

Article

Impact of Spatiotemporal Rainfall Distribution and Underlying Surface Changes on Flood Processes in Meijiang River Basin, China

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Abstract: This study reports on the impact of rainfall patterns and land surface changes on flood dynamics in the Meijiang River Basin, located in the upper reaches of the Ganjiang River. We formulated a range of rainfall patterns and spatial distribution scenarios and employed the MIKE SHE model to evaluate variations in flood volume, flood peak, and the timing of flood peaks. We found that under comparable areal rainfall conditions, flood volumes fluctuated by up to 6.22% among the different rainfall patterns, whereas flood peaks exhibited differences of up to 36.23%. When the rainfall center moved from upstream to downstream, both flood volume and flood peak initially increased before decreasing, with maximum values of 4.2 billion m³ and 4900 m³/s, respectively. We selected three basin scales (i.e., 10,000, 1000, and 100 km²) for comparative analysis. In the period between 1985 and 2020, the changes in land surface conditions resulted in decreases in the flood peaks of the three basins by 7.61, 11.53, and 15.79%, respectively; a reduction in the flood volumes of the three basins by 6.58, 9.60, and 10.48%, respectively; and delayed peak times by 3, 2, and 2 h, respectively. The results of this study show the significant influence exerted by rainfall patterns, the location of the rainfall centers, and the impact of changes in land surface conditions on flood processes. In particular, when the area of the basin was reduced, the influence of the underlying surface was more obvious. These results also show that flood prediction needs to consider the complex interaction of multiple factors.

Keywords: rainfall spatiotemporal distribution; underlying surface changes; MIKE SHE; flood simulation; Meijiang River Basin



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1. Introduction

Extreme rainfall events exert a substantial influence on people's daily lives, productive activities, and ecosystems [1–4]. In recent years, the frequency of extreme rainfall events has increased globally, accompanied by rising irregularities in the temporal and spatial distribution of rainfall [5,6]. The spatiotemporal distribution of rainfall directly influences flood formation and evolution [7]. Furthermore, human activities have significantly altered the underlying surface conditions of basins, further complicating flood processes and making them more difficult to predict [8–10] and thereby influencing flood magnitude and dynamics [11]. Hence, a comprehensive analysis of the response of flood processes

to variations in spatiotemporal rainfall distribution and changes in underlying surface conditions is important.

The spatiotemporal distribution of rainfall plays a crucial role in determining flood formation [12]. Increased spatiotemporal heterogeneity in rainfall not only affects flood peaks but also alters the shape of the flood process [13]. In particular, the spatial positioning of the rainfall center, along with the rainfall pattern, has a direct impact on flood processes within a basin. When the total amount and intensity of rainfall is comparable, it exceeds a specific threshold in the spatiotemporal rainfall distribution. This rainfall distribution significantly increases the likelihood of extreme flood events [14,15] and indicates that even smaller rainfall events could lead to larger flood peaks. Changes in the spatial distribution of rainfall are reflected by movements in the rainfall center across the basin. Saharia et al. [16] introduced the flashiness index, which reflects flood severity, to study flood responses. They demonstrated that spatial variability in rainfall affects both the flood volume and flood peak. Chen et al. [17] used the K-means++ clustering method to classify 63 rainfall events, with a quantitative classification of basin rainfall spatial patterns derived flood characteristics for different patterns. Zhou et al. [18] further demonstrated that the maximum flow of extreme rainfall is closely related to the spatial structure of rainfall, in particular to the coverage area of the rainfall core, even in smaller basins.

Compared with changes in the spatial distribution of rainfall, variations in rainfall timing have equally significant impacts on rainfall pattern characteristics [19]. Post-peak rainfall patterns (in which rainfall intensity gradually increases) generate approximately 25% more runoff compared to early peak patterns (in which rainfall intensity gradually decreases), highlighting rain patterns that indicate that increasing rain intensity lead to greater flooding [20]. Forestieri et al. [21] used a topography-based probabilistic distributed model to analyze the effects of different rainfall timing patterns on rainfall and flood warning mechanisms. Mu et al. [22] proposed four designed rainfall patterns based on the timing of peak rainfall to simulate the flood depth and inundation area.

Changes in the underlying surface are one of the key factors affecting flood processes, including urbanization, soil and water conservation measures, and vegetation changes [23,24]. Janizadeh et al. [25] employed various machine learning models and ensemble methods to predict flood risk, demonstrating that urbanization increased the proportion of high-risk areas by approximately 11%, while areas of extremely high risk grew by 6%. In contrast, soil and water conservation measures, such as afforestation, mountain closure, and terrace construction, effectively mitigated the occurrence, peaks, and magnitudes of floods within the basin [26]. Liu et al. [27] examined the effects of vegetation and farmland terraces on flood peaks in 75 small basins. Compared to basins dominated by slope farmland, the flood peak coefficients in basins dominated by forests, grasslands, and farmland terraces were reduced by 54.75, 47.80, and 53.65%, respectively. The peak-shaving effect of soil and water conservation measures was more pronounced during smaller flood events. The flood reduction effect of forest vegetation, however, was influenced by factors such as prior rainfall, soil moisture content, forest canopy, and leaf litter wetness, as well as by the intensity of rainfall events [28].

Experimental numerical models are effective tools to reveal the key mechanisms of water resource systems [29]. With the growing use of distributed hydrological models and the increasing availability of high-resolution rainfall, topographic, and other data, these tools play a crucial role in simulating and capturing flood processes [30]. The MIKE Systeme Hydrologique European (MIKE SHE) model, a distributed hydrological framework, robustly encapsulates physical mechanisms that reflect the spatiotemporal variability of rainfall and underlying surface conditions. MIKE SHE, which has been extensively applied to simulate river channels [31], basin rainfall [32], and flood evolution dynamics [33],

facilitates terrain grid mapping and integrates underlying surface conditions while also regulating rainfall in different regions. Through scenario settings, MIKE SHE simulates typical flood processes under the joint influence of spatiotemporal rainfall distribution and changes in the underlying surface. Although previous studies have explored the impacts of either spatiotemporal rainfall distribution or underlying surface changes on flood processes, few studies have focused on constructing underlying surface scenarios for the same basin across different periods, quantifying spatial distribution and rainfall patterns. Additionally, the use of distributed rainfall scenarios is essential in rapid flood response analyses. In this study, we used the MIKE SHE model to simulate the synergistic effects of the temporal and spatial distribution of rainfall and the changes in the underlying surface on the flood process. Overall, this study provides a scientific and operational model framework and practical decision-making basis for flood prediction and prevention in the Meijiang River Basin and similar basins and also provides a reference direction for future research.

The Meijiang River Basin, located in the upper reaches of the Ganjiang River Basin and encompassing a vast area, features significant topographical differences between the upstream and downstream areas as well as an uneven distribution of rainfall in time and space. Different flood processes formed by the same rainfall make it difficult to predict floods. In this study, we constructed a MIKE SHE model for the Meijiang River Basin and carried out the response of a flood process under the joint action of the temporal and spatial distribution of rainfall and underlying surface changes. We quantitatively analyzed the effects of different rainfall patterns and rainfall centers on the flood process. The ability to study the response of the flood process under the joint action of the temporal and spatial distribution characteristics of rainfall and the underlying surface change in the Meijiang River Basin holds great significance for accurately predicting the flood process and taking effective flood control measures.

2. Study and Data

2.1. Study Area

The Meijiang River is a tributary of the right bank of the upper reaches of the Ganjiang River, which flows into Gongshui by the confluence of the Meijiang River (main branch), Qinjiang River (east river), and Mianjiang River (south river) in Duxian County. It has a basin area of 16,033 km² and a main river channel of 223 km, which features a subtropical monsoon climate, with high temperature and rainfall in the summer and warm and humid weather in the winter. The average temperature of the region for many years was 19.3 °C, and the main land use types included forest land, agricultural land, and urban construction land. The forest land was dominated by artificial coniferous forest and subtropical evergreen broadleaf forest. Over the past 40 years, however, with the intensification of soil erosion, human activity has significantly changed the region as a result of afforestation and reservoir construction and the acceleration of urbanization. As the outlet control hydrological station of the basin, the Xiashan Hydrological Station has documented several extreme flood events with their respective peak flood flows as follows: 1962 with a flow of 7500 m³/s (approximately 50 a), 1995 with 7400 m³/s (approximately 50 a), and 2010 with 7100 m³/s (approximately 10 a), respectively. In addition, the peak flood flow in 1964 reached 8700 m³/s (approximately 100 a), and these flood disasters affected the local economy as well as the lives of residents. Figure 1 shows the distribution of water system maps and hydrological stations in the Meijiang River Basin.

