

Article

Probabilistic Risk Assessment of Dam Breach Floods: A Stochastic Framework Integrating Multi-Model Uncertainty and HEC-RAS Coupling

Dan Li ^{1,2,*} , Jie Luo ³ , Junyu He ¹ , Runqiu Huang ^{1,4} , Zhijie He ², Yuanyuan Wang ² , Zhiming Mei ²  and Wei Tan ²

¹ Ocean College, Ocean Academy, Zhejiang University, Zhoushan 316021, China; jyhe@zju.edu.cn (J.H.); rqhuang@zju.edu.cn (R.H.)

² Zhejiang Lab, Hangzhou 311121, China; hezhijie@zhejianglab.edu.cn (Z.H.); wangyy2022@zhejianglab.com (Y.W.); meizhm@zhejianglab.org (Z.M.); tanw_hd@zhejianglab.org (W.T.)

³ College of Communication Engineering, Hangzhou Dianzi University, Hangzhou 310018, China; luojie@hdu.edu.cn

⁴ Fishery College, Zhejiang Ocean University, Zhoushan 316022, China

* Correspondence: danl@zju.edu.cn; Tel.: +86-1588-881-1360

Abstract

Deterministic empirical formulas often fail to capture the epistemic uncertainties of dam failure mechanisms, leading to biased risk estimations. To address this, we propose the Probabilistic Hydro-Risk Forecasting System (PHRFS), a stochastic framework integrating Latin Hypercube Sampling (LHS) with HEC-RAS 2D hydrodynamic modeling. Applied to the Honghu-Erji Reservoir (Inner Mongolia), an ensemble of 60 stratified scenarios was generated based on a multi-model envelope of breach parameters and simulated over a 12.5 m ALOS PALSAR DEM using the Full Momentum Shallow Water Equations with the Eulerian–Lagrangian method (SWE-ELM). The SWE-ELM simulations reveal a heavy-tailed distribution of peak discharge (mean $2.65 \times 10^4 \text{ m}^3/\text{s}$; max $5.85 \times 10^4 \text{ m}^3/\text{s}$), significantly exceeding deterministic estimates. Sensitivity analysis identifies a physical dichotomy: breach depth (D_b) primarily controls flood magnitude ($r \approx 0.7$), whereas formation time (t_f) governs the arrival timeline. This temporal uncertainty propagates downstream, creating a distinct longitudinal gradient in SWE-ELM-derived warning time—ranging from rapid onset ($33.0 \pm 19.3 \text{ min}$) in proximal zones to a substantial lead time ($33.1 \pm 4.2 \text{ h}$) in the distal Hailar District. Consequently, a moderate coupling ($r = 0.65$) emerges between economic loss and loss of life, while their spatial patterns remain strongly differentiated by warning time and exposure. Upstream settlements face high mortality risks due to insufficient evacuation windows, whereas the downstream urban center faces high economic exposure (~ 1.57 billion CNY) but limited life loss (~ 12.15 persons). These findings provide a scientific basis for differentiating emergency strategies, shifting from immediate life-saving in upstream reaches to asset protection in downstream areas.

Keywords: dam breach; probabilistic flood modeling; HEC-RAS 2D; epistemic uncertainty; risk analysis; inner mongolia



Academic Editors: Wei Ge, Lifeng Wen, Yantao Zhu and Yadong Zhang

Received: 27 May 2026

Revised: 30 June 2026

Accepted: 3 July 2026

Published: 8 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Dam failures are low-probability but high-consequence events that pose severe risks to downstream ecosystems and communities [1]. Past events, such as the Banqiao dam failure, show the severe impacts of structural collapse [2]. In recent decades, these risks

have increased due to aging infrastructure and more frequent hydrological extremes linked to climate change [3,4]. At the same time, population growth in floodplains has increased exposure to rare but extreme flood events, which further raises the potential consequences of dam failure [5]. Recent global assessments indicate that the safety of aging dams is becoming a growing concern, with statistical analyses suggesting that approximately 23 large dam failures may occur worldwide between 2023 and 2035 [1]. This issue is especially relevant for reservoirs located in cold–arid transition zones, such as the Honghu-Erji Reservoir, where non-stationary hydroclimatic conditions challenge traditional safety assumptions. Changes in precipitation patterns are expected to increase failure probability, particularly for reservoirs designed using stationary historical flood records [3,6]. For this reason, the development of effective Emergency Action Plans (EAPs) has become an important component of reservoir safety management.

A key challenge in dam-break risk assessment is the prediction of breach outflow hydrographs. Many studies estimate breach parameters using empirical regression equations based on historical failure data [7,8]. These methods are widely used because of their simplicity, but they show strong site dependence and large uncertainty. For example, equations developed for arch dams may perform poorly when applied to earth–rock dams in cold regions. Physically based models (e.g., [9,10]) can represent erosion processes in more detail, but their use in probabilistic analysis is often limited by high computational cost and the lack of reliable geotechnical data. As a result, probabilistic approaches that use ensembles of empirical models are often more suitable for representing epistemic uncertainty than relying on a single deterministic simulation [11].

Another source of uncertainty arises during flood wave propagation. Dam-break flow simulation requires solving the Saint-Venant equations. One-dimensional models are efficient for channel flow, but they often simplify lateral flow exchange and floodplain inundation [12]. In contrast, two-dimensional hydrodynamic models better represent rapid flow changes and multi-directional spreading over complex terrain, which are typical of dam-break floods [13]. Although tools such as HEC-RAS 2D are widely used, simulation results remain sensitive to terrain representation [14]. Digital Elevation Model (DEM) resolution affects flow routing and local inundation patterns, which makes careful DEM selection necessary [15].

In practice, many risk assessments address these uncertainties by selecting a single conservative breach scenario or a single DEM product. This approach treats a stochastic process as deterministic and can lead to biased estimates of downstream risk. Such simplifications may result in either overestimation of mitigation costs or underestimation of potential life loss. Therefore, there is a need to move from deterministic estimates toward probabilistic approaches that represent uncertainty explicitly. From a risk analysis perspective, this requires a framework that combines stochastic breach characterization with hydraulic routing to quantify downstream impacts [16].

This study addresses these needs by developing a Probabilistic Hydro-Risk Forecasting System (PHRFS) for the Honghu-Erji Reservoir. The framework combines multiple breach parameter models with high-resolution two-dimensional hydrodynamic simulations. Specifically, this study aims to: (1) use Latin Hypercube Sampling (LHS) to generate an ensemble of 60 plausible breach scenarios and represent uncertainty in breach formation; (2) simulate flood propagation using the HEC-RAS 2D model with an ALOS PALSAR (12.5 m) DEM to produce probabilistic hazard maps; and (3) separate hydraulic outputs into static economic loss and dynamic loss-of-life indicators.

2. Study Area and Materials

2.1. The Yimin River Basin

The study focuses on the Yimin River Basin (Figure 1), located in Hulunbuir City, Inner Mongolia, Northeast China ($119^{\circ}18'–121^{\circ}15' \text{ E}$, $47^{\circ}35'–49^{\circ}18' \text{ N}$). Geographically, the watershed lies in the ecotonal transition zone between the Greater Khingan Mountains and the Hulunbuir grasslands.

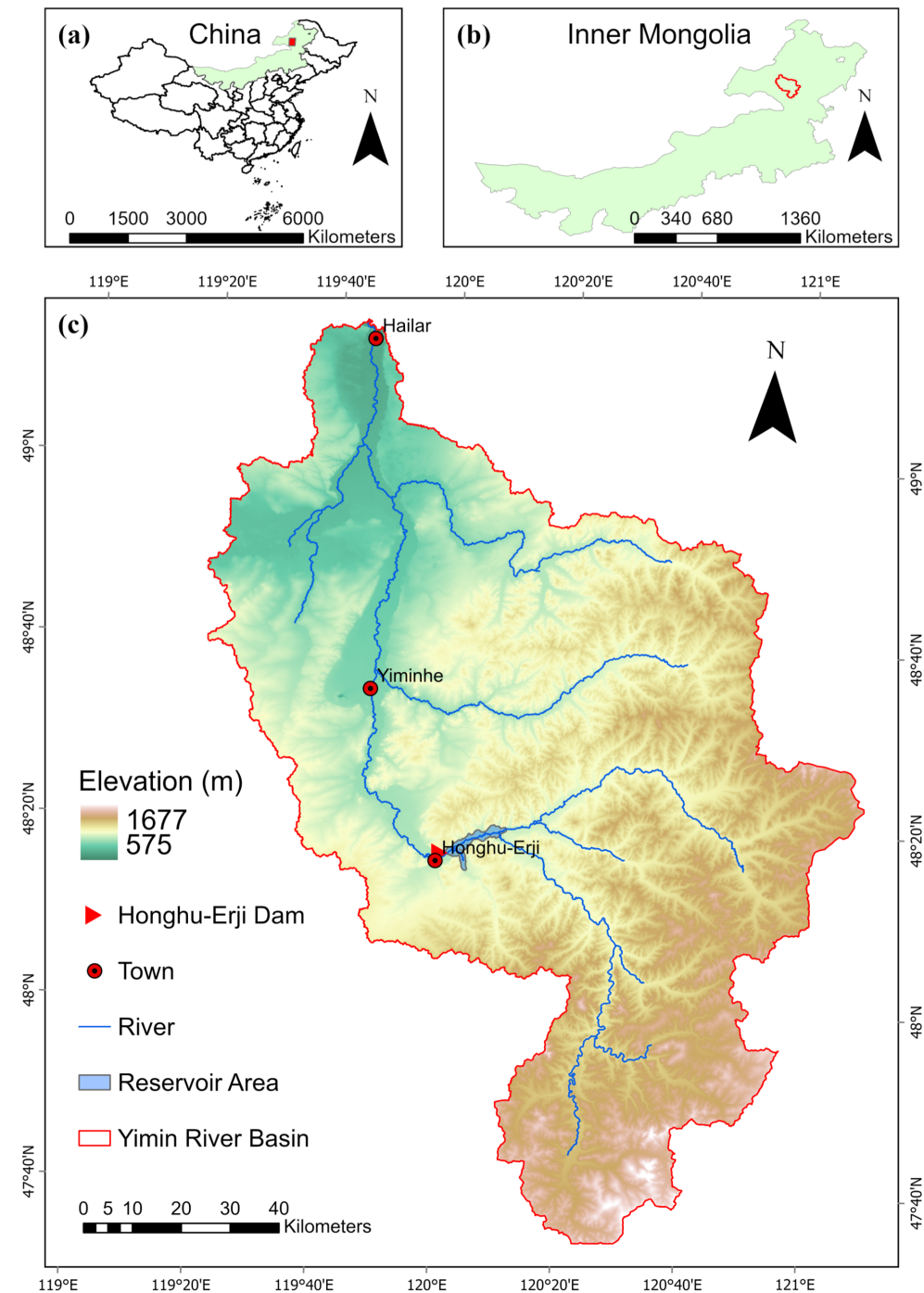


Figure 1. Overview of the study area. (a) location of Inner Mongolia within China; (b) location of the Yimin River Basin within Inner Mongolia; (c) ALOS PALSAR-derived topography of the Yimin River Basin, showing the Honghu-Erji Dam, reservoir area, towns, and river network. The Yimin River Basin is located at $119^{\circ}18'–121^{\circ}15' \text{ E}$ and $47^{\circ}35'–49^{\circ}18' \text{ N}$.

