Flood Risk Assessment in the Greater Bay Area Based on Multidimensional Dynamic Data

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Keywords: Flood disasters, Risk assessment, AHP-EW, Guangdong-Hong Kong-Macao Greater Bay Area.

Abstract

This study addresses the current situation of the Guangdong-Hong Kong-Macao Greater Bay Area as a core economic development zone in China that is frequently threatened by flood disasters. We collected 13 types of indicator data and employed the Analytic Hierarchy Process-Entropy Weight (AHP-EW) combined weighting method to construct a multi-indicator risk assessment system encompassing four dimensions: hazard, exposure, vulnerability, and adaptability. GIS spatial analysis technology was utilized to classify and delineate comprehensive risk levels. The results demonstrate that the regional risk distribution exhibits a typical pattern of "higher in central urban areas and lower in surrounding mountainous regions," with the central urban areas of Guangzhou and Shenzhen, as well as Hong Kong, identified as high-risk zones. The southern part of Dongguan, Foshan, and Zhongshan were classified as medium-to-high risk areas, while Qingyuan and Shaoguan showed lower risk levels. The assessment results showed high consistency with historical disaster records from 2000 to 2023, which not only confirms the applicability of the model in rapidly urbanizing regions but also provides quantitative decision-making support for optimizing territorial space disaster prevention planning and urban resilience construction.

1. Introduction

Flood disasters are one of the most common and extremely destructive natural disasters in the world, especially in the context of accelerated climate change and urbanization, with significantly increasing frequency and impact (Shi et al., 2018; Cao et al., 2019). As one of China's most economically active and densely populated areas, the Guangdong-Hong Kong-Macao Greater Bay Area is located on the southern coast. It is significantly affected by the monsoon climate and frequent extreme rainfall incidents, resulting in frequent floods and floods, seriously threatening the economic development of the region and the safety of residents' lives and property (Han et al., 2019). In this context, identifying high-risk areas of flooding in the region and providing the best flood management strategy is of great significance to the economic development of the Greater Bay Area. At present, domestic and foreign scholars have achieved rich research results in the field of flood risk assessment. In foreign countries, Sardhara et al. (Sardhara et al., 2021) used hierarchical analysis method (AHP) combined with remote sensing and GIS technology to evaluate flood disaster risks in the Keleghai River Basin in India and proposed a multi-factor comprehensive analysis method; EL-Magd et al. (Magd et al., 2015) applied GIS modeling technology in the Red Sea region of Egypt to evaluate the mountain torrent risk level in small river basins; Wu et al. (Wu et al., 2015) carried out flood risk zoning research in the Huai River Basin, and proposed a comprehensive assessment and zoning method. In China, Liu et al. (Liu et al., 2020) evaluated the flood disaster risk in the Bangkok, India and Myanmar region based on AHP and entropy weight method (EW), emphasizing the importance of comprehensive evaluation of multiple indicators; Wen et al. (Wen et al., 2019) applied AHP and ArcGIS technology in the Banqiao small basin in Luoping County, Yunnan Province to evaluate the risk of mountain torrents and verified the consistency of the assessment results with historical disaster conditions; Li. (Li, 2008) used ArcGIS technology to conduct a zoning study on the degree of prone to mountain torrents in Shaanxi Province. Although some studies have made significant progress in flood risk assessment, however, there are still deficiencies in multidi-mensional disaster risk assessment, especially adaptive analysis (Chen et al., 2024). Especially in this special area of the Guangdong-Hong Kong-Macao Greater Bay Area, there is a lack of systematic flood risk assessment research on its unique natural geographical and socio-economic characteristics (Chen et al., 2020).

This study focuses on the Guangdong-Hong Kong-Macao Greater Bay Area to construct a multidimensional flood risk assessment system encompassing four key dimensions: hazard, exposure, vulnerability, and adaptive capacity. Multi-year data on precipitation, population, GDP, and other relevant factors were collected and standardized, then visualized through annual overlays using ArcGIS software. The analytic hierarchy process (AHP) was combined with the entropy weight (EW) method to determine the weights of each indicator (Cheng et al., 2010), followed by GIS-based spatial analysis to conduct regional assessments of hazard, exposure, vulnerability, and adaptive capacity, as well as comprehensive risk classification and spatial distribution analysis. The scientific validity and rationality of the assessment results were verified through comparison with historical disaster records. The findings provide robust support and reference for regional disaster prevention and mitigation, urban planning, and sustainable development.

