

Article

Improving Flood Simulation Performance of Distributed Hydrological Model in the Plain–Hilly Transition Zone via DEM Stream Burning and PSO

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Highlights

What are the main findings?

- Proposes to improve the flood simulation of the Liuxihe Model by combining DEM stream burning and PSO algorithm.
- Verifies the improvement strategy in the Beimiaoji Watershed, a typical plain–hilly transition zone in the upper Huaihe River Basin.

What are the implications of the main findings?

- Provides a cost-effective way to enhance DEM applicability for hydrological simulation, avoiding high costs of high-resolution DEMs.
- Confirms that the Liuxihe Model shows potential in plain–hilly transition zones, providing a reference for flood forecasting in similar regions.

Abstract

Accurate flood simulation and forecasting in plain–hilly transition zones remain challenging due to limitations of medium- and low-resolution digital elevation models (DEMs), which often produce discontinuous drainage networks and misaligned confluence paths. This study evaluates an integrated improvement framework that combines DEM stream-burning and automatic parameter calibration to enhance the flood-simulation performance of a physically based distributed hydrological model (the Liuxihe Model). The framework was tested in the Beimiaoji Watershed (upper Huaihe River Basin) using 12 observed flood events: one event for parameter calibration via Particle Swarm Optimization (PSO) and 11 events for independent validation. Model performance was assessed using multiple metrics, including the Nash–Sutcliffe Efficiency (NSE), peak error (PE), and peak-timing error (PT). Results indicate that stream-burning substantially improves river-network extraction, and that the combined application of DEM correction and PSO-based calibration markedly enhances model performance. The findings suggest that the proposed, cost-effective correction–calibration pathway can improve operational flood simulations in terrain-sensitive regions without relying on costly high-resolution DEMs, and thus provides a practical reference for similar basins.

Keywords: flood forecasting; distributed hydrological model; Liuxihe Model; DEM Correction; plain–hilly transition zone; Beimiaoji Watershed



Academic Editor: Monica Rivas Casado

Received: 14 November 2025

Revised: 24 January 2026

Accepted: 5 February 2026

Published: 10 February 2026

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1. Introduction

Flood disasters are among the most common and destructive natural hazards worldwide. Their high suddenness and severe impacts pose substantial threats to socioeconomic development and human safety [1–3]. Under the dual impacts of global climate change and human activities, extreme rainfall events have become increasingly frequent, while the underlying surface structure of watersheds (e.g., land use patterns and urbanization) has undergone drastic changes. Together, these factors have further increased the frequency and risk level of flood disasters [4,5]. Therefore, developing high-precision flood simulation and forecasting technologies is of vital significance for effective flood control and mitigation, risk assessment, and water resource management. As a major river system in central-eastern China, the Huaihe River Basin is characterized by a large drainage area, concentrated rainfall, and pronounced interannual variability in precipitation. Flood disasters have occurred frequently throughout its history, particularly in the extensively distributed plain-hilly transition zones in its upper reaches. Due to the gentle terrain and dense river networks in these zones, even minor topographic fluctuations can alter runoff paths, leading to deviations in river network extraction and distortions in confluence paths. These issues severely restrict the accuracy of flood forecasting [6,7].

Hydrological models are essential tools for simulating watershed hydrological processes and supporting flood forecasting, risk assessment, and flood control decision-making. Compared traditional empirical formulas, physically based hydrological models provide a more comprehensive representation of runoff generation and confluence processes by explicitly incorporating governing equations, including water balance equations and the Saint-Venant equations [8,9]. Hydrological models can be divided into lumped and distributed hydrological models based on spatial discretization [10]. Lumped models—such as the Tank Model [11,12] and the Xinanjiang Model [13,14]—offer advantages including simple structure and high computational efficiency. However, they often inadequately represent the spatial heterogeneity of watershed characteristics, exhibit parameters with limited physical interpretability, and rely heavily on measured data for calibration [15,16]. In contrast, distributed models leverage Geographic Information System (GIS) technology to divide watersheds into spatial units and integrate rainfall interpolation methods. This enables more detailed simulation of the mechanisms by which terrain, vegetation, soil, and rainfall interact, thereby improving the accuracy and physical authenticity of flood simulations. Representative distributed models include semi-distributed models such as HEC-HMS [17,18] and SWAT [19,20], as well as fully distributed physical models such as SHE [21] and the Liuxihe Model [22,23].

Among these models, the Liuxihe Model exhibits distinct advantages including a clear physical mechanisms, easy access to input data, and broad applicability. By introducing the PSO algorithm to establish an automatic parameter calibration framework, it only requires one high-quality flood event to optimize parameters [24]. Moreover, it has achieved high simulation accuracy across various types of watersheds: for instance, in simulating inflow floods to reservoirs such as Baipenzhu, Fengshuba, and Xinfengjiang, the NSE generally exceeds 0.80, with the highest flood peak simulation accuracy reaching 96.3% [25–27]. Similarly, high forecasting accuracy has been achieved in small and medium-sized watersheds in Jiangxi Province and in highly urbanized catchments such as the Chebei Chong Watershed, with maximum peak-flow accuracy reported at 97.06% [28–30]. However, the applicability of this model in plain-hilly transition zones remains unvalidated.

In distributed hydrological models, DEM are critical input data, and their quality directly affects unit division, slope extraction, flow direction identification, and watershed boundary determination [31]. However, commonly used medium- and low-resolution DEMs (such as those from the Shuttle Radar Topography Mission, SRTM) often fail to

capture subtle elevation differences in plain areas. This limitation frequently leads to discontinuous river networks, pseudo-channel generation, and watershed-boundary offsets [32–34]. Although high-resolution DEMs (e.g., those derived from Light Detection and Ranging, LiDAR) can significantly improve accuracy [35,36], they are associated with high acquisition costs, complex processing procedures, and increased computational burden, which limit their large-scale application. Thus, improving the hydrological applicability of medium- and low-resolution DEMs through topographic correction technologies has become an urgent issue.

To address this challenge, various DEM-correction approaches have been developed. Based on data requirements and operational complexity, these methods can be broadly categorized into manual or hydraulic correction techniques and data-driven, high-resolution approaches. For instance, Chen Huili et al. [37] proposed a hydraulic correction method to improve SRTM DEM accuracy in flood simulations by eliminating vegetation-induced biases and random errors. Although validated during extreme flood events in the Huifa River Basin, this method relies heavily on manual interaction using tools such as Google Earth, resulting in limited efficiency for large-scale applications. Data-driven approaches that leverage high-resolution auxiliary datasets have also been explored. Xing Yun et al. [38] developed a GIS-based method to correct DEM distortions caused by urban features such as buildings and bridges, while Zeeshan Khalid et al. [39] proposed the DEMend method, which integrates LiDAR data to automatically rectify hydrological errors associated with bridges and culverts. Despite their high correction accuracy, these methods are constrained by the availability and cost of high-resolution datasets. In comparison, the stream burning method provides a more cost-effective and broadly applicable alternative for regions characterized by gentle terrain slopes. By embedding vector river networks into DEMs through artificial lowering of channel elevations, this method enforces hydrologically consistent flow paths during terrain processing [40,41]. In plain–hilly transition zones, stream burning can effectively mitigate common DEM-induced problems, such as disconnected drainage networks, incorrect flow directions, and displaced watershed outlets, without reliance on expensive high-resolution elevation data. Moreover, its high computational efficiency and compatibility with standard hydrological modelling workflows make it suitable for large-scale and data-limited applications. Accordingly, the stream burning method is adopted in this study to correct the original DEM.

Based on the above context, this study selects the Beimiaoji Watershed in the Huaihe River Basin—a typical plain–hilly transition zone—as the research area. Plains account for more than 85% of the watershed area, and the combination of gentle terrain and complex drainage networks makes it an ideal test case for integrating DEM correction with distributed hydrological modelling. This study makes three primary contributions. First, it provides a systematic evaluation of the applicability of the Liuxihe Model in a plain–hilly transition watershed, a terrain type that has received limited attention in previous studies. Second, by integrating the stream burning method into the DEM preprocessing workflow, this study quantitatively assesses the effects of topographic correction on river network extraction using metrics such as Channel Overlap Percentage (COP) and Confluence Node Matching Rate (HNMR), and evaluates flood simulation performance. Third, by coupling DEM correction with PSO-based parameter optimization, this study establishes an integrated modelling framework to enhance flood simulation accuracy under data-limited and low-relief conditions. The findings of this study provide methodological references and practical guidance for flood forecasting and flood control in plain–hilly transition regions.

