

Article

Real-Time Estimation of Loss of Life from Urban Dam Breach Based on Population Heat Maps and Land Use Data

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Abstract

Accurate estimation of loss of life caused by dam breaches is critical for reservoir risk management and emergency planning. Traditional methods rely on static population data with poor timeliness and low spatial resolution. This study proposes a real-time estimation method by integrating population heat maps with land use data. A temporal variable is introduced to distinguish newly inundated populations from those already counted in previous time steps, thereby avoiding double counting during flood routing, while differences in public understanding of flood severity are considered to evaluate loss of life under various warning conditions. Taking the Shiyan Reservoir in Shenzhen as a case study, the BREACH model and HEC-RAS 2D are employed to simulate dam breach and flood routing. Results show that the final inundation area reaches 16.99 km², with residential areas accounting for 97.13%. The total at-risk population after land use correction is 200,963, which is 32.7% higher than the uncorrected estimate of 151,482. Loss of life estimates are highly sensitive to warning time and public understanding, reaching 129,691 under the most adverse conditions (no warning, vague understanding) but dropping to 20 when warning time exceeds 1 h with precise understanding. The proposed method provides an effective tool for real-time urban dam breach risk assessment.

Keywords: dam breach; flood routing; population heat map; land use data; loss of life estimation; real-time assessment

1. Introduction

Reservoir dams are critical infrastructure for safeguarding economic and social development. While they provide comprehensive benefits including flood control, water supply, irrigation, and power generation, they also face non-negligible potential safety risks [1]. In recent years, dam breach disasters have occurred frequently worldwide, causing severe casualties and property losses. In 2023, the collapse of two reservoir dams in Derna, Libya, resulted in over 10,000 fatalities, fully exposing the weaknesses in dam safety management [2]. Dam break flash floods pose particular threats to urban areas, where dense populations and complex infrastructure amplify the disaster consequences [3]. A study by Rentschler et al. [4] based on multi-country data demonstrated that approximately 1.81 billion people globally are exposed to river flooding, with the most significant growth in exposed population occurring in low-income countries. Tellman et al. [5] utilized satellite remote sensing data to reveal that the proportion of the global population exposed to flooding increased from 58% to 78% between 2000 and 2015, with urban expansion being the primary driving factor. China possesses the largest number of reservoir dams



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in the world, with approximately 95,000 reservoirs and a total storage capacity exceeding 1 trillion m³. Against the backdrop of global climate change, extreme rainstorm events are becoming more frequent and intense, further increasing the uncertainty in the spatiotemporal distribution of precipitation [6]. The situation regarding dam breach risk prevention and control remains severe. Meanwhile, China's urbanization rate of permanent residents has increased from 36.22% in 2000 [7] to 67.89% in 2025 [8]. Downstream of reservoir dams, densely populated areas with highly concentrated infrastructure mean that a dam breach could result in severity and impact far exceeding that in most other countries. In densely populated areas downstream of reservoirs, comprehensive risk assessment frameworks that integrate flood simulation with population exposure analysis are essential for effective disaster management [9]. Therefore, conducting research on dam breach loss of life estimation to provide scientific and technological support and decision-making basis for reservoir dam safety management and disaster prevention and mitigation is of great theoretical significance and engineering value.

Dam breach loss of life assessment is a core component of reservoir dam risk management and emergency evacuation planning research. It is typically conducted on the basis of dam breach simulation and flood routing analysis results, evaluating the losses caused by dam breach and conducting impact assessment. Accurate loss of life estimation depends not only on the scientific characterization of dam breach flood characteristics but also on the reasonable representation of key elements such as the at-risk population size, warning time, public understanding level, and evacuation capacity. Mathematical and physical models are the most commonly used technical approaches, capable of simulating breach development and flood propagation processes based on hydraulic and sediment transport principles, providing fundamental data support for loss of life assessment.

Reservoir dam breach simulation primarily involves the analysis of dam breach initiation time, breach development process, and breach outflow hydrograph. Methods based on dam breach models such as the DAMBRK model [10] and the BREACH model [11] for simulating earthen dam breach processes and calculating breach outflow hydrographs have matured. Singh [12] systematically summarized the development history and main methods of dam breach simulation technology in a monograph. Based on dam breach analysis theory, researchers have widely adopted hydrodynamic simulation methods to model various flow regimes during dam breach flood routing. To simulate the flood routing process and the inundation extent of dam breach floods, numerous computational software packages have been developed, including MIKE, HEC-RAS, DAMBRK, and FLADWAV. In recent years, dam breach simulation technology has made significant progress. Kadam et al. [13] conducted systematic dam breach analysis and damage assessment of the 2023 Nova Kakhovka dam breach event using satellite remote sensing and one-dimensional and two-dimensional hydrodynamic models; Shrestha et al. [14] employed a HEC-RAS 2D model to simulate the dam breach flood of the proposed Nalgad Dam in Nepal.

Research on dam breach loss of life primarily involves the effects of at-risk population size, warning time, dam breach flood severity, and the at-risk population's understanding of flood severity on estimation results. Graham [15] expanded upon the Brown-Graham method [16] and the DeKay and McClelland (D & M) method [17] based on analyses of previous dam breach cases, fully considering flood severity and the public's understanding of dam breach flood severity, and proposed a recommended table of fatality rate values for dam breach loss of life. In recent years, numerous researchers have conducted in-depth studies on dam breach loss of life assessment methods and achieved substantial results. Peng et al. [18] proposed an improved method for assessing loss of life caused by dam breach floods, considering the spatial distribution of population and evacuation behavior. El Bilali et al. [19] proposed a practical probabilistic method for simulating loss of life

caused by dam breach floods in urban areas. These studies have advanced and refined dam breach loss of life assessment methods from various perspectives.

Previous analyses of loss of life from dam failure have primarily relied on conventional survey and census data, which suffer from long update cycles and low spatial resolution, making them inadequate for capturing real-time population size and spatial distribution. In recent years, land use data [20] and nighttime light (NTL) data [21,22] have been widely used for population spatialization studies; however, the former is limited by the homogeneity assumption within the same land use category, while the latter is affected by weather interference [23], sensor inconsistencies, and data saturation issues, resulting in insufficient stability [24]. Given that populations are mobile and tend to avoid hazards, it is necessary to introduce more timely and accurate population data sources to more comprehensively characterize population distribution and risk exposure.

Against the backdrop of the rapid development of big data technology, population heat maps, which capture the number of mobile device users in located areas, provide real-time visualization of population density distribution in specific areas, offering new approaches for real-time research on dam breach loss of life. Wang and Wang [25] were the first to utilize mobile phone data for dynamic population mapping, pioneering the analysis of spatial population distribution based on mobile communication big data. Bergroth et al. [26] constructed a 24-h population distribution dataset based on mobile phone data from the Helsinki metropolitan area in Finland, revealing the spatial distribution patterns of urban population at different times throughout the day. As a real-time monitoring and dynamically updated indicator, heat values are not affected by external natural environmental factors, can objectively reflect the real-time status of target areas, and possess high spatial and temporal resolution, enabling more refined data analysis results. Population heat maps are widely used in daily life, but their application in the water resources sector, particularly in dam breach risk research, has not been fully promoted.

In view of the above, this study improves upon traditional methods based on population heat maps. After analyzing and comparing conventional dam breach loss of life estimation models and methods, and fully considering the spatial characteristics of real-time population distribution, this study addresses the challenges of population estimation accuracy and authenticity by incorporating land use data to construct a real-time dam breach loss of life estimation model based on population heat maps and land use data. The method is applied to the loss of life analysis of the Shiyan Reservoir dam breach in the urban area of Shenzhen, estimating the at-risk population size and loss of life, analyzing the key influencing factors of loss of life, and validating the feasibility and effectiveness of the proposed method.

2. Methodology and Data

2.1. Study Area

Shenzhen is located on the southern coast of Guangdong Province, China, and is one of the core cities of the Guangdong–Hong Kong–Macao Greater Bay Area. According to the 2025 Shenzhen Statistical Communiqué on National Economic and Social Development, the permanent resident population at the end of 2025 was 18,248,500 [27], with one of the highest population densities in the country. Multi-hazard stress testing for Shenzhen has demonstrated the city's vulnerability to compound disaster scenarios, highlighting the need for integrated risk assessment frameworks [28].

This study selected the Shiyan Reservoir, located in the urban area of Shenzhen, as the research object. The Shiyan Reservoir is a medium-sized reservoir with a homogeneous earthfill main dam, a maximum dam height of 18.5 m, a dam crest width of 8.5 m, and a total storage capacity of 31.18 million m³. The reservoir flood protection standard is

designed for a 100-year return period and verified for a 2000-year return period. The typical cross-section of the main dam is shown in Figure 1.

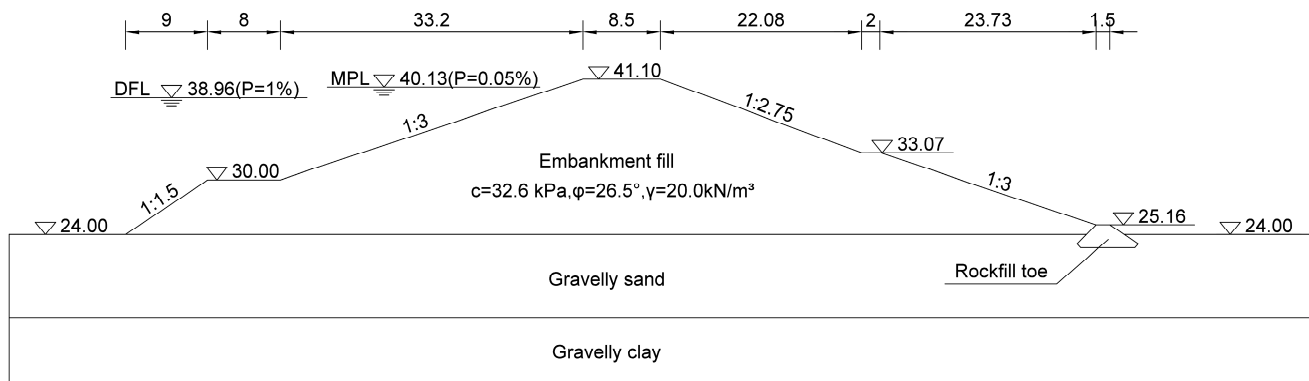


Figure 1. Typical cross-section of the main dam of the Shiyen Reservoir (units: m; DFL, Design Flood Level; MPL, Maximum Pool Level).

Detailed parameters of the main dam and embankment materials are provided in Table 1.

Table 1. Parameters of the main dam and embankment materials.