The Honghu-Erji River system constitutes the primary tributary network (Figure 1c), with the Honghu-Erji Reservoir (shaded area) impounding runoff from the upstream mountainous catchment. The regional topography exhibits a distinct gradient, decreasing from the southern uplands toward the broad downstream fluvial plains. This north–south-oriented channel geometry provides favorable conditions for rapid flood wave propagation during extreme events, making the basin a critical domain for dam-break inundation modeling.

As a strategic hydraulic control node, the Honghu-Erji Reservoir is anchored by a large-scale earth–rock embankment dam. Situated in a cold-arid climatic zone, the facility endures intense seasonal temperature fluctuations ($-40\text{ }^{\circ}\text{C}$ to $+35\text{ }^{\circ}\text{C}$). These conditions subject the embankment materials to severe freeze–thaw cycles, a critical factor influencing the long-term geotechnical stability of the structure.

Climatologically, the region is governed by a cold–temperate continental monsoon regime. The mean annual temperature ranges from $-3\text{ }^{\circ}\text{C}$ to $1\text{ }^{\circ}\text{C}$, and annual precipitation varies between 350 and 450 mm, predominantly concentrated in the summer monsoon season (June to August). Additionally, spring snowmelt contributes significantly to seasonal runoff, driving the basin’s distinct hydrological variability.

2.2. Datasets and Model Inputs

2.2.1. Digital Elevation Model

The basin topography was represented by a 12.5 m ALOS PALSAR DEM (Figure 1c), pre-processed to mitigate sinks and noise artifacts. Given the study’s primary focus on breach-parameter uncertainty, a comparative DEM analysis was not performed. The 12.5 m resolution was deemed optimal [15], providing a necessary balance between capturing geomorphic fidelity and maintaining computational feasibility for the extensive LHS-based stochastic simulations. Crucially, the selection of the ALOS PALSAR dataset is reinforced by recent benchmarking from Sayeed et al. [17], who demonstrated that high-resolution DEMs are indispensable for minimizing errors in flood depth and extent compared to coarser global products (e.g., SRTM), a finding further corroborated by Lima et al. [18].

2.2.2. Land Use and Downstream Exposure Zones

The LULC distribution (Figure A1) reveals a concentration of built-up areas and croplands along low-lying river valleys, creating high-exposure zones coincident with primary flood pathways. To reflect surface heterogeneity, Manning’s roughness coefficients (n) were assigned by integrating LULC categories with soil texture data (Table 1). This combined parameterization captures variations in vegetation density and infiltration-ponding behavior across the hydraulic domain.

Table 1. Manning’s roughness coefficients (n , unit: $\text{s}/\text{m}^{1/3}$) assigned to land cover categories.

Type	Water	Grass	Crop	Wetland	Built-Up	Shrub	Forest
n Value	0.025	0.035	0.040	0.045	0.060	0.080	0.100

2.2.3. Soil Data

Soil texture data (Figure A2) were extracted from the Harmonized World Soil Database (HWSD v1.2) [19]. This dataset informed the parameterization of infiltration rates. Note that in the context of catastrophic dam-break scenarios, vertical infiltration losses are considered secondary to the dominant advective flow processes.

2.2.4. Population Distribution

The spatial distribution of the exposed population was derived from the WorldPop gridded dataset (2020) [20], which provides estimates at a resolution of ~ 100 m. Prior to risk assessment, the population and hydraulic output rasters were projected to a common consequence-analysis grid for spatial overlay. This harmonization was used only to minimize geometric misalignment during raster algebra and does not imply population or hydraulic information finer than the original WorldPop data or the HEC-RAS computational mesh.

2.2.5. Reservoir Stage-Storage Curve

The dam spans an axis length of 1010.3 m with a crest elevation of 760.2 m. Hydrologically, the reservoir operates at a Normal Water Level (NWL) of 752.4 m. Its flood mitigation capacity is defined by a Design Flood Level ($P = 1\%$) of 755.40 m and an extreme Check Flood Level ($P = 0.05\%$) of 758.75 m. Geometric characteristics were defined by the stage-storage relationship provided in Appendix A (Figure A3).

2.2.6. Data Summary

Table 2 summarizes the multi-source datasets integrated into the PHRFS, detailing their specifications and specific roles in the modeling framework.

Table 2. Summary of datasets and hydraulic parameters used in the PHRFS.

Category	Dataset	Resolution	Key Attributes	Application in PHRFS
Topography	ALOS PALSAR DEM	12.5 m	Pre-processed for sink filling and smoothing.	Geometric foundation for the 2D hydraulic domain.
Land Cover	LULC Map	Basin-scale	Grassland, forest, cropland, built-up, etc.	Defines exposure zones; basis for Manning's n .
Soil Properties	HWSD v1.2	Grid-based	Soil texture and moisture.	Informs infiltration and surface micro-roughness.
Population	WorldPop (2020)	~ 100 m	Projected to a common consequence-analysis grid.	Quantifies human exposure for Loss of Life (LOL).
Reservoir	Design Docs	N/A	Key operating levels (NWL, Design, Check).	Initial boundary conditions and breach storage.

3. Methodology

3.1. Overview of the Probabilistic Forecasting Framework

As illustrated in Figure 2, the proposed Probabilistic Hydro-Risk Forecasting System (PHRFS) establishes a systematic framework to propagate epistemic uncertainty from data input to decision support. The architecture operates through five interconnected phases. Initially, multi-source geospatial datasets—including ALOS PALSAR DEM (12.5 m) and land use layers—are synthesized to construct geometric and roughness boundary conditions. Central to the framework is a stochastic breach strategy that employs Latin Hypercube Sampling (LHS) to generate $N = 60$ stratified failure scenarios, thereby sam-

pling the uncertainty envelope represented by the selected breach relations and physical constraints. These scenarios subsequently drive the HEC-RAS 2D engine, which computes unsteady flood propagation using the Full Momentum Shallow Water Equations with the Eulerian–Lagrangian method (SWE-ELM) on a sub-grid bathymetry mesh. The resulting hydraulic outputs are then decoupled into static depth and dynamic intensity metrics ($D \times V$) and overlaid with socio-economic data to quantify direct consequences. Ultimately, the ensemble results are aggregated to produce exceedance probability curves and probabilistic risk maps, providing an evidence-based foundation for Emergency Action Plans (EAPs).

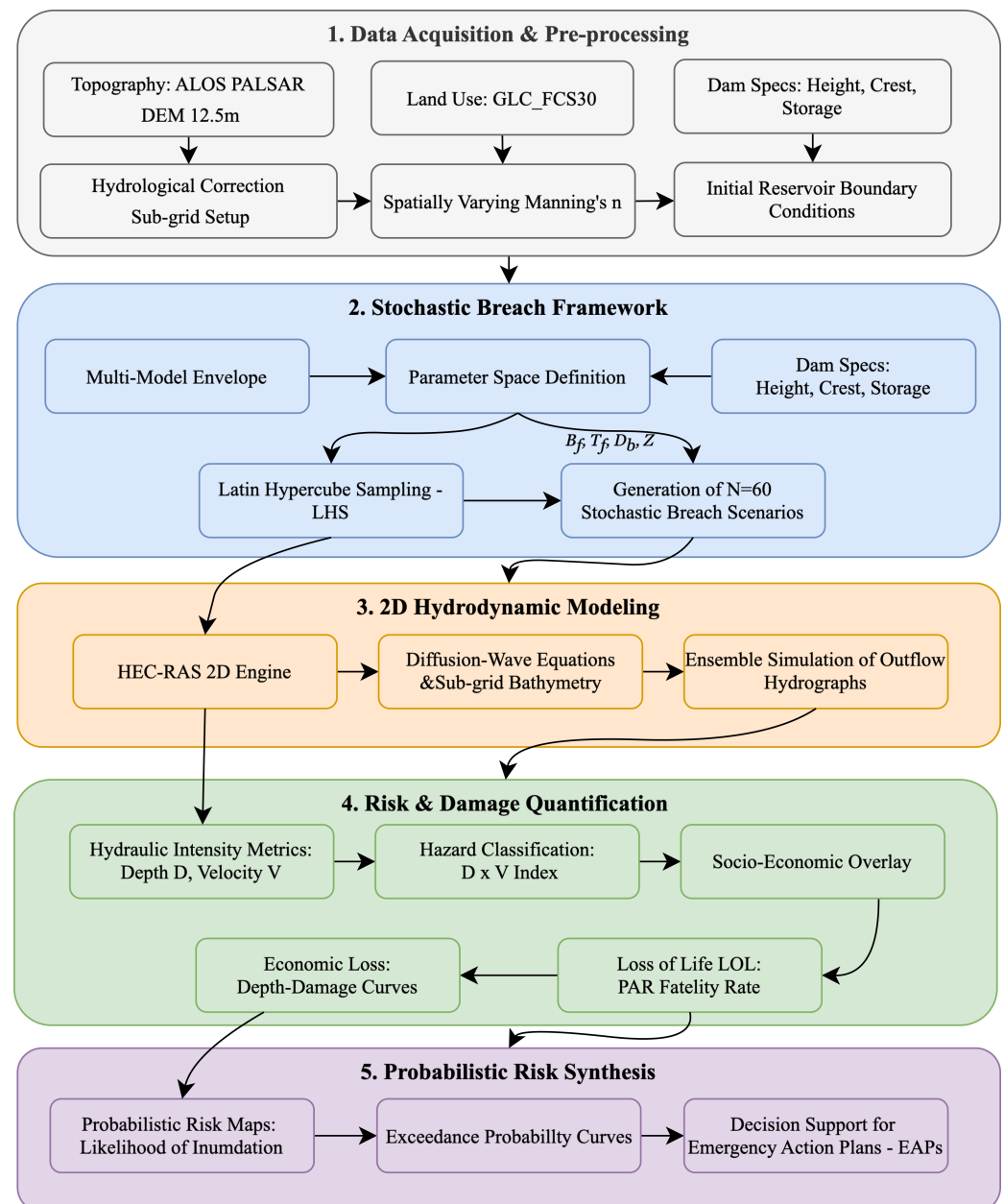


Figure 2. Methodological workflow of the proposed PHRFS. The framework is organized into five interconnected phases, illustrating the propagation of data and epistemic uncertainty through the modeling chain: (1) Data Acquisition and Pre-processing; (2) Stochastic Breach Framework ($N = 60$ scenarios); (3) 2D Hydrodynamic Modeling; (4) Risk and Damage Quantification; and (5) Probabilistic Risk Synthesis for decision support.

3.2. Stochastic Breach Parameterization

3.2.1. Quantifying Epistemic Uncertainty via a Multi-Model Envelope

To rigorously propagate epistemic uncertainty across competing breach parameterizations, we constructed a multi-model ensemble and applied Latin Hypercube Sampling (LHS) to achieve stratified coverage of the resulting parameter space. This stochastic design significantly improves space-filling properties and mitigates the clustering artifacts often associated with naïve Monte Carlo simulations [21].

Five widely cited regression methods were selected to estimate the key breach parameters: final breach width (B_f), breach depth (D_b), breach formation time (t_f), and side slopes (z). These methods include Froehlich [7,22], MacDonald and Langridge-Monopolis [23], Von Thun and Gillette [24], and Xu and Zhang [8]. This selection integrates both geometry-based and volume-based predictors, ensuring a comprehensive assessment of potential failure mechanisms (Table 3).

The empirical relations were not treated as fully independent evidence streams, because several of them were derived from overlapping historical dam failure case compilations. In particular, Von Thun and Gillette [24], Froehlich [22], and Froehlich [7] are related through the broader historical embankment-dam failure literature, whereas MacDonald and Langridge-Monopolis [23] and Xu and Zhang [8] provide complementary formulations based on different or expanded case compilations. Therefore, the LHS ranges used here should be interpreted as an uncertainty envelope represented by the selected empirical relations and physical constraints, rather than the full range of possible breach uncertainty.

