Spatiotemporal variation characteristics of extreme precipitation in the upper reaches of the Hongshui River Basin during 1959–2016

Ya Huang, Ling Yi, Weihua Xiao, Guibing Hou and Yuyan Zhou

ABSTRACT

Understanding changes in the intensity and frequency of extreme precipitation is vital for flood control, disaster mitigation, and water resource management. In this study, 12 extreme precipitation indices and the best-fitting extreme value distribution were used to analyze the spatiotemporal characteristics of extreme precipitation in the upper reaches of the Hongshui River Basin (UHRB). The possible links between extreme precipitation and large-scale circulation were also investigated. Most extreme precipitation indices increased from west to east in the UHRB, indicating that the eastern region is a humid area with abundant precipitation. The indices for consecutive wet days (CWD) and precipitation events (R0.1) decreased significantly, indicating that the UHRB tends to be dry, with few precipitation events. The probability distribution functions of most extreme precipitation indices, especially that of R0.1, shifted significantly to the left in 1988–2016 compared with 1959–1987, further indicating that the UHRB has experienced a significant drying trend in recent decades. The East Asian summer monsoon and the El Niño–Southern Oscillation/Pacific Decadal Oscillation were confirmed to influence extreme precipitation in the UHRB. These findings are helpful for understanding extreme precipitation variation trends in the UHRB and provide references for further research.

Key words | extreme distribution, extreme precipitation, Hongshui River Basin, large-scale climate indices

HIGHLIGHTS

- We do not focus on the Pearl River Basin (453,690 km²) but pay attention to a sub-basin (98,500 km²) within it.
- Most extreme precipitation indices decreased slightly and nonsignificantly in the UHRB.
- The number of consecutive wet days and precipitation events decreased significantly.
- The UHRB has tended to be dry, with few precipitation events.
- The El Niño–Southern Oscillation/Pacific Decadal Oscillation and East Asian summer monsoon have strong effects on extreme precipitation.

INTRODUCTION

In recent years, extreme climate and weather events have attracted worldwide attention and have become one of the most important topics in climate research (Easterling et al.)
2000; Dore 2005; Alexander et al. 2006). With global warming, the spatiotemporal distribution characteristics of regional precipitation have changed dramatically (Dore 2005; Guibert et al. 2015; Li et al. 2015; Guan et al. 2017; Yang et al. 2017). The results from analyses of precipitation events around the world show that the variations in extreme precipitation have strong regional characteristics (Alexander et al. 2006). For example, the frequency and intensity of extreme precipitation events are increasing in Japan, Australia, South Korea, Thailand, and India (Roy & Balling 2004; Duan et al. 2015; Fiddes et al. 2015; Min et al. 2015; LimsaKul & SinghruK 2016) but decreasing in western Central Africa and Mongolia (Aguilar et al. 2009; Choi et al. 2009). Extreme precipitation events commonly trigger extreme hydrological events such as floods or droughts at local or regional scales, resulting in significant economic losses (Kunkel et al. 1999; Zong & Chen 2000). Moreover, as one of the most important components of global climate change, precipitation changes have indirect and direct impacts on natural vegetation, modern urban construction, the farming industry, energy generation, water resources, and the environment (Estrela & Vargas 2012; Capra et al. 2013; Wu et al. 2013; Liu et al. 2016; Wang et al. 2016). Therefore, an accurate understanding of the spatiotemporal variation characteristics of extreme precipitation is essential for the effective management of water resources and the formulation of climate change adaptation measures (Easterling et al. 2000).

In China, changes in extreme precipitation have also attracted the interest of many scholars. Previous studies have shown that the spatiotemporal changes in precipitation in China show great variability (You et al. 2011; Fu et al. 2013; Chen et al. 2014; Song et al. 2015; Song & Bai 2016; Sun et al. 2016; Zhang et al. 2019). For example, You et al. (2011) used precipitation indices to study the trend of extreme precipitation changes in China and found that for all precipitation indices, stations in the Yangtze River Basin and in southeastern and northwestern China have the largest positive trend magnitudes, while stations in the Yellow River Basin and northern China have the largest negative magnitudes. Fu et al. (2013) used the trend analysis method to analyze extreme precipitation indices and found that extreme rainfall events in Northeast China, North China, and the Yellow River Basin showed decreasing trends, while extreme rainfall events in the Yangtze River Basin, Southeast Coast, South China, Northwest China, and the Qinghai-Tibet Plateau showed increasing trends. Through the statistical analysis of extreme precipitation in the Yangtze River Basin by using three distributions (Pearson type III, general extreme value, and general normal), Chen et al. (2014) found that the precipitation amount increases gradually from the upper to the lower Yangtze River Basin, showing higher risks of floods and droughts in the middle and lower reaches of the Yangtze River Basin. Song et al. (2015) found that the regionally averaged total precipitation (PRCPTOT), very wet-day precipitation (R95), and extremely wet-day precipitation (R99) exhibited a tendency to increase, and the simple daily intensity index (SDII) showed a significant negative trend in the Songhua River Basin through the trend analysis of 11 precipitation indices. Song & Bai (2016) studied the variation characteristics of precipitation in Central Asia through cluster analysis and the Mann–Kendall (MK) method and found that precipitation in the southeastern region of Central Asia (Xinjiang, China) increased significantly. Sun et al. (2016) used the trend analysis method to analyze the extreme precipitation indices in the central part of the Yellow River Basin and found that the daily rainfall intensity exhibited a significant decrease over time. By the trend and statistical analysis of 12 extreme precipitation indices in the middle of the Yellow River Basin, Zhang et al. (2019) found that precipitation extremes presented a drying trend with fewer frequent precipitation events. In general, the above studies show that extreme precipitation is decreasing in Northeast China, North China, and the Yellow River Basin and increasing in Xinjiang, the eastern Qinghai-Tibet Plateau, the middle and lower reaches of the Yangtze River, and the southeastern coastal areas.

