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Flood Disaster Risk Assessment of the Beijing-Tianjin-Hebei Region Based on Variable Fuzzy Recognition and Combined Weighting

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Abstract:
Intensified by climate change and rapid urbanization, flood disasters have become a major challenge to regional sustainable development, highlighting the need for reliable risk assessment. Taking the Beijing–Tianjin–Hebei region as a case study, this study integrates game theory-based weighting with variable fuzzy recognition to quantify the contributions of multiple risk factors and to identify the spatial distribution pattern of flood risk.The results reveal a distinct spatial pattern of flood risk characterized by "high in the southeast and low in the northwest", with high-risk areas concentrated in Beijing, Tianjin, Langfang, and the southeastern Hebei Plain. Maximum rainfall intensity (0.1210), water-system buffer distance (0.1192), and flood protection standard (0.1092) were identified as the dominant controlling factors. Validation using inundation points showed that the combined weighting method increased the proportion of inundation points located in medium–high and high-risk zones to 77.50%, while the incorporation of VFPR further improved this value to 79.10%, outperforming conventional approaches. The proposed framework effectively captures the spatial heterogeneity and fuzzy transition characteristics of flood risk and provides scientific support for regional flood mitigation and land-use planning.

Keyword：Flood disaster，risk assessment， game theory-based combined weighting，variable fuzzy recognition

I Introduction

Flood disaster is one of the natural disasters with the highest occurrence frequency, the widest impact range and the most severe economic losses globally. With the advancement of global climate change and rapid urbanization, atmospheric warming has significantly increased the frequency and intensity of extreme precipitation events, leading to a continuous upward trend in flood disaster risk[1].The Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) points out that extreme precipitation events will intensify further across most regions of the globe in the future, and the flood disasters induced by such events will become a crucial risk factor affecting regional sustainable development[2].As a country with a typical monsoon climate, China has long ranked flood disasters first among all natural disasters in terms of economic losses[3]. In particular, the catastrophic "July 20" extreme rainstorm in Zhengzhou and the "July 2023" extraordinary flood in the Hai River Basin, which caused severe economic losses and social impacts, reflect that regional flood risk prevention and control is facing new challenges under the background of extreme climate change[4]、[5].Therefore, scientifically identifying the spatial distribution characteristics of flood disaster risk and its driving mechanism has become an important research topic in the field of disaster prevention and mitigation.

Flood disaster risk assessment constitutes a critical foundation for disaster risk management. Early investigations primarily rely on hydrological statistical analysis and flood frequency analysis methods, and establish risk prediction models based on historical rainfall and disaster data[6].With the development of hydrological and hydrodynamic theories, models such as HEC-RAS, MIKE FLOOD, and LISFLOOD-FP have been widely applied in the simulation of flood routing processes, enabling the quantitative assessment of disaster hazard indicators including flood inundation extent, water depth and flow velocity[7]-[9].Nevertheless, this category of methods is highly dependent on high-precision topographic data and hydrological parameters, and can hardly fully reflect the impact of non-natural factors such as socio-economic exposure and regional vulnerability on the formation of flood risks.According to disaster system theory, flood risk is the joint outcome of the interaction among hazard-inducing factors, disaster-pregnant environments, hazard-affected bodies and disaster prevention and mitigation capabilities[10].On this basis, the multi-index comprehensive evaluation method has gradually become the mainstream technical approach for flood risk assessment at the regional scale. In relevant research, comprehensive flood risk identification and spatial differentiation analysis are achieved by constructing an evaluation index system covering such factors as rainfall, topography, hydrology, land use, population and economy, and disaster prevention capability[11]、[12].Based on the fuzzy comprehensive evaluation model, Wang et al. conducted a systematic assessment of flood risk in the Beijing-Tianjin-Hebei region, revealing the spatial differentiation pattern of flood risk in urban agglomerations[13].Li et al. constructed a comprehensive hazard-exposure-vulnerability framework to carry out urban waterlogging risk assessment in Zhengzhou, and verified the applicability of the multi-index evaluation system in urban flood risk research.Compared with hydrodynamic simulation methods, the multi-index evaluation method boasts advantages including convenient data acquisition, flexible evaluation scales and strong comprehensiveness, and thus it has been widely applied in regional flood risk assessment[14].In the process of multi-indicator evaluation, the determination of indicator weights is a key link affecting the reliability of evaluation results. Currently, commonly used weighting methods mainly include Analytic Hierarchy Process (AHP), Fuzzy Analytic Hierarchy Process (FAHP), Entropy Weight Method, CRITIC Method, etc.Both Analytic Hierarchy Process (AHP) and Fuzzy Analytic Hierarchy Process (FAHP) can fully utilize expert experience and knowledge, and exhibit favorable theoretical interpretability, but they suffer from certain subjectivity[15]、[16].By contrast, the entropy weight method and the CRITIC method determine indicator weights based on the dispersion and conflictivity of indicators, which can objectively reflect data characteristics but struggle to capture the actual functional mechanism of indicators[17].To address the limitations of single weighting methods, combined weighting has gradually emerged as a research hotspot[18].Among the existing weighting methods, the combination weighting method based on game theory minimizes the deviation between different weighting results and realizes the dynamic coordination of subjective weights and objective weights[19].This method can effectively improve the rationality and stability of weight allocation, and has been widely applied in flood risk assessment, urban resilience assessment, ecological security assessment and other fields.Meanwhile, the risk of flood disasters presents remarkable characteristics of uncertainty and ambiguity, and there is often no absolute boundary between different risk levels. However, most existing studies still adopt methods such as the natural break method, equal interval method or cluster analysis to conduct discrete classification of evaluation results, which is prone to produce grade boundary effects and lead to the loss of the characteristics of continuous risk variation[20]、[21].The Variable Fuzzy Pattern Recognition (VFPR) model, by constructing a relative membership function, continuously expresses the relationship between evaluation objects and different grade standards, which can effectively describe the fuzzy transition characteristics of risk levels, and has demonstrated sound applicability and stability in such fields as water resource evaluation, ecological environment evaluation and disaster risk identification[22].