The stochastic parameterization was designed to represent epistemic uncertainty in the central predictions of competing empirical methods. Where the original studies report prediction errors or scatter around their regression equations, these residual uncertainties indicate additional model uncertainty that is not fully resolved by simply comparing equation means. In this study, the adopted ranges therefore combine the spread among selected empirical predictions with site-specific physical constraints on breach geometry and formation time. They should be interpreted as a conservative engineering envelope for scenario generation, while acknowledging that regression residuals and database overlap may still leave part of the full breach-model uncertainty unrepresented.

Table 3. Summary of empirical regression equations for estimating dam breach parameters.

Method	Breach Width/Volume Equations	Formation Time (t_f)	Slope (z)
Froehlich [22]	$B_f = 0.1803K_o V_w^{0.32} h_b^{0.19}$	$t_f = 0.00254 V_w^{0.53} h_b^{-0.90}$	1.4/0.9 ^a
Froehlich [7]	$B_f = 0.27K_o V_w^{0.32} h_b^{0.04}$	$t_f = 63.2 \sqrt{V_w / (g h_b^2)}$	1.0/0.7 ^a
MacDonald [23]	$V_{\text{eroded}} = 0.0261 (V_{\text{out}} h_w)^{0.769}$	$t_f = 0.0179 V_{\text{eroded}}^{0.364}$	0.5
Von Thun [24]	$B_f = 2.5 h_w + C_b$	$0.015 h_w \leq t_f \leq 0.025 h_w$	0.5
Xu & Zhang [8]	$\frac{B_f}{h_b} = \zeta_1 \left(\frac{V_w^{1/3}}{h_w} \right)^{0.652} e^{B_3}$	$\frac{t_f}{T_r} = \zeta_2 \left(\frac{V_w^{1/3}}{h_w} \right)^{1.228} e^{B_5}$	Calc. Eq.

Note: V_w : Reservoir volume (m^3); h_b : Breach height (m); h_w : Water depth above invert (m); V_{out} : Outflow volume (m^3); K_o : Failure mode factor. ^a Values for overtopping/piping respectively. ζ_1, ζ_2 denote geometric coefficients; T_r is reference time (1 h).

3.2.2. Latin Hypercube Sampling (LHS)

To quantify the epistemic uncertainty arising from these empirical equations, we transitioned from deterministic “worst-case” scenarios to a probabilistic framework. The variability ranges of four key parameters—final breach width (B_f), breach formation time (t_f), breach depth (D_b), and side slope (z)—defined by the multi-model envelope and physical feasibility constraints served as the boundary conditions for the sampling space (Table 4).

LHS was employed to generate the input vectors due to its computational efficiency in stratifying the parameter space [25]. A total of $N = 60$ unique parameter sets were generated, where each set represents a plausible realization of the dam breach event. These scenarios were simulated using the HEC-RAS 2D engine to derive full probability distributions of downstream flood consequences, specifically focusing on peak discharge (Q_p), flood arrival time (T_{arr}), maximum inundation depth (D_{max}), and maximum flow velocity (V_{max}).

Because most empirical breach relations directly predict breach width and formation time rather than breach depth, D_b was derived from reservoir and dam geometry instead of being treated as a direct output of every empirical equation. Specifically, breach depth was defined as the difference between the initial reservoir water surface elevation and the final breach-bottom elevation:

$$D_b = Z_{initial} - Z_{bottom} \quad (1)$$

where $Z_{initial}$ was set to the check flood level (758.75 m) and Z_{bottom} was sampled within physically feasible breach-bottom elevations constrained by the dam and valley geometry. The resulting D_b range was therefore used as a physically constrained uncertain variable coupled with the empirical width and formation-time estimates.

Table 4. Prior distributions and physical constraints for breach parameters used in the stochastic framework.

Parameter	Unit	Prior $U(min, max)$	Constraints	Derivation/Source
Final Bottom Width (B_f)	m	$U(20.0, 404.0)$	$0 < B_f \leq L_{crest}$	Multi-model empirical envelope and dam-crest length constraint.
Formation Time (t_f)	h	$U(0.3, 6.0)$	$t_f > 0$	Multi-model empirical envelope from breach-formation-time equations.
Breach Depth (D_b)	m	$U(19.3, 32.2)$	$0 < D_b \leq H_{dam}$	Derived from $D_b = Z_{initial} - Z_{bottom}$ using the check flood level and feasible breach-bottom elevations.
Side Slope (z)	–	$U(0.5, 3.0)$	$z > 0$	Empirical side-slope recommendations and physical feasibility bounds.

3.3. Hydraulic Modeling Setup

The propagation of the dam-break flood wave was simulated using HEC-RAS 2D (Version 6.6), which provides an integrated framework for unsteady hydraulic routing and explicit resolution of floodplain connectivity. The HEC-RAS 2D solver has been extensively validated for complex unsteady flows, proving capable of accurately capturing flood wave propagation in irregular terrains where 1D approximations fail [14,26].

3.3.1. 2D Hydraulic Model Configuration

To balance the computational demand of the stochastic ensemble ($N = 60$) with terrain representation, the computational domain was reconstructed using a structured 2D mesh with a global cell size of 50 m and local refinement to 30 m along the main river valley, key downstream flow corridors, and important towns and residential areas. Breaklines were applied along the main channel and key hydraulic corridors. The ALOS PALSAR DEM was incorporated through HEC-RAS sub-grid bathymetry, which pre-computes elevation-storage relationships and face conveyance properties from the underlying 12.5 m terrain. This approach improves the representation of storage and conveyance within computational cells, while velocity-sensitive indicators are interpreted at the computational-mesh scale.

In response to the rapidly varied nature of dam-break flow, the revised simulations used the HEC-RAS 2D Full Momentum Shallow Water Equations with the Eulerian-Lagrangian method (SWE-ELM). Unlike the diffusion-wave approximation, this solver retains the local and convective acceleration terms and is therefore more appropriate for representing inertial wave propagation, rapid flow-regime transitions, and momentum-dominated flow immediately downstream of the breach. Because neglecting inertial terms can attenuate peak discharge and delay near-field arrival time in dam-break routing, the revised values of Q_p and T_{arr} reported in the abstract and results were recalculated from the SWE-ELM simulations rather than from diffusion-wave routing. All 60 breach scenarios were rerun with SWE-ELM, and the exported maximum depth, maximum velocity, arrival time, and $D \times V$ rasters were used for the subsequent consequence analysis.

3.3.2. Boundary and Initial Conditions

The simulation was driven by the upstream boundary defined by the initial reservoir stage, where breach progression was dynamically calculated based on the LHS-generated parametric inputs (B_f, t_f, D_b, z). The breach outflow was computed internally by HEC-RAS according to the prescribed breach geometry, reservoir stage, and local hydraulic conditions, rather than being imposed as a manually redistributed point inflow across selected boundary cells. A Normal Depth condition was applied at the downstream boundary, defined by the average friction slope of the valley, to prevent artificial backwater effects. To ensure numerical stability, an adaptive time step controlled by the Courant-Friedrichs-Lewy (CFL) condition was employed, allowing the time step to vary dynamically (seconds to minutes) during the rapid breach release phase.

3.4. Consequence Assessment Framework

The hydraulic results from the multi-scenario simulations (Section 3.3) are used as inputs for the consequence assessment. This study uses a framework that combines hydraulic hazard intensity with socio-economic exposure to estimate downstream risk in a probabilistic manner.

3.4.1. Hydraulic Hazard Classification

Flood hazard intensity is not determined by water depth alone. Flow velocity also affects human stability and structural damage, especially during the rapid rise of a dam-break flood. For this reason, a combined depth-velocity ($D \times V$) severity index was employed to classify hazard zones. In the revised simulations, both maximum inundation depth and maximum velocity were derived from the HEC-RAS 2D SWE-ELM results, which retain the inertial terms required for rapidly varied dam-break flow. Recent post-flood investigations in Northern China have demonstrated that mortality rates in flash floods are highly sensitive to flow mechanics, with vulnerability increasing significantly as a function of impact force and velocity [27–29]. Based on commonly used flood hazard criteria for

people and vehicles, the inundated area was divided into six hydraulic hazard classes (Table 5). Because velocity is solved at the computational-mesh scale, the resulting $D \times V$ classes are interpreted as reach- to cell-scale hazard indicators rather than building-scale impact forces.

Table 5. Hydraulic hazard classification based on the depth–velocity intensity index.

Class	Hydraulic Intensity ($D \times V$, m ² /s)	Interpretation
I (Low)	<0.3	Generally safe for people, vehicles, and buildings under shallow-flow conditions.
II (Minor)	0.3–0.6	Unsafe for small vehicles and vulnerable pedestrians; wading becomes difficult for children and elderly people.
III (Moderate)	0.6–1.0	Unsafe for most vehicles and general public wading; only trained personnel may move under controlled conditions.
IV (Significant)	1.0–2.0	Unsafe for people and vehicles; light-frame structures may be damaged and debris hazards increase.
V (Extreme)	2.0–4.0	High risk of structural damage and vehicle instability; survival requires immediate refuge.
VI (Catastrophic)	>4.0	Potential for severe structural failure; survival is unlikely for people directly exposed to the flow.

In addition to hydraulic intensity, available warning time controls whether exposed populations can evacuate before the flood peak arrives. Table 6 defines evacuation zones using flood arrival time (T_a) and related fatality assumptions. Areas with short arrival times have limited or no warning, while areas with longer arrival times allow for partial or complete evacuation, depending on the available time.

Table 6. Evacuation zone classification based on flood arrival time (T_a) and fatality assumptions.

Zone	Arrival Time	Evacuation and Fatality Assumption
Rapid response zone	$T_a < 60$ min	No effective warning. Evacuation is unlikely. Fatality rate depends mainly on hydraulic intensity ($D \times V$).
Effective evacuation zone	$60 \text{ min} \leq T_a < 6$ h	Partial evacuation possible. Fatality rate varies with flood severity and evacuation efficiency.
Low life-loss risk zone	$T_a \geq 6$ h	Sufficient warning for evacuation under the model assumptions. Fatality rate is assumed to be negligible.

3.4.2. Spatially Distributed Loss of Life (LOL) Modeling

To address the limitations of static exposure assumptions, this study adopts a dynamic, spatially distributed approach to estimate loss of life (LOL). The method is built on the framework of Graham [30] and is conceptually consistent with the Reclamation Consequence Estimating Methodology (RCCEM) widely used in dam safety risk analysis [31]. Flood arrival times (T_a) derived from HEC-RAS 2D simulations are incorporated to enable grid-based estimation, allowing for spatial variability in flood hazard and population exposure to be explicitly represented.

LOL is estimated by jointly considering flood hazard intensity, warning and evacuation effectiveness, and population distribution. Hazard intensity is quantified using the

depth–velocity index ($D \times V$), while flood arrival time (T_a) is used to define evacuation effectiveness through available warning time. Fatality rates are assigned as a function of both hydraulic intensity and effective warning time and aggregated with gridded population data to estimate scenario-specific life loss.

The total loss of life for each stochastic scenario S_k is calculated as

$$LOL_k = \sum_{i=1}^N [POP_i \cdot F(D_i, V_i, T_{w,i})] \quad (2)$$

where POP_i is the population count in analysis cell i , derived from the WorldPop dataset and overlaid with the hydraulic outputs on the common consequence-analysis grid, and $F(\cdot)$ is the fatality rate function defined by hydraulic intensity ($D \times V$) and warning time (T_w).