2. Study Area and Data

2.1. Study Area

This study selects the controlled watershed upstream of the Beimiaoji Hydrological Station of the Huaihe River (hereafter abbreviated as the “Beimiaoji Watershed”) as the research area (Figure 1). Located in the middle and upper reaches of the Bailu River—a first-order tributary of the Huaihe River—the watershed originates from the northern foot of the Dabie Mountains, flows from southwest to northeast through Xinyang City, Henan Province, China, and eventually empties into the Huaihe River. Geographically, the watershed belongs to the plain–hilly transition zone in southeastern Henan. Its terrain slopes from south to north, with an elevation ranging from approximately 26 m to 886 m. Plain areas dominate the watershed, accounting for roughly 85% of its total area, and the catchment area is about 1710 km².

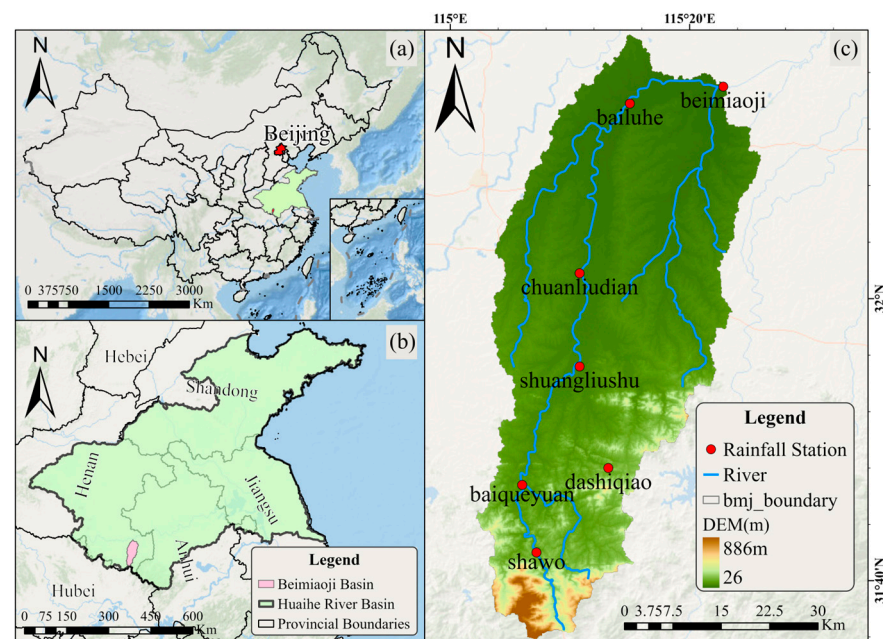


Figure 1. Geographical Distribution of the Beimiaoji Watershed and Locations of Rain Gauge Stations. This figure is compiled based on the map with the map review number GS(2024)0650 from the National Platform for Common GeoSpatial Information Services, and the base map remains unmodified: (a) Location of the study area in China (b) Location of the study area in the Huai River Basin (c) Study area map.

Climatically, the watershed has a subtropical monsoon climate and falls within the humid–semi-humid transition zone. Influenced by the East Asian monsoon, rainfall is concentrated in the period from June to September, with an average annual precipitation of around 1000 mm—characterized by high intensity and strong concentration. In terms of hydrological features, the watershed transitions from steep hilly areas in the upper reaches to plain areas in the middle and lower reaches; here, river network density increases, which easily leads to sedimentation and poor drainage. Under the combined effects of such complex terrain and intense monsoon rainfall, extreme precipitation events are prone to triggering large-scale floods, posing threats to infrastructure and the production and daily lives of local residents.

2.2. Data

2.2.1. Watershed Underlying Surface Data

The modeling data required for the Liuxihe Model primarily includes DEM (Figure 2a), soil type data (Figure 2b), and land use data (Figure 2c). Among these, the DEM used in

this study is from the SRTM v4.1 dataset. The dataset is provided by Geospatial Data Cloud site, Computer Network Information Center, Chinese Academy of Sciences. (<http://www.gscloud.cn>), with a resolution of 90 m. For the soil type data, the Soil and Terrain Database (SOTER) for China released by the International Soil Reference and Information Centre (ISRIC) (<http://www.isric.org/>) was selected [42], and this dataset has a spatial resolution of 1000 m. As for the land use data, it is derived from the China Land Cover Dataset (CLCD), developed by Huang Xin's research team. By comparing land use conditions across the years from 2015 to 2024, it was found that changes were insignificant; therefore, the 2021 dataset was selected to represent the study period; the CLCD dataset classifies land use into 9 categories, namely Cropland, Forest, Shrubland, Grassland, Water Body, Snow/Ice, Barren Land, Impervious Surfaces, and Wetland, with a resolution of 30 m [43]. Slope, flow direction, and river network are all derived from the DEM. To conduct computations, the Liuxihe Model partitions the watershed into grid cells, whose size directly influences computational efficiency and model accuracy. Smaller grid cells can improve model accuracy to a certain extent but require longer computation time, while larger grid cells reduce computation time but lead to lower accuracy [29]. Therefore, considering the actual conditions of the study watershed and accuracy requirements, the grid cell size was set to 90 m, and accordingly, the land use and soil type data were resampled to 90 m using the nearest-neighbor interpolation method, which was selected to preserve the original categorical attributes of soil and land use data, avoiding the generation of non-existent classes.

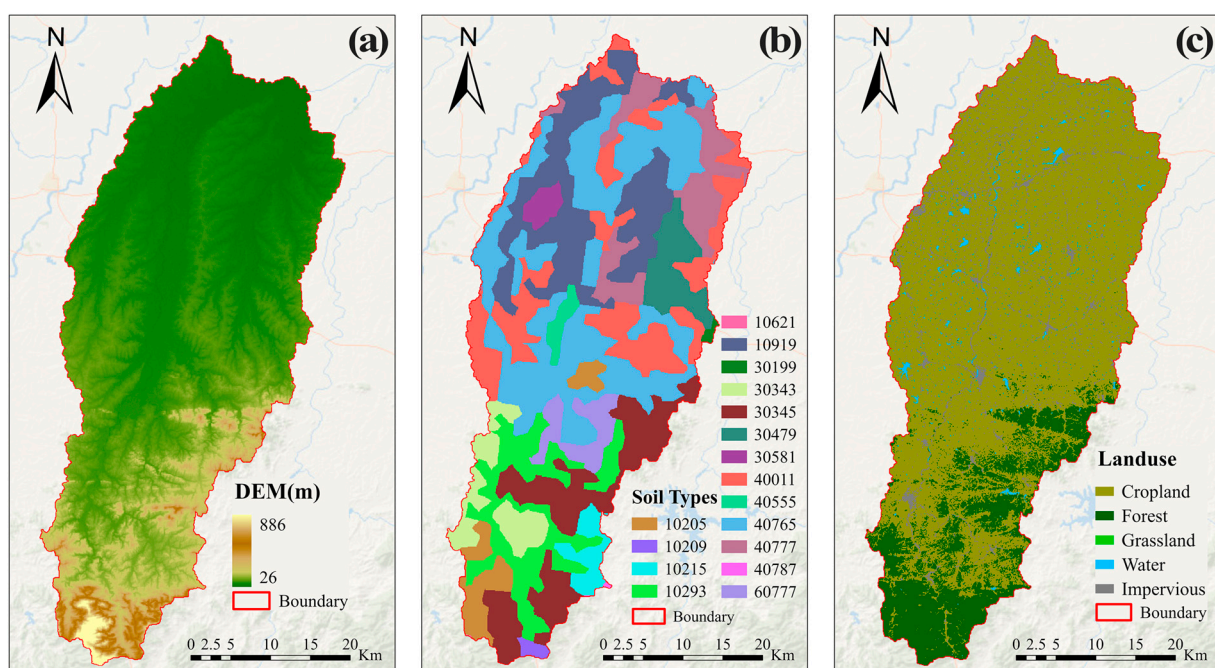


Figure 2. Physical Characteristics Data of the Beimiaoji Watershed: (a) DEM, (b) soil type, (c) land use.

2.2.2. Hydrological Data

The hydrological data required for the model mainly includes hourly rainfall data from 7 rain gauge stations (Figure 1) in the watershed from 2015 to 2024, and measured flood process discharge data from the Beimiaoji Hydrological Station of the Huaihe River. All the data were provided by the Hydrology Bureau (Information Center) of the Huaihe River Water Conservancy Commission. The rainfall data is complete and of good quality, requiring no cleaning or supplementation. According to the institution's recommendations, flood events greater than the warning water level (i.e., peak discharge greater than 500 m³/s) with complete rising processes were selected and extracted (12 events in total) as the

research objects, and information such as their duration, peak discharge, and total rainfall is shown in Table 1. As indicated in Table 1, the flood events in the Beimiaoji Watershed generally have a long duration, with most exceeding 200 h, which is basically consistent with the characteristics of slow flood processes and long durations in plain areas. The input form of rainfall in the Liuxihe Model is hourly grids. This study adopts the Thiessen Polygon method for rainfall interpolation, which is suitable for watersheds with uniformly distributed and a small number of rain gauge stations.

