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Research on Regional Resilience After Flood-Waterlogging Disasters Under the Concept of Urban Resilience Based on DEMATEL-TOPSIS-AISM

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Abstract

Under the dual pressures of global climate change and accelerated urbanization, the impacts of flood disasters on urban systems are becoming increasingly pronounced. Enhancing regional resilience has emerged as a critical factor in achieving sustainable urban development. Compared with existing methods such as CRITIC–Entropy, PCA–AHP, or SWMM-based resilience evaluations, grounded in urban resilience theory, this study takes Fangshan District in Beijing as empirical research to construct a post-flood disaster resilience evaluation index system spanning five dimensions (ecological, social, engineering, economic, and institutional) and leverages the integrated DEMATEL-TOPSIS-AISM model to synergistically identify key drivers, evaluate performance, and uncover internal hierarchies, thereby overcoming the limitations of existing research approaches. The findings indicate that the DEMATEL analysis identified the frequency of heavy rainfall (a12 = 0.889) and the proportion of flood disaster information databases (c51 = 1.153) as key driving factors. The TOPSIS assessment reveals that Fangshan District exhibits the strongest resilience in the economic dimension (Relative Closeness C = 0.21200), while the institutional dimension is the weakest (C = 0.00000), the AISM model constructs a hierarchical topology from a cause–effect priority perspective, elucidating the causal relationships and transmission mechanisms among factors across different dimensions. This study pioneers a novel perspective for urban resilience assessment, thereby establishing a theoretical foundation and practical references for enhancing flood resilience and advancing resilient city development.

Keywords: flood-waterlogging disasters; urban resilience; Decision-Making Trial and Evaluation Laboratory; Technique for Order Preference by Similarity to Ideal Solution; Adversarial Interpretive Structural Modeling Method; resilience; index system

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1. Introduction

Under the interplay of global climate change and accelerating urbanization, cities are confronting a diverse array of disaster challenges. Among these, typical disaster challenges posing global risks include tsunamis, floods, earthquakes, hurricanes, droughts, bushfires, and heatwaves [1–3]. Studies have shown that as of 2024, flood disasters have affected approximately 52.7893 million people nationwide, resulting in 309 fatalities or missing persons, with direct economic losses reaching 186.472 billion CNY [4]. This indicates that floods, as a major category of natural disasters, are impacting human society with unprecedented frequency and intensity, posing severe threats particularly to highly populated and

systemically complex urban areas. Such events not only cause substantial damage to urban infrastructure but also significantly endanger lives and property [5,6], thereby undermining the stable development of the socio-economy. In this context, the theory of "urban resilience" provides a crucial analytical framework for understanding and enhancing the ability of urban systems to withstand disturbances and their capacity for recovery.

The term "resilience" originates from the Latin word "resillo," meaning "to bounce back," that is, "to return to the original state" [7–9].The concept originally stems from the field of psychology, referring to an individual's capacity to recover from adversity. It was later introduced to ecology by Holling (1973) [10], who defined it as a system's ability to absorb disturbances while maintaining its fundamental structure and functions. The concept has since been extensively extended to domains such as engineering, economics, society, and institutions, evolving into five corresponding dimensions of urban resilience: ecological, engineering, economic, social, and institutional resilience. In contemporary research, resilience is no longer simplistically interpreted as "returning to the original state" but emphasizes the system's capacity, through adaptation and learning, to attain a new, more resilient equilibrium. Urban resilience theory thus provides a key framework for analyzing how urban systems can maintain basic functions, recover rapidly, and achieve sustainable transformation when confronting pressures and shocks. Accordingly, urban resilience specifically refers to the capacity of a city to rapidly adapt, recover, and rebuild when confronted with various stresses, shocks, and disasters [11,12].

Despite significant progress in flood resilience assessment within academia, current research methodologies still exhibit notable limitations and gaps. On one hand, mainstream simulation models—such as the Storm Water Management Model (SWMM) [13], hydrodynamic models [14], and rainstorm flood inundation models [15]—alongside static weighting methods like CRITIC-Entropy [16], are proficient in risk scenario simulation or performance ranking. However, they fall short in revealing the causal mechanisms among the various factors influencing resilience. On the other hand, emerging data-driven approaches, such as utilizing nighttime light data to assess disaster losses [17], face the challenge of being "black-box" in nature, which hinders the interpretation of their internal mechanisms and intervention pathways. To the best of our knowledge, although some scholars have attempted to analyze factor relationships using methods like DEMATEL [18,19], few studies have applied a comprehensive framework integrating causal identification, performance evaluation, and hierarchical structure analysis. Consequently, there is an urgent need for an integrated analytical approach that can synergistically achieve "key driver identification—multidimensional performance evaluation—internal hierarchical structure analysis" to bridge this methodological gap and facilitate the development of resilience strategies from a systemic perspective.

To address these challenges, this study aims to propose and apply an integrated DEMATEL-TOPSIS-AISM model to systematically diagnose the formation mechanism of regional flood resilience. This research seeks to answer the following core questions: (1) What are the key driving factors influencing regional flood resilience, and what are their causal relationships? (2) How does the relative performance vary across different resilience dimensions in the study area? (3) What hierarchical structure and internal transmission pathways exist among these influencing factors?