The effective warning time (T_w) is defined as the time between the release of an official warning and the arrival of the flood front. Flood arrival time (T_a) represents the physical travel time of the flood wave. A dissemination delay (Δt_{delay}) of 30–60 min is included to represent information transmission and response delays under regional emergency conditions. The effective warning time is therefore calculated as $T_w = \max(0, T_a - \Delta t_{\text{delay}})$. Based on the resulting warning time and evacuation efficiency, the floodplain is divided into three evacuation zones (Table 6).

3.4.3. Economic Loss Assessment

Direct economic damage was quantified using Depth-Damage Functions (DDFs). While maximum asset values were derived from local statistical yearbooks (Table 7), the fractional damage susceptibility curves were cross-referenced with the global flood damage guidelines developed by the Joint Research Centre [32]. This approach ensures that the non-linear relationship between inundation depth and asset depreciation is consistent with international standards, particularly for residential and agricultural assets. Furthermore, a velocity-based correction was applied to account for total structural failure induced by high-momentum flows. Specifically, for grid cells where the hydraulic intensity exceeded a critical threshold ($D \times V > 4.0 \text{ m}^2/\text{s}$), a damage ratio of 100% was assigned regardless of the static inundation depth. The total economic loss is calculated as

$$L_{\text{total}} = \sum_{i=1}^N \sum_{j=1}^M (A_{i,j} \cdot V_{\text{max},j} \cdot \alpha(h_i)) \quad (3)$$

where

- L_{total} is the total aggregated economic loss;
- $A_{i,j}$ is the area of land use type j within grid cell i ;
- $V_{\text{max},j}$ is the maximum asset value (replacement cost) per unit area for land use type j ;
- $\alpha(h_i)$ is the damage percentage (0–100%) corresponding to the maximum water depth h_i , subject to the velocity override condition mentioned above.

Table 7. Economic parameters for land use categories used in flood loss estimation.

ID	Category	Unit Value ^a (CNY/m ²)	Depth-Damage Sensitivity	Reference/Basis
1	Cropland	4.5	High	Statistical Yearbook
2	Forest	8.0	Low	Restoration Cost
3	Shrubland	5.0	Low	Restoration Cost
4	Grassland	1.2	Medium	Animal Husbandry Value

Table 7. Cont.

ID	Category	Unit Value ^a (CNY/m ²)	Depth-Damage Sensitivity	Reference/Basis
5	Water	0	None	–
6	Barren	0	None	–
7	Built-up	1200	High	Housing Construction Cost
8	Wetland	0.5	Low	Ecosystem Service (Partial)

Note: ID corresponds to the classification code in the GLC_FCS30 dataset. ^a Unit values are estimated based on regional market prices (2024 level) and replacement costs.

4. Results

4.1. Probabilistic Breach Outflow Dynamics

The proposed PHRFS sampled the uncertainty envelope represented by the selected empirical breach relations and physical constraints, generating a peak discharge (Q_p) distribution that extends beyond the limitations of single deterministic equations. The application of LHS generated $N = 60$ plausible breach scenarios, resulting in a substantial range of hydraulic loading conditions.

As illustrated in Figure 3a, the peak discharges exhibited significant variability, ranging from a minimum of 6213 m³/s to a maximum of 58,525 m³/s, with a mean value of 26,490 m³/s. The empirical breach relations were used to define the stochastic ranges of breach width, breach depth, side slope, and formation time, whereas Q_p was obtained from the revised SWE-ELM hydraulic simulations rather than from a single empirical peak-flow equation.

However, exclusive reliance on a single deterministic relation or parameter set would fail to capture the “heavy-tailed” risk revealed by the PHRFS, particularly where the upper quantile (10% of stochastic scenarios) produced discharges exceeding 45,800 m³/s. By integrating the multi-model envelope, the system effectively mitigates the site-specific bias inherent in individual regression methods.

Figure 3 presents an integrated analysis of how epistemic uncertainty in breach parameters propagates to the dam-breach outflow response. The sensitivity analysis (Figure 3c–f) shows that breach depth (D_b) has the strongest control over peak discharge (Q_p), with a clear positive correlation (Pearson’s $r \approx 0.7$). This reflects the role of breach depth in controlling the effective hydraulic head driving the outflow. Breach formation time (T_f) exhibits a negative correlation with Q_p (Figure 3d), as shorter formation times lead to more rapid release of reservoir storage. In contrast, final breach width (B_f) and side slope (Z) show weaker correlations with peak discharge, indicating a secondary influence under the sampled parameter ranges.

The ensemble of dam-breach hydrographs derived from the 60 LHS scenarios (Figure 3g) shows substantial variability in peak magnitude and rising limb shape, while recession behavior is more consistent across scenarios. The ensemble mean is consistently lower than the upper envelope, and the worst-case hydrograph exceeds the mean by a large margin, reflecting the spread introduced by parameter uncertainty.

To assess whether the identified sensitivity patterns are supported by a sufficient sample size, a convergence analysis of Q_p was performed (Figure 3b). The cumulative mean of peak discharge stabilizes as the number of simulations increases and shows limited variation beyond approximately 40 realizations. At the same time, the 95% confidence interval of the cumulative mean progressively narrows with increasing sample size, indicating that the LHS ensemble provides a stable statistical representation of peak discharge for the subsequent analysis.

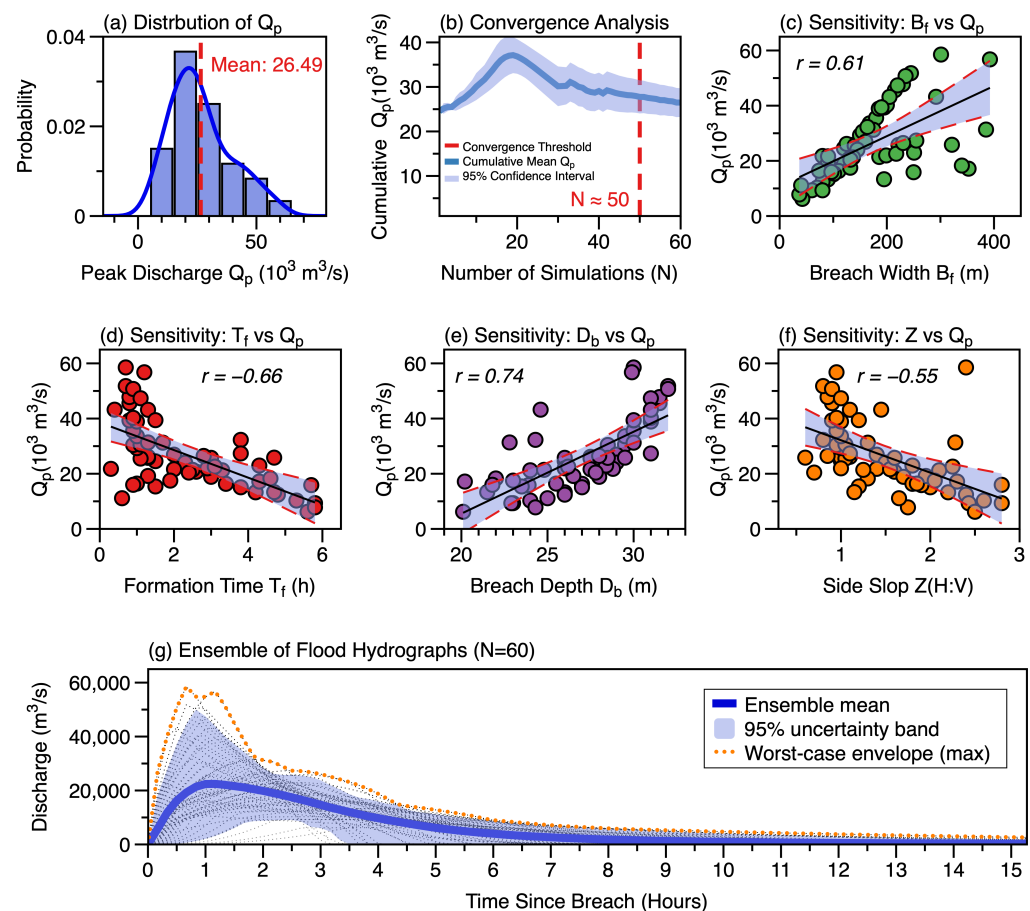


Figure 3. Probabilistic characterization and sensitivity analysis of dam-breach peak discharge (Q_p) based on 60 Latin Hypercube Sampling (LHS) scenarios. (a) Probability distribution of Q_p , shown by a normalized histogram and a kernel density curve. The red dashed line marks the sample mean ($26.49 \times 10^3 \text{ m}^3/\text{s}$). (b) Convergence analysis of the cumulative mean of Q_p as the number of simulations increases. The shaded area shows the 95% confidence interval of the cumulative mean, and the vertical dashed line indicates the convergence threshold ($N \approx 50$). (c–f) Sensitivity of Q_p to key breach parameters, including final breach width (B_f), formation time (T_f), breach depth (D_b), and side slope (Z). Scatter plots show LHS samples, while dashed lines indicate linear trends. Pearson correlation coefficients (r) are reported for each parameter. (g) Ensemble of dam-breach outflow hydrographs generated from the 60 scenarios. The solid line shows the ensemble mean, the shaded area represents the 95% uncertainty band, and the dotted line shows the worst-case envelope.

4.2. Probabilistic Propagation and Warning Windows

The simulation results show how the flood wave changes as it moves from the dam to the downstream plain. Figure 4 illustrates these changes at three key locations. In the first zone (Honghu-Erji Town, $\sim 3 \text{ km}$), the settlement faces the immediate impact of the breach outflow (Figure 4a). The analysis shows that the flood front arrives almost instantly (Mean $T_{\text{arr}} = 33.0 \pm 19.3 \text{ min}$), and the peak flow follows very quickly at $T_p = 122.3 \pm 61.6 \text{ min}$. Because the warning time before first inundation is extremely short, organized evacuation is nearly impossible. Therefore, Honghu-Erji is a “Zero-Warning Zone” where safety depends on the strength of buildings. As the flood moves to the middle zone (Yimin Town, $\sim 45 \text{ km}$), it changes slightly (Figure 4b). Although the river channel reduces the flow, the wave remains powerful, with scenario peak discharges averaging $12,720 \text{ m}^3/\text{s}$ and reaching up to $19,651 \text{ m}^3/\text{s}$. The arrival time is delayed to about $7.0 \pm 1.8 \text{ h}$ ($419.8 \pm 105.2 \text{ min}$), and the peak flow arrives at $T_p = 468.7 \pm 105.9 \text{ min}$. The time between first arrival and peak flow remains short ($T_p - T_{\text{arr}} \approx 48.9 \text{ min}$). Thus, automated early warning systems are needed

to use this brief time effectively. Further downstream in the Hailar District (~ 120 km), the flood wave spreads out significantly (Figure 4c). Floodplain storage and friction reduce the mean scenario peak discharge from $12,720 \text{ m}^3/\text{s}$ at Yimin Town to $1438 \text{ m}^3/\text{s}$ at Hailar, corresponding to an attenuation of about 88.7%. The arrival time is delayed to $33.1 \pm 4.2 \text{ h}$ ($1988.5 \pm 249.2 \text{ min}$). The peak flow arrives later at $T_p = 39.5 \pm 4.5 \text{ h}$ ($2369.7 \pm 271.3 \text{ min}$). This delay gives people enough time to reach safety. However, the flood lasts longer, shifting the main risk from fast-moving water to long-term flooding, which threatens underground infrastructure.