Category	Parameter	Unit	Value
Dam geometry	Maximum dam height	m	18.5
	Crest elevation	m	41.10
	Crest width	m	8.5
	Upstream slope	—	1:3 (upper), 1:1.5 (lower)
	Downstream slope	—	1:2.75 (upper), 1:3 (lower)
Material properties	Soil type	—	Embankment fill
	Unit weight, γ	kN/m ³	20.0
	Cohesion, c	kPa	32.6
	Friction angle, ϕ	°	26.5
	Porosity, n	—	0.39
	D50	mm	0.2
	D90/D30	—	50
	Manning's n	—	0.030

The protective scope of the Shiyen Reservoir involves Bao'an District and Guangming District of Shenzhen. Bao'an District covers a total area of 397 km², with a land area of 381.2 km². The terrain is predominantly low hills and terraces, with an overall elevation pattern of higher terrain in the northeast and lower terrain in the southwest. The north-eastern part is mainly characterized by low mountains and hills, while the southwestern part consists largely of coastal alluvial plains with flat terrain and few mountains. Guangming District covers a total area of 155.38 km², with an overall elevation pattern of higher terrain in the northeast and lower terrain in the southwest. The eastern part belongs to the low mountain and hill region, while the western part is predominantly low hill basins and plains.

The flood protection scope of the Shiyen Reservoir covers Gongming Subdistrict, Songgang Subdistrict, the Guangming High-Tech Industrial Park, parts of the Guangming Farm area, as well as transportation corridors such as the Songbai Highway and the industrial zones along them. This area is densely populated and has concentrated industrial facilities. Should a dam breach accident occur, it would pose a severe threat to the lives and

property of downstream residents and to urban infrastructure, with potentially catastrophic consequences. The location of the reservoir within the study area is shown in Figure 2.



Figure 2. Study Area and Reservoir Location Map.

2.2. Earthen Dam Breach Model and Flood Routing Model

2.2.1. Earthen Dam Breach Model Construction

Embankment dam breach models can be classified by complexity into parametric models, simplified physically-based models, and detailed multidimensional physically-based models [29]. Among these, simplified physically-based models calculate breach discharge using the broad-crested weir relationship and describe breach evolution through a simplified sediment transport model, balancing computational efficiency with physical mechanisms and making them suitable for rapid dam breach risk assessment. BREACH [11] is a typical representative of this class. It has been incorporated into the standard computational system of the U.S. National Weather Service (NWS) and validated in numerous dam breach cases. Subsequent improved models, including those of Mohamed et al. [30], Wu [31], and Van Damme [32], have each developed their own erosion parameterization schemes based on this framework.

This study employs the BREACH model to simulate the earthen dam breach process. The BREACH model is a physics-based earthen dam breach erosion model that predicts breach characteristics (including dimensions, morphology, and formation time) and the breach outflow hydrograph by coupling the reservoir water balance equation with the sediment transport capacity of the breach channel. The model accounts for dam material properties, dam geometry parameters, and reservoir characteristics (storage curve, spillway characteristics, and inflow hydrograph), and is applicable to both overtopping and piping failure modes.

The failure mode considered in this study is overtopping. For breach failure caused by overtopping, the reservoir water level must exceed the dam crest before erosion of the dam body begins. The initial phase of erosion occurs only on the downstream face of the dam. A scour channel, with width varying with depth, progressively cuts into the downstream face. The flow entering the channel is determined by the broad-crested weir flow relationship:

$$Q_b = 1.7B_0(H - H_c)^{1.5} \quad (1)$$

where Q_b is the breach flow rate; B_0 is the initial breach width; H is the reservoir water level; H_c is the elevation of the breach bottom. The coefficient 1.7 is the broad-crested weir discharge coefficient in SI units.

The stability of the breach side slopes is closely related to the depth of breach down-cutting. When the breach cuts down to a critical depth H_k , the side slopes become unstable and collapse, transforming the initial rectangular breach into a trapezoidal one. The critical depth H_k at which slope instability and collapse occur is related to the internal friction angle (φ), cohesion (c), and unit weight (γ) of the dam material, as follows:

$$H_k = \frac{4c \cos \varphi \sin \theta_{k-1}}{\gamma [1 - \cos(\theta_{k-1} - \varphi)]}, \quad k = 1, 2, 3 \quad (2)$$

where k is a subscript denoting the collapse type, encompassing three collapse modes as detailed in reference [11]; θ is the angle between the breach side slope and the horizontal.

The breach erosion rate depends not only on the erosion capacity of the flow but also on the physical and mechanical properties of the dam material. The Smart-modified Meyer-Peter and Müller erosion formula [33] is used for breach sediment transport calculations, as follows:

$$Q_s = 3.64 \left(\frac{D_{90}}{D_{30}} \right)^{0.2} P \frac{D^{2/3}}{n} S^{1.1} (DS - \Omega). \quad (3)$$

$$\Omega = \frac{b}{62.4} (PI)^c \quad (4)$$

where Q_s is the sediment transport rate; D_{30} , D_{50} , and D_{90} are the particle sizes for which 30%, 50%, and 90% of the material by weight is finer; P is the wetted perimeter; D is the hydraulic depth of flow; n is Manning's roughness coefficient; S is the downstream slope gradient of the dam; Ω is the soil moisture content; PI is the plasticity index of the cohesive soil; and b and c are empirical coefficients.

The broad-crested weir flow formula is used to calculate the breach discharge [11,12,34], as follows:

$$Q_b = C_v k_s \left[1.7 b_i (h - h_b)^{1.5} + 1.3 z (h - h_b)^{2.5} \right] \quad (5)$$

$$C_v = 1.0 + 0.023 \frac{Q_b^2}{[B_d^2 (h - h_{bm})^2 (h - h_b)]} \quad (6)$$

where C_v is the correction coefficient for approach velocity; k_s is the submergence correction coefficient for tailwater effects on outflow; b_i is the instantaneous breach bottom width; h is the reservoir water surface elevation; h_b is the breach bottom elevation; z is the breach side slope ratio; B_d is the water surface width upstream of the dam; and h_{bm} is the final breach bottom elevation. The coefficients 1.7 and 1.3 are the broad-crested weir discharge coefficients in SI units.

In the case study of Shiyan Reservoir, the reservoir surface area is much larger than the breach flow area, resulting in a negligible approach velocity; the approach velocity correction coefficient C_v approaches 1.0. Meanwhile, submergence conditions may only occur in the late stage of the breach after the reservoir water level has dropped significantly, at which point the flow is already in the recession phase and has minimal impact on the peak and overall shape of the breach outflow hydrograph; therefore, the submergence correction coefficient k_s is set to 1.0.

It is assumed that Shiyan Reservoir encounters a 5000-year return period extreme flood, based on which the breach discharge is calculated. Preliminary model runs indicate that a simulation duration of 12 h fully covers the entire breach discharge process from rise through peak to recession. Accordingly, the total simulation duration is set to 12 h with a computational time step of 0.1 s.

2.2.2. Dam Breach Flood Routing Model Construction

The propagation and inundation process of dam breach floods in downstream areas is a typical unsteady open-channel flow problem. This study employs the HEC-RAS 2D (Version 5.0.7; U.S. Army Corps of Engineers, Hydrologic Engineering Center, Davis, CA, USA) hydrodynamic model for dam breach flood routing analysis.

HEC-RAS (River Analysis System), developed by the U.S. Army Corps of Engineers Hydrologic Engineering Center (USACE-HEC), is currently one of the most widely used hydraulic computation software packages in dam breach flood simulation [35,36]. The one-dimensional module solves the cross-section-averaged form of the Saint-Venant equations; the two-dimensional module (HEC-RAS 2D) solves the complete two-dimensional Saint-Venant equations under full momentum formulation, employing unstructured finite volume meshes capable of simulating dynamic propagation, mixed flow regimes, and wetting–drying processes of dam breach floods [35,36].

The governing equations of HEC-RAS 2D are the two-dimensional shallow water equations (Saint-Venant equations), derived by integrating the three-dimensional incompressible Navier–Stokes equations along the water depth direction and introducing the hydrostatic pressure assumption [35–37].

The continuity equation of the two-dimensional shallow water equations is:

$$\frac{\partial H}{\partial t} + \nabla \cdot hV + q = 0 \quad (7)$$

The momentum equation is:

$$\frac{\partial V}{\partial t} + V \cdot \nabla V = -g\nabla H + v_t \nabla^2 V - c_f V + fk \times V \quad (8)$$

where H is the water surface elevation; t is time; h is the water depth; V is the depth-averaged velocity vector; q is the lateral inflow per unit area; g is the gravitational acceleration; v_t is the horizontal eddy viscosity coefficient; c_f is the bottom friction coefficient; f is the Coriolis parameter; and k is the unit vector in the vertical direction.

The significant influence of the Coriolis force typically occurs in computational domains with large horizontal scales and at relatively high latitudes. Shiyan Reservoir is located at 22.7 °N, and the horizontal scale of the reservoir area and the downstream flood routing region is only a few kilometers. The Coriolis parameter $f \approx 5.6 \times 10^{-5} \text{ s}^{-1}$ is relatively small. Therefore, the Coriolis force is not considered in this study for its effects on dam-break flood routing and inundation extent.

The study area is discretized with a mesh size of 30 m × 30 m, totaling approximately 1.07×10^5 computational cells. The total duration of the dam breach flood routing simulation is 12 h. Considering that a dam breach may occur at any time, and that breaches during daytime and nighttime would have different impacts on the at-risk population, the dam breach initiation time is set at midnight (0:00) so that the simulation covers all periods from daytime to nighttime, enhancing the representativeness and reliability of the at-risk population estimation.

To analyze the temporal characteristics of the population in affected areas during flood routing and to avoid double counting of at-risk population at adjacent time steps, a 2-h sampling interval is selected, dividing the entire dam breach process into six statistical time points at 2 h, 4 h, 6 h, 8 h, 10 h, and 12 h, respectively characterizing the distribution and quantity differences of at-risk population at each time point.

Regarding boundary conditions, the upstream boundary is located at the dam breach, with the flow hydrograph provided by the BREACH model; the downstream boundary is set at the farthest end of the computational domain, with the water level set at a constant

depth of 0.01 m. The terrain surrounding the reservoir has relatively high elevations, making natural drainage of dam breach floodwaters difficult; the flood will concentrate toward downstream urban areas, causing severe impacts.