Table 1. Information Table of Flood Events.

Flood Name	Duration (h)	Peak Flow ($\text{m}^3 \cdot \text{s}^{-1}$)	Total Rainfall (mm)
2015061414	213	512.00	124.36
2015062319	422	948.00	209.43
2016063014	127	547.14	98.00
2017070808	173	1080.00	163.50
2017092307	426	630.00	219.43
2018050414	228	685.92	143.43
2020062708	216	516.00	103.81
2020070908	505	1760.00	480.43
2021062508	148	511.07	86.43
2021070116	270	636.00	195.43
2022031912	260	562.00	172.29
2024070809	249	1340.00	327.21

Furthermore, the vector river network data required for correcting the DEM used in this study is derived from the hydrological data within the 2021 National 1:1,000,000 Public Version Fundamental Geospatial Data, which is available from the National Geospatial Information Resource Catalog Service System (<https://www.webmap.cn/>).

3. Methods

3.1. Overview of the Methodology

Figure 3 presents the technical framework for investigating the applicability of the Liuxihe Model in plain–hilly transition zones, which is logically divided into three modules: data preparation, DEM correction, and modeling and analysis.

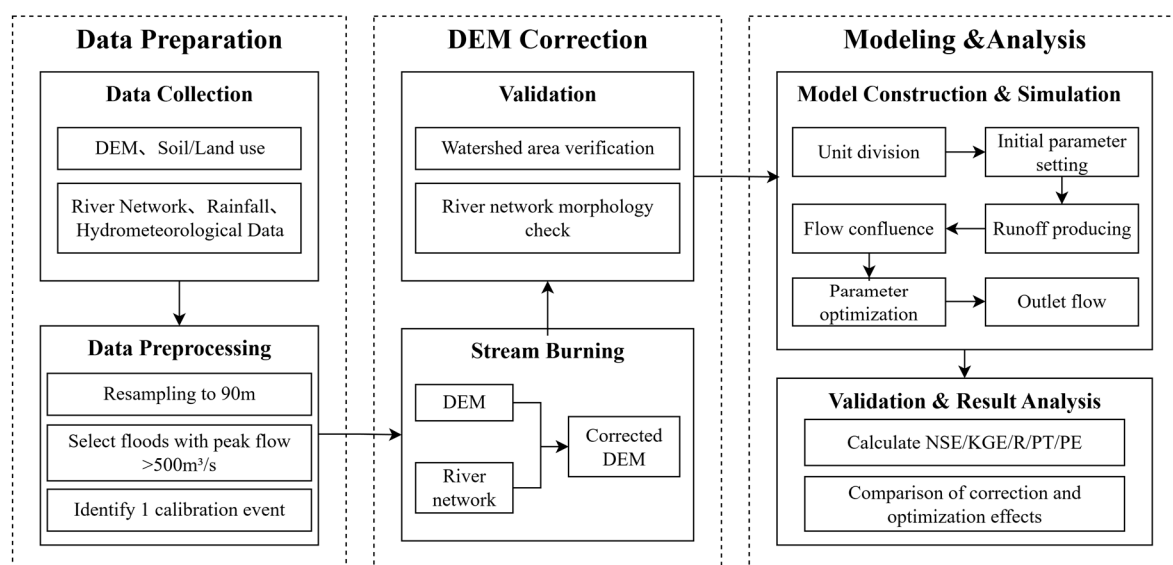


Figure 3. Framework for Studying the Applicability of the Liuxihe Model in the Plain–Hilly Transition Zone.

In the data preparation phase, DEM, soil, land use, river network, and hydro-meteorological data are collected and resampled to a resolution of 90 m. Flood events with a peak discharge greater than 500 m³/s are screened, among which one representative flood event is selected for parameter calibration, while the remaining events are used for model validation.

For the DEM correction phase, the vector river network is first embedded into the DEM using the stream burning method, and the channel elevation is adjusted to force water flow along the actual path, thereby generating a corrected DEM. Subsequently, differences in watershed delineation results and river network morphology between the original and corrected DEMs are subsequently evaluated. In the modeling and analysis phase, the Liuxihe Model is constructed based on the corrected DEM, and the PSO algorithm is adopted for automatic parameter calibration and simulation. Indicators such as NSE, KGE (Kling-Gupta Efficiency), R (Correlation coefficient), PT, and PE are used to assess the fitting degree and flood peak characteristics. By comparing the results before and after correction, the mechanism of accuracy improvement is revealed.

3.2. Liuxihe Model

Liuxihe Model is a fully distributed, physically based hydrological model developed for watershed-scale flood simulation and forecasting [44]. The model consists of six core modules: watershed delineation, evapotranspiration estimation, runoff generation, flow routing, parameter determination, and hydrological simulation. It relies on DEM data with good availability, reliable quality, and appropriate spatial resolution to perform detailed spatial discretization of the study watershed. In the vertical direction, each hydrological unit is divided into a vegetation layer, a surface layer, and a groundwater layer. In the horizontal direction, the watershed is further partitioned into hillslope units, channel units, reservoir units, and other functional elements. Regular grid cells are used as the minimum computational units. Topographic attributes, land use properties, and soil parameters of each unit are jointly derived from DEM data, land use maps, and soil type datasets. For rainfall input, the model can incorporate multi-source precipitation data, including radar-based estimates and rain gauge observations. Spatial allocation methods are applied to estimate rainfall for each hydrological unit. Evapotranspiration is calculated based on unit-scale precipitation and antecedent soil moisture conditions, which allows the estimation of evapotranspiration losses for each unit.

Runoff generation occurs when effective rainfall, defined as precipitation after evapotranspiration losses, is greater than zero and the surface layer reaches saturation. Excess water is converted into surface runoff. Infiltration processes are simulated to generate subsurface flow and groundwater flow. The model does not strictly distinguish between saturation-excess runoff and infiltration-excess runoff mechanisms, which improves its applicability under different underlying surface conditions. For flow routing, different methods are adopted for different hydrological units. Hillslope flow is simulated using the one-dimensional kinematic wave method, while channel flow is routed using the one-dimensional diffusion wave method. Reservoir routing is performed using a translation method. Subsurface flow and groundwater flow are also considered. The simulated discharge at the watershed outlet is obtained by integrating all routing processes [45].

3.3. Parameter Optimization Framework

Most initial parameters of distributed hydrological models are determined based on the physical characteristics of the watershed. These parameters have clear physical meanings, and their values depend on the physical properties of the corresponding units—thus, there is theoretically a true value for each parameter. However, due to factors such as

model generalization and simplification, insufficient accuracy of input data, and modeling errors, parameter optimization and calibration remain necessary.

To address this issue, the Liuxihe Model has established a general framework for parameter optimization of distributed models [24], which includes four steps: parameter generalization, determination of initial values and value ranges, selection of optimization methods, and performance evaluation. First, parameters with the same physical properties (e.g., parameters of units with consistent soil types) are integrated into independent parameters for optimization to reduce the optimization dimension. Second, initial parameter values are set based on the watershed's physical characteristics, and the parameter value ranges are unified through normalization to avoid significant deviations between the optimized results and the initial values. Third, optimization algorithms—such as the Shuffled Complex Evolution-University of Arizona (SCE-UA) [46] and PSO [47]—are introduced to iteratively update parameters and gradually approach the optimal solution. Finally, indicators are used to evaluate the optimization effect, enabling efficient and reasonable parameter calibration.

In specific implementation, the Liuxihe Model adopts the PSO algorithm as its optimization method. Proposed by Eberhart et al. [48], this algorithm simulates the foraging behavior of bird swarms. Through collaboration and competition among particles, it incorporates both individual experience and group information during the search process, thereby effectively finding the global optimal solution. Relying on the automatic parameter optimization framework coupled with the PSO algorithm, parameter calibration in this study is performed using a single high-quality flood event. This strategy is adopted based on model characteristics. First, as a physically based distributed hydrological model, most parameters in the Liuxihe Model are constrained by measurable watershed attributes (e.g., soil type, land use, and topography), and bounded search ranges are imposed during optimization, which limits parameter freedom and effectively reduces the risk of overfitting. Second, the selected calibration event is characterized by a single dominant flood peak, moderate-to-high peak discharge, a complete hydrograph, and a stable rainfall–runoff relationship. Such flood events contain sufficient hydrological information to adequately constrain model parameters and can be validated in other flood events. Consequently, reliable parameter estimation can be achieved without requiring multiple calibration events, while maintaining computational efficiency.

