Regional Frequency Analysis of Precipitation Extremes and Its Spatio-Temporal Patterns in the Hanjiang River Basin, China

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Abstract: Extreme events such as rainstorms and floods are likely to increase in frequency due to the influence of global warming, which is expected to put considerable pressure on water resources. This paper presents a regional frequency analysis of precipitation extremes and its spatio-temporal pattern characteristics based on well-known index-flood L-moments methods and the application of advanced statistical tests and spatial analysis techniques. The results indicate the following conclusions. First, during the period between 1969 and 2015, the annual precipitation extremes at Fengjie station show a decreasing trend, but the Wuhan station shows an increasing trend, and the other 24 stations have no significant trend at a 5% confidence level. Secondly, the Hanjiang River Basin can be categorized into three homogenous regions by hierarchical clustering analysis with the consideration of topography and mean precipitation in these areas. The GEV, GNO, GPA and P III distributions fit better for most of the basin and MARE values range from 3.19% to 6.41% demonstrating that the best-fit distributions for each homogenous region is adequate in predicting the quantiles estimates. Thirdly, quantile estimates are reliable enough when the return period is less than 100 years, however estimates for a higher return period (e.g., 1000 years) become unreliable. Further, the uncertainty of quantiles estimations is growing with the growing return periods and the estimates based on R95P series have a smaller uncertainty to describe the extreme precipitation in the Hanjiang river basin (HJRB). Furthermore, In the HJRB, most of the extreme precipitation events (more than 90%) occur during the rainy season between May and October, and more than 30% of these extreme events concentrate in July, which is mainly impacted by the sub-tropical monsoon climate. Finally, precipitation extremes are mainly concentrated in the areas of Du River, South River and Daba Mountain in region I and Tianmen, Wuhan and Zhongxiang stations in region III, located in the upstream of Danjiangkou Reservoir and Jianghan Plain respectively. There areas provide sufficient climate conditions (e.g., humidity and precipitation) responsible for the occurring floods and will increase the risk of natural hazards to these areas.

Keywords: extreme rainfall; regional frequency analysis; L-moments; Hanjiang river basin

1. Introduction

Extreme climate events are expected to change in many regions due to the influence of global warming. Daily precipitation extremes do appear to be increasing in magnitude and frequency at a global or continental scale, in both dry and wet regions. This phenomena has a potential to trigger floods and droughts [1–3]. The Intergovernmental Panel on Climate Change (IPCC) special report on...
managing the risks of extreme events and disasters to advance climate adaptation indicates that it is likely that the frequency of heavy precipitation or the proportion of total rainfall from heavy falls will increase in the twenty-first century in many areas of the world [4]. In China, there are the same variations. The average intensity and extreme precipitation values tend to increase, so does the extreme precipitation occurrence [5]. Heavy precipitation events present a challenge to public safety, life, and lead to huge economic loss and low food crop productivity [6]. Additionally, precipitation is a key component of the hydrological cycle and a primary input for hydrometeorological models [7]. Hence, extreme precipitation events have received an unprecedented level of attention in recent decades.

The Hanjiang River Basin (HJRB), the largest drainage basin of the Yangtze River, is the central hinge of economic joints between south and north, west and east of China due to the advantages of location and physical geographical environment [8]. The Danjiangkou Reservoir, located in the middle and upper reaches of Hanjiang River, is both a key flood control project for the middle and lower reaches of Hanjiang River and the water source for the middle line South-to-North water diversion project of China with its multiple purposes including flood control, water supply, hydropower generation, navigation, etc., which play an important role in the sustainable development of China [9]. However, frequent extreme precipitation events and floods in the Hanjiang River Basin lead to a considerable loss with respect to both the economy and human life. The continuous rainstorm during August 1981 caused a rare flood disaster in the Hanzhong area of HJRB [10]. On 30 July 1983, a catastrophic flood caused by regional heavy rain resulted in a devastating disaster to Ankang City [11]. During 5–7 July 1990, the regional heavy rain in the area of Hanzhong led to a flood disaster, which caused the economic loss about 400 million RMB [12]. There were different levels of floods caused by the rainstorms that occurred in the Hanjiang River Basin in 2003, 2005, 2007, 2010 and 2011 [13,14]. Considering the significance of water security in the HJRB, a large amount of research has been undertaken in order to improve regional water resource management for the basin. A lot of researchers analyzed all previous storm floods occurring in the Hanjiang River in detail, specifically in terms of the process and characteristics of precipitation and flooding [14–17]. To give an important technological support to flood control decision making and integrated water resource management for this basin, Guo and Zhang et al. designed and developed a GIS-based flood forecasting system for the Hanjiang River Basin [18,19]. Yin et al. analyzed the temporal and spatial changes of monthly/annual precipitation in the upper reaches of the Hanjiang River, and found that annual precipitation manifested a decreasing trend during the last 50 years on the whole, but the enhanced southeast monsoon possibly caused an increase in the occurrence of rainstorms and flooding in late July and August [11]. The impact of climate change on extreme events is a prevailing focus of research. Xu et al. predicted the runoff in the upper reaches of the Hanjiang River basin under A2 and B2 climate scenarios by coupling the GCM and HBV model and found that the floods will occur more frequently under both scenarios in these areas [20]. In order to reflect the true feature of extreme rainfall and floods, Chen et al. studied the joint distribution of the extreme rainfall and floods for the upper-middle reaches of the Hanjiang River based on the Copula function [21]. Xu et al. used the index-flood method to analyze the regional flood frequency upstream in the Hanjiang River and found that regional flood frequency analysis is an effective way to estimate flood quantiles and can satisfy engineering design requirements [22]. These studies were beneficial to understanding the behaviors of precipitation and flooding in the HJRB, but the investigation of regionalization of precipitation extremes and its spatial patterns in the HJRB is limited.

Hosking and Wallis designed and developed the L-moments technique with the advantages of characterizing a wider range of distributions and more robustness with respect to outliers in data to undertake regional frequency analysis [23–25]. Regarding the advantages of this technique, a variety of L-moments based methods have been extensively employed in the regional frequency analysis of extreme precipitation and floods [22,26–30]. Although the L-moments method is being increasingly used in the regional frequency analysis, this technique has not acquired popularity in China because the Pearson-III distribution is still widely used as the official recommendation in hydrological frequency
analysis [29]. Only a few reports concerning regional frequency analysis using the L-moments method can be found in China, especially in the HJRB. Chen et al. used the L-moments technique to do the regional low flow frequency analysis in the Dongjiang basin based on five frequency distributions and the results indicated that the LN3 distribution was identified as the most appropriate distribution for the area [31]. Yang et al. conducted regional frequency analysis using the well-known L-moments method to identify the spatial pattern of flooding and found that the flood frequency of the whole Pearl River basin gradually decreases from upstream to downstream [32]. Excepting the regional frequency analysis of flooding, the regional frequency analysis of precipitation extremes using the L-moments approach was conducted in the Pearl River Basin by Yang et al., which is helpful for understanding the occurrence of floods and droughts across both space and time [29]. Similar studies have been reported in the Huai River Basin and Guangdong Province [26,33]. Additionally, extreme precipitation events are the main causes for the flood hazards in the Hanjiang River Basin [5].