2. Literature

2.1. Flood-Waterlogging Disasters

"Flood disaster" and "waterlogging disaster" are collectively referred to as flood and waterlogging disasters, both caused by prolonged rainfall and excessive precipitation. Among them, "flood disaster" manifests in two forms: one is flash floods in mountainous

areas, and the other is a rapid rise in the water levels of rivers, lakes, and seas exceeding normal levels. The occurrence of either or both of these phenomena is termed a flood disaster. "Waterlogging disaster" primarily refers to disasters causing agricultural losses. Its direct cause is short-term heavy rainfall leading to the inability of surface runoff to drain in time, resulting in water accumulation in farmland exceeding the tolerance capacity of crops and consequently causing reduced agricultural output [20,21]. As a global natural hazard, flood disasters exert multidimensional and profound impacts. Their direct consequences include casualties, infrastructure damage, and economic disruption; secondary disasters can trigger environmental pollution, public health crises, and social disorder; long-term effects manifest as heavy burdens of post-disaster reconstruction, imbalanced regional development, and negative feedback loops with climate change. Concurrently, amid persistent challenges such as continuously rising population density, deteriorating ecological environments, intensifying social conflicts, and increasing economic pressures in urban communities [22], traditional post-disaster recovery models—which predominantly emphasize short-term emergency response and physical reconstruction—often lack a holistic consideration of the resilience of complex urban systems, rendering them inadequate to address the cascading effects and uncertainties of disasters. Within this context, the theory of "urban resilience" has emerged.

2.2. Urban Resilience

Urban resilience is a complex concept with multiple dimensions. The existing research mainly focuses on the following five core dimensions, as shown in Table 1.

Table 1. Summary of Conceptual Perspectives on Urban Resilience.

Perspective	Definition	Scholars
Ecological Perspective	The capacity of socio-economic systems to withstand shocks, recover from crises, and continue to adapt autonomously to external changes.	Xiao, J. et al. [23] and Peng, C. et al. [24]
	It refers to the ability of a system to return relatively quickly to its original state or, through self-adjustment and transformation, attain a new equilibrium, while maintaining the normal operation of its structure and functions.	Dalziell, E.P. [25]
Engineering Perspective	The capacity of quality infrastructure and ecosystems to protect, provision for, and connect communities during times of crisis.	Rockefeller Foundation [26]
	The bearing capacity and rapid recovery capability of hardware infrastructure systems—such as urban buildings, roads, and transportation networks—to withstand damage caused by external shocks or abrupt changes and quickly return to their original state.	Olson M [27]
	The ability of a system to cope with sporadic disasters and return to an equilibrium level, emphasizing robustness during accidental hazards and the capacity for recovery and adaptation post-impact.	Wildavsky A. et al. [28]
Economic Perspective	The ability of an urban system to implement flexible strategies to avoid potential losses in the wake of sporadic disasters.	Rose A. et al. [29]
Social Perspective	The capacity of a group or community to confront threats and overcome external pressures and disturbances arising from social, political, and environmental changes by accessing capital and creating opportunities.	Adger, W.N. [30], Obrist, B. [31]
	The ability of a system to maintain normal performance, mobilize resources, and address challenges under external disturbances.	Paton D. et al. [32]
Organizational and Comprehensive Perspective	The capacity of a city to ensure its safe operation in the face of various disasters and risks by enhancing the coupling effects of its economic, social, institutional, and infrastructural systems, thereby improving its resistance, adaptability, rapid recovery, and transformative learning capabilities.	Chen, M.R. et al. [33]

Based on this, this paper defines urban resilience as the capacity of a city to maintain its basic functions, recover rapidly, learn from experiences, and adapt to future changes when confronted with pressures and shocks such as natural and human-induced disasters, climate change, and economic fluctuations. The theory of urban resilience provides a crucial analytical framework for understanding and enhancing the ability of urban systems to cope with disturbances and recover from disasters. This theory emphasizes that a system should possess the capacity to absorb disruptions, engage in adaptive learning,

and achieve sustainable transformation. Its core lies not only in resistance but, more importantly, in recovery. It follows that a city needs the capability to recover effectively from disturbances, and post-disaster recovery capacity is precisely the core dimension for measuring urban resilience.

In 1973, Holling [10] first applied the concept of "resilience" to the field of ecology, defining it as the capacity of a system to absorb disturbances or stresses without altering its fundamental structure and function, thereby serving as a measure of system persistence. Subsequently, it has been described as the ability of a system to resist, adapt to, and recover from disasters [34]. Within this framework, the resistance phase refers to the city's capacity to withstand and minimize losses from flood disasters; the adaptation phase denotes the city's ability to self-regulate and maintain stability when confronting rainstorm and flood events of varying magnitudes; and the recovery phase represents the city's capability to return to its pre-disruption state after suffering flood impacts [35]. Although a universally accepted definition and conceptualization of resilience have not yet been fully established within academia, there is general consensus that resilience embodies two key characteristics: process continuity and hazard-specific adaptability. The former necessitates comprehensively describing system resilience by examining its state transitions across the pre-disaster, during-disaster, and post-disaster phases, integrating the entire cycle of resistance, adaptation, and recovery. The latter acknowledges that different types of disasters lead to distinct system states and require correspondingly specific quantification methods, thus demanding tailored approaches from the initial impact. This study primarily focuses on post-disaster recovery.

In 1984, Pimm [36], while studying ecosystems, proposed using the time required for an ecosystem to return to its original equilibrium after being disrupted as a measure of its recovery. A longer recovery time indicates weaker resilience. Since then, research in this area has expanded and deepened, focusing primarily on three key aspects:

(1) Infrastructure Recovery

In the domain of infrastructure recovery, scholars generally recognize green infrastructure as an effective measure for addressing flood disasters. Shi et al. [37] established a theoretical and methodological framework for Urban Resilient Infrastructure (URI) to analyze its resilience development. Their research indicates that this field primarily focuses on nature-based solutions and climate change adaptation.

Ahern [38] highlighted in his research that green infrastructure—such as wetlands, green spaces, and rain gardens—can effectively mitigate urban flood risks while simultaneously enhancing the ecological functions of cities and the quality of life for residents. Soz et al. [39] explored the role of green infrastructure in urban flood risk management, emphasizing the enhancement of urban flood disaster resilience through nature-based solutions.