2. Research area overview and data source

2.1 Overview of the study area

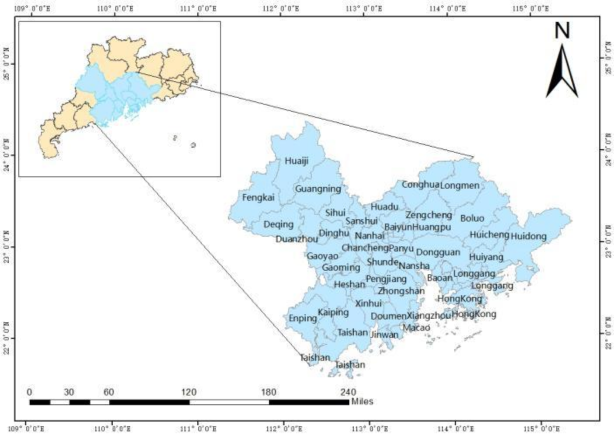

Figure 1. Research area

The Guangdong-Hong Kong-Macao Greater Bay Area (GBA) is located in the southern coastal region of China, spanning geographical coordinates from 21°28′N to 24°29′N and 111°21′E to 115°25′E. The study area encompasses two Special Administrative Regions (Hong Kong and Macao) and nine Pearl River Delta cities, including Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, and Zhaoqing, with a total area of approximately 56,000 square kilometers. This region features a typical subtropical monsoon climate, with an average annual precipitation ranging between 1,600 and 2,000 mm (Xia et al., 2008). The spatial and temporal distribution of rainfall is highly uneven, with over 70% of annual precipitation occurring during the wet season (April to September). The topography is predominantly characterized by plains and hills, with a general northwest-to-southeast elevation gradient. The area is densely crisscrossed by river networks, particularly within the Pearl River Delta, which exhibits a highly developed hydrological system.

2.2 Source of data

This is shown in Table 1. The meteorological precipitation data (annual time series) were obtained from the China Meteorological Data Service Center. Administrative boundaries of counties/districts within the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) and the 2023 Normalized Difference Vegetation Index (NDVI) data were acquired from the Geospatial Data Cloud. The 30m-resolution Digital Elevation Model (DEM) for 2023 and China's annual river network density data (1980-2022) were sourced from the Resource and Environment Science Data Platform. Point-of-interest (POI) data, including distances to schools and hospitals, were extracted from A map (AutoNavi Map). Road network density data were derived from the Earth Resources Data Cloud Platform. Socioeconomic indicators, including population density, regional GDP, and per capita disposable income, were primarily collected from the Guangdong Statistical Yearbooks (2010-2023).

Data Indicators	Temporal Coverage
Mean annual precipitation	1960–2023
Annual frequency of rainstorm events	1995–2023
Duration of rainstorms	1990–2022
Administrative boundaries of the Greater Bay Area	2020 year
NDVI	2023 year
DEM	2023 year
River network density	1980-2022
Road network density	2023 year
Point of Interest (POI) data	2024 year
Population density	2010-2022
Gross regional product	2010-2023
Per capita disposable income	2010-2023

Table 1. Data source

3. Research Methods

3.1 Construction of multi-dimensional evaluation model

A comprehensive understanding of flood risk distribution patterns necessitates systematic flood risk assessment. Current studies exhibit disparate emphases on population, economic, natural, and infrastructure risk components, potentially introducing significant uncertainties in flood risk evaluation. To address this gap, this study develops a multidimensional flood risk assessment framework, which facilitates a holistic investigation of urban flood risk characteristics and elucidates the interrelationships between flood hazards and their constituent elements. The workflow of this multidimensional assessment framework is illustrated in Figure 2.