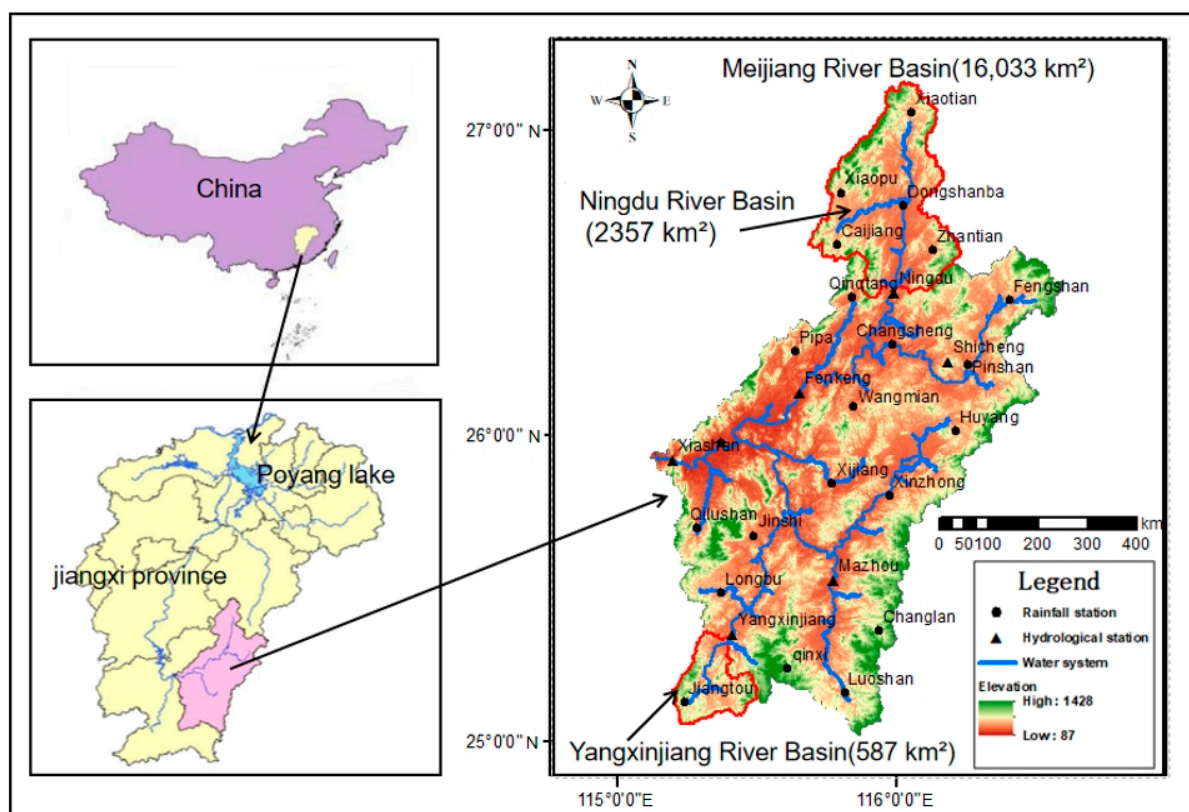


Figure 1. Hydrological station distribution in the study area.

2.2. Data

The digital elevation model (DEM) of the study area featured ASTERGDEM 30 m resolution digital elevation data from the Geospatial Data Cloud (<https://www.gscloud.cn/>) (accessed on 1 June 2024). The land use data were from the PIE-Engine remote sensing and geographic information cloud service platform (<https://engine.piesat.cn/>) (accessed on 1 June 2024), with a resolution of 30 m. Soil type data were derived from the World Soil Database V1.2 (HWSD) constructed by the Food and Agriculture Organization of the United Nations (<https://www.fao.org/>) (accessed on 1 June 2024), with a resolution of 1 km. We calculated each soil attribute in the study area based on SPAW (Version 6.02.75) software and divided the data into five categories: loam, silty loam, clay, sandy clay loam, and sandy loam. The hydrological data were from the Jiangxi Provincial Hydrological Monitoring Center, including extracted flood elements from 1980 to 2020 from 27 rainfall stations, including the Xiashan Hydrological Station, Ningdu Hydrological Station, and Yangxinjiang Hydrological Station (Table 1). To match the flow and rainfall data in time, we set the time step to 1 h.

Table 1. Data summary.

Name	Basic Information	Data Source
DEM	1985, 2000, and 2020 with 30 m resolution	Geospatial Data Cloud
Land Use	1985–2020 with 30 m resolution	CLCD 1985–2020 National 30 m Land Cover Dataset
Soil	2020 with 1:1,100,000 scale	HWSD Dataset
Flood Excerpt (Water Level/Flow)	1980–2020 data from Xiashan, Ningdu, and Yangxinjiang Stations	Jiangxi Provincial Hydrological Monitoring Center
Precipitation	1980–2020 data from 27 rainfall stations	
Evaporation	1980–2020 data from Zhangdou Station	

3. Research Methods

3.1. MIKE SHE Model Principles and Construction

The MIKE SHE model, a distributed hydrological framework with robust physical mechanisms, was developed by the Danish Hydraulic Institute in the early 1990s [34]. Compared to traditional hydrological empirical models such as SLM [35] and LPM [36], MIKE SHE can more comprehensively reflect spatial variation factors such as topography, soil type, vegetation coverage, and precipitation intensity in a basin. Therefore, it can provide more accurate hydrological simulation results and higher simulation calculation efficiency. The model is composed of five submodules: Overland Flow (OL), Open-Channel Flow (OC), Unsaturated-Zone Flow (UZ), Evapotranspiration (ET), and Saturated-Zone Flow (SZ). OL is computed using two-dimensional Saint–Venant equations to simulate net rainfall runoff across a slope. The UZ submodule employs the dual-layer water balance approach to simulate infiltration, replenishing soil moisture deficits. The SZ simulates groundwater runoff using the linear reservoir method. Actual ET is determined using meteorological and vegetation data, including the reference ET, leaf area index (LAI), and root depth (RD) of vegetation. Each submodule represents a key hydrological process, and their integration enables a comprehensive depiction of the watershed hydrological cycle [37]. MIKE SHE does not incorporate river routing calculations directly. Instead, river routing is managed by coupling the one-dimensional hydrodynamic module of MIKE Hydro River, which resolves the Saint–Venant equations to simulate river channel flow [38].

During the coupling process, we projected river channels onto adjacent computational grid boundaries and intermittently applied the finite difference method to calculate water levels and flow points. We utilized the Muskingum method to simulate the propagation of water flow. The key formulas are as follows.

(1) One-dimensional unsteady flow Saint–Venant equation:

$$\begin{cases} B_s \frac{\partial h}{\partial t} + \frac{\partial Q}{\partial x} = q \\ \frac{\partial Q}{\partial t} + \frac{\partial}{\partial x} \left(\frac{\alpha Q^2}{A} \right) + gA \frac{\partial h}{\partial x} + \frac{gQ|Q|}{C^2 AR} = 0 \end{cases} \quad (1)$$

where B_s is the river width; h is the water surface elevation at the cross-section; t is the time coordinate; Q is the discharge at the cross-section; q is the lateral inflow rate; α is the vertical velocity distribution coefficient; A is the cross-sectional flow area; and C is the Chezy coefficient.

(2) Finite difference method:

The three-dimensional Boussinesq equation can be used to simulate dynamic changes in groundwater. We used the implicit finite difference method to iteratively solve

$$\frac{\partial}{\partial x} (K_{xx} \frac{\partial h}{\partial x}) + \frac{\partial}{\partial y} (K_{yy} \frac{\partial h}{\partial y}) + \frac{\partial}{\partial z} (K_{zz} \frac{\partial h}{\partial z}) - Q = S \frac{\partial h}{\partial t} \quad (2)$$

where K_{xx} , K_{yy} , and K_{zz} are the hydraulic conductivities along the x-, y-, and z-axes, respectively; h is the hydraulic head in the saturated zone (m); Q is the source-sink term; and S is the storage coefficient.

(3) Muskingum equation:

$$\begin{cases} O_{t+1} = C_1 I_{t+1} + C_2 I_t + C_3 O_t \\ C_1 = \frac{\Delta t - 2KX}{2K(1-X) + \Delta t} \\ C_2 = \frac{\Delta t + 2KX}{2K(1-X) + \Delta t} \\ C_3 = 1 - C_1 - C_2 \end{cases} \quad (3)$$

where O_{t+1} and O_t both represent the outflow at the downstream end; I_{t+1} and I_t both represent the outflow at the upstream end; and the coefficients C_1 , C_2 , and C_3 are determined by the model's time step, Δt , the river's travel time, K , and the storage coefficient, X .

We constructed the model according to the simulation scope, precision, and time step, which consisted of 120 horizontal by 185 vertical grids, with each grid measuring $1404 \text{ m} \times 1404 \text{ m}$. We entered the DEM data into the model to set surface elevations. We employed the Thiessen polygon method to calculate the basin's areal average rainfall. In the land use module, we referenced the LAI from the relevant literature and sourced RD values from the model's vegetation attribute files [39]. We assigned LAI and RD values throughout the year based on growth cycles. We categorized the basin's land use types into six classes, with major flood events occurring between May and August (Table 2). In the model's discrete grid system, we assigned each grid in the land use module corresponding LAI and RD values [40]. After importing land use vector files from different periods, changes in area contributed to corresponding grid parameter adjustments to reflect these land use changes. The hydrological constants for the five soil types calculated using SPAW are presented in Table 3.

Table 2. Monthly changes in LAI and RD in different land use types from May to August.

Month	Shrub		Water		Built-Up Area		Farmland		Broadleaf Forest		Coniferous Forest	
	LAI	RD/mm	LAI	RD/mm	LAI	RD/mm	LAI	RD/mm	LAI	Rd/mm	LAI	RD/mm
May	1	200	0	0	1	200	4	800	4.8	700	5.5	600
June	3	500	0	0	0.95	170	4	500	5.4	750	7.5	700
July	3	500	0	0	0.9	150	3.5	500	5.4	750	7.5	700
August	2	400	0	0	0.9	150	3	400	4.8	700	5.5	650

Table 3. Soil hydrological constant values.

Soil Type	Saturated Water Content/%	Field Capacity/%	Porosity/%	Saturated Hydraulic Conductivity/ $10^{-6} \cdot \text{m} \cdot \text{s}^{-1}$
Loam	45.7	28.0	14.3	4.05
Silt loam	47.2	30.6	14.2	3.54
Clay	44.4	27.6	16.0	3.34
Sandy clay loam	44.6	27.2	15.4	3.66
Sandy loam	41.9	24.5	10.5	1.68

This model delineated the primary river channels by establishing the basin's hydrological network and utilized water level data from the Xiashan Hydrological Station as the downstream boundary condition. We assigned closed upstream boundaries to the primary tributaries, situated in mountainous regions, and applied the Muskingum method to the river channel calculations. In this study, we considered only large reservoirs, adding cross-sections at reservoir locations and importing elevation data. The reservoir function was simplified by employing the additional storage area method, which was based on water retention and release structures. We simulated reservoir operations by configuring control expressions. The Tuanjie reservoir, a large (class II) reservoir within the basin, operated under the following regulations: When the water level fell below the flood control limit, the gates remained closed for water storage, and the reservoir was operated for irrigation and power generation. When the water level reached the flood control limit of 242.0 m but stayed below the flood safety level of 244.06 m, flood discharge was regulated by either the actual inflow or the downstream safety discharge limit of $300 \text{ m}^3/\text{s}$. When the water level exceeded 244.06 m, the floodgates were opened to permit free outflow to ensure safety.