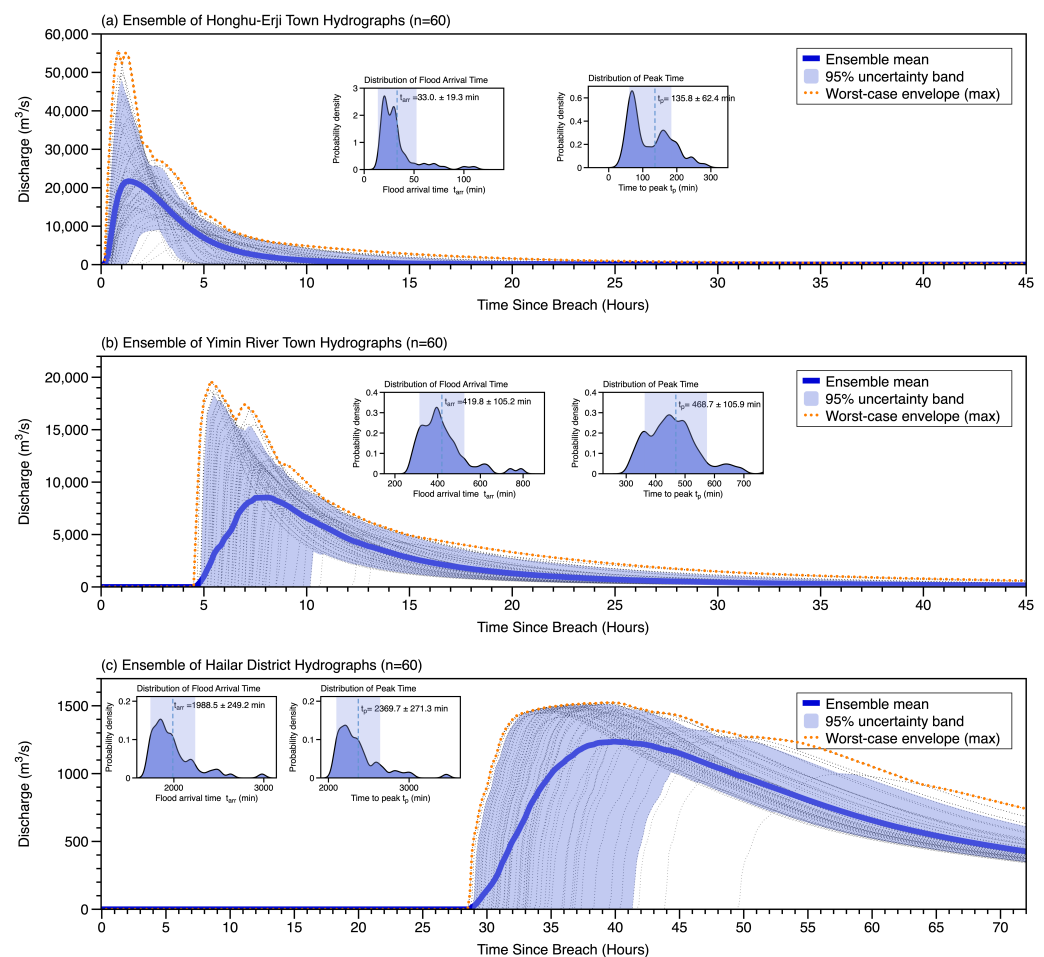


Figure 4. Spatiotemporal evolution of flood wave dynamics at three strategic downstream receptors. (a) Proximal Zone (Honghu-Erji Town, ~ 3 km): The section experiences an instantaneous hydraulic shock with negligible lag time, constituting a “Zero-Warning” high-risk zone. (b) Transitional Zone (Yimin Town, ~ 45 km): The hydrograph retains impulsive energy but exhibits a discernible arrival delay, offering a finite yet critical evacuation window. (c) Distal Zone (Hailar District, ~ 120 km): The wave undergoes significant diffusive attenuation and temporal dispersion. The widened uncertainty band reflects the cumulative stochasticity in flood arrival times. Note: The orange dashed line indicates the worst-case envelope, while the solid colored line represents the ensemble mean.

4.3. Spatial–Temporal Characteristics of Hydraulic Hazards

4.3.1. Spatial Decoupling of Hydrodynamic Variables

A comparative analysis of Figure 5a,b reveals a distinct spatial decoupling between static and dynamic hazard components. The maximum inundation depth ($D_{\max}$) is predominantly topographically controlled, with deep-water zones ($>5.0 \text{ m}$) accumulating in agricultural depressions. This distribution suggests that while asset damage may be widespread due to submergence, it does not necessarily correlate with immediate life

safety risks. Conversely, high-velocity zones (>3.0 m/s) are strictly confined to the main river thalweg. Notably, the floodplain exhibits a characteristic “High-Depth, Low-Velocity” regime ($V < 1.0$ m/s); although sufficient to cause structural degradation, the reduced dynamic intensity allows for feasible wading or vehicle evacuation, provided adequate warning time is available.

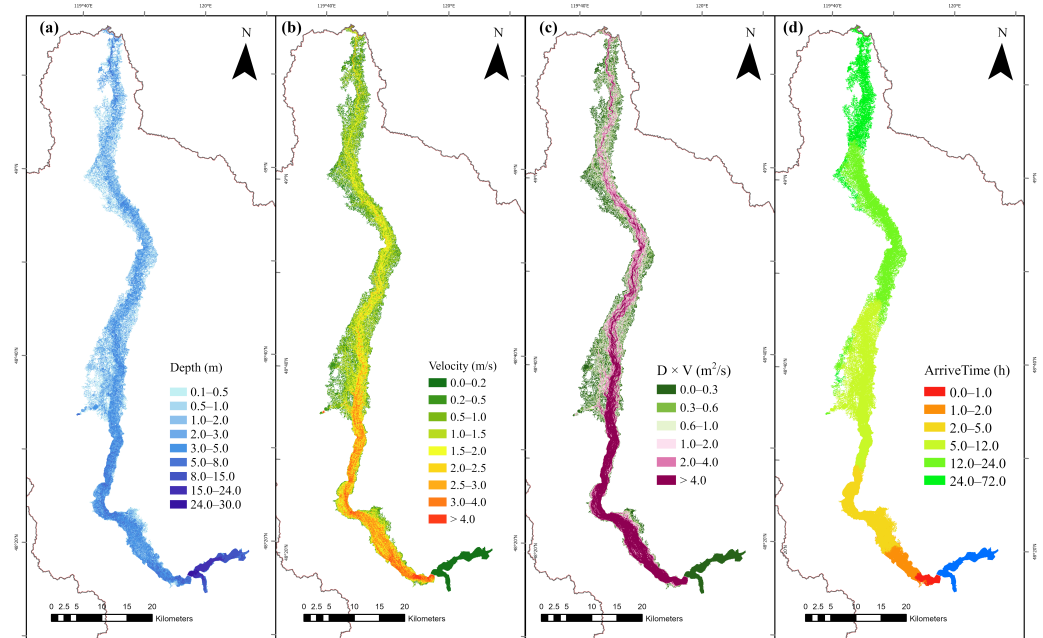


Figure 5. Spatial-temporal distribution of hydrodynamic hazard indicators under the worst-case breach scenario. (a) Maximum Inundation Depth ($D_{\max}$): Highlighting deep-water accumulation in the reservoir backwater and low-lying floodplains. (b) Maximum Flow Velocity ($V_{\max}$): Showing high-velocity jets confined to the main channel. (c) Hydraulic Hazard Index ($D \times V$): Identifying “Critical Instability Zones” where specific force exceeds human stability thresholds (>1.5 m²/s). (d) Flood Arrival Time (T_{arr}): Illustrating the longitudinal gradient of warning time, ranging from <30 min in upstream Yimin Town to >30 h in downstream Hailar.

4.3.2. Zonation of Critical Instability

Figure 5c synthesizes depth and velocity into the Hydraulic Hazard Index, establishing a spatially explicit basis for risk stratification. **Zone I: The High-Intensity Core.** A catastrophic corridor characterized by $D \times V > 4.0$ m²/s dominates the primary channel and the immediate breach path (Class VI). In this zone, the momentum flux is sufficient to induce total failure of reinforced concrete structures, rendering survival unlikely for any exposed population regardless of protective measures. **Zone II: The Transitional Hazard Belt.** Surrounding the core, a transitional zone exhibits intensities between 1.0 and 4.0 m²/s (Class IV–V). While masonry structures face a significant collapse risk, the primary threat to life in the distal fringe arises from the loss of pedestrian and vehicular stability. This creates a “conditional survival zone” where safety is contingent upon reaching vertical refuge immediately. **Zone III: The Low-Intensity Downstream Zone.** Downstream areas are characterized by lower hydraulic intensity ($D \times V < 1.0$ m²/s) and slower floodplain flow than the upstream breach corridor. Under the evacuation assumptions adopted in this study, these hydraulic conditions correspond to substantially lower life-loss potential, provided that residents receive timely warnings.

4.3.3. Longitudinal Gradient of Arrival Time

The spatial–temporal evolution of the flood front (Figure 5d) establishes the warning window as the primary determinant for risk mitigation. The analysis reveals a pronounced upstream–downstream gradient: proximal settlements endure an immediate shock where the flood front arrives in less than 1 h ($T_{arr} < 60$ min), precluding organized evacuation. This temporal constraint serves as the key driver for the mortality clusters observed in Honghu-Erji Town. In contrast, significant channel attenuation and floodplain storage delay the arrival time to >30 h in the Hailar District. This substantial lead time ($T_{arr} \gg T_{safe}$) effectively neutralizes the lethal potential of the flood in high-exposure urban areas, ensuring that evacuation from low-velocity inundation zones can be completed prior to the peak stage.

4.4. Probabilistic Consequence Analysis: Risk Decoupling

To visually verify the transition from exposure to consequence, Figure 6 presents a side-by-side comparison of population density and simulated fatality distribution. While the population (Figure 6a) is clustered in the upstream settlements (Honghu-Erji and Yimin Towns) and the downstream Hailar District, the fatality distribution (Figure 6b) reveals a distinct spatial contraction.