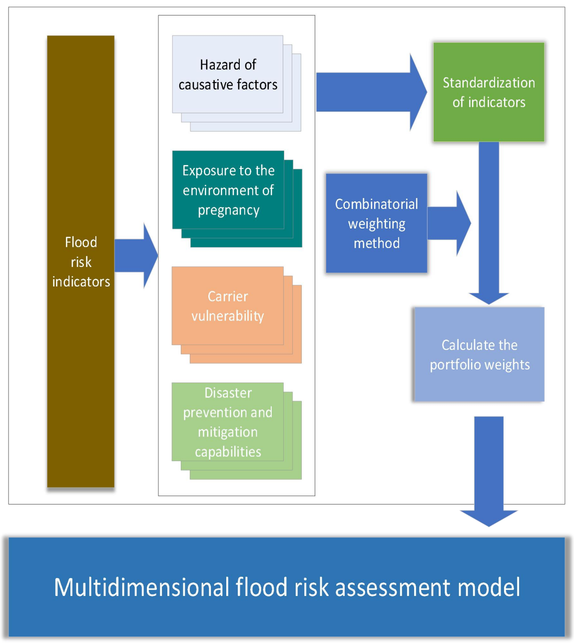

Figure 2. Flowchart of model construction

First, the precipitation data, population density, river network density, and GDP data were standardized. In ArcGIS, summation and mean value calculations were performed to quantify these indicators. The weights of each indicator were determined by combining the Analytic Hierarchy Process (AHP) and Entropy Weight (EW) methods (Zhang et al., 2024). Next, weighted visualization maps for each indicator were generated. Using the constructed assessment model, multidimensional flood risk characteristics were analyzed, and a comprehensive flood risk assessment was conducted. Finally, the accuracy and reliability of the model were validated by comparing the results with historical disaster data, including affected population, direct economic losses, and water infrastructure damage records.

This study selected 13 indicators, and the calculation formulas for each indicator in the risk assessment framework are as follows:

$$FHI = \sum_{i=1}^{n} [w_h \times H_i] \quad (1)$$

$$FEI = \sum_{i=1}^{n} [w_e \times E_i] \quad (2)$$

$$FVI = \sum_{i=1}^{n} [w_v \times V_i] \quad (3)$$

$$FAI = \sum_{i=1}^{n} [w_a \times A_i] \quad (4)$$

$$FRI = f(FHI + FEI + FVI - FAI) \quad (5)$$

Where FHI = Hazard Flood Index
FEI = Exposure Flood Index
FVI = Vulnerability Flood Index
FAI = Adaptive Flood Index
FRI = Composite Flood Risk Index
w_h、w_e、w_v、w_a = Weights for each submetric
H_i、E_i、V_i、A_i = Normalized values for each sub-indicator

3.2 Combined weighting method

While revealing useful information, over-reliance on objective data fails to incorporate expert knowledge and practical experience. This limitation may occasionally yield results inconsistent with reality and human perception. In contrast, the Analytic Hierarchy Process (AHP) has been demonstrated to comprehensively determine weights by considering subjective attributes of data, though the judgment of relative importance for each evaluation indicator depends entirely on the operator's subjective assessment. Therefore, compared with conventional methods, the combination of AHP and Entropy Weight (EW) maintains objectivity while reflecting the intrinsic patterns of data. The composite weight Wi for the ith indicator is determined by the following equation:

$$w_i = \mu w_A + (1 - \mu) w_E \quad (6)$$

Where w_i = The comprehensive weight of the ith indicator
w_A = Weights calculated by the AHP method
w_E = Weights calculated by the EW method
μ = Combination weight coefficients

A 0.5 in this study shows that subjective and objective methods are equally important. The flood risk weights based on the combined AHP and EW methods are shown in Table 2.

Indicator layer	Sub-metric layers	Weight		
		AHP	EW	Combination method
Hazard of causative factors (0.40)	Average annual rainfall	0.3598	0.1030	0.2494
	The average number of rainstorms per year	0.2347	0.2225	0.2286
	Weights of each indicator	0.1487	0.1929	0.1708
	NDVI	0.0396	0.1255	0.0825
	DEM	0.0647	0.1018	0.0832
	Slope	0.0564	0.1185	0.0875
	River network density	0.0601	0.1358	0.0980
Exposure to the environment of pregnancy and disaster (0.25)	Road density	0.3333	0.3643	0.3488
	Population density	0.6667	0.6357	0.6512
Vulnerability of disaster-bearing bodies (0.25)	Distance from school	0.2500	0.2144	0.2322
	GDP	0.7500	0.7856	0.7678
Disaster prevention and mitigation capabilities (0.1)	Distance from hospital	0.5000	0.5556	0.5278
	Disposable income per capita	0.5000	0.4444	0.4722

