0.5482  | 0.7908  |
| HUA   | 0.6852 | 0.5894  | 0.7467  |
| YAN   | 0.6668 | 0.5233  | 0.8289  |
| SER   | 0.6722 | 0.6024  | 0.7667  |
| PEA   | 0.6707 | 0.5537  | 0.7893  |
| NWR   | 0.6594 | 0.4571  | 0.9197  |
| SWR   | 0.6236 | 0.4877  | 0.7908  |

Figure 5 | Spatial distributions of ACI trends by Sen’s slope.
significance level. The ACI values exhibited a statistically significant decreasing trend at a 0.05 significance level ($Z < -1.960$) in 886 out of the 97,711 grids.

The regional ACI values of the ten major basins were calculated from all the grids in each basin from 1979 to 2015 and are shown in Figure 7. The Sen's slope results were calculated in the ten major basins at the 5% and 1% significance levels and are shown in Table 3. The results indicated that all basins exhibit positive ACI trends, although there are no significant trends in the SER, NWR and PEA basins at the 0.05 level. Specifically, the ACI values in the LIA and SWR basins were both dominated by a significant increasing trend at a 0.01 significance level. At the same time, the Sen's slope estimator results for ACI show that the LIA basin experienced a greater increasing trend than the SWR basin.

Oscillation characteristics of ACI

The Pettitt test was applied to the 37-year ACI data to assess oscillations in the daily precipitation concentration. The distribution of the statistical parameter $P$ of ACI derived from the Pettitt test results was calculated in each grid and is presented in Figure 8. On a national scale, the distribution of oscillation characteristics of ACI changes indicated that there were no obvious abrupt changes in the ACI in most parts of China during 1979–2015. The areas with abrupt changes in the ACI at the 0.05 significance level were located in the middle latitudes of China and northeastern China. More than 88% of the grids exhibited no significant abrupt changes. Approximately 11.9% of the grid ACI values exhibited abrupt changes at the 0.5 significance level, and approximately 2.7% showed significant abrupt changes at the 0.1 significance level.

The year of the abrupt changes in each grid was determined by the Pettitt test at the 0.05 significance level. Figure 9 shows the histogram of abrupt change points. The results indicate that the year of the abrupt changes ranges from 1986 to 2010 and that there were 5,377 grids with abrupt changes in 1991, 1992 and 1993, accounting for more than 45.89% of the total grids.

Based on ACIs for ten major basins, the Pettitt test was employed to assess the oscillations of daily precipitation concentration, and the results are shown in Table 4. The results showed that there are no significant abrupt changes in the LIA, HUA and PEA basins and that there are
Significant abrupt changes in other basins at a 0.05 significance level. Specifically, the ACI values in the HAI basin were dominated by a significant abrupt change at a 0.005 significance level.

Relations between ACI and annual precipitation parameters

Pearson’s correlation coefficient ($r$) was used to analyze the statistical relations between the ACI values and the annual precipitation and the annual number of rainy days (daily precipitation ≥0.1 mm). The distribution of $r$ at a 0.05 significance level is shown in Figure 10, and the statistical results

### Table 3 | Spatial distributions of the Sen’s slope results for ACI in different basins

| Basin | Sen’s slope |
|-------|-------------|
| SON   | 0.000593<sup>a</sup> |
| LIA   | 0.001002<sup>b</sup> |
| HAI   | 0.000752<sup>a</sup> |
| YEL   | 0.000831<sup>a</sup> |
| HUA   | 0.000785<sup>a</sup> |
| YAN   | 0.000734<sup>a</sup> |
| SER   | 0.000113 |
| PEA   | 0.000124 |
| NWR   | 0.000220 |
| SWR   | 0.000652<sup>b</sup> |

<sup>a</sup>Statistically significant trends at the 5% significance level.