2.3. Real-Time Estimation Method for Dam Breach Loss of Life Based on Population Heat Maps and Land Use Data

2.3.1. At-Risk Population Enumeration Method Based on Population Heat Maps

Traditional at-risk population estimation methods primarily include the average density method and the cumulative estimation method based on the number of residential units [38]. Both methods use administrative divisions as study units, assuming uniform population distribution within each unit, without considering spatial heterogeneity and temporal dynamics of population distribution. The dam breach inundation extent typically does not coincide with administrative division boundaries—it may encompass only a portion of an administrative division or span multiple divisions. Therefore, estimation methods based on administrative divisions inevitably lead to biased results [20].

Population heat values are derived from terminal location data collected by mobile communication base stations. Each time a mobile device engages in a location interaction with a base station, it is counted as one heat value record, which is essentially a real-time count of human activity locations and constitutes a counting unit rather than a spatial area unit [39]. The number of heat values within a given area reflects the relative intensity of human activity in that area. Aggregating the heat values across regions by spatial location and overlaying them on a geographic base map in different colors produces a population heat map.

Population heat maps are spatial visualization tools for real-time population distribution generated based on mobile device positioning service data. The fundamental principle is as follows: mobile communication base stations continuously collect signal strength and location information from terminal devices; after statistical processing, a population density distribution map of a specific area during a specific period is generated, displayed as color overlays on a geographic base map to represent population aggregation levels. Compared with traditional census data, population heat map data offer advantages of high real-time performance, high spatiotemporal resolution, and broad coverage, capable of reflecting the spatial distribution dynamics of population at hourly or even minute-level time scales. Building on this approach, Wang and Wang [25] combined remote sensing imagery with mobile phone data to generate fine-resolution population maps, confirming that population distributions derived from multi-source data achieve higher accuracy than traditional census data and are capable of revealing spatial heterogeneity in population distribution at the regional scale.

However, population heat map data also have certain limitations. Heat maps primarily reflect the macro-level spatial trends of population distribution but cannot accurately distinguish between different types of land use areas (e.g., residential, commercial, and industrial areas) or provide detailed information about building functions and living conditions. Additionally, heat map data depend on mobile device coverage and user activity levels; in remote areas or regions with lower device penetration rates, the data may be less precise [25]. When the study area is relatively small, direct averaging of heat map data may deviate substantially from the actual population distribution [20].

Land use data can reflect the spatial distribution, area characteristics, and functional attributes of different land types within a region, serving as an important parameter for characterizing the spatial pattern of human activities [40,41]. In population spatialization studies, land use data are commonly used as weighting factors for population distribution, decomposing the statistical population of administrative units into finer spatial grids by establishing the correspondence between land use types and population density [41].

Ensemble machine learning approaches using multi-source geospatial data have further improved population mapping accuracy in complex terrain regions [42].

Different land use types correspond to different population aggregation characteristics. Typically, residential land exhibits the highest nighttime population density, commercial land has relatively high daytime population density, while industrial land, water bodies, and green spaces have lower permanent population densities [40,41]. A significant coupling relationship exists between land use types and population distribution patterns. However, considerable population distribution differences may still exist within the same land use type, and population estimation relying solely on land use data may overlook this heterogeneity [20,41].

2.3.2. Dam Breach At-Risk Population Estimation Method

Given the complementarity of population heat maps and land use data, this study combines the two to establish a coupled estimation model. The population heat map provides a real-time dynamic overview of population distribution, while land use data provide spatial classification and constraints for land cover types. Through spatial correction of heat map data using land use types, the accuracy of at-risk population estimation can be effectively improved.

Specifically, based on the population heat data of the study area, a heat value-to-population conversion coefficient w_t is first defined:

$$w_t = \frac{D}{Q_t} \quad (9)$$

where w_t is the heat value-to-population conversion coefficient at time t (Persons/Heat Element); Q_t is the total population heat value at time t (Heat Element); and D is the total population of the study area (Persons).

Note: Heat Element is a relative indicator that characterizes population density in the population heat map; higher values correspond to greater population density.

The study area is divided into different land use type zones based on land use data, and the population heat density $\rho_i(t)$ for each land use type is calculated:

$$\rho_i(t) = \frac{q_i(t)}{A_i} \quad (10)$$

where $\rho_i(t)$ is the population heat density of the i -th land use type at time t (Heat Element/km²); $q_i(t)$ is the total population heat value of the i -th land use type at time t (Heat Element); and A_i is the area of the land use zone (km²).

The land use data used in this study are derived from the 2025 National Land Use Remote Sensing Monitoring Dataset published by the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences, with a spatial resolution of 30 m. According to research requirements and the actual land use characteristics of Shenzhen, the land types in the study area are reclassified into five categories: cultivated land, forest land, grassland, water body, and residential area. The land use distribution is shown in Figure 3.

All spatial overlay analyses, including raster alignment, zonal statistics, and the coupling of inundation extents with land use and population heat map layers, were performed using ArcGIS Pro (Version 3.0.1; Esri Inc., Redlands, CA, USA).

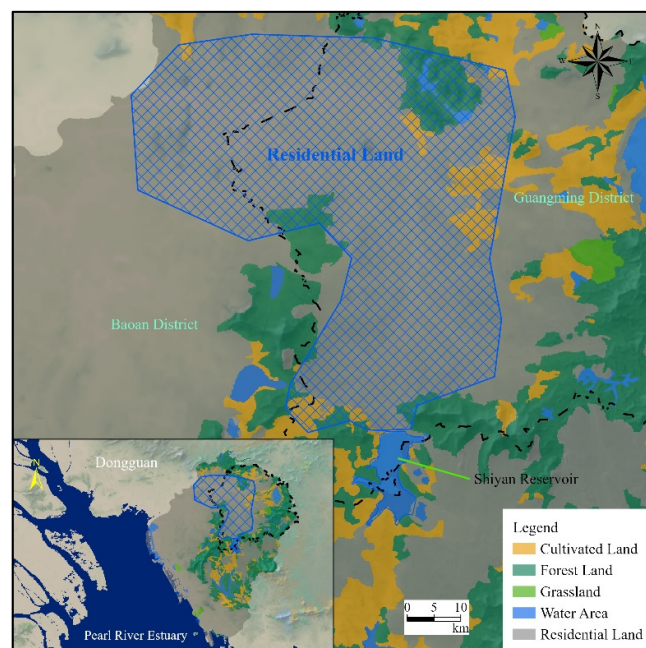


Figure 3. Land Use Distribution Map.

Multiplying the heat value-to-population conversion coefficient by the population heat density of each land use category yields the corrected population density for each land use type under the coupled model:

$$P_i(t) = w_i \times \rho_i(t) \quad (11)$$

where $P_i(t)$ is the corrected population density of the i -th land use type at time t (Persons/km²).

As the dam breach flood develops, the inundation area gradually changes. Since the warning time-related fatality rate of at-risk population has already been considered in the loss of life calculation, population movement due to warning time is not considered when computing the at-risk population. To reflect the temporal variation in the affected population within the inundation extent at different times during the dam breach flood routing process and to avoid double counting of at-risk population across time steps, only the newly inundated areas of each grid cell are counted. Spatial overlay analysis is performed between the dam breach flood inundation extent and the corrected population distribution raster data to calculate the number of newly added at-risk population at each time interval. The calculation formula is as follows:

$$P_{AR}(t) = P_i(\Delta t) \cdot S_i(\Delta t) \quad (12)$$

where $P_{AR}(t)$ is the estimated cumulative newly added at-risk population within the dam-break inundation extent (Persons); and $S_i(\Delta t)$ is the newly inundated area of land use type i during unit time step Δt (km²).

The schematic diagram illustrating the coupled estimation framework was prepared using Jimeng AI (web version, ByteDance; <https://jimeng.jianying.com>, accessed on 15 July 2026) solely to generate the schematic layout showing the vertical mapping relationships among the four data layers (geographic base map, land use, population heat map, and inundation extent). The AI tool was not used to generate, process, or modify any data, analysis results, or scientific content; all underlying data were obtained through standard GIS spatial overlay analysis as described above.

2.3.3. Dam Breach Loss of Life Estimation Method

Using the real-time at-risk population, the newly added dam-break loss of life L_{OL} is estimated using the loss of life evaluation model of Li-Zhou [43], which was improved from Graham [15]:

$$L_{OL} = \sum L_{OL}(t) \quad (13)$$

$$L_{OL}(t) = P_{AR}(\Delta t) \times f \times \alpha \quad (14)$$

$$\alpha = m_1 + bm_2 \quad (15)$$

where L_{OL} is the total loss of life from dam-break flooding (Persons); $L_{OL}(t)$ is the newly added loss of life from dam-break flooding (Persons); f is the fatality rate of the at-risk population, determined by comprehensive classification based on the flood severity level as quantified by the flood severity parameter (S_d), warning time (W_T), and the at-risk population's understanding of flood severity—the lower the flood severity level, the longer the W_T , and the more precise the understanding, the lower the fatality rate; α is the severity coefficient of the dam-break event, i.e., the correction coefficient for the at-risk population fatality rate; m_1 is the disaster severity influence factor for direct factors affecting loss of life, with $m_1 \leq 1$; m_2 is the disaster severity influence factor for indirect factors affecting loss of life, with $m_2 \leq 1$; and b is the coefficient of the disaster severity influence factor for indirect factors affecting loss of life, with $0 < b < 1$.

This method was calibrated using measured data from eight breached dams in China and is better aligned with the social environment and demographic characteristics of Chinese dam-break scenarios than foreign empirical models. The flood severity level of each grid cell is determined by the product of its time-varying water depth D and velocity V ($S_d = DV$), both of which are obtained from the two-dimensional hydrodynamic simulation results of HEC-RAS; W_T is the interval between dam breach occurrence and warning issuance, and the understanding level represents the at-risk population's reception and perception of warning information and flood risk. These three factors jointly determine the fatality rate f of each grid cell according to the empirical classification of Zhou [43]. HEC-RAS also provides the time at which each grid cell is actually inundated by the flood wave. The population within a given grid cell is counted as newly added at-risk population only during its inundation period, and the loss of life is calculated based on the S_d , W_T , and understanding level of that period.

3. Results

3.1. Earthen Dam Breach Outflow Calculation and Flood Routing Simulation

3.1.1. Earthen Dam Breach Outflow Calculation

The BREACH model described in Section 2.2.1 was employed to calculate the dam-break outflow hydrograph under the assumption that Shiyan Reservoir encounters a 5000-year return period extreme flood.