To sum up, in view of the problems such as subjective and objective deviations in weight determination and difficulties in accurately characterizing the boundaries of risk levels in existing flood disaster risk assessment, this paper takes the Beijing-Tianjin-Hebei region as the research object, carries out research on flood disaster risk assessment, and reveals the spatial differentiation characteristics of regional flood risk and its main driving factors, so as to provide a scientific basis for regional flood risk prevention and control as well as disaster prevention and mitigation decision-making.

II Materials and Methods

A. Study Area

The Beijing-Tianjin-Hebei region is located in the core area of northern China, covering the entire administrative areas of Beijing, Tianjin, and Hebei Province, with a total area of approximately 216,000 km², as shown in Fig 1. The region has an overall topography that is "higher in the northwest and lower in the southeast," with the Yan Mountains–Taihang Mountains in the northwest and the North China Plain in the southeast, making it easy for mountain floods to rapidly rush down into the downstream plain areas. The Haihe River basin is densely networked with waterways, and its downstream area features low-lying terrain with limited flood discharge channels. The accumulation of sediment in the Yellow River and Haihe River channels has led to significant problems with flood conveyance, further increasing the risk of flooding disasters. The region is under the influence of a temperate monsoon climate, with precipitation concentrated in July and August. Frequent short-duration heavy rainfall and extreme downpours are the direct triggers for flooding disasters. Meanwhile, as regional core cities, Beijing and Tianjin have achieved extremely high levels of urbanization, with both cities exceeding 85% urbanization rates in 2024[23]. Population and economic resources are highly concentrated—just the central urban areas of Beijing and Tianjin account for nearly 40% of the region's population and over 60% of its economic activities—making the characteristics of compound disaster risks in the region increasingly evident[24].

In recent years, the frequency and intensity of floods in the Beijing-Tianjin-Hebei region have continued to rise. Since 1970, regional heavy rain and flooding events have occurred at an average rate of 2.6 per year, with extreme rainfall becoming increasingly frequent. Events such as the severe "July 21" storm in Beijing in 2012 and the regional extreme flooding in 2023 indicate a growing flood risk trend. As a core economic region in northern China, with a resident population exceeding 111 million, the area faces severe threats to livelihoods and economic development from flooding. In 2023, extreme floods caused direct economic losses exceeding 150 billion yuan, with Hebei Province suffering the heaviest impact[25]-[27].Severe urban flooding in the Beijing-Tianjin metropolitan area has caused damage to infrastructure and disrupted public service systems. Regional flood control infrastructure development is uneven, with insufficient drainage capacity in plains and weak flood prevention foundations in mountainous areas. Therefore, identifying the four-dimensional characteristics of flood risks and delineating high-risk areas and vulnerable points is of significant practical importance for improving regional flood prevention and control capabilities and optimizing disaster mitigation resource allocation.

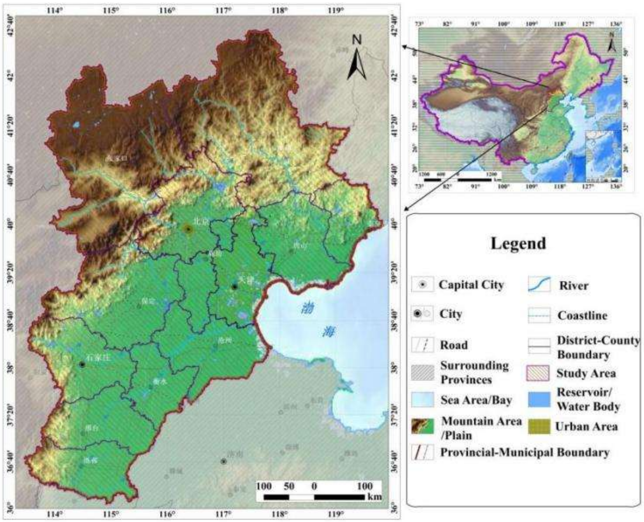

Fig 1 Overview of the Beijing-Tianjin-Hebei Study Area

B. Research Methodology

1) Construction of the Evaluation Indicator System: Based on the disaster risk system theory, a flood disaster risk assessment indicator system for the Beijing-Tianjin-Hebei region is constructed from four dimensions: hazard danger of disaster-causing factors, sensitivity of disaster-prone environment, vulnerability of exposed elements, and disaster prevention and mitigation capacity, as shown in Table I.

Disaster-causing factors are the direct triggers of flood disasters, and precipitation characteristics directly determine the probability of occurrence and potential destructive power of such disasters. Selecting "average rainfall, maximum intensity of heavy rain, and frequency of heavy rain" as hazard indicators, this approach comprehensively represents the potential triggering capacity and risk intensity of regional flood disasters from three aspects: basic precipitation, extreme rainfall, and occurrence frequency.

The disaster-prone environment refers to the surface conditions that foster and influence the development of flood disasters, where topography, hydrology, and vegetation significantly affect the processes of flood accumulation and spread. Selecting "vegetation cover, elevation, slope, and distance to water bodies" as disaster-prone environmental sensitivity indicators, which respectively reflect ecological impedance, topographic runoff characteristics, terrain undulation effects, and hydrological influences of water systems, comprehensively characterizes the regional natural environment's sensitivity to flood disasters.

Disaster bearing body is the social and economic object of flood disaster, and its exposure scale and vulnerability degree directly affect the level of disaster loss. Selecting GDP, proportion of arable land, population density, and building height as indicators of vulnerability for disaster-bearing entities, these variables represent the exposure level and vulnerability of regional socio-economic systems in terms of economic asset exposure, agricultural resources, population exposure scale, development intensity of construction, and the degree of concentration of socio-economic factors. Quantify the exposure and vulnerability of socioeconomic factors in the Beijing-Tianjin-Hebei region to flood disasters.