3.4. DEM Stream Burning Method

The Beimiaoji Watershed is dominated by plains. Its gentle terrain leads to deviations in river network extraction from low-resolution DEMs (e.g., discontinuous channels and misjudged flow directions). To address this issue, this study adopted the stream burning method for DEM topographic correction. Proposed by Hutchinson [40], the core principle of this method is to “embed” high-precision vector river networks into the DEM in raster format. By adjusting the elevation values of channel grids, the method forces flow paths to align with the actual river network, thereby eliminating systematic errors in river network extraction in gentle terrain [41]. Characterized by simplicity and efficiency, this method has been widely applied in hydrology and other fields: for example, in the modeling of the Jackpine Watershed in Canada, DEMs corrected via the stream burning method improved the accuracy of river network matching enhances the accuracy of model construction; however, it is necessary to set the flow threshold reasonably to reduce topological errors [49]. Liao et al. proposed a hybrid topological relationship method that combines the stream burning method with depression filling, which is compatible with multiple grid types and improves the generalization ability of flow direction modeling [50].

In this study, the FillBurn and TopologicalBreachBurn modules implemented in the WhiteboxTools software v2.4.0 were adopted to perform DEM stream burning correction [41]. The core implementation procedure is described as follows. First, tributary scale was quantified using the Total Upstream Channel Length (TUCL) metric. Based on this criterion, the vector river network was pruned to remove small tributaries that were incompatible with the spatial resolution of the DEM, thereby reducing topological inconsistencies caused by scale mismatch. In this study, minor tributaries were manually removed from the vector dataset, and topological consistency checks were conducted to ensure network continuity prior to rasterization. Subsequently, the vector river network was rasterized, and the elevations of grid cells along the flow paths were uniformly reduced by a fixed burn depth. Following the default configuration of the WhiteboxTools implementation, the FillBurn method applies a constant elevation reduction of 10,000 m to all channel cells. This value serves as a topological constraint rather than a physical hydraulic variable, ensuring that vector-defined channels are strictly prioritized over surrounding terrain artifacts to enforce the prescribed flow routing. After stream burning, depressions were filled using the priority flood algorithm. The filling process starts from the lowest-elevation grid cells along the DEM boundary and proceeds inward in ascending order of elevation, thereby guaranteeing hydrologically consistent drainage across the entire domain. This procedure was executed using the default settings of the WhiteboxTools modules, requiring no additional parameters (for details, refer to the WhiteboxTools User Manual, https://www.whiteboxgeo.com/manual/wbt_book/preface.html (accessed on 4 February 2026)).

3.5. Model Performance Evaluation Indicators

To verify the model's performance, five evaluation indicators were selected in this study, namely NSE, KGE, R, PT, and PE. The NSE is mainly used to measure the overall consistency between simulated values and observed values, with a value range of $(-\infty, 1]$; the closer the value is to 1, the better the model's simulation effect. The KGE comprehensively evaluates the model's performance by considering the mean, standard deviation, and correlation coefficient; similarly, the closer its value is to 1, the better the model's performance [51,52]. The R characterizes the linear correlation between the simulated and observed sequences; the PT reflects the deviation between the simulated flood peak occurrence time and the measured time; and the PE measures the accuracy of flood peak discharge simulation. Through the combined evaluation of the above five indicators, the model's performance can be tested from multiple dimensions, including overall fitting degree, comprehensive performance, correlation, flood peak timing, and flood peak magnitude. The calculation formulas for each indicator are as follows:

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^n (Q_{obs,i} - \bar{Q}_{obs})^2} \quad (1)$$

$$KGE = 1 - \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \quad (2)$$

$$R = \frac{\sum_{i=1}^n (Q_{obs,i} - \bar{Q}_{obs})(Q_{sim,i} - \bar{Q}_{sim})}{\sqrt{\sum_{i=1}^n (Q_{obs,i} - \bar{Q}_{obs})^2} \sqrt{\sum_{i=1}^n (Q_{sim,i} - \bar{Q}_{sim})^2}} \quad (3)$$

$$PT = t_{obs,peak} - t_{sim,peak} \quad (4)$$

$$PE = \frac{|Q_{sim,peak} - Q_{obs,peak}|}{Q_{obs,peak}} \quad (5)$$

where $Q_{obs,i}$ is the observed discharge value at time i , in m^3/s ; $Q_{sim,i}$ is the simulated discharge value at time i , in m^3/s ; $\bar{Q}_{obs}$ is the average of observed discharge values,

in m^3/s ; $\bar{Q}_{\text{sim}}$ is the average of simulated discharge values, in m^3/s ; n is the number of data samples (corresponding to the total number of time steps), dimensionless; r is the correlation coefficient, dimensionless; β is the bias coefficient, dimensionless; γ is the variability coefficient, dimensionless; $t_{\text{obs,peak}}$ is the observed flood peak occurrence time, in hour; $t_{\text{sim,peak}}$ is the simulated flood peak occurrence time, in hour; $Q_{\text{sim,peak}}$ is the simulated flood peak discharge, in m^3/s ; and $Q_{\text{obs,peak}}$ is the observed flood peak discharge, in m^3/s .

4. Result

4.1. DEM Correction

The original DEM was corrected using the stream burning method to generate a new DEM. The D8 algorithm [53] was adopted for flow direction calculation and river network extraction. Figure 4 compares river networks extracted from the original and corrected DEMs with the reference vector river network. It can be observed that the river network extracted from the original DEM has significant deviations in morphology and flow direction compared with the reference vector river network, especially in the watershed outlet area, where spatial dislocation and flow direction misjudgment are more obvious. In terms of watershed boundaries: the watershed area extracted from the original DEM is approximately 1784 km^2 , while that from the corrected DEM is about 1700 km^2 , which is more consistent with the watershed range mentioned in existing studies ($\sim 1710 \text{ km}^2$). In particular, the outlet location has a higher matching degree with the location of Beimiaoji Hydrological Station.

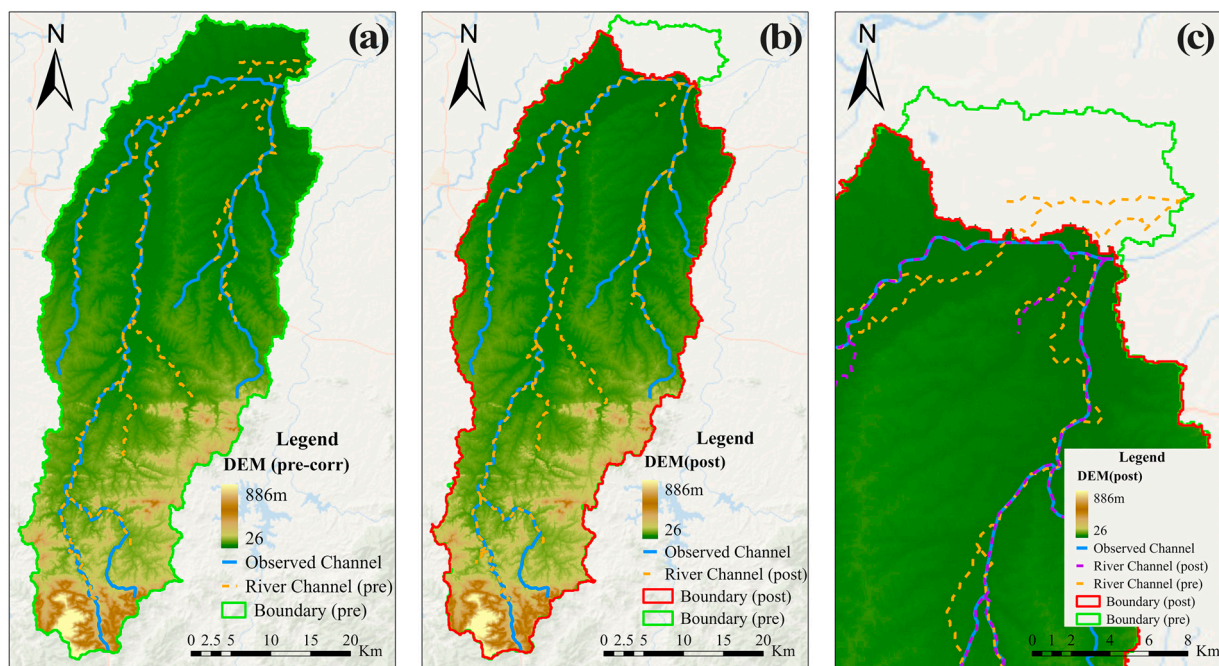


Figure 4. Watershed and River Network Extraction Before (a) and After (b) DEM Correction, and Enlarged Comparison of the Outlet Area (c).