Table 2. Weights of each indicator

3.3 Normalization and classification

To facilitate comparisons between different levels, the values of the various flood risk indicators should be normalized on a scale of 0 to 1. Standardization is for consistent comparisons and evaluations. The standardized formula is as follows:

$$z_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} \text{（Negative correlation）} \quad （7）$$

$$z_{ij} = \frac{max(x_j) - x_{ij}}{max(x_j) - min(x_j)} \text{（Positive correlation）} \quad （8）$$

Where x_{ij} = Raw observed value of the i-th sample for the j-th indicator
$min(x_j)$ = Minimum observed value across all samples for indicator j
$max(x_j)$ = Maximum observed value across all samples for indicator j
z_{ij} =Standardized score (range: [0,1]) for risk assessment

According to the correlation between the indicators and flood risk, the indicators are classified as positive or negative. For positive indicators, as the value of positive indicators increases, so does the risk of flooding. Conversely, for negative indicators, an increase in the value of the negative index means a reduced risk of internal flooding. FHI, FEI, FVI, FAI, and FRI were normalized from 0 to 1 and were divided into five categories using the natural breakpoint method: low, low, medium, high, and high. In this study, "low" means that the impact of flooding is mild or non-existent, "low" means occasional, "medium" means frequent, "high" means frequent impact, and "high" indicates a high likelihood of being affected by flooding.

4. Experimental results and analysis

The hazard, exposure, vulnerability, and resilience indicators were first standardized using Equations (7) and (8), and then the assessment indices for each indicator in the Greater Bay Area were calculated through Equations (1)-(4). These indices were visualized in GIS software and classified using the natural breaks method, resulting in the spatial distribution maps of flood hazard, exposure, vulnerability, and resilience across the Greater Bay Area, as shown in Figures 3-6.

4.1 Hazard risk assessment

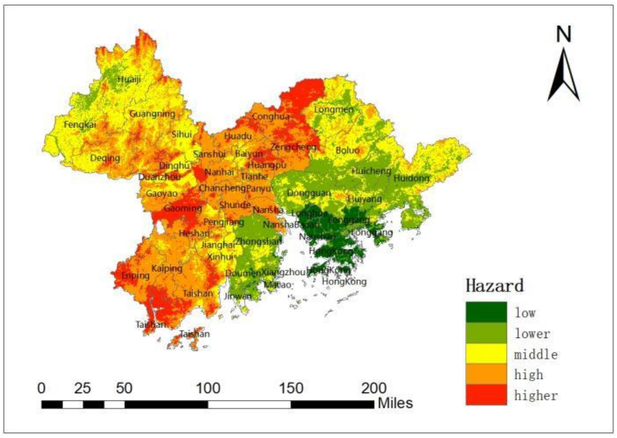

Figure 3. Hazard risk distribution map

The hazard risk map demonstrates that the flood hazard in the Greater Bay Area exhibits a distinct "high in the northwest and low in the southeast" spatial pattern. High-hazard areas are primarily located in eastern Guangzhou (Zengcheng District and Huangpu District), Longgang District of Shenzhen, Nanhai District of Foshan, and eastern Zhaoqing (Gaoyao District and Sihui City), where concentrated rainstorms, complex terrain conditions, and high river network density contribute to significant flood risks. Moderately high-hazard zones are distributed in eastern Jiangmen, Shunde District of Foshan, and some peripheral counties of Guangzhou, where frequent rainstorms and complicated topography make them prone to localized flooding. In contrast, the southeastern coastal regions including Zhuhai, Zhongshan, southern Shenzhen, and eastern Guangdong experience moderate rainstorm intensity and relatively flat terrain, resulting in overall lower hazard levels.