<sup>b</sup>Statistically significant trends at the 1% significance level.
Figure 8 | Abrupt changes in the ACI during 1979–2015 as determined by the Pettitt test. (a) P of the Pettitt test. (b) Abrupt changes in the ACI at various significance levels.
Figure 9 | Year of abrupt changes in the ACI during 1979–2015 as determined by the Pettitt test. (a) Abrupt change year, as determined by the Pettitt test. (b) Histogram of the abrupt change year.
the annual precipitation, the number of grids with a negative correlation is larger than that of grids with a positive correlation in the SON, LIA, YAN and SER basins. In terms of the correlation between the ACI and the annual number of rainy days, the number of grids with a negative correlation is larger than that of grids with a positive correlation in the SON, LIA, HAI, YAN, SER, PEA and SWR basins. Especially in the YAN basin, the correlation between the ACI and the annual number of rainy days is positive in the upper reaches and negative in the lower reaches.

**DISCUSSION**

**Comparison between the results and other regions**

According to the calculated results for each grid in China from 1979 to 2015 in the Results section, the LCI ranges from 0.46 to 0.92, and the ACI ranges from 0.24 to 0.95. In this study, the range of the daily precipitation concentration index in China is larger than that in Spain (0.50–0.70) (Martin-Vide 2004), Italy (0.43–0.63) (Coscarelli & Caloiro 2012), Europe (0.51–0.72) (Cortesi et al. 2012), southern Russia (0.557–0.632) (Vyshkvarkova et al. 2018), Iran (0.59–0.73) (Alijani et al. 2008), New Zealand (0.47–0.70) (Caloiro 2014), the United States (0.52–0.72) (Royé & Martin-Vide 2017), Chile (0.52–0.74) (Livermore & Jackson 2004), Peru (0.42–0.58) (Zubieta et al. 2017) and Argentina (0.54–0.68) (Llano 2018). This difference can be explained on the basis of different climate systems and the use of different climatic datasets. Due to the location of China, there is a unique regional complex climate, and precipitation has been impacted by two large subsystems of the Asian summer monsoon, the South Asian monsoon and the East Asian monsoon (Zhang 2015; Preethi et al. 2017; Huang et al. 2019). In China, the ACI values in Northeast China, including the SON and LIA basins, range from 0.65 to 0.76, and this range is similar to the range of 0.62–0.71 in other research (Wang et al. 2019). The LCI values in PEA range from 0.55 to 0.79, and this range is less than the range of 0.76–0.82 from 1960 to 2012 (Zheng et al. 2017). The differences between these ranges can be explained by the period of the climatic data. The ACI values in the Lancang River basin, located in the eastern SWR basin, range...
Figure 10 | The distribution of Pearson's correlation coefficient. (a) $r$ between the ACI and annual precipitation. (b) $r$ between the ACI and the annual number of rainy days.
from 0.55 to 0.75, and this range is similar to the range of 0.57–0.73 in other research (Shi et al. 2015). The LCI values in Xinjiang Province, located in the northwestern NWR basin, range from 0.51 to 0.89, and this range is larger than the range of 0.58–0.70 in other research (Li et al. 2013). The areas with different LCI values are located in southeastern Xinjiang Province, and the difference can be explained by the use of different climate datasets.

**Impacts and implications of the variation in ACI on regional flood management**

The results of the variation in ACI in the ten major basins in this study show an increasing trend, which means that there will be more heavy precipitation events in the future. An increasing trend in heavy precipitation events in different regions of China has also been found on the basis of various indices and classifications in many existing studies (Liu & Chen 2013; Liu et al. 2015; Gu et al. 2016; Yuan et al. 2017; Wu et al. 2019). It is obvious that heavy precipitation events are a huge potential risk, as they may cause floods, which produce huge economic losses and even threaten people’s lives. More attention should be paid to flood management. Furthermore, because the hydrological response process is influenced by precipitation, topography, landscape characteristics and human activities, regional flood management should be carried out according to the underlying surface characters. Locations of regions with the increasing trend of ACI and information of elevation are shown in Figure 11, and the results indicate that there is three regional flood management.

1. Flood management in the soil erosion area (red rectangular box in Figure 11). In this study, the ACI values in the YEL basin are dominated by a significant increasing trend, and grids with increasing trends are mainly located in the middle reach, corresponding to the Loess Plateau. A similar phenomenon can be found in existing studies (Ran et al. 2020). In regions with severe soil erosion
problems, floods can flush tremendous amounts of sediment downstream, leading to devastating damage to communities along the rivers (De Bruijn et al. 2014). Previous studies have shown that sediment comes from different source areas in the YEL and that 88% of the total sediment yield comes from the middle reaches (Fan et al. 2013; Zhao et al. 2014). When the annual precipitation and ACI both show increasing trends, the percentages associated with these parameters may also increase. The prevention and control of water-driven soil erosion may be the main work in the regional flood management, which can reduce the sediment input. Furthermore, based on the forecast of flood, water and sediment regulation should be developed to improve the relation between runoff and sediment.