Although detailed large- and small-scale studies on extreme precipitation have been conducted in different regions of China, only a few related studies have been conducted in the upper reaches of the Hongshui River Basin (UHRB). Previous studies have covered large areas or considered few indicators (Zhang et al. 2009; Yang et al. 2010; Fischer et al. 2011, 2012b). Zhang et al. (2009) applied the MK test and the Bayesian model to systematically explore trends and abrupt changes in the precipitation series in the Pearl River Basin. The main findings of this study are that
increased precipitation variability and high-intensity rainfall were observed, although rainy days and low-intensity rainfall decreased. Using four extreme value statistical distributions, Yang et al. (2010) found that the spatial variations in precipitation in different return periods increase from upstream to downstream in the Pearl River Basin. Fischer et al. (2011) analyzed the trends of nine precipitation indices and found that the annual mean and extreme precipitation in the Pearl River Basin had almost no significant trends, but the dry period became longer and the wet period became shorter. Fischer et al. (2012b) analyzed the probability distribution of annual precipitation extremes using four distribution functions (gamma, generalized extreme value (GEV), generalized Pareto (GP), and Wakeby), and the results showed that the GEV is the most reliable and robust distribution in the estimation of the precipitation index over the Pearl River Basin. These above findings indicate potentially increased risk for locations subject to flooding, both urban and rural, across the Pearl River Basin. Extreme precipitation often causes serious socioeconomic losses and human casualties, so it is necessary to conduct a comprehensive and in-depth analysis of the spatiotemporal and statistical characteristics of changes in extreme precipitation.

In this study, we analyzed the spatiotemporal changes in extreme precipitation in the UHRB and the large-scale circulation factors that may be related to extreme precipitation changes. As many indices as possible were used to reflect the characteristics of extreme precipitation in the UHRB, and the best-fitting statistical distribution model was used to analyze the statistical characteristics of all the extreme precipitation indices. The next section introduces the data and methods used in this study. The section ‘Results’ provides an analysis of the spatiotemporal variation characteristics of extreme precipitation indices in the past 58 years to determine whether precipitation has become more extreme. Moreover, probability distributions are used to study the statistical variation characteristics of extreme precipitation events to evaluate changes in the potential risk of extreme precipitation in different periods. In addition, the potential links between large-scale atmospheric circulation and extreme precipitation events are also discussed. The last two sections provide discussion and conclusions, respectively. This study explores the unique and complex characteristics of extreme precipitation in the UHRB, and the results can provide important information for policymakers and stakeholders to use in addressing water management and environmental issues.

DATA SOURCES AND METHODS

Study area

The Hongshui River has abundant hydropower resources and is one of the important hydropower generation areas in China. The UHRB covers an area of approximately 98,500 km², accounting for 71.2% of the total area of the Hongshui River Basin (Huang et al. 2018). The terrain of the UHRB is very diverse, including highlands, hills, and plains. The elevation gradually increases from east to west, ranging from 200 to 3,300 m. Due to the combined influences of the South Asian monsoon and the East Asian monsoon, the precipitation in the flood season accounts for more than 80% of the total annual precipitation, making the UHRB vulnerable to flood disasters.

Observed data

Daily observed precipitation datasets from 18 meteorological stations from 1959 to 2016 were used to analyze the temporal, spatial, and statistical variation characteristics of extreme precipitation events in the UHRB (Figure 1; Table 1). These high-quality data were provided by the China Meteorological Administration. Figure 2 shows the data processing and analysis process. The software packages RelimDex and RHtests were developed by Zhang & Feng (2004) and Wang & Feng (2013) and have been extensively used for precipitation data quality control and homogenization (Huang et al. 2014; Qian 2016). In this study, these two software programs are used for quality control evaluation and the homogeneity assessment of daily precipitation data. The analysis results show that the daily observed precipitation series of 18 meteorological stations passed the homogeneity test, indicating that the data used have good reliability.

To examine the links between large-scale atmospheric circulation extreme precipitation events, three East Asian summer monsoon indices (the East Asian summer monsoon
index, EASMI; the South Asian summer monsoon index, SASMI; and the South China Sea summer monsoon index, SCSSMI) and the El Niño–Southern Oscillation (ENSO)/Pacific Decadal Oscillation (PDO) systems were analyzed. The EASMI, SCSSMI, and SASMI data were developed by Li & Zeng (2003, 2005) and can be downloaded from the following website: http://ljp.gcess.cn/dct/page/1. The Niño 3.4 and PDO indices were used to represent the state of the ENSO/PDO systems. The Niño 3.4 and PDO data were downloaded from the following website: www.esrl.noaa.gov/psd/data/climateindices/list/.

