

Article

The Response of Small Watershed Storm Floods to Climate Change

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Abstract: This study utilizes historical monitoring data from the Xu Fan small watershed spanning 1962 to 2021 and employs the K-means clustering algorithm to classify extreme rainfall events into three distinct categories: short-duration high-intensity rainfall, sustained moderate-intensity rainfall, and long-duration heavy rainfall. Through the application of the Random Forest model, key factors influencing flood characteristics are identified, including total rainfall, maximum rainfall intensity, the timing of maximum intensity, and rainfall duration. The comparative analysis of data before and after 1990 highlights that climate change has led to increased maximum rainfall intensity, reduced rainfall duration, and shifts in the temporal distribution of rainfall, thereby exerting a significant influence on the flood generation process.

Keywords: climate change; small watershed; random forest algorithm; extreme rainfall; flood



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1. Introduction

Floods in small watersheds are primarily triggered by extreme rainfall events, characterized by rapid hydrological responses due to limited storage capacity and steep terrain. These events pose significant challenges to flood management and disaster mitigation, especially under the context of global climate change [1,2]. Rainfall intensity, duration, and temporal distribution are critical factors influencing flood characteristics. Short-duration high-intensity rainstorms typically produce steep hydrographs with high peak discharges, while long-duration low-intensity rainfall leads to extended but milder flood responses [3,4]. The response of small watersheds to extreme rainfall is further influenced by catchment-specific factors such as soil saturation, land cover, and slope gradient, which amplify the hydrological risks associated with intense precipitation [5,6].

The intensification of global climate change has accelerated changes in extreme rainfall patterns, including increased intensity, frequency, and temporal variability. Recent studies confirm that rising global temperatures have enhanced atmospheric water-holding capacity, thereby intensifying extreme precipitation events across the globe [4,7–9]. For instance, global-scale analyses indicate significant increases in the magnitude and frequency of extreme rainfall over recent decades, particularly in regions with monsoonal climates or pronounced topographic variability [10,11]. Regionally, China has experienced a significant rise in extreme daily rainfall events over the past 60 years, with the eastern regions and the Huang-Huai River Basin recording increases exceeding 10% [12]. These trends have heightened flood risks, particularly in small watersheds where hydrological responses are more sensitive to changes in rainfall variability [13–15].

Historical extreme rainfall events in China underscore the destructive potential of these phenomena. For example, the 1300 mm rainfall in Kuangping, Shaanxi (1998), the 1146.8 mm single-day rainfall in Zhanjiang, Guangdong (2007), the 624.1 mm rainfall in Zhengzhou, Henan (2021), and the 1003 mm rainfall in the Beijing-Tianjin-Hebei region (2023) caused catastrophic flooding, significant economic losses, and widespread fatalities [15–17]. These events demonstrate the necessity of improving flood management strategies, particularly in small watersheds where rapid hydrological responses leave limited time for intervention. According to the “China Climate Change Blue Book (2024)”, the next 30 years are expected to bring increasingly severe extreme weather events, including heavy rainfall, posing heightened challenges for flood management and climate adaptation [18].

While significant progress has been made in understanding the impacts of extreme rainfall and floods in large watersheds, small watersheds remain underexplored [19–21]. Unlike large watersheds, which are heavily influenced by urbanization and land-use changes, small watersheds often retain more natural hydrological characteristics, making them ideal for studying the direct impacts of climate change on hydrological processes [20]. Their unique attributes—rapid response times, limited buffering capacity, and heightened sensitivity to rainfall variability—make them critical for examining flood generation mechanisms [2,13,22]. These same traits, however, also make small watersheds particularly vulnerable to climate-driven changes, necessitating further investigation.

This study focuses on the Xu Fan small watershed in Zhejiang Province, China, which provides an ideal case for examining these dynamics. With its long-term, high-resolution hydrological data and minimal anthropogenic disturbances, the watershed allows for a detailed exploration of extreme rainfall events and their impact on flood characteristics. Furthermore, its distinct seasonal and interannual hydrometeorological variability offers valuable insights into the broader implications of climate change on small watershed hydrology. By combining state-of-the-art clustering and machine learning techniques, this study aims to bridge the knowledge gap in understanding how different types of extreme rainfall events influence flood characteristics in small watersheds.

The objectives of this study are:

1. **Characterize extreme rainfall events:** Analyze their frequency, intensity, duration, maximum rainfall intensity, and temporal distribution trends based on historical data from 1962 to 2021.
2. **Assess flood responses:** Evaluate how short-duration high-intensity rainstorms and long-duration low-intensity rainfall influence flood characteristics, including peak discharge, timing, and duration.
3. **Investigate climate change impacts:** Quantify how changes in extreme rainfall patterns due to climate change affect flood formation and dynamics in minimally disturbed small watersheds.

This paper is organized as follows: Section 2 introduces the study area and its geographical and hydrological characteristics. Section 3 details the research methods, including extreme rainfall event classification and flood impact analysis. Section 4 presents the results, highlighting trends in extreme rainfall events and their effects on small watershed floods under climate change. Finally, Section 5 summarizes the findings and provides recommendations for future research and flood risk management.

2. Overview of Study Area

Zhejiang Province is located on the southeast coast of China, with its Fuyang District situated in the northwest hinterland of the province. The terrain gently slopes from the northwest to the southeast towards the Fuchun River. The elevation in this area ranges

from 6 m to 1068 m. The topography is mainly composed of mountains and hills, plains, and water bodies, accounting for 79.05%, 16.45%, and 5.05% respectively.

Fuyang District inherits the typical characteristics of a subtropical monsoon climate, with an average annual rainfall of 1441.9 mm, exhibiting significant interannual fluctuations. The highest annual rainfall on record was 1964.4 mm in 1983, while the lowest was 992.3 mm in 1967. The rainfall pattern presents a bimodal distribution, with the first peak occurring from late spring to early summer (March to July), featuring spring rains and the plum rain season. The second peak appears in mid-autumn (late August to September), with typhoons and autumn rains contributing to abundant water resources and a complex hydrological ecology.

The Xu Fan small watershed, located in Pingshan Village, Wanshi Town, Fuyang District, is the core focus of this study (see Figure 1). It has a catchment area of 63.5 square kilometers, with the main river channel meandering for 20.22 km and an average slope of approximately 8.9‰. The steep terrain and short river course result in rapid floods with high peaks and large volumes. Historical years such as 1955, 1969, 1983, 1984, 1996, 1997, 2017, and 2023 have witnessed devastating mountain floods triggered by heavy rainfall.

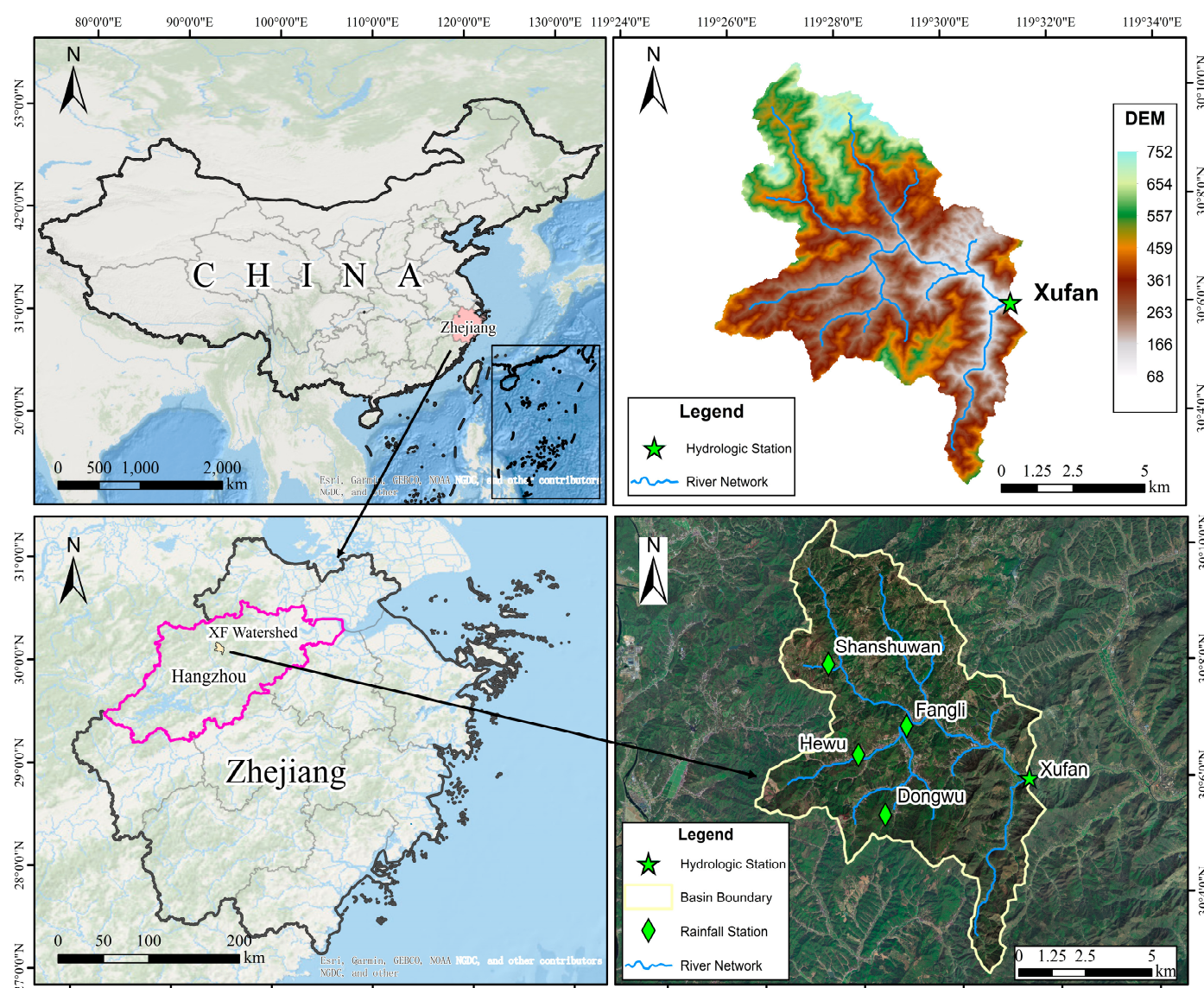


Figure 1. Geographic location and distribution of hydrological stations in the Xu Fan watershed.