(2) Social Recovery

Regarding social recovery, international studies place significant emphasis on community participation, psychological assistance, and the restoration of social capital, underscoring its importance in post-flood recovery. Aldrich [40] emphasized the critical role of social capital—including community networks and trust relationships—in post-disaster recovery, noting that communities rich in social capital often recover more rapidly from disasters. Norris et al. [41], through studies of multiple post-disaster communities, highlighted the importance of psychological assistance in recovery, stressing the need for psychological interventions to help affected residents return to normal life as quickly as possible. Mileti [42] pointed out that community participation can enhance residents' capacity to cope with disasters and promote the stability of social systems post-disaster.

(3) Economic Recovery

In terms of economic recovery, scholars argue that it is a crucial component of post-flood recovery and have proposed various strategies to diversify disaster risks and promote sustainable regional economic development. Adam et al. [43], in their study on business interruption losses caused by natural hazards, found that post-disaster recovery could reduce approximately 80% of disaster-related losses. Hallegatte [44] proposed in his research that establishing post-disaster reconstruction funds and introducing insurance mechanisms can effectively diversify disaster risks and mitigate the long-term economic impacts of disasters. Rose [29] introduced the concept of "economic resilience," emphasizing the promotion of sustainable regional economic development through post-disaster innovation and transformation—for instance, by introducing new technologies and industries to facilitate regional economic restructuring and upgrading. Adger [30] also conducted assessments of flood disaster recovery from an economic perspective.

Furthermore, a number of scholars advocate for interdisciplinary collaboration, integrating perspectives from ecology, sociology, economics, and other disciplines to explore more comprehensive and sustainable recovery pathways. Cutter et al. [45] proposed the DROP (Disaster Resilience of Place) model, emphasizing the enhancement of a community's comprehensive recovery capacity in the face of disasters through multidisciplinary cooperation. This model encompasses multiple dimensions, including infrastructure, society, and economy, providing a holistic theoretical framework for post-flood disaster recovery. Tierney [46] explored the interplay of social, economic, and political factors in disaster recovery, underscored the importance of interdisciplinary collaboration in the post-disaster context, and proposed strategies for enhancing community resilience through social transformation. Proag et al. [47] introduced the concepts of "Hard Resilience" and "Soft Resilience," suggesting that regional post-flood disaster recovery should be comprehensively evaluated from two aspects: the ability to resist flood disasters and the capacity to restore to pre-disaster levels. Chen et al. [48] developed an integrated analytical framework combining XGBoost–SHAP to identify the specific impacts of urban morphology on flood risk clustering patterns under different rainfall scenarios in high-density urban areas. Liu et al. [49] adopted a life cycle perspective to evaluate economic costs, environmental impacts, and hydrological performance of infrastructure layouts under climate change conditions, employing multi-objective optimization to identify optimal configurations for integrated grey–green infrastructure systems.

3. Materials and Methods

3.1. Study Areas

Located in the southwestern part of Beijing, China, Fangshan District (Figure 1) covers an area of 2019 square kilometers. It experiences a warm temperate semi-humid monsoon continental climate, with an average annual temperature of 11 °C and an average annual precipitation of 590 mm. The unique hydrological setting makes it highly prone to flooding. Seventy percent of its terrain transitions abruptly from mountainous areas to alluvial plains, where strong orographic lift effects force moisture ascent and generate intense precipitation. Historically, the area experienced a severe flood disaster in 2023, with water depths exceeding 2.5 m in residential zones. The current drainage system has a pipeline density of approximately 8 km/km^2 in urbanized areas, which, while designed to withstand 10-year rainfall events, remains inadequate during heavy precipitation. Records indicate that Fangshan District in Beijing has encountered more than ten major flood disasters between 1950 and 2023, with a river network density of only 0.2 km/km^2. As a typical case of an urban–rural fringe area confronting compound flood challenges, it presents an ideal subject for studying flood resilience mechanisms.

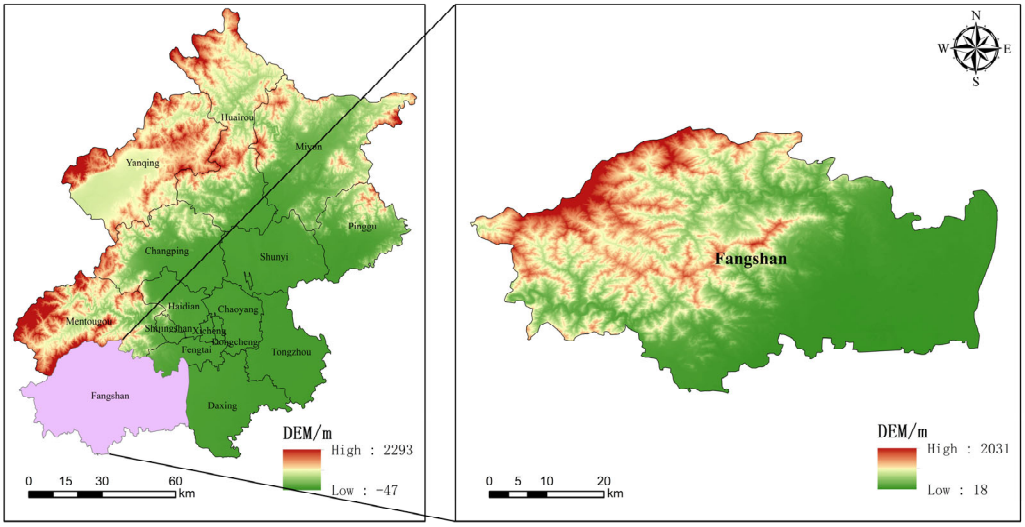


Figure 1. Geographical Location Map of Fangshan District, Beijing.

