

Article

An Integrated Framework for Dam-Break Flood Risk Assessment Considering Hydraulic Hazard and Socioeconomic Vulnerability Using Hydrodynamic Modeling, GIS, and Fuzzy Comprehensive Evaluation

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Abstract

Dam-break floods pose severe threats to downstream urban areas due to their sudden onset, rapid propagation, and potentially catastrophic socioeconomic consequences. This study develops a multi-indicator fuzzy comprehensive evaluation framework for urban flood risk assessment under dam-break scenarios. The framework integrates hydrodynamic simulation outputs with geographic information system-based spatial analysis to characterize spatial variations in flood risk. It incorporates flood hazard factors (inundation depth, arrival time, and inundation duration) derived from a coupled one-dimensional/two-dimensional hydrodynamic model and socioeconomic vulnerability factors (population density and road network density) derived from spatial statistics. Indicator weights were determined using a combined Analytic Hierarchy Process and entropy-weight method, and risk levels were obtained through membership-function calculation and spatial overlay analysis. The framework was applied to the Dongpu and Dafangying reservoirs in Hefei, China, under a scenario of simultaneous dam failure during a probable maximum flood. Results show that, compared with hazard-only assessment, the comprehensive evaluation substantially reduced the extent of high-risk areas and altered their spatial distribution. Very high-risk zones were concentrated along the upstream main channel, where high-velocity floodwaters coincide with dense population and economic activity. Flood arrival time and population density were identified as the most influential indicators in the proposed risk assessment framework. The proposed framework provides a more comprehensive and spatially refined tool for urban dam-break flood risk management and emergency decision-making.



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Keywords: dam-break flood; flood risk assessment; fuzzy comprehensive evaluation; GIS spatial analysis; AHP–entropy weighting

1. Introduction

Reservoirs play an essential role in regional flood control and storage regulation, urban water supply, agricultural irrigation, hydropower generation, and ecological environment regulation, making them one of the key infrastructures supporting regional socioeconomic

development [1,2]. Meanwhile, climate change has increased the frequency of extreme rainfall events [3]. Regional analyses have also identified a significant intensification of extreme precipitation across the middle and lower Yangtze River basin, where the study area is located [4]. Dam failure may result from seismic activity, piping erosion, or structural instability. Once failure occurs, large volumes of stored water can be released within a very short period, generating highly destructive flood waves. The consequences can be particularly severe in densely populated urban areas [5]. Recent studies have emphasized that effective dam-break risk management requires integrating hydrodynamic simulation with spatial risk assessment and emergency decision support. However, such management relies on accurate quantitative assessment of dam-break flood inundation extent and disaster consequences. Therefore, more advanced risk assessment methods and technical approaches are required.

From the perspective of disaster risk theory, disaster risk is generally understood as the joint outcome of hazard, exposure, and vulnerability [6–8]. Hazard reflects the intensity and spatial influence of the disaster-causing factor itself, while vulnerability reflects the degree of exposure and damage sensitivity of the elements at risk. For dam-break floods, given their sudden onset, rapid propagation, and limited decision-making and response time windows, the risk assessment indicator system needs to reflect both the physical disaster process and socioeconomic attributes while maintaining computational efficiency and operability. For this reason, some studies combine exposure and vulnerability into a single dimension, emphasizing the joint role of flood hazard and socioeconomic vulnerability in controlling overall risk [9,10]. This study follows this approach, decomposing dam-break flood risk into two core elements: flood hazard factors and socioeconomic vulnerability factors.

Recent flood research has widely employed hydrodynamic numerical models to simulate flood propagation and inundation characteristics [11–13]. These models provide spatially distributed information on key hydraulic variables, including inundation extent, inundation depth, flood arrival time, and inundation duration, which are essential inputs for flood risk assessment. Geographic Information System (GIS) methods have also been widely used for flood hazard mapping and spatial vulnerability analysis [14,15].

Multicriteria decision-making (MCDM) approaches have increasingly been applied to integrate multiple hazard and vulnerability indicators in flood risk assessment. Common methods include the Analytic Hierarchy Process (AHP), the entropy-weight method, and fuzzy comprehensive evaluation [14,16]. Examples include set pair analysis combined with variable fuzzy sets and fuzzy AHP for comprehensive flood risk zoning [17], improved AHP combined with maximum-likelihood clustering for flash-flood risk assessment [18], and multicriteria analysis of hydrogeomorphological factors for flood hazard mapping in data-scarce river basins [19]. Fuzzy comprehensive evaluation is particularly suitable for integrating the membership degrees of multiple indicators, while combined AHP–entropy weighting can incorporate both expert judgment and objective data variability [14,16]. Nevertheless, reviews of urban flood risk modeling have shown that dynamic exposure and management-oriented decision support remain insufficiently integrated with hydrodynamic simulations [20,21]. Recent frameworks coupling hydrological–hydraulic modeling with bottom-up vulnerability analysis have begun to address this limitation [22].

Previous dam-break flood studies have frequently emphasized inundation depth as an important indicator for characterizing flood hazard and potential consequences [23]. However, the relative importance of inundation depth compared with temporal factors and population exposure may vary under different spatial contexts, particularly in highly urbanized downstream areas. Therefore, whether warning and evacuation time constraints

and population exposure can exert comparable or even greater influences than inundation depth on overall risk remains an important research question addressed in this study.

Despite considerable progress in dam-break flood simulation and risk assessment, several research gaps remain. First, previous flood studies based primarily on hydrodynamic modeling have generally focused on simulating flood propagation and characterizing hydraulic hazards [11–13], with comparatively limited integration of socioeconomic vulnerability factors such as population exposure and transportation infrastructure [20,21]. Second, indicator-based flood risk assessments are often conducted independently of outputs from hydrodynamic numerical models, which may limit their ability to represent spatially heterogeneous flood impacts. Third, existing studies are frequently conducted at watershed or administrative scales, while fine-scale spatial variations in flood risk in highly urbanized downstream areas require further investigation. Finally, indicator weighting methods based solely on subjective judgment or objective data characteristics may not fully exploit the complementary advantages of expert knowledge and measured information.

To address these research gaps, this study develops an integrated, grid-based dam-break flood risk assessment framework for a highly urbanized dual-reservoir setting. The framework couples one-dimensional/two-dimensional hydrodynamic simulation outputs with socioeconomic vulnerability indicators through GIS-based multi-indicator fuzzy comprehensive evaluation. The main objective is to determine how the integration of hydraulic hazard characteristics and socioeconomic vulnerability affects the spatial distribution of dam-break flood risk in densely urbanized downstream areas.

The specific contributions of this study are threefold. First, it establishes a grid-based assessment framework that integrates dam-break hydrodynamic outputs with population exposure and road network density, the latter serving as a proxy for transportation infrastructure exposure. Second, flood arrival time is incorporated as an emergency-oriented temporal indicator to explicitly represent the limited warning and evacuation window associated with dam-break floods. Third, the transition from hydraulic hazard to comprehensive risk is quantitatively examined using a risk-transition matrix and population-exposure statistics, thereby identifying areas where socioeconomic vulnerability either amplifies or moderates the final risk level.

2. Materials and Methods

2.1. Study Area

The study area is located in Hefei City, Anhui Province, China, spanning approximately 116°41′–117°58′ E and 30°57′–32°32′ N, with a total area of 11,445 km². The terrain of the main urban area slopes from northwest to southeast. The Dongpu Reservoir and Dafangying Reservoir are both located in the northwestern part of Hefei City and serve as important control engineering structures within the Nanfei River basin. The total storage capacity of the Dongpu Reservoir is approximately 2.49×10^8 m³, while that of the Dafangying Reservoir is approximately 1.84×10^8 m³; together, the two reservoirs are responsible for important regional flood control, storage regulation, and urban water supply functions. The Nanfei River is one of the principal tributaries draining into Chaohu Lake, and regional flood resilience assessments of the broader Chaohu Lake Basin have indicated that flood disaster resilience varies considerably in space, with the Hefei municipal area exhibiting comparatively higher resilience than some surrounding administrative regions, reflecting differences in infrastructure, management capacity, and socioeconomic development across the basin [24].

The downstream area of the study region is highly urbanized, with a dense population distribution, well-developed transportation infrastructure, and concentrated economic activity. Since the overall terrain of the southeastern urban area of Hefei is relatively low-

lying, a dam-break event could result in rapid flood propagation toward densely populated areas, causing severe socioeconomic losses. The study area is shown in Figure 1.