Comparing the land use types in the Xu Fan small watershed between 1990 and 2022 (see Figure 2), although there have been changes in the land use pattern (see Table 1), the extent of these changes is moderate. This suggests that human activities have had relatively limited interference with the natural environment, and natural elements such as terrain, soil, and vegetation within the watershed have maintained relatively stable conditions over time and space.

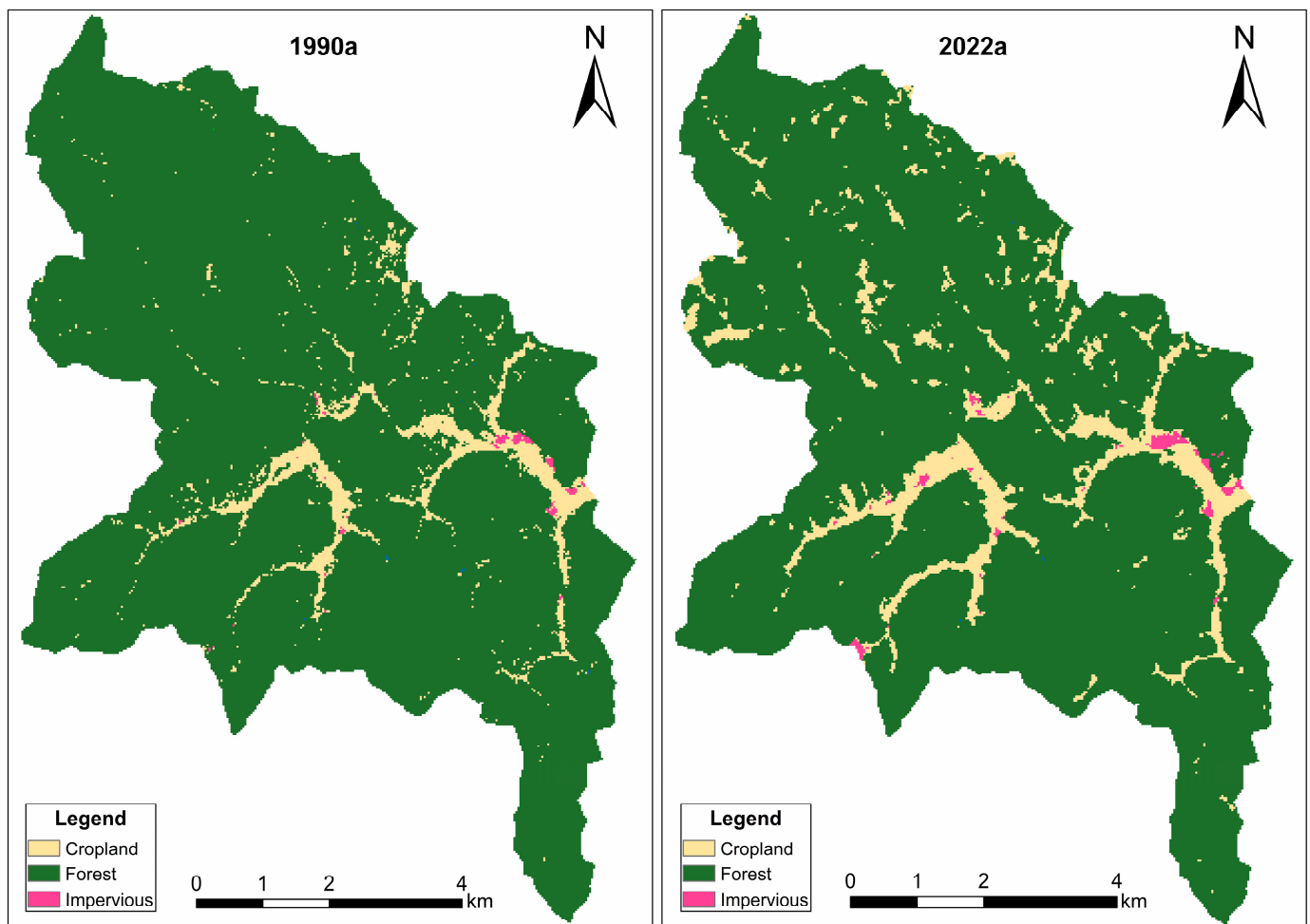


Figure 2. Comparison of land use types in Xu Fan watershed between 1990 and 2022.

Table 1. Comparison of land use types in the Xu Fan small watershed in 1990 and 2022.

Year	Cropland (km ²)	Forest (km ²)	Impervious (km ²)	Total Area (km ²)
1990	3.3	60.0	0.1	63.5
2022	5.6	57.5	0.3	63.5

Overall, the Xu Fan small watershed exhibits distinct characteristics of a subtropical monsoon climate, complemented by an evenly distributed network of hydrological stations. The hydrological data are minimally influenced by human activities, ensuring a long, accurate, and reliable data series. These attributes collectively make the watershed an exemplary and dependable subject for scientific research.

3. Methodology

3.1. Extreme Rainfall Events

3.1.1. Definition of Extreme Rainfall Events

The classification criteria for rainfall events remain a topic of debate. According to Nicótina et al. [23] and Jamshadali et al. [24], rainfall event intervals shorter than 60 min can influence the statistical analysis of rainfall characteristics. Given that the convergence time in the Xu Fan small watershed is typically less than 3 h, this study defines the minimum interval time for rainfall events as 3 h (see Figure 3). Additionally, a rainfall process with cumulative rainfall exceeding 3 mm is considered a rainfall event [25].

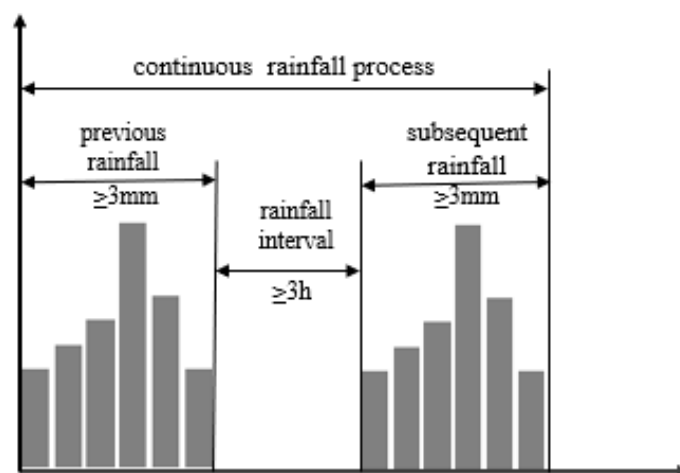


Figure 3. Diagram of rainfall event division.

In alignment with the standards of the China Meteorological Administration, a rainfall process with cumulative rainfall exceeding 50 mm within 24 h is classified as a rainstorm. In the context of watershed flood control, phenomena such as debris flows and mountain floods are often precipitated by rainstorms, heavy rainstorms, and extraordinary rainstorms. Therefore, this study defines an extreme rainfall event as a rainfall process with a maximum 24 h cumulative rainfall exceeding 50 mm.

3.1.2. Extreme Rainfall Indicators

1. Number of extreme rainfall events

Let m_{ij} be the number of extreme rainfall events in j -th month of i -th year, then the number of extreme rainfall events in i -th year is:

$$M_i = \sum_{j=1}^{12} m_{ij} \quad (1)$$

the number of extreme rainfall events in each season of i -th year is:

Spring (January to March):

$$S_i = \sum_{j=1}^3 m_{ij} \quad (2)$$

Summer (April to June):

$$Su_i = \sum_{j=4}^6 m_{ij} \quad (3)$$

Autumn (July to September):

$$A_i = \sum_{j=7}^9 m_{ij} \quad (4)$$

Winter (October to December):

$$W_i = \sum_{j=10}^{12} m_{ij} \quad (5)$$

2. Accumulated extreme rainfall series

$P_i = \{p_{i1}, p_{i2}, \dots, p_{it}, \dots, p_{iT}\}$ represents the hourly rainfall time series for the i -th rainfall event. The accumulated rainfall for the i -th extreme rainfall event is given by:

$$R_i = \sum_{t=1}^T p_{it} \quad (6)$$

The accumulated 24-h rainfall for the i -th extreme rainfall event at the j -th time interval is:

$$r_{24,j}^i = \sum_{t=j}^{j+23} p_{it} \quad (7)$$

The maximum 24-h rainfall for the i -th extreme rainfall event is determined by:

$$R_{m24,i} = \max(r_{24,1}^i, r_{24,2}^i, \dots, r_{24,j}^i, \dots, r_{24,N}^i)$$

where T is the total rainfall duration, N is the number of 24-h intervals, and p_{it} is the rainfall accumulation for the i -th rainfall event during the t -th period.

$$p_{it} = \sum_{j=1}^J \frac{f_j}{F} r_{ij}^t \quad (8)$$

where r_{ij}^t is the rainfall value at the j -th rainfall station for the i -th rainfall event during the t -th period, J is the number of rainfall stations, f_j is the catchment area determined by the Thiessen polygon for the j -th rainfall station, and F is the area of the watershed.

The maximum accumulated rainfall within a certain time span is:

$$R_m = \max\{R_1, R_2, \dots, R_i, \dots, R_K\} \quad (9)$$

where R_i is the accumulated rainfall for the i -th rainfall event, and K is the number of extreme rainfall events.