3.2. Research Methodology

This study employs an integrated DEMATEL-TOPSIS-AISM model to analyze the regional post-flood disaster resilience evaluation system (Figure 2). DEMATEL method establishes the foundation by revealing quantitative relationships among factors. TOPSIS enables the prioritization of resilience levels across different dimensions or cases. AISM analyzes hierarchical linkages among influencing factors from both cause-first and effect-first perspectives, thereby clarifying internal correlations and transmission pathways within the disaster system. Currently, there is limited research applying the combined use of these methods in flood disaster resilience studies. This paper represents the first application of the integrated DEMATEL-TOPSIS-AISM model to investigate resilience within regional flood disaster systems, aiming to clarify the hierarchy, positions, and roles of various factors following flood disaster formation, demonstrating certain innovativeness.

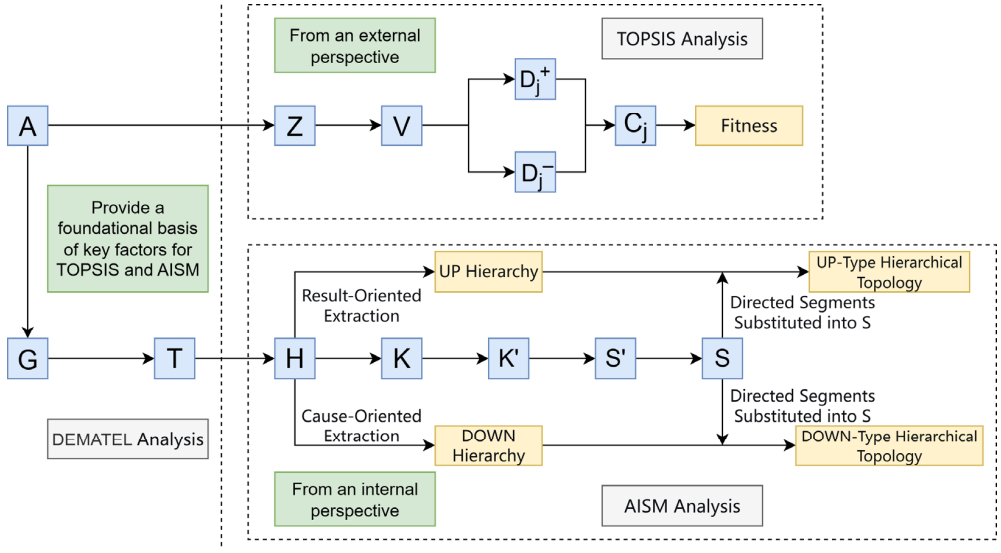


Figure 2. Flowchart of the DEMATEL-TOPSIS-AISM Model Analysis. A: Initial Direct Influence Matrix; G: Normalized Direct Influence Matrix; T: Comprehensive Influence Matrix; Z: Normalized Matrix; V: Weighted Normalized Decision Matrix; D_j^+: Positive Ideal Solution; D_j^-: Negative Ideal Solution; C_j: Fitness; H: Adjacency Matrix; K: Reachability Matrix; K′: Reduced-Point Matrix; S′: Reduced-Edge Matrix; S: General Skeleton Matrix.

The specific computational procedures are as follows:

Step 1. Establishing the Direct Impact Matrix.

The urban flood disaster resilience evaluation indicators are designated as x1, . . ., xn. Experts score the influence of each factor using a 0–4 scale (4 for extremely high, 3 for high, 2 for moderate, 1 for low, and 0 for no impact). An initial direct impact matrix A is constructed using association rules. A = [aij]m × n, where aij represents the influence of factor i on factor j.

Step 2. Establishing the Comprehensive Impact Matrix.

The comprehensive impact matrix T is calculated by standardizing the direct effect matrix A to G in order to provide the comprehensive impact matrix of urban flood catastrophe resilience evaluation indicators. The identity matrix is denoted by E.

$$\left[\frac{1}{\max\limits_{1\le i\le n}\left(\sum_{j=1}^{n} x_{ij}\right), \max\limits_{1\le j\le n}\left(\sum_{i=1}^{n} x_{ij}\right),}\right] \tag{1}$$

$$G = \beth \times A \tag{2}$$

$$T = G + G^2 + \cdots + G^n \approx G(E - G)^{-1} \tag{3}$$

where n is sufficiently large, and t_{ij} represents the degree to which element x_i influences element x_j.

Step 3. Calculating Impact Degree, Affected Degree and Centrality.

The impact degree Ri is obtained by summing the elements of each row of the comprehensive impact matrix T, while the affected degree Dj is obtained by summing the elements of each column. The centrality is the sum of the impact degree and the affected degree. The formulas are as follows:

$$\begin{gathered} R_i = \sum_{j=1}^{n} T_{ij} \quad D_j = \sum_{i=1}^{n} T_{ij} \\ (1 \le i \le n,\ 1 \le j \le n) \end{gathered} \tag{4}$$

Centrality reflects the position and importance of an indicator within the indicator system. Causality reflects the net impact of an indicator on the system. If causality > 0, the indicator is a causal indicator (input indicator); if causality < 0, it is a result indicator (output indicator); if causality = 0, the indicator can be eliminated.

Step 4. Eliminating Inefficient Indicators.

Inefficient indicators are eliminated, and the remaining indicators are used to determine the benefit evaluation indicators.

Step 5. Standardization Processing.

The original data matrix is normalized to mitigate dimensional effects. The standardized matrix is denoted as Z, with each element zij calculated as follows:

$$Z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \ (i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n) \tag{5}$$

Step 6. Constructing the Weighted Standardized Decision Matrix V.