However, no systematic research on the regional frequency analysis of precipitation extremes using the L-moments approach, the pattern characteristics of rainfall extremes, seasonality of the precipitation extremes, and the potential link between heavy rain and floods has been conducted across the entire Hanjiang River Basin. Therefore, considering the significance of water security in the HJRB, efforts should be made for the regional frequency analysis of extreme precipitation in the basin. The present study aims to: (1) investigate and identify the hydrological homogeneous sub-regions for annual precipitation extremes in the Hanjiang River Basin; (2) hunt for the best probability distribution for precipitation extremes using the L-moments methods taking accuracy and uncertainty analysis into consideration; (3) analyze the characteristics of spatio-temporal patterns of extreme rainfall events in order to reveal the underlying impacts of climate variations dominated in the Hanjiang River Basin. Overall, this study is expected to benefit the understanding of the behaviors of precipitation and floods and the characteristics of extreme precipitation in the HJRB, which will be helpful for the policymaker to formulate reasonable flood control strategies in order to protect peoples’ lives and property safety, and to ensure the safe and reliable operation of the Middle Route Project of the South-to-North Water Diversion Project.

2. Study Area and Data

The Hanjiang River Basin (HJRB) (106°12′–114°14′ E and 30°08′–34°11′ N, Figure 1) is situated in the central part of China and is involved in the provinces of Shanxi, Hubei, Henan, Sichuan, Gansu, and Chongqing [34,35]. The Hanjiang River (HJR) is the biggest tributary of the Yangtze River, covering a total drainage area of 159,000 km² with a length of 1557 km [36,37]. The mainstream of the river originates from the southern slope of the Qinling Mountains and finally pours into the Yangtze River at Wuhan City. The average annual temperature of HJRB ranges from 15 °C to 17 °C [38]. The general climate in HJRB is mild, and it is characterized by a sub-tropical monsoon climate. The sub-tropical monsoon climate and varying topography result in a dramatic spatio-temporal diversity of water resource distribution. The average annual precipitation of HJRB ranges from 700 mm to 1800 mm [39]. There are big inter-annual variations and an uneven distribution of the precipitation in the HJRB, with 70%–80% of the annual total during May–October [38,39]. The runoff of HJR is closely related to rainfall and the runoff during May–October accounts for about 75% of the annual total. Flood and drought disasters take place frequently in this region. The Danjiangkou Reservoir (DJKR) located in the upper HJR, consisting of the Dan Reservoir (DR) and the Han Reservoir (HR), was constructed between 1958 and 2005. Designed as an important water source for the Middle Route Project of the South-to-North Water Diversion Project (SNWDP) [37], the HJRB is one of the important production bases of fresh water aquaculture in China, and is of crucial importance in both the economy and ecology of this region [35].
Daily precipitation observations for the time period 1951–2015 were provided by the China Meteorology Administration (CMA) and the National Climate Center, which is officially in charge of monitoring, collecting, compiling and releasing high-quality hydrological data in China. Hence the quality of data can be guaranteed in this study [29]. Note that the time period 1969–2015 was used in this study because the length of continuous missing values are more than one year before 1969. Between 1969 and 2015, the continuous missing daily precipitation data (less than 0.01%) were filled by using the average values of the same days [40–42]. A total of 25 stations in and around the HJRB were used, 13 of which are within the HJRB and the rest are outside but close to the edges of the basin. The detailed information is shown in Table 1. Based on the daily precipitation observations, four indices are derived for analysis: (1) the maximum 1-day precipitation amount (RX1day); (2) the maximum 5-day precipitation amount (RX5day); (3) the maximum 7-day precipitation amount (RX7day); and (4) the total amount of precipitation on those days that have precipitation above the 95th percentile, i.e., precipitation on very wet days (R95P). Similar indices have also been used in previous studies and are recommended by the World Meteorological Organization (WMO), the project on Climate Variability and Predictability (CLIVAR) and the Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDMI) [26,29,30,43].

Table 1. List of 25 stations and associated characteristics in the Hanjiang River Basin (HJRB).

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Station Name</th>
<th>Abbreviation</th>
<th>Latitude (N)</th>
<th>Longitude (E)</th>
<th>Altitude (m)</th>
<th>Annual Precipitation Total (mm)</th>
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<tbody>
<tr>
<td>57034</td>
<td>Wugong</td>
<td>WG</td>
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<td>110.08</td>
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<td>111.03</td>
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<td>Luanchuan</td>
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<td>33.78</td>
<td>111.60</td>
<td>750.3</td>
<td>808.53</td>
</tr>
<tr>
<td>57106</td>
<td>Lveyang</td>
<td>LY</td>
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<td>106.15</td>
<td>794.2</td>
<td>772.34</td>
</tr>
<tr>
<td>57127</td>
<td>Hanzhong</td>
<td>HZ</td>
<td>33.07</td>
<td>107.03</td>
<td>509.5</td>
<td>849.14</td>
</tr>
<tr>
<td>57134</td>
<td>Foping</td>
<td>FP</td>
<td>33.52</td>
<td>107.98</td>
<td>827.2</td>
<td>903.01</td>
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<tr>
<td>57143</td>
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<td>761.49</td>
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### Table 1. Cont.

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<tr>
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<th>Station Name</th>
<th>Abbreviation</th>
<th>Latitude (N)</th>
<th>Longitude (E)</th>
<th>Altitude (m)</th>
<th>Annual Precipitation Total (mm)</th>
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<td>FJ</td>
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<td>1106.58</td>
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<td>111.30</td>
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</tr>
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<td>23.1</td>
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<td>1410.85</td>
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### 3. Methodology

#### 3.1. Stationarity Test and Serial Correlation Check

The trend test is employed to examine the stationarity in hydrological series [29]. Trend identification is an important issue in hydrological time series analysis. It is the basis not only for understanding the long-term variations of hydrological processes, but also for revealing periodicities and other characteristics of hydrological processes. As a nonparametric test with the advantages of not requiring the data to conform to any particular distribution and its low sensitivity to outliers, the Mann-Kendall (M-K) method recommended by the WMO is applied in this study to assess the significance of monotonic trends in hydrological series [44–46]. To eliminate the effect of the serial correlation on the MK test, the trend free pre-whitening (TFPW) technique developed by Yue et al. was employed in this study [47,48].

The independence test was carried out for examining the autocorrelation coefficients of the time series. When the absolute values of the autocorrelation coefficients of different lag times calculated for a time series consisting of n observations are not larger than the typical critical value, i.e., $1.96 / \sqrt{n}$ corresponding to the 5% significance level, the observations in the time series can be accepted as being independent from each other. According to the calculated autocorrelation coefficients of lag-1, lag-5 and lag-10 for each annual series, the observations in that series can be accepted as being independent at the 5% significance level [49,50].