Disaster prevention and mitigation capacity is a human-controlled factor in resisting flood risks and reducing disaster losses, and an important manifestation of regional disaster resilience. Selecting "agriculture, forestry, and water expenditure; medical capacity; flood control standards; and emergency investment" as indicators of disaster prevention and mitigation capability, we assess the region's comprehensive prevention, control, and response capacity for flood disasters from the dimensions of financial support, emergency treatment, engineering protection, and emergency reserves.

Table I Flood Disaster Risk Assessment Indicator System for the Beijing-Tianjin-Hebei Region

Target layer	Principle layer	Index leve	Indicator Impact	Data source
Risk Assessment of Flood Disasters	Hazardousness of Disaster-Forming Factors	Average annual rainfall	+	China Meteorological Data Network
		Maximum intensity of Heavy Rainfall	+	China Meteorological Data Network
		Frequency of Heavy Rain	+	China Meteorological Data Network
	Sensitivity of Environmental Susceptibility to Disaster	Normalized Difference Vegetation Index	-	Global Soil Cover Database
		Digital Elevation Model	-	Geospatial Data Cloud
		Slope	-	Geospatial Data Cloud
		Water System Distance	+	Geospatial Data Cloud
	Vulnerability of Exposed Elements	Gross Domestic Product	+	NASA's Goddard Space Flight Center
		Cultivated Land Ratio	+	OpenStreetMap
		Population Density	+	OpenStreetMap
		Building Height	+	county/district government websites
	Disaster Prevention and Mitigation Capability	Expenditure for Agriculture, Forestry and Water Resources	-	county/district government websites
		Medical Capacity	-	OpenStreetMap
		Flood Protection Level	-	regional flood control planning documents
		Expenditure for Emergency Management	-	county/district government websites

2) Determination of Weights for the Evaluation Factor System: Determination of Subjective Weights of Indicators by Fuzzy Analytic Hierarchy Process.Fuzzy Analytic Hierarchy Process combines fuzzy mathematical theory to address problems involving uncertainty and ambiguity[28]. This paper uses triangular fuzzy numbers M = {l, m, u} instead of precise values in traditional AHP to represent decision-makers' subjective judgments, thereby more accurately reflecting the fuzziness inherent in complex decision-making problems. The membership function of M is expressed by formula (2-1), where l is the minimum possible value, m is the most likely value, and u is the maximum possible value; $\mu(x|M)$ indicates the weight magnitude of each indicator. The steps for calculating the weights of each factor are as follows.

$$\mu(x|M)=\begin{cases}\frac{x-l}{m-l} & (l<x<m)\\ \frac{u-x}{u-m} & (m<x<u)\\ 0 & (others)\end{cases} \qquad (2\text{-}1)$$

(1) Construction of the fuzzy judgment matrix

Compare each pair of elements at every level to construct a fuzzy judgment matrix, allowing decision-makers to provide judgment ranges using triangular fuzzy numbers instead of exact values.

(2) Calculate the fuzzy comprehensive degree value $\widetilde{S_i}$

Calculate the fuzzy comprehensive degree value $\widetilde{S_i}$ for each row of the triangular fuzzy judgment matrix, using the formula shown in equation (2-2).

$$\widetilde{S_i}=\sum_{j=1}^{n}\widetilde{a_{ij}}\otimes\left(\sum_{i=1}^{n}\sum_{j=1}^{n}\widetilde{a_{ij}}\right)^{-1} \qquad (2\text{-}2)$$

Among them, $\otimes$ stands for fuzzy multiplication, and $\widetilde{a_{ij}}$ represents the reduced fuzzy number.

(3) Comparison of Possibilities of Fuzzy Numbers

Calculate the fuzzy judgment confidence level for the comprehensive fuzzy degree value of each factor, where the formula for computing the fuzzy judgment confidence level of one factor being greater than another is shown in Equation (2-3).

$$V(\tilde{S}_i \geq \tilde{S}_j) = \begin{cases} 1 & (m_i \geq m_j) \\ 0 & (l_j \geq u_i) \\ \dfrac{l_j - u_i}{(m_i - u_i) - (m_j - l_j)} & (others) \end{cases} \quad (2\text{-}3)$$

(4) Determination of the weight vector

A possibility matrix $P = [V(\tilde{S}_i \geq \tilde{S}_j)]$ is constructed, and the final weights are obtained after normalization via Formula (2-4).

$$\omega_i = \frac{min_{j\neq i} V(\tilde{S}_i \geq \tilde{S}_j)}{\sum_{k=1}^{n} min_{j\neq k} V(\tilde{S}_k \geq \tilde{S}_j)} \quad (2\text{-}4)$$

Objective Weight Determination of Indicators via the CRITIC Method[29].The CRITIC method is an objective weighting method based on the contrast intensity and conflictiveness among indicators1.It takes into account both the dispersion degree of data and the correlation between indicators, and can scientifically determine the weight of each indicator in multi-factor evaluation systems such as flood evaluation. The calculation procedures are as follows.

(1) Calculate the standard deviation of the j-th indicator

This indicator reflects the degree of data dispersion of the indicator itself. The greater the dispersion, the larger the amount of information, and the calculation formula is shown in Formula (2-5) below.

$$\sigma_j = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(x'_{ij} - \bar{x}'_j)^2} \quad (2\text{-}5)$$

$\bar{x}'_j$ is the normalized mean of the j-th indicator, and n is the sample size.

(2) Calculation of indicator conflict

The weaker the correlation between indicators, as measured by the Pearson correlation coefficient, the stronger their conflict and the less information overlap, with the calculation formula shown in equation (2-6).

$$R_j = \sum_{k=1}^{m}(1 - |r_{jk}|) \quad (2\text{-}6)$$

r_{jk} is the Pearson correlation coefficient between indicators j and k, and m is the total number of evaluation indicators.