Methods

Extreme precipitation indices

A common opinion in the climate science community is that the more indices are used in an analysis, the better and more reliable the representation of the changes in extreme precipitation events in a specified region will be (Croitoru et al. 2013). Therefore, 12 indices that can reflect variation characteristics in intensity, frequency, and duration of extreme precipitation events in the UHRB were analyzed (Table 2). Most of them (nine indices) were selected from the list established by the climate community (the core indices of the Expert Team on Climate Change Detection, Monitoring, and Indices (ETCCDMI)). The other two indices (precipitation days (R0.1) and extremely heavy precipitation days (R30)) were selected by the authors to complete the list. Indices of low precipitation (R0.1) were also necessary because serious drought hazards frequently affect the UHRB and are also very important for agriculture. The number of extremely heavy precipitation days, which refers to a day with precipitation amounts exceeding 30 mm/day, was also considered. The indices established by the ETCCDMI have been extensively used to evaluate variation characteristics in extreme precipitation.
precipitation events in different areas of the world (Alexander et al. 2006; You et al. 2011; Sun et al. 2016). To keep the discussion and analysis concise, the selected extreme precipitation indices were divided into two groups. The SDII, PRCPTOT, R95 and R99, and maximum 1-day and 5-day precipitation (RX1day and RX5day) were categorized into one group to describe precipitation intensity, while the remaining indices were categorized into another group to reflect the number of days of precipitation.

### Trend analysis

The nonparametric MK method (Mann 1945; Kendall 1975) was used to analyze the trends of the temporal variations in extreme precipitation indices, and the statistical significance of the trends was performed with the MK test at the 95% confidence level. The nonparametric MK method is considered a simple and effective way of conducting climate change analysis and has been extensively used in the analysis of hydrometeorological time-series sets (Alexander et al. 2006; Capra et al. 2015; Chen et al. 2014). The MK statistical test is given as follows:

$$Z = \begin{cases} \frac{S - 1}{\sqrt{\text{Var}(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S + 1}{\sqrt{\text{Var}(S)}} & S < 0 \end{cases}$$

where statistic $S$ can be calculated as follows:

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

where $x_i$ and $x_j$ are the observations at the $i$th and $j$th moments, respectively, and $n$ is the length of the series. When $x_j - x_i$ is greater than, equal to, or less than 0, $\text{sgn}(x_j - x_i)$ equals 1, 0, or −1, respectively.

The statistic $Z$ can be used as a measure of a trend. $Z > 0$ and $Z < 0$ indicate increasing and decreasing trends, respectively. A larger $|Z|$ value refers to a more significant trend. In this study, a significance level of 0.05 is considered, which means that $Z > 1.96$ and $Z < -1.96$ indicate significant increasing and decreasing trends, respectively.

Since the autocorrelation of time series may affect the accuracy of trend analysis, the method developed by Yue & Wang (2002) was used to eliminate the possible autocorrelation in the extreme precipitation data series for the UHRB. In addition, Sen’s (1968) slope was also used to determine the degree of trend, as it can eliminate the impact of missing data or anomalies on the trend test. The slope is estimated by the following equation:

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

where $\beta$ is the estimate of the slope of the trend, and $x_i$ and $x_j$ are the observations at the $i$th and $j$th moments, respectively.

### Distribution functions selected

Statistical distribution functions were used to analyze the statistical variation characteristics of extreme precipitation events in the UHRB. Here, some possible distributions that are widely applied for modeling extreme events in
hydrometeorological and many other fields, such as gamma, exponential, GEV, Gumbel, and GP distributions, were used to study the statistical variation characteristics of extreme precipitation indices (Yang et al. 2010; Chen et al. 2014; Shin et al. 2013; Liang et al. 2012). The cumulative distribution functions of the GEV, Gumbel, GP, gamma, and exponential distributions are presented in Table 3. The parameters of all selected distributions were obtained using the L-moment method (Hosking & Wallis 1997). In addition, the Kolmogorov–Smirnov (KS) statistical test was used to choose the best-fitting model. The best-fitting statistical distribution of extreme precipitation was selected through the KS test, which was used to accurately analyze the statistical variation characteristics of extreme precipitation indices.
Cross-wavelet transform method

Cross-wavelet transform (CWT) analysis combines wavelet transform analysis with cross-spectrum analysis to diagnose the change characteristics of two time series as well as oscillation periods that are coupled between the frequency and time fields. In addition, the change in the phase angle can be used to analyze whether there is a significant correlation between two time series, and their interaction physical mechanism can be obtained (Torrence & Compo 1998; Grinsted et al. 2004). In this study, CWT analysis was applied to analyze the potential links between large-scale atmospheric circulation and extreme precipitation events in the UHRB, which can help us to understand how changes in large-scale atmospheric circulation affect extreme precipitation. The details of CWT analysis are given below.

For two time series $x_n$ and $y_n$, the cross-wavelet spectrum is defined as follows:

$$W_{XY} = W_X W_Y^*$$  \hspace{1cm} (4)

where $W_X$ and $W_Y$ represent the wavelet transforms and $^*$ denotes the complex conjugation. The cross-wavelet power
is further defined as $|W^{XY}|$. The complex argument $(W^{XY})$ can be interpreted as the local relative phase between $x_n$ and $y_n$ in time-frequency space.

The theoretical distribution of the cross-wavelet power of two time series with background power spectra $P_k^x$ and $P_k^y$ is given in Torrence & Compo (1998) as follows:

$$D \left( \frac{|W_n^x(s)W_n^y(s)|}{\sigma_x \sigma_y} \right) = \frac{Z_v(p)}{v} \sqrt{P_{k+}^xP_{k-}^y}$$  \hspace{1cm} (5)$$

where $Z_v(p)$ is the confidence level associated with the probability $p$ for a probability density function defined by the square root of the product of two $\chi^2$ distributions. In this study, the 5% significance level is calculated using $Z_2 (95\%) = 3.999$. More details of the CWT can be found in Grinsted et al. (2004), and the relevant codes can be downloaded from the following website: http://grinsted.github.io/wavelet-coherence/.