3.2. Evaluation Methods

According to the “Hydrological Information and Forecasting Standards” (GB/T 22482-2008) [41], we based the evaluation of an individual flood event on the following four key indicators: the deterministic coefficient (DC), the relative error of the flood peak, the relative error of the flood volume, and the difference in peak time. We evaluated the overall forecasting performance through a comprehensive flood forecasting accuracy assessment model. The standards specify that the relative errors for flood peak and flood volume must be constrained within 20% (Formula (4)) and the peak time error must be limited to within 3 h. The peak time error refers to the discrepancy between the forecasted and observed peak times. We considered a forecast to be qualified when the error fell within the permissible range. For multiple forecasts, we employed the qualification rate (QR) for evaluation, where the QR represents the ratio of qualified forecasts to the total number of forecasts. We categorized the forecasting accuracy of the project into three levels, determined by the qualification rate or the value of the deterministic coefficient. A detailed explanation of the accuracy levels is presented in Table 4, along with Formulas (5) and (6).

Table 4. Flood forecasting accuracy level.

Accuracy Level	A	B	C
QR (%)	$QR \geq 85$	$85 > QR \geq 70$	$70 > QR \geq 60$
DC	$DC > 0.9$	$0.9 \geq DC \geq 0.7$	$0.7 > DC \geq 0.5$

The relative error is the ratio of the absolute error between the simulated value and the observed value to the observed value. The calculation formula is as follows:

$$RE = \frac{y_i - y_0}{y_0} \times 100\% \quad (4)$$

where RE is the relative error (%); y_i is the forecasted value; and y_0 is the observed value.

The calculation formula for the qualification rate is as follows:

$$QR = \frac{n}{m} \times 100\% \quad (5)$$

where QR is the qualification rate (%); n is the number of qualified simulations (times); and m is the total number of simulations (times).

The determination coefficient (DC) measures the similarity between the flood simulation process and the observed process. The calculation formula is as follows:

$$DC = 1 - \frac{\sum_{i=1}^n [y_s(i) - y_0(i)]^2}{\sum_{i=1}^n [y_0(i) - \bar{y}_0]^2} \quad (6)$$

where DC is the determination coefficient; $y_0(i)$ is the observed value; $y_s(i)$ is the forecasted value; $\bar{y}_0$ is the mean of the observed values; and n is the length of the data series.

3.3. Scenario Simulation Approach for Spatiotemporal Variability of Rainfall

A typical rainfall pattern design should encapsulate the key characteristics of most rainfall events within the basin. We derived these patterns through the analysis of rainfall statistics based on observed data from the hydrometeorological stations, rainfall duration, frequency of rainfall peaks, and timing of those peaks to generate a representative pattern. We used the Lorenz curve and its corresponding Gini coefficient to characterize the unifor-

mity of spatiotemporal rainfall distribution. A Gini coefficient closer to 0 indicated a more uniform distribution of rainfall, whereas a coefficient closer to 1 reflected a more uneven distribution. The calculation formula was as follows: According to the size of the Gini coefficient, we divided the rain patterns into uniform, uneven, and concentrated patterns, and then we combined these results with the historical common rainfall characteristics of the Meijiang River Basin. We recorded the rain peaks as I, II, and III and denoted the uniform pattern (Gini) in the front, rear, and middle unimodal patterns ($0.65 < \text{Gini}$). We denoted ($\text{Gini} < 0.45$) as pattern IV and divided the uneven pattern according to the time course position of the double peak. We recorded the location of the rain peak as V and VI, respectively (Formulas (7) and (8)), and set the rainfall duration to 7 days. According to the maximum annual 7-day surface rainfall in the past 40 years, we fitted the P-III curve and obtained six typical return periods (100, 50, 20, 10, 5, 2 a). We obtained the rain patterns with different return period sizes as the rainfall pattern design (Figure 2).

$$\text{Gini} = \frac{\sum_{i=1}^n \sum_{j=1}^n |r_i - r_j|}{2n^2 \bar{r}} \quad (7)$$

where r_i and r_j represent the rainfall amounts in the i -th and j -th spatiotemporal units, respectively. n denotes the total number of spatiotemporal units, and $\bar{r}$ represents the average rainfall across all spatiotemporal units.

$$\text{Gini} = \begin{cases} \text{Gini} < 0.45, \text{uniform type} \\ 0.45 < \text{Gini} < 0.65, \text{uneven type (double peak)} \\ 0.65 < \text{Gini}, \text{concentrated type (single peak)} \end{cases} \quad (8)$$

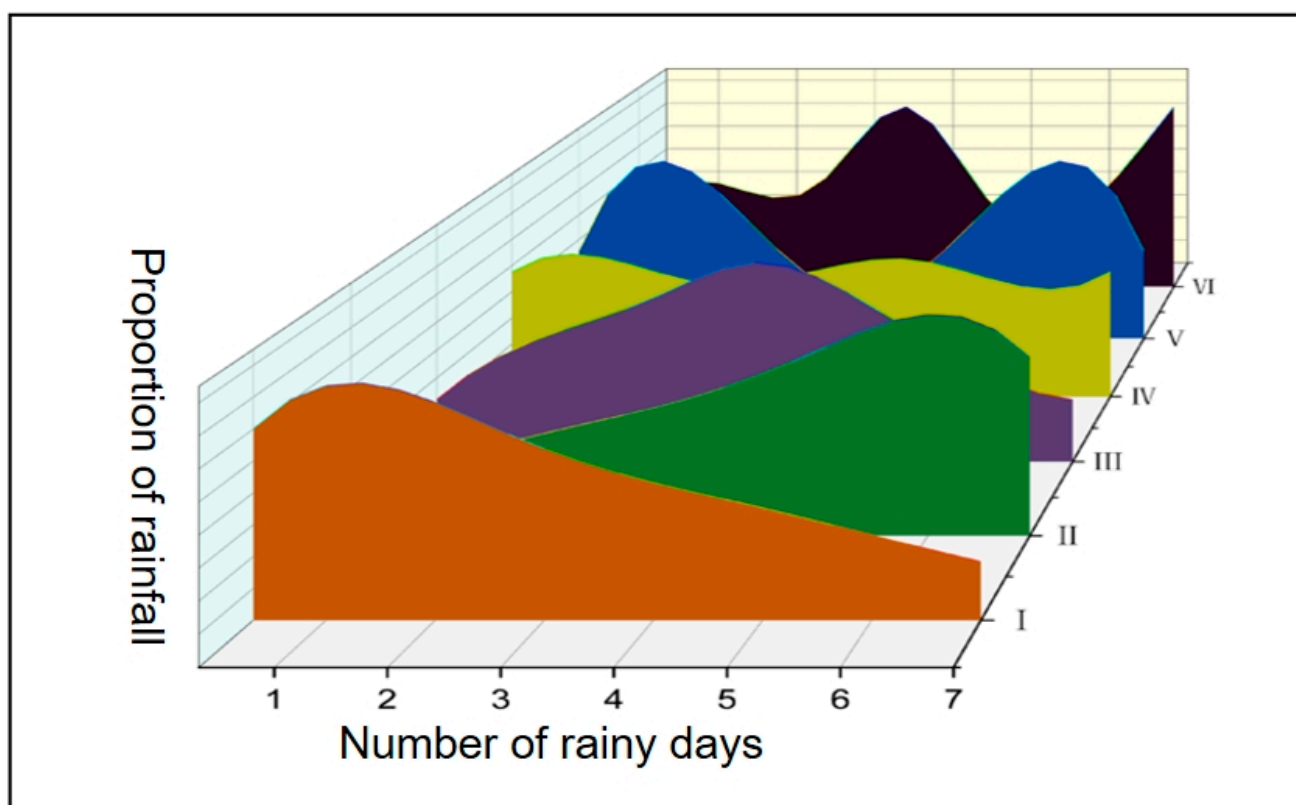


Figure 2. Rainfall pattern design.

We used rainfall characteristics to quantify the spatial variation in rainfall and selected the rainfall center position (C_L) and the areal rainfall as evaluation indicator (Formulas (9) and (10)). The areal rainfall reflected the rainfall situation of the whole region by weighting the rainfall data from multiple measurement points, whereas the rainfall relative center quantified the shift in the rainfall position relative to the outlet of the watershed, as follows.

(1) The areal rainfall is the weighted average of rainfall from multiple stations:

$$P_m = \sum_{i=1}^n a_i P_i \quad (9)$$

where a_i is the Thiessen polygon area weighting factor and P_i is the accumulated rainfall at the i -th rainfall station.

(2) The rainfall center position (C_L) is as follows:

$$C_L = \frac{\sum_{i=1}^n P_i d_i}{\sum_{i=1}^n P_i} \quad (10)$$

where P_i is the accumulated rainfall at the i -th rainfall station, and d_i represents the flow distance from the i -th rainfall station to the basin outlet.

By calculating the product of the flow distance and the accumulated rainfall of each rain gauge, the rainfall center position C_L was obtained. This value reflects the relative position of the rainfall center; that is, the farther the rainfall center is from the basin outlet, the higher the C_L value is. In order to more accurately analyze the impact of spatial rainfall on the flood process, the experiment divided the C_L value into five intervals based on the actual topography and rainfall conditions in the Meijiang River Basin. To eliminate the influence of underlying surface conditions and areal rainfall amounts on the experiment, we applied a consistent underlying surface condition and standardized all rainfall patterns to 100 a. The experiment simulated the gradual migration of the rainfall center from the upstream to the downstream regions of the Meijiang River Basin. We categorized the position of the rainfall center into five levels according to the C_L value, where a higher C_L value indicated proximity to the upstream region and a lower C_L value indicated proximity to the downstream region (Table 5). This approach enabled a quantitative analysis of the joint effects of rainfall center positioning and rainfall pattern variations on flood processes.