The weights of the indicators are determined, and the weighted standardized decision matrix V is constructed by integrating the weights into the standardized matrix Z. For calculating the geometric distances from the positive and negative ideal solutions, the Euclidean distance is generally used:

$$V_{ij} = \omega * z_{ij} \tag{6}$$

Step 7. Determining the Positive Ideal Solution Y^+ and Negative Ideal Solution Y^-.

$$Y^+ = \left(max\ z_{1j}, max\ z_{2j}, \ldots, max\ z_{mj}\right) \tag{7}$$

$$Y^- = \left(min\ z_{1j}, min\ z_{2j}, \ldots, min\ z_{mj}\right) \tag{8}$$

Step 8. Calculating the Geometric Distances from the Positive and Negative Ideal Solutions. The Euclidean distance is generally used:

$$D_j^+ = \sqrt{\sum_{j=1}^{n}\left(V_{ij} - Y_j^+\right)^2} \tag{9}$$

$$D_j^- = \sqrt{\sum_{j=1}^{n}\left(V_{ij} - Y_j^-\right)^2} \tag{10}$$

Step 9. Calculating the Closeness Coefficient to the Positive Ideal Solution.

$$C_j = \frac{D_j^-}{D_j^+ + D_j^-} \tag{11}$$

The greater the degree of fit, the closer it is to the positive ideal solution; conversely, the closer it is to the negative ideal solution. When the value approaches 1, it indicates a higher level of resilience, meaning the plan is more optimal; when the value approaches 0, it indicates a lower level of resilience, meaning the plan is less favorable.

Step 10. Calculating the adjacency matrix H.

Based on the data in the comprehensive influence matrix T, a threshold is determined to define the adjacency matrix H as follows:

$$h_{ij} = \{^{1,\ h_{ij} \geq \gamma}_{0,\ h_{ij} < \gamma}, H = \left[h_{ij}\right]_{n \times n} \tag{12}$$

$$\gamma = \mathrm{x}^- + \sigma \tag{13}$$

$$\mathrm{x}^- = \frac{\sum \mathrm{t_{ij}}}{\mathrm{n}*\mathrm{n}}, \sigma = \sqrt{\frac{\sum\left(\mathrm{t_{ij}} - \mathrm{x}^-\right)^2}{\mathrm{n}*\mathrm{n}}} \tag{14}$$

where: represents the threshold, with $\gamma = \mathrm{x}^- + \sigma, \mathrm{x}^-$ is the mean of all elements in matrix T, and is the standard deviation [48]. A higher γ value leads to a more significant simplification of the model structure and stronger independence among the factors.

Step 11. Determining the reachability matrix K.

The reachability matrix is derived as follows:

$$\mathrm{K} = (\mathrm{H} + \mathrm{E})^{\mathrm{n}+1} = (\mathrm{H} + \mathrm{E})^{\mathrm{n}} \neq (\mathrm{H} + \mathrm{E})^{\mathrm{n}-1} \neq (\mathrm{H} + \mathrm{E}) \tag{15}$$

Step 12. Determining the reduced-point matrix K' and the reduced-edge matrix S'.

The point reduction principle involves merging factors that exhibit identical influence relationships in both their corresponding rows and columns. The edge reduction method is expressed by Equation (7).

$$S' = K' - \left(K' - E\right)^2 - E \tag{16}$$

Step 13. Obtaining the general skeleton matrix S.

Based on the reduced-edge matrix S′, the general skeleton matrix S is derived by reintroducing the circuits [49].

Step 14. Determining the hierarchy of the AISM model.

Using the general skeleton matrix S, compute the reachable set ($R(s_i)$), the antecedent set ($A(s_i)$), and the common set ($C(s_i)$), where i = 1,2,. . .,n + 1.

$$R(s_i) = \{s_i \in S | s_{iJ} = 1\} \quad (17)$$

$$A(s_i) = \{s_i \in S | s_{iJ} = 1\} \quad (18)$$

$$C(s_i) = \{s_i \in S | s_{iJ} = 1\} \quad (19)$$

Step 15. Constructing the AISM hierarchical model.

According to the hierarchical partitioning criteria, the UP-type and DOWN-type hierarchies are determined using Equation (11) and Equation (12), respectively. The UP-type hierarchy diagram, which reflects result-oriented prioritization, places elements extracted in each iteration at the topmost level, arranging them from top to bottom [50]. Conversely, the DOWN-type hierarchy diagram, representing cause-oriented prioritization, places extracted elements at the bottommost level and arranges them upward from the bottom. This process yields a multi-level AISM model.

$$U(s_i) = \{s_i \in S | R(s_i) \cap C(s_i)\} \quad (20)$$

$$U(s_i) = \{s_i \in S | R(s_i) \cap C(s_i)\} \quad (21)$$

3.3. Construction of the Evaluation Index System

3.3.1. Data Sources

Data for this study were obtained through the following sources:

1. Data for the DEMATEL model were collected using the expert scoring method.
2. Indicator data for the TOPSIS and AISM models were compiled from the Beijing Statistical Yearbook (2014–2023) and the Beijing Fangshan District Statistical Yearbook (2014–2023), accessed via the China National Knowledge Infrastructure (CNKI) and the Beijing Municipal People's Government website. This provided a decade (2014–2023) of natural, ecological, and socio-economic indicator data for Fangshan District.

3.3.2. Index System

The factors influencing regional flood disaster resilience are numerous and interconnected. Building upon a synthesis of previous research and considering the objectives outlined in the "14th Five-Year Plan for National Comprehensive Disaster Prevention and Reduction" [51] and the "14th Five-Year Plan for National Meteorological Development" [52], a preliminary flood disaster resilience indicator system was developed. This process incorporated extensive expert consultation and was guided by the need for theoretical completeness. The resulting framework comprises 5 first-level indicators, 23 s-level indicators, and 53 third-level indicators (Table 2).

Table 2. Post-Flood Disaster Resilience Indicator System.