BREACH [11] is a physics-based earthen dam breach erosion model developed by the U.S. National Weather Service. It couples the reservoir water balance equation with breach sediment transport capacity to predict breach characteristics and the outflow hydrograph. This study adopts the overtopping failure mode, with sediment transport calculated using the Smart-modified Meyer-Peter and Müller erosion formula [33]. The erosion module couples headcut migration with continuous bed degradation and assesses block instability and collapse through slope stability analysis; when the undercut slope exceeds the critical angle determined by cohesion c and internal friction angle ϕ , block slumping occurs, and the breach cross-section transitions from rectangular to trapezoidal. The simulation duration was 12 h with a computational time step of 0.1 s. The results show that the

reservoir water level rises gradually; after overtopping occurs, the breach progressively develops, and the breach discharge rises rapidly to its peak within approximately 1 h after breach initiation, then gradually recedes as the reservoir water level declines, stabilizing between 10 and 12 h. The peak breach discharge was $3036 \text{ m}^3/\text{s}$, the final breach depth was 18.50 m, the bottom width was 40.75 m, the top width was 63.7 m, and the stable side slope gradient was 1:0.62. The breach outflow hydrograph is shown in the Figure 4.

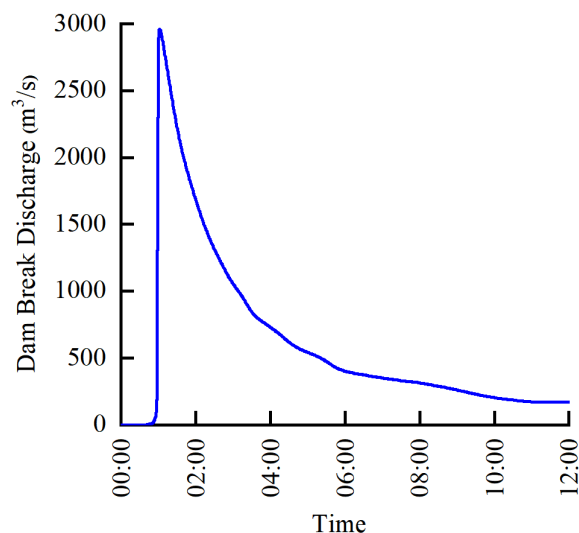


Figure 4. Dam Break Outflow Hydrograph.

3.1.2. Dam Breach Flood Routing Simulation Results

The HEC-RAS 2D model was employed for dam breach flood routing calculation of the Shiyao Reservoir. The results show that two hours after the dam breach, the inundation area reaches 4.44 km^2 , with a maximum water depth of 8.48 m and a maximum flow velocity of 6.36 m/s within the area. As the dam breach progresses, the inundation area gradually increases, reaching a maximum of 16.99 km^2 by the end of the simulation, while the maximum flow velocity in the area gradually decreases and the water depth in each area gradually stabilizes. The growth rate of the dam breach flood inundation extent exhibits a pattern of initial rapid expansion, followed by deceleration, and eventually stabilizes. After the dam breach simulation, residential areas account for 97.13% of the inundation extent, cultivated land accounts for 1.88%, and forest land and water bodies account for 0.99%. The residential area far exceeds other land use types, and the population is highly concentrated in residential areas, indicating that the dam breach flood has a severe impact on the at-risk population downstream of the reservoir. The dam breach inundation maps are shown in Figure 5.

The flood severity parameter S_d , defined as the product of water depth D and flow velocity V , serves as a critical threshold indicator for human toppling instability in floodwaters [44] and is widely used for flood severity classification. Following the dam-break loss of life estimation method of Zhou [43], this study classifies flood severity into three levels based on the DV product: $DV \geq 7.0 \text{ m}^2/\text{s}$ is classified as high severity, $3.0\text{--}7.0 \text{ m}^2/\text{s}$ as medium severity, and $<3.0 \text{ m}^2/\text{s}$ as low severity; the fatality rate f is assigned according to this classification. The DV product has limitations in deep-water, low-velocity quiescent zones—as V approaches zero, DV also approaches zero, making it difficult to capture the hazard dominated by water depth. Beffa [45] proposed addressing this issue with a piecewise intensity function: when $V < 1 \text{ m/s}$, the hazard is controlled solely by water depth, and when $V \geq 1 \text{ m/s}$, the DV product term is introduced. This study introduces a velocity floor and water depth envelope rule: when $D > 2.0 \text{ m}$ and $V < 1.0 \text{ m/s}$, 1.0 m/s is

used as the effective lower velocity limit; when $D > 2.0$ m, the flood severity is no lower than medium. The statistical scope is limited to the newly inundated area within each time step, consistent with the spatial distribution of the at-risk population. In the newly inundated area at 10 h, one localized deep-water depression ($D = 8.80$ m, accounting for 1.04% of that period's newly inundated area) yields a corrected $DV = 8.80$ after applying the velocity floor, ensuring that the hazard is not overlooked; however, due to its spatial isolation, it does not alter the overall severity level of the entire area. The results indicate that the DV in newly inundated areas during the early phase (2–6 h) ranges from 7.0 to $18.91 \text{ m}^2/\text{s}$, corresponding to high severity, while in the middle-to-late phase (8–12 h) it decreases to $3.23\text{--}4.74 \text{ m}^2/\text{s}$, corresponding to medium severity. Basic parameters for each dam breach condition are listed in Table 2.

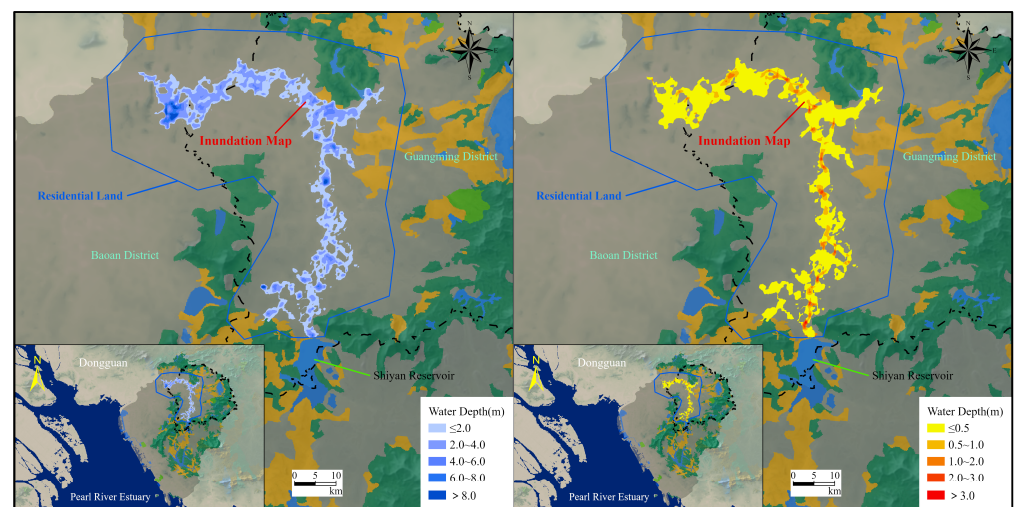


Figure 5. Dam Breach Inundation Maps.

Table 2. Basic parameters for each dam breach condition.

Simulation Time	Maximum Water Depth (m)	Maximum Flow Velocity (m/s)	DV (m^2/s)	S_d
2:00	8.48	6.36	18.91	High
4:00	11.18	3.93	10.92	High
6:00	7.00	3.28	7.00	High
8:00	4.74	1.97	4.74	Medium
10:00	8.80	3.27	3.79	Medium
12:00	3.23	1.37	3.23	Medium

3.2. At-Risk Population Analysis Based on Population Heat Maps

Visualization analysis of the dam breach results was performed, overlaid with population heat map data, to generate the at-risk population heat map within the dam breach inundation extent.

Figure 6a (2 h after dam breach, 2:00 AM): During late-night hours, the population of Shenzhen is primarily concentrated near residential communities and apartments, with fewer people in commercial areas, office districts, and public areas such as schools and hospitals within the urban area. Figure 6b (4 h after dam breach, 4:00 AM): Still in the late-night period, population activity drops to the lowest level of the day; the vast majority of the population is concentrated in residential areas, with virtually no activity in commercial areas, office districts, and public areas. The population heat distribution is essentially consistent with that at 2 h. Figure 6c (6 h after dam breach, 6:00 AM): The population distribution pattern begins to change gradually, as people start to move toward office

areas, shopping malls, and other public areas. Figure 6d (8 h after dam breach, 8:00 AM): The morning rush hour is now underway, with large-scale population movement from residential areas to office areas and commercial districts. The population density in public areas rises significantly, presenting a stark contrast to the late-night period. Figure 6e (10 h after dam breach, 10:00 AM): Daytime has arrived, and public areas have high population density. Figure 6f (12 h after dam breach, 12:00 PM): The simulation ends, and the population distribution within the inundation extent remains essentially unchanged, with the water depth basically stabilized.

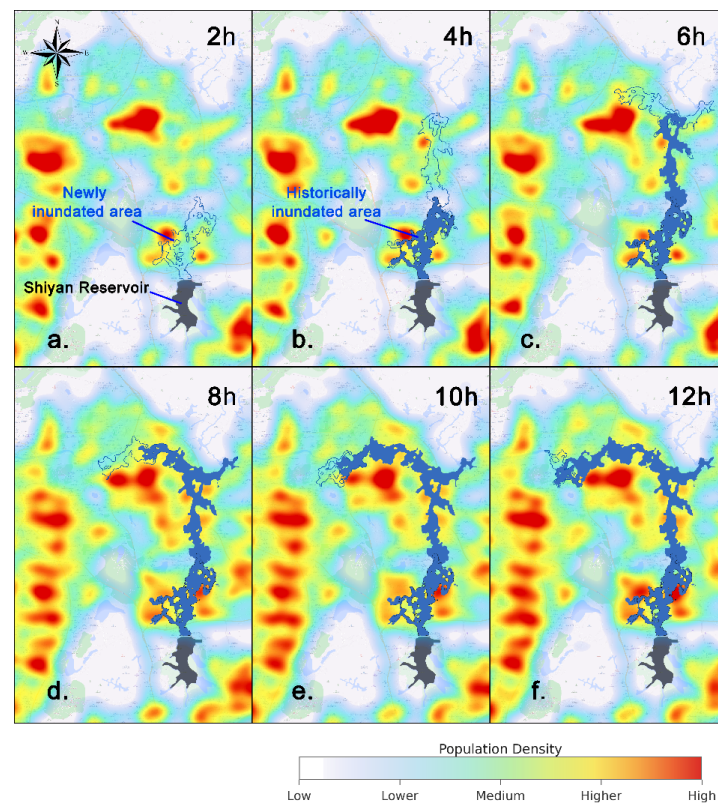


Figure 6. At-risk population heat map within the dam breach inundation extent at different time steps after dam breach: (a) 2 h (2:00 AM); (b) 4 h (4:00 AM); (c) 6 h (6:00 AM); (d) 8 h (8:00 AM); (e) 10 h (10:00 AM); (f) 12 h (12:00 PM).