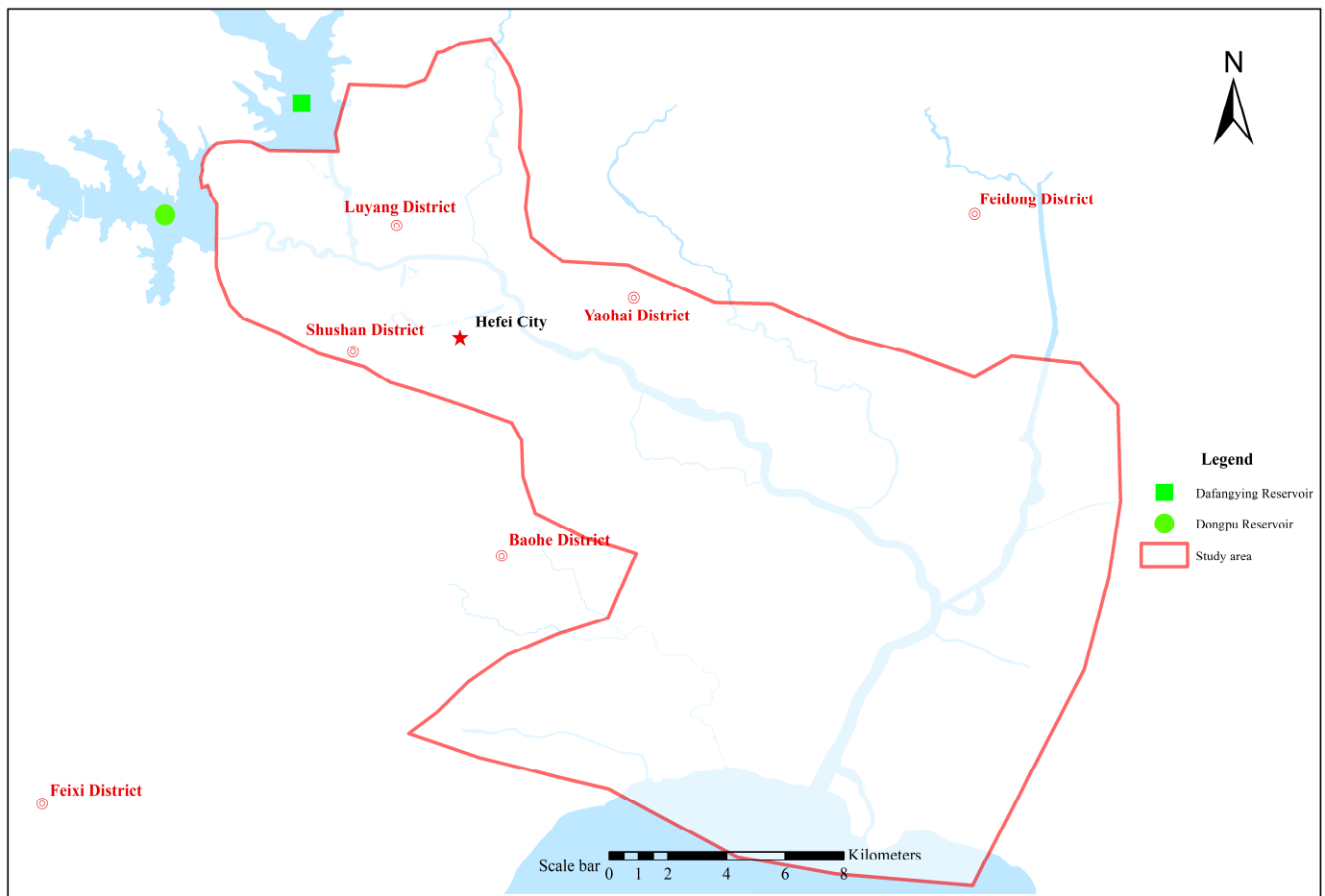


Figure 1. Location of the study area in Hefei City, Anhui Province, China, showing Dongpu and Dafangying reservoirs, the assessment boundary, major administrative districts, and principal water bodies.

2.2. Multi-Indicator Fuzzy Comprehensive Evaluation Model

2.2.1. Indicator Selection

Indicators were selected according to the principles of representativeness, scientific validity, measurability, and data availability [14,15]. The MFCE model comprises two categories of indicators:

- (1) **Hazard factors.** These indicators directly characterize flood hazard and include inundation depth, arrival time, and inundation duration. Inundation depth represents flood hazard intensity, flood arrival time determines the effective warning and evacuation window available to downstream residents, and inundation duration reflects the persistence of flood impacts. Together, these three indicators characterize dam-break flood hazard from the perspectives of intensity, timeliness, and persistence, respectively. Flow momentum was not included as a separate hazard indicator because the present framework was designed to characterize flood propagation, warning time, and socioeconomic exposure rather than to estimate direct structural damage caused by hydrodynamic forces. The exclusion of flow momentum and its implications are further discussed as a limitation in Section 4.4.
- (2) **Vulnerability factors.** Socioeconomic vulnerability reflects the exposure and damage sensitivity of elements at risk [5,15]. Population density was selected to represent

human exposure because casualties constitute the most severe social consequence of dam-break flooding. Road network density was used as a proxy for transportation infrastructure exposure rather than as a direct measure of actual road damage or evacuation capacity. In this framework, a greater road network density represents a higher concentration of road infrastructure potentially exposed to flooding within a grid cell [25]. Evacuation performance was not quantified using road network density because it also depends on network connectivity, flood-induced road blockage, traffic demand, warning dissemination, and population behavior. Other vulnerability indicators, such as building characteristics, demographic composition, household income, critical facilities, and emergency response capacity, were not included because consistent fine-scale spatial data were unavailable across the entire inundation area. To maintain a measurable and reproducible grid-based assessment at a common spatial resolution, the present study therefore focused on population density and road network density.

2.2.2. Overall Framework of Risk Assessment

By decomposing the assessment problem and considering the relationships among indicators, the MFCE framework was structured as a multi-indicator system comprising a target layer, a criterion layer, and an indicator layer. The hazard factors were derived from hydrodynamic simulations, while the vulnerability factors were derived from map-based spatial statistics. Finally, the indicator weights and membership degrees were integrated through fuzzy comprehensive evaluation, and the resulting values were mapped in GIS to obtain the comprehensive flood risk assessment results. The overall framework is shown in Figure 2.

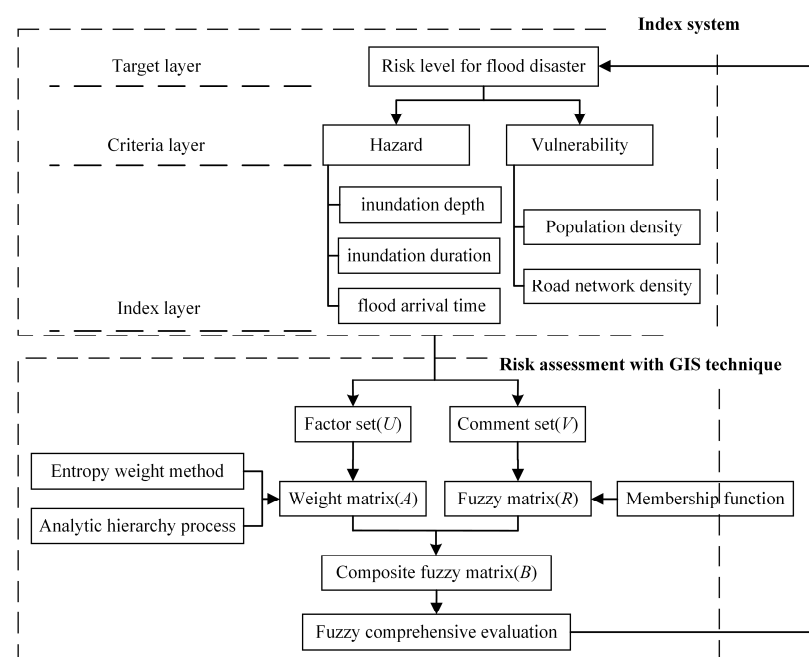


Figure 2. Workflow of the multi-indicator fuzzy comprehensive evaluation (MFCE) framework for dam-break flood risk assessment. Hydrodynamic and socioeconomic indicators are integrated through AHP–entropy weighting, membership-function calculation, and GIS-based spatial classification.

2.3. Dam-Break Flood Simulation

The DAMBRK model, based on the transient hydraulic dam-breach simulation approach developed by Fread and Harbaugh [26], is a one-dimensional numerical model used to simulate breach development and generate breach outflow hydrographs. It has

been widely applied in dam-break flood analysis. Accordingly, this study employed a breach model to calculate breach outflow, with the resulting outflow used as the boundary condition for flood-routing simulation. The breach parameters were derived from the breach simulation based on the engineering characteristics of the two reservoirs and the assumed piping failure mode. The final breach geometry, including breach width and depth, was obtained from the simulated breach development process and subsequently used to generate the breach outflow hydrograph for downstream flood routing. For the case of a piping-type breach, the model describing the flow of reservoir water into the pipe conduit is expressed as follows:

$$Q_b = A \left[\frac{2g(H - H_p)}{1 + fL/D} \right]^{0.5} \quad (1)$$

where Q_b is the discharge through the pipe conduit; A is the cross-sectional area of the breach; g is the gravitational acceleration; H_p is the centerline inclination angle; $(H - H_p)$ is the hydraulic head at the breach; L is the length of the pipe conduit; D is the pipe diameter; and f is the friction coefficient.

The dam-break scenario was established using the PMF-related check flood conditions specified in the available reservoir engineering documentation. The check flood levels of the Dongpu and Dafangying reservoirs were 34.30 m and 33.64 m, respectively. These check flood conditions were obtained from the existing engineering design dataset rather than recalculated in the present study. The pre-flood initial water levels of the Dongpu and Dafangying reservoirs were set at 28.00 m and 27.50 m, respectively. When the two reservoirs reached their respective check flood levels, simultaneous piping-induced failure of the two main dams was assumed as a hypothetical extreme scenario for dam-break risk assessment and emergency planning. The breach development processes were simulated using the DAMBRK model based on the engineering characteristics of the two reservoirs and the assumed piping-failure mode.