#### 3.2. L-moments Theory

L-moments are statistical quantities that are derived from probability weighted moments (PWMs) and increase the accuracy and ease of use of PWM-based analysis. Compared to the convention moments, L-moments have the advantage of characterizing a wider range of distributions and are more robust towards outliers in datasets [51]. Further, L-moments enable more reliable inferences to be made from small samples about an underlying probability distribution [52]. Details about the L-moments approach and the advantages offered by L-moments over conventional moments in hypothesis testing, boundedness of the moment ratios and identification of distribution have been discussed by Hosking [23,25]. Basically, L-moments are linear functions of probability weighted moments (PWMs) and defined as follows [25].

Assuming $F(x)$ is the distribution function of random variable $X$, $X_{1:n} \leq \ldots \leq X_{n:n}$ are the order statistics of the samples. The L-moment of $r$ is
\[ \lambda_r = r^{-1} \sum_{k=0}^{r-1} (-1)^k \binom{r-1}{k} E(X_{r-k}^r), \quad r = 1, 2, \ldots \]  

(1)

L-moment ratio is defined as

\[ \tau_2 = \frac{\lambda_2}{\lambda_1} \quad \text{and} \quad \tau_r = \frac{\lambda_r}{\lambda_1} \quad r = 3, 4, \ldots \]  

(2)

Where \( \tau_2 \), \( \tau_3 \) and \( \tau_4 \) are L-variation (L-CV), L-skewness, and L-kurtosis coefficient, respectively. The sample L-moment ratios are defined as

\[ t = l_2/l_1 \quad \text{and} \quad t_r = l_r/l_2 \quad r = 3, 4, \ldots \]  

(3)

\( l_r \) is the unbiased \( r \)th L-moments; \( t \), \( t_3 \) and \( t_4 \) is the coefficient of variation (L-CV), L-skewness and L-kurtosis, respectively. The L-moment ratios will be used for homogeneity analysis in the regional frequency analysis.

3.3. Regional Frequency Analysis Based on L-moments Method

Suppose that there are \( N \) sites in the region with sample size \( n_1, n_2, \ldots, n_N \), respectively. The sample L-moment ratios (L-CV, L-Skewness and L-Kurtosis) at-site \( i \) are denoted by \( t^i \), \( t_3^i \) and \( t_4^i \). The regional weighted average L-moment ratios are given by:

\[ t = \frac{\sum_{i=1}^{N} n_i t^i}{\sum_{i=1}^{N} n_i} \quad \text{and} \quad t_r = \frac{\sum_{i=1}^{N} n_i t_r^i}{\sum_{i=1}^{N} n_i} \quad r = 3, 4, \ldots \]  

(4)

Based on the L-moment method proposed by Hosking and Wallis, five steps of the regional frequency analysis method used in this study were summarized as follows: (1) identification of homogenous regions by cluster analysis; (2) screening the data using the discordancy measure; (3) homogeneity testing using the heterogeneity measure; (4) distribution selection using the goodness-of-fit measure; (5) regional extreme rainfall quantile estimations [24, 25]. Therefore, these five steps were employed to conduct the regional frequency analysis for extreme precipitation in the Hanjiang River Basin.

3.3.1. Identification of Homogenous Regions by Cluster Analysis

Cluster analysis (CA) is the task of grouping a set of objects in such a way that objects in the same group are more similar to each other than to those in other groups. CA is a common technique for statistical data analysis, used in hydrology to form regions for regional frequency analysis. A homogeneous region is defined as a group of stations the data of which can be described by the same probability distribution [25, 53]. Recommended by Hosking and Wallis, Ward’s method is employed to form homogeneous sub-regions in this study [25]. Ward’s method is a criterion applied in hierarchical clustering analysis, which is based on minimizing the Euclidean distance in site characteristics space within each cluster. Four variables are selected to describe the precipitation climate, which are latitude, longitude, elevation and the mean annual precipitation. Considering that the observed scales of cluster analysis are very different and the methods are sensitive to such scale difference, the location and precipitation amount were rescaled to lie between 0 and 1 so that the ranges of these variables can be comparable.

3.3.2. Screening the Data using the Discordancy Measure

Given a group of sites, the aim of the discordancy measure is to identify those sites that are grossly discordant with the group as a whole. Discordancy is measured in terms of the L-moments of the sites’ data.
Let \( u_i = \left[ t^{(i)}, t_3^{(i)}, t_4^{(i)} \right]^T \) be the vector containing the \( t, t_3 \) and \( t_4 \) values for site \( i \) where the superscript \( T \) denotes the transposition of a vector or matrix. Let

\[
\overline{\pi} = \frac{1}{N} \sum_{i=1}^{N} u_i / N
\]

be the (unweighted) regional average. Hosking and Wallis defined the discordancy measure \( D_i \) as follows.

\[
D_i = \frac{1}{3} (u_i - \overline{\pi})^T A^{-1} (u_i - \overline{\pi})
\]

where \( A = \sum_{i=1}^{N} (u_i - \overline{\pi})(u_i - \overline{\pi})^T \); \( N \) is the number of stations.

A large value of \( D_i \) indicates that the site \( i \) is discordant with other sites in a sub-region. Hosking and Wallis found that the definition of “large” depends on the number of sites in the group and suggested that a site be regarded as discordant if its \( D_i \) value exceeds the critical value [25].

3.3.3. Homogeneity Testing using the Heterogeneity Measure

The aim of homogeneity testing is to estimate the degree of heterogeneity in a group of sites and to assess whether the sites might reasonably be treated as a homogenous region. The regional average L-CV, L-skewness and L-kurtosis, denoted by \( l_3^R \), \( l_4^R \) and \( l_4^R \), respectively, are computed as [24,29,30]:

\[
l_R = \sum_{i=1}^{N} n_i t^{(i)} / \sum_{i=1}^{N} n_i
\]

(7)

\[
l_3^R = \sum_{i=1}^{N} n_i t_3^{(i)} / \sum_{i=1}^{N} n_i
\]

(8)

\[
l_4^R = \sum_{i=1}^{N} n_i t_4^{(i)} / \sum_{i=1}^{N} n_i
\]

(9)

where \( n_i / \sum_{i=1}^{N} n_i \) denotes the weight applied to sample L-moment ratios at site \( i \), which is proportional to the recorded length of the site. The regional average mean \( l_3^R \) is set to be 1.