The exact timing of a dam breach cannot be known in advance. This study sets 0:00 midnight as the initiation time, intending to select a conservative scenario in which the population is concentrated in residential areas under the least favorable evacuation conditions, rather than to predict the actual failure time. The simulation covers a 12-h routing process at 2-h intervals, with the heat map at each time reflecting the population distribution characteristics of the corresponding period: during late-night hours (2:00–4:00), most residents are asleep, resulting in the lowest efficiency in receiving and responding to warning information; during daytime hours (8:00–12:00), people are awake and dispersed across office, commercial, and public areas, providing relatively favorable conditions for warning dissemination and understanding. In the subsequent loss of life estimation, four W_T values ($W_T = 0$ h, 0.5 h, 1 h, and >1 h) and two understanding levels (precise/vague) are configured for each time period, yielding eight scenarios. The aforementioned temporal differences are already encompassed through this factorial design, eliminating the need for a deterministic one-to-one mapping of warning effectiveness at each time. This coupled framework does not depend on a specific initiation time; if breach scenarios during other

time periods need to be assessed, it is only necessary to replace the corresponding heat map layer.

3.3. At-Risk Population Estimation Based on Population Heat Maps and Land Use Data

To achieve refined estimation of the at-risk population within the dam breach inundation extent, this study designed a spatial overlay coupling method based on geographic base maps, land use data, population heat maps, and dam breach inundation extent (Figure 7). First, the spatial extent and terrain characteristics of the study area are determined based on the geographic base map; second, land use data are used to classify the study area into five land cover types—cultivated land, forest land, grassland, water body, and residential area—to obtain the spatial distribution and area information of each land use type; simultaneously, population heat map data are introduced to obtain the spatial distribution of population heat values in the study area at each time point, reflecting the real-time dynamic aggregation characteristics of population; finally, the inundation extent maps at each time point of the dam breach flood are spatially overlaid with the land use distribution map and the population heat map, respectively, to extract the heat values of each land use type within the inundation extent, calculate the population heat density of each land use type and the population heat density weight coefficient of the study area, and subsequently estimate the corrected population of each land use type through coupling. This method achieves the organic integration of real-time population distribution and land cover type information through spatial overlay mapping of multi-source data, effectively improving the spatial accuracy and timeliness of at-risk population estimation.

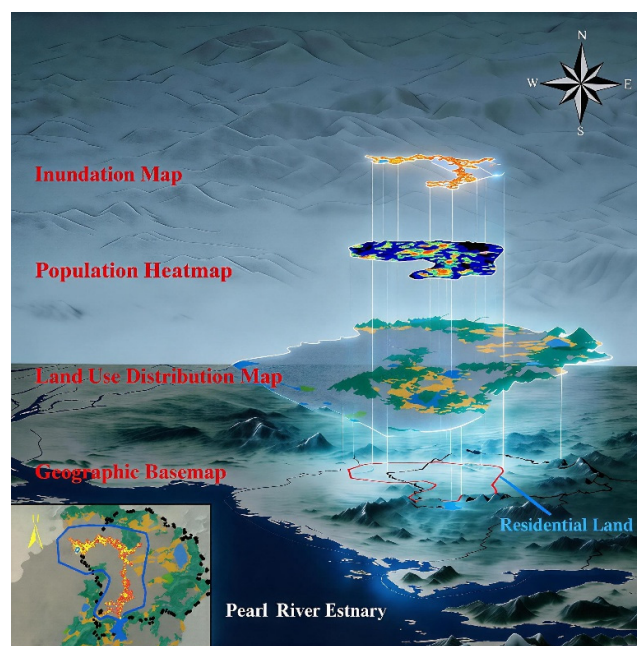


Figure 7. Coupled Estimation Model Based on Population Heat Maps and Land Use Data.

The calculation parameters are listed in Table 3.

The residential population heat density far exceeds that of other land use types, reaching the highest value of 277.15 Heat Element/km² at 12 h and the lowest of 66.19 Heat Element/km² at 4 h, exhibiting a trend of initial decline followed by an increase. The heat value-to-population conversion coefficient w_t shows the opposite trend, exhibiting an initial increase followed by a decline, reaching the highest value of 198 Persons/Heat Element at 4 h and the lowest of 46 Persons/Heat Element at 12 h.

Table 3. Calculation Parameters for At-risk Population of Dam Breach.

Simulation Time	$\rho_i(t)$ (Heat Element/km ²)					w_t (Persons/Heat Element)
	Cultivated Land	Forest Land	Grassland	Water Area	Residential Land	
2:00	10.22	5.84	0.56	1.09	95.84	137
4:00	6.76	4.43	0.56	1.4	66.19	198
6:00	12.04	8.06	3.91	1.24	79.05	161
8:00	29.93	22.18	6.15	3.57	178.16	70
10:00	46.62	38.46	17.90	2.80	262.05	47
12:00	43.27	27.30	22.93	3.57	277.15	46

Based on the dam breach at-risk population estimation parameters, the real-time at-risk population is calculated and presented below, along with a comparison with the real-time at-risk population calculated without considering land use correction. The real-time at-risk populations with and without land use correction are compared in Figure 8.

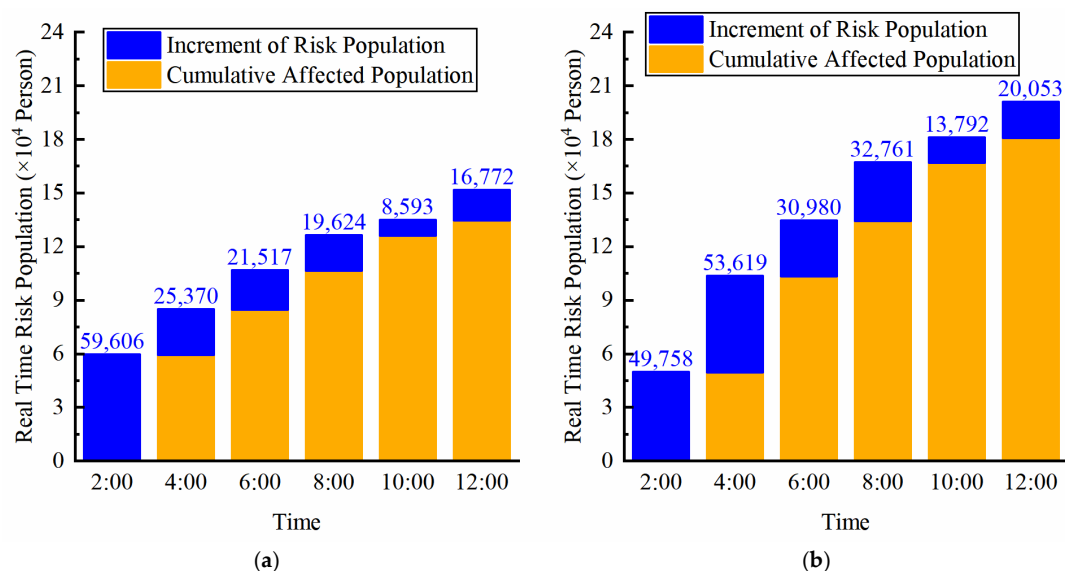


Figure 8. (a) Real-Time At-Risk Population Without Land Use Correction; (b) Real-Time At-Risk Population With Land Use Correction.

Without land use correction, the real-time at-risk population grows rapidly within the first 2 h after the breach, with growth slowing after 4 h and stabilizing between 10 and 12 h, yielding a final total at-risk population of 151,482. With land use correction, the newly added at-risk population grows rapidly within the first 4 h, with growth decelerating after 6 h and stabilizing between 10 and 12 h, reaching a final total at-risk population of 200,963, an increase of 32.7% compared with the uncorrected result. The growth trends of the two approaches are generally consistent, but the estimates incorporating land use correction are higher than the uncorrected results at every time step.

3.4. Dam Breach Loss of Life Estimation

Based on the real-time newly added at-risk population count, considering the at-risk population's understanding of dam breach flood severity and the impact of warning time on the at-risk population, the dam breach loss of life under different conditions is estimated using the method based on population heat maps and land use data. The incremental dam breach loss of life calculation results are shown in Figure 9.

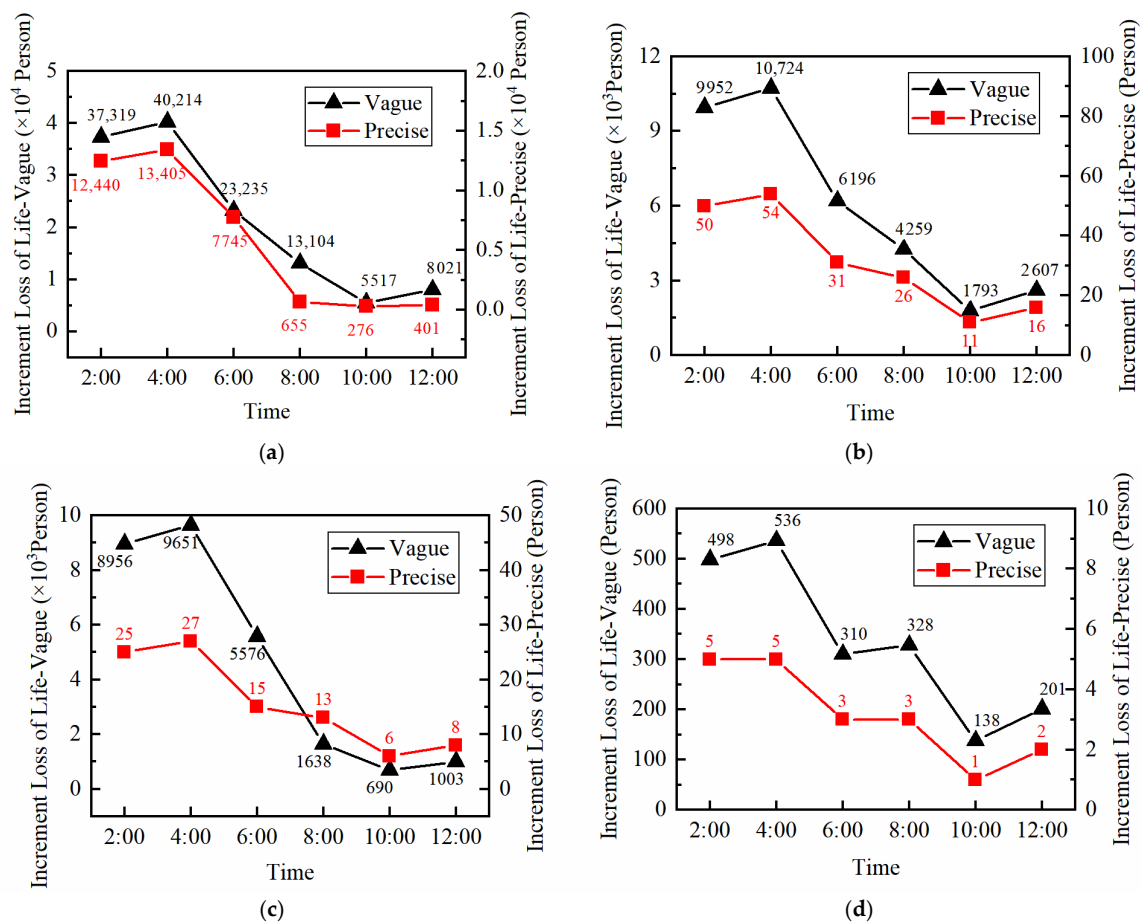


Figure 9. Incremental Dam Breach Life Loss Under Different Warning Times; (a) $W_T = 0$ h, (b) $W_T = 0.5$ h, (c) $W_T = 1.0$ h, and (d) $W_T > 1.0$ h.