If the time span is a year, R_m is the maximum accumulated rainfall in a single event within the year. If the time span is a quarter, R_m is the maximum accumulated rainfall in a single event within the quarter.

Similarly, the maximum 24-h accumulated rainfall within a certain time span is:

$$R_{m24} = \max\{R_{m24,1}, R_{m24,2}, \dots, R_{m24,i}, \dots, R_{m24,K}\} \quad (10)$$

If the time span is a year, R_{m24} is the maximum 24-h accumulated rainfall in a single event within the year. If the time span is a quarter, R_{m24} is the maximum 24-h accumulated rainfall in a single event within the quarter.

Rainfall intensity refers to the amount of rainfall in a unit of time (usually in hours) and is expressed in mm/hour (mm/h). The maximum rainfall intensity for the i -th event is:

$$I_{mi} = \max\{p_{i1}, p_{i2}, \dots, p_{it}, \dots, p_{iT}\} \quad (11)$$

The maximum rainfall intensity I_{mi} occurs at the time period t_{mi} , and the duration from the start of rainfall t_{0i} to the time of maximum intensity is:

$$TI_{mi} = t_{mi} - t_{0i} \quad (12)$$

The maximum rainfall intensity within a certain time span is:

$$I_m = \max\{I_{m1}, I_{m2}, \dots, I_{mi}, \dots, I_{mK}\} \quad (13)$$

where I_m is the maximum rainfall intensity within the time span.

3.1.3. Method for Classifying Extreme Rainfall Events

Rainfall is one of the most direct factors influencing flooding. Increases in total rainfall often lead to a higher frequency and intensity of flooding events [26]. High-intensity rainfall events facilitate a rapid increase in surface runoff within a short period, subsequently causing floods. Prolonged periods of sustained rainfall can result in saturated soils, which increase the volume of surface runoff and exacerbate flood risks [27].

In this study, rainfall characterization factors are selected based on rainfall amount and duration. These factors include the maximum rainfall intensity (I_m) and its occurrence time (TI_m), total rainfall (R), and rainfall duration (T). These parameters are used as feature vectors to cluster rainfall events.

K-means is an unsupervised learning algorithm widely used in data clustering analysis. The algorithm operates based on an iterative optimization method, continuously adjusting the position of the cluster centers to achieve the optimal allocation of data points. The specific steps of the K-means algorithm are as follows:

1. Define the feature vector.

The feature vector for each rainfall event is defined as:

$$X_i = \{I_{mi}, TI_{mi}, R_i, T_i\} \quad i = 1, 2, \dots, K \quad (14)$$

2. Initialization

Randomly select C initial cluster centers:

$$\{\mu_1, \mu_2, \dots, \mu_C\} \quad (15)$$

3. Assignment

Calculate the Euclidean distance from each data point to the cluster centers and assign each point to the cluster with the nearest center:

$$d(X_i, \mu_j) = \sqrt{\sum_{k=1}^6 (x_{ik} - \mu_{jk})^2} \quad (16)$$

$$C_j = \{X_i : d(X_i, \mu_j) \leq d(X_i, \mu_l), \forall l, 1 \leq l \leq C\} \quad (17)$$

4. Updating the cluster centers

Calculate the new cluster centers as the average of the data points assigned to each cluster:

$$\mu_j = \frac{1}{|C_j|} \sum_{X_i \in C_j} X_i \quad (18)$$

5. Iteration

Repeat steps 3 and 4 until the positions of the cluster centers stabilize, i.e., they do not change significantly, or until a predetermined maximum number of iterations is reached.

3.2. Flood Analysis in Small Watersheds

3.2.1. Flood Characteristics

Based on the fundamental characteristics of the runoff situation and the specifications for hydrological forecasting [28], key indices such as runoff, time of emergence, frequency, duration, and variability are selected to describe changes in flash flood processes. These flood characteristic indices are used to assess the severity of flood events, including flood peak discharge (Q_m), peak occurrence time (T_m), and the flood time scale (T') to characterize the intensity and timing of the flood peak.

Among these, Q_m and T_m are fundamental elements of floods that are the focus of flood forecasting in China and have been widely used to determine flash flood warning indicators [25]. The flood time scale (T') is an important indicator for analyzing flood causes and frequency. It describes the concentration degree of the flood process through the peak discharge relationship, where a lower T' value indicates a more concentrated flood energy, leading to more severe damage within a short period [29].

In this study, three characteristic indicators were selected to characterize changes in the flood process: flood peak discharge, peak occurrence time, and flood duration (see Table 2). These indicators provide a comprehensive characterization of the flood events.

Table 2. Characteristics of flood.

	Indicator	Formula
flood characteristics	flood peak discharge Q_m (m^3/s)	$Q_m = \max(Q_t)$
	peak occurrence time T_m (h)	$T_m = T(Q_m)$
	flood duration T' (h)	$T' = T_e - T_s + 1$

Where Q_t is the flood process, and T_e and T_s are the end time and start time of the flood, respectively.

3.2.2. Analysis of Key Rainfall Factors Affecting Flood Characteristics Based on the Random Forest Algorithm

Extreme rainfall significantly impacts flood formation, requiring advanced methods to analyze the contributions of various rainfall factors. Recent studies have highlighted the potential of machine learning in hydrological analysis. Oyeboode et al. and Zhu et al. demonstrated the efficiency of Artificial Neural Networks (ANN) in capturing nonlinear relationships and predicting flood characteristics, while Yaseen et al. and Mosavi et al. validated its high accuracy under diverse hydrological conditions [30–33]. Nayak et al. [34] confirmed ANN's strength in modeling complex rainfall-flood relationships. Wright et al. [35] showed that Random Forest (RF) effectively addresses overfitting and handles nonlinear interactions, outperforming traditional regression and other machine learning models. Wang et al. [36] further emphasized RF's ability to rank rainfall factors by importance, identifying key contributors to flood risk.

1. Random Forest Model

$$\min_{\Theta} \frac{1}{n} \sum_{i=1}^n (y_i - f(x_i; \Theta))^2 \quad (19)$$

Here, n is the number of samples, y_i is the observed value of the i -th sample, $f(x_i; \Theta)$ is the predicted value of the i -th sample using the random forest model, and Θ represents the model parameters (such as decision tree structure, feature selection, and leaf node partitioning).

2. Feature Importance Calculation

In Random Forest Model, the importance I_j of feature j can be calculated by accumulating its contribution to the splits across all decision trees:

$$I_j = \frac{1}{B} \sum_{b=1}^B \sum_{q \in T_b} \Delta \text{MSE}(q, j) \quad (20)$$

where $\Delta \text{MSE}(q, j)$ is the reduction in Mean Squared Error (MSE) resulting from the split at node q due to feature j .

3. Feature Importance Ranking and Analysis

After calculating the feature importance I_j for each rainfall factor, the values are normalized and ranked:

$$I_j^{\text{norm}} = \frac{I_j}{\sum_{k=1}^d I_k} \quad (21)$$

where I_j^{norm} is the normalized importance of feature j , and d is the total number of rainfall factors.

Based on the normalized I_j^{norm} values, the rainfall factors with the highest importance are selected as the key factors that primarily influence flood characteristics.

4. Results and Discussion

4.1. Analysis of Extreme Rainfall Characteristics

4.1.1. Characteristics Analysis of Extreme Rainfall Events

By analyzing historical data from 1962 to 2021, a total of 2765 independent rainfall events were identified from the hourly areal rainfall time series in the Xu Fan watershed. These events were further classified into the following categories (see Figure 4):

Light rain: 1147 events, accounting for 41.48%

Moderate rain: 924 events, accounting for 33.41%

Heavy rain: 459 events, accounting for 16.60%

Rainstorm: 192 events, accounting for 6.94%

Severe rainstorm: 43 events, accounting for 1.55%

Defining rainstorms and severe rainstorms as extreme rainfall events, there were a total of 235 such events, accounting for 8.5% of all rainfall events.

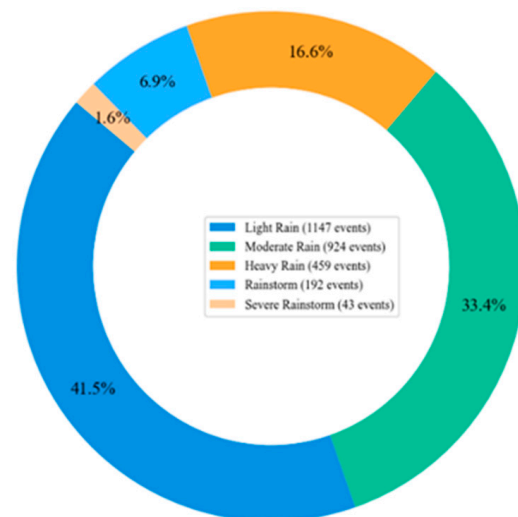


Figure 4. Distribution of rainfall events.

From the 1960s to the 1990s, the frequency of extreme rainfall events increased significantly, peaking in the 1990s with more than 50 recorded events (see Figure 5). This trend aligns with the findings of Philander [37], who noted that the 1990s experienced strong El Niño activity, particularly the 1997–1998 super El Niño event, which triggered extreme rainstorms and floods globally. Although the number of extreme rainfall events decreased after entering the 21st century, the overall frequency of extreme summer rainfall events continues to rise (see Figure 6).

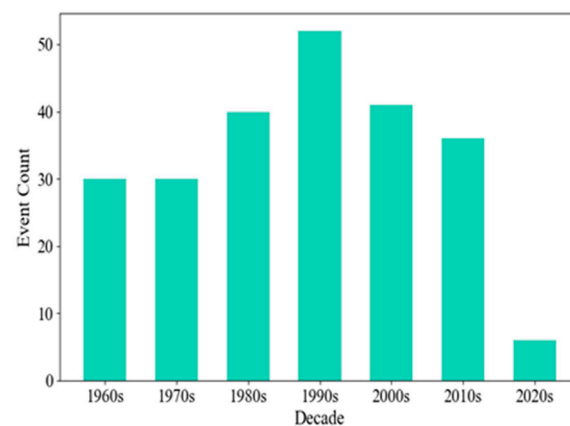


Figure 5. The decadal variation in the frequency of extreme rainfall events.