To further quantitatively evaluate the geometric matching degree and topological rationality of river network extraction, two quantitative indicators were supplemented:

- (1) COP, defined as the ratio of the number of overlapping grids between the extracted river network and the reference river network to the total number of grids of the reference river network, characterizes the spatial location matching degree of the river network. The calculation results show that the COP of the original DEM river network

- is only 23.3%, and it significantly increases to 61.8% after correction, an increase of 38.5 percentage points compared with that before correction, indicating a substantial improvement in the spatial fit between the river network and the actual river channel.
- (2) HNMR takes 5 confluence nodes (i.e., tributary confluences) of the reference river network as the evaluation objects. The effective matching criterion is set as the Euclidean distance of nodes ≤ 180 m (the size of 2 grid cells), and the proportion of matched nodes is counted. The results show that only 2 nodes are matched in the original DEM river network (matching rate 60%), while all 5 nodes are effectively matched after correction (matching rate 100%), meaning the hierarchical structure and confluence relationship of the river network are more consistent with the actual hydrological process.

Together, these results demonstrate that stream burning substantially improves both the geometric accuracy and topological rationality of river network extraction in low-relief terrain, providing a more reliable structural basis for subsequent hydrological simulation.

4.2. Model Structure Building

In the model initialization phase, the study area was first partitioned into slope units and channel units. Reservoir units were excluded, however, owing to the sparse distribution of reservoir projects across the study area. Meanwhile, areal precipitation inputs were derived using Thiessen polygon interpolation based on gauge-based precipitation datasets. The basic parameters of the Liuxihe Model can be categorized into three types based on calculation modules: (1) Evapotranspiration parameters, including soil field capacity (Cfc), wilting point moisture content (Wl), potential evaporation rate (Ep), and evaporation coefficient (v); (2) Runoff generation parameters, including saturated moisture content (Csat), soil thickness (Zs), saturated hydraulic conductivity (Ks), soil characteristic parameter (b), and soil infiltration coefficient (a); (3) Confluence parameters, including flow direction, unit slope, slope unit roughness (n_slope), channel unit roughness (n_channel), channel bottom width (bw), channel bed slope (bs), and channel side slope (ss). Among these, flow direction and slope (Figure 5) are non-adjustable parameters, while the remaining parameters are subject to subsequent calibration. Initial parameters related to soil types are shown in Table 2, where b is uniformly set to 2.5; other soil water characteristic parameters are estimated using the Soil Water Characteristic software developed by the United States Department of Agriculture (USDA) based on soil properties (such as sand content, clay content, and salt concentration) [54]. Initial parameters related to land use are presented in Table 3; v is an insensitive parameter and uniformly set to 0.7 based on experience. Both n_channel and n_slope are the parameter n in the Manning's equation for confluence calculation: n_slope is determined according to different land use types with reference to existing studies [29], and n_channel is uniformly set to 0.025 based on experience.

For channel-related parameters among the confluence parameters, the Liuxihe Model uses virtual nodes to segment each channel reach, forming multiple virtual channel segments. Within the scope of each virtual channel segment, the model assumes that the channel cross-section is trapezoidal with consistent shape and size, thereby simplifying the process of estimating the shape and size of the channel cross-section. Specifically, the bw is measured using satellite remote sensing image data; the bs is calculated based on the elevation difference and length of units within the virtual channel segment; and the ss is estimated using empirical formulas and existing topographic data, with a uniform value of 30° adopted in this study.

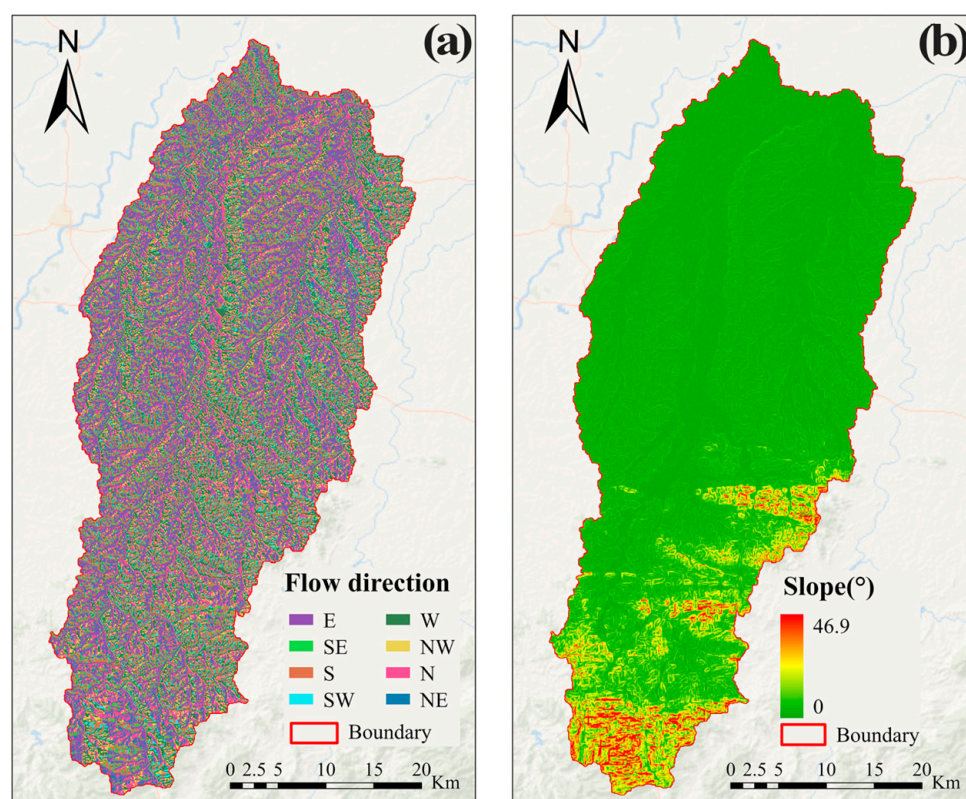


Figure 5. Non-adjustable Parameters: (a) Flow Direction. (b) Slope.

Table 2. Initial Values of Soil Type Parameters.

ID	Zs (mm)	Csat	Cfc	Ks (mm/h)	b	WI
10205	1900	0.45	0.177	51.11	2.5	0.081
10209	2300	0.429	0.246	14.66	2.5	0.155
10215	430	0.441	0.23	23.19	2.5	0.126
10293	1000	0.632	0.534	1.83	2.5	0.551
10919	1000	0.507	0.375	6.14	2.5	0.205
30199	630	0.491	0.416	1.05	2.5	0.293
30343	300	0.465	0.104	113.42	2.5	0.045
30345	900	0.466	0.093	121.39	2.5	0.044
30479	780	0.439	0.208	30.07	2.5	0.115
30581	1000	0.438	0.239	19.33	2.5	0.138
40011	1130	0.493	0.384	3.27	2.5	0.244
40555	1300	0.484	0.337	8.72	2.5	0.169
40765	1000	0.476	0.324	9.53	2.5	0.164
40777	1000	0.485	0.36	5.01	2.5	0.212
40787	1000	0.466	0.31	9.95	2.5	0.164
60777	690	0.449	0.191	44.19	2.5	0.087

Table 3. Initial Values of Land-Use Parameters.

Land Use Type	v	n
Cropland	0.7	0.5
Forest	0.7	0.6
Grassland	0.7	0.1
Water	0.7	0.2
Impervious	0.7	0.1

4.3. Model Parameter Optimization

In this study, the flood event numbered 2016063014 was selected for parameter optimization, while the remaining flood events were used for model validation. The parameter configuration for the PSO algorithm was determined as follows: (1) The swarm size was set to 24 particles, calculated based on the parameter dimensionality ($D = 15$) using the heuristic formula (Equation (6)) to ensure adequate coverage of the search space. (2) The cognitive and social learning factors (c_1 and c_2) were both set to 1.4962, following the stability and convergence criteria proposed by Clerc and Kennedy [55]. (3) A linearly decreasing inertia weight strategy was adopted, decreasing from 0.7298 to 0.3 over 100 iterations to balance global exploration and local refinement since the initial values of relevant parameters such as soil and land use have certain physical meanings, the parameter adjustment range was set to [0.5, 1.5] with reference to similar studies [28], ensuring that the optimized parameters would not deviate significantly from their physical implications; the objective function was defined as Residual Sum of Squares (Equation (7)). The iterative process and results of parameter optimization for the selected flood event are shown in Figure 6.