Table 5. Value classification for rainfall centers.

	Center 1	Center 2	Center 3	Center 4	Center 5
C_L value	$145.37 < C_L$	$140.54 < C_L < 145.37$	$135.74 < C_L < 140.54$	$128.92 < C_L < 135.74$	$C_L < 128.92$

4. Analysis of Spatiotemporal Rainfall Distribution and Underlying Surface Changes in the Meijiang River Basin

4.1. Analysis of Spatiotemporal Variations in Rainfall

Based on the data of 82 measured rainfall events in the past 40 years, we analyzed the temporal and spatial distribution and rainfall pattern characteristics of rainfall events in this region. We found that 34 single-peak rainfall events accounted for a large proportion, accounting for 41.46% of the total. We further subdivided the unimodal rainfall events into early-peak (18), mid-peak (14), and post-peak (2) events, with early-peak rainfall being the most common. We identified 20 bimodal rainfall events, accounting for 24.39%, mainly the bimodal rainfall pattern V (15 events), 26 irregular rainfall events, accounting for 31.7%,

and only 2 uniform rainfall events, accounting for 2.4%. Further analysis of the rainfall distribution in the basin is shown in Figure 3, and the upstream areas, including Fengshan (233.99 mm), Pingshan (230.92 mm), and Qingtang (229.59 mm), had relatively high hourly rainfall depths. These areas were prone to form heavy rainfall belts because of the rise and condensation of moist air as a result of the mountainous and hilly terrain. In contrast, the flat terrain in the middle and upstream areas led to less rainfall and relatively low hourly rainfall depths, including Xiashan (178.22 mm), Yudu (182.37 mm), and Qilushan (183.72 mm). According to the center analysis of the C_L value of rainfall in the center of the historic flood rainfall area, the C_L value was most frequent in centers 3 and 4, with 23 and 25 rainfall events, respectively, which indicated that the rainfall was concentrated mainly in the upstream and middle reaches. However, the rainfall center occurred the least in the downstream center 5, only five times. The center of the rainfall was mainly in centers 1 and 2, with 14 and 15 occurrences, respectively.

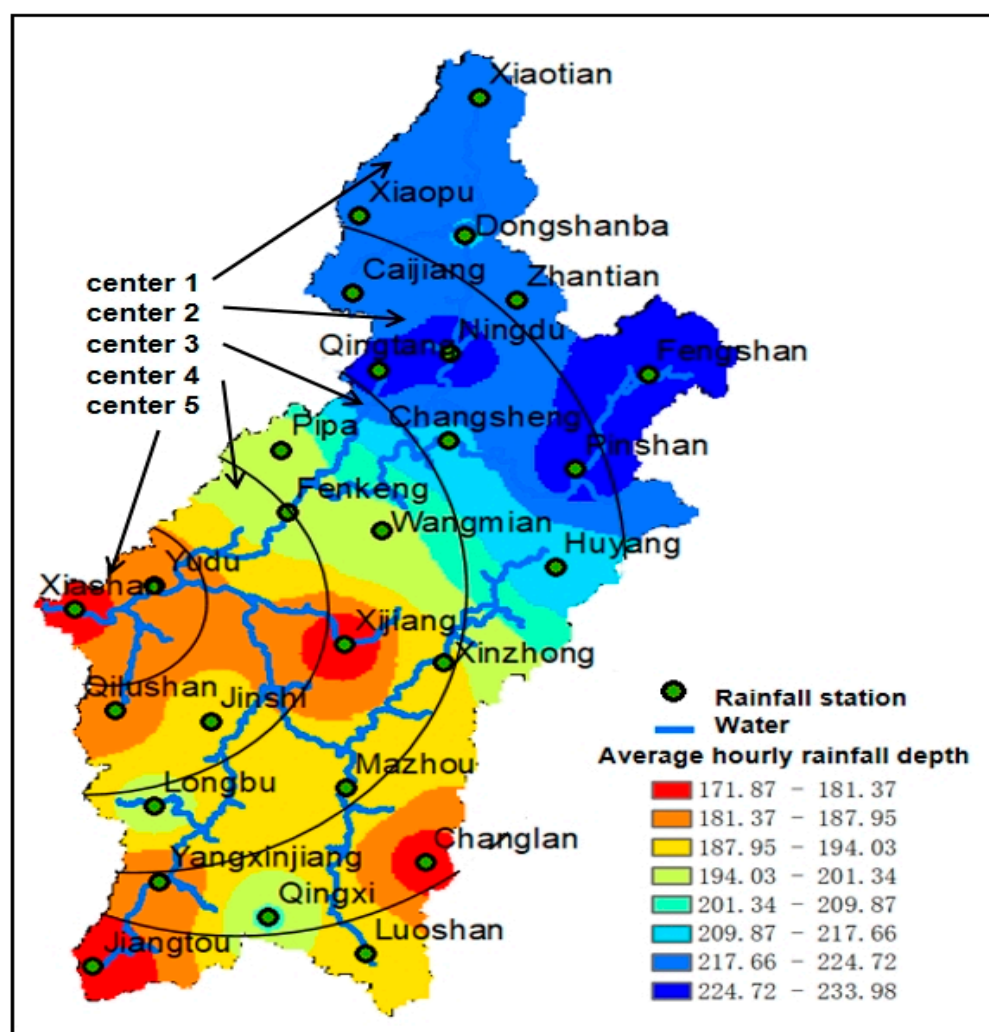


Figure 3. Average hourly rainfall depth and C_L centers.

The topography of the Meijiang River Basin is complex and diverse, and the combined effects of various landforms, such as river valleys, hills, and mountains, contributed to significant differences in rainfall characteristics and runoff processes in different regions. The rainfall process was not only significantly affected by the topography but was also closely related to regional climate change. In particular, the moist air brought in by the monsoon climate rose in the highlands to form a heavy rainfall belt. In addition, the distribution and type of vegetation in the basin also had an important impact on the runoff process,

and the areas with better vegetation coverage had stronger interception and infiltration capacities, which slowed down the conversion of rainfall to runoff. Rainfall and runoff demonstrated high temporal and spatial heterogeneity, and the distinct characteristics of various rainfall patterns further amplified the complexity of hydrological processes in the basin, underscoring the diversity of hydrological phenomena within the Meijiang River Basin.

4.2. Analysis of Changes in the Underlying Surface

According to the Ganzhou high-quality development plan for soil and water conservation (2021–2030) issued by the Ganzhou municipal government, the area affected by soil erosion in Ganzhou decreased from 11,187 km² in 1980 to 6949 km² in 2020. The primary counties and cities within the Meijiang River Basin—Yudu County, Ningdu County, and Ruijin City—collectively account for more than 60% of the basin’s total area. All of these regions are among the 29 counties (cities) in the province severely affected by soil erosion. In Ningdu County, the area affected by soil erosion reached 1258 km², representing 31% of its total land area. In Yudu and Ruijin, the areas affected by soil erosion accounted for 51 and 45.2% of their respective mountainous areas. In 1993, Yudu County was designated as part of the “Eight counties across the country for the second phase of key soil and water conservation prevention and control projects”, and in 1998, Yudu and Ningdu Counties collaboratively initiated the second phase of soil and water conservation efforts. A series of soil and water conservation projects, including collapse control, terrace construction, and mountain closure for afforestation, were implemented across the basin, effectively mitigating soil erosion. Between 1993 and 2000, afforestation projects were implemented, which led to significant fluctuations in the underlying surface conditions; therefore, we excluded this period from this study. From 2001 to 2010, the Meijiang River Basin underwent a significant phase of forest vegetation restoration, progressively enhancing the ecological environment. From 2011 to 2020, the region entered a phase of rapid urbanization, where urban expansion and infrastructure development led to significant population and economic growth. Consequently, in this study, we divided the land use in the Meijiang River Basin from 1980 to 2020 into three subperiods: the baseline (1980–1992), restoration (2000–2011), and stable (2012–2020) periods. Because of data limitations, the underlying surface conditions for 1985, 2000, and 2020 were selected to represent these three periods, respectively (Table 6, Figure 4).

Table 6. Land type areas and changes across three typical years in the Meijiang River Basin.

Land Use Type	1985 Period		2000 Period		2020 Period		Change from 1985 to 2000/km ²	Change from 2000 to 2020/km ²	Change from 1985 to 2020/km ²
	Area/km ²	Proportion/%	Area/km ²	Proportion/%	Area/km ²	Proportion/%			
Shrub	1.60	0.01	117.04	0.73	158.73	0.99	115.44	41.69	157.12
Water	99.40	0.62	84.97	0.53	104.21	0.65	14.43	19.24	4.81
Built-up land	113.83	0.71	152.31	0.95	315.85	1.97	38.48	163.54	202.02
Farmland	5072.84	31.64	4676.83	29.17	5024.74	31.34	−396.02	347.92	−48.10
Broadleaf forests	7910.68	49.34	5983.52	37.32	5682.10	35.44	−1927.17	−301.42	−2228.59
Coniferous forests	2834.63	17.68	5018.33	31.3	4747.37	29.61	2183.69	−270.96	1912.74
Total	16,033	100	16,033	100	16,033	100	−	−	−

Notes: “−” indicates a decrease in the area of land use types.

In order to further analyze the changes in land use, we calculated the corresponding land use area and proportion based on the number of grids in the grid map. We observed significant land use changes in the Meijiang River Basin from 1985 to 2020, with forests and farmland remaining the predominant land types, accounting for more than 96% of the total area. During this period, farmland area declined by 0.3%, broadleaf forests shrank

by 13.9%, and coniferous forests expanded by 11.93%. The total forest area contracted by 1.97%, shrubland expanded by 0.98%, and construction land grew by 1.26%. Major land use changes primarily involved the conversion of broadleaf forests into coniferous forests and construction land. The primary factor of this shift was the widespread planting of coniferous species, including Chinese fir and Masson pine, in southern China for timber production because of their faster growth rates and greater economic value. During the period from 1985 to 2000, the area of farmland decreased, while the area of forest land increased. This was mainly the result of the measures of returning farmland to forest and planting trees to conserve water sources and conserve soil and water in the watershed to control water and soil erosion. During the period from 2000 to 2020, the changing trend in farmland area and forest land area was the opposite; that is, the area of construction land increased more than that from 1985 to 2000. Following successful soil erosion control, the Ganzhou municipal government's general land spatial plan emphasized preserving a defined area of farmland for the development of basic farmland to support the grain industry, while simultaneously accelerating urbanization efforts.