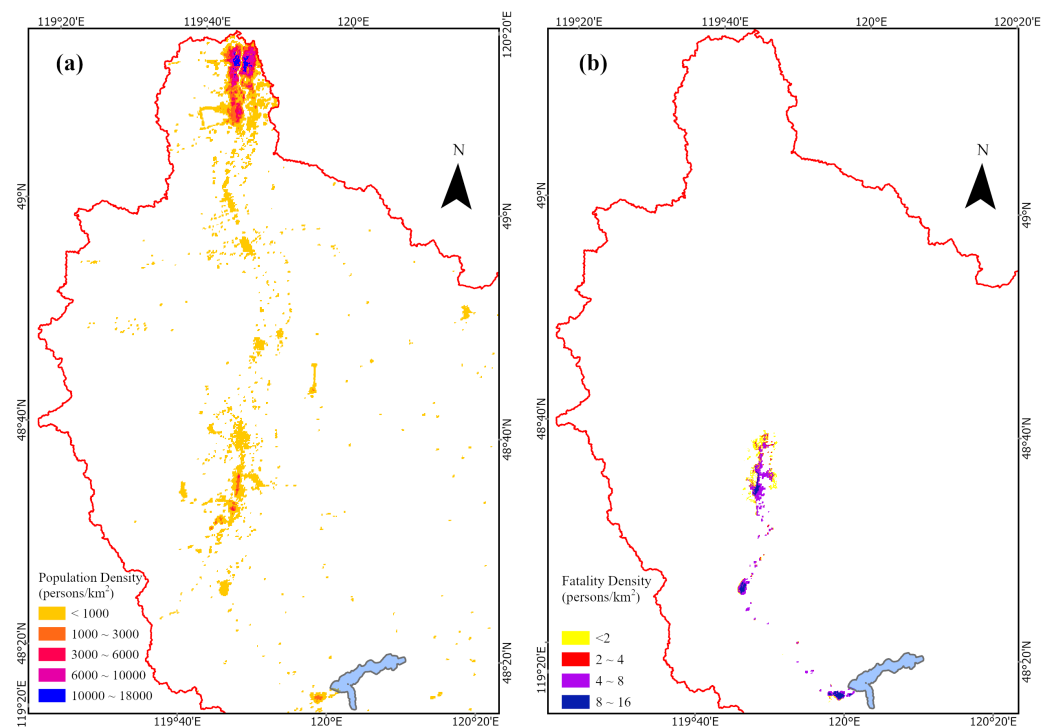


Figure 6. Spatial heterogeneity of population exposure and simulated loss of life (LOL). (a) Population Density (P_d): Clustered in both riverside towns and distal urban districts. (b) Fatality Density (L_d): Strictly confined to upstream high-velocity zones. The comparison visually confirms the “Spatial Decoupling” effect, where downstream urban centers (Hailar) show high population but near-zero fatalities due to sufficient warning time.

Significant loss of life (LOL) is strictly confined to the proximal reach (Honghu-Erji Town) and the narrow riparian corridor of Yimin Town. In Honghu-Erji Town, two critical conditions converge: (i) high hydraulic intensity ($D \times V > 1.0 \text{ m}^2/\text{s}$) and (ii) minimal warning time ($T_{arr} < 1$ h). In contrast, Yimin Town benefits from a longer warning window of approximately 6 h. However, the high flow velocity within its narrow river corridor still poses a significant risk to anyone who fails to evacuate in time.

Notably, despite Hailar District having the highest population density in the basin, the fatality density there is near-zero. This spatial pattern corroborates the decisive role of the temporal variable in our framework: the adequate lead time (>30 h) available in distal reaches successfully decouples high population exposure from high mortality risk. In these downstream areas, the hazard is effectively transformed from a life-threatening surge into a manageable economic displacement event, as residents have sufficient time to exit Class II–III hazard zones before the arrival of the flood peak.

The stochastic simulations reveal distinct distributional characteristics for the two consequence dimensions (Figure 7). The estimated economic loss concentrates around a mean of 1.57 billion CNY, driven by widespread inundation of downstream assets. In contrast, the life loss exhibits a low mean of 12.15 persons (Figure 7d). Unlike deterministic estimates that might assume static exposure, our dynamic evacuation modeling indicates that catastrophic mass-fatality events are rare outliers in this basin.

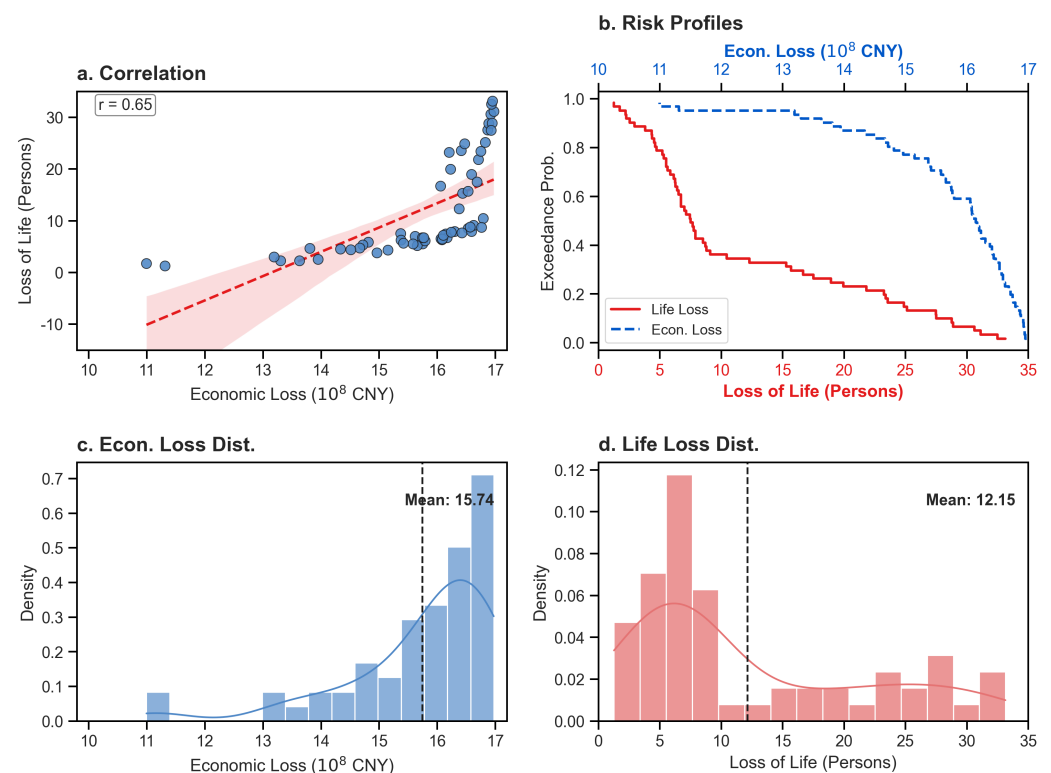


Figure 7. Integrated probabilistic risk assessment of economic loss and loss of life (LOL). (a) Scatter plot illustrating the correlation between economic damage and human casualties ($r = 0.65$). (b) Comparative risk profiles via dual-axis Exceedance Probability Curves (EPCs), where the red and blue curves represent the EPCs for economic loss and LOL, respectively. (c) Frequency distribution of economic loss, with the blue bars and blue curve representing the histogram and kernel density estimate, respectively; the dashed vertical line indicates the mean economic loss (Mean: 1.57 billion CNY). (d) Frequency distribution of life loss, with the red bars and red curve representing the histogram and kernel density estimate, respectively; the dashed vertical line indicates the mean LOL (Mean: 12.15 persons).

A critical finding is presented in Figure 7a, which investigates the relationship between financial and human consequences. The analysis yields a moderate positive correlation ($r = 0.65$), while also showing that the two consequence dimensions are not spatially equivalent: scenarios with high economic damages, often corresponding to broad downstream inundation, do not necessarily produce proportional fatalities. This partial decoupling is attributed to the role of warning time: downstream urban areas benefit from sufficient

lead time for evacuation, restricting residual life risks primarily to the immediate upstream vicinity of the dam.

5. Discussion

5.1. Model Robustness and Comparative Performance

Given the absence of observed dam-break hydrographs for the Honghu-Erji Reservoir, this study does not aim to reproduce a specific historical event but rather to quantify the propagation of epistemic uncertainty. To validate the plausibility of the PHRFS, the stochastic ensemble was benchmarked against established deterministic regression methods.

The comparative analysis reveals that deterministic estimates can strongly depend on the selected breach relation and hydraulic-routing assumptions, because empirical breach equations primarily constrain breach geometry and formation time rather than the full routed hydrograph. Reliance on a single deterministic parameter set therefore masks critical tail risks. The probabilistic forecast generated by PHRFS exposes a “risk profile” with heavy tails, where the upper quantile (10% probability) yields discharges exceeding $45,800 \text{ m}^3/\text{s}$. This confirms that deterministic “point estimation” fails to capture low-probability, high-consequence scenarios, whereas the proposed framework successfully uncovers these hidden hazards.

Furthermore, it is pertinent to contextualize this physics-based approach within the emerging landscape of data-driven hydrology. While recent advances in deep learning, such as Transformer-based models and LSTM networks, offer rapid real-time forecasting capabilities [33,34], their application is fundamentally constrained by the need for extensive historical training datasets. In the context of dam breaches—which are rare, “black swan” events with virtually no site-specific training samples—the proposed PHRFS remains the most robust methodology. By generating synthetic yet physically plausible hazard scenarios, it overcomes the data scarcity barrier that currently limits the applicability of AI surrogates in catastrophic risk assessment.

5.2. Uncertainty Propagation and Parameter Sensitivity

Using LHS ($N = 60$) for stratified parameter coverage, this study quantifies the propagation of breach uncertainties. Results confirm the site-specific sensitivity emphasized by Schmitz et al. [35], revealing a clear physical dichotomy: (1) Magnitude control: Breach depth (D_b) dominates peak discharge ($r \approx 0.70$) by controlling the hydraulic head. (2) Timing control: Breach formation time (t_f) governs the flood arrival time (T_{arr}). Notably, uncertainty in t_f generates a temporal variability of $\sim 4.2 \text{ h}$ (249.2 min) downstream. This significant dispersion invalidates deterministic arrival predictions, necessitating the adoption of *probabilistic arrival windows* to avoid dangerous delays or premature safety declarations in emergency response.

5.3. The Role of Early Warning and Risk Decoupling

A pivotal finding is the differentiated relationship between economic loss and loss of life ($r = 0.65$), mechanistically mediated by warning time (T_w). Consistent with Jiao et al. [36], our results confirm that fatality distribution is non-linear and time-dependent. Upstream settlements (e.g., Honghu-Erji) face a “Zero-Warning” shock ($T_{\text{arr}} < 60 \text{ min}$), where the narrow evacuation window concentrates fatalities (~ 12), necessitating automated sensor-linked alerts. In contrast, the downstream Hailar District benefits from a $> 30 \text{ h}$ safety window, which weakens the translation from high asset exposure to mortality [5]. By incorporating these dynamic arrival times, the model underscores that the primary value of EWS lies in managing the time variable.

5.4. Implications for Emergency Decision-Making

This probabilistic framework improves emergency decision-making in three ways. First, it replaces fixed safety boundaries with continuous risk levels. This helps identify “Hidden Risk Zones” that appear safe under average conditions but still require evacuation planning. Second, it supports the use of probability-based evacuation triggers (e.g., issuing warnings when the probability of $T_{arr} < 1$ h exceeds 5%). This approach accounts for the uncertainty in breach formation time. Finally, quantifying risk probabilities helps allocate resources more effectively. It suggests directing structural investments toward likely hazards, while using financial tools to manage rare, extreme events.

5.5. Limitations and Future Work

Despite the robust probabilistic framework, this study acknowledges several limitations. First, the breach-parameter ranges represent the uncertainty envelope of selected empirical relations and physical constraints, but they do not explicitly sample the full regression-residual uncertainty of each empirical equation; partial overlap among historical case databases may also reduce the effective independence of the selected formulas. Second, the hydraulic simulations adopted a clear-water assumption, neglecting sediment transport and bed morphological evolution, which are common in earth-dam failures. Third, the 12.5 m DEM resolution, while superior to global datasets, may oversimplify flow paths in the complex urban environments of the Hailar District compared to LiDAR data. Fourth, although the SWE-ELM solver improves the representation of rapidly varied flow relative to the diffusion-wave approximation, velocity-sensitive indicators such as V_{max} and $D \times V$ are still interpreted at the computational-mesh scale and should not be treated as building-scale impact forces. Fifth, the evacuation model assumes rational response behavior; future iterations should incorporate agent-based modeling to simulate traffic dynamics and social compliance. Finally, given the cold-arid context, future research should investigate the compounding effects of river ice breakup and freeze–thaw cycles on flood propagation dynamics.