$$N = \text{ceil}(16 + 2\sqrt{D}) \quad (6)$$

$$\text{Obj} = \sum_{i=1}^n (Q_{\text{obs},i} - Q_{\text{sim},i})^2 \quad (7)$$

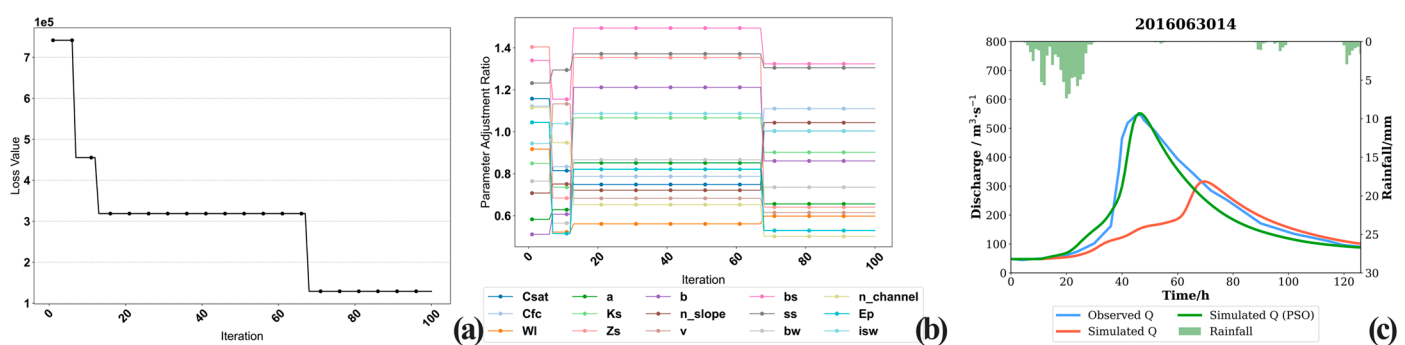


Figure 6. Parameter optimization results: (a) Parameter variation. (b) Objective function variation. (c) Comparison of parameters before and after optimization for the event on 2016063014.

The parameter optimization results showed that, after nearly 70 iterations, the objective function decreased by 85%. When this set of optimized parameters was applied to the simulation of the 2016063014 flood event, the simulation performance was significantly improved: the NSE increased to 0.936, the KGE rose to 0.912, and the R increased to 0.977, the PE decreased to 1%, and the PT deviation was reduced to 0 h. These results indicate that the optimized parameters can be effectively used for the simulation of this flood event.

4.4. Model Performance

The optimized parameters derived in the preceding section were employed as the final model parameters for simulating the remaining 11 flood events. The comparison of representative simulation results is shown in Figure 7, and the evaluation indicators for all flood events (including results before and after optimization) are listed in Table 4.

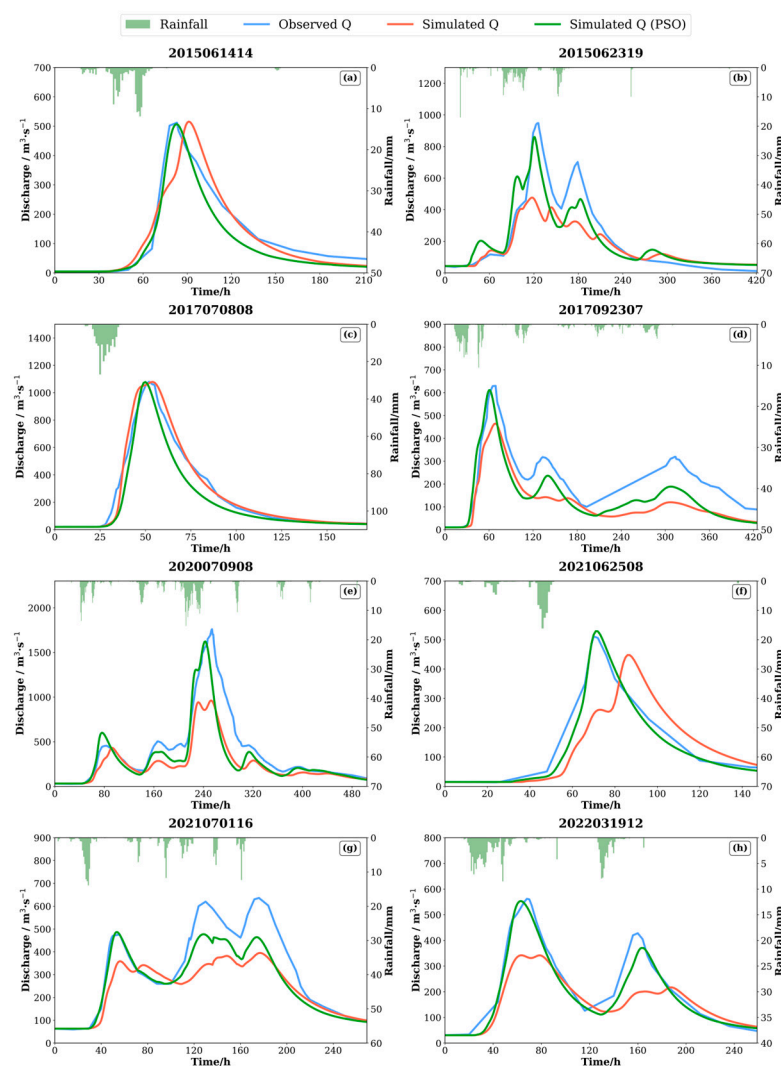


Figure 7. Comparison of Simulation Results Before and After Parameter Optimization: (a) 2015061414 (b) 2015062319 (c) 2017070808 (d) 2017092307 (e) 2020070908 (f) 2021062508 (g) 2021070116 (h) 2022031912.

Table 4. Statistical metrics of Simulations Before and After Parameter Optimization.

Flood Number	Type	NSE	KGE	R	PT (h)	PE
2015061414	pre-optimization	0.879	0.915	0.940	8	0.007
	optimization	0.924	0.713	0.981	0	0.010
2015062319	pre-optimization	0.658	0.595	0.934	−7	0.497
	optimization	0.849	0.815	0.931	−4	0.093
2016063014	pre-optimization	0.121	0.374	0.531	24	0.422
	optimization	0.936	0.912	0.977	0	0.008
2017070808	pre-optimization	0.976	0.945	0.992	2	0.001
	optimization	0.929	0.769	0.980	−2	0.002
2017092307	pre-optimization	0.222	0.348	0.902	0	0.263
	optimization	0.516	0.434	0.914	−8	0.030

Table 4. Cont.

Flood Number	Type	NSE	KGE	R	PT (h)	PE
2018050414	pre-optimization	0.637	0.471	0.890	16	0.247
	optimization	0.669	0.282	0.929	3	0.007
2020062708	pre-optimization	0.340	0.442	0.874	−3	0.587
	optimization	0.857	0.786	0.965	3	0.228
2020070908	pre-optimization	0.634	0.617	0.962	−1	0.454
	optimization	0.752	0.757	0.892	−11	0.078
2021062508	pre-optimization	0.561	0.757	0.767	16	0.124
	optimization	0.964	0.859	0.986	1	0.035
2021070116	pre-optimization	0.558	0.666	0.917	1	0.379
	optimization	0.801	0.811	0.958	−2.3	0.235
2022031912	pre-optimization	0.620	0.682	0.892	−5	0.392
	optimization	0.951	0.899	0.983	−5	0.016
2024070809	pre-optimization	0.872	0.774	0.963	1	0.139
	optimization	0.836	0.768	0.938	−8	0.003
Average Value	pre-optimization	0.590	0.632	0.880	4.333	0.293
	optimization	0.832	0.734	0.953	−2.775	0.062

Note: The flood event numbered 2021070116 is a multi-peak flood, with an overall PT error of −123 h. When the three main peaks are counted separately, their errors are −3 h, −2 h, and −2 h respectively, with an average value of −2.3 h.

Evaluation of the 12 flood events indicates that the Liuxihe Model demonstrates high stability and reliability in simulating the hydrological response of the Beimiaoji watershed. Regarding the NSE, the average NSE value of the 12 flood events reached 0.832, with 8 of these events having an NSE exceeding 0.8—indicating that the model can accurately replicate the hydrological flow process in the watershed under most conditions. The KGE exhibited moderate variability, it maintained a robust average of 0.734, with 7 events surpassing 0.7. This further verifies that the model still possesses reliable simulation capabilities when comprehensively considering factors such as flow mean, data variability, and variable correlation. In terms of the R, the model showed more robust performance: all events had an R value higher than 0.89, with an average of 0.953, demonstrating a high degree of linear correlation between the simulated and measured discharge. For the PE and PT—which are of the greatest concern in flood forecasting—the model also exhibited high accuracy. The absolute value of PE was less than 10% for most events, with an average of 0.062, indicating that the model accurately characterizes flood peak intensity and can effectively capture extreme flow characteristics. Regarding PT, against the background of the overall long duration of flood processes in the watershed, the absolute PT deviation of 10 flood events was controlled within 8 h. Although the overall PT deviation of the 2021070116 event was relatively large, this event is a typical multi-peak flood. When considering its three main peaks separately, the PT errors were −3 h, −2 h, and −2 h, with an average of −2.3 h—still within a reasonable range. This indicates that the model also has a certain level of temporal prediction capability for complex flood processes.