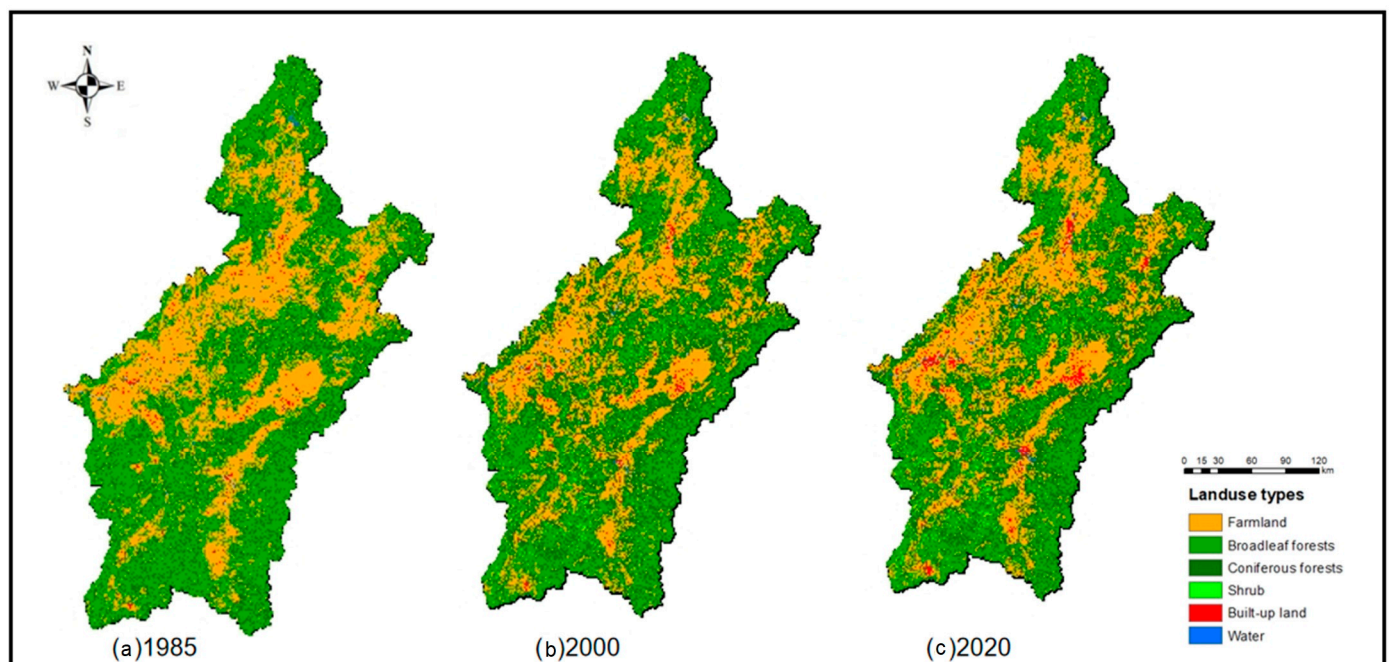


Figure 4. Land use maps of the Meijiang River Basin for the 1985, 2000, and 2020 periods.

5. Results and Analysis

5.1. Model Calibration and Validation

Simulations of typical flood processes were conducted for the 1985, 2000, and 2020 periods. For rainfall events, excluding dry years and the non-studied period from 1993 to 2000, we selected one representative event annually, which resulted in 24 rainfall events for calibration and validation. For underlying surface changes, we entered soil, vegetation, and land use data files corresponding to each period into the model. Using the controlled variables method, we proportionally adjusted the key parameters in the MIKE SHE model affecting flood peaks and peak time during runoff generation and concentration processes (e.g., parameters related to OL, the saturated zone, and river routing). We calibrated optimal parameter values for each of the three periods using rainfall and flood data from their respective periods. In total, we calibrated 18 parameters, including 11 key sensitivity parameters: the surface water retention depth, initial surface water depth, unit storage of interflow, time constants for interflow outflow and infiltration, unit storage of fast baseflow

and its time constant, land use Manning coefficient, river roughness, delay parameter, and shape parameter. The calibration results for the primary sensitivity parameters are presented in Table 7.

Table 7. Calibration of key parameters in different periods.

Type	Model Parameters	1985 Period	2000 Period	2020 Period
Surface runoff	Surface detention depth/mm	100	150	120
	Initial surface water depth/m	0.12	0.1	0
	Unit storage of interflow	0.07	0.2	0.25
	Interflow outflow time constant/d	4	3	2.5
	Interflow infiltration time constant/d	15	12	11
	Unit storage of fast baseflow	0.18	0.16	0.14
	Fast baseflow outflow time constant/d	22	20	18
Surface runoff Manning coefficient/ $\text{m}^{1/3} \cdot \text{s}^{-1}$	Shrub	5	5	5
	Water	50	50	50
	Built-up land	25	25	25
	Farmland	7	7	7
	Broadleaf forests	2.86	2.86	2.86
	Coniferous forests	3.33	3.33	3.33
Channel flow	Manning's roughness coefficient/ $\text{s} \cdot \text{m}^{-1/3}$	0.028	0.025	0.029
	Delay parameter	5	10	12
	Shape parameter	0.2	0.15	0.3

According to the “Specifications for Hydrological Information and Forecasting” (GB/T 22482-2008), the results indicated that of the 24 simulated floods, 20 met the qualification criteria, yielding a qualification rate of 83.33%. Specifically, during the 1985 period, seven events were calibrated, six of which met the criteria, producing a qualification rate of 85.7%. Both validation events were qualified, resulting in a 100% qualification rate. During the 2000 period, five events were calibrated, four of which were qualified, yielding a qualification rate of 80.0%, while two out of three validation events were qualified, with a qualification rate of 66.7%. During the 2020 period, five events were calibrated, four of which were qualified, producing a qualification rate of 80%. Both validation events were qualified, yielding a 100% qualification rate. Overall, the simulation accuracy conformed to the grade B evaluation standard. Partial flood simulation evaluation results are presented in Table 8, and typical flood simulations are illustrated in Figure 5.

Table 8. Evaluation of flood simulations in Meijiang River Basin.

	Flood Number	Flood Forecasting Accuracy						Qualified (Q)/Failed (F)
		Measured Peak	Simulated Peak	REP (%)	REV (%)	Δt (h)	DC	
Calibration	19800509	5370	5061	−5.75%	0.194	0	0.961	Q
	19810409	6160	6780.82	10.08%	0.213	5 h	0.892	F
	19810606	3200	3545.5	10.80%	0.129	−1 h	0.932	Q
	19840526	6550	7649	−0.18%	−0.036	−2 h	0.742	Q
	20100414	3900	4792.04	22.87%	0.172	1 h	0.983	F
	20190705	6180	6104	−1.23%	0.076	−1 h	0.849	Q
	20190607	7160	7398.94	3.34%	0.175	2 h	0.942	Q
Verification	20160715	3240	2960.93	−8.61%	0.151	−3 h	0.726	Q
	20140513	4000	4483.53	12.09%	0.182	−1 h	0.916	Q
	19970601	5330	5974.55	12.09%	0.117	−2 h	0.95	Q

Notes: “−” positive value: simulation > or earlier than measurement; negative value: simulation < or later than measurement.

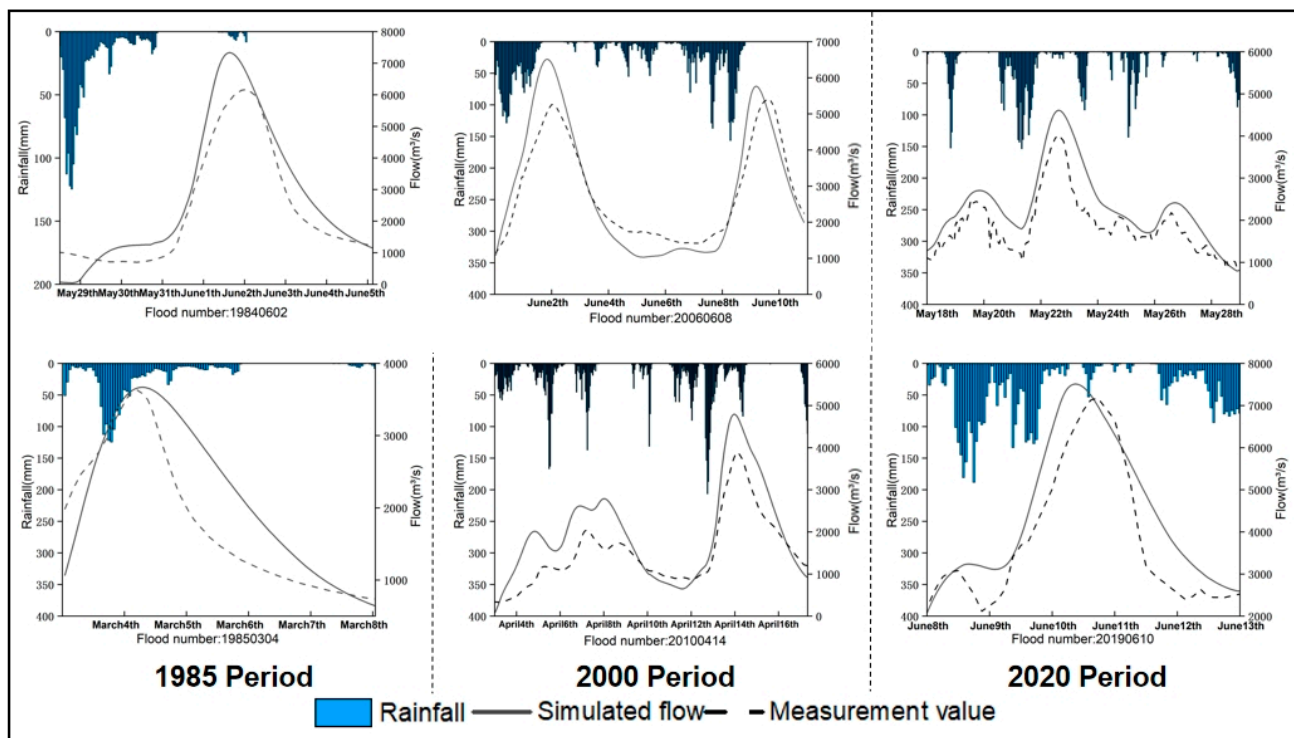


Figure 5. Observed and simulated flow processes of typical floods.