**RESULTS**

Spatiotemporal variation characteristics of extreme precipitation

Variation characteristics of precipitation intensity indices

Figures 3(a)–3(f) and 4(a)–4(f) show the spatial patterns and interannual trends of the precipitation intensity indices, respectively. At the same time, the $Z$-statistic values of extreme precipitation indices of all stations are also presented in Table 4. As shown in Figure 3(a), there were obvious precipitation centers in the eastern and central parts of the UHRB. In general, the PRCPTOT gradually decreased from east to west. PRCPTOT exhibited significant positive correlations with SDII, RX1day, RX5day, R95, and R99 at the 0.05 significance level, indicating that the spatial patterns of other extreme precipitation intensity indices are consistent with those of PRCPTOT (Table 5). According to the spatial pattern of the precipitation intensity indices, the

<table>
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<th>Z values and trends of extreme precipitation indices for each station in the UHRB</th>
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<td>WN</td>
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<td>SC</td>
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<td>ZYI</td>
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<td>PX</td>
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<td>DS</td>
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<td>FS</td>
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The bold value in Table 5 represents that the distribution did pass the 0.95 confidence level.

*↑* indicates an upward trend, while the unmarked indicates a downward trend.
central and eastern parts of the UHRB are relatively wet regions, while the western parts are relatively dry regions; this also means that the probability of extreme precipitation events in the eastern and central regions is higher than that in the western region. As shown in Figure 3(a), the PRCPTOT at 16 of the 18 meteorological stations showed a decreasing trend. Among them, the SC and AS stations in the northern part of the UHRB and the LX and ZYI stations in the western part of the UHRB showed significant decreasing trends. The interannual change trend of PRCPTOT was not significant, but PRCPTOT decreased at a rate of $-2.02 \text{ mm/decade}$ ($P > 0.05$, Figure 4(a)). As shown in Figure 4(b), the SDII increased slightly at a rate of $0.007 \text{ mm/day/decade}$ ($P > 0.05$). Among all 11 stations that showed an increasing trend for SDII, only HS, LD, and WM stations in the eastern part of the UHRB and the MZ station in the southwestern part of the UHRB showed significant increasing trends (Figure 3(b)). Most of the precipitation intensity indices in the UHRB exhibited slight and nonsignificant decreasing trends.

Figure 3 | Spatial patterns of values and trends in extreme precipitation indices in the UHRB from 1959 to 2016. A significance level of 0.05 is considered.
trends. For example, RX1day, RX5day, R95, and R99 decreased at rates of $-0.085$, $-0.145$, $-0.606$, and $-0.278$ mm/decade, respectively (Figure 4(c)–4(f)). Among the stations where precipitation intensity indices showed decreasing trends, only a few stations showed significant decreasing trends, such as those of R95 at the PX and ZYI stations and R99 at the LX station. Note that SDII, RX1day, RX5day, R95, and R99 generally increased (or significantly increased) at the stations in the eastern part of the basin and decreased (or significantly decreased) at the stations in the western part of the basin (Figure 3(b)–3(f)). Although the above five indices show a slight decrease during 1959–2016 in the UHRB, the trend is not significant. However, due to the large difference in precipitation in the east and west of the UHRB, under the influence of this slight decreasing trend, the possibility of extreme rainstorms in the east of the basin will increase, and the risk of extreme drought in the west will also increase.

**Variation characteristics of the number of precipitation day indices**

Figures 3(g)–3(l) and 4(g)–4(l) show the spatial patterns and interannual trends of the number of precipitation day indices, respectively. As shown in Figure 3(g), the consecutive dry days (CDDs) gradually increased from east to west in the UHRB, and its value ranged from 23.3 to 48.7 days/year. The consecutive wet days (CWDs) ranged from 6.7 to 8.1 days/year, with the highest value occurring in the middle of the UHRB (Figure 3(h)). Most indices (except the CWD and CDD) increased from west to east in the UHRB, which was consistent with the spatial variation characteristics in precipitation intensity indices in the region (Figure 3(j)–3(l)). All of the above results revealed that the western part of the UHRB was the driest, while the eastern region was relatively wet, which is consistent with previous studies in similar areas, such as Fischer et al. (2011).

The average CDD in the UHRB increased significantly at a rate of 0.119 days/decade ($P < 0.05$); increasing trends were observed at 78% of the stations, but a significant increasing trend was observed only at station HS in the northeastern UHRB (Figures 3(g) and 4(g)). The average CWD of the UHRB decreased significantly at a rate of $-0.023$ days/decade ($P < 0.05$), and significant decreasing trends were observed at 28% of the stations (Figures 3(h) and 4(h)). The average R0.1 of the UHRB decreased significantly at a rate of $-0.787$ days/decade, and the decreasing trends at all stations passed the significance test at the 99% level (Figures 3(i) and 4(i)). The average R10 of the UHRB decreased significantly at a rate of $-0.064$ days/decade ($P < 0.05$), but a significant decreasing trend was observed at only five stations (Figures 3(j) and 4(j)).