A coupled one-dimensional/two-dimensional hydrodynamic modeling framework, MIKE FLOOD, was adopted to simulate dam-break flood propagation. The framework couples the one-dimensional MIKE 11 model, which represents flow propagation through the river-channel system, with the two-dimensional MIKE 21 FM model, which represents flood spreading across the downstream floodplain. The model was constructed using the available engineering parameters, river-channel cross-section data, and project-specific 1:10,000 topographic survey data. The original terrain input consisted of topographic survey data rather than a fixed-resolution raster DEM. Terrain elevations were represented through the unstructured triangular computational mesh; therefore, a single raster-cell resolution was not applicable to the terrain representation used in the model. The maximum mesh area was controlled to be no greater than 0.05 km², and local refinement was applied in areas with substantial terrain variation, important hydraulic features, complex flow conditions, and potential inundation impacts. The upstream boundary condition was defined using the breach hydrographs generated by the DAMBRK model, whereas the downstream boundary condition was specified using the PMF water level of Chaohu Lake obtained from the project-specific flood-control design documentation. Manning's roughness coefficients were assigned according to the land-use categories within the inundation area. The adopted values were 0.025 for water surfaces, 0.070 for rural settlements, 0.050 for croplands, and 0.060 for urban areas, as summarized in Table 1. These values were selected based on the local terrain characteristics, land-use conditions, available engineering information, and previous hydraulic modeling experience.

Table 1. Manning’s roughness coefficients used in the MIKE FLOOD model.

Land-Use Category	Manning’s n
Water surface	0.025
Rural settlements	0.070
Croplands	0.050
Urban areas	0.060

Individual buildings were not explicitly represented as impermeable obstacles in the two-dimensional computational domain. Their aggregate influence on flood-wave resistance was represented indirectly through the land-use-specific Manning’s roughness coefficients, including 0.060 for urban areas and 0.070 for rural settlements. The main-dam breach processes were represented by the DAMBRK-generated breach hydrographs used as the upstream boundary conditions. Other reservoir hydraulic structures, including outlet culverts, spillways, and gates, were not represented separately in the coupled flood-routing model for the prescribed simultaneous piping-failure scenario.

The finite volume method was used to simulate the dam-break flood-routing process and calculate the flow velocity, flow direction, and water depth at each time step. The total simulation duration was set to 30 h, with a computational time step of 1 s. A dry-bed depth of 0.005 m and a wet-bed depth of 0.1 m were used to define the wetting and drying conditions. The overall hydraulic model setup, boundary conditions, and key input parameters are summarized in Table 2.

Direct validation of the dam-break simulation against observed data was not feasible because no actual dam-break event has occurred at either Dongpu or Dafangying Reservoir. The simultaneous piping-failure scenario examined in this study represents a hypothetical extreme condition established for dam-break risk assessment and emergency planning rather than the reconstruction of a historical event. The plausibility of the simulation results was therefore assessed using indirect evidence. First, the DAMBRK-type breach model and the MIKE FLOOD hydrodynamic modeling framework have been extensively applied and evaluated in previous dam-break and flood-routing studies [26,27]. Second, the breach development curves obtained for both reservoirs exhibit the characteristic rapid increase, temporary reduction, renewed increase, and subsequent recession associated with piping-induced breach development. The peak discharges occurred approximately 3 h and 4 h after breach initiation at Dongpu and Dafangying reservoirs, respectively, and the model calculations satisfied the internal water-balance check described in Section 3.1. Third, the final breach geometry, breach-development duration, and peak discharge were examined with reference to the definitions, controlling factors, and empirical ranges reported in previous breach-parameter studies [28,29]. However, this comparison should be regarded as an order-of-magnitude plausibility assessment rather than independent empirical validation because empirical breach equations are themselves associated with considerable uncertainty and require site-specific inputs.

The principal hydraulic uncertainties are associated with breach geometry, Manning’s roughness coefficients, terrain representation, and numerical discretization. The breach geometries were obtained from the DAMBRK simulations, whereas Manning’s roughness coefficients and mesh configurations were specified according to land-use characteristics, available engineering information, and hydraulic modeling requirements. A systematic multi-parameter sensitivity analysis was not conducted because the available hydrodynamic dataset represents a prescribed design scenario and does not contain the controlled parameter ensembles required for such an analysis. This limitation is explicitly acknowledged, and the pathway through which these uncertainties may influence the final risk zoning is discussed in Section 4.4.

Table 2. Summary of hydraulic model setup and input parameters.

Parameter	Description
Scenario basis	PMF-related check flood conditions obtained from the available reservoir engineering documentation
Dam-break scenario	Simultaneous piping-induced failure of Dongpu and Dafangying reservoirs under the PMF-based check flood condition
Initial reservoir water level	28.00 m for Dongpu Reservoir; 27.50 m for Dafangying Reservoir
Check flood level	34.30 m for Dongpu Reservoir; 33.64 m for Dafangying Reservoir
Breach type	Piping-induced breach
Breach-development duration	22.00 h for Dongpu Reservoir; 24.00 h for Dafangying Reservoir
Final breach width	50.70 m for Dongpu Reservoir; 38.30 m for Dafangying Reservoir
Final breach depth	26.00 m for Dongpu Reservoir; 24.50 m for Dafangying Reservoir
Peak breach discharge	5194 m ³ /s for Dongpu Reservoir; 3096 m ³ /s for Dafangying Reservoir
Terrain data	Project-specific 1:10,000 topographic survey data
Mesh type	Unstructured triangular mesh
Maximum mesh area	≤0.05 km ²
Mesh refinement	Local refinement in areas with substantial terrain variation, important hydraulic features, complex flow conditions, and potential inundation impacts
Manning's roughness coefficient	Assigned according to land-use category, as listed in Table 1
Upstream boundary condition	DAMBRK-generated breach hydrograph
Downstream boundary condition	PMF water level of Chaohu Lake obtained from project-specific flood-control design documentation; the exact value is not publicly reported
Simulation duration	30 h
Time step	1 s
Numerical method	Finite volume method
Wetting and drying thresholds	Dry-bed depth of 0.005 m and wet-bed depth of 0.1 m

2.4. Data Preparation and Processing

2.4.1. Selection of Membership Functions

The core of the MFCE model lies in the calculation of membership degrees, making it necessary to select appropriate membership functions. Because the five indicators have monotonic but directionally different relationships with flood risk, ascending and descending half-trapezoidal and triangular piecewise membership functions were adopted to calculate the membership degree of each indicator. Let U denote the factor set of the evaluation set P [30]. The membership functions are given in the following equations:

$$u_i p_1 = \begin{cases} 1 & 0 < x \leq C_1 \\ \frac{C_2 - x}{C_2 - C_1} & C_1 < x < C_2 \\ 0 & x \geq C_2 \end{cases} \quad (2)$$

$$u_{ip_2} = \begin{cases} 0 & x \leq C_1 \text{ or } x \geq C_3 \\ \frac{x - C_1}{C_2 - C_1} & C_1 < x \leq C_2 \\ \frac{C_3 - x}{C_3 - C_2} & C_2 < x < C_3 \end{cases} \quad (3)$$

$$u_{ip_3} = \begin{cases} 0 & x \leq C_2 \text{ or } x \geq C_4 \\ \frac{x - C_2}{C_3 - C_2} & C_2 < x \leq C_3 \\ \frac{C_4 - x}{C_4 - C_3} & C_3 < x < C_4 \end{cases} \quad (4)$$

$$u_{ip_4} = \begin{cases} 0 & x \leq C_3 \text{ or } x \geq C_5 \\ \frac{x - C_3}{C_4 - C_3} & C_3 < x \leq C_4 \\ \frac{C_5 - x}{C_5 - C_4} & C_4 < x < C_5 \end{cases} \quad (5)$$

$$u_{ip_5} = \begin{cases} 0 & x \leq C_4 \\ \frac{x - C_4}{C_5 - C_4} & C_4 < x < C_5 \\ 1 & x \geq C_5 \end{cases} \quad (6)$$

In these equations, C_1 to C_5 denote the five discontinuity points corresponding to the five relative risk levels. Because the membership functions of adjacent risk levels overlap, a given indicator value may have non-zero membership degrees in two adjacent risk levels. According to the principle of maximum membership, the indicator value is assigned to the risk level with the highest membership degree [31].

2.4.2. Data Preparation

Hazard factor data were derived from the hydrodynamic model. Among the vulnerability factors, population data were obtained from statistical yearbooks, and the spatial distribution of population density within the study area was obtained through spatial interpolation. The population density raster was further converted into population count data according to the grid cell area ($100 \text{ m} \times 100 \text{ m}$), which was used to quantify the exposed population under different flood risk levels. To further quantify population exposure under different flood risk levels, the population density raster was converted into population counts for each grid cell by considering the raster cell area. Road network data were obtained using a map data downloader, and the spatial distribution of road network density was obtained through GIS-based statistical analysis and spatial interpolation.

2.4.3. Data Processing

Data processing refers to the calculation of indicator weights and membership degrees. To calculate the weight of each indicator, the MFCE model employed both the AHP and the entropy weight method to determine combined weights.

(1) Standardization

All factors were first classified into positive factors and negative factors and then normalized to the range of 0 to 1 to eliminate dimensional effects among different factors. For positive factors, higher values indicate greater flood risk, whereas for negative factors, higher values indicate lower flood risk. Positive and negative factors were normalized using Equations (7) and (8), respectively.

$$y_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \quad (7)$$

$$y_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \quad (8)$$

where y_{ij} is the normalized value, ranging from 0 to 1; x_{ij} is the original value of factor j ; $\max(x_{ij})$ is the maximum value of factor i ; and $\min(x_{ij})$ is the minimum value of factor j .