The number of lives lost in dam breach events is linearly correlated with the at-risk population. When the understanding of dam breach flood severity is vague, the loss of life among the at-risk population far exceeds that under precise understanding conditions at the same warning time. As the warning time increases, the loss of life shows a decreasing trend.

The loss of life throughout the entire dam breach flood routing process under different warning times is summarized in Table 4.

Table 4. Dam Breach Loss of Life Calculation Results.

W_T	L_{OL}			
	L_{OL} —Vague	L_{OL}/P_{AR}	L_{OL} —Precise	L_{OL}/P_{AR}
0 h	129,691	64.53%	35,036	17.43%
0.5 h	36,272	18.05%	193	0.10%
1.0 h	27,799	13.83%	96	0.05%
>1.0 h	2068	1.03%	20	0.01%

The results indicate that when the warning time is less than or equal to 1 h and the at-risk population's understanding of dam breach flood severity is vague, the loss of life is high. When the warning time exceeds 1 h and the at-risk population's understanding of dam breach flood severity is precise, the loss of life is minimal.

4. Discussion

4.1. Analysis of Reservoir Dam Breach and Flood Routing Results

The Shiyan Reservoir has no measured dam breach flood data. The core objective of the simulation analysis in this study is to validate the feasibility of the proposed coupled population heat map and land use loss of life estimation method, rather than to reproduce an actual dam breach event. Therefore, the dam breach scenario is set as a hypothetical condition under a 5000-year return period design flood. On this basis, the breach outflow process and flood routing patterns are analyzed and compared with existing research results for verification.

1. The simulation results show that the breach outflow rises sharply to its peak within approximately 1 h after breach initiation, then gradually declines as the reservoir water level drops, and stabilizes after 10 h. This three-stage pattern—“rapid rise, gradual decline, and final stabilization”—reflects the coupling between breach erosion dynamics and reservoir storage regulation: initially, rapid breach incision and widening under high hydraulic head drive the outflow to peak; as the water level drops and the breach approaches its limiting dimensions, the erosion rate slows and the outflow decreases accordingly. These simulated patterns corroborate the breach evolution observed by Elalfy et al. [46] in laboratory experiments on non-cohesive embankment dam breaches, and closely parallel the experimental findings of Chen et al. [47].
2. The dam breach flood inundation area grows rapidly in the first 6 h after the dam breach, with the growth rate decelerating between 8 h and 10 h, and stabilizing by 12 h, ultimately reaching 16.99 km², exhibiting a “rapid-then-gradual” routing characteristic. This pattern is consistent with the spatiotemporal attenuation patterns of flood propagation in the probabilistic risk assessment of dam breach floods based on HEC-RAS 2D by Li et al. [1]. The flood severity gradually transitions from high severity in the early stage to moderate severity in the middle and late stages, reflecting the spatial distribution characteristics of shallow water at high velocity near the breach and deeper water at lower velocity at the far end of the dam breach flood.

4.2. Analysis of At-Risk Population Estimation Results

Shenzhen has a large proportion of residential land and a dense population, and the upstream reservoir dam breach risk exacerbates the disaster impact. Population heat data reflect population activities in real time and are closely related to dam breach flood routing and changes in the at-risk population. However, late-night data may be distorted, requiring integration with land use data for accurate risk assessment.

1. Shenzhen is economically developed with a high level of urbanization. The areas of cultivated land, forest land, grassland, and water bodies within the city are limited, while residential land constitutes a large proportion, resulting in a highly dense population distribution. When a reservoir located upstream of the urban area experiences a dam breach, a large volume of water discharges into the densely populated urban district, leading to particularly severe disaster consequences. The land use classification results in this study show that residential areas have a high proportion and their heat density far exceeds that of the other four land use types (Figure 3, Table 3), indicating that the study area has a large at-risk population base and severe potential disaster impacts from dam breach.
2. Population heat map data, collected via mobile device positioning, reflect real-time population distribution and activity patterns, closely tracking the dynamic changes in at-risk population during flood routing. However, such data exhibit diurnal fluctua-

tions: heat density is relatively low at night when activity decreases and sampling drops, and higher during daytime—consistent with actual activity patterns and with the findings of Wang and Wang [25]. Sole reliance on heat map data may thus introduce bias, necessitating land use correction. Additional error sources include: (1) varying smartphone penetration across age and income groups, potentially causing systematic bias; (2) limited sampling frequency (typically 5–15 min), which may miss rapid population changes such as mass evacuations; and (3) incomplete data due to users disabling location services. Future research should address these issues through multi-source data fusion and error correction.

3. From the perspective of the dynamic response between dam breach flood routing and at-risk population, the real-time at-risk population grows rapidly in the early stage of the dam breach and stabilizes in the middle and late stages, consistent with the patterns of the breach outflow hydrograph and flood severity parameter changes. The final total at-risk population after land use correction is 200,963, an increase of 32.7% compared to the uncorrected 151,482, with the difference being particularly significant in the early stage of the dam breach. The reason is that the dam breach initiation time is set at midnight (0:00), when mobile device activity declines during the late-night hours, leading to underestimation by heat data; the land use correction compensates for this with the significantly higher heat density of residential areas compared to other land use types, effectively addressing the data distortion during late-night hours.

4.3. Analysis of Dam Breach Loss of Life Estimation Results

The urgency of reservoir dam-break warning time is directly related to the severity of disaster consequences. The shorter the warning time, the more limited the response time available to the at-risk population, and the higher the risk of loss of life. Meanwhile, the at-risk population's understanding of flood severity and the time of day at which the breach occurs also influence disaster outcomes.

1. Warning time is the key factor determining dam-break loss of life. Sensitivity analysis shows that when the understanding level is “vague,” the loss of life decreases substantially as W_T increases: from 129,691 persons at $W_T = 0$ h to 36,272 at 0.5 h (a 72% reduction), 27,799 at 1 h, and 2068 beyond 1 h (a 98% reduction from 0 h). However, the area downstream of Shiyan Reservoir is highly densely populated; even with W_T exceeding 1 h, 2068 casualties still occur under vague understanding, and the disaster consequences should not be underestimated. When the understanding level is “precise,” the loss of life is 35,036 persons at $W_T = 0$ h and drops to fewer than 20 persons when W_T exceeds 1 h, far lower than the results under vague understanding at the same warning time. Overall, the marginal benefit diminishes and the fatality rate approaches a low level once W_T exceeds 1 h.
2. The at-risk population's understanding of flood severity significantly affects the estimation results. Taking $W_T = 0.5$ h as an example, the loss of life is 36,272 persons under vague understanding but only 193 persons under precise understanding, a difference of approximately two orders of magnitude. Under conditions of daytime or well-lit urban nighttime with diverse information dissemination channels, the perception of the at-risk population should lean toward “precise”; therefore, the “vague” assumption can be regarded as an extremely unfavorable scenario, while the “precise” assumption is more realistically reasonable.
3. The breach timing significantly affects disaster consequences. The breach initiation time in this study is set at 0:00 midnight. During 2–6 h after the breach, flood severity is at a high level ($S_d = 7.0$ – 18.91 m²/s), coinciding with late night to early morning when

human activity is low, evacuation conditions are poor, and risk exposure is high; had the breach occurred during daytime, the loss of life would have been notably lower. In addition, flood propagation from upstream to downstream takes time, so distal areas have longer warning times, and the population exhibits avoidance behavior. The estimates under the midnight breach and vague understanding assumptions are therefore conservative.

4. Validation of the rationality of the estimation results. The fatality rate f in this study adopts the Li-Zhou method [43], which was improved from Graham [15], and the L_{OL}/P_{AR} ratios across all scenarios range from 0.01% to 64.53%. The most unfavorable scenario ($W_T = 0$ h, vague understanding) yields 64.53%, which falls within the recommended range for high severity in Graham's original table (30–100%), while the most favorable scenario ($W_T > 1$ h, precise understanding) yields 0.01%, close to the recommended value for low severity (0.02%), indicating that the estimation results of this study are in good agreement with Graham's empirical framework. Taking $P_{AR} = 200,963$ in this study as an example, the Brown and Graham model [16] predicts a loss of life of approximately 1521 persons, whereas this study yields 27,799 persons even at 1 h of warning, indicating that this early model has limited extrapolation capability for high-PAR urban dam-break scenarios. Brazdova and Riha [48], based on 19 Central European inland flood cases and using the Saaty method to rank causative factors, identified preparedness level, warning time, and hydrodynamic conditions (water depth, flow velocity, and flood extent) as the leading factors, which is consistent with this study's conclusion that warning time is the most critical factor and that understanding level and flood severity jointly influence the fatality rate. The L_{OL}/P_{AR} ratios in this study are spatially weighted aggregated values across high-, medium-, and low-severity zones rather than single-level lookup table results, which is the primary reason for the numerical differences.

4.4. Rationality Analysis of the Real-Time Urban Dam Breach Loss of Life Estimation Method

In dam-break flood routing, conventional at-risk population enumeration methods suffer from distortion and double-counting problems and fail to account for the spatiotemporal variability in flood severity. This study introduces a temporal variable to distinguish newly inundated populations from those already counted in previous time steps, thereby enabling a more accurate assessment of loss of life. Compared with conventional models, the estimation results are more reasonable and provide a new tool for dam-break disaster management.