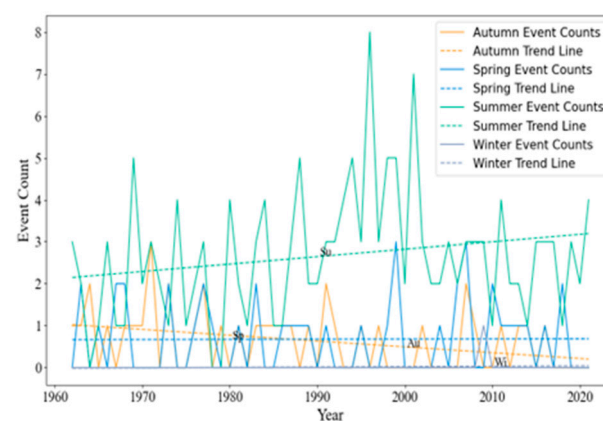


Figure 6. The annual variation in the seasonal frequency of extreme rainfall events.

The maximum single extreme rainfall event shows significant interannual fluctuations, ranging from a minimum of 50.0 mm in 1969 to a maximum of 449.9 mm in 1996 (see Figure 7), nearly nine times the former. Although the annual maximum single rainfall amount does not show a clear trend, the maximum single summer rainfall amount has significantly increased, indicating that extreme summer rainfall events have become more intense (see Figure 8). Loo et al. [38] found that the enhancement of the East Asian summer monsoon, stable monsoon fronts, and the strengthening of the western North Pacific subtropical high are key factors contributing to the frequent occurrence of extreme summer rainfall. Additionally, the increased water vapor content in the atmosphere due to global warming also contributes to the increased frequency of extreme summer rainfall events in the subtropical monsoon region [39].

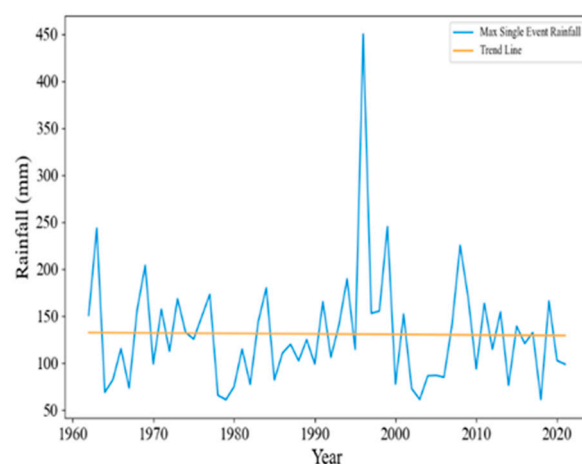


Figure 7. The annual trend in the variation of maximum extreme rainfall.

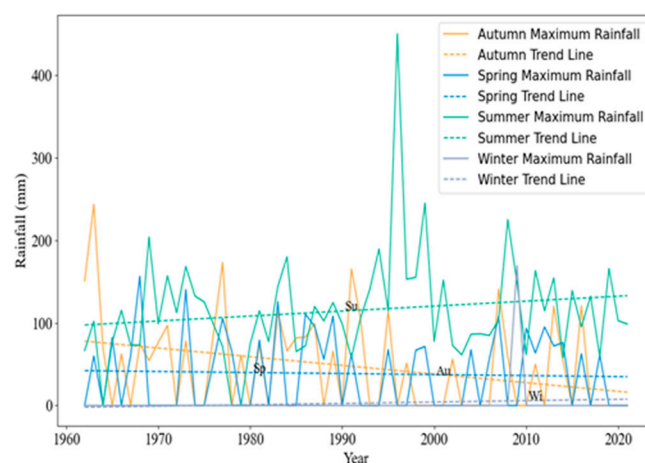


Figure 8. The annual trend in seasonal maximum extreme rainfall variation.

4.1.2. Classification of Extreme Rainfall Events

Using maximum rainfall intensity I_m , occurrence time TI_m , total rainfall R , rainfall duration T as feature vectors, the K-means clustering algorithm identified 235 extreme rainfall events into three major types of unique rainfall patterns (see Table 3 and Figure 9).

Cluster 1: Short-Duration, High-Intensity Rainfall

The median and mean of the maximum rainfall intensity are 40 mm/h and 42.5 mm/h, respectively. The maximum intensity peaks early in the rainfall event (median: 2.0 h, mean: 2.8 h), with the peak of the storm occurring shortly after the onset of rainfall.

The statistics on rainfall duration (median: 7.0 h, mean: 9.1 h, standard deviation: 5.9 h) and total rainfall (mean: 79.9 mm, standard deviation: 27.2 mm) further highlight the rapid accumulation of a significant amount of rainfall within a short duration. The total rainfall for this cluster is intermediate among the three types of extreme rainfall.

Cluster 2: Sustained, Moderate-Intensity Rainfall

The median maximum rainfall intensity is 13.1 mm/h, and the mean is 14.6 mm/h. In comparison, the median of the average rainfall intensity is 2.6 mm/h, and the mean is 3.1 mm/h. This comparison reveals that, although the maximum intensity is significantly higher than the average, the prolonged rainfall duration dilutes the intensity over time, resulting in a lower average rainfall intensity.

The maximum intensity usually occurs in the mid-stage of the rainfall event (median: 9.0 h, mean: 10.3 h), and the entire rainfall event can last up to approximately 25 h (median: 25.0 h, mean: 25.3 h). The total rainfall for this cluster is the smallest among the three types of extreme rainfall.

Cluster 3: Persistent, Moderate-High Intensity Rainfall

The median maximum rainfall intensity is 17.3 mm/h, and the mean is 17.8 mm/h. Although the maximum intensity remains at a moderate-high level, the significant fluctuations in intensity highlight the uneven distribution of the rainfall event.

The median and mean times for the occurrence of the maximum intensity are 22.5 h and 23.7 h, respectively, indicating that the peak of rainfall tends to occur in the mid-to-late stages of the rainfall event. This characteristic, when the soil moisture is near saturation, may intensify the flood event.

The total rainfall for this cluster (median: 135.8 mm, mean: 146.9 mm) is the largest among the three types of extreme rainfall.

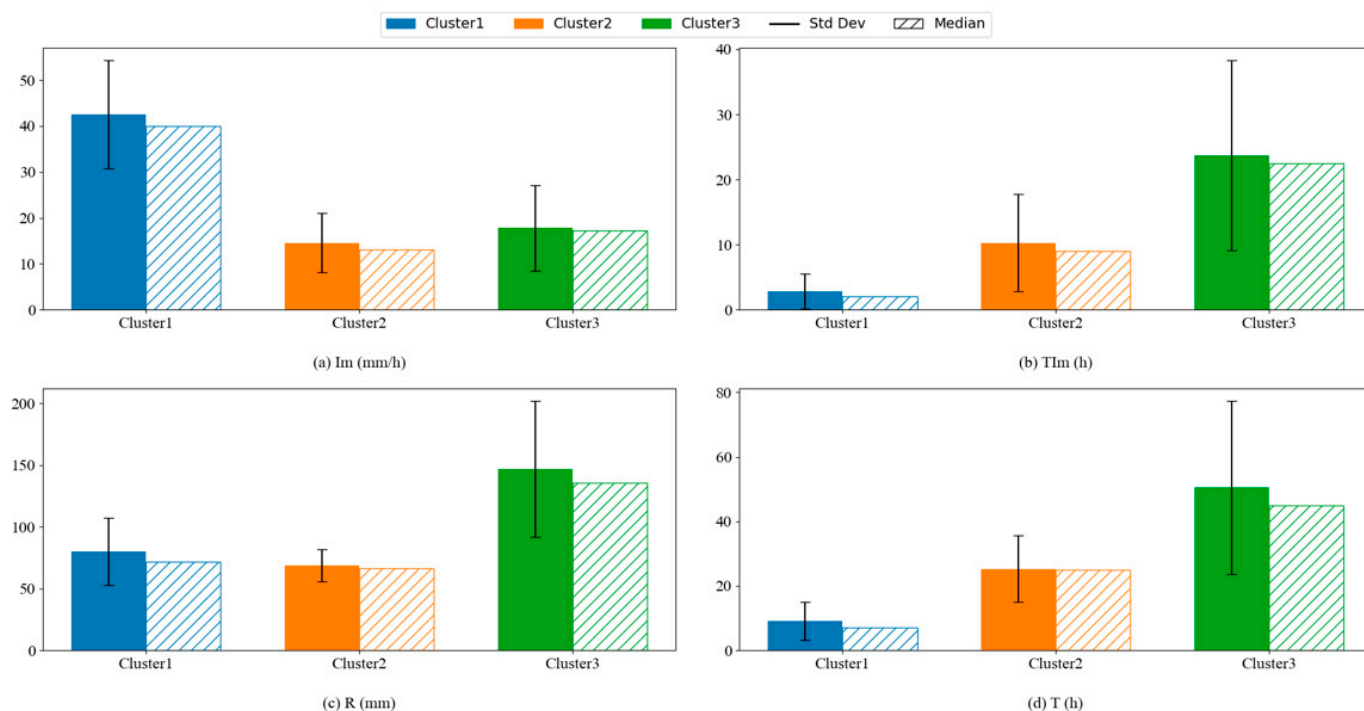


Figure 9. Characteristics of extreme rainfall.