### Table 5: Correlation coefficients for extreme precipitation indices in the UHRB during 1959–2016

<table>
<thead>
<tr>
<th></th>
<th>PRCPTOT</th>
<th>SDII</th>
<th>RX1day</th>
<th>RX5day</th>
<th>R95</th>
<th>R99</th>
<th>CDD</th>
<th>CWD</th>
<th>R0.1</th>
<th>R10</th>
<th>R20</th>
<th>R30</th>
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<tbody>
<tr>
<td>PRCPTOT</td>
<td>1</td>
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<tr>
<td>SDII</td>
<td>0.69**</td>
<td>1</td>
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<tr>
<td>RX1day</td>
<td>0.37*</td>
<td>0.36*</td>
<td>1</td>
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<tr>
<td>RX5day</td>
<td>0.73**</td>
<td>0.61**</td>
<td>0.16</td>
<td>1</td>
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<tr>
<td>R95</td>
<td>0.77**</td>
<td>0.84**</td>
<td>0.12</td>
<td>0.77**</td>
<td>1</td>
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<tr>
<td>R99</td>
<td>0.56**</td>
<td>0.64**</td>
<td>0.19</td>
<td>0.72**</td>
<td>0.83**</td>
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<tr>
<td>CDD</td>
<td></td>
<td>-0.16</td>
<td>0.15</td>
<td>-0.02</td>
<td>0.07</td>
<td>0.05</td>
<td>0.16</td>
<td>1</td>
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<tr>
<td>CWD</td>
<td></td>
<td></td>
<td>0.16</td>
<td>-0.03</td>
<td>0.45**</td>
<td>0.29**</td>
<td>0.14</td>
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<td>-0.18</td>
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<tr>
<td>R0.1</td>
<td></td>
<td></td>
<td></td>
<td>0.55**</td>
<td>-0.12</td>
<td>0.15</td>
<td>0.34**</td>
<td>0.19</td>
<td>0.13</td>
<td>-0.32*</td>
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<td>R10</td>
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<td></td>
<td>0.94**</td>
<td>0.56**</td>
<td>0.05</td>
<td>0.60**</td>
<td>0.55**</td>
<td>0.32*</td>
<td>-0.22</td>
<td>0.56**</td>
<td>0.60**</td>
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<td>R20</td>
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<td></td>
<td>0.94**</td>
<td>0.79**</td>
<td>-0.01</td>
<td>0.65**</td>
<td>0.75**</td>
<td>0.48**</td>
<td>-0.13</td>
<td>0.42**</td>
<td>0.58**</td>
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<td>R30</td>
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<td></td>
<td>0.84**</td>
<td>0.86**</td>
<td>0.07</td>
<td>0.65**</td>
<td>0.88**</td>
<td>0.57**</td>
<td>-0.03</td>
<td>0.33**</td>
<td>0.30**</td>
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*Significant at 0.05 level.
**Significant at 0.01 level.
Comparing the change trends of R0.1, R10, R20, and R30 revealed that as the precipitation intensity increased, the decreasing trend of the number of precipitation days gradually weakened (Figure 4(j)–4(l)). For example, for the average R30 of the UHRB, the decrease rate was only −0.003 days/decade. No significant interannual change trend was observed in the extreme precipitation indices, except for the CDD, CWD, R0.1, and R10 (Figure 4). The significant decrease in the CWD and R0.1 and the significant increase in the CDD clearly indicate that the decrease in the PRCPTOT and the increase in the SDII were affected by the decrease in the number of wet days.

**Statistical variation characteristics of extreme precipitation events**

**Selection of the appropriate distribution**

The GEV, Gumbel, GP, gamma, and exponential distributions were used to analyze the statistical variation
characteristics of the extreme precipitation indices in the UHRB from 1959 to 2016. The corresponding statistical test results are shown in Tables 6 and 7. Compared with those for the GP and exponential distributions, the KS statistics for the GEV, Gumbel, and gamma distributions were better, indicating that these three distributions have good applicability for the statistical modeling of time-series data for extreme precipitation indices (Table 6). Further analysis found that compared with the Gumbel and gamma distributions, the GEV distribution exhibited better fitting performance for the statistical modeling of time-series extreme precipitation index data except for RX1DAY, and the KS test statistical values for the extreme precipitation indices at most stations passed the significance test (Table 7). In fact, comparisons with other extreme value distributions indicated that the GEV distribution has the best performance for fitting extreme precipitation indices in many regions (Fischer et al. 2012b). Note that although the GP distribution has been extensively applied to some previous studies and has achieved good results (Bhunya et al. 2013; She et al. 2015), it performed poorly for fitting extreme precipitation indices in the UHRB. In summary, considering the good fitting performance of the GEV distribution to the extreme precipitation indices at each station in the UHRB, the GEV distribution was used to analyze the statistical variation characteristics of extreme precipitation.