1. Conventional at-risk population enumeration has two limitations. First, estimation based on the final inundation extent using population data at a single time cannot capture the dynamic changes in flood severity and population distribution over time. Second, simply summing the population within the cumulative inundation extent across time steps leads to double counting. To address these issues, this study introduces a temporal variable that identifies newly inundated areas at each time step, counts the population within these areas as newly added at-risk population, and computes loss of life according to the flood severity and warning time at the moment of inundation. Within the final 12 h inundation extent, the conventional method yields an at-risk population of 151,482, whereas the proposed method yields 200,963, a difference of approximately 32.7%. This discrepancy arises from the pronounced temporal dynamics of population spatial distribution—the actual population present in inundated areas varies across time steps, and data from a single moment cannot fully represent population exposure throughout the entire process. Under $W_T = 0$ h, the estimated loss of life is 129,691 (vague understanding) and 35,036 (precise under-

standing), which is more reasonable than applying a single fatality rate uniformly across the entire inundation area.

2. The proposed population-heat-map-based method for estimating dam-break loss of life offers the following advantages. First, by introducing a temporal variable to distinguish newly inundated populations from those already counted in previous time steps, it ensures that each person is counted only once throughout the dynamic time-step estimation, thereby avoiding double counting. Second, by incorporating differences in understanding level, the estimation results can reflect the range of loss of life under various warning conditions—from 129,691 at $W_T = 0$ h (vague) to fewer than 20 at $W_T > 1$ h (precise), spanning nearly four orders of magnitude. The estimation results of this study are close to the loss of life estimates from dam-break flood scenarios reported by Zhou et al. [43], validating the applicability and rationality of the proposed method for urban dam-break risk assessment.

4.5. Applicability and Limitations of the Method

Based on the results in Table 4, loss of life is jointly determined by flood severity, warning time, and public understanding level, with marked differences in the relative influence of each factor. Warning time is the most critical: increasing W_T from 0 h to >1 h can reduce loss of life by more than two orders of magnitude. Understanding level is next in importance; under the same warning time, the difference between vague and precise understanding can range from several-fold to two orders of magnitude. Breach timing indirectly affects risk exposure by altering the spatial distribution of population—during late-night hours, residents are concentrated in residential areas with poor evacuation conditions, making this scenario more adverse than a daytime breach. Brazdova and Riha, using pairwise comparisons of historical flood cases, obtained a similar ranking of factor significance, in which warning time and flood severity were identified as the most dominant factors [48]. The results of this study further indicate that the marginal benefit of warning time is the most pronounced, and that extending the warning window is the most effective means of reducing loss of life.

The applicability of the proposed method is not confined to a specific region. Population heat maps, land use classification, DEM, and other foundational data are now available in most urbanized regions worldwide; where mobile positioning data coverage is insufficient, alternative data sources such as WiFi hotspots and transit smart cards can be used. The accuracy of application is governed primarily by data completeness rather than by geography per se.

This study nevertheless has several limitations. First, heat values are derived from mobile communication base-station positioning records and are affected by device penetration and user activity: persons not carrying a device may be underestimated, while those carrying multiple devices may be overestimated. A 30 m grid resolution is suitable for block-scale estimation but cannot capture variations at the individual-building level; in densely built-up areas, a 5–10 m grid would improve identification accuracy. Second, the BREACH model used for dam-break simulation simplifies the actual breach expansion process revealed by the IMPACT project field tests—particularly with respect to the uniform erosion assumption and the rectangular breach cross-section [49]; the coupled continuous-erosion and slope-instability lateral expansion model proposed by Mohamed et al. can serve as a direction for future improvement [30]. The fatality rate f is determined according to the empirical classification of Zhou [43]; as no measured dam-break data are available for Shiyao Reservoir, validation relies mainly on indirect comparison with the recommended values of Graham [15], and future work should conduct local parameter calibration using historical cases. Third, the representation of warning and population response is simplified:

age structure, mobility, emergency training, and warning dissemination probability are not explicitly incorporated. Coupling probabilistic warning dissemination with pedestrian evacuation behavior models is a direction for future improvement.

5. Conclusions

Addressing the challenges of real-time estimation of dynamic population distribution and rapid assessment of casualties in dam breach disasters, this study integrates population heat maps with land use data to optimize traditional casualty assessment methods and establishes a real-time dam breach loss of life estimation model. Taking the urban dam breach scenario of the Shiyao Reservoir in Shenzhen as a case study, the dam breach at-risk population and loss of life are quantified, and the key driving factors of casualties are systematically identified. The main conclusions are as follows:

1. The model introduces a temporal dimension to characterize dynamic population distribution, distinguishing newly inundated populations from those already counted in previous time steps and ensuring that the at-risk population is not double-counted throughout the flood routing process. The cumulative newly added at-risk population over the entire flood routing process totals 200,963, which is approximately 32.7% higher than the result obtained by the conventional static enumeration based on the final 12 h inundation extent (151,482). This discrepancy arises from the temporal dynamics of population spatial distribution: data from a single moment cannot fully represent population exposure throughout the entire process. Relying on real-time spatial population data, the proposed model can provide quantitative support for dam-break warning and emergency response decision-making.
2. Dam breach disasters exhibit significant phase-specific risk differences. In the initial stage, flood routing is rapid and the disaster intensity is high, with the at-risk population and estimated casualties rising rapidly, indicating extremely strong destructive power. In the middle and late stages, flood movement tends to stabilize and the disaster intensity slightly decreases, with the rate of new casualties slowing down. However, due to the high population concentration in urban areas, the cumulative total of casualties remains at a high level, and the overall dam breach risk is prominent, necessitating strengthened risk understanding among management personnel and routine implementation of reservoir operation and maintenance and dispatch control.
3. Warning duration is the core factor determining the number of casualties from dam breach. An insufficient warning window severely compresses the time available for the public to take protective actions, evacuate, and seek shelter, thereby exacerbating disaster losses. Therefore, it is essential to establish a standardized dam breach emergency warning system, improve flood hazard identification accuracy, and issue warnings as early as possible to extend the evacuation buffer time for the public.
4. The public's understanding level of dam breach risk directly affects casualty outcomes. When the public is well informed about flood hazards and protective measures, personnel losses are significantly reduced; vague risk understanding can lead to heavy casualties. Regularly conducting emergency drills and disaster prevention education can enhance the public's self-rescue, mutual rescue, and coordinated evacuation capabilities, thereby reducing dam breach casualties and property losses at the source.
5. The model still has the following aspects that warrant improvement. (1) Field validation of dam-break loss of life estimates. Shiyao Reservoir has no measured dam-break data, and the estimation results of this study were validated only through indirect comparison with the recommended values of Graham [15], lacking direct verification against actual dam-break casualty data. If opportunities arise in the future to obtain actual casualty data from dam-break events in similar high-density urban built-up areas,

the applicability of the proposed method to urban scenarios can be further validated. (2) Refinement of warning and population response. The public understanding level currently adopts a “vague/precise” dichotomy, which is relatively subjective; age structure, mobility, warning dissemination probability, and evacuation accessibility have not been explicitly incorporated. Future work could quantify understanding level as a continuous indicator through post-disaster survey scales or community socioeconomic attribute regression, and advance the coupling of probabilistic warning dissemination models with pedestrian evacuation behavior models. However, in urban dam-break scenarios, warning dissemination involves multiple channels and multi-level nodes, with large variations in transmission efficiency across channels and in population response probability; the parameter calibration for such coupled modeling lacks support from measured data. (3) Spatial resolution and building vulnerability differentiation. Both the current flood computation grid and land use data adopt a 30 m spatial resolution, making it difficult to capture variations at the individual-building level; meanwhile, heat data are affected by device penetration and user activity, and their spatial distribution deviates from the true population distribution. In densely built-up areas, the grid could be refined to 5–10 m and building structural attenuation coefficients introduced to differentiate the vulnerability of building types such as urban villages and commercial housing; however, such data are not yet systematically compiled in most cities, and acquisition costs are relatively high. (4) Improvement of the breach physical process model. The BREACH model simplifies the coupling between lateral erosion mechanisms and slope instability; future work could introduce physically based process models to improve breach simulation accuracy, and further integrate multi-source data such as remote sensing imagery and traffic flow to enhance the real-time performance and comprehensiveness of estimation. However, key parameters such as the soil erosion coefficient during breach erosion are highly sensitive to breach dimensions, while measured breach development data remain extremely limited both domestically and internationally; in addition, breach expansion involves the coupling of multiple processes including scour erosion, slope instability, and block slumping, and the calibration and validation of model improvements are constrained by the scarcity of measured data.