First-Level Indicator	Second-Level Indicator	Third-Level Indicator
Ecological (A)	Precipitation Factor (a1)	Rainstorm intensity (a11)
		Frequency of Heavy Rainfall (a12)
	Water System Factor (a2)	River Network Density (a21)
	Topographic Factor (a3)	Absolute Elevation (a31)
		Relative Elevation (a32)
	Land Factor (a4)	Land Use Type (a41)
		Soil Type (a42)
		Vegetation Coverage (a43)
Social (B)	Population Factor (b1)	Population Density (b11)
		Labor Force Proportion (b12)
		Gender Ratio (b13)
	Medical and Health Rescue Capacity (b2)	Per Capita Medical Bed Number (b21)
	Social Security Capacity (b3)	Per Capita Social Welfare Bed Number (b31)
	Public Disaster Prevention and Reduction Awareness (b4)	Flood Knowledge Popularization Rate (b41)
Engineering (C)	Flood Control Water Conservancy Project Construction Level (c1)	Proportion of Population Protected by Dikes (c11)
		Proportion of Farmland Protected by Dikes (c12)
		Reservoir Capacity Regulation Coefficient (c13)
		Proportion of Farmland with Drought and Flood Protection (c14)
		Proportion of Drainage Area (c15)
	Life-line Project Construction Level (c2)	Traffic Density and Accessibility (c21)
		Proportion of Villages Benefiting from Tap Water (c22)
		Flood Protection Performance of Gas Supply System (c23)
		Flood Protection Performance of Communication System (c24)
		Flood Protection Performance of Power Supply System (c25)
		Proportion of Villages with Traffic Access (c26)
		Drainage Pipe Network Density (c27)
		Per Capita Vehicle Ownership (c28)
	Monitoring and Warning Capacity Construction Level (c3)	Meteorological Station Density (c31)
		Hydrological Monitoring Station Density (c32)
		Broadcast and Television Popularization Rate (c33)
		Mobile Phone Popularization Rate (c34)
		Internet Popularization Rate (c35)
	Building Flood Protection Capacity (c4)	Proportion of Reinforced Concrete Houses (c41)
	Flood Information Informatization Level (c5)	Proportion of Flood Disaster Information Database (c51)
Economic (D)	Regional Economic Strength (d1)	Per Unit Area GDP (d11)
		Proportion of Agricultural Output Value (d12)
	Government Fiscal Support Capacity (d2)	Per Unit Area Fiscal Revenue (d21)
		Per Unit Area Fiscal Expenditure (d22)
	Personal Financial Support Capacity (d3)	Per Capita Net Income of Farmers (d31)
		Per Capita Disposable Income of Urban Residents (d32)
		Per Capita Bank Deposit Balance of Urban and Rural Residents (d33)
	Material Support Capacity (d4)	Disaster Relief Material Reserve Depot Density (d41)
		Per Capita Grain Output (d42)
Institutional (E)	Professional Talent Team Construction Level (e1)	Number of Meteorological and Water Conservancy Professionals (e11)
	Disaster Policy and Regulations (e2)	Proportion of Flood Control Laws and Regulations (e21)
		Proportion of Flood Disaster Insurance Claims (e22)
		Proportion of Flood Control Planning (e23)
		Proportion of Flood Control Emergency Plans (e24)
	Flood Disaster Information Management and Service Capacity (e3)	Speed of Flood Disaster Information Release and Update (e31)
	Command System Construction Level (e4)	Number of Flood Control and Disaster Reduction Command Institutions (e41)
	Social Mobilization Capacity (e5)	Scale of Mobilized Personnel (e51)
	Disaster Reduction Culture Construction Level (e6)	Number of Flood Control and Disaster Reduction Drills (e61)
		Number of Flood Control and Disaster Reduction Publicity and Education Activities (e62)

4. Results

Nine experts from government agencies, research institutions, and related industries were invited to fill out the questionnaire. SPSS29.0 software was used to analyze the reliability of the questionnaire, and the Cronbach's α value was found to be 0.935, indicating excellent reliability. While this study provides a detailed empirical assessment of flood resilience in Fangshan District, its findings highlight the need for future research to engage in comparative case studies with other regions to test the transferability of the proposed framework. Furthermore, the identified hierarchical relationships among factors offer a foundation for future theoretical development in modeling urban resilience dynamics.

4.1. DEMATEL Model Results Analysis

Based on the specific calculation results of the impact degree, affected degree, and centrality of various influencing factors on urban flood disaster resilience, factors with an impact degree of 0 have been excluded, and the final calculation results are shown in Table 3.

Table 3. DEMATEL Calculation Results.

Third-Level Indicator	Impact Degree	R Affected Degree	Centrality	Cause Degree
a12	0.889	0.164	1.052	0.725
a31	0.061	0.166	0.227	−0.105
b11	0.149	0.133	0.282	0.016
b13	0.041	0.288	0.329	−0.247
b31	0.589	0.197	0.786	0.393
c12	0.11	0.179	0.289	−0.07
c13	0.639	0.184	0.823	0.455
c23	0.118	0.222	0.341	−0.104
c24	0.045	0.146	0.191	−0.101
c26	0.181	0.241	0.422	−0.061
c27	0.084	0.151	0.235	−0.067
c31	0.709	0.271	1.18	0.638
c33	0.049	0.135	0.184	−0.086
c51	1.153	0.187	1.34	0.966
d11	0.76	0.115	0.875	0.645
d22	0.701	0.116	0.817	0.585
d32	0.068	0.087	0.155	−0.019
e61	0.091	0.119	0.21	−0.027
e62	0.781	0.119	0.899	0.662

This table only includes indicators with a non-zero influence degree.

Regarding the degree of influence, both the frequency of rainstorms (a12) and the proportion of flood disaster information databases (c51) rank highest with a significant value of 0.889 and 1.153, indicating their dominant roles as influencing factors and identifying them as key drivers of flood disaster impacts. Their high influence values signify that an increase in the frequency of rainstorms substantially elevates potential flood risks, while a higher proportion of flood disaster information databases enhances early warning effectiveness, thereby exerting extensive effects on other factors within the system. This analysis highlights these factors as critical leverage points for intervention. And, improving the information infrastructure represented by c51 not only strengthens early warning capabilities but also provides data-driven decision support for the scientific siting, performance simulation, and long-term operation and maintenance of GGI systems, thereby helping to synergistically enhance overall regional resilience at both institutional and technical levels.