### Variation characteristics of extreme precipitation in different subperiods

To further study the variation in extreme precipitation events in the UHRB, the GEV distribution was used to analyze the probability distribution function (PDF) change

### Table 6 | The KS test values for the extreme precipitation index data series

<table>
<thead>
<tr>
<th>Index</th>
<th>Regionally averaged value</th>
<th>Best distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GEV</td>
<td>Gumbel</td>
</tr>
<tr>
<td>PRCPTOT</td>
<td>0.20</td>
<td>0.13</td>
</tr>
<tr>
<td>SDII</td>
<td>0.13</td>
<td>0.23</td>
</tr>
<tr>
<td>RX1day</td>
<td>0.70</td>
<td>0.77</td>
</tr>
<tr>
<td>RX5day</td>
<td>0.15</td>
<td>0.5</td>
</tr>
<tr>
<td>RX95</td>
<td>0.13</td>
<td>0.23</td>
</tr>
<tr>
<td>RX99</td>
<td>0.20</td>
<td>0.23</td>
</tr>
<tr>
<td>CDD</td>
<td>0.23</td>
<td>0.5</td>
</tr>
<tr>
<td>CWD</td>
<td>0.13</td>
<td>0.2</td>
</tr>
<tr>
<td>R0.1</td>
<td>0.13</td>
<td>0.2</td>
</tr>
<tr>
<td>R10</td>
<td>0.23</td>
<td>0.13</td>
</tr>
<tr>
<td>R20</td>
<td>0.17</td>
<td>0.16</td>
</tr>
<tr>
<td>R30</td>
<td>0.07</td>
<td>0.13</td>
</tr>
</tbody>
</table>

The bold value indicates that the distribution did not pass the 0.9% confidence level.

### Table 7 | The numbers of optimal distributions and unqualified distributions

<table>
<thead>
<tr>
<th>Index</th>
<th>GEV</th>
<th>Gumbel</th>
<th>Gamma</th>
<th>GP</th>
<th>Exp.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$H - 0$</td>
<td>$H - 1$</td>
<td>$H - 0$</td>
<td>$H - 1$</td>
<td>$H - 0$</td>
</tr>
<tr>
<td>PRCPTOT</td>
<td>18</td>
<td>0</td>
<td>7</td>
<td>11</td>
<td>18</td>
</tr>
<tr>
<td>SDII</td>
<td>18</td>
<td>0</td>
<td>8</td>
<td>10</td>
<td>18</td>
</tr>
<tr>
<td>RX1DAY</td>
<td>17</td>
<td>1</td>
<td>18</td>
<td>0</td>
<td>16</td>
</tr>
<tr>
<td>RX5DAY</td>
<td>17</td>
<td>1</td>
<td>18</td>
<td>0</td>
<td>16</td>
</tr>
<tr>
<td>RX95p</td>
<td>17</td>
<td>1</td>
<td>18</td>
<td>0</td>
<td>18</td>
</tr>
<tr>
<td>RX99p</td>
<td>18</td>
<td>0</td>
<td>17</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>CDD</td>
<td>16</td>
<td>2</td>
<td>17</td>
<td>1</td>
<td>14</td>
</tr>
<tr>
<td>CWD</td>
<td>17</td>
<td>1</td>
<td>15</td>
<td>3</td>
<td>15</td>
</tr>
<tr>
<td>R0.1</td>
<td>18</td>
<td>0</td>
<td>7</td>
<td>11</td>
<td>18</td>
</tr>
<tr>
<td>R10</td>
<td>17</td>
<td>1</td>
<td>6</td>
<td>12</td>
<td>18</td>
</tr>
<tr>
<td>R20</td>
<td>18</td>
<td>0</td>
<td>6</td>
<td>12</td>
<td>18</td>
</tr>
<tr>
<td>R30</td>
<td>17</td>
<td>1</td>
<td>15</td>
<td>3</td>
<td>18</td>
</tr>
</tbody>
</table>

$H - 0$ represents the number of optimal distribution stations in the KS test, while $H - 1$ represents the number of stations that have not passed the KS test.
characteristics of the extreme precipitation indices in two subperiods of the same length (Figure 5). The black and red lines represent 1959–1987 and 1988–2016, respectively. The shaded fills on the left and right are 5 and 95% cumulative percentage values, respectively. As shown in Figure 5, except for those of the CDD and SDII, the PDFs of most extreme precipitation indices show a leftward shift. For example, the PDF value of PRCPTOT corresponding to the 95th percentile was 1,344.3 mm/year from 1959 to 1987, while it was 1,296.5 mm/year from 1988 to 2016 (Figure 5(a)). The PDF value of the CWD corresponding to the 95th percentile was 10.3 days/year from 1959 to 1987, while it was 9.2 days/year from 1988 to 2016 (Figure 5(h)). The PDF value of R0.1 corresponding to the 95th percentile was 190.2 days/year from 1959 to 1987, while it was 168.2 days/year from 1988 to 2016 (Figure 5(i)). Of the PDFs of R0.1, R10, R20, and R30, the PDF of R0.1 showed the largest leftward shift from 1988 to 2016.
followed by that of R10, while those of R20 and R30 showed slight leftward shifts. All the above results indicate that the UHRB tended to be dry and have very little precipitation in recent decades, which is consistent with the results in the ‘Spatiotemporal variation characteristics of extreme precipitation’ section.

**CWT analysis between extreme precipitation indices and large-scale atmospheric circulation**

CWT analysis was used to study the relationships between the atmospheric circulation indices and the extreme precipitation indices (Figures 6–10). Using this method allowed us to understand whether there is a significant oscillatory period between large-scale atmospheric circulation and extreme precipitation. For brevity, the results for only RX1DAY, R0.1, and CWD, which represent the extreme precipitation intensity, frequency, and duration, respectively, are described. More details about the CWT analysis between extreme precipitation indices and large-scale atmospheric circulation indices can be found in Figures 6–10.