(3) Calculation of indicator information volume

The larger the value of C_j, the more valid information the indicator contains, and accordingly the higher its weight. The calculation formula is shown as follows in Equation (2-7).

$$C_j = \sigma_j \times R_j \quad (2\text{-}7)$$

(4) Calculation of the final objective weights

The final weight w_j is normalized by the comprehensive coefficient C_j, and the calculation formula is as follows (2-8).

$$\omega_j = \frac{C_j}{\sum_{j=1}^{m} C_j} \quad (2\text{-}8)$$

Determination of Combined Index Weights Based on Game Theory Combined Weighting Method.Game theory-based combined weighting aims to integrate the advantages of different weighting methods through strategic interaction and equilibrium analysis, thereby improving the rationality of weight allocation[30].The specific steps are as follows.

(1) Calculate the initial weights

Obtain the weight vectors ω_1, ω_2 using subjective (FAHP) and objective (CRITIC) methods, respectively, and perform an arbitrary linear combination of the two weight vectors as shown in formula (2-9).

$$\omega = \sum_{k=1}^{2} \alpha_k \omega_k^T, (\alpha_k > 0) \quad (2\text{-}9)$$

Among them, ω denotes the weight vector after document merging and combination, α_k denotes the weight coefficient, and k denotes the number of methods.

(2) Finding the optimal weight vector ω^* is achieved by minimizing the deviation between ω and each ω_k, and the formulation is given by Equation (2-10) below.

$$min \left\| \sum_{k=1}^{2} \alpha_k \omega_k^T - \omega_k \right\|_2 \quad (2\text{-}10)$$

(3) Based on the fundamental properties of matrices, the optimal first-order derivative condition for ω can be transformed into a system of linear equations.

$$\begin{pmatrix} \omega_1\omega_1^T & \omega_1\omega_2^T \\ \omega_2\omega_1^T & \omega_2\omega_2^T \end{pmatrix}\begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} = \begin{pmatrix} \omega_1\omega_1^T \\ \omega_1\omega_2^T \end{pmatrix} \quad (2\text{-}11)$$

Solve the system of equations and normalize it to obtain the values of α_1^* and α_1^*.

(4) The combined weight$\omega^*$is obtained, with the calculation formula given by Equation (2-12).

$$\omega^* = \sum_{k=1}^{2} \alpha_k^* \omega_k^T, (k = 1,2) \quad (2\text{-}12)$$

Based on the comprehensive weights of indicators determined by the game-theoretic combination weighting method, this study introduces the Variable Fuzzy Pattern Recognition (VFPR) model to dynamically and continuously identify the flood disaster risk levels of each evaluation unit in the Beijing-Tianjin-Hebei region[22]、[31]. This model can avoid the information loss problem associated with traditional discrete classification methods, and outputs continuous membership degrees of samples for each risk level, better aligning with the fuzzy characteristics of flood risk assessment. The specific steps are as follows:

(1) Establishment of risk rating standards

Based on the distribution characteristics of the comprehensive risk index, the natural breaks method is used to determine the standard intervals for risk levels. Let the number of risk levels be c; the interval corresponding to the h-th risk level is:

$$I_h = [a_h, b_h] \quad (2\text{-}13)$$

Here, $a_h$and $b_h$represent the lower and upper limits of the HTH risk level, respectively.

(2) Construction of hierarchical characteristic parameters

To characterize the typical features of each level, calculate the central value of each level interval:

$$M_h = \frac{a_h + b_h}{2} \quad (2\text{-}14)$$

Also calculate the half-interval width of the grade:

$$D_h = \frac{b_h - a_h}{2} \quad (2\text{-}15)$$

Among them, M_h denotes the central value of the h-th grade, and D_h denotes the half-interval width of the h-th grade.

(3) Calculation of grade membership degree

Let the comprehensive risk index of evaluation unit i be x_i, then its original membership degree to the h-th risk level is defined as:

$$u_{ih} = \frac{1}{1 + \left(\frac{x_i - M_h}{D_h}\right)^2} \quad (2\text{-}16)$$

Here, u_{ih} represents the degree of membership of evaluation unit i to the h-th risk level. The closer the risk index of an evaluation unit is to the central value of a certain level, the higher its corresponding membership degree.

(4) Normalization of membership degree

Since the sum of the original membership degrees for each level does not necessarily equal 1, normalization is required:

$$u_{ih'} = \frac{u_{ih}}{\sum_{h=1}^{c} u_{ih}} \quad (2\text{-}17)$$

Here, $u_{ih'}$ represents the membership degree after normalization.

(5) Calculation of level characteristic values

To comprehensively reflect the degree to which evaluation units belong to each risk level, a level characteristic value H_i is introduced:

$$H_i = \sum_{h=1}^{c} h\, u_{ih'} \quad (2\text{-}18)$$

Here, H_i represents the level characteristic value of evaluation unit i, and h is the risk grade number. The larger the level characteristic value, the higher the flood disaster risk level associated with the corresponding evaluation unit.

(6) Risk Level Classification

A risk level spatial distribution map was constructed based on the calculated level characteristic values, and the natural breaks method was used to classify these values, ultimately resulting in the flood disaster risk level distribution for the study area.

3) Flood Disaster Risk Assessment Model[32]*:* This paper uses the comprehensive index method to calculate the hazard risk of flood disaster factors, the sensitivity of disaster-prone environments, the vulnerability of exposed elements, disaster prevention and mitigation capacity, and overall risk, with the calculation formula as follows (2-19).

$$R = \sum_{i=1}^{n} Z_i \times W_i \quad (2\text{-}19)$$

In the formula, R represents flood disaster risk, which is jointly determined by hazard factor danger level, disaster-prone environmental sensitivity, vulnerability of exposed elements, and disaster prevention and mitigation capacity; Z_i denotes the value of each indicator, and W_i represents the weight of each indicator.

III Results

A. Data standardization

Spatial visualization analysis was conducted for 15 evaluation indicators (Fig 2). Overall, all indicators exhibited significant spatial heterogeneity, with notable differences observed across regions for different dimensions.