A comprehensive analysis considering both centrality and causality reveals that the reservoir storage regulation coefficient (c13) exhibits relatively high centrality (0.823) and a positive causality value (0.455). This indicates that this factor is not only influenced by other elements within the system but also exerts significant influence on them. As critical hydraulic engineering infrastructure, reservoirs play a pivotal role in flood regulation and regional flood safety. Enhancing their storage regulation capacity can effectively mitigate flood risks in downstream areas and contributes substantially to the stable operation of the entire flood control system.

Similarly, metrics such as meteorological station density (c31), which demonstrate both high influence and susceptibility to influence, show positive causality (0.638). This confirms their central position within the flood disaster monitoring and early warning framework. By increasing the density and precision of meteorological monitoring, these systems provide more accurate and timely information support for early warnings and emergency response, thereby strengthening overall societal capacity for disaster prevention and mitigation.

4.2. TOPSIS Model Results Analysis

The Dematel analysis method was employed to establish causal relationships and identify key drivers within the resilience indicator framework. To quantify the relative performance and disparities among different resilience dimensions in post-flood recovery, this study utilized the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) model. The Dematel method provided a robust foundation for TOPSIS evaluation, ensuring subsequent priority rankings were based on the most influential indicators. Based on the foundational insights from DEMATEL, the entropy weighting method is used to determine the weight of indicators, so as to determine the recovery degree of different resilience in urban resilience.

The results calculated by the TOPSIS model indicate significant variation in post-flood disaster resilience levels across different dimensions in Fangshan District, Beijing. The ranking of resilience capabilities for various dimensions is presented in Table 4. Specifically, Fangshan District demonstrates relatively strong resilience in the economic dimension, followed by the social dimension. However, resilience levels are notably weaker in the engineering and ecological dimensions, with the institutional dimension exhibiting the lowest recovery capacity.

Table 4. Ranking of Post-Flood Disaster Recovery Capacity across Different Resilience Dimensions in Fangshan District, Beijing.

Item	Relative Closeness C	Ranking Result
Economic Resilience	0.21200	1
Social Resilience	0.00140	2
Engineering Resilience	0.00075	3
Ecological Resilience	0.00060	4
Institutional Resilience	0.00000	5

4.3. AISM Model Results Analysis

Proceeding from different resilience perspectives, the general skeleton matrix S was calculated using Equations (13)–(19). This matrix served as the basis for constructing the hierarchical model within the AISM framework. The AISM model generates two distinct hierarchical topologies—UP-type and DOWN-type—which exhibit an adversarial relationship due to their different partitioning criteria, namely result priority and cause priority, respectively.

Within the model, directed line segments represent the influential relationships between factors. In the UP-type hierarchy, factors characterized by stronger dependency are positioned in the upper layers, whereas in the DOWN-type hierarchy, factors with stronger driving forces occupy the upper layers.

This study integrates the UP-type and DOWN-type hierarchical topological relationships, categorizing them according to the first-level indicators (the five resilience dimensions). By conducting a relational analysis of effective influencing factors within each category, the hierarchical causal relationships among factors at different levels within the regional flood disaster system are clarified, thereby identifying the effective transmission pathways.

(1) Ecological Resilience Dimension

Within the ecological resilience dimension, rainstorm frequency (a12) and absolute elevation (a31) function as fundamental driving factors within the system, exerting top-down control over underlying elements such as rainstorm intensity (a11).Specifically, vegetation coverage (a43) and soil type (a42), acting as critical land surface parameters, directly influence the intensity characteristics of rainstorm events by regulating hydrological

processes like the surface runoff coefficient and soil infiltration rate. Simultaneously, topographic factors such as river network density (a21) and absolute elevation indirectly modulate the hydrological response magnitude to rainstorm events by controlling the regional drainage capacity. Furthermore, land use type (a41), serving as a significant indicator of anthropogenic disturbance, further affects the spatial distribution pattern and intensity features of rainstorms by altering underlying surface characteristics, including surface roughness and permeability. The relationships and hierarchical structure among these factors are illustrated in Figure 3.