Three heterogeneity measures \( H_1, H_2 \), and \( H_3 \) are computed as:

\[
H_1 = \frac{V_1 - \mu_{v_1}}{\sigma_{v_1}}
\]

(10)

\[
H_2 = \frac{V_2 - \mu_{v_2}}{\sigma_{v_2}}
\]

(11)

\[
H_3 = \frac{V_3 - \mu_{v_3}}{\sigma_{v_3}}
\]

(12)

where \( V_1 \) denotes the weighted standard deviation of the at-site sample L-CVs and is computed as:

\[
V_1 = \left\{ \sum_{i=1}^{N} n_i \left[ t^{(i)} - l_R \right]^2 / \sum_{i=1}^{N} n_i \right\}^{1/2}
\]

\( V_2 \) denotes the weighted average distance from the site to the group weighted mean in the two-dimensional space of L-CV and L-skewness and is calculated as:

\[
V_2 = \sum_{i=1}^{N} n_i \left\{ \left( t_2^{(i)} - l_2^R \right)^2 + \left( t_3^{(i)} - l_3^R \right)^2 \right\} / \sum_{i=1}^{N} n_i
\]

\( V_3 \) denotes the weighted average distance from the site to the group weighted mean in the two-dimensional space of L-skewness and L-kurtosis and is calculated as:

\[
V_3 = \sum_{i=1}^{N} n_i \left\{ \left( t_3^{(i)} - l_3^R \right)^2 + \left( t_4^{(i)} - l_4^R \right)^2 \right\} / \sum_{i=1}^{N} n_i
\]

\( \mu_{v_1}, \mu_{v_2} \) and \( \mu_{v_3} \) denote the mean and \( \sigma_{v_1}, \sigma_{v_2} \) and \( \sigma_{v_3} \) the standard deviation values of \( V_1, V_2 \) and \( V_3 \), respectively, computed on the basis of a large number of simulated homogeneous regions.
In order to obtain reliable values of \( \mu_v \) and \( \sigma_v \), the number of \( N_{sim} \) of Monte Carlo simulations need to be large and \( N_{sim} = 1000 \) was used in this study. Hosking and Wallis suggested that the region be regarded as “acceptably homogeneous” if \( H < 1 \), “possibly heterogeneous” if \( 1 \leq H < 2 \), and “definitely heterogeneous” if \( H \geq 2 \) [25].

In the above three measures, \( H_1 \) is the standard deviation of the at-site L-CVs and a large value of \( H_1 \) indicates that the observed L-moments are more dispersed than what is consistent with the hypothesis of homogeneity [24,27]. \( H_2 \) indicates whether the at-site and regional estimates are close to each other and a large value of \( H_2 \) indicates a large deviation between at-site and regional estimates. \( H_3 \) measure indicates whether the at-site and the regional estimate will agree and a large value of \( H_3 \) indicates a large deviation between at-site estimates and observed data. Hosking and Wallis found that \( H_1 \) has a much better discriminatory power than \( H_2 \) [25]. In this study, \( H_1 \) and \( H_2 \) were chosen to test the heterogeneity because the L-CV and L-skewness are required for fitting regional frequency curves with a GEV or GLO according to the method recommended by Norbiato et al. [27].

3.3.4. Distribution Selection using the Goodness-of-Fit Measure

For each candidate distribution, the generalized extreme-value (GEV), generalized logistic (GLO), generalized normal (GNO), generalized Pareto (GPA), and Pearson type 3 (P III), the goodness-of-fit measure is computed as follows:

\[
Z_{DIST}^{DIST} = \left( \frac{\tau_{DIST}^{DIST} - \bar{\tau}_4}{\bar{\tau}_4} + \beta_4 \right) / \sigma_4
\]

where \( \tau_{DIST}^{DIST} \) is the L-kurtosis of the fitted distribution to the data using the candidate distribution; \( \beta_4 = \frac{\sum_{m=1}^{N_{sim}} (\bar{\tau}_4^{(m)} - \bar{\tau}_4) / N_{sim}}{1} \) and \( \sigma_4 = \left\{ \left( \frac{N_{sim} - 1}{\sum_{m=1}^{N_{sim}} (\bar{\tau}_4^{(m)} - \bar{\tau}_4)^2 - N_{sim} \beta_4^2} \right)^{1/2} \right\}^{1/2} \) are the bias and standard deviation of the regional average L-kurtosis \( \bar{\tau}_4^{(m)} \) estimated using the Monte Carlo simulation samples by Kappa distribution.

If \( |Z_{DIST}^{DIST}| \) is close to zero, the fit by the candidate distribution is considered to be adequate. If the criterion \( |Z_{DIST}^{DIST}| \leq 1.64 \), it indicates that the fit is acceptable at a confidence level of 90%. If more than one candidate distribution is acceptable, the one with the lowest \( |Z_{DIST}^{DIST}| \) is regarded as the best-fit distribution. Besides, an L-moment ratio diagram is also used for selecting a probability distribution function by comparing its closeness to the L-skewness and L-kurtosis combination in the L-moment ratio diagram for regional frequency analysis. In this study, \( |Z_{DIST}^{DIST}| \) measure and an L-moment ratio diagram were used to select a candidate distribution.

3.3.5. Regional Extreme Rainfall Quantile Estimations

Index-flood procedures are a convenient way of pooling summary statistics from different data samples. Dalrymple applied the procedure to flood data in hydrology and then the term “index flood” arose [54]. The method is used to obtain extreme rainfall quantiles of the best-fit frequency distribution. The quantile estimates \( Q_i(F) \) at site \( i \) is calculated by

\[
Q_i(F) = \mu_i q(F)
\]

where \( F \) is the non-exceedance probability; \( q(F) \) is the estimated regional growth curve, a dimensionless quantile function common to every site; \( \mu_i \) is the index rainfall or flood value. In this study, the mean extreme precipitation is used as the index rainfall, which is the site-specific scale factor.

In order to assess the results of regional frequency analysis, a large amount of the quantiles given by the best-fit distribution for each HOM region were compared with the observations having the same probabilities. The Gringorten formula is used to estimate the empirical frequency of an element in the series and is given by [55]:

\[
P(i) = \frac{i - 0.44}{n + 0.12}
\]
where $i$ is the $i$th element in the series arranged in ascending order and $n$ is the number of the elements in the series.

And the mean absolute relative errors ($MARE$) is defined as [28]:

$$MARE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{P_{\text{observed}} - P_{\text{simulated}}}{P_{\text{observed}}} \right|$$

where $n$ is the number of elements in the series; $P_{\text{observed}}$ is the extreme precipitation observation values; $P_{\text{simulated}}$ is the extreme precipitation simulated values.

3.4. Accuracy Assessments and Uncertainty Analysis

The Monte Carlo simulation method was employed to evaluate the accuracy and uncertainty of the estimated extreme precipitation quantiles. The simulated data was generated from the best-fit distribution with the same number of stations in the sub-region and the same record lengths in each station. In order to obtain the reliable simulated data, the number of the simulations need to be large and 1000 was used in this study. Due to the large numbers of simulations, the evaluation would not be affected by the outliers generated from the Monte Carlo simulations. The root mean square error (RMSE) of the estimated quantiles was employed to assess the accuracy of frequency analysis [26,27,56]. The relative RMSE given by Hosking and Wallis can be expressed as percentages of site-$i$ quantile estimator [25].

$$R_i(F) = (M^{-1} \sum_{m=1}^{M} \frac{\hat{Q}_i^m(F) - Q_i(F)}{Q_i(F)})^{1/2}$$

where $M$ is the number of simulations; $\hat{Q}_i^m(F)$ is the site $i$ quantile estimate for non-exceedance probability $F$ in the $m$th Monte Carlo simulation; $\frac{\hat{Q}_i^m(F) - Q_i(F)}{Q_i(F)}$ represents the relative error of the quantile estimate for non-exceedance probability $F$. The regional average relative RMSE of the estimated quantiles is computed by

$$R^R(F) = N^{-1} \sum_{i=1}^{N} R_i(F)$$

The corresponding 95% error bounds that are recommended by Hosking and Wallis were employed to assess the estimation uncertainty. And the smaller error bounds indicate the smaller estimation uncertainty [24,25].