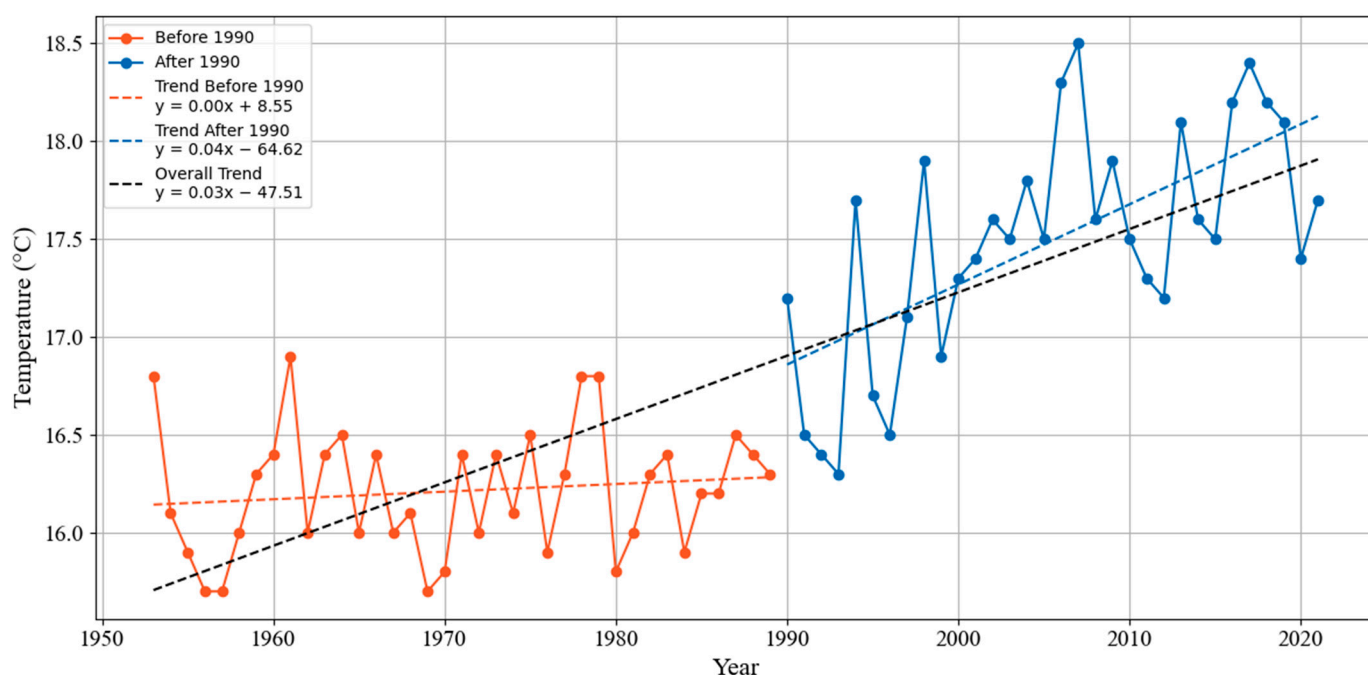
Table 3. Characteristics of extreme rainfall.

Cluster	Indicator	Median	Mean	Standard Deviation
Cluster 1 extreme rainfall	I_m (mm/h)	40.0	42.5	11.8
	TI_m (h)	2.0	2.8	2.7
	R (mm)	71.4	79.9	27.2
	T (h)	7.0	9.1	5.9
Cluster 2 extreme rainfall	I_m (mm/h)	13.1	14.6	6.5
	TI_m (h)	9.0	10.3	7.5
	R (mm)	66.4	68.6	13.0
	T (h)	25.0	25.3	10.3
Cluster 3 extreme rainfall	I_m (mm/h)	17.3	17.8	9.3
	TI_m (h)	22.5	23.7	14.6
	R (mm)	135.8	146.9	55.0
	T (h)	45.0	50.5	26.9

4.1.3. Response of Classified Extreme Rainfall Characteristics to Climate Change

The Xu Fan watershed lacks direct temperature monitoring facilities, but indirect analysis can be conducted using long-term temperature records from the nearby Hangzhou meteorological station, located approximately 65 km away. Data from the Hangzhou station spans from 1953 to 2021. According to the historical temperature change curve (see Figure 10), the average annual temperature increased by 0.3 °C per decade from 1953 to 2021, aligning with the data presented in the “China Climate Change Blue Book (2024)”. This publication indicates that the global climate system continues to warm, with China’s annual average surface temperature rising by 0.3 °C per decade from 1961 to 2023, surpassing the global average warming rate during the same period.

Before 1990, the temperature changes in the Xu Fan watershed were relatively stable. However, after 1990, the annual average temperature in the watershed exhibited a steady upward trend, with a warming rate of 0.4 °C per decade, culminating in an increase of approximately 1.3 °C (see Figure 10).

**Figure 10.** Average annual temperature.

Changes in monthly average temperature and cumulative rainfall (see Figure 11) demonstrate pronounced seasonal variations, with peak rainfall occurring from May to September and reduced rainfall from November to February. Prior to 1990, rainfall distribution was more dispersed, whereas after 1990, rainfall predominantly concentrated between June and August. The monthly average temperature displays typical seasonal fluctuations, with the highest temperatures recorded from June to August and the lowest from December to February. Before 1990, winter temperatures were lower, and summer temperatures were higher. After 1990, both summer and winter temperatures increased significantly compared to before 1990 levels.

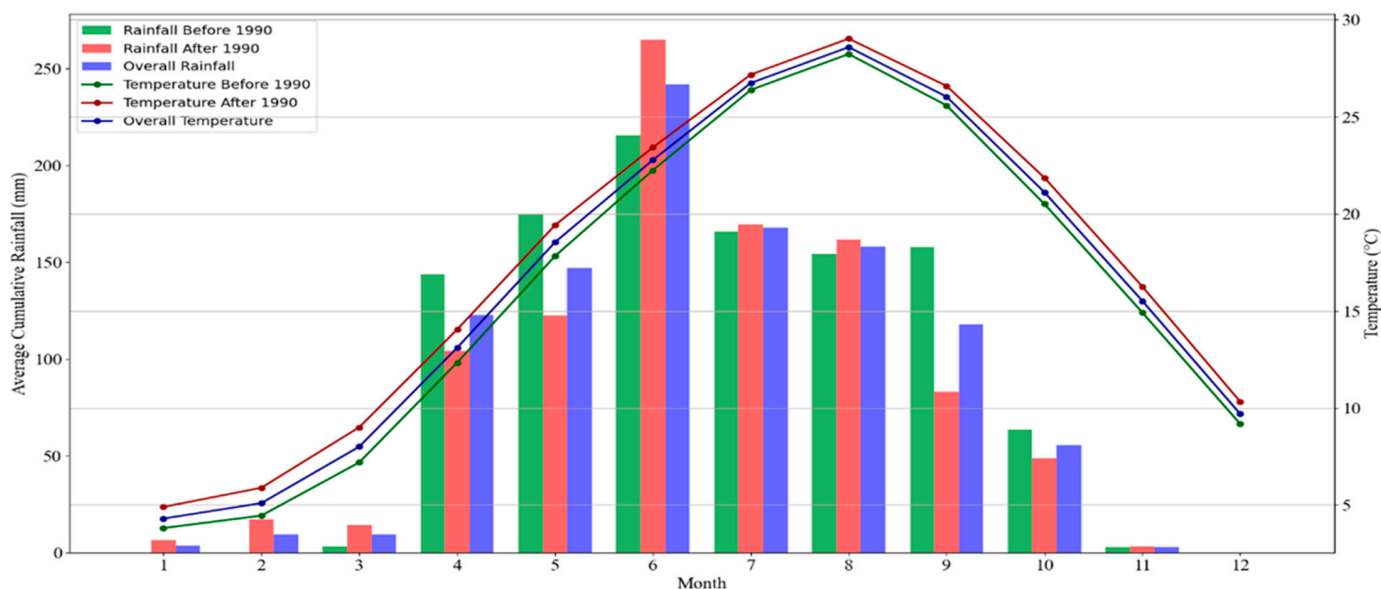


Figure 11. Monthly average temperature and cumulative rainfall.

In this study, 1990 was designated as a pivotal year, enabling a comparative assessment of rainfall characteristics before and after this period to be conducted (Table 4).

Table 4. Average changes in extreme rainfall characteristics before and after 1990.

Indicator	Cluster 1			Cluster 2			Cluster 3		
	Before 1990	After 1990	Change Rate (%)	Before 1990	After 1990	Change Rate (%)	Before 1990	After 1990	Change Rate (%)
λ (event/decade)	4.0	7.0	75.0	25.0	24.0	−4.0	7.0	11.0	57.1
I_m (mm/h)	40.7	43.2	6.2	14.3	15.3	7.6	17.3	18.9	9.4
TI_m (h)	4.2	1.8	−57.6	12.2	9.3	−23.8	25.7	18.8	−26.8
R (mm)	96.1	74.0	−23.0	69.1	69.6	0.7	138.5	150.1	8.4
T (h)	13.2	7.4	−44.3	26.9	22.6	−15.7	52.6	44.1	−16.2

Cluster 1: Short-Duration, High-Intensity Rainfall

Since 1990, the frequency of Cluster 1 extreme rainfall events has shown a significant upward trend, increasing by 75.0%, with the events primarily concentrated in May, June, and July. Although the rainfall in certain months, such as June, has increased, the overall annual total rainfall after 1990 has significantly decreased by 23% compared to before 1990, with a particularly significant decrease in rainfall during August and September. Notably, the maximum intensity of extreme rainfall events has significantly increased after 1990, especially in July, where the rainfall intensity exceeds the historical average. The timing of the maximum rainfall intensity has shifted earlier by 57.6%, mainly concentrated between

May and August. The duration of extreme rainfall events has significantly shortened by 44.3%, especially in July and August (see Figure 12).