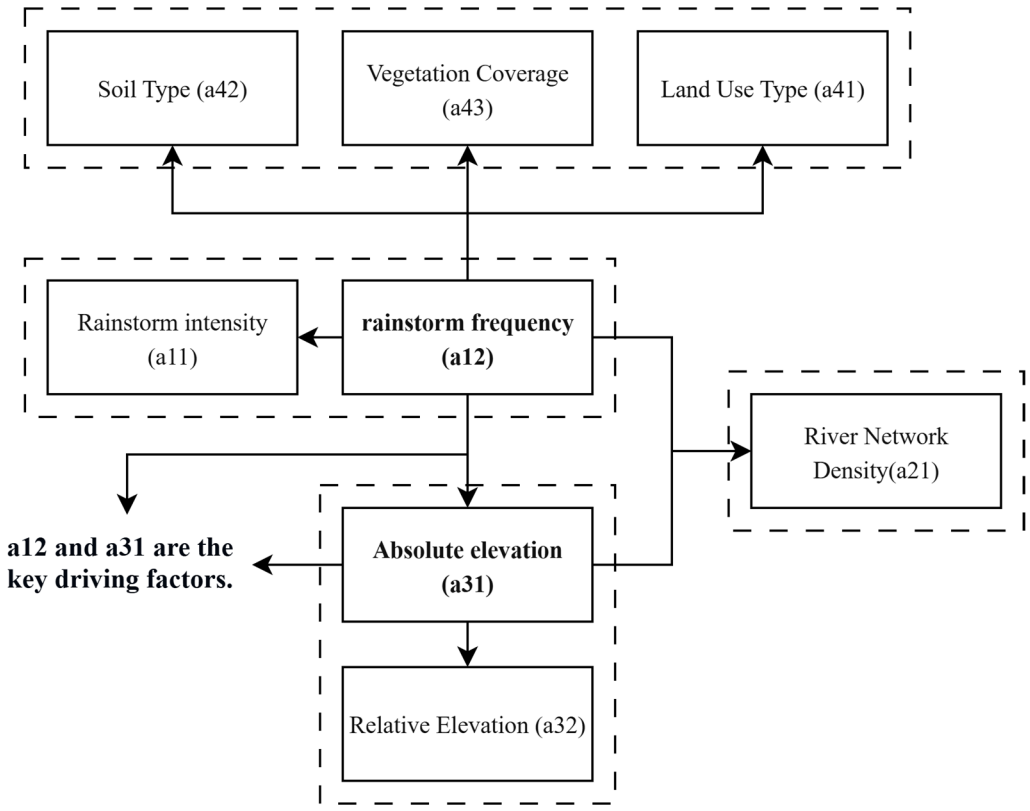


Figure 3. Hierarchical Topology of Factors in the Ecological Resilience Dimension.

(2) Social Resilience Dimension

Within the social resilience dimension, flood resilience manifests as a complex systemic characteristic whose formation mechanism is influenced by the synergistic effects of multi-dimensional factors. Research indicates that demographic characteristics significantly impact regional flood resilience: higher population density correlates with greater flood control pressure, while the labor force ratio, as a key demographic indicator, shows a significant positive correlation with emergency response efficacy.

Further research indicates that the popularization rate of flood control knowledge (b41) significantly enhances the overall disaster resilience of the social system by improving public risk perception and emergency response capabilities. Furthermore, the allocation of medical and health resources serves as a crucial social security factor. Specifically, the number of hospital beds per capita (b21) and the number of social welfare beds per capita (b31) significantly improve the effectiveness of flood emergency response by providing essential medical services and social support during disasters. The interrelationships and hierarchical structure among these factors are depicted in Figure 4.

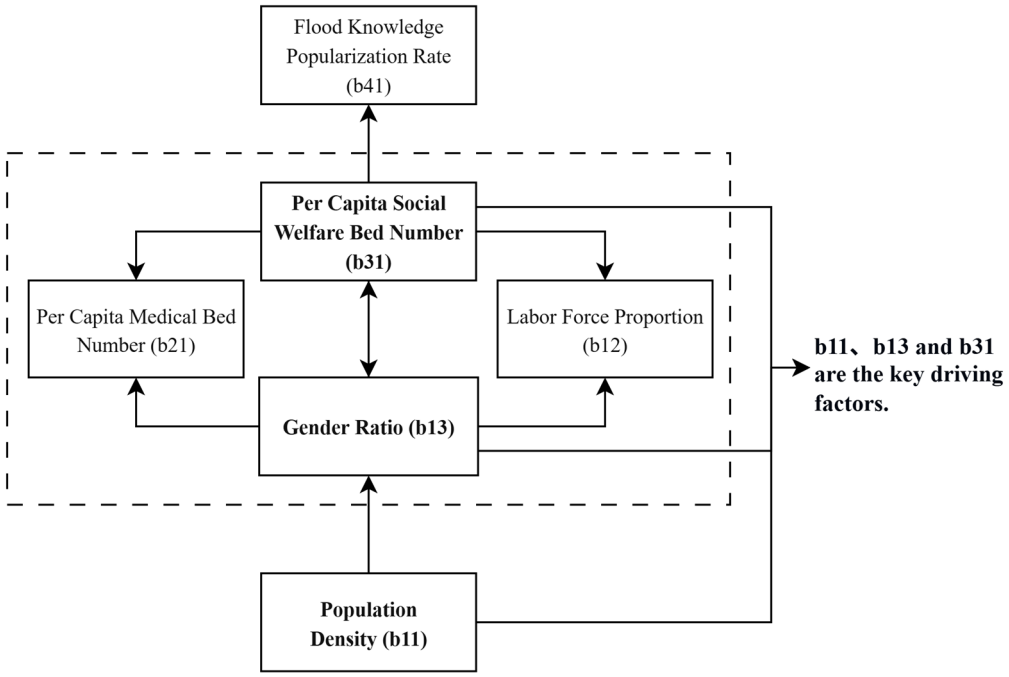


Figure 4. Hierarchical Topology of Factors in the Social Resilience Dimension.

(3) Engineering Resilience Dimension

Within the engineering resilience dimension, the construction of a flood control system requires multi-dimensional coordination and optimization, focusing on key elements such as the protection of cultivated land resources, the configuration of infrastructure, and the establishment of communication networks. Research indicates that the cultivated land protection index and the proportion of stable-yield cropland area, as core agricultural indicators, significantly influence regional agricultural flood resilience. Specifically, the cultivated land protection index shows a significant negative correlation with flood disaster losses.

Regarding infrastructure, drainage ditch density (c15) and drainage pipe network density (c27) effectively enhance regional flood control performance by improving surface runoff discharge capacity. Simultaneously, metrics such as the flood resilience of the communication system (c24), radio and TV coverage rate (c33), and the fixed-line telephone penetration rate significantly improve emergency response efficiency by optimizing the transmission of disaster information. The interrelationships and hierarchical structure among these factors are depicted in Figure 5.

(4) Economic Resilience Dimension

Within the economic resilience dimension, the economic foundation of a region's disaster prevention capacity primarily depends on the systematic support of key economic indicators. Empirical studies indicate that GDP per unit area (d11) and per capita grain output (d42), as core economic resilience indicators, most directly influence the regional economic base and food security. Among these, the spatial density of relief material reserve depots (d41) and fiscal expenditure per unit area (d22) significantly enhance regional emergency response efficacy by establishing a material guarantee system and a fiscal support mechanism. Furthermore, the per capita net income of rural residents (d31) and the per capita disposable income of urban residents (d32) exert a significant positive impact on the overall disaster prevention capacity of the region by raising the economic resilience threshold of residents. The relationships among these factors are illustrated in Figure 6.