In summary, after parameter optimization, the Liuxihe Model achieved relatively favorable results in flood simulation for the Beimiaoji Watershed and is capable of supporting flood forecasting in this watershed.

5. Discussions

5.1. Flow Routing Network Improvement of DEM Correction

The accuracy of river network extraction directly determines the Liuxihe Model's ability to depict the physical authenticity of the confluence processes. After correction using the stream burning method, the physical rationality of the confluence network is substantially restored. This improvement is not limited to the alignment between the river network morphology and vector data (see details in Section 4.1, Figure 4); more importantly, it reconstructs the water flow movement logic that conforms to reality. Its impacts are reflected in the simulation deviations of PT, PE, and rising and receding limb processes (as shown in Figure 8 and Table 5).

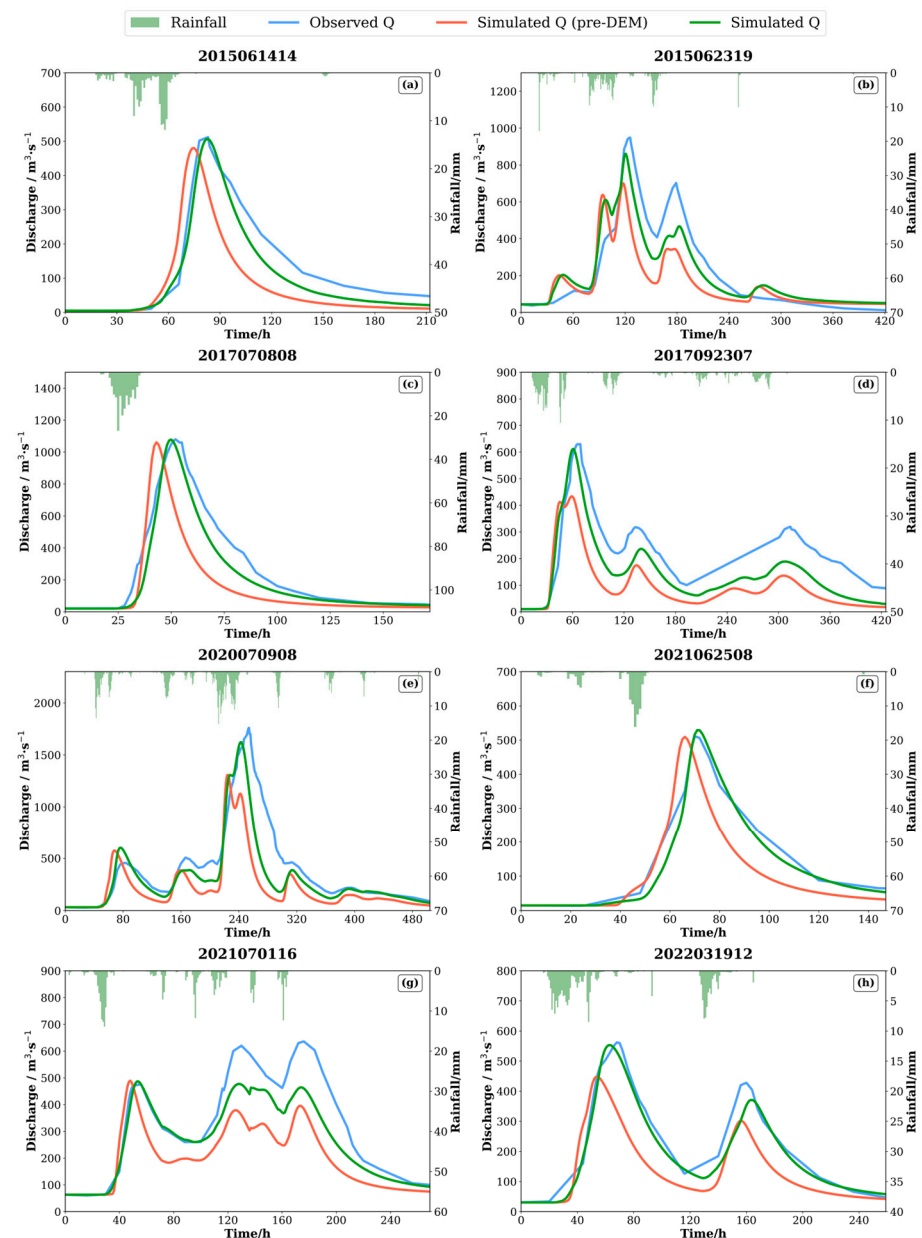


Figure 8. Comparison of simulation results before and after DEM correction: (a) 2015061414 (b) 2015062319 (c) 2017070808 (d) 2017092307 (e) 2020070908 (f) 2021062508 (g) 2021070116 (h) 2022031912.

Table 5. Statistical metrics of Simulations Before DEM Correction.

Flood Name	NSE	KGE	R	PT (h)	PE
2015061414	0.529	0.410	0.812	−8	0.062
2015062319	0.572	0.650	0.807	−7	0.261
2016063014	0.605	0.660	0.934	−2	0.194
2017070808	0.568	0.441	0.829	−9	0.018
2017092307	−0.311	0.048	0.774	−10	0.311
2018050414	0.190	−0.054	0.781	−6	0.129
2020062708	0.416	0.603	0.820	−6	0.346
2020070908	0.367	0.481	0.745	−29	0.257
2021062508	0.721	0.637	0.891	−4	0.003
2021070116	0.315	0.616	0.879	−5	0.231
2022031912	0.536	0.608	0.889	−14	0.202
2024070809	0.525	0.602	0.780	−11	0.005
Average Value before Correction	0.419	0.475	0.828	−9.250	0.168
Average Value after Correction	0.832	0.734	0.953	−2.775	0.062

Note: The flood event numbered 2021070116 is a multi-peak flood, with an overall PT error of −128 h. When the three main peaks are counted separately, their errors are −8 h, −4 h, and −3 h respectively, with an average value of −5 h.

In terms of PT, the river network extracted from the original DEM exhibits discontinuities and deviations, leading water to follow incorrect paths within the model have a significant average lag of 9.25 h. This phenomenon aligns with the “digital dam” effect described by Khalid et al. [39], where uncorrected topographic obstructions act as unphysical barriers that artificially retard runoff velocity and our results quantitatively demonstrate that uncorrected DEMs in transition zones function as artificial barriers, delaying peak timing; additionally, the absence of some tributaries leads to an underestimation of the actual confluence distance. The corrected river network restores the real channel direction and connectivity, aligning the water flow paths with the actual situation and thereby reducing the average PT error to 2.78 h.

Regarding PE, some unconnected tributaries in the original DEM prevent runoff generation in certain areas from converging into the main stream, leading to an underestimation of the flood peak. By restoring the connection between tributaries and the main stream, the corrected river network enables effective convergence of runoff generated in each grid cell along the real path, allowing the accurate simulation of the superposition effect of runoff. Only when the river network structure is consistent with the actual situation can the model fully capture the synergistic contribution of runoff from different regions, thereby simulating a reasonable flood peak intensity.

For the impact on rising and receding limb processes: Deviations in the river network path result in excessively slow initiation of the rising phase and distorted attenuation in the receding phase. By forcing water flow to move along the vector river network path, the corrected river network eliminates such interferences, making the rising and receding limb processes more consistent with the measured hydrograph.

5.2. Improvement of Model Performance with Parameter Optimization

Based on the results in Figure 7 and Table 4, it can be observed that parameters optimized via PSO significantly improved the overall performance of the model. In general, the average NSE of the 12 flood events increased to 0.832 (an improvement of approximately 41% compared with pre-optimization results), while the KGE and R also increased by approximately 16% and 8%, indicate that the optimized parameter set enables the Liuxihe Model to better reproduce the overall shape, magnitude, and timing of flood hydrographs. Flood peak characteristics also showed notable improvements: the average PT error was

reduced by approximately one-third, and the PE decreased by nearly 80%. Furthermore, as observed in Figure 9, the optimized simulation results exhibited higher central tendency, reduced volatility, and fewer extreme values, demonstrating stronger stability and ability to resist anomalies.