Cluster 2: Sustained, Moderate-Intensity Rainfall

The frequency and total rainfall of Cluster 2 extreme rainfall events have remained relatively unchanged before and after 1990. However, the maximum rainfall intensity increased by 7.6%, and the average rainfall intensity showed a significant increase of 24.3%, with the events mainly occurring in June and July. The timing of the maximum rainfall intensity has advanced by 23.8%, mainly occurring between May and September. The rainfall duration has shortened by 15.7%, primarily between May and August (see Figure 13).

Cluster 3: Persistent, Moderate-High Intensity Rainfall

Since 1990, the frequency of Cluster 3 extreme rainfall events has increased significantly by 57.1%, especially in June and July. The maximum rainfall intensity increased by 9.4%, particularly from August to October. The timing of the maximum rainfall intensity advanced by 26.8%, mainly occurring in May, September, and October. The total rainfall per event increased by 8.4%, mainly occurring in June, August, and October. The rainfall duration has shortened by 16.2% after 1990, mainly concentrated between August and October (see Figure 14).

In summary, for all types of extreme rainfall, the maximum rainfall intensity has increased, the timing of the maximum rainfall intensity has advanced, and the rainfall duration has shortened.

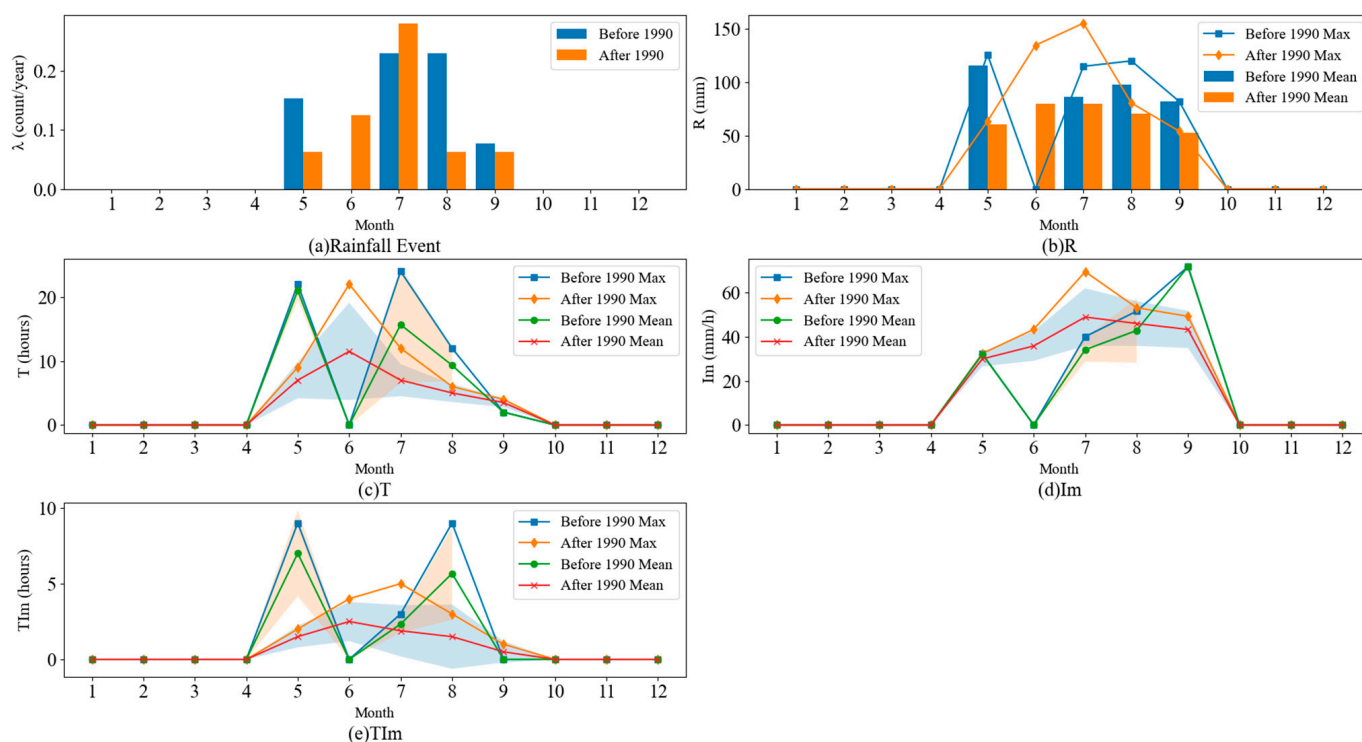


Figure 12. Comparison of annual characteristics of Cluster 1 Rainfall.

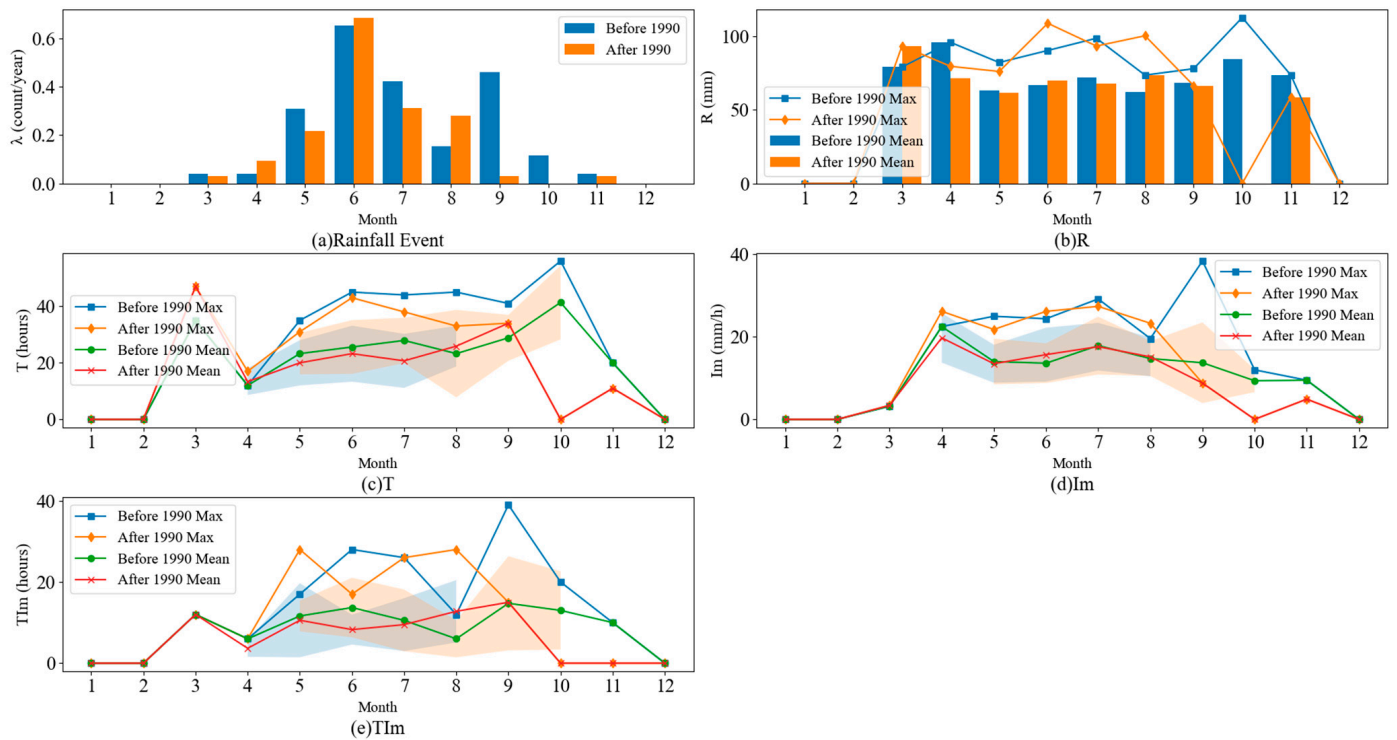


Figure 13. Comparison of annual characteristics of Cluster 2.

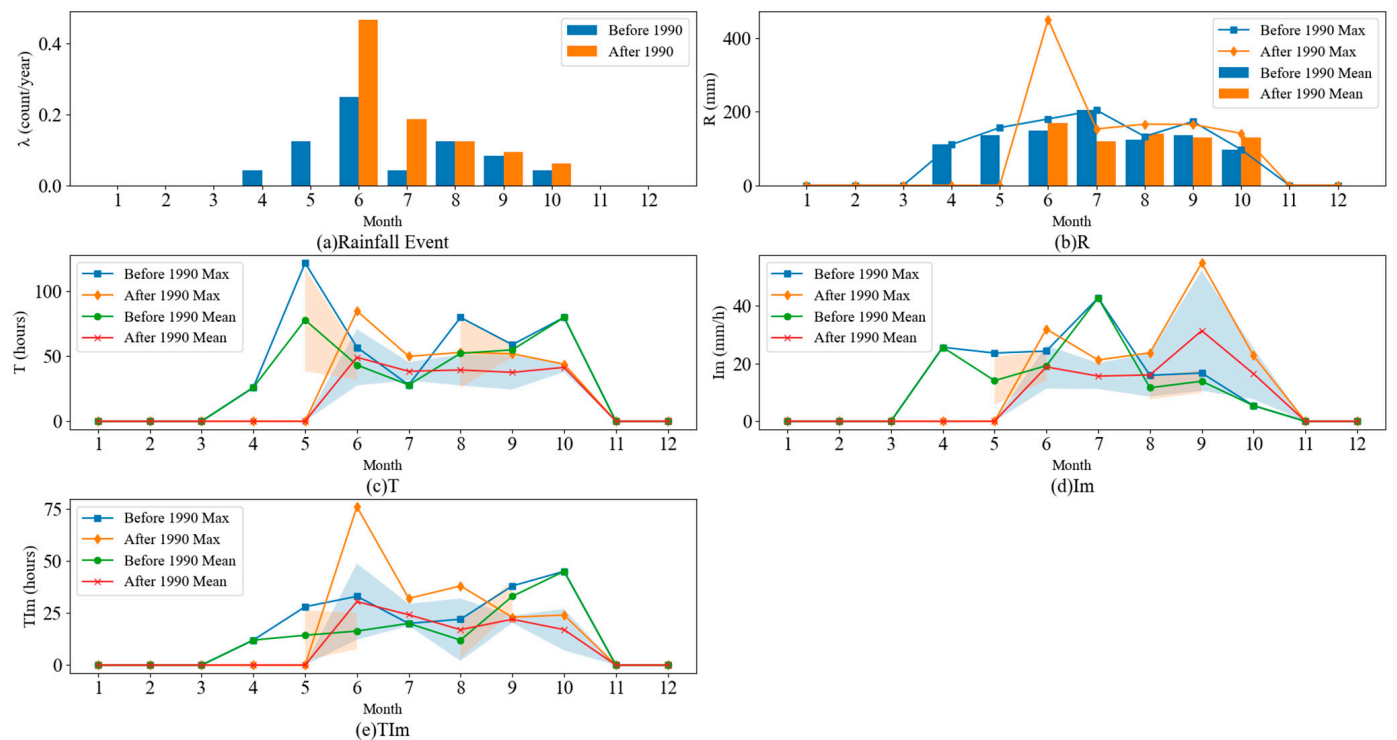


Figure 14. Comparison of annual characteristics of Cluster 3.