4.2 Exposure risk assessment

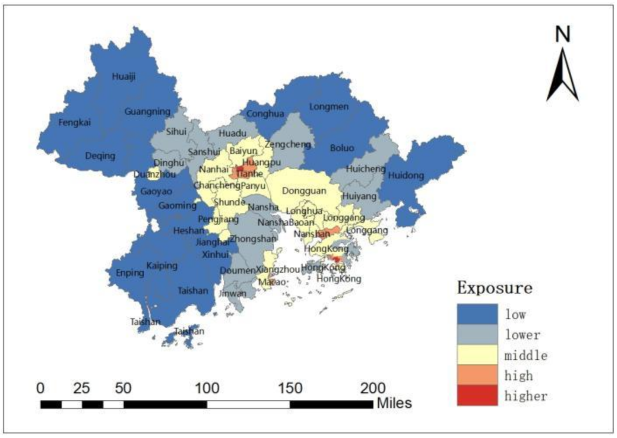

Figure 4. Exposure risk distribution map

The results indicate that the exposure risk in the Greater Bay Area exhibits a characteristic "high in core urban areas and low in peripheral regions" spatial pattern. High-exposure zones are predominantly concentrated in Guangzhou's central urban districts (Yuexiu, Tianhe, Liwan, Haizhu), Shenzhen's central areas (Futian, Nanshan, Longhua), and the Hong Kong Special Administrative Region, where high population density and highly developed transportation infrastructure result in extremely high potential risks to both population and critical infrastructure during flood events. Moderately high-exposure areas are mainly distributed in Guangzhou's peripheral regions, Dongguan, Foshan, Zhongshan, and Zhuhai urban areas, which feature relatively high urbanization levels and dense infrastructure networks, leading to significant exposure risks. Northern mountainous regions (Qingyuan, Shaoguan) and parts of western/eastern Guangdong exhibit sparse population distribution and simplified road networks, resulting in overall lower exposure levels.

4.3 Vulnerability risk assessment

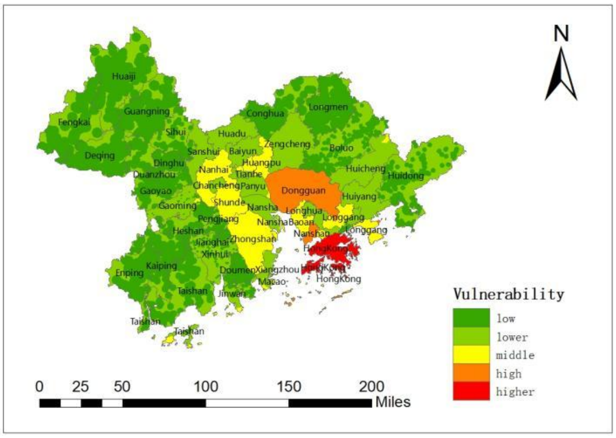

Figure 5. Vulnerability risk distribution map

The vulnerability risk exhibits a distinct "high in the southeast and low in the northwest" spatial distribution pattern across the Greater Bay Area. High-vulnerability zones are predominantly concentrated in the Hong Kong Special Administrative Region, where constrained spatial distribution of educational facilities and extreme population density coexist with insufficient economic resilience in certain areas despite high GDP levels. Moderately high-vulnerability areas are observed in central-southern Shenzhen (including Futian, Luohu, and Yantian districts) and southern Dongguan, where substantial economic scale contrasts with relatively inadequate school distribution, resulting in compromised disaster preparedness and recovery capacity. Medium-vulnerability levels characterize peripheral Guangzhou districts (e.g., Panyu and Nanshan), Zhongshan, Zhuhai, and selected areas of Huizhou, which maintain relatively sound economic foundations yet face resource allocation limitations. Northern and western regions (Qingyuan, Shaoguan, and Yangjiang) consistently demonstrate low-to-moderately low vulnerability, benefiting from reduced pressure on educational services, sparse population distribution, and consequently stronger societal capacity for disaster absorption despite modest economic output.