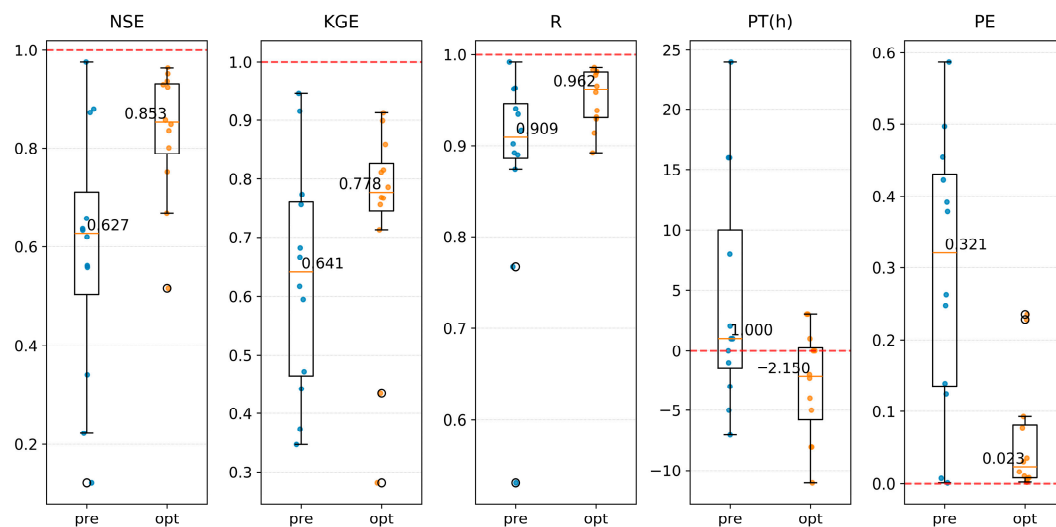


Figure 9. Box plot of simulated results before and after parameter optimization.

The most pronounced improvements were observed in flood peak characteristics. After optimization, both the PE and PT were substantially reduced for most flood events, indicating a more accurate model response under high-flow conditions. This improvement is particularly important for flood forecasting applications, where accurate simulation of peak discharge and its occurrence time is more critical than minor discrepancies during low-flow periods. The performance of the multi-peak flood event 2021070116 further demonstrates the robustness of the optimized parameter set. Although this event exhibits complex temporal characteristics, the optimized model was still able to capture the timing of the main flood peaks with reasonable accuracy when the peaks were evaluated separately. This suggests that the calibrated parameters are not limited to single-peak flood conditions. For a small number of events (e.g., 2017070808), slight fluctuations were observed in individual performance metrics. However, since their pre-optimization performance was already close to optimal, these variations did not compromise the overall simulation quality.

Overall, the results indicate that single-event PSO calibration can provide parameter sets with good generalization capability for a physically based distributed model, enabling reliable simulation of independent flood events without evident overfitting. Therefore, parameter optimization plays a key role in improving the accuracy and stability of the model.

5.3. The Synergy Between DEM Correction and PSO

The experimental results demonstrate a profound synergy between DEM correction and PSO-based parameter optimization. While DEM correction eliminates structural errors in flow-routing paths, PSO refines process parameters within this rectified framework. Comparisons between Tables 4 and 5 reveal that parameter optimization yields substantial improvements in NSE, KGE, and PT only when applied to physically realistic flow paths. In contrast, simulations using the original DEM consistently exhibit poor performance—characterized by reduced NSE and persistent peak time lags—even after optimization.

These findings confirm that the two approaches are strictly complementary: DEM correction restores hydraulic connectivity and removes systematic pathway biases, while parameter optimization ensures that runoff generation and attenuation are accurately

represented along these paths. The control experiments further indicate that parameter optimization alone cannot compensate for fundamental structural deficiencies in the flow-routing network. This aligns with the findings of Xing et al. [38], who emphasized that the accurate representation of physical structures is a prerequisite for reliable modeling results. The results strongly support the ‘structure-before-parameter’ principle discussed by Xing et al. [38]. Without the stream burning correction, the PSO algorithm would likely force parameters into unrealistic ranges to compensate for the wrong flow paths, leading to poor generalization in validation periods. Consequently, in plain–hilly transition zones, rectifying the flow-routing structure serves as the primary driver of model reliability, providing a physically consistent foundation that enables parameters to function effectively. This synergistic framework provides a reliable and cost-effective tool for decision-makers to mitigate flood threats in topography-sensitive and data-scarce transition zones.

5.4. DEM Resolution Considerations in Study Areas

Although the Stream Burning approach effectively restores hydrological connectivity and improves flow routing, it should be noted that the 90 m SRTM DEM used in this study has inherent limitations in representing micro-topographic features in plain areas. At this spatial resolution, small terrain elements such as field ridges and drainage ditches may be smoothed, which can affect the detailed simulation of flood processes to some extent. Meanwhile, for watershed-scale hydrological models, higher DEM resolution does not necessarily result in better simulation performance [29]. Excessively fine-resolution DEMs may introduce topographic “noise”, leading to unrealistic flow paths or model instability, and can substantially increase computational costs. For example, in theory, increasing the DEM resolution from 90 m to 30 m would result in approximately a ninefold increase in computational demand, which is often impractical for operational regional flood forecasting.

Therefore, in the context of regional-scale flood forecasting, the combination of a 90 m DEM and the Stream Burning approach provides a cost-effective balance between simulation accuracy and computational efficiency. It should be emphasized that this study focuses on watershed-scale reservoir inflow flood simulation rather than the detailed representation of micro-scale surface flow processes. Further investigation of the effects of ultra-fine micro-topography on flood simulation would require high-resolution datasets, such as UAV-derived DEMs, which involve higher data acquisition and processing costs and may be explored in future studies.

6. Conclusions

Taking the Beimiaoji Watershed as the study area, this study conducted flood simulation and accuracy enhancement research based on the Liuxihe Model, and improved the model performance through parameter optimization and DEM topographic correction techniques. The main conclusions are as follows:

- **Model Applicability and Generalization:** With appropriate preprocessing and calibration strategies, the Liuxihe Model demonstrates robust applicability in plain–hilly transition zones. The PSO-based optimization framework effectively reduces parameter uncertainty derived from surface heterogeneity. Crucially, single-event calibration within physically constrained ranges achieves satisfactory generalization across multiple independent flood events without evident overfitting, proving the model’s reliability for operational flood forecasting.
- **Fundamental Role of Topographic Accuracy:** DEM correction is a prerequisite for effective distributed modeling in low-relief environments. Stream burning restores hydraulic connectivity and flow-path realism, thereby reducing errors in peak timing

and hydrograph shape. Our findings highlight that parameter optimization alone cannot compensate for simulation errors caused by structural deficiencies in flow-routing paths, emphasizing that topographic integrity must precede process calibration.

- **Transferability and Broader Implications:** The proposed “DEM Correction + PSO” framework offers a cost-effective methodological reference for topography-sensitive regions where high-resolution DEMs may be unavailable. This approach provides a reliable technical basis for flood-control decision-making in areas with similar geomorphological conditions.
- **Limitations:** While the 90 m SRTM DEM combined with stream burning effectively captures watershed-scale confluence logic, its ability to represent micro-topographic features remains limited. Future research could explore multi-source data fusion to further refine simulations in highly complex terrains.

Overall, this study demonstrates that prioritizing the correction of the “digital drainage skeleton” alongside automated parameter refinement significantly enhances the reliability of distributed hydrological models in complex transition zones.

Author Contributions: Conceptualization, Y.C. and Z.H.; methodology, Z.H.; validation, Z.H.; formal analysis, Z.H.; investigation, Z.H.; resources, Z.H. and K.W.; data curation, Z.H. and K.W.; writing—original draft preparation, Z.H.; writing—review and editing, Y.C.; visualization, Z.H.; supervision, Y.C.; project administration, Y.C.; funding acquisition, Y.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Natural Science Foundation of China (Grant No. U2243227) and the Open Research Fund of Anhui Provincial Key Laboratory of Water Conservancy and Water Resources (Grant No. 2023SKJ04).

Data Availability Statement: Hydrological data are not available for privacy reasons; remote sensing data and DEMs are publicly available for download online.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CLCD	China Land Cover Dataset
DEM	Digital Elevation Model
GIS	Geographic Information System
HCM	Hydraulic Correction Method
ISRIC	International Soil Reference and Information Centre
KGE	Kling–Gupta Efficiency
LiDAR	Light Detection and Ranging
NSE	Nash–Sutcliffe Efficiency
PE	Flood Peak Error
PSO	Particle Swarm Optimization
PT	Peak Occurrence Time Error
R	Correlation Coefficient
SCE-UA	Shuffled Complex Evolution-University of Arizona
SOTER	Soil and Terrain Database
SRTM	Shuttle Radar Topography Mission

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