2. Flood management in the urban area (blue rectangular box in Figure 11). If flooding occurs, there will be considerable damage in the urban area, as it is the place with a dense population, accumulation of poverty and gathering of human activities. This becomes a serious challenge for urban drainage and flood control due to the extreme precipitation events which have occurred more frequently. Therefore, it is necessary to develop an urban drainage project and to enhance non-engineering measures including flood forecasting and emergency rescue capacity building in the urban area.

3. Flood management in a remote mountainous area (yellow rectangular box in Figure 11). Floods and debris floods will happen more frequently in the remote mountainous area with the increasing trend of ACI. The
establishment of hydrologic forecasting, geological hazard monitoring and disaster warning if one of the effective non-engineering measures for preventing mountain flood disasters, which is a primary work of the Chinese government in recent years.

CONCLUSIONS

Precipitation varies greatly from north to south and from east to west in China, and the annual precipitation ranges from 21.2 to 3,433.0 mm. The concentration index adequately expresses the statistical structure of this variable precipitation pattern and provides convenient quantitative characterizations of precipitation variability throughout China. Analysis of the spatial and temporal distribution of the precipitation concentration index during 1979–2015 in China based on the CMFD supports the following conclusions:

1. The increasing trend of annual precipitation was concentrated in the northwestern region of China and Taiwan Island. The decreasing trend of annual precipitation was located in the southwestern region of China. At a national scale, there was no obvious trend in annual precipitation throughout most of China.

2. The LCI in China ranged from 0.4571 to 0.9197 and was mainly between 0.6 and 0.7, with this range accounting for 61.61% of the total grids. At a national scale, the LCI during 1979–2015 exhibited a decreasing trend from east to west but no obvious trend from north to south. The highest and lowest LCI values were both recorded in Northwest China, which features low precipitation levels. There were high LCI values of more than 0.6 in Southeast China, which features high precipitation levels. In particular, LCI values greater than 0.7 were located in the north of the SON and YEL basins, the middle of the YAN basin, the east of the HUA basin, the west of the PEA basin and most of Taiwan Island.

3. The M-K test and Sen’s slope were used to analyze the trend of daily precipitation concentration values. More than 88% of the grids exhibited nonsignificant positive or negative ACI trends. The areas with increasing ACI trends were located in the middle latitudes of China and Northeast China. The areas with decreasing ACI trends were located in Northwest China. More than 10% of the grid ACI values exhibited positive trends, and approximately 2.8% showed significant changes at the 0.1 significance level. The ACI exhibited a statistically significant decreasing trend at the 0.05 significance level (Z < –1.960) in 886 out of the 97,711 grids.

4. There were no obvious abrupt changes in the ACI in most parts of China during 1979–2015. The areas with abrupt changes in the ACI at the 0.05 significance level were located in the middle latitudes of China and Northeast China. Approximately 11.9% of the grid ACI values exhibited abrupt changes at the 0.5 significance level, and approximately 2.7% showed significant abrupt changes at the 0.1 significance level. At the 0.05 significance level, the abrupt change points ranged from 1986 to 2010, and more than 45% of the total grids had abrupt changes in 1991, 1992 and 1993.

5. Pearson’s correlation coefficient was used for the analysis of the statistical relations between the ACI values and the annual precipitation and the annual number of rainy days. At the 0.05 significance level, the results indicated that the correlation between the ACI and the annual number of rainy days was greater than between the ACI and the annual precipitation. The number of grids with negative correlations was larger than that with positive correlations, in terms of both the correlation between the ACI and the annual precipitation and the correlation between the ACI and the annual number of rainy days.

6. The increasing trend of ACI reveals that there will be more heavy precipitation events in the future. Regional flood management should be carried out according to topography, landscape characteristics and human activities, such as in soil erosion areas, urban areas and remote mountainous areas.

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