From the perspective of disaster-causing factors, average rainfall, maximum intensity of heavy rain, and frequency of heavy rain generally show a spatial distribution pattern increasing from northwest to southeast. High-value areas are mainly concentrated in the Beijing-Tianjin region and southeastern Hebei, while low-value areas are primarily located in northern Zhangjiakou and Chengde.

From the perspective of disaster-prone environmental factors, elevation and slope exhibit a distribution pattern characterized by "high in the northwest and low in the southeast," consistent with the overall regional topography. Areas with high vegetation cover are primarily concentrated in the Yan Mountains and Taihang Mountains regions. The distance to water systems shows a distinct gradient variation along major rivers and their tributaries.

From the perspective of vulnerability of exposed assets, areas with high values of GDP, population density, and building height are mainly concentrated in Beijing, Tianjin, and surrounding core urban regions, showing a clear pattern of urban agglomeration; whereas areas with high proportions of arable land are primarily distributed in the central and southern plains of Hebei Province.

From the perspective of disaster prevention and mitigation capacity, agricultural, forestry, and water expenditures, medical capabilities, flood control standards, and emergency investments generally exhibit a spatial distribution pattern characterized by higher levels in central cities and lower levels in peripheral areas, with Beijing, Tianjin, and core regions of certain prefecture-level cities showing particularly distinct advantages.

Overall, various indicators in the Beijing-Tianjin-Hebei region exhibit significant spatial differences. Natural environment indicators show clear regional gradient characteristics, socioeconomic indicators display a concentration pattern around core cities, and disaster prevention and mitigation capacity indicators reveal certain spatial imbalances, providing a foundation for subsequent comprehensive assessment of flood risk.

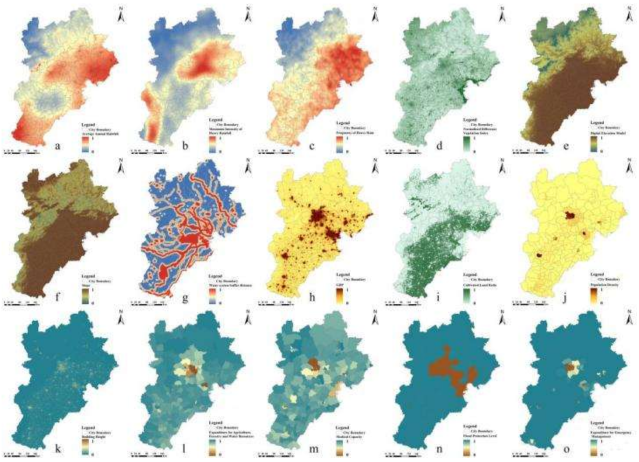

Fig 2 Distribution of 15 risk influencing factors of flood disaster in the Beijing-Tianjin-Hebei region: (a)Average Annual Rainfall, (b)Maximum Intensity of Heavy Rainfall, (c)Frequency of Heavy Rain, (d)Normalized Difference Vegetation Index, (e)Digital Elevation Model, (f) Slope, (g)Water System Distance, (h)Gross Domestic Product, (i)Cultivated Land Ratio, (j)Population Density, (k) Building Height, (l)Expenditure for Agriculture, Forestry and Water Resources,(m)Medical Capacity, (n)Flood Protection Level, (o)Expenditure for Emergency Management.

B. Weight

There are certain differences in indicator weights obtained through different weighting methods (Table II), reflecting the varying representations of indicator importance between subjective and objective weighting approaches.

The FAHP weighting results show that the maximum rainfall intensity has the highest weight of 0.158, followed by buffer distance to water systems, flood protection standards, and average precipitation. Overall, weights are primarily concentrated on indicators related to rainfall conditions, hydrological environment, and flood control capacity, while vegetation cover, proportion of cropland, and building height have relatively lower weights.

The CRITIC weighting results indicate that the proportion of arable land has the highest weight at 0.1457, followed by flood control standards and buffer distance from water systems. Compared to FAHP, the distribution of weights among indicators is more balanced, with relatively smaller differences between them.

The game-theoretic combination weighting result integrates the weighting outcomes from FAHP and CRITIC, with the weight rankings lying between those of the two methods. Among them, maximum rainfall intensity has the highest weight at 0.1210, followed by water system buffer distance at 0.1192, both ranking in the top two positions. Flood control standards and farmland proportion also possess relatively high weights.

TableII Game theory combination weights

	FAHP Weights	**CRITIC Weights**	**Game theory combination weights**
Average Annual Rainfall	0.095	0.0566	0.0793
Maximum Intensity of Heavy Rainfall	0.158	0.0677	0.1210
Frequency of Heavy Rain	0.084	0.0485	0.0694
Normalized Difference Vegetation Index	0.026	0.0880	0.0514
Digital Elevation Model	0.071	0.0557	0.0647
Slope	0.060	0.0468	0.0546
Water System Distance	0.1240	0.1122	0.1192
Gross Domestic Product	0.0510	0.0750	0.0608
Cultivated Land Ratio	0.0340	0.1457	0.0798
Population Density	0.0780	0.0444	0.0642
Building Height	0.0210	0.0320	0.0255
Expenditure for Agriculture, Forestry and Water Resources	0.0140	0.0316	0.0212
Medical Capacity	0.0360	0.0346	0.0354
Flood Protection Level	0.1030	0.1180	0.1092
Expenditure for Emergency Management	0.0450	0.0432	0.0443

C. Flood Disaster Risk Assessment Results

Based on the combined weighting results derived from game theory and calculations conducted via the variable fuzzy recognition model, we obtained the spatial distribution of flood disaster risk levels in the Beijing-Tianjin-Hebei region (Fig 3). Overall, the flood disaster risk in the study area exhibits significant spatial heterogeneity, and follows an overall distribution pattern of "high in the southeast and low in the northwest", with the risk level gradually decreasing from the southeastern plain to the northwestern mountainous area.