In Figures 12–14, these figures illustrate the changes in annual rainfall characteristics for three different rainfall categories (Cluster 1, Cluster 2, and Cluster 3).

- (a) λ (count/year) displays the monthly frequency of rainfall events before and after 1990. **Blue bar chart** represents the average frequency of rainfall events before 1990. **Orange bar chart** represents the average frequency of rainfall events after 1990.

- (b) **R (mm)** shows the average total monthly rainfall and the maximum monthly rainfall before and after 1990. **Blue bar chart** represents the average monthly rainfall before 1990, **Orange bar chart** represents the average monthly rainfall after 1990, **Blue line** represents the maximum monthly rainfall before 1990, **Orange line** represents the maximum monthly rainfall after 1990.
- (c) **T (hours)** compares the changes in rainfall duration across months before and after 1990. **Blue line** represents the maximum monthly rainfall duration before 1990, **Orange line** represents the maximum monthly rainfall duration after 1990, **Blue shaded area** represents the standard deviation range of the average monthly rainfall duration before 1990, **Orange shaded area** represents the standard deviation range of the average monthly rainfall duration after 1990.
- (d) **Im (mm/h)** displays the changes in maximum monthly rainfall intensity before and after 1990. **Blue line** represents the maximum monthly rainfall intensity before 1990, **Orange line** represents the maximum monthly rainfall intensity after 1990, **Blue shaded area** represents the standard deviation range of the average monthly rainfall intensity before 1990, **Orange shaded area** represents the standard deviation range of the average monthly rainfall intensity after 1990.
- (e) **TIm (hour)** shows the changes in the duration of maximum rainfall intensity before and after 1990. **Blue line** represents the maximum duration of monthly maximum rainfall intensity before 1990, **Orange line** represents the maximum duration of monthly maximum rainfall intensity after 1990, **Blue shaded area** represents the standard deviation range of the average duration of maximum rainfall intensity before 1990, **Orange shaded area** represents the standard deviation range of the average duration of maximum rainfall intensity after 1990. In Figure 15, the figure illustrates the average changes in extreme rainfall characteristics before and after 1990.

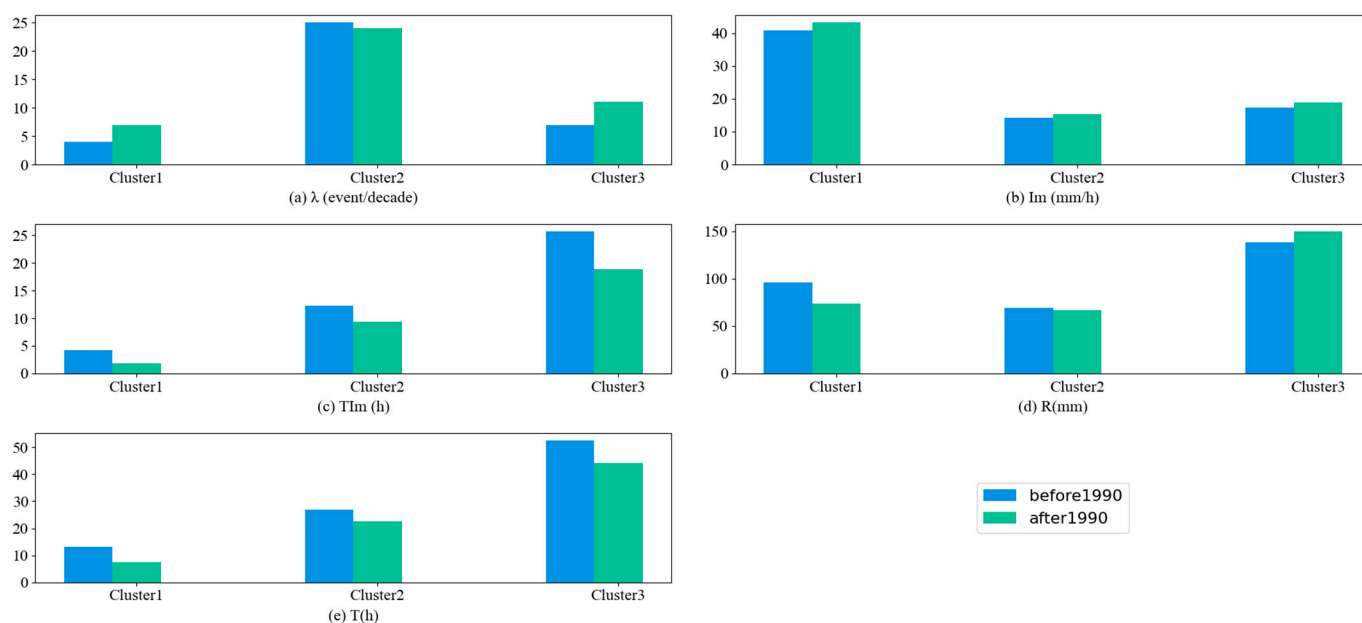


Figure 15. Average changes in extreme rainfall characteristics before and after 1990. (a) λ (event/decade) represents the frequency of events per decade for the three clusters before and after 1990. (b) Im (mm/h) represents the average rainfall intensity in millimeters per hour for the clusters before and after 1990. (c) TIm (h) represents the average time of maximum rainfall intensity in hours for the clusters. (d) R (mm) represents the total cumulative rainfall in millimeters for the clusters. (e) T (h) represents the total duration of rainfall events in hours for the clusters.

4.2. Flood Response Analysis

4.2.1. Characteristics of Clustered Floods

Based on the classification criteria of extreme rainfall, we performed a statistical analysis of floods caused by different clusters of extreme rainfall events (see Table 5 and Figure 16).

Cluster 1 Extreme Rainfall Floods

The median peak discharge is $63.3 \text{ m}^3/\text{s}$, with a mean peak discharge of $73.4 \text{ m}^3/\text{s}$. The median time to peak is 4.0 h, and the mean time to peak is 5.9 h. The median flood duration is 7.5 h, with a mean flood duration of 10.3 h. This cluster of flood is characterized by high intensity and short duration, with the peak occurring in the middle of the flood duration.

Cluster 2 Extreme Rainfall Floods

The median peak discharge is $52.3 \text{ m}^3/\text{s}$, with a mean peak discharge of $52.7 \text{ m}^3/\text{s}$. The median time to peak is 15.0 h, and the mean time to peak is 15.5 h. The median flood duration is 25.0 h, with a mean flood duration of 25.8 h. This cluster of flood has low intensity and moderate duration, with the peak occurring in the middle of the flood duration.

Cluster 3 Extreme Rainfall Floods

The median peak discharge is $108.0 \text{ m}^3/\text{s}$, with a mean peak discharge of $124.3 \text{ m}^3/\text{s}$. The median time to peak is 28.0 h, and the mean time to peak is 31.4 h. The median flood duration is 45.0 h, with a mean flood duration of 48.2 h. This cluster of flood has high intensity and long duration, with the peak occurring towards the end of the flood duration.