5.2. Analysis of the Impact of Movements in Rainfall Centers on Floods

Based on the underlying surface conditions in the 2020 period, in this study, we comprehensively analyzed the changes in flood elements according to the location of rainfall centers and different rainfall patterns. The effects of different rainfall center locations on the flood volume, flood peak, and peak time are shown in Figure 6. We found that the change in flood volume was similar to the trend in the flood peak, and as the rainfall center moved from upstream (center 1) to downstream (center 5), both the flood volume and peak flow followed a trend of first increasing and then decreasing. The flood volume gradually increased from 3.9 billion m^3 in center 1 to a peak of 4.16 billion m^3 in center 3 and then gradually decreased to 4 billion m^3 in centers 4 and 5. The peak flood flow gradually increased from 4400 m^3/s in center 1 to 4900 m^3/s in center 2 and center 3 and then gradually decreased to 4600 m^3/s in center 4 and center 5. This trend was due to the topography and storage characteristics of the Meijiang River Basin with a large area and different underlying surfaces: the topography in the upper reaches was steep, rainwater quickly formed runoff, and the flood peaks were both large and small, which were constantly flattened in the process of flowing downstream. When the rainfall center was located in the middle reaches, the terrain was gentle, the storage capacity of the basin was enhanced, and the runoff convergence range increased, resulting in rainwater pooling, and the flood volume and flood peak reached the maximum value. Downstream, close to the outlet, the water flowed out rapidly, and the scale of the peak flood volume decreased accordingly. Therefore, the flood volume and flood peak followed a trend of increasing first and then decreasing during the movement of the rainfall center from upstream to downstream, which reflected the complexity of the combined effects of different rainfall patterns and the underlying surfaces on flood elements.

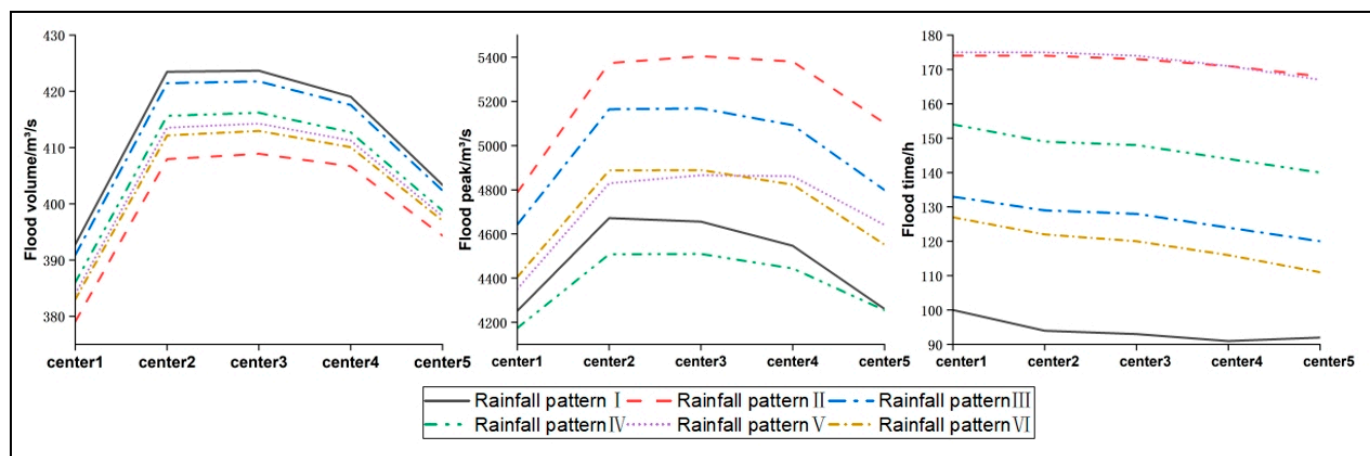


Figure 6. Impact of rainfall center location on various flood characteristics.

In addition, we found that the peak time gradually advanced as the rainfall center moved from upstream to downstream, from 125 h in center 1 to 115 h in center 5. Different rainfall patterns also had a significant impact on the peak occurrence time; for example, the peak occurrence time of rain pattern II was usually shorter, showing the characteristics of concentrated rainfall and rapid confluence. These results show that the downward shift in the rainfall center shortened the path of runoff and accelerated the speed of water flow downstream, thus advancing the peak occurrence time. At the same time, forest vegetation had the function of water conservation, such as regulating the peak flood flow and delaying runoff generation in the basin [42]. As a result, the rain peak of the forward rainfall pattern II and the rain pattern V was 120 h earlier than that of the post-peak rain pattern I, whereas the difference in the peak time of the peak flood volume was only 78 h.

5.3. Analysis of the Impact of Different Rainfall Patterns on Floods

To further explore the influence of different rain patterns on the flood process, in this study, we analyzed the simulation results of six rain patterns under different return periods, which followed the trend of the flood volume and flood peak shown in Figure 7. The results showed that in the case of 100 a, rain pattern I and rain pattern III of the early-peak and mid-peak rainfall were larger, with 3.64 and 3.61 billion m³, respectively, whereas rainfall pattern II of the post-peak rainfall had the smallest flood volume of 3.42 billion m³. The difference in the rainfall time course significantly affected the flood volume because continuous heavy rainfall caused the forest vegetation and soil to have no excess water storage capacity. Most of the rainfall in the basin was converted into runoff [43]. However, the post-peak rainfall, such as rain pattern II, had sufficient time for storage and absorption. In addition, in terms of flood peaks, we found that the flood peak caused by rain pattern II of the post-peak rainfall was the largest; for example, in the case of 100 a, its flood peak reached 8800 m³/s, followed by rain pattern III. For the central pattern of rainfall, the flood peak of the forward pattern I was similar to that of the bimodal rain pattern V, which was generally lower than that of the bimodal rain pattern VI. Rain pattern IV of uniform rainfall had the lowest flood peak under each return period, which was only 6400 m³/s in 100 a. Under the same rainfall, the maximum difference between the flood peaks caused by different rainfall patterns was 36%. This difference further confirmed that uniform rainfall had the least impact on flood hazards, whereas post-peak rainfall may have posed a more serious flood risk because the early rainfall was fully absorbed by the soil, and the soil moisture gradually approached saturation over time; that is, rainfall patterns with increasing rainfall intensity produced floods with larger flood peaks [44].

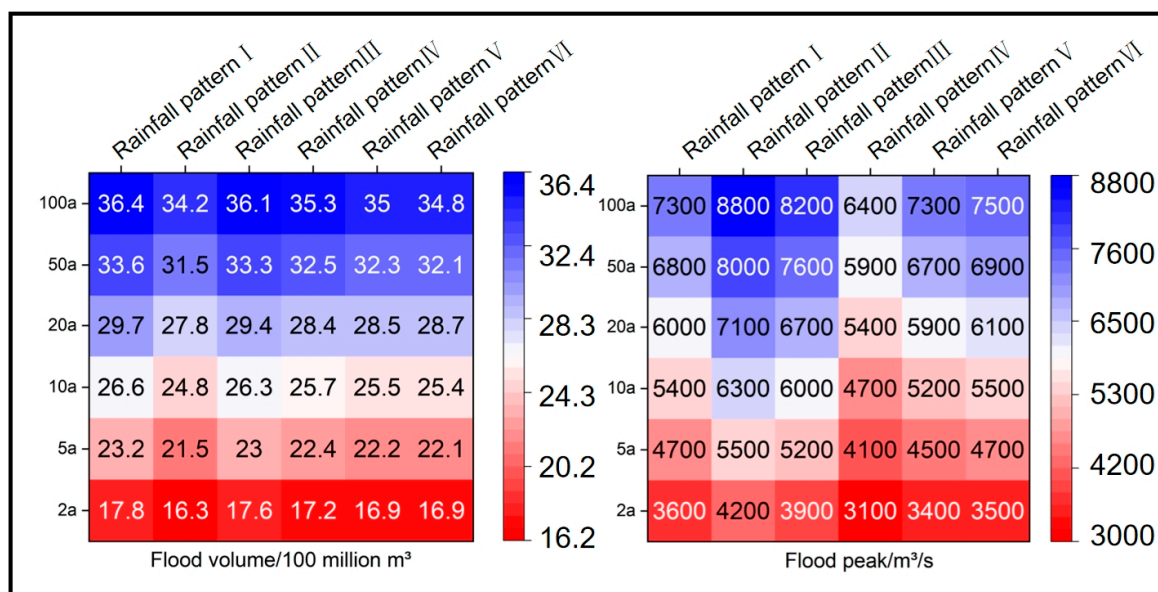


Figure 7. Flood volume and peak across different return periods and rainfall patterns.