4. Results

4.1. Stationarity Test and Serial Correlation Check

In this study, the Mann-Kendall method is carried out for the trend test of precipitation extremes (RX1day, RX5day, RX7day, R95P) over the period between 1969 and 2015 in the HJRB. The results are tabulated in Table 2, from which it can be seen that for precipitation extremes, SZ station shows an increasing trend for RX1day series with 5% confidence level, FJ station shows a decreasing trend for RX5day and RX7day series with 5% confidence level, WH station shows an increasing trend for RX5day and RX7day series with 5% confidence level, and the remaining 22 stations have no significant trends (at the 5% confidence level). Consequently, apart from SZ, FJ and WH station, the observations have no trends and can be treated as stationarity series on the basis of the results of Mann-Kendall test.

Besides, it is beneficial to conduct the autocorrelation test for precipitation extremes before analysis. If the autocorrelation coefficients of lag-1, lag-5 and lag-10 for precipitation extremes are smaller than $1.96/\sqrt{n}$, the stations are considered as independent. The results showed that all of the autocorrelation coefficients are smaller than $1.96/\sqrt{n}$. Thus, the observations of the 22 stations with the exception of SZ, FJ and WH stations can be considered as independent series at the 5% confidence level and can be applied to precipitation frequency analysis.
Table 2. Results of trend test for the precipitation extremes (RX1day, RX5day, RX7day and R95P) over the period (1969–2015) in the Hanjiang River Basin (HJRB) using MK test.

<table>
<thead>
<tr>
<th>Station Name</th>
<th>RX1day</th>
<th>RX5day</th>
<th>RX7day</th>
<th>R95P</th>
</tr>
</thead>
<tbody>
<tr>
<td>WG</td>
<td>0.559</td>
<td>N+</td>
<td>0.211</td>
<td>N+</td>
</tr>
<tr>
<td>LS</td>
<td>1.403</td>
<td>N+</td>
<td>0.917</td>
<td>N+</td>
</tr>
<tr>
<td>LC</td>
<td>1.394</td>
<td>N+</td>
<td>1.284</td>
<td>N+</td>
</tr>
<tr>
<td>LY</td>
<td>-1.11</td>
<td>N-</td>
<td>-1.211</td>
<td>N-</td>
</tr>
<tr>
<td>HZ</td>
<td>0.559</td>
<td>N+</td>
<td>-0.238</td>
<td>N-</td>
</tr>
<tr>
<td>FP</td>
<td>1.073</td>
<td>N+</td>
<td>1.348</td>
<td>N+</td>
</tr>
<tr>
<td>SZ</td>
<td>2.173</td>
<td>Y+</td>
<td>0.734</td>
<td>N+</td>
</tr>
<tr>
<td>ZA</td>
<td>0.862</td>
<td>N+</td>
<td>0.44</td>
<td>N+</td>
</tr>
<tr>
<td>NY</td>
<td>0.009</td>
<td>N-</td>
<td>-0.22</td>
<td>N-</td>
</tr>
<tr>
<td>SQ</td>
<td>0.101</td>
<td>N+</td>
<td>1.449</td>
<td>N+</td>
</tr>
<tr>
<td>WY</td>
<td>0.724</td>
<td>N+</td>
<td>1.706</td>
<td>N+</td>
</tr>
<tr>
<td>AK</td>
<td>-0.807</td>
<td>N-</td>
<td>-1.036</td>
<td>N-</td>
</tr>
<tr>
<td>YX</td>
<td>-0.605</td>
<td>N-</td>
<td>-0.266</td>
<td>N-</td>
</tr>
<tr>
<td>FX</td>
<td>-0.477</td>
<td>N-</td>
<td>-1.357</td>
<td>N-</td>
</tr>
<tr>
<td>LHK</td>
<td>-1.513</td>
<td>N-</td>
<td>-1.834</td>
<td>N-</td>
</tr>
<tr>
<td>XY</td>
<td>-0.099</td>
<td>N-</td>
<td>-0.238</td>
<td>N-</td>
</tr>
<tr>
<td>FJ</td>
<td>-1.045</td>
<td>N-</td>
<td>-2.467</td>
<td>Y-</td>
</tr>
<tr>
<td>BD</td>
<td>0.22</td>
<td>N+</td>
<td>-0.688</td>
<td>N-</td>
</tr>
<tr>
<td>ZX</td>
<td>-0.981</td>
<td>N-</td>
<td>-0.917</td>
<td>N-</td>
</tr>
<tr>
<td>YC</td>
<td>0.147</td>
<td>N+</td>
<td>-0.688</td>
<td>N-</td>
</tr>
<tr>
<td>JZ</td>
<td>-0.037</td>
<td>N-</td>
<td>0.624</td>
<td>N+</td>
</tr>
<tr>
<td>TM</td>
<td>0.761</td>
<td>N+</td>
<td>0.147</td>
<td>N+</td>
</tr>
<tr>
<td>WH</td>
<td>1.742</td>
<td>N+</td>
<td>2.265</td>
<td>Y+</td>
</tr>
<tr>
<td>JY</td>
<td>-0.22</td>
<td>N-</td>
<td>0.138</td>
<td>N+</td>
</tr>
</tbody>
</table>

Note: The absolute statistic of series is compared with the threshold of 1.96 with 5% significance level. If being bigger than 1.96, the trend is statistically significant (denoted as "Y"); if being smaller than 1.96, the trend is not statistically significant (denoted as "N"). The "+" sign means an upward trend, the "-" sign means a downward trend. The bold values denote 95% confidence level.