6. Conclusions

This study developed a Probabilistic Hydro-Risk Forecasting System (PHRFS) to quantify the propagation of epistemic uncertainties in dam breach modeling. The main conclusions are as follows:

1. Identification of Heavy-Tailed Risks: Deterministic empirical formulas typically capture only part of the response distribution and fail to represent extreme scenarios. The stochastic ensemble analysis shows that the upper 10% quantile of peak discharge ($>45,800 \text{ m}^3/\text{s}$) is significantly higher than deterministic estimates. This highlights the critical need for probabilistic safety margins in risk assessment.
2. Differentiated Economic and Life-Safety Risks: A moderate positive correlation ($r = 0.65$) was observed between economic loss and loss of life, but their spatial patterns remain differentiated by warning time and exposure. Sensitivity analysis attributes this to distinct parameter controls: breach depth (D_b) primarily drives flood magnitude, whereas formation time (t_f) governs the arrival timeline. In downstream areas, the significant arrival delay (>30 h) weakens the translation from high economic exposure (~ 1.57 billion CNY) to mortality risk.
3. Implications for Emergency Management: The identification of an upstream “Zero-Warning” zone (<60 min) underscores the necessity for automated early warning systems. In contrast, the substantial safety buffer in downstream reaches suggests that emergency response should prioritize property protection over immediate evacuation.

Future research will focus on integrating real-time data assimilation to further reduce predictive uncertainty.

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

Funding: This research was supported by the Key R&D Program of Zhejiang (Grant No. 2025SSYS0001).

Data Availability Statement: Publicly available datasets were analyzed in this study. The ALOS PALSAR DEM data can be found at the Alaska Satellite Facility (<https://asf.alaska.edu/>) (accessed on 16 September 2025). The WorldPop population data is available at <https://www.worldpop.org/> (accessed on 26 September 2025). The Harmonized World Soil Database (HWSD) is available at the Food and Agriculture Organization (FAO) portal (<https://www.fao.org/> accessed on 26 September 2025). The simulation data and hydraulic model files generated during the current study are available from the corresponding author upon reasonable request.

Acknowledgments: The authors acknowledge the Alaska Satellite Facility (ASF) for providing the ALOS PALSAR DEM data, and WorldPop for the open-access demographic datasets.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

PHRFS	Probabilistic Hydro-Risk Forecasting System
LHS	Latin Hypercube Sampling
LOL	Loss of Life
DEM	Digital Elevation Model
LULC	Land Use and Land Cover
HWSD	Harmonized World Soil Database
HEC-RAS	Hydrologic Engineering Center—River Analysis System
WSE	Water Surface Elevation
PDF	Probability Density Function

Appendix A

Appendix A.1. Land Use and Land Cover (LULC)

The spatial heterogeneity of surface roughness in the hydraulic model was parameterized based on the Land Use and Land Cover (LULC) classification (Figure A1). The dataset reveals that the Yimin River Basin is predominantly characterized by grassland in the alluvial plains, with forest and shrubland concentrated in the mountainous upper reaches. Agricultural activities (cropland) and built-up areas are spatially clustered along the river valley, representing the primary exposure zones. This LULC map served as the primary basis for assigning spatially distributed Manning's roughness coefficients (n) in the HEC-RAS 2D domain. Distinct roughness values were calibrated for each land cover class to accurately simulate flow resistance across the floodplain.

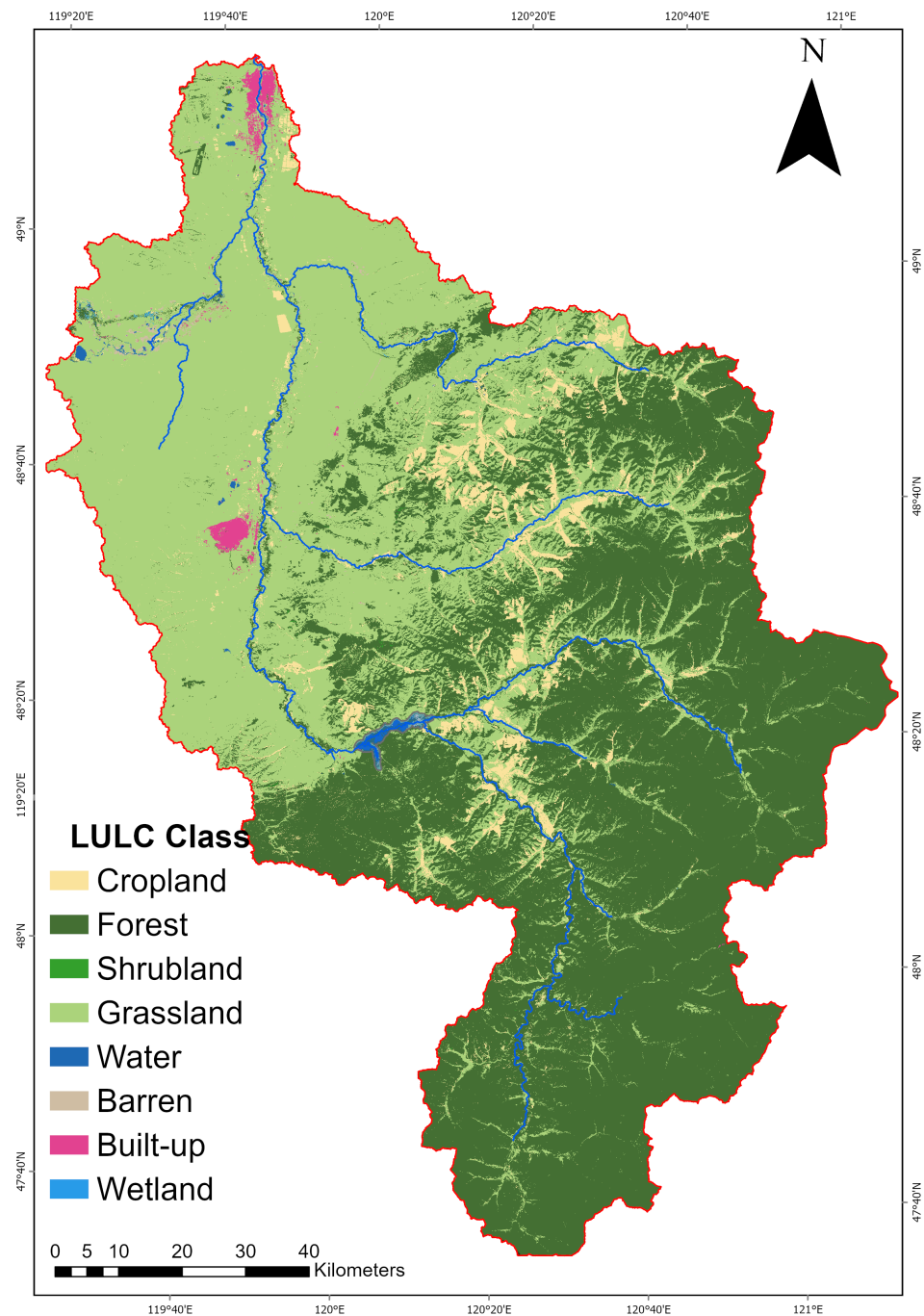


Figure A1. Spatial distribution of Land Use and Land Cover (LULC) classes in the Yimin River Basin. The classification identifies key roughness zones, including water bodies, built-up land, forest, grassland, and cropland.

Appendix A.2. Soil Properties

Soil texture and physical properties were derived from the Harmonized World Soil Database (HWSD v1.2) to characterize surface permeability and refine roughness parameterization (Figure A2). While infiltration losses during a catastrophic dam-break event are secondary to advection, soil data were integrated to account for the spatial variability of surface micro-topography and saturation potential. The dominant soil types in the basin influence both the initial abstraction of the flood wave and the stability of the river banks.

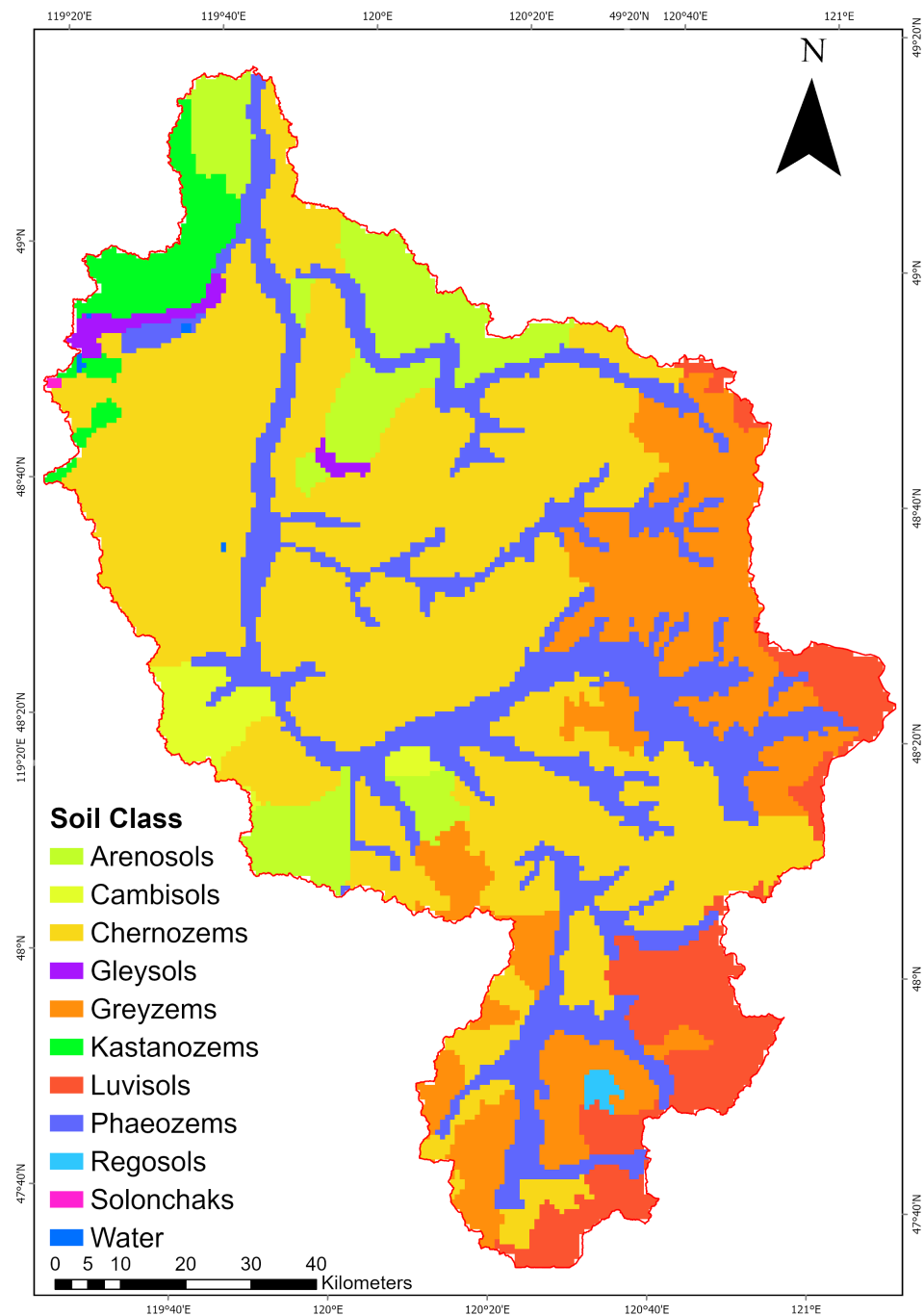


Figure A2. Soil texture distribution map derived from the Harmonized World Soil Database (HWSD v1.2), used to characterize infiltration potential and surface physical properties across the study area.