We also found that when the return period gradually increased from 2 to 100 a, the flood volume and flood peak of each rain pattern followed a significant upward trend. In terms of flood volume, the average increase in rain pattern I was the largest, while that of rain pattern II was the smallest. In the process of the return period from 2 to 100 a, the rain pattern I and rain pattern II hourly scale rain depths rose by an average of 100 mm and the average increase in flood volume in rain pattern I and rain pattern II increased by 46.5 and 44.8 million m³, respectively. In terms of the flood peak, the average increase in rain pattern II was the largest, with an average increase of 115 m³/s for every 100 mm of hourly rain depth and a gradual increase from 4200 m³/s in 2 a to 8800 m³/s in 100 a. The average increase in rain pattern IV was the smallest, however, with an average increase of 82.5 m³/s for every 100 mm of hourly rain depth. A flood peak of 3100 m³/s was identified in 2 a, which rose to 6400 m³/s in 100 a. These results showed that with an increase in the return period, the flood volume of rain pattern II increased the smallest amount, while that of rain pattern I increased the most. In terms of the flood peak increase, rain pattern II had the largest increase, while the uniform rain pattern IV had the smallest increase.

5.4. Flood Response to Changes in Underlying Surface Conditions Across Different Basins

The Yangxinjiang Hydrological Station and the Ningdu Hydrological Station in the Meijiang River Basin are located in the downstream outlet sections of Anyuan County and Ningdu County, respectively, on the two main tributaries of the Meijiang River Basin. These stations hold great significance for analyzing the hydrological characteristics of the basin and predicting flood risk. In this study, we used these two hydrological stations as control stations to divide the Ningdu sub-basin and the Yangxinjiang sub-basin, with areas of 2357 and 587 km², respectively (refer to Figure 1). Compared with the entire Meijiang River Basin (16,033 km²), Meijiang River Basin, Ningdu sub-basin and Yangxinjiang sub-basin were divided as 10,000, 1000, and 100 km², respectively. We analyzed the impact of flood elements under the combined action of the underlying surface changes and the three magnitudes of the basins' areas. We found that the proportion of farmland and forest land in the main land use types of the two sub-basins was similar to that of the Meijiang River Basin, and the soil types were similar, which could be compared and analyzed. In this study, we compared 24 representative disaster-causing rainfall events to analyze the

average effects of different basin areas on the flood volume, flood peak, and peak time in the two sub-basins and the Meijiang River Basin (Table 9, Figure 8).

Table 9. Average variations in flood characteristics of different magnitudes in the basin over three periods.

Elements	Basin	1985 Period	2000 Period	2020 Period	Change Rate from 1985 to 2000 (%)	Change Rate from 2000 to 2020 (%)	Change Rate from 1985 to 2020 (%)
Flood peak ($\text{m}^3 \cdot \text{s}^{-1}$)	Meijiang	4898.67	4728.88	4583.45	−3.85%	−3.91%	−7.61%
	Ningdu	992.76	888.49	858.41	−7.03%	−4.41%	−11.53%
	Yangxinjiang	363.73	334.27	314.11	−8.81%	−6.42%	−15.79%
Flood volume (100 million m^3)	Meijiang	11.39	11.05	10.64	−2.99%	−3.71%	−6.58%
	Ningdu	1.25	1.22	1.13	−2.40%	−7.38%	−9.60%
	Yangxinjiang	7.63	7.16	6.83	−6.14%	−4.63%	−10.48%
Peak time (h)	Meijiang	37	38	40	2.70%	5.26%	8.11%
	Ningdu	24	25	26	4.17%	4.00%	8.33%
	Yangxinjiang	10	11	12	10.00%	9.09%	20.00%

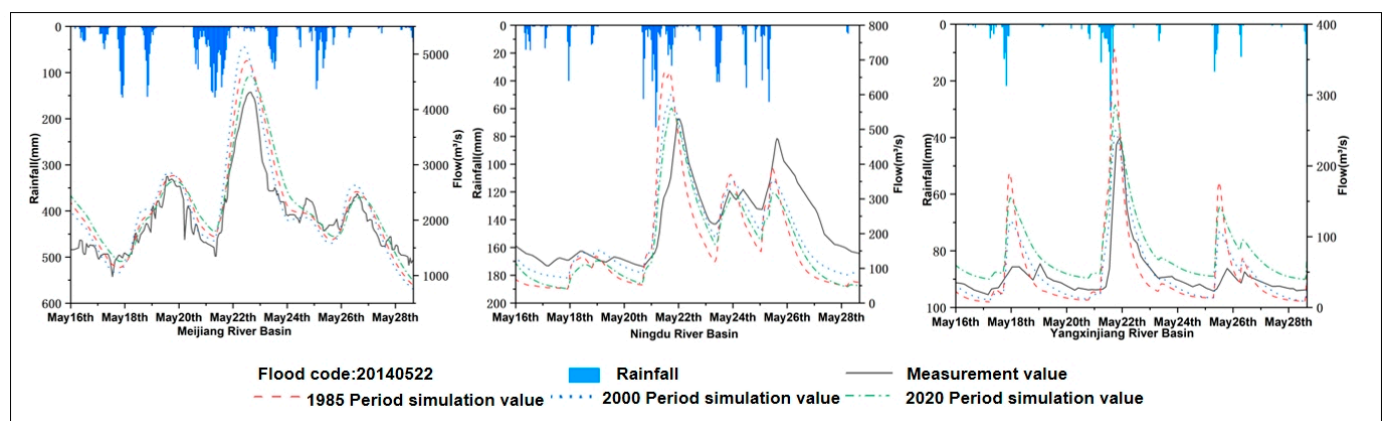


Figure 8. Maps showing changes in the three basins across different periods.

According to the table's data, we observed significant changes in the average flood characteristics across three basin scales—the Meijiang Basin, the Ningdu sub-basin, and the Yangxinjiang sub-basin—under land surface changes from 1985 to 2020. Regarding the flood volume, the Meijiang Basin experienced a reduction of 2.99% from 1985 to 2000, followed by a further reduction of 3.71% from 2000 to 2020, resulting in a total decrease of 6.58%. The Ningdu sub-basin showed a 2.40% decrease from 1985 to 2000 and a 7.38% decrease from 2000 to 2020, with a total reduction of 9.60%. Meanwhile, the Yangxinjiang sub-basin experienced reductions of 6.14 and 4.63% during the same periods, with a total decrease of 10.48%. For the flood peaks, the Meijiang Basin saw a reduction of 3.85% from 1985 to 2000 and an additional decrease of 3.91% from 2000 to 2020, leading to a total reduction of 7.61%. Similarly, the Ningdu sub-basin experienced flood peak reductions of 7.03 and 4.41%, resulting in a total decrease of 11.53%. The Yangxinjiang sub-basin exhibited larger reductions of 8.81 and 6.42%, with a total decrease of 15.79%. Regarding the peak time, the Meijiang Basin saw an increase of 2.70% from 1985 to 2000, followed by an additional increase of 5.26% from 2000 to 2020, totaling an increase of 8.11%. The Ningdu sub-basin recorded increases of 4.17 and 4.05%, for a total increase of 8.33%, whereas the Yangxinjiang sub-basin saw increases of 10.00 and 9.09%, resulting in a total increase of 20.00%.

From the perspective of vegetation changes in the period between 1985 and 2020, measures such as reforestation and terrace construction in Ganzhou City effectively controlled

soil erosion, influencing flood characteristics by reducing flood peaks and volumes and increasing peak time. Reforestation improved soil water retention, absorbing more rainfall and reducing runoff [45,46]. Terrace construction altered the topography, slowing water flow and increasing soil infiltration, which further reduced flood peaks and volumes. These measures delayed runoff formation and extended convergence time, effectively mitigating flood risks.

During the same period, the average changes in the flood elements in the basins of different magnitudes showed significant differences under the same underlying surface conditions. From 1985 to 2020, the smaller basins showed higher flood peak increases, rising from 7.61% to 15.79%. The flood volume increased from 6.58 to 9.60 and 10.48%. The peak arrival time increased from 8.11 to 8.33% and finally to 20%. Similarly, from 1985 to 2000 and from 2000 to 2020, the flood peak, flood volume, and peak time increased or delayed by varying degrees. With the decrease in the basin area, the influence of the underlying surface change on the flood process became more significant, because the buffering effect of forest vegetation on the flooding was more obvious in the smaller watersheds. In contrast, in the larger watersheds, because of the spatial heterogeneity of the topography, vegetation, and climate, the overall watershed had a strong antisturbance ability. The role of forests was relatively weakened [47], and the role of river troughs was more prominent [48,49].

The results shown in Figure 9 indicate that for the period from 1985 to 2000, the interquartile range (IQR) for the flood volume in the Meijiang River Basin was $[-6.73, -6.46\%]$ and the median was -6.63% ; the IQR of Ningdu sub-basin was $[-10.24, -9.25\%]$ and the median was -9.72% ; and IQR of the Yangxinjiang sub-basin was $[-10.94, -9.91\%]$ and the median was -10.2% . In addition, the results show that the IQR of the peak-present time change rate in the Meijiang River Basin was $[8.0, 8.19\%]$ and the median was 8.11% ; the IQR of the peak-present time change rate in the Ningdu sub-basin was $[8.24, 8.43\%]$ and the median was 8.32% ; and the peak-present time change rate in the Yangxinjiang sub-basin was $[19.85, 20.05\%]$ and the median was 19.93% . Overall, we found that the Meijiang River Basin had the shortest interquartile interval and the lowest absolute median value, which was followed by the Ningdu sub-basin. The Yangxinjiang sub-basin had the longest IQR interval and the largest absolute median value. The flood peaks in the Meijiang River Basin and the Ningdu sub-basin were of equal interquartile ranges, whereas the Yangxinjiang sub-basin had the longest one.