4.2. Regionalization of Precipitation Extremes Using L-Moment Technique

Homogenous regions were initially formed by the clusters which were not the final results. The final results should be adjusted by taking into account the topography and physical reasons to form interpretable homogeneous regions. The discordancy test and heterogeneity measure were applied to examine whether the data of one site are discordant with the group in the sub-region and assess whether the sites might reasonably be treated as a homogenous region, respectively. Initially, 22 stations of the HJRB were divided into three clusters: Cluster I (Wugong, Lveyang, Hanzhong, Foping, Zhenan, Shiquan, Wanyuan, Ankang), Cluster II (Huashan, Lushi, Luanchuan, Nanyang, Yunxi, Fangxian, Laohekou), and Cluster III (Xinyang, Badong, Zhongxiang, Yichang, Jinzhou, Tianmen, Jiayu). Then, the sub-regions were refined manually. The Wugong station was regrouped into cluster II because the \( D_i \) value of Wugong station was greater than the critical discordancy thresholds. Finally, the 22 stations in the HJRB can be divided into three regions: Region I (Lveyang, Hanzhong, Foping, Zhenan, Shiquan, Wanyuan, Ankang), Region II (Wugong, Huashan, Lushi, Luanchuan, Nanyang, Yunxi, Fangxian, Laohekou), and Region III (Xinyang, Badong, Zhongxiang, Yichang, Jinzhou, Tianmen, Jiayu). The results of discordancy measure and heterogeneity test for the 22 stations in HJRB are shown in Table 3, which can be seen that all \( D_i \) values are less than the critical discordancy thresholds. Consequently, all the 22 stations in the HJRB are regarded to pass the discordancy test and the whole heterogeneity measures are less than 1 (Table 3). So the final set of regions is shown in Figure 2, which indicates that the entire Hanjiang River Basin can be categorized into three homogeneous regions (named HOM) for each extreme daily precipitation index with heterogeneity measure \( H_1, H_2 < 1 \) according to the method recommended by Norbiato et al. [27]. The heterogeneity test results indicate that the three regions are reasonable to be considered homogeneous.
Table 3. Results of discordance, heterogeneity, goodness-of-fit tests and MARE for 24 stations in the Hanjiang River Basin (HJRB).

| Item  | HOM Region | Containing Sites (Di)                              | $D_{critical}$ | Heterogeneity | $|Z| \leq 1.64$ | Best Fit | MARE(%) |
|-------|------------|---------------------------------------------------|----------------|---------------|----------------|----------|---------|
|       |            |                                                   | $H_1$ | $H_2$ | $H_3$ |                  |          |         |
| RX1day| I (7 sites)| LY(1.4), HZ(0.58), FP(0.42), ZA(1.78), SQ(1.41), WY(0.61), AK(0.79) | 1.917 | 0.64 | -0.48 | -0.13 | 0.04 | GNO: 4.05 |
|       | II (8 sites)| WG(0.32), HS(1.19), LS(1.58), LC(0.42), NY(1.92), YX(2.26), FX(0.48), LHK(0.99) | 2.140 | -0.28 | -0.84 | -1.11 | -0.26 | GLO: 6.41 |
|       | III (7 sites)| XY(1.31), BD(0.54), ZX(0.94), YC(0.36), JZ(0.66), TM(1.59), JY(1.60) | 1.917 | -0.25 | -0.99 | -1.55 | 0.12 | GEV: 5.65 |
| RX5day| I (7 sites)| LY(1.74), HZ(1.49), FP(1.37), ZA(0.17), SQ(1.21), WY(0.55), AK(0.48) | 1.917 | 0.03 | 0.27 | -0.28 | 0.41 | PE3: 4.27 |
|       | II (8 sites)| WG(2.01), HS(0.49), LS(0.86), LC(0.05), NY(0.52), YX(0.56), FX(0.58), LHK(2.47) | 2.140 | 0.70 | -0.82 | -1.31 | -0.11 | GEV: 4.04 |
|       | III (7 sites)| XY(1.26), BD(0.61), ZX(1.60), YC(1.00), JZ(1.53), TM(0.25), JY(0.74) | 1.917 | -0.57 | 0.10 | 0.64 | -0.01 | GEV: 5.46 |
| RX7day| I (7 sites)| LY(1.89), HZ(0.32), FP(1.54), ZA(0.40), SQ(0.25), WY(1.34), AK(1.26) | 1.917 | -0.58 | -0.14 | 0.37 | 0.13 | PE3: 3.19 |
|       | II (8 sites)| WG(0.44), HS(1.55), LS(0.68), LC(1.35), NY(0.38), YX(1.03), FX(0.72), LHK(2.04) | 2.140 | -0.04 | -0.95 | -0.71 | -0.57 | GEV: 5.18 |
|       | III (7 sites)| XY(1.35), BD(0.97), ZX(1.46), YC(0.66), JZ(0.54), TM(0.57), JY(1.46) | 1.917 | 0.30 | 0.10 | -0.38 | 0.37 | GNO: 5.66 |
| R95P  | I (7 sites)| LY(1.25), HZ(0.22), FP(0.46), ZA(1.89), SQ(1.66), WY(0.38), AK(1.14) | 1.917 | -0.01 | 0.38 | 0.98 | -0.06 | PE3: 3.72 |
|       | II (8 sites)| WG(1.56), HS(1.16), LS(0.53), LC(0.61), NY(0.46), YX(1.84), FX(0.77), LHK(0.62) | 2.140 | 0.63 | 0.81 | 0.61 | -0.93 | GNO: 6.11 |
|       | III (7 sites)| XY(1.39), BD(1.16), ZX(1.44), YC(0.33), JZ(1.19), TM(0.57), JY(1.46) | 1.917 | 0.72 | -0.44 | -1.13 | -0.08 | PE3: 5.92 |
4.3. Selection of Best-Fit Distribution

Five distributions including GEV, GLO, GNO, GPA, and P III are investigated in each of the homogeneous regions for RX1day, RX5day, RX7day and R95P in the goodness-of-fit test [30]. The results, tabulated in Table 3, indicate that they are satisfactory with $|Z| \leq 1.64$, corresponding to an acceptance of the hypothesized distribution at a confidence level of 90% [24,25]. For RX1day series, GNO distribution is the optimal distribution for HOM region I, GLO distribution is the best-fit distribution for HOM region II, and the GEV distribution performs well in fitting the precipitation extremes in HOM region III. For RX5day series, P III distribution is the optimal distribution for HOM region I, while GEV distribution is the best-fit distribution for HOM region II and III. For RX7day series, P III distribution is the optimal distribution for HOM region I, GEV distribution is the best-fit distribution for HOM region II, and the GNO distribution performs well in fitting the precipitation extremes in HOM region III. For R95P series, P III distribution is the optimal distribution for HOM region I and Region III, while the GNO distribution is the best-fit distribution for HOM region II.

In conclusion, GNO, GEV, GLO and P III distributions perform well in fitting the precipitation extremes in HJRB.

In addition, an L-moment ratio plot is also used for selecting a probability distribution function by comparing its closeness to the L-skewness and L-kurtosis combination. The L-moment diagrams for RX1day, RX5day, RX7day and R95P in three regions are illustrated in Figures 3 and 4, respectively. In terms of RX1day series as a paradigm, Figure 3a–c show that the GNO distribution is closer to the corresponding regional average value in region I, the GLO distribution is closer to the corresponding regional average value in region II, and the GEV distribution is closer to the corresponding regional average value in region III. Therefore, these figures demonstrate that the results of L-moment ratio plots are consistent with the results of the goodness-of-fit measure.
Figure 3. L-moment ratio plot for RX1day (a,b,c) and RX5day (d,e,f) series at three HOM regions.
Figures 5 and 6 plot the observed and simulated values for each region of RX1day, RX5day, RX7day, R95P series, respectively. They show that the points fall on the line closely enough for the optimal distributions for each HOM region. The MARE results for each HOM region of RX1day, RX5day, RX7day, R95P series summarized in the last column of Table 3 demonstrate that the MARE values range from 3.19% to 6.41% and the best-fit distribution for each HOM region can describe the
precipitation extremes well. Hence, it is reasonable that the best-fit distributions for each of the HOM regions are adequate in predicting the quantile estimates according to the results above.