Figure 6 shows the CWT analysis between Niño 3.4 and the extreme precipitation indices. Niño 3.4 and the CWD had significant oscillation periods of 2–3 years from 1965 to 1975 and from 1995 to 2005 (Figure 6(b)). However, Niño 3.4 and R0.1 had several significant oscillation periods of approximately 3, 6, and 15 years from 1959 to 2016 (Figure 6(c)). From 1985 to 2005, Niño 3.4 and RX1DAY had a significant oscillation period of approximately 5 years (Figure 6(i)). In addition, Niño 3.4 had a long-term significant relationship with the mesoscale cycles of R0.1 and RX1DAY. For example, in the 3–6-year oscillation period, Niño 3.4 and R0.1 had significant negative correlations from 1960 to 1970 and 1980 to 2016, while in the 15-year oscillation period, there was a significant positive correlation from 1980 to 2010. All of the above results indicate

**Figure 6 |** CWT analysis between the Niño3.4 and extreme precipitation indices in the UHRB from 1959 to 2016. The relative phase relationship is indicated by the arrow direction (anti-phase points left and in-phase points right). The 5% significance level against red noise is shown as a thick contour line. Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/wcc.2021.339.
that the changes in precipitation intensity, frequency, and duration in the UHRB are closely related to the occurrence of ENSO events.

Figure 7 shows the CWT analysis between the PDO and the extreme precipitation indices. As shown in Figure 7(b), the PDO and CWD had a significant oscillation period of approximately 1–2 years from 1980 to 1985. Similarly, Figure 7(c) shows that PDO was significantly positively correlated with R0.1, with an oscillation period of 5–6 years, from 1980 to 2016. However, the PDO was significantly positively correlated with RX1day, with an oscillation period of 5–6 years, from 2006 to 2010. All of the above results indicate that the changes in precipitation intensity, frequency, and duration in the UHRB are also closely related to the PDO.

Figures 8–10 show the CWT analysis between the extreme precipitation indices and the EASMI, SASMI, and SCSMI. As shown in Figures 8(b), 9(b), and 10(b), CWD and the EASMI, SASMI, and SCSMI all had significant oscillation periods of approximately 1–3, 4–6, and 15–20 years, and the oscillation periods among these indices were usually significantly positively correlated. Among them, the relationship between CWD and the SCSMI was the strongest because a significant oscillation period of 15–20 years can be observed from 1959 to 2016, indicating that the SCSMI may have a greater impact on the duration of precipitation in the UHRB than the other indices. R0.1 and RX1day had significant small-scale oscillation periods (e.g., 2, 4, 8, and 15 years) with the East Asian summer monsoon indices (EASMI, SASMI, and SCSMI) from 1959 to 2016, indicating that the changes in precipitation frequency and intensity in the UHRB are closely related to the East Asian summer monsoon (Figures 8–10).
DISCUSSION

Although an increase in the frequency of extreme precipitation events has been observed in many regions of the world and in China (Alexander et al. 2006; Wang et al. 2013; Chen et al. 2014; Limskul & Singhruck 2016; Song & Bai 2016), our study found that the frequency of extreme precipitation events in the UHRB did not increase significantly, indicating that the risk of flooding in the region may not have changed significantly. However, the variation characteristics of most extreme precipitation indices in the UHRB indicated that the region is becoming drier, with less frequent precipitation events, which is consistent with the previous studies of Xiao et al. (2016), Deng et al. (2018), and Huang et al. (2018). The significant decrease in the CWD and R0.1 and the significant increase in the CDD may be related to the increase in drought throughout the UHRB (Figure 4) and may partly explain why Southwest China has suffered from frequent droughts in recent years (Fischer et al. 2011; Barriopedro et al. 2012; Zhang et al. 2013). Meteorologists (Li et al. 2011; Barriopedro et al. 2012; Tan et al. 2017) have suggested that the transfer of humid and warm moisture from the Bay of Bengal to southwestern China is affected by the westward shift of the enhanced western Pacifiﬁc subtropical high, which leads to droughts in the rainy season. According to Su et al. (2006), in recent decades, the summer temperature over Central Asia has decreased slightly, while the temperature over the northwestern Pacific has warmed, which has led to the weakening of the summer monsoon and a reduction in the number of rainy days.

Changes in extreme precipitation are related to large-scale climate changes and local geographic features (Li et al. 2012). For the geographical elements of the UHRB, elevation and longitude are the main factors affecting the spatial distribution of precipitation (Huang et al. 2018). The
southeastern part of the UHRB is flat, the western part is a plateau, and the central part is hilly, which is conducive to water vapor moving from the ocean to the mainland in summer. When water vapor reaches the central part of the UHRB, its movement is affected by the western plateau (Ueno et al. 2011), and a large amount of precipitation forms on the windward slope (Houze & Medina 2005); these conditions explain why precipitation in the UHRB shows strong spatial variability. Therefore, there is an obvious precipitation difference between the eastern and western UHRB, and the hilly region in the middle of the UHRB receives the most precipitation (Figure 3(a)).