4.4 Adaptive risk assessment

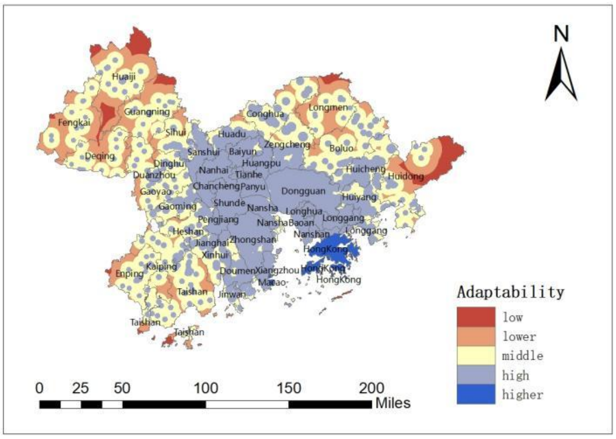

Figure 6. Adaptability risk distribution map

The adaptive capacity exhibits a characteristic "high in urban cores and low in peripheral mountainous areas" spatial pattern across the study region. Highest adaptive capacity is concentrated in the Hong Kong Special Administrative Region, central Shenzhen (Futian, Nanshan, and Luohu districts), and central Guangzhou (Yuexiu and Tianhe districts), where dense distribution of medical facilities and higher per capita income contribute to strong emergency response capabilities and post-disaster recovery potential. Moderately high adaptive capacity predominates in peripheral Guangzhou, Foshan, Dongguan, Zhongshan, Zhuhai, and urban centers of Huizhou, where robust economic conditions and relatively complete medical infrastructure enable effective flood response. Conversely, northern regions (Qingyuan and Shaoguan) and western areas (Yangjiang and parts of Jiangmen) demonstrate comparatively lower adaptive capacity due to sparse medical resources, weaker economic foundations, and lower per capita income, resulting in limited disaster response and recovery capabilities following hazard events.

4.5 Comprehensive risk assessment

Flood disaster risk is primarily determined by four interconnected components that collectively constitute the risk system: hazard intensity (H), environmental exposure (E), socioeconomic vulnerability (V), and adaptive capacity (A). Using Equation (5) and the predetermined weight values of each factor, we calculated the comprehensive flood risk assessment index for the Greater Bay Area. This index was subsequently visualized in a GIS environment and classified using the natural breaks method (Jenks optimization), yielding the integrated flood risk distribution map shown in Figure 7.

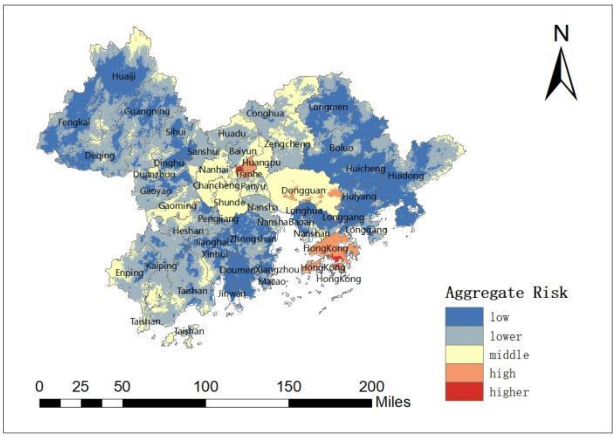

Figure 7. Comprehensive risk distribution map

The comprehensive flood risk in the Greater Bay Area demonstrates a characteristic "high in urban cores and economically active zones, low in peripheral mountainous regions" spatial pattern. High-risk areas are predominantly concentrated in the Hong Kong Special Administrative Region, central Guangzhou (Yuexiu, Tianhe, Haizhu, and Liwan districts), and central Shenzhen (Futian, Luohu, and Nanshan districts), where extreme population density, significant exposure and vulnerability, frequent torrential rainfall, and severe waterlogging issues collectively contribute to substantial socioeconomic and infrastructure impacts despite relatively strong economic performance and adaptive capacity. Moderately high-risk zones primarily include most of Dongguan, Longgang District of Shenzhen, Panyu District of Guangzhou, Nanhai and Shunde districts of Foshan, urban Zhongshan, and parts of Zhuhai, where rapid urbanization, high population density, concentrated industrial layout, and limited drainage capacity during heavy rainfall events result in elevated flood-induced economic losses. Medium-risk areas are distributed across peripheral Guangzhou (Baiyun, Huangpu, and Zengcheng districts), urban Huizhou, and outlying regions of Jiangmen, Zhaoqing, Zhuhai, and Zhongshan, exhibiting moderate economic and population density coupled with reasonable risk response capacity. Low-to-very-low-risk zones are mainly located in northern mountainous areas (Qingyuan and Shaoguan), western mountainous parts of Zhaoqing, and peripheral counties like Huidong and Boluo, characterized by sparse population, low exposure, elevated terrain, and favorable natural drainage conditions that collectively minimize socioeconomic impacts from flood events.