Figure 5. Observation and simulation value of precipitation extremes in each region of RX1day (a,b,c) and RX5day (d,e,f) series.
Figure 6. Observation and simulation value of precipitation extremes in each region of RX7day (a,b,c) and R95P (d,e,f) series.
Table 4. Accuracy measures for estimated growth curve of the HJRB precipitation extreme.

<table>
<thead>
<tr>
<th>HOM Region</th>
<th>RX1day</th>
<th>RX5day</th>
<th>RX7day</th>
<th>R95P</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>q(F)</td>
<td>RMSE</td>
<td>Bounds0.05</td>
<td>Bounds0.95</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region I</td>
<td>0.500</td>
<td>0.919</td>
<td>0.013</td>
<td>0.898</td>
</tr>
<tr>
<td></td>
<td>0.800</td>
<td>1.239</td>
<td>0.009</td>
<td>1.224</td>
</tr>
<tr>
<td></td>
<td>0.900</td>
<td>1.467</td>
<td>0.022</td>
<td>1.435</td>
</tr>
<tr>
<td>Region II</td>
<td>0.950</td>
<td>1.698</td>
<td>0.045</td>
<td>1.628</td>
</tr>
<tr>
<td></td>
<td>0.980</td>
<td>2.012</td>
<td>0.084</td>
<td>1.885</td>
</tr>
<tr>
<td></td>
<td>0.990</td>
<td>2.260</td>
<td>0.120</td>
<td>2.086</td>
</tr>
<tr>
<td></td>
<td>0.999</td>
<td>3.165</td>
<td>0.283</td>
<td>2.756</td>
</tr>
<tr>
<td>Region III</td>
<td>0.500</td>
<td>0.924</td>
<td>0.014</td>
<td>0.900</td>
</tr>
<tr>
<td></td>
<td>0.800</td>
<td>1.226</td>
<td>0.010</td>
<td>1.209</td>
</tr>
<tr>
<td></td>
<td>0.900</td>
<td>1.454</td>
<td>0.022</td>
<td>1.419</td>
</tr>
<tr>
<td>Region III</td>
<td>0.950</td>
<td>1.706</td>
<td>0.047</td>
<td>1.639</td>
</tr>
<tr>
<td></td>
<td>0.980</td>
<td>2.096</td>
<td>0.097</td>
<td>1.960</td>
</tr>
<tr>
<td></td>
<td>0.990</td>
<td>2.447</td>
<td>0.152</td>
<td>2.236</td>
</tr>
<tr>
<td></td>
<td>0.999</td>
<td>4.110</td>
<td>0.492</td>
<td>3.440</td>
</tr>
</tbody>
</table>

Note: Accuracy measures for the estimated growth curve are defined by Equations (17) and (18) but with $Q_i(F)$ and $\hat{Q}_{i,m}(F)$ replaced by $q(F)$ and $\hat{q}_{i,m}(F)$, respectively. Tabulated values are, for each nonexceedance probability $F$, the estimated regional quantiles, regional average relative RMSE of estimated growth curve and their 95% error bounds for the estimated growth curve.
4.4. Accuracy and Uncertainty Analysis of Quantile Estimations

The estimated regional quantiles, regional average relative RMSE of estimated growth curve and their 95% error bounds for the estimated growth curve are tabulated in Table 4. The results indicate that the RMSE values for three sub-regions of HJRB basically increase with the increase of frequency for all series, and RMSEs range from 0.008 to 0.152 when return periods are less than 100 years; however, the RMSE values are relatively larger and range from 0.110 to 0.492 when the return period is 1000 years, which implies that the quantile estimates are reliable enough when return periods are less than 100 years, and estimates of a higher return period (e.g., 1000 years) become unreliable. In addition, it can be seen from Figure 7 that the RMSEs of R95P series are about 0.1 and the values of the three regions are very close when the return period is equal to 1000 years. If the historical records are not sufficient and the estimated quantiles are needed when the return period is 1000 years, the estimated quantiles of R95P series are relatively reliable in the HJRB.

![Figure 7](image.png)

**Figure 7.** The RMSE values of three HOM regions for RX1day, RX5day, RX7day and R95P when return period is 100 years.

4.5. Spatial Characteristics of Annual Rainfall Extremes

The spatial associations of precipitation extremes between sites and the map of precipitation for HJRB are quantified by kriging interpolation. Estimated maps of annual precipitation extremes in HJRB for RX1day, RX5day, RX7day and R95P with the 100 years return periods are illustrated in Figure 8. It can be observed from Figure 8A–D that precipitation extremes in region I increase gradually from north to south, and plenty of precipitation observations were made upstream in the south of the HJRB next to the Du River, South River and Daba Mountain areas which are close to the Danjiangkou Reservoir. This provides sufficient climate conditions (e.g., humidity and precipitation) responsible for the occurring floods in these regions from the meteorological point of view. In region II and III of HJRB, it can be observed that the precipitation extremes gradually increase from the northwest to the southeast and the precipitation extremes are mainly concentrated in the area of Tianmen, Wuhan and Zhongxiang stations which are located in Jianghan Plain in the downstream part of the HJRB. The results of seasonality of precipitation extremes in 3 HOM regions are illustrated in Figure 9. It can be observed that, for RX1day, RX5day and RX7day in the HJRB, more than 90% of the precipitation extreme events occur during the rainy season from May to October and more than 30% of the extreme events concentrate in July. These events will trigger floods with different magnitudes, and July and August are well recognized as the primary flood-season for such regions.
Figure 8. Spatial mapping of estimated annual precipitation extremes in HJRB when return periods are 100 years using L-moments based regional frequency analysis approach, (A): RX1day; (B): RX5day; (C): RX7day; (D): R95P.

Figure 9. Seasonality of precipitation extremes in the three typical HOM regions.
5. Discussion

In the literature, a single index was often used in the analysis of extreme precipitation events [57,58]. However, the comprehensive characterization of extreme precipitation events should be described from multiple indicators, due to the limitations of a single index to capture the full picture of extreme precipitation events. In this study, four indices including RX1day, RX5day, RX7day and R95P are derived for analysis. These indices can be enough to capture the full picture of extreme precipitation events in the HJRB.