According to the results of the CWT analysis (Figures 6–10), the indices Niño 3.4, PDO, EASMI, SASMI, and SCSSMI had significant statistical correlations with the extreme precipitation indices within a certain period, indicating that the ENSO, PDO, and summer monsoon systems all have a certain degree of influence on the precipitation in this region. These findings are basically consistent with the conclusions of Huang et al. (2018). Changes in monsoon activities and large-scale atmospheric circulation are crucial factors affecting the global climate and are strongly correlated with extreme precipitation in many parts of the world (Sun et al. 2015; Zhang et al. 2016; Jiang et al. 2017). Globally, extreme precipitation events are closely related to changes in the ENSO and PDO systems (Krichak et al. 2014; Limsakul & Singhruck 2016). Ouyang et al. (2014) found that precipitation in most parts of China decreased during the warm period of El Niño/PDO and increased during the cold period of La Niña/PDO. Fischer et al. (2022a) and Preethi et al. (2017) proposed that the East Asian summer monsoon, which strongly affects precipitation in most parts of China, is one of the vital components of the global climate system. It is not a coincidence that there are larger areas with significant oscillation periods in Figures 8(b) and 10(b) than in
Figure 9(b). Compared with the South Asian summer monsoon, the East Asian summer monsoon has a significantly greater impact on extreme precipitation in the UHRB, while the South China Sea summer monsoon, as an important subsystem of the East Asian summer monsoon, also has a strong impact on extreme precipitation in the UHRB.

CONCLUSIONS

Based on daily precipitation data in the UHRB from 1959 to 2016, the spatiotemporal variation characteristics of extreme precipitation indices that reflect the frequency, intensity, and duration of extreme precipitation events were analyzed. In addition, the links between extreme precipitation indices and East Asian summer monsoon and large-scale circulation indices were also analyzed. The findings are summarized as follows:

1. Spatially, most extreme precipitation indices (except those of the CDD and CWD) increase from west to east in the UHRB, indicating that the eastern region is wetter than the western region. Except for the CDD and SDII, most of the extreme precipitation indices in the UHRB showed a nonsignificant decrease from 1959 to 2016. Among them, the regional average CDD increased significantly at a rate of 0.119 days/decade ($P < 0.05$), while the CWD, R0.1, and R10 decreased significantly at rates of $-0.023$, $-0.787$, and $-0.064$ days/decade, respectively ($P < 0.05$). The change trends of the extreme precipitation indices indicated that the UHRB tends to be dry, with few precipitation events.

2. The GEV distribution was the best-fitting distribution for most extreme precipitation indices in the UHRB, followed by the gamma distribution. Using the GEV distribution to fit the precipitation indices showed that the PDFs of most extreme precipitation indices, especially that of R0.1,
shifted significantly to the left in 1988–2016 compared with 1959–1987, indicating that the region has experienced a significant drying trend in recent decades.

(3) According to the results of the CWT analysis, the large-scale circulation indices, including Niño 3.4, PDO, EASM, SASM, and SCSSM, have significant statistical correlations with extreme precipitation indices (such as CWD, RX1day, and R0.1), indicating that the ENSO, PDO, and summer monsoon systems have a strong influence on the frequency, intensity, and duration of extreme precipitation events in the UHRB. Compared with the South Asian summer monsoon, the East Asian summer monsoon and its subsystem, and the South China Sea summer monsoon have a stronger influence on UHRB precipitation.

The regional change characteristics of the extreme precipitation in the UHRB reflect the spatial variability of the extreme precipitation changes in the region, which can be attributed to the complex interactions among large-scale atmospheric circulation, summer monsoon systems, and the local topography. In this study, only limited observational data were used to analyze extreme precipitation events in the basin, and the potential influence of human activities on extreme precipitation was not considered. Further research could use regional climate models to conduct high-resolution climate simulations of the basin, analyze how human activities (afforestation, urbanization, and carbon dioxide emissions) affect extreme precipitation events, and study the relationship between global extreme temperature changes and the accompanying extreme precipitation changes. The results in this study help to more comprehensively understand the characteristics of extreme precipitation changes and their relationship with global climate change and can provide references for further research.

ACKNOWLEDGEMENTS

The observed meteorological data were provided by the China Meteorological Administration and are available at http://data.cma.cn/data. The data for the summer monsoon indices were provided by Dr Jianping Li (Professor, Beijing Normal University, China) and are available at http://ljp.gcess.cn/dct/page/1. The Niño 3.4 and PDO indices are available at http://www.esrl.noaa.gov/psd/data/climateindices/list/. The software packages of RclimDex and RHtests V4 are available at http://etccdi.pacificclimate.org/software.shtml. The MATLAB toolbox for calculating the CWT was provided by Dr Aslak Grinsted (Climate Scientist, University of Copenhagen, Denmark) and is available at http://grinsted.github.io/wavelet-coherence/.

AUTHOR CONTRIBUTIONS

Y.H. conceptualized the article, developed the methodology, conducted a formal analysis, investigation, and data curation, wrote the original draft and the review, and edited the article. L.Y. validated the article, wrote the review, edited the article, and engaged in funding acquisition. W.X. conceptualized the whole article, wrote the review, and edited the article. G.H. validated the article and developed the methodology. Y.Z. devised the methodology and performed the investigation.

CONFLICT OF INTEREST

The authors declare that there are no competing financial interests.

FUNDING

This study was jointly funded by the National Key Research and Development Program (nos. 2018YFC1508200 and 2017YFC0404701), the National Natural Science Foundation of China (no. 51909275), and the Innovation Project of Guangxi Graduate Education (no. YCBZ2018023).

DATA AVAILABILITY STATEMENT

All relevant data are available from an online repository or repositories. Data can be downloaded from: http://data.cma.cn/data/cddetail/dataCode/SURF_CLI_CHN_MUL_DAY_V3.0.html


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First received 7 December 2020; accepted in revised form 23 February 2021. Available online 15 March 2021