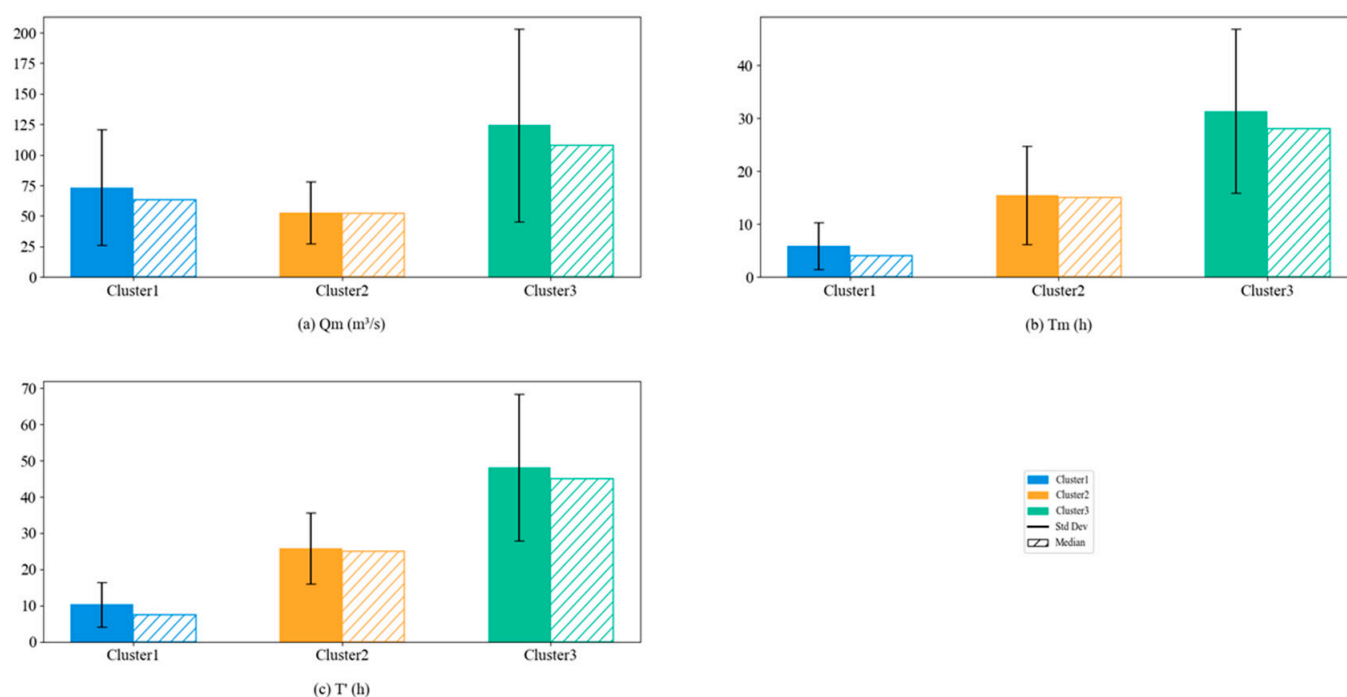


Figure 16. Characteristics of flood clusters. (a) $Q_m \text{ (m}^3/\text{s)}$ represents the mean discharge for each cluster. (b) $T_m \text{ (h)}$ represents the mean duration of rainfall events for each cluster. (c) $T \text{ (h)}$ represents the total duration of rainfall events for each cluster. Blue represents rainfall characteristics for Cluster 1, Orange represents rainfall characteristics for Cluster 2, Green represents rainfall characteristics for Cluster 3, Hatched Bars indicate the median value for each cluster, Error Bars show the variability (standard deviation) around the mean for each cluster.

Table 5. Characteristics of flood clusters.

	Characteristics	Median	Mean	Standard Deviation
Cluster1 flood	Q_m (m ³ /s)	63.3	73.4	47.2
	T_m (h)	4.0	5.9	4.4
	T' (h)	7.5	10.3	6.2
Cluster2 flood	Q_m (m ³ /s)	52.3	52.7	25.2
	T_m (h)	15.0	15.5	9.3
	T' (h)	25.0	25.8	9.8
Cluster3 flood	Q_m (m ³ /s)	108.0	124.3	78.8
	T_m (h)	28.0	31.4	15.5
	T' (h)	45.0	48.2	20.3

4.2.2. Analysis of Rainfall Influencing Factors on Clustered Floods

The results calculated by the Random Forest method show that varying impacts are exerted by different rainfall factors on the characteristics of each type of flood. By comparing the changes in rainfall characteristic factors (see Table 6) before and after 1990 and flood characteristic factors (see Table 7), it is evident that the flood formation process is affected by climate change, through the enhancement of rainfall intensity, shortening of rainfall duration, and alteration of rainfall distribution.

Flood Peak Discharge:

The average peak discharge of Cluster 1 and Cluster 3 floods decreased by 29.1 m³/s (20%) and 22.2 m³/s (16%), respectively. However, the average peak discharge of Cluster 2 floods increased by 9.8 m³/s (20.3%). For all three types of floods, the peak time advanced: by 3.8 h (45.2%) for Cluster 1, 6 h (32.4%) for Cluster 2, and 5.9 h (16.8%) for Cluster 3. The flood durations for all three clusters also shortened: by 5.8 h (41.2%) for Cluster 1, 4.3 h (15.6%) for Cluster 2, and 8.5 h (15.9%) for Cluster 3.

Flood Peak Discharge Factors:

Cluster 1 Floods: The peak discharge is significantly correlated with total rainfall and rainfall duration. Due to the decrease in total rainfall and the shortening of rainfall duration, the peak discharge has relatively decreased (see Figure 17a).

Cluster 2 Floods: The peak discharge is mainly influenced by maximum rainfall intensity, total rainfall, and the timing of maximum rainfall intensity. As the total rainfall remains unchanged, the increase in maximum rainfall intensity leads to an increase in peak discharge (see Figure 17b).

Cluster 3 Floods: The peak discharge is primarily affected by total rainfall and the timing of maximum rainfall intensity. The total rainfall for this cluster does not vary significantly, but the earlier occurrence of maximum rainfall intensity leads to a relatively smaller peak discharge (see Figure 17c).

Table 6. Importance coefficients of rainfall features on flood characteristics.

	Rainfall Features	Q_m (m ³ /s)	T_m (h)	T'
Cluster1 flood	I_m (mm/h)	0.04	0.07	0.01
	TI_m (h)	0.04	0.11	0.02
	R (mm)	0.57	0.53	0.03
	T (h)	0.35	0.29	0.94
Cluster2 flood	I_m (mm/h)	0.44	0.41	0.00
	TI_m (h)	0.20	0.20	0.00
	R (mm)	0.33	0.25	0.02
	T (h)	0.06	0.14	0.98

Table 6. Cont.

	Rainfall Features	Q_m (m ³ /s)	T_m (h)	T'
Cluster3 flood	I_m (mm/h)	0.09	0.04	0.01
	TI_m (h)	0.36	0.25	0.00
	R (mm)	0.49	0.64	0.02
	T (h)	0.05	0.07	0.97

Table 7. Average changes in flood characteristics before and after 1990.

Indicator	Cluster 1 Flood			Cluster 2 Flood			Cluster 3 Flood		
	Before 1990	After 1990	Change Rate (%)	Before 1990	After 1990	Change Rate (%)	Before 1990	After 1990	Change Rate (%)
Q_m (m ³ /s)	93.1	64.0	−31.3	48.0	57.8	20.3	138.5	116.3	−16.0
T_m (h)	8.4	4.6	−45.2	18.4	12.4	−32.4	35.2	29.3	−16.8
T'	14.2	8.4	−41.2	27.8	23.5	−15.6	53.6	45.1	−15.9

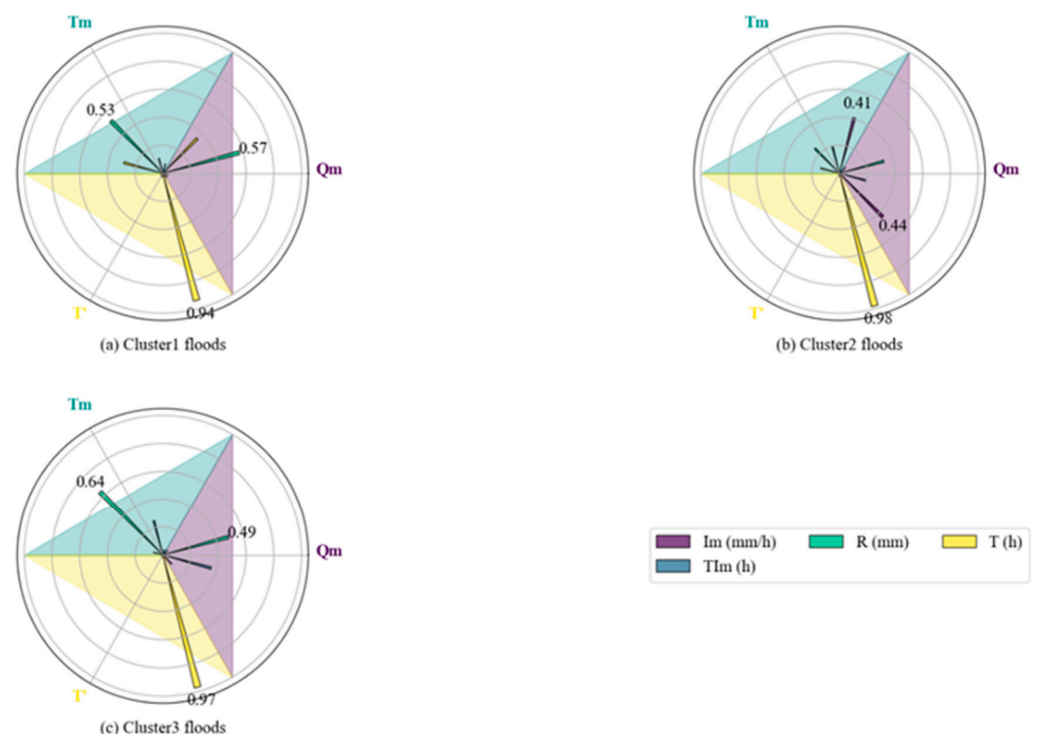


Figure 17. Important coefficients of extreme rainfall characteristics.

5. Conclusions

1. Climate change will lead to long-term changes in rainfall intensity and distribution patterns, increasing the frequency and intensity of extreme rainfall events. Although short-duration heavy rainfall may reduce peak discharge, frequent extreme rainfall events will exacerbate the suddenness and unpredictability of floods, posing greater challenges for flood management in small watersheds.
2. Floods from sustained moderate-intensity rainfall tend to have longer durations and more gradual rainfall processes. In the long term, climate change may enhance rainfall intensity and shorten the rainfall duration, leading to increased peak discharge. Therefore, future flood control facility designs, and emergency response systems must be capable of adapting to more frequent sustained moderate-intensity rainfall events.
3. With the intensification of climate change, increased rainfall intensity and shortened rainfall duration have become significant features of hydrological changes in small

watersheds. Due to their steep slopes and small catchment areas, small watersheds respond rapidly to rainfall. The increase in rainfall intensity and shortening of rainfall duration result in rapid accumulation of surface runoff, which will have a significant impact on the geological disaster risk in small watersheds, particularly landslides and debris flows.

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