(2) Analytic Hierarchy Process (AHP)

AHP is a robust and flexible tool that enables the evaluation of multiple variables based on expert knowledge and judgment to support decision-making. It establishes a hierarchical structure for multiple indicators by assigning weights to each criterion, thereby reducing decision-making complexity. In addition, AHP offers relative advantages in criterion ranking, allowing flexible ordering of parameters according to specific circumstances. As one of the most reliable and flexible multi-criteria analysis methods, AHP is commonly used to help decision-makers conduct pairwise comparisons of factors using an importance scale [32]. Accordingly, AHP has been widely applied across different research fields and has become increasingly common in flood risk assessment in recent years [14,16].

The first step of this method involves establishing a comparison matrix A based on the Saaty importance scale, through which hazard factors or vulnerability factors are pairwise compared. Matrix A contains nine integers ranging from 1 to 9, representing increasing levels of relative importance, as detailed in Table 3.

$$C = \begin{bmatrix} 1 & C_{12} & \dots & C_{1n} \\ C_{21} & 1 & \dots & C_{2n} \\ \dots & \dots & 1 & \dots \\ C_{n1} & C_{n2} & \dots & 1 \end{bmatrix} \quad (9)$$

Table 3. Importance scale in AHP.

Scale Number	Description
1	Equally important
3	Moderately important
5	Strongly important
7	Very strongly important
9	Extremely important
2,4,6,8	The intermediate situation between the above two adjacent judgments
Reciprocals	Inverse comparison

In this notation, C_{ij} represents the relative importance value of element compared with element with respect to the target. The pairwise comparison results for hazard factors and vulnerability factors are shown in Tables 4 and 5, respectively, and the comparison matrix between hazard and vulnerability dimensions is shown in Table 6. In this study, the priority scores for all five factors were assigned based on expert opinion. Specifically, a total of ten experts with more than ten years of relevant professional experience, primarily in the fields of hydraulic engineering and disaster prevention and mitigation, were invited to independently assign the relative importance of the criteria/sub-criteria using the importance scale (Table 3). Each expert completed the pairwise comparison matrices independently and without communication with other panel members, in order to minimize anchoring bias. The consistency ratio (CR) of each individual expert's judgment matrix was calculated separately, and all ten experts' judgment matrices satisfied $CR < 0.1$, confirming the internal consistency and reliability of the pairwise comparisons used to derive the final weights. The final pairwise comparison values used in this study were obtained by taking the arithmetic mean of the individual judgment matrices across all ten experts.

Table 4. Risk comparison matrix for flood disasters.

The Danger of Flood Disasters	The Time of Flood Arrival	Submerged Water Depth	Duration of Inundation
The time of flood arrival	1	2	3
Submerged water depth	1/2	1	2
Duration of inundation	1/3	1/2	1

Table 5. Comparison matrix of economic and social vulnerability.

Economic and Social Vulnerability	Density of Population	Density of Road Network
Density of population	1	3
Density of road network	1/3	1

Table 6. Comparison matrix of flood disaster hazard and socioeconomic vulnerability.

Flood Disaster Risk	The Danger of Flood Disasters	Economic and Social Vulnerability
The danger of flood disasters	1	2
Economic and social vulnerability	1/2	1

The consistency index was then calculated using Equation (10).

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (10)$$

Finally, the consistency of the judgments was examined through the consistency ratio (CR), which reflects the quality of the comparisons. Saaty [32] recommended that CR should be less than 0.1; otherwise, the pairwise comparison matrix should be reconstructed, where $\lambda_{\max}$ is the maximum eigenvalue of the comparison matrix.

$$CR = \frac{CI}{RI} \quad (11)$$

where is the consistency ratio and is the random consistency index. The value of RI can be obtained from a reference table, as shown in Table 7.

Table 7. Random index (RI).

Number of Criteria	1	2	3	4	5	6	7	8	9	10	11
RI	0	0	0.58	0.09	1.12	1.24	1.32	1.41	1.45	1.49	1.51

(3) Entropy Weight Method

Shannon combined entropy with information theory and proposed the entropy weight method for determining objective weights based on indicator variability. The greater the degree of variability in an indicator, the more information it provides [33]; therefore, it plays a greater role and is assigned a higher weight in the comprehensive evaluation. The weight calculation procedure is as follows:

Step 1: For m evaluation objects and n evaluation factors, a normalized evaluation matrix is obtained, where p_{ij} is the normalized value. The entropy of factor j is calculated using Equation (12).

$$e_j = \frac{-\sum_{i=1}^m p_{ij} \ln p_{ij}}{\ln m} \quad (12)$$

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^m y_{ij}} (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (13)$$

When $p_{ij} = 0$, $\lim_{p_{ij} \rightarrow 0} p_{ij} \ln p_{ij} = 0$.

Step 2: The entropy weight of factor j is calculated using Equation(14).

$$\omega_{oj} = \frac{1 - e_j}{\sum_{j=1}^n (1 - e_j)} \quad (14)$$

(4) AHP–Entropy Combined Weighting Method Based on Minimum Relative Entropy

The AHP–entropy combined method integrates AHP and the entropy weight method based on the principle of minimum relative entropy. According to the minimum relative entropy principle [16], the weight of each factor obtained from different methods should be relatively consistent. Therefore, this study combines AHP and the entropy weight method to obtain the combined weight of each factor, on the grounds that the AHP–entropy combined approach produces more reasonable results than either model used independently. The objective function is expressed as:

$$\min F = \sum_{j=1}^m \omega_j (\ln \omega_j - \ln \omega_{sj}) + \sum_{j=1}^m \omega_j (\ln \omega_j - \ln \omega_{oj}) \quad (15)$$

$$s.t. \sum_{j=1}^m \omega_j = 1, \omega_j > 0 \quad (16)$$

Assume that the subjective weights calculated by AHP are represented by ω_{sj} , and the objective weights calculated by the entropy weight method are represented by ω_{oj} . The objective function can be solved using the Lagrangian function:

$$\omega_j = \frac{(\omega_{sj}\omega_{oj})^{1/2}}{\sum_{j=1}^m (\omega_{sj}\omega_{oj})^{1/2}} (j = 1, 2, \dots, m) \quad (17)$$

Based on the principle of minimum relative information entropy, the combined subjective–objective weight of each indicator was calculated using Equation (17) to obtain the final combined weights. The results are presented in Table 8.

Table 8. Summary table of combined weights of indicators for dam-break flood disaster risk.

Evaluation Index	Analytic Hierarchy Process Weight	Information Entropy Weight	Combination Weight
The time of flood arrival	0.3597	0.1659	0.349
Submerged water depth	0.198	0.1248	0.144
Duration of inundation	0.1089	0.2538	0.162
density of population	0.25	0.1269	0.185
density of road network	0.0833	0.3286	0.160

When calculating the membership degree, the evaluation set $P = (P_1, P_2, \dots, P_5)$ was first defined. The five components of set PPP correspond to five relative risk levels: very low risk (P_1), low risk (P_2), moderate risk (P_3), high risk (P_4), and very high risk (P_5). For each indicator, the observed value range between its minimum and maximum values was divided into four equal intervals, resulting in five discontinuity points, C_1, C_2, C_3, C_4 , and C_5 . This equal-interval procedure provides a transparent and internally consistent method for generating case-specific classification thresholds for indicators with different dimensions and value ranges. The direction of risk was determined according to the physical or socioeconomic meaning of each indicator. A shorter flood arrival time represents a higher risk level, whereas greater inundation depth, longer inundation duration, higher population density, and greater road network density represent higher risk levels. Because

the purpose of this study is to identify the relative spatial distribution of flood risk within the study area, the resulting discontinuity points are used as case-specific thresholds for relative risk zoning. They should not be interpreted as universal disaster-loss thresholds or regulatory classification standards. The discontinuity points and corresponding interval values for each indicator are presented in Table 9.

Table 9. Data-driven equal-interval discontinuity points used in the case-specific membership functions.

Evaluation Indicator	Δ	C_1	C_2	C_3	C_4	C_5
Flood arrival time (h)	4.40	0.25	4.65	9.05	13.45	17.85
Inundation depth (m)	2.73	0.01	2.74	5.47	8.20	10.93
Inundation duration (h)	4.48	0.25	4.73	9.21	13.69	18.17
Population density (persons/km ²)	8981	200	9181	18,162	27,143	36,124
Road network density (km/km ²)	4.82	0.15	4.97	9.79	14.61	19.43

3. Results

3.1. Dam-Break Flood Simulation Results

Based on the engineering characteristics of the Dongpu and Dafangying reservoirs and the principle of scenario severity, the dam-break condition was defined as simultaneous piping-induced failure of the main dams of both reservoirs under the PMF-based check flood condition. The pre-flood initial water levels of the Dongpu and Dafangying reservoirs were set at 28.00 m and 27.50 m, respectively.

When the water levels of the Dongpu and Dafangying reservoirs reached 34.30 m and 33.64 m, respectively, piping-induced breaches occurred simultaneously at both reservoirs. The breach model was used to simulate the breach development process, with the failure simulation lasting 22.00 h and 24.00 h, respectively. The simulation results indicate that the final breach top widths of the Dongpu and Dafangying reservoirs were 50.70 m and 38.30 m, respectively, with breach depths of 26.00 m and 24.50 m. Figures 3 and 4 show the breach outflow hydrographs of the Dongpu and Dafangying reservoirs, respectively. As shown in the figures, the breach discharge increased rapidly as the piping channel developed, followed by a sudden drop in discharge as the upper dam body above the breach collapsed. The breach subsequently redeveloped and expanded, with discharge rising again to a peak before gradually decreasing. The peak discharges of the Dongpu and Dafangying reservoirs were 5194 m³/s and 3096 m³/s, occurring at approximately 3 h and 4 h after breach initiation, respectively. The computed results are consistent with the typical development pattern of piping-induced dam breaches, and water balance verification confirmed the reasonableness of the computed results.