High-risk areas are mainly concentrated in Beijing, Tianjin, Langfang and the southeastern Hebei Plain, forming a continuous agglomerated distribution pattern. As the core area of the Beijing-Tianjin-Hebei urban agglomeration, Beijing and Tianjin feature high population density, concentrated economic activities and intensive development intensity, leading to significantly higher disaster-bearing body exposure than other regions. Meanwhile, this region is characterized by low and flat terrain and dense river networks, and is prone to the overlapping risk of urban waterlogging and river basin flooding under extreme rainfall, resulting in a relatively high comprehensive risk level. The southeastern Hebei Plain presents typical agricultural flood risk characteristics, where a high proportion of cultivated land and relatively limited drainage capacity make it more vulnerable to flood disasters.

Medium- and high-risk areas are mainly distributed in plain regions including Baoding, Cangzhou, Hengshui and Tangshan, serving as a transition zone for the outward diffusion of high-risk areas. Precipitation conditions, hydrological environments and land use structure in these regions show strong similarity with those in high-risk areas, while the agglomeration degree of population and economy is relatively lower, thus the overall risk level is slightly lower than that in the core high-risk areas.

Low-risk and relatively low-risk areas are mainly distributed in Zhangjiakou, Chengde, and the mountainous regions of the Taihang Mountains and Yanshan Mountains. This region is characterized by generally high altitude and steep slopes, relatively low population density and economic activity intensity, as well as limited exposure of hazard-affected bodies. Meanwhile, the high vegetation coverage in mountainous areas can enhance rainfall interception and soil infiltration capacity, and weaken the formation of surface runoff to a certain extent. Therefore, although mountain torrent disasters may occur in local mountainous areas, the overall flood risk level of this region is relatively low according to the comprehensive assessment results at the regional scale.

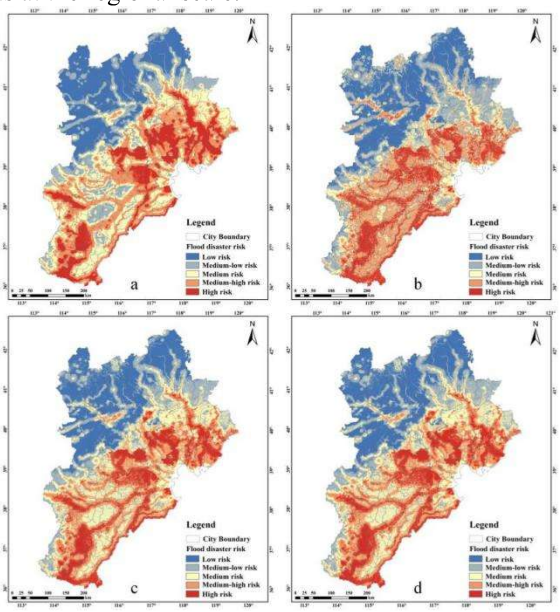

Fig 3 Flood disaster risk distribution maps: (a) FAHP, (b) CRITIC, (c) combined weighting, (d) VFPR classification

IV Discussion

A. Driving Mechanism of the Spatial Pattern of Flood Disaster Risk in the Beijing-Tianjin-Hebei Region

Essentially, flood disaster risk is a comprehensive characterization formed by the combined interaction of natural hazard and socio-economic exposure, and its spatial distribution characteristics reflect the coupling relationship among regional natural environment, socio-economic system and disaster prevention capacity.The assessment results show that the flood disaster risk in the Beijing-Tianjin-Hebei region exhibits a distinct spatial pattern characterized by "high risk in the southeast and low risk in the northwest." High-risk areas are mainly concentrated in Beijing, Tianjin, and the southeastern plain of Hebei, while low-risk zones are primarily located in Zhangjiakou, Chengde, and the Yan Mountains–Taihang Mountains region.This spatial pattern is highly consistent with the topographic pattern, rainfall characteristics and agglomeration pattern of socio-economic factors in the Beijing-Tianjin-Hebei region, indicating that regional flood risk is characterized by the dual attributes of natural environment control and human activity driving.

From the perspective of natural hazard, the occurrence probability of regional flood disasters is jointly determined by disaster-inducing factors and disaster-pregnant environments. The results of combined weighting show that the weights of maximum rainstorm intensity, river system buffer distance, average rainfall and rainstorm frequency rank among the top, with a cumulative weight of 0.389, indicating that rainfall processes and hydrological environments are the core factors determining the spatial differentiation of regional flood risk. In recent years, extreme rainfall events have occurred frequently in the Beijing-Tianjin-Hebei region. In particular, the catastrophic flood disaster in the Haihe River Basin in 2023 shows that short-duration heavy rainfall has become the main inducing factor for the formation of regional flood disasters. The southeastern plain area not only has high rainfall and frequent rainstorms, but is also widely distributed in the middle and lower reaches of the Haihe River Basin, with high river network density and relatively gentle terrain. The confluence and accumulation effect of flood is significant, thus forming a high-value agglomeration area of regional hazard.

Nevertheless, relying solely on natural hazard intensity is insufficient to fully explain the spatial distribution characteristics of risk. The formation of risk is also significantly affected by the vulnerability of disaster-bearing bodies. Beijing, Tianjin and surrounding core cities in China are regions with high agglomeration of population, industries and infrastructure, where indicators such as population density, GDP and building height all exhibit remarkably high values. Although these regions boast relatively high disaster prevention and mitigation capacity, their extremely high socio-economic exposure implies that they may suffer far more severe losses once hit by flood disasters. Therefore, high-risk areas do not only correspond to high-hazard zones, but also represent areas with high exposure of socio-economic systems. The spatial superposition effect of these two factors further intensifies risk aggregation.