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References

- Li, D.; Luo, J.; He, J.; Huang, R.; He, Z.; Wang, Y.; Mei, Z.; Tan, W. Probabilistic Risk Assessment of Dam Breach Floods: A Stochastic Framework Integrating Multi-Model Uncertainty and HEC-RAS Coupling. *Water* **2026**, *18*, 1657. [\[CrossRef\]](#)
- Armon, M.; Shmilovitz, Y.; Dente, E. Anatomy of a foreseeable disaster: Lessons from the 2023 dam-breaching flood in Derna, Libya. *Sci. Adv.* **2025**, *11*, eadu2865. [\[CrossRef\]](#)
- Liu, Y.; Liu, Y.; Yu, Q.; Liu, S. Urban Flood Risk Sustainable Management: Risk Analysis of Dam Break Induced Flash Floods in Mountainous Valley Cities. *Sustainability* **2025**, *17*, 5863. [\[CrossRef\]](#)
- Rentschler, J.; Salhab, M.; Jafino, B.A. Flood exposure and poverty in 188 countries. *Nat. Commun.* **2022**, *13*, 3527. [\[CrossRef\]](#)
- Tellman, B.; Sullivan, J.A.; Kuhn, C.; Kettner, A.J.; Doyle, C.S.; Brakenridge, G.R.; Erickson, T.A.; Slayback, D.A. Satellite imaging reveals increased proportion of population exposed to floods. *Nature* **2021**, *596*, 80–86. [\[CrossRef\]](#)
- IPCC. Weather and Climate Extreme Events in a Changing Climate. In *Climate Change 2021—The Physical Science Basis*; Masson-Delmotte, V., Zhai, P., Pirani, A., Eds.; Cambridge University Press: Cambridge, UK, 2021; pp. 1513–1766. [\[CrossRef\]](#)
- National Bureau of Statistics of China. *China Statistical Yearbook 2025*; China Statistics Press: Beijing, China, 2025.
- National Bureau of Statistics of China. *Achievements of the 14th Five-Year Plan for Economic and Social Development*; China Statistics Press: Beijing, China, 2026.
- Yu, H.; Du, L.; Lai, C.; Luo, P.; Wang, Z.; Zeng, Z. An assessment framework of dam-break flood risk in highly populated and property-intensive area: Case study for the Longdong reservoir. *J. Hydrol. Reg. Stud.* **2025**, *58*, 102201. [\[CrossRef\]](#)
- Fread, D.L. *DAMBRK: The NWS Dam-Break Flood Forecasting Model*; National Weather Service, NOAA: Silver Spring, MD, USA, 1984.
- Fread, D.L. *BREACH: An Erosion Model for Earthen Dam Failures (Model Description and User Manual)*; National Weather Service, NOAA: Silver Spring, MD, USA, 1988.
- Singh, V.P. *Dam Breach Modeling Technology*; Kluwer Academic Publishers: Dordrecht, The Netherlands, 1996.
- Kadam, P.B.; Thakur, P.K.; Dwivedi, S.K.; Garg, V.; Dhote, P.R. Dam Breach Analysis and Damage Assessment of Nova Kakhovka Dam using Satellite data and 1D and 2D Hydrodynamic Modeling. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2024**, *48*, 251–256. [\[CrossRef\]](#)
- Shrestha, B.; Kafle, M.R.; Bhattarai, S.; Degertekin, S.O. Downstream Flood Inundation Assessment Due to Dam Breach of Dudhkoshi Storage Hydroelectric Project Using HEC-RAS 2D. *Adv. Civ. Eng.* **2025**, *2025*, 2856022. [\[CrossRef\]](#)
- Graham, W.J. *A Procedure for Estimating Loss of Life Caused by Dam Failure*; DSO-99-06; Bureau of Reclamation: Denver, CO, USA, 1999.
- Brown, C.A.; Graham, W.J. Assessing the Threat To Life from Dam Failure. *JAWRA J. Am. Water Resour. Assoc.* **1988**, *24*, 1303–1309. [\[CrossRef\]](#)
- DeKay, M.L.; McClelland, G.H. Predicting Loss of Life in Cases of Dam Failure and Flash Flood. *Risk Anal.* **1993**, *13*, 193–205. [\[CrossRef\]](#)
- Peng, J.; Zhang, J.; Sayama, T. Assessment of loss of life owing to dam-failure flooding considering population distribution and evacuation. *Int. J. Disaster Risk Reduct.* **2024**, *112*, 104737. [\[CrossRef\]](#)
- El Bilali, A.; Taleb, I.; Nafii, A.; Taleb, A. A practical probabilistic approach for simulating life loss in an urban area associated with a dam-break flood. *Int. J. Disaster Risk Reduct.* **2022**, *76*, 103011. [\[CrossRef\]](#)
- Leyk, S.; Gaughan, A.E.; Adamo, S.B.; de Sherbinin, A.; Balk, D.; Freire, S.; Rose, A.; Stevens, F.R.; Blankespoor, B.; Frye, C.; et al. The spatial allocation of population: A review of large-scale gridded population data products and their fitness for use. *Earth Syst. Sci. Data* **2019**, *11*, 1385–1409. [\[CrossRef\]](#)
- Cheng, H.; Geng, M.; Li, X.; Li, S.; Zhao, M.; Lin, C.; Wang, J.; Gong, P.; Zhou, Y. A temporally consistent global 500 m-resolution monthly VIIRS-like nighttime light dataset (1992–2024). *Earth Syst. Sci. Data* **2026**, *18*, 3449–3479. [\[CrossRef\]](#)
- Duan, H.; Shi, Z.; Ge, J.; Wu, F.; Liu, Y.; Zhang, H.; Wang, C. High-resolution population mapping based on SDGSAT-1 glimmer imagery and deep learning: A case study of the Guangdong-Hong Kong-Macao Greater Bay Area. *Int. J. Digit. Earth* **2024**, *17*, 2407519. [\[CrossRef\]](#)
- Wang, Z.; Román, M.O.; Kalb, V.L.; Miller, S.D.; Zhang, J.; Shrestha, R.M. Quantifying uncertainties in nighttime light retrievals from Suomi-NPP and NOAA-20 VIIRS Day/Night Band data. *Remote Sens. Environ.* **2021**, *263*, 112557. [\[CrossRef\]](#)
- Zhao, C.; Cao, X.; Chen, X.; Cui, X. A consistent and corrected nighttime light dataset (CCNL 1992–2013) from DMSP-OLS data. *Sci. Data* **2022**, *9*, 424. [\[CrossRef\]](#)

25. Wang, S.; Wang, L. A Novel Framework for Mapping Updated Fine-resolution Populations with Remote Sensing and Mobile Phone Data. *J. Remote Sens.* **2024**, *4*, 0227. [\[CrossRef\]](#)
26. Bergroth, C.; Järvi, O.; Tenkanen, H.; Manninen, M.; Toivonen, T. A 24-hour population distribution dataset based on mobile phone data from Helsinki Metropolitan Area, Finland. *Sci. Data* **2022**, *9*, 39. [\[CrossRef\]](#)
27. National Bureau of Statistics. *Shenzhen 2025 Statistical Communiqué on National Economic and Social Development*; Shenzhen Municipal Bureau of Statistics and Shenzhen Survey Team of the National Bureau of Statistics: Shenzhen, China, 2026.
28. Qiang, Y.; Xiao, T.; He, J.; Zhang, L. Multi-hazard stress testing under extreme rainstorms in the Shenzhen metropolitan area. *Georisk Assess. Manag. Risk Eng. Syst. Geohazards* **2024**, *19*, 467–485. [\[CrossRef\]](#)
29. ASCE/EWRI Task Committee on Dam/Levee Breaching. Earthen Embankment Breaching. *J. Hydraul. Eng.* **2011**, *137*, 1549–1564. [\[CrossRef\]](#)
30. Mohamed, M.A.A.; Samuels, P.G.; Morris, M.W.; Ghataora, G.S. Improving the accuracy of prediction of breach formation through embankment dams and flood embankments. In Proceedings of the International Conference on Fluvial Hydraulics (River Flow 2002), Louvain-la-Neuve, Belgium, 4–6 September 2002; pp. 663–673.
31. Wu, W. Simplified Physically Based Model of Earthen Embankment Breaching. *J. Hydraul. Eng.* **2013**, *139*, 837–851. [\[CrossRef\]](#)
32. van Damme, M. Modelling Embankment Breaching Due to Overflow. Ph.D. Thesis, University of Oxford, Oxford, UK, 2014.
33. Smart, G.M. Sediment Transport Formula for Steep Channels. *J. Hydraul. Eng.* **1984**, *110*, 267–276. [\[CrossRef\]](#)
34. Wu, W. *Introduction to DLBreach—A Simplified Physically-Based Dam/Levee Breach Model, Version 2016.4*; Department of Civil and Environmental Engineering, Clarkson University: Potsdam, NY, USA, 2016; p. 119.
35. Brunner, G.W. *HEC-RAS River Analysis System Hydraulic Reference Manual, Version 5.0*; USACE Hydrologic Engineering Center: Davis, CA, USA, 2016.
36. Brunner, G.W. *HEC-RAS River Analysis System 2D Modeling User's Manual, Version 5.0*; USACE Hydrologic Engineering Center: Davis, CA, USA, 2016.
37. Chow, V.T. *Open-Channel Hydraulics*; McGraw-Hill: Columbus, OH, USA, 1959.
38. Yu, Z.; Cheng, J.; Yu, L.; Xiang, S.; Li, Z. Study on Population Estimation Model of Dam Break Risk Based on Remote Sensing Images. *Yellow River* **2025**, *47*, 44–50. [\[CrossRef\]](#)
39. Deville, P.; Linard, C.; Martin, S.; Gilbert, M.; Stevens, F.R.; Gaughan, A.E.; Blondel, V.D.; Tatem, A.J. Dynamic population mapping using mobile phone data. *Proc. Natl. Acad. Sci. USA* **2014**, *111*, 15888–15893. [\[CrossRef\]](#)
40. Lei, Z.; Zhou, S.; Cheng, P.; Xie, Y. Improved Population Mapping for China Using the 3D Building, Nighttime Light, Points-of-Interest, and Land Use/Cover Data within a Multiscale Geographically Weighted Regression Model. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 335. [\[CrossRef\]](#)
41. Bonnevie, I.M.; Hansen, H.S.; Schröder, L. Dasymetric Algorithms Using Land Cover to Estimate Human Population at Smaller Spatial Scales. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 427. [\[CrossRef\]](#)
42. Zhang, H.; Fu, J.; Li, F.; Chen, Q.; Ye, T.; Zhang, Y.; Yang, X. Fine-scale population mapping on Tibetan Plateau using the ensemble machine learning methods and multisource data. *Ecol. Indic.* **2024**, *166*, 112307. [\[CrossRef\]](#)
43. Zhou, K. Study on Life Loss Estimation Methods for Dam Failure. Master's Thesis, Nanjing Hydraulic Research Institute, Nanjing, China, 2006.
44. Jonkman, S.N.; Penning-Rowsell, E. Human Instability in Flood Flows. *JAWRA J. Am. Water Resour. Assoc.* **2008**, *44*, 1208–1218. [\[CrossRef\]](#)
45. Beffa, C. A Statistical Approach for Spatial Analysis of Flood Prone Areas. In *River Flood Defence: Proceedings of the International Symposium on Flood Defence, Kassel, Germany, 20–23 September 2000*; Toensmann, F., Koch, M., Eds.; Kassel Reports of Hydraulic Engineering; Herkules Verlag: Kassel, Germany, 2000; Volume 1, pp. F.87–F.94.
46. Elalfy, E.; Czapiga, M.J.; Viparelli, E.; Imran, J.; Hanif Chaudhry, M. Modeling Breach Evolution in Noncohesive Earthen Dams by Overtopping. *J. Hydraul. Eng.* **2025**, *151*, 04024064. [\[CrossRef\]](#)
47. Chen, S.C.; Hung, C.Y.; Chen, P.Y.; Tfwala, S.S.; Liang, M.C.; Jiang, C.H.; Chao, W.A. Synchronized Multidisciplinary Observations in Large-Scale Dam Breach Experiments to Enhance the Understanding of Dam Failure Evolution. *Water Resour. Res.* **2025**, *62*, e2025WR040786. [\[CrossRef\]](#)
48. Brazdova, M.; Riha, J. A simple model for the estimation of the number of fatalities due to floods in central Europe. *Nat. Hazards Earth Syst. Sci.* **2014**, *14*, 1663–1676. [\[CrossRef\]](#)
49. Morris, M.W.; Hassan, M.A.A.M.; Vaskinn, K.A. Breach formation: Field test and laboratory experiments. *J. Hydraul. Res.* **2007**, *45*, 9–17. [\[CrossRef\]](#)

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