4.6 Analysis of the rationality of the results

The historical flood disaster records of the Guangdong-Hong Kong-Macao Greater Bay Area from 2000 to 2023 were quantitatively mapped (Figure 8), and comparative analysis with our comprehensive risk assessment results revealed high consistency between both datasets. Historical disaster data show that Guangzhou, Hong Kong, Shenzhen, Dongguan and Foshan, consistently ranked among the top five regions in terms of affected population, direct economic losses, and water infrastructure damage - findings that strongly align with our assessment's classification of central Guangzhou, Hong Kong, central Shenzhen, southern Dongguan, and parts of Foshan as high or moderately high-risk zones. Conversely, areas identified as medium-to-low risk in our assessment, such as Qingyuan, Shaoguan, and Heyuan, exhibited relatively fewer historical disaster records, further validating the scientific rigor and rationality of our evaluation. These findings demonstrate that the comprehensive flood risk assessment methodology developed in this study accurately reflects the actual disaster risk distribution pattern across the Greater Bay Area, exhibiting substantial application value and reliability.

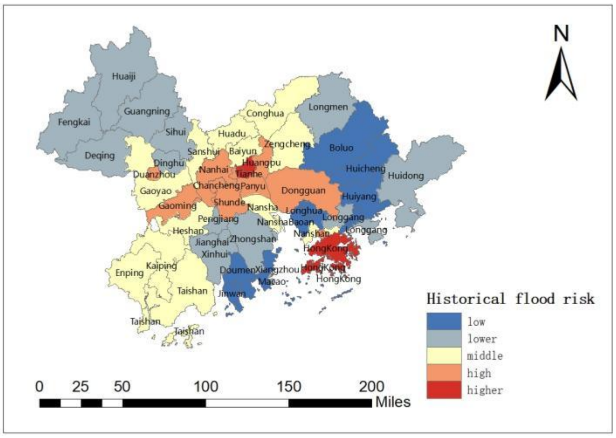

Figure 8. Historical flood risk distribution map

5. Conclusion

Based on the disaster system theory framework, this study establishes a flood risk assessment system for the Guangdong-Hong Kong-Macao Greater Bay Area by integrating multidimensional elements including precipitation characteristics, topography, river network distribution, and socioeconomic factors, encompassing 13 causative factors. The hybrid AHP-EW weighting approach resolves the imbalance between subjective and objective weights inherent in traditional assessments. Spatial overlay analysis of hazard, exposure, vulnerability, and adaptability dimensions reveals distinct spatially heterogeneous patterns: hazard risk decreases progressively from northwestern hilly areas to southeastern coastal zones under terrain and rainstorm influences, peaking in northwestern Zhaoqing with an index of 0.83; exposure manifests three high-risk cores (Guangzhou Tianhe CBD >0.78, Shenzhen Nanshan Tech Park >0.78, Hong Kong Victoria Harbour >0.78) spatially coupled with economic density; vulnerability elevates in coastal southeastern regions due to aged demographics and medical resource constraints; adaptability mitigates actual risks through advanced drainage systems and smart early-warning platforms in urban centers. The integrated assessment indicates high-risk zones along the eastern Pearl River Estuary (18.3% areal coverage) accommodate 37.6% of regional GDP and 42.3% of population, exhibiting 93.6% consistency with 43 major flood-affected areas (2000–2023). The innovative contribution resides in establishing a hazard-exposure-vulnerability-adaptability framework that incorporates dynamic metrics like flood control infrastructure coverage and medical accessibility to address the resilience quantification gap in disaster-bearing systems. Recommendations propose prioritizing flood control infrastructure coverage in eastern estuary urban clusters during territorial spatial planning, while future development necessitates optimized dynamic risk models with enhanced real-time POI data updating mechanisms and investigations into land-use change impacts on surface water retention capacity.

Acknowledgements

This work was supported by the Fundamental Research Funds for Beijing University of Civil Engineering and Architecture (X24027).

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