Notably, the weight of cultivated land proportion in the combined empowerment reaches 0.0798, which is higher than that of most socio-economic indicators, reflecting the critical influence of agricultural exposure on the formation of flood risk in the Beijing-Tianjin-Hebei region. As an important grain production base in North China, the southeast Hebei Plain is characterized by large-scale contiguous distribution of cultivated land, making the local agricultural system extremely sensitive to flood disasters. When extreme rainfall occurs, the risk of agricultural loss increases significantly, which in turn promotes the formation of contiguous high-risk zones in this region.Meanwhile, as the indicator with the third highest weight, flood control standard plays a significant regulating role in risk formation. Theoretically, the stronger the disaster prevention and mitigation capacity, the lower the risk level should be. However, the research results show that the core areas of Beijing and Tianjin still present a relatively high risk level. This indicates that under the background of high exposure, although disaster prevention and mitigation capacity can reduce disaster losses, it is difficult to completely offset the risk accumulation effect brought by extreme rainfall and high-density hazard-affected bodies. This phenomenon reflects the typical mechanism of "hazard domination, exposure amplification and disaster prevention capacity regulation" in the process of risk formation.

Overall, the spatial differentiation of flood disaster risk in the Beijing-Tianjin-Hebei region results from the coupled interaction of natural hazard, socioeconomic exposure and disaster prevention and mitigation capacity. Among these factors, the maximum rainfall intensity and hydrological environment constitute the dominant driving forces for risk formation, while high-density population and intensive economic activities further amplify the risk effect, and disaster prevention and mitigation capacity mainly plays a risk mitigation role. The three factors jointly shape the regional risk spatial pattern characterized by "high risk in the southeast and low risk in the northwest".

B. Rationale of the Methodology

Weighting methods and risk classification approaches are two key links that affect the accuracy of flood disaster risk assessment results. Existing studies generally adopt either a single subjective weighting method or a single objective weighting method, and combine the natural break method for risk classification. However, single weighting methods are prone to generate weight deviations, while traditional classification approaches can hardly characterize the continuous transition features between different risk levels. Therefore, this paper constructs an integrated evaluation framework of "FAHP-CRITIC-Game Theory Combined Weighting-VFPR" to improve the accuracy of risk identification.

The validation results of inundation points show that in the weight assignment results obtained by FAHP, the proportion of inundation points in grade IV and grade V risk zones reaches 77.01%, that of the CRITIC weight assignment result is 69.51%, and this proportion increases to 77.50% after combined weight assignment. This result indicates that when determining weights only based on the statistical characteristics of indicators, it is easy to neglect the actual mechanism of flood disaster formation, which consequently leads to a decline in the identification capability for high-risk areas. In comparison, FAHP can fully reflect the disaster mechanism and expert knowledge, but it inevitably introduces subjective deviations. Game theory-based combined weight assignment minimizes the deviation between different weight assignment results, and realizes the dynamic equilibrium of subjective and objective information, enabling the weights to reflect both the actual action mechanism of indicators and the characteristics of sample data, thus obtaining better validation results.

After further adopting VFPR for risk classification, the proportion of inundation points in high-risk areas increases to 79.10%. This result indicates that the variable fuzzy recognition model can effectively improve the accuracy of risk classification. The conventional natural break method forcibly divides continuous risk values into discrete grades, which inevitably induces boundary effects and causes misclassification of some evaluation units in a critical state. By contrast, VFPR continuously expresses the relationship between evaluation objects and different risk levels through constructing a relative membership function, which makes risk classification more consistent with the objective law of gradual change and fuzzy transition of flood disaster risk. Therefore, VFPR can improve the recognition capability of high-risk areas while retaining the continuous information of risk.

Based on the verification results, combined weighting achieves higher spatial identification accuracy than single weighting methods, while the VFPR further improves the rationality of risk classification. Collectively, the two approaches constitute an evaluation framework that accommodates both theoretical mechanisms and data characteristics, providing a methodological system with high applicability and generalizability for flood disaster risk assessment at the regional scale.

C. Reliability of Results

To further verify the reliability of the evaluation results, this paper conducts a multi-dimensional comparative analysis using flood inundation point data and existing research findings. The verification results show that the proportion of inundation points falling within Grade IV and Grade V regions in the hazard evaluation results reaches 84.11%, which is significantly higher than that in the comprehensive risk evaluation results, indicating that the actual locations of flood disasters are highly consistent with the spatial distribution of flood hazard. From the perspective of disaster formation mechanism, inundation points record the actual occurrence areas of flood disasters, and their spatial distribution is mainly controlled by natural factors such as rainfall conditions, topography and geomorphology, and water system distribution. Flood hazard evaluation, in contrast, focuses on reflecting the occurrence probability and disaster-inducing intensity of regional flood disasters, which explains the high spatial coupling between the two. This indirectly verifies that the hazard index system and weight configuration proposed in this paper are of favorable scientificity and rationality.

In addition to the validation at inundation sites, this study further conducts a comparative analysis between the research findings and the existing results of flood disaster risk assessment in the Beijing-Tianjin-Hebei region. Wang et al. carried out a grid-scale study on flood disaster risk in the Beijing-Tianjin-Hebei metropolitan area based on the fuzzy comprehensive evaluation method, and found that the regional flood risk generally presents a spatial differentiation characteristic of gradual decline from the southeast plain to the northwest mountainous area[13]. High-risk areas are mainly concentrated in Beijing, Tianjin and central-eastern Hebei, while the northwest mountainous areas such as Zhangjiakou and Chengde are low-risk areas. Based on a county-scale construction of the flood disaster risk assessment system, Zhang et al. also pointed out that Beijing, Tianjin and the central-eastern Hebei plain are the main agglomeration areas of regional flood risk, while the risk levels of the Bashang Plateau, Yanshan Mountains and Taihang Mountains are relatively low[33].

Compared with the aforementioned studies, the risk distribution results obtained in this paper exhibit a high degree of consistency. The research findings indicate that high-risk areas are mainly concentrated in Beijing, Tianjin, Langfang and the southeastern Hebei Plain. Medium-high risk areas are primarily distributed in Baoding, Cangzhou, Hengshui, Tangshan and other regions, while low-risk areas are mainly located in Zhangjiakou, Chengde and the Yanshan-Taihang Mountains. Overall, the risk presents a significant spatial pattern of "high in the southeast and low in the northwest". The results obtained in this study are highly consistent with existing research findings both in terms of the location identification of high-risk areas and the variation trend of regional risk gradients.