L-moments based methods have been widely used in the regional frequency analysis [59,60]. In previous studies, limited attention was paid to testing stationarity and serial correlation to guarantee reliable estimates, which may lead to incorrect results and conclusions. In this study, the Mann-Kendall method and autocorrelation coefficients were employed to test the stationarity and independence of extreme precipitation, respectively. The stations (Shangzhou, Fengjie and Wuhan) showing significant trends were non-stationary and not included in the further analysis. The stations in Jianghan Plain have no significant trends except the Wuhan station which shows a significant increasing trend. As a megacity, Wuhan has a population of over 10 million. Many factors (e.g., global warming, land use change and urbanization) may lead to the upward trend for extreme precipitation in Wuhan. Urban environments are playing an increasingly important role in land-surface processes and climate change [61]. Urban areas modify boundary layer processes through the creation of “urban heat islands”. Early investigations noted evidence of warm seasonal rainfall increases of 9%–17% downwind of major cities [62,63]. Kishtawal et al. assessed the urbanization impacts on the heavy rainfall climatology during the Indian summer monsoon and concluded that the observed increasing trend in the frequency of heavy rainfall events over Indian monsoon regions is more likely to be over regions where the pace of urbanization is faster [61]. Analysis at a site-based scale is difficult in understanding the changing pattern and possible relations between external drivers, mainly due to the local scale variation (e.g., land use change and urbanization). Therefore, a regionalization by cluster analysis was employed to identify the homogeneous sub-regions and to study the spatio-temporal pattern characteristics of extreme precipitation in the HJRB. Hydrological regionalization is generally based on factors that affect the frequency distribution of precipitation. The stations that have the same or similar impact factors can be categorized into the same sub-region. There are many factors affecting precipitation, such as latitude, longitude, elevation, distance to water bodies, slope, etc., especially in mountainous areas. Geographic proximity is not the only criteria for hydrological regionalization and does not mean that the frequency distribution of the two sites is similar. The site characteristics used are judged to be of importance in defining a site’s precipitation climate, including indicators of precipitation amounts and the sites’ geographic location [29]. In this study, four variables are selected to describe the precipitation climate, which are latitude, longitude, elevation and the mean annual precipitation.

Five distributions including GEV, GLO, GNO, GPA, and P III are investigated in each homogeneous region for RX1day, RX5day, RX7day and R95P in the goodness-of-fit test. MARE values range from 3.19% to 6.41% are calculated by using the best-fit distribution for each HOM region demonstrate that the best-fit distributions for each HOM regions are adequate in predicting the quantiles estimates.

The RMSE values of the estimated quantiles for three HOM regions in the HJRB range from 0.008 to 0.152 when return periods are less than 100 years. However, the RMSE values are relatively large and range from 0.110 to 0.492 when the return period is 1000 years. These results indicate that quantile estimates are reliable enough when return periods are less than 100 years. Yang et al. utilized an index variable method and L-moments to analyze the extreme precipitation for the Pearl River Basin in China and pointed out that the quantile estimates from regional frequency analysis were reliable enough to support flood risk assessment and water resources management when return periods were less than 100 years [29]. Meanwhile, estimates for higher return periods were unreliable and required longer time series in order to enhance the reliability in the quantile estimation. Results also indicated
that the estimated quantiles of R95P series are relatively reliable in the HJRB when return period is 1000 years, which is in line with the findings by Du et al. [29].

Floods occurred frequently in the HJRB and lead to considerable loss on economy and human life [10,13,14]. Actually, the floods are mainly caused by extreme precipitation events and an improved knowledge of extreme precipitation is required for better understanding the flood behavior and mitigating the hazard. The spatial patterns of annual rainfall extremes play an important role in integrated water resources management. Results indicated that excessive precipitation magnitude records are observed in the areas of Du River, South River and Daba Mountain and Jianghan plain, which provides sufficient climate conditions (e.g., humidity and precipitation) responsible for the occurring floods in these regions.

In the HJRB, most of the precipitation extreme events (more than 90%) occur during rainy season from May to October and more than 30% of the extreme events concentrate in July, which is affected by the sub-tropical monsoon climate. In the upstream of HJRB, the prevailing southwest monsoon and the Qinling Mountains play an important role in forming the storm floods in July. Big floods occur in August because the southeast monsoon is very active. The precipitation characteristics for the HJRB are affected by the sub-tropical monsoon climate. It can also reveal the seasonal patterns of precipitation extremes for the three regions from Figure 9A–C. The precipitation extremes events occurring in May and June increase from region I to region III and the opposite trend in September and October. This means that the precipitation extremes events mainly concentrated in autumn in region I and summer in region III, which is consistent with the previous researches on precipitation extremes in HJRB [64,65]. The trough between Baikal Lake and Balkhash Lake produced by the strong western Pacific subtropical high and Ural Mountain high pressure lead to the vapor transport from Bengal Bay to the upstream of HJRB. At the same time, the trough in Baikal Lake is gradually split leading the cold air south and making the warm and cold air converge, which exerts influences on the extreme precipitation events in the region I, especially in the area of Du River, South River and Daba Mountain which is the center of the precipitation events (Figure 8) [64]. Yue analyzed the water vapor of the heavy rain in detail and found that the water vapor transport at 700 hPa had a great contribution to forming a rainstorm in the west of China in autumn [66]. He et al. analyzed the temporal and spatial characteristics of the circulation pattern at 500 hPa and vapor field at 700 hPa during the autumn waterlogging upstream of the Han River with NECP data and found that the primary sources of vapor at 700 hPa came from the Bay of Bengal and the South China Sea, which provides the source of adequate water vapor for the precipitation events [64]. Additionally, the precipitation extremes concentrated in the Tianmen, Wuhan and Zhongxiang stations which are located in Jianghan Plain in the downstream of HJRB are climatically dominated by a strong convection in spring and summer and the precipitation pattern for this region is strongly affected by the East Asian monsoon system [67]. The flux of water vapor transport has an increasing trend from northwest to southeast and there is a good correlation between precipitation water and water vapor transport in the area of Tianmen, Wuhan and Zhongxiang stations. All these mentioned above affect the extreme precipitation events over this region in summer months [65]. Two areas of the HJRB, located in the upstream of Danjiangkou Reservoir and Jianghan Plain respectively, have the larger extreme precipitation records, which will increase the risk of natural hazards to these areas. The findings from this study are of great scientific and practical merit in the integrated basin-scale water resource and flood risk management.

6. Conclusions

This study is motivated by the increasing frequency of extreme precipitation events and the growing impacts of the extreme precipitation events on human health and safety across the China and the world. In this paper, the L-moments methods were employed to conduct the regional frequency analysis of annual extreme precipitation records (1969–2015) at 25 stations in the HJRB, as well as the investigation of spatio-temporal pattern characteristics of extreme rainfall events in a regional scale after regionalization. Some conclusions summarized from this investigation are as follows:
(1) The HanJiang River Basin can be categorized into three homogenous regions with the consideration of spatially continuous and physical reasons in the areas. The optimal distribution for each HOM region is adequate in predicting the quantile estimates.

(2) The spatial patterns of the extreme precipitation with different return periods are similar. The extreme precipitation amount increases gradually from middle north to southwest and southeast in the HJRB. Excessive precipitation magnitude records are observed in the areas of Du River, South River and Daba Mountain and Jianghan plain, which provide sufficient climate conditions (e.g., humidity and precipitation) responsible for the occurring floods in these regions.

(3) Most of the precipitation extreme events (more than 90%) occur during the rainy season from May to October and more than 30% of the extreme events concentrate in July.

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