Appendix A.3. Reservoir Characteristics and Storage Capacity

The hydraulic boundary conditions for the breach simulation were defined by the geometric characteristics of the Honghu-Erji Reservoir. Figure A3 illustrates the stage-storage curve, describing the non-linear relationship between water surface elevation and reservoir capacity. The breach simulations were initialized at the Check Flood Level ($P = 0.05\%$) to represent the most critical loading condition (Worst-Case Scenario).

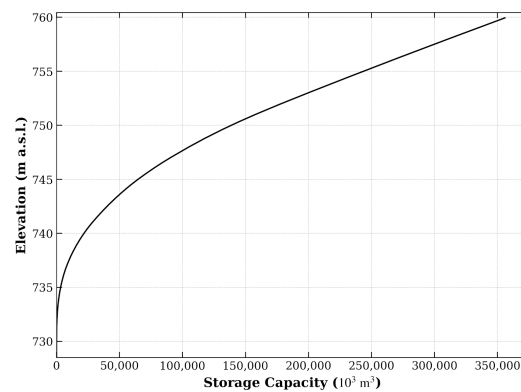


Figure A3. Stage–storage curve of the Honghu-Erji Reservoir. The curve defines the relationship between pool elevation (m) and available storage capacity (10^3 m^3), serving as the volumetric boundary condition for the unsteady flow routing.

References

- Moreno-Rodenas, A.; Mantilla-Jones, J.D.; Valero, D. Age, climate and economic disparities drive the current state of global dam safety. *Nat. Water* **2025**, *3*, 284–295. [\[CrossRef\]](#)
- Liu, W.; Carling, P.A.; Hu, K.; Wang, H.; Zhou, Z.; Zhou, L.; Liu, D.; Lai, Z.; Zhang, X. Outburst floods in China: A review. *Earth-Sci. Rev.* **2019**, *197*, 102895. [\[CrossRef\]](#)
- Mallakpour, I.; AghaKouchak, A.; Sadegh, M. Climate-Induced Changes in the Risk of Hydrological Failure of Major Dams in California. *Geophys. Res. Lett.* **2019**, *46*, 2130–2139. [\[CrossRef\]](#)
- Chen, B.; An, J.; Huang, Y.; Chen, X.; Wu, S.; Lin, C.; Gong, P. Multifaceted impacts of Ukraine’s Kakhovka Dam destruction. *Sci. Bull.* **2024**, *69*, 1642–1646. [\[CrossRef\]](#) [\[PubMed\]](#)
- Devitt, L.; Neal, J.; Coxon, G.; Savage, J.; Wagener, T. Flood hazard potential reveals global floodplain settlement patterns. *Nat. Commun.* **2023**, *14*, 2801. [\[CrossRef\]](#) [\[PubMed\]](#)
- Fluixá-Sanmartín, J.; Morales-Torres, A.; Escuder-Bueno, I.; Paredes-Arquiola, J. Quantification of climate change impact on dam failure risk under hydrological scenarios: A case study from a Spanish dam. *Nat. Hazards Earth Syst. Sci.* **2019**, *19*, 2117–2139. [\[CrossRef\]](#)
- Froehlich, D.C. Embankment Dam Breach Parameters and Their Uncertainties. *J. Hydraul. Eng.* **2008**, *134*, 1708–1721. [\[CrossRef\]](#)
- Xu, Y.; Zhang, L.M. Breaching Parameters for Earth and Rockfill Dams. *J. Geotech. Geoenviron. Eng.* **2009**, *135*, 1957–1970. [\[CrossRef\]](#)
- Fread, D.L.; Lewis, J.M. *NWS FLDWAV MODEL: Theoretical Description and User Documentation*; Technical Report; Hydrologic Research Laboratory, Office of Hydrology, National Weather Service (NWS): Silver Spring, MD, USA, 1998; 335p.
- Visser, K.; Tejral, R.D.; Neilsen, M.L. WinDAM C earthen embankment internal erosion analysis software. In Proceedings of the Joint Federal Interagency Sedimentation and Hydrologic Modeling Conference (SEDHYD), Reno, NV, USA, 19–23 April 2015; pp. 1–10.
- Ahmadisharaf, E.; Kalyanapu, A.J.; Thames, B.A.; Lillywhite, J. A probabilistic framework for comparison of dam breach parameters and outflow hydrograph generated by different empirical prediction methods. *Environ. Model. Softw.* **2016**, *86*, 248–263. [\[CrossRef\]](#)
- Horritt, M.; Bates, P. Evaluation of 1D and 2D numerical models for predicting river flood inundation. *J. Hydrol.* **2002**, *268*, 87–99. [\[CrossRef\]](#)
- Brunner, M.I.; Swain, D.L.; Wood, R.R.; Willkofer, F.; Done, J.M.; Gilleland, E.; Ludwig, R. An extremeness threshold determines the regional response of floods to changes in rainfall extremes. *Commun. Earth Environ.* **2021**, *2*, 173. [\[CrossRef\]](#)
- Aureli, F.; Maranzoni, A.; Petaccia, G. Advances in Dam-Break Modeling for Flood Hazard Mitigation: Theory, Numerical Models, and Applications in Hydraulic Engineering. *Water* **2024**, *16*, 1093. [\[CrossRef\]](#)
- Zhang, J.; Yang, X.; Fan, G.; Li, H.; Zhou, J. Physical and numerical modeling of a landslide dam breach and flood routing process. *J. Hydrol.* **2024**, *628*, 130552. [\[CrossRef\]](#)
- Peramuna, P.D.; Neluwala, N.G.; Wijesundara, K.K.; Venkatesan, S.; Silva, S.D.; Dissanayake, P.B. Novel approach to the derivation of dam breach parameters in 2D hydrodynamic modeling of earthquake induced dam failures. *Sci. Total Environ.* **2024**, *927*, 171505. [\[CrossRef\]](#) [\[PubMed\]](#)
- Sayeed, M.; Sahu, R.T.; Joshi, N.; Azam, M.; Joshi, S.S.; Khobragade, P.P.; Gawali, N.; Memon, K.K. Impact of DEM Resolution on Dam Breach Flood Modelling: A HEC-RAS 2D Case Study of Dhora Dam, India. *J. Environ. Inform. Lett.* **2025**, *14*, 71–79. [\[CrossRef\]](#)

18. Lima, R.P.; Elmiro, M.A.T.; Nero, M.A.; da Costa Temba, P.; Fonseca, B.M.; Castiglione, L.H.G. Assessment of digital terrain models in dam break simulation studies. *Bol. Cienc. Geod.* **2021**, *27*, e2021005. [[CrossRef](#)]
19. Fischer, G.; Nachtergaele, F.; Prieler, S.; van Velthuizen, H.T.; Verelst, L.; Wiberg, D. *Global Agro-Ecological Zones Assessment for Agriculture (GAEZ 2008)*; IIASA Research Report; IIASA: Laxenburg, Austria; FAO: Rome, Italy, 2008.
20. Bondarenko, M.; Priyatikanto, R.; Tejedor-Garavito, N.; Zhang, W.; McKeen, T.; Cunningham, A.; Woods, T.; Hilton, J.; Cihan, D.; Nosatiuk, B.; et al. *Constrained Estimates of 2015–2030 Total Number of People per Grid Square at a Resolution of 3 Arc (Approximately 100 m at the Equator) R2025A Version v1*; Dataset; WorldPop, University of Southampton: Southampton, UK, 2025. [[CrossRef](#)]
21. Goodarzi, E.; Shui, L.T.; Ziaei, M. Risk and uncertainty analysis for dam overtopping: Case study of Doroudzan Dam, Iran. *J. Hydro-Environ. Res.* **2014**, *8*, 50–61. [[CrossRef](#)]
22. Froehlich, D.C. Peak Outflow from Breached Embankment Dam. *J. Water Resour. Plan. Manag.* **1995**, *121*, 90–97. [[CrossRef](#)]
23. MacDonald, T.C.; Langridge-Monopolis, J. Breaching Characteristics of Dam Failures. *J. Hydraul. Eng.* **1984**, *110*, 567–586. [[CrossRef](#)]
24. Von Thun, J.L.; Gillette, D.R. *Guidance on Breach Parameters*; Technical Report; U.S. Bureau of Reclamation: Denver, CO, USA, 1990.
25. McKay, M.D.; Beckman, R.J.; Conover, W.J. A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics* **1979**, *21*, 239–245. [[CrossRef](#)]
26. Costabile, P.; Costanzo, C.; Ferraro, D.; Barca, P. Is HEC-RAS 2D accurate enough for storm-event hazard assessment? Lessons learnt from a benchmarking study based on rain-on-grid modelling. *J. Hydrol.* **2021**, *603*, 126962. [[CrossRef](#)]
27. Meng, Y.; Bai, M.; Dong, Z. Study on disaster-causing threshold and quantitative risk assessment of flash flood in Inner Mongolia. *Torrential Rain Disasters* **2020**, *39*, 285–292. (In Chinese with English abstract) [[CrossRef](#)]
28. Wang, X.; Wang, X.; Huang, H.; Liu, C. Research on storm surge disaster risk early warning method based on GIS. *China Flood Drought Manag.* **2021**, *31*, 15–20. (In Chinese with English abstract) [[CrossRef](#)]
29. Liu, T.; Wang, Y.; Yu, H.; Chen, Y. Using statistical functions and hydro-hydraulic models to develop human vulnerability curves for flash floods: The flash flood of the Taitou catchment (China) in 2016. *Int. J. Disaster Risk Reduct.* **2022**, *73*, 102876. [[CrossRef](#)]
30. Graham, W.J. *A Procedure for Estimating Loss of Life Caused by Dam Failure*; Technical Report DSO-99-06; U.S. Department of the Interior, Bureau of Reclamation: Denver, CO, USA, 1999.
31. U.S. Bureau of Reclamation. *Best Practices in Dam and Levee Safety Risk Analysis*; Technical Report; U.S. Department of the Interior, Bureau of Reclamation: Denver, CO, USA, 2015.
32. Huizinga, J.; De Moel, H.; Szweczyk, W. *Global Flood Depth-Damage Functions: Methodology and the Database with Guidelines*; Technical Report; Joint Research Centre: Luxembourg, 2017. [[CrossRef](#)] [[PubMed](#)]
33. Pianforini, M.; Dazzi, S.; Pilzer, A.; Vacondio, R. Real-time flood maps forecasting for dam-break scenarios with a transformer-based deep learning model. *J. Hydrol.* **2024**, *635*, 131169. [[CrossRef](#)]
34. Kordi-Karimabadi, F.; Fadaei-Kermani, E.; Ghaeini-Hessaroeiyeh, M.; Farhadi, H. Integrating numerical models with deep learning techniques for flood risk assessment. *Sci. Rep.* **2025**, *15*, 8913. [[CrossRef](#)] [[PubMed](#)]
35. Schmitz, V.; Arnst, M.; Abderrezzak, K.E.K.; Pirotton, M.; Erpicum, S.; Archambeau, P.; Dewals, B. Global Sensitivity Analysis of a Dam Breaching Model: To Which Extent Is Parameter Sensitivity Case-Dependent? *Water Resour. Res.* **2023**, *59*, e2022WR033894. [[CrossRef](#)]
36. Jiao, H.; Li, W.; Ma, D. Assessment of life loss due to dam breach using improved variable fuzzy method. *Sci. Rep.* **2022**, *12*, 3237. [[CrossRef](#)] [[PubMed](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.