Further analysis reveals that both existing studies and the present paper demonstrate that the flood risk in the Beijing-Tianjin-Hebei region presents a distinct characteristic of "aggregation in plains and attenuation in mountainous areas". In the plain areas of Beijing, Tianjin and southeastern Hebei, favorable rainfall conditions, dense river networks, low-lying terrain, and the high concentration of population and economic activities lead to the spatial superposition effect of natural hazard and exposure of disaster-bearing bodies, thus forming a continuous high-risk zone. By contrast, in Zhangjiakou, Chengde, and the Yanshan-Taihang mountainous areas, due to higher altitudes, steeper slopes, better vegetation coverage and relatively lower population density, the overall risk level is significantly lower than that of plain areas. This spatial differentiation law of risk is not only consistent with the conclusions of existing studies, but also highly aligns with the actual geographical environment and the occurrence pattern of flood disasters in the Beijing-Tianjin-Hebei region.

Notably, compared with the studies by Wang Guangpeng et al. and Zhang Yaowen et al., this paper demonstrates superior spatial continuity and aggregation characteristics in identifying high-risk zones. Particularly in the Beijing-Tianjin-Langfang urban belt and the southeastern plain of Hebei Province, risk concentration centers are more pronounced. This is primarily due to the game-theoretic combined weighting method, which effectively reconciles discrepancies between subjective expertise and objective data, while the variable fuzzy recognition model accurately captures the gradual transitions among different risk levels, thereby enhancing the capability of identifying high-risk areas. Consequently, validation results from inundation points, hazard assessments, and comparative analyses with existing literature collectively indicate that the flood disaster risk assessment model developed in this study can accurately reflect the spatial differentiation patterns of flood risks in the Beijing-Tianjin-Hebei region, yielding highly scientific and reliable evaluation outcomes.

Conclusions

Taking the Beijing-Tianjin-Hebei region as the research object, this paper constructs a flood disaster risk assessment index system covering four dimensions: disaster-causing factor hazard, disaster-pregnant environment sensitivity, disaster-bearing body vulnerability, and disaster prevention and mitigation capacity based on the disaster risk system theory. A game theory combined weighting method integrating Fuzzy Analytic Hierarchy Process (FAHP) and CRiteria Importance Through Intercriteria Correlation (CRITIC) is adopted to determine index weights, and the Variable Fuzzy Pattern Recognition (VFPR) model is introduced to carry out flood disaster risk assessment. The main conclusions are as follows:

(1) The flood disaster risk in the Beijing-Tianjin-Hebei region presents significant spatial heterogeneity, and generally exhibits a spatial distribution pattern of "high in the southeast and low in the northwest". High-risk areas are mainly concentrated in Beijing, Tianjin, Langfang and the southeastern plain of Hebei Province; medium-high risk areas are mainly distributed in Baoding, Cangzhou, Hengshui, Tangshan and other regions; while low-risk areas are mainly located in Zhangjiakou, Chengde and the Yanshan-Taihang Mountains. The risk level gradually decreases from the southeastern plain to the northwestern mountainous area, showing an obvious characteristic of regional gradient differentiation.

(2) The indicator weighting results demonstrate that maximum rainstorm intensity (0.1210), water system buffer distance (0.1192) and flood control standard (0.1092) are the key factors influencing the formation of flood disaster risk in the Beijing-Tianjin-Hebei region. Among these, maximum rainstorm intensity and rainfall frequency represent the natural driving force for the occurrence of regional flood disasters, water system buffer distance reflects the spatial heterogeneity of flood convergence and diffusion processes, and flood control standard mirrors the regulatory effect of regional flood prevention and disaster reduction capacity on disaster risk. This study indicates that the flood disaster risk in the Beijing-Tianjin-Hebei region is essentially the result of the coupled interaction among natural hazard, socio-economic exposure and disaster prevention and reduction capacity.

(3) Significant differences are observed in the validation results obtained from different weighting methods. The proportions of submerged points in medium-high risk and

high risk zones derived from the combined weighting based on FAHP, CRITIC and game theory are 77.01%, 69.51% and 77.50% respectively. The combined weighting method yields the highest spatial matching degree, which indicates that the game theory-based combined weighting can effectively coordinate the discrepancy between subjective experience and objective data, and improve the rationality of index weight configuration and the accuracy of risk identification.

(4) After introducing the variable fuzzy pattern recognition (VFPR) model based on combined weighting, the proportion of inundation points in medium-high risk areas and high-risk areas further increases to 79.10%, indicating that VFPR can effectively overcome the boundary effect problem of traditional discrete classification methods, realize the continuous expression of risk levels, and improve the identification capability of high-risk areas. Meanwhile, the proportion of inundation points corresponding to the hazard assessment results reaches 84.11%, which demonstrates that the constructed index system can accurately reflect the occurrence pattern of flood disasters.

(5) By comparing with the existing flood disaster risk assessment research results in the Beijing-Tianjin-Hebei region, it is found that the spatial distribution characteristics of risk obtained in this paper are highly consistent with the overall pattern of "high risk in plains, low risk in mountainous areas" and "high risk in the southeast, low risk in the northwest" revealed by existing studies. Meanwhile, validation based on inundation points, hazard validation and comparative literature validation all show that the "FAHP-CRITIC-Game Theory Combination Weighting-VFPR" assessment framework constructed in this paper features high scientific validity and reliability, and can provide a scientific basis for flood disaster risk prevention and control, territorial spatial planning and optimal allocation of disaster prevention and mitigation resources in the Beijing-Tianjin-Hebei region.

Declarations

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Authors' statement

All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Data availability

The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Author contributions

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Yao Fan: Resources, Writing – review and editing

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