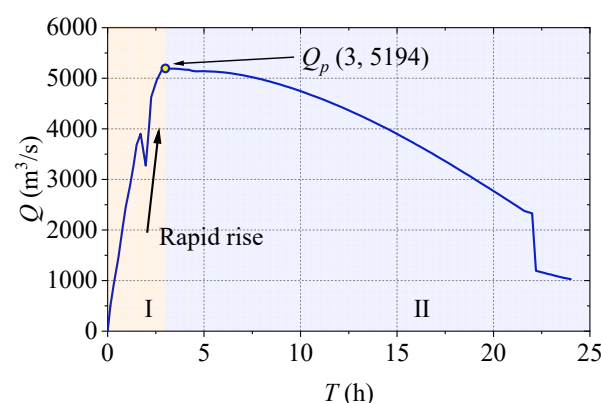


Figure 3. Flow process curve of the piping-induced dam break at Dongpu Reservoir. "I" and "II" denote the stages before and after the breach discharge reaches its peak value (Q_p), respectively.

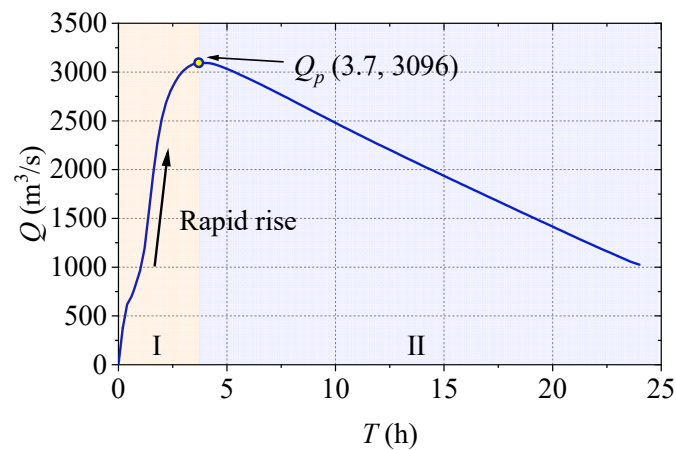


Figure 4. Flow process curve of the piping-induced dam break at Dafangying Reservoir. “I” and “II” denote the stages before and after the breach discharge reaches its peak value (Q_p), respectively.

To ensure simulation stability, the total computation time was set to 30 h with a time step of 1 s. A dry-bed depth of 0.005 m and a wet-bed depth of 0.1 m were used to define the dry-wet boundary. The finite volume method was then applied for numerical simulation to obtain the downstream flood-routing process. Partial results are shown in Figure 5, which are consistent with the general evolution pattern of dam-break floods.

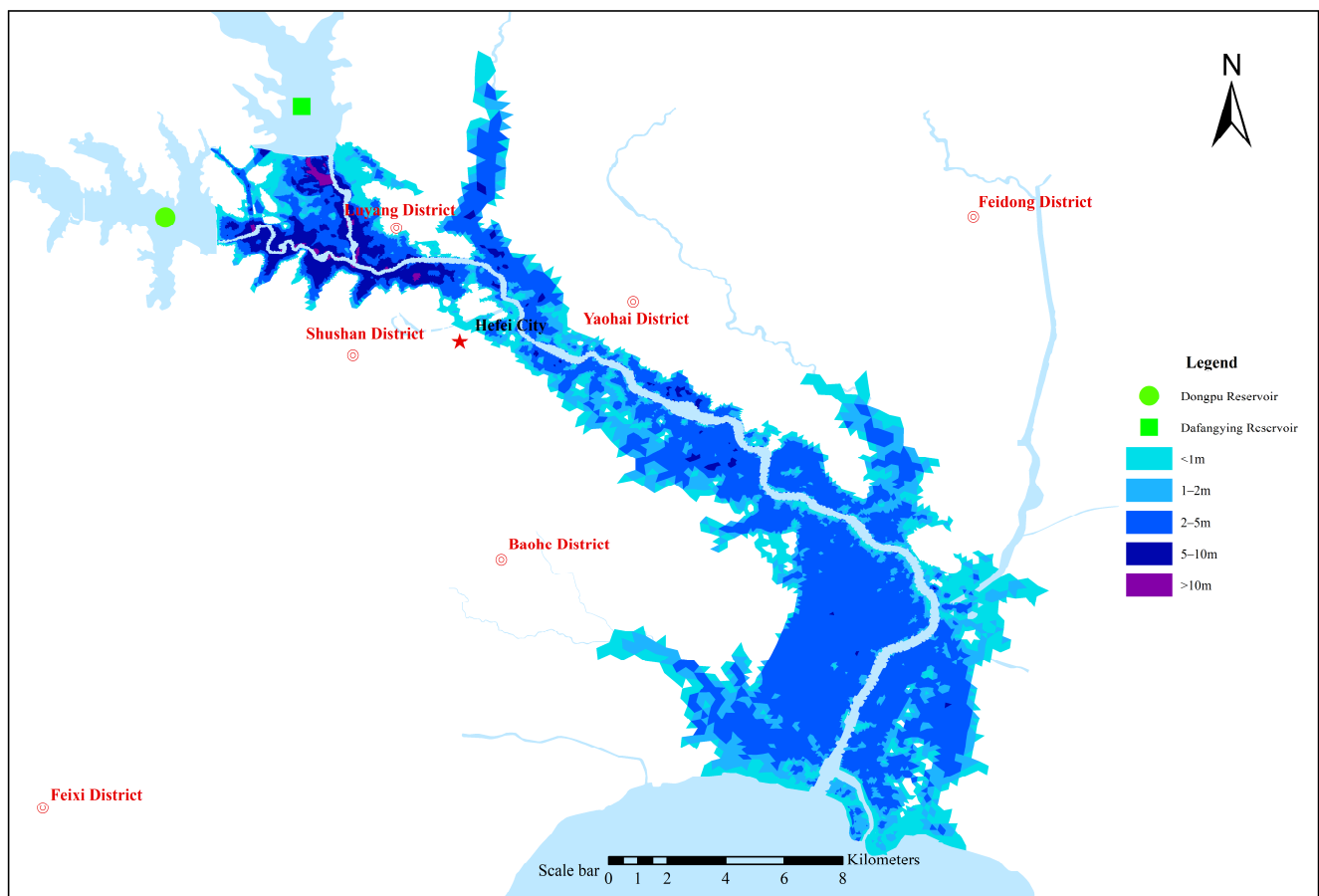


Figure 5. Map of flood inundation extent.

3.2. Fuzzy Comprehensive Evaluation of Flood Risk

First, the five indicators were grouped into factor set U , comprising flood arrival time (u_1), inundation depth (u_2), inundation duration (u_3), population density (u_4), and road network density (u_5). Based on the principles of the MFCE model, the complete fuzzy comprehensive evaluation result matrix B was obtained, as shown in Equation (18).

$$B = A \circ \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} = A \circ \begin{bmatrix} A_1 \circ \begin{bmatrix} u_1p_1 & u_1p_2 & u_1p_3 & u_1p_4 & u_1p_5 \\ u_2p_1 & u_2p_2 & u_2p_3 & u_2p_4 & u_2p_5 \\ u_3p_1 & u_3p_2 & u_3p_3 & u_3p_4 & u_3p_5 \end{bmatrix} \\ A_2 \circ \begin{bmatrix} u_4p_1 & u_4p_2 & u_4p_3 & u_4p_4 & u_4p_5 \\ u_5p_1 & u_5p_2 & u_5p_3 & u_5p_4 & u_5p_5 \end{bmatrix} \end{bmatrix} \quad (18)$$

$$A_1 = (0.349, 0.144, 0.162), A_2 = (0.185, 0.160), A = (0.6667, 0.3333).$$

In the formula, A_1 and A_2 denote the weight matrices of flood hazard and socioeconomic vulnerability, respectively; B_1 and B_2 denote their corresponding result matrices; $u_i p_j$ is the membership degree of the index u_i for the comment p_j .

The result matrix B of the MFCE model can be expressed as the following formula for the membership degree $B_1 P_i$ of each risk level.

$$\begin{aligned} BP_1 &= 0.6667 \times B_1 P_1 + 0.3333 \times B_2 P_1 \\ BP_2 &= 0.6667 \times B_1 P_2 + 0.3333 \times B_2 P_2 \\ BP_3 &= 0.6667 \times B_1 P_3 + 0.3333 \times B_2 P_3 \\ BP_4 &= 0.6667 \times B_1 P_4 + 0.3333 \times B_2 P_4 \\ BP_5 &= 0.6667 \times B_1 P_5 + 0.3333 \times B_2 P_5 \end{aligned} \quad (19)$$

According to the principle of maximum membership degree, each grid cell was assigned to the risk level corresponding to the maximum value among the five membership degrees obtained from Equation (19). The final result matrix B was thus obtained, as shown in Equation (20).

$$\begin{aligned} B &= \text{Con}(\max(BP_1, BP_2, BP_3, BP_4, BP_5) = BP_1, 1, \\ &\text{Con}(\max(BP_1, BP_2, BP_3, BP_4, BP) = BP_2, 2, \\ &\text{Con}(\max(BP_1, BP_2, BP_3, BP_4, BP) = BP_3, 3, \\ &\text{Con}(\max(BP_1, BP_2, BP_3, BP_4, BP) = BP_4, 4, 5))) \end{aligned} \quad (20)$$

Similarly, based on the above formulas, the socioeconomic vulnerability assessment result B_2 is shown in Figure 6.

The results show that higher socioeconomic vulnerability is mainly distributed in areas with denser population and road networks, particularly in the urbanized upstream portion of the dam-break flood impact area. Overall, the risk level decreases from the upstream to the downstream sections of the main channel, and no very high-risk areas were identified. The areas of each risk level are generally spatially contiguous, indicating that the socioeconomic distribution within the study area exhibits spatial continuity with few abrupt transitions.

To compare the influence of flood hazard factors on the evaluation results, the flood hazard assessment results (Figure 7) and the MFCE model assessment results (Figure 8) are presented together. Because the raster overlay operation in GIS is based on the intersection principle, the output raster extent of the MFCE model is consistent with the assessment extent of the hazard factors.

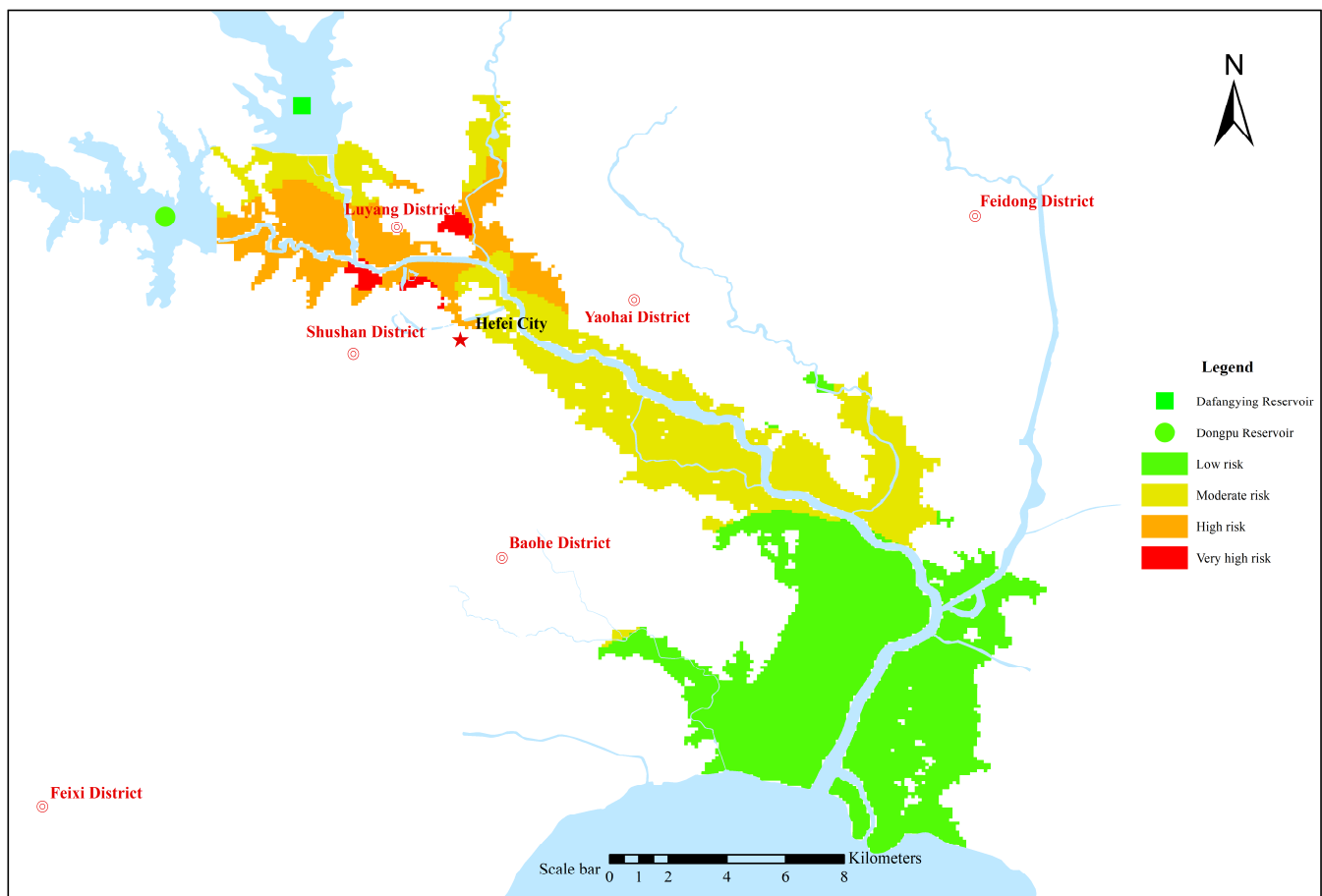


Figure 6. The evaluation results of economic vulnerability.

Comparing Figures 7 and 8 with the hazard-factor assessment results, it can be observed that the proportion of high-risk areas within the study area decreases. This is because dam-break flood disaster risk depends not only on the hazard of the dam-break flood itself, but also on the amplifying or moderating effect of the socioeconomic conditions within the flood-affected area on disaster risk. Therefore, after the fuzzy comprehensive evaluation overlay of the five indicators, grid cells that were originally classified as high hazard risk had their risk level reduced after being overlaid with grid cells of lower socioeconomic vulnerability. This demonstrates that the fuzzy comprehensive evaluation, by jointly considering both hazard-causing factors and the elements at risk, yields more comprehensive and scientifically sound assessment results.

To further analyze the change in risk distribution, the risk areas obtained from the hazard-factor assessment were compared with those obtained from the MFCE model, as shown in Table 10. The results show that, after fuzzy comprehensive evaluation, the ranking of the area proportions of each risk level changed relative to the flood hazard assessment results. The area change rates from very low risk to very high risk were -27.75% , 114.10% , -50.62% , -59.75% , and -40.05% , respectively. Except for the low-risk area, which increased, the areas of all other risk levels decreased after fuzzy comprehensive evaluation. The substantial decrease in high-risk areas, which originally accounted for the largest proportion, indicates that many areas with high hydraulic hazard were reassigned to lower comprehensive risk levels after considering socioeconomic vulnerability.

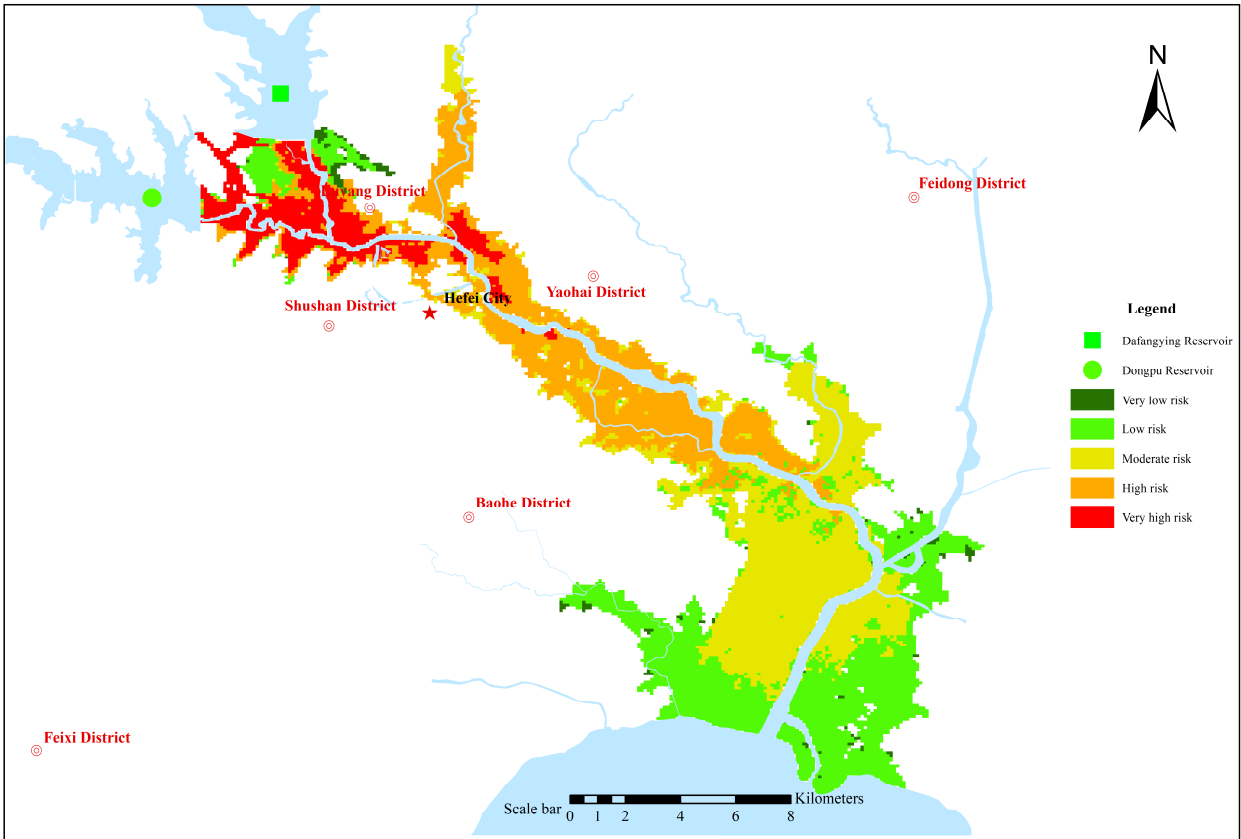


Figure 7. Evaluation results of flood disaster hazard risk.

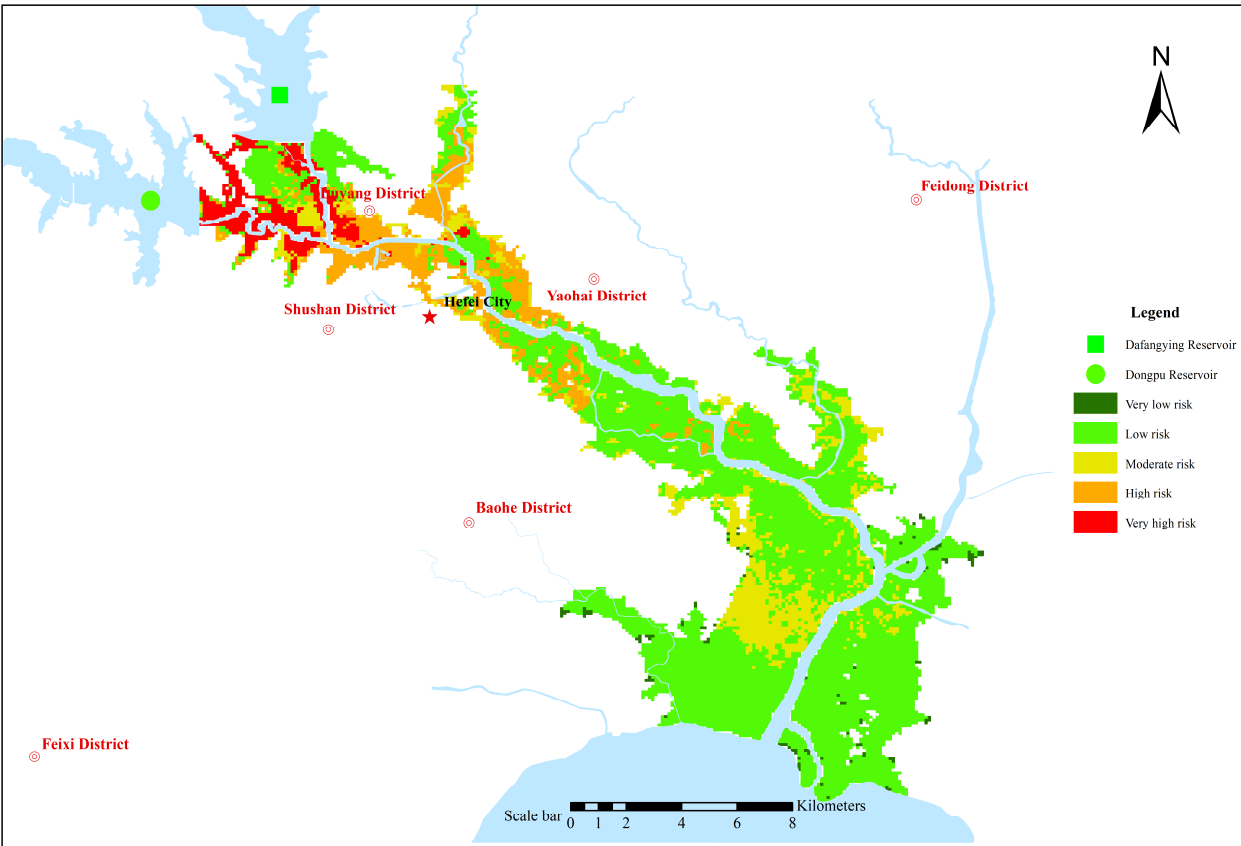


Figure 8. The fuzzy comprehensive evaluation result of the risk of dam-break flood disasters.

Table 10. Comparison of changes in the area of each risk level within the dam-break flood impact area.

Risk Category	Hazard Assessment Area (km ²)	Fuzzy Comprehensive Evaluation Area (km ²)	Area Change Rate (%)
Very low risk	1.73	1.25	−27.75
Low risk	40.84	87.44	114.10
Moderate risk	37.32	18.43	−50.62
High risk	34.36	13.83	−59.75
Very high risk	13.66	6.96	−40.05

However, the integration of socioeconomic vulnerability indicators also resulted in risk upgrading in some areas. To quantify this spatial redistribution, a cell-by-cell transition analysis between the hazard assessment results and the final MFCE risk assessment results was conducted, as shown in Table 11. The results indicate that a total area of 0.89 km² experienced risk upgrading, accounting for approximately 0.70% of the total assessed area. Specifically, 0.77 km² was transferred from very low hazard to low risk, 0.01 km² was transferred from very low hazard to moderate risk, and 0.11 km² was transferred from moderate hazard to high risk. Comparison of Figures 7 and 8 indicates that these upgraded cells are spatially limited and are mainly associated with the more urbanized portion of the inundation area and the principal flood-propagation corridors, where population density and road network density are relatively high. These results demonstrate that socioeconomic vulnerability can increase the comprehensive risk level in some grid cells even when the corresponding hydraulic hazard intensity is relatively limited.

Table 11. Transition matrix between the hazard assessment and the MFCE risk assessment (km²).

Final Risk Level After MFCE Hazard Level Before MFCE					
	Very Low Risk	Low Risk	Moderate Risk	High Risk	Very High Risk
Very low hazard	0.79	0.77	0.01	0	0
Low hazard	0.44	39.32	0	0	0
Moderate hazard	0.02	24.44	15.28	0.11	0
High hazard	0	20.52	1.79	11.38	0
Very high hazard	0	2.39	1.35	2.34	6.96

To further quantify the influence of socioeconomic vulnerability on the redistribution of flood risk, population exposure under different risk levels was calculated by integrating the final risk map with the population count raster. The results are summarized in Table 12. The total exposed population within the assessed inundation area was 810,941. The very low-, low-, moderate-, high-, and very high-risk areas contained 2685, 379,065, 109,935, 213,186, and 106,070 residents, respectively. The high-risk and very high-risk areas jointly covered 20.79 km², accounting for approximately 16.25% of the total assessed area, but contained 319,256 residents, accounting for approximately 39.37% of the total exposed population. This contrast indicates that population exposure is disproportionately concentrated in the higher-risk zones. Although the very high-risk area occupied a relatively small spatial extent, its exposed population remained considerable because of the concentration of residents in urbanized areas. These results demonstrate that socioeconomic vulnerability can significantly amplify the consequences of dam-break flooding in densely populated regions.

Table 12. Population exposure under different flood risk levels.

Risk Level	Area (km ²)	Exposed Population (Persons)
Very low risk	1.25	2685
Low risk	87.44	379,065
Moderate risk	18.43	109,935
High risk	13.83	213,186
Very high risk	6.96	106,070

The comprehensive risk distribution is shown in Figure 8. High-risk areas are mainly located downstream of the reservoirs and along the main flood propagation channels. Moderate-risk areas are mainly distributed in transition zones between high- and low-risk areas, whereas low-risk areas are concentrated in peripheral regions farther from the flood propagation channels. This spatial heterogeneity reflects the combined influence of hydraulic hazard intensity and socioeconomic exposure conditions.

4. Discussion

4.1. Mechanisms Underlying the Spatial Distribution of Flood Risk

The spatial distribution of dam-break flood risk is jointly controlled by hydrodynamic processes, topographic conditions, and the spatial pattern of urban exposure. High-risk areas are mainly located downstream of the reservoirs and near the main flood propagation channels; moderate-risk areas are located in the transition zones between high- and low-risk areas; and low-risk areas are concentrated in peripheral areas farther from the flood propagation channels. This spatial pattern is closely related to the hydrodynamic evolution of the dam-break flood during propagation. In the early stage of dam failure, the breach discharge increases rapidly within a very short period and reaches a peak flow, releasing substantial hydrodynamic energy and forming a high-velocity, high-energy flood wave that propagates downstream. As the flood continues to advance downstream, its energy gradually attenuates. This attenuation process is mainly governed by channel friction, flow resistance at the ground surface, storage effects within the floodplain, and complex topographic conditions [34]. As a result, flood hazard generally decreases with increasing distance from the dam. At the same time, local topographic conditions exert an important influence on flood inundation processes. Low-lying areas and flat floodplains, owing to their limited drainage capacity, tend to retain floodwater for longer periods, leading to a significant increase in inundation duration and thereby raising the overall risk level of these areas. These results indicate that the spatial risk distribution of urban dam-break floods is jointly determined by the hydrodynamic attenuation mechanism during flood propagation and the controlling effect of local topography, a pattern that is also consistent with the findings of urban waterlogging risk assessment studies conducted in the Lijiang River Basin in Guilin [35] and the Dongfeng Canal area in Zhengzhou [36].

4.2. Analysis of the Contribution of Different Risk Indicators

The indicator weighting results show that the contribution of different evaluation indicators to overall flood risk differs substantially. Among all evaluation indicators, flood arrival time had the highest weight (0.349), far exceeding that of the other indicators, indicating that warning time is the most critical factor affecting evacuation efficiency and reducing casualties and property losses. The shorter the flood arrival time, the more limited the effective time window for resident evacuation and emergency response, often resulting in more severe disaster consequences. Population density ranked second, with a weight of 0.185, reflecting the important influence of the scale of population exposure within the affected area on overall risk; once densely populated areas are struck by flooding, the

potential casualties and social impacts are more pronounced. Inundation duration had a weight of 0.162, slightly higher than that of road network density (0.160). The former reflects the cumulative effects of prolonged flooding on buildings, underground facilities, and regional recovery, whereas the latter represents transportation infrastructure exposure within the evaluated grid cells and does not quantify evacuation or emergency-access capacity. The similarity in their weights suggests that, within the evaluation system of this study, the duration effect of flooding and the degree of infrastructure exposure contribute to overall risk at a comparable magnitude. Inundation depth had the lowest weight (0.144), indicating that, compared with indicators such as arrival time and population density, the contribution of instantaneous hydrodynamic intensity to overall risk is relatively limited. Overall, these results indicate that, in highly urbanized settings, the timeliness of warning and evacuation and the scale of population exposure have the most significant influence on comprehensive flood risk, exceeding the contribution of traditional hydrodynamic hazard parameters such as inundation depth. This finding suggests that, in urban dam-break flood risk assessment, greater emphasis should be placed on incorporating the warning time window and population exposure characteristics, rather than focusing solely on traditional hydrodynamic parameters such as inundation depth. The population exposure analysis further verifies this conclusion, demonstrating that areas with concentrated populations may experience elevated comprehensive risk even when their hydraulic hazard intensity is relatively limited.

4.3. Comparison with Existing Studies

Closely related studies have already demonstrated the applicability of hydrodynamic modeling, GIS spatial analysis, fuzzy comprehensive evaluation, and combined weighting methods in flood risk assessment. Cai et al. [14] integrated hydrodynamic modeling with GIS and fuzzy comprehensive evaluation, indicating that the combination of these techniques is an established approach rather than the principal methodological novelty of the present study. Chen et al. [15] incorporated dynamic population distribution into urban flood risk assessment, while Wu et al. [16] applied an AHP–entropy weighting method to assess long- and short-term flood risk. Recent dam-break studies have also advanced probabilistic life-loss mapping under dam-break scenarios [37]. Building on these studies, the present work focuses specifically on a simultaneous dual-reservoir dam-break scenario affecting a highly urbanized downstream area. Its added value lies in coupling 1D–2D dam-break hydrodynamic outputs with an emergency-oriented flood-arrival-time indicator, population exposure, and road-network exposure, and in quantitatively examining hazard-to-risk redistribution through a transition matrix and risk-level-specific population statistics. Therefore, the advancement of this study does not arise from any individual method alone, but from their integration into a grid-based framework for identifying vulnerability-driven risk redistribution under an urban dam-break scenario. Previous studies have commonly emphasized hydraulic hazard indicators, particularly maximum inundation depth, to characterize flood impacts. In contrast, this study integrates flood arrival time and socioeconomic vulnerability indicators into the risk assessment framework, allowing the influence of emergency response constraints and population exposure to be explicitly considered. Furthermore, compared with approaches that apply subjective or objective weighting methods separately, the AHP–entropy combination adopted in this study integrates expert knowledge with indicator variability, providing a weighting strategy that considers both subjective judgment and objective information characteristics. Compared with existing studies, the MFCE framework developed in this study integrates hydrodynamic simulation results with urban socioeconomic vulnerability indicators within a unified spatial assessment framework. This approach provides a more comprehensive

representation of spatial risk distribution characteristics in urban dam-break flood scenarios and facilitates the identification of high-risk areas. It is worth noting that, in contrast to traditional dam-break studies that generally emphasize inundation depth as the dominant hazard factor [23], the results of this study indicate that, in highly urbanized environments, socioeconomic vulnerability factors, particularly population exposure and infrastructure-related characteristics, can substantially influence the spatial distribution of overall risk. This finding suggests that future urban flood risk management strategies should move beyond traditional flood-control-oriented approaches toward comprehensive risk management frameworks that consider both hydraulic hazards and the resilience of exposed urban systems [38].

4.4. Uncertainty and Limitations

Although the comprehensive evaluation framework proposed in this study demonstrates good applicability for urban dam-break flood risk assessment, several sources of uncertainty remain. First, the dam-break process itself involves substantial uncertainty. The development of a dam breach is influenced by multiple factors, including the material properties of the dam body, internal erosion mechanisms, and the specific failure mode, and different failure conditions may lead to significantly different breach development processes and flood propagation characteristics. This study only considered the extreme scenario of simultaneous piping failure at both reservoirs under the PMF-based check flood condition, while other failure modes may produce different results [28,29]. Second, the hydrodynamic simulation results are affected by uncertainties in breach geometry, boundary conditions, DEM representation, Manning's roughness coefficients, and computational mesh discretization [34,39]. These uncertainties propagate through the assessment framework in different ways. Changes in breach width, depth, and development time may alter the magnitude and temporal shape of the breach hydrograph. Uncertainty in Manning's roughness coefficients may affect flood-wave attenuation, flow velocity, arrival time, and inundation duration, whereas DEM and mesh uncertainties may influence local flow paths, inundation boundaries, and simulated water depths. These hydraulic outputs are subsequently used as three input indicators in the fuzzy comprehensive evaluation. Consequently, variations in the simulated hydraulic variables may change their normalized values and membership degrees and may cause grid cells located near classification thresholds to shift between adjacent risk levels. The influence is expected to be most pronounced in transitional areas between risk classes, whereas grid cells with consistently high or low indicator values are likely to be less sensitive. Because a systematic multi-parameter sensitivity analysis was not conducted, the magnitude of this uncertainty propagation and its effect on the total area assigned to each risk level remain unquantified. Future studies should therefore conduct controlled multi-scenario simulations across plausible parameter ranges and, where possible, compare the resulting inundation patterns with analogous historical events, remote-sensing-derived flood extents, or independent hydrodynamic models. Although the combined AHP–entropy weighting method improves the objectivity of weight calculation, the expert judgment process cannot entirely eliminate subjective uncertainty; in particular, although all ten experts achieved consistency ratios below 0.1, the relatively small panel size and its concentration in the fields of hydraulic engineering and disaster prevention and mitigation limit the extent to which the aggregated weights can be considered representative of broader professional consensus across other relevant disciplines (e.g., urban planning, emergency management, and public administration); future studies could benefit from a larger and more interdisciplinary expert panel or a Delphi-based iterative elicitation process. In addition to weighting uncertainty, the selection of membership-function thresholds may influence the final fuzzy evaluation results.

In this study, the discontinuity points were generated from the observed minimum and maximum values of each indicator using an equal-interval procedure, while the direction of risk was determined according to the physical or socioeconomic meaning of the indicators. This procedure provides a transparent and reproducible basis for relative spatial risk zoning but does not represent a disaster-loss-based or regulatory classification standard. Because a quantitative threshold-perturbation analysis was not conducted, the classification stability of grid cells located near the discontinuity points remains uncertain. Future studies should compare alternative threshold-generation methods and conduct systematic threshold-perturbation tests to quantify the robustness of the resulting risk classification. In addition, flow momentum, which combines water depth and flow velocity, is an important hydraulic parameter for characterizing the destructive capability of dam-break floods. This study did not incorporate flow momentum as an independent indicator because the proposed framework was designed to evaluate comprehensive flood risk by integrating flood propagation characteristics with socioeconomic vulnerability factors. Future studies could further incorporate flow momentum and other dynamic hydraulic parameters to improve the representation of flood-induced physical damage [40]. In addition, the arithmetic mean was used to aggregate the individual judgment matrices across experts; compared with the geometric mean, which is generally regarded as more consistent with the ratio-scale nature of AHP pairwise comparisons, the arithmetic mean is computationally more straightforward but may be comparatively more sensitive to outlying judgments from individual experts. In addition, this study mainly considered static flood hazard factors and socioeconomic vulnerability factors, without incorporating dynamic factors such as real-time population evacuation behavior, emergency response capacity, and disaster adaptive capacity. Future research could further incorporate probabilistic dam-break scenario analysis, building on Bayesian inference-based breach modeling and Monte Carlo-based uncertainty propagation approaches developed in recent studies [41,42], together with evacuation modeling and dynamic emergency management simulation, to further improve the reliability of risk assessment results. Data-driven and machine learning-based methods, which have recently shown promise for rapid flood depth and inundation estimation [43], may also offer a computationally efficient complement to physically based hydrodynamic simulation in future extensions of this framework.

5. Conclusions

This study developed a comprehensive urban flood risk assessment framework based on the coupling of hydrodynamic simulation, GIS spatial analysis, and multi-indicator fuzzy comprehensive evaluation, and applied it to assess urban flood risk in Hefei City under a reservoir dam-break scenario. The results show that dam-break flood risk exhibits pronounced spatial heterogeneity within the downstream urban area. High-risk areas are mainly concentrated near the reservoirs and along the main flood propagation channels, where strong hydrodynamic hazard and high socioeconomic exposure typically coincide. Among the five selected evaluation indicators, flood arrival time and population density had the most significant influence on the overall flood risk distribution, with combined weights of 0.349 and 0.185, respectively. The findings indicate that, in highly urbanized environments, the timeliness of warning and evacuation and the degree of population exposure play a more decisive role in determining overall risk than instantaneous hydrodynamic intensity. The proposed framework, coupling hydrodynamic simulation with fuzzy comprehensive evaluation, integrates the physical flood process and socioeconomic vulnerability within a unified spatial analysis system, improving the comprehensiveness and precision of traditional flood risk assessment. This approach can provide scientific support for urban reservoir emergency management, urban flood prevention planning, and

dam-break risk decision-making. Future research could further incorporate probabilistic dam-break scenarios, evacuation modeling, and uncertainty quantification analysis to improve the reliability of risk assessment under complex real-world conditions.

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