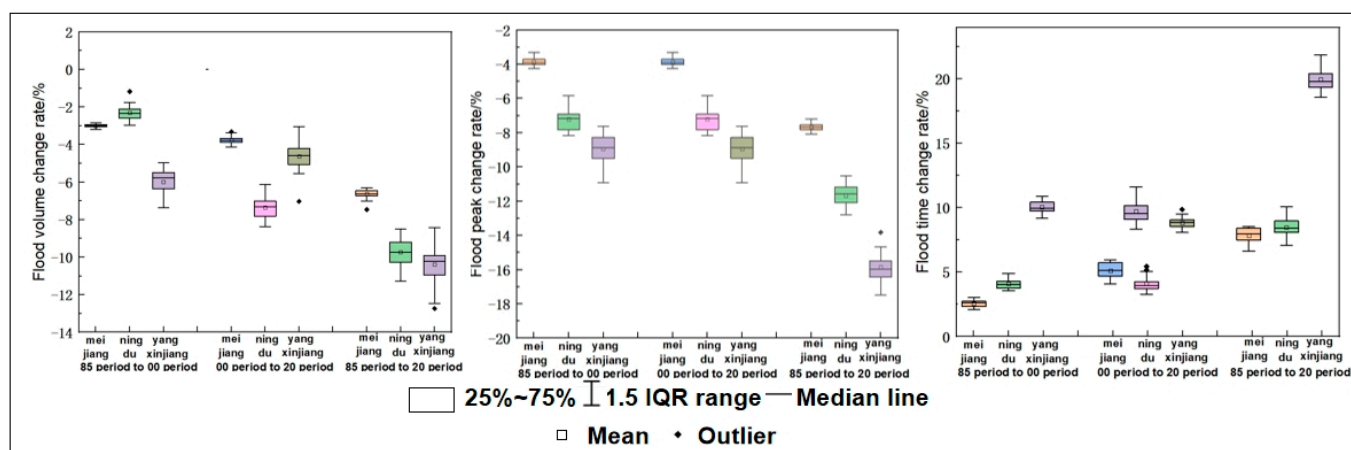


Figure 9. Impact of underlying surface changes on different basins over three periods.

We further analyzed the period from 1985 to 2000 and found that the interquartile intervals of the flood volume, flood peak, and peak-present time in the Meijiang River Basin were still the smallest. In terms of the absolute values of the median flood peak

and peak-present time, those in the Meijiang River Basin were the smallest and those in the Yangxin River sub-basin were the largest. The absolute median flood volume was the largest in the Yangxinjiang sub-basin, followed by that in the Meijiang River Basin, and the smallest was in the Ningdu sub-basin. The trend of the interquartile range was consistent with that of the 1985–2020 period. In addition, we found that from 2000 to 2020, the absolute values of the interquartile intervals and medians of the flood volume and flood peak in the Meijiang River Basin were still the smallest, and those in the Ningdu and Yangxinjiang sub-basins were the largest. We also found that the Meijiang River Basin had the largest interquartile range for the peak occurrence time, while the Yangxinjiang sub-basin had the smallest. In terms of median values, the Yangxinjiang sub-basin recorded the highest, followed by the Meijiang River Basin, with the Ningdu sub-basin having the lowest.

Overall, the interquartile range increased from the Meijiang River Basin to the Yangxinjiang sub-basin as the basin size decreased. The data fluctuations in the Meijiang River Basin were relatively small, indicating a weaker response to changes in the underlying surface, which suggested that larger basins possessed stronger regulatory capacities. During the period from 1985 to 2020, afforestation efforts and improvements in soil erosion control within the basin enhanced flood management, as evidenced by reductions in flood volume and peak flow as well as by delays in peak flow occurrence.

6. Discussion

6.1. Flood Response of Watershed Under Spatial and Temporal Distribution of Rainfall

We simulated different rainfall scenarios, altering the location of the rainfall center and the type of rainfall, and studied the impact of rainfall patterns and the location of the rainfall center on the flood process. Our analysis showed that the spatial distribution and temporal pattern of rainfall had a significant impact on flood volume, flood peaks, and flood timing. Especially when the rainfall center was located in the middle reaches of the basin, or in post-peak rainfall events, the impact of floods was most serious. The spatial distribution of rainfall determined the accumulation area of precipitation. In particular, in areas with complex terrain, the delay in water flow propagation upstream and downstream changed the timing of floods.

The classification of rainfall patterns has a long history of research. In the 1940s, the Soviet scholar M.B. Molokov first proposed seven typical rainfall types. With the deepening of rainfall research, scholars from many countries and regions have expanded and refined the classification methods of rainfall types, such as the Chicago rainfall type [50], P&C rainfall type [51], and Huff rainfall type methods [52]. Based on the original rain type classification, we localized the rainfall pattern in the Meijiang River Basin, quantified the temporal distribution of the rainfall, and divided it into six different types, ranging from uniform precipitation to concentrated precipitation patterns. The rainfall pattern designed in the model effectively reflected the impact of the spatial distribution of rainfall on the flood process and met the needs of this study.

The spatial distribution of rainfall has also been crucial. Previous studies, such as those by Emmanuel et al. [53] and Zoccatelli et al. [54], have highlighted the important role of spatial variability in rainfall in influencing runoff and flood responses. These studies have usually evaluated the relationship between the spatial distribution of rainfall and flood responses by analyzing the statistical characteristics of rainfall spaces or using indicators such as rainfall width functions. These methods have mostly focused on the overall characteristics of the spatial distribution of rainfall. In our study, the C_L value was selected to quantify the location of the rainfall center relative to the basin outlet, simulate the process of rainfall from upstream to downstream, and deeply explore the impact of specific changes in the location of the rainfall center on the flood process.

Although this study deepens the understanding of the impact of the spatial and temporal distribution of rainfall on flood processes, it still has several limitations. The model's simplifying assumptions may have introduced inaccuracies, especially in areas of complex terrain. Furthermore, although we investigated the effects of the location and type of rainfall centers, we were unable to fully account for the dynamic nature of rainfall under changing climate conditions. Future research should combine real-time data with dynamic flood forecasting models to further improve the accuracy of flood predictions.

6.2. Flood Response of Watershed Under Land Use Change

This study selected 1985, 2000, and 2020 as typical years. Based on the land use conditions in each year, the MIKE SHE model was constructed, representing the baseline (1980–1992), restoration (2000–2011), and stable (2012–2020) periods. By calibrating and validating the model using measured rainfall data from different periods, we obtained three sets of model parameters corresponding to the periods and performed simulations under the same rainfall event. Such an approach aimed to clearly separate the effects of rainfall and land use change on flood processes through simulation results. In addition, we divided the basin into sub-basins of different areas to explore the impact of basin area on flood response. Through the simulation analysis of watersheds of different sizes, the interactive effects of land use change and watershed area on flood occurrence were revealed. The research results showed that rainfall could affect the flood process by up to 36%, while the impact of surface changes was about 7%, indicating that rainfall was the dominant factor in the flood process.

Costa et al. [55] found that increased agricultural land use in the Tocantins River region increased annual and rainy season flows, while deforestation in southeast Amazonia simulated an increase in annual flows of 16%. Research by Wang et al. [56] showed that under extreme precipitation conditions, increasing the area of forest and grassland could help effectively reduce flood runoff. These studies indicate that land cover changes have impacts on watersheds' hydrological processes in different geographical areas, especially in altering the paths and velocity of water flow. On the other hand, the study by Bronstert et al. [57] showed that urbanization increases peak discharge and flood volume in high-precipitation-intensity events but has less impact on low-precipitation-intensity events. In addition, some scholars have proposed the FLUS model, which uses adaptive inertia and competition mechanisms to deal with the complex interactions between land use types, and analyzed the impact of human activities and natural ecological effects under different scenarios [58]. These studies fully reveal the profound impact of land use change on hydrological processes, especially hydrological responses in different regions, different land use types, and different climatic conditions, and emphasize the importance of land use change in hydrological models. This study used the MIKE SHE distributed model to generalize the underlying surface conditions in the Meijiang River Basin at different times, and by simulating the differences in flood responses under different basin areas, it deeply explored the relationship between land use change and basin area in the flood process interaction.

Although this study considered the impact of rainfall and land use change on flood runoff, it failed to fully reflect the impact of these factors on the flood process due to the spatiotemporal heterogeneity of rainfall and the complexity of land use change. In the future, remote sensing technology and high-resolution data can be combined to improve the spatial resolution of the model, which would help to more accurately predict flood risks under different scenarios.

7. Conclusions

In this study, we divided the underlying surface periods in the Meijiang River Basin into the 1985, 2000, and 2020 periods, and we analyzed land use changes over the past 40 years. We employed the MIKE SHE model to design experiments addressing land use changes, rainfall patterns, and spatial distribution in different sub-basins. The following main conclusions were obtained.

1. The position of the rainfall center significantly influenced flood dynamics. Our analysis showed that as the rainfall center moved downstream, both flood volume and flood peak initially increased, reaching maximum values at mid-basin locations, before decreasing with maximum values of 4.2 billion m³ and 4900 m³/s, respectively. The timing of the flood peak advanced as the rainfall center shifted downstream.
2. Flood characteristics changed significantly across different return periods. As the return period increased from 2 to 100 a, flood peaks and flood volumes rose considerably for all rainfall patterns. Among them, rainfall pattern II showed the largest increase in the flood peak, whereas its flood volume increase was the smallest; conversely, rainfall pattern I showed the largest increase in the flood volume. The significant influence of different rainfall patterns on flood processes across return periods indicated that flood dynamics depended not only on the amount of rainfall but also were intricately linked to the temporal distribution of rainfall and basin characteristics.
3. Changes in the underlying surface had a substantial impact on flood processes. Changes in the underlying surface from 1985 to 2020 caused the flood peak to decrease by 7.61%, the flood volume to decrease by 6.58%, and the flood time to be extended by 3 h. Reforestation and terraces controlled soil erosion, reducing the flood peaks and volumes while delaying the peak time.
4. Under the same underlying surface conditions, the response to underlying surface changes varied according to the basins' scale: as the basin area decreased, the changes in the flood peaks, flood volume, and peak occurrence time gradually increased. In particular, during the period from 1985 to 2020, the flood peaks increased from the entire basin to the Ningdu sub-basin and then to the Yangxinjiang sub-basin. The growth rates increased from 7.61% to 15.79%, the flood volume increased from 6.58% to 10.48%, and the flood time was delayed from 8.11% to 20%. In addition, as the watershed area decreased, the buffering effect of forest vegetation on floods became more significant, while in larger watersheds, due to their stronger anti-interference ability, the role of forests was relatively weakened, and the regulation and storage role of river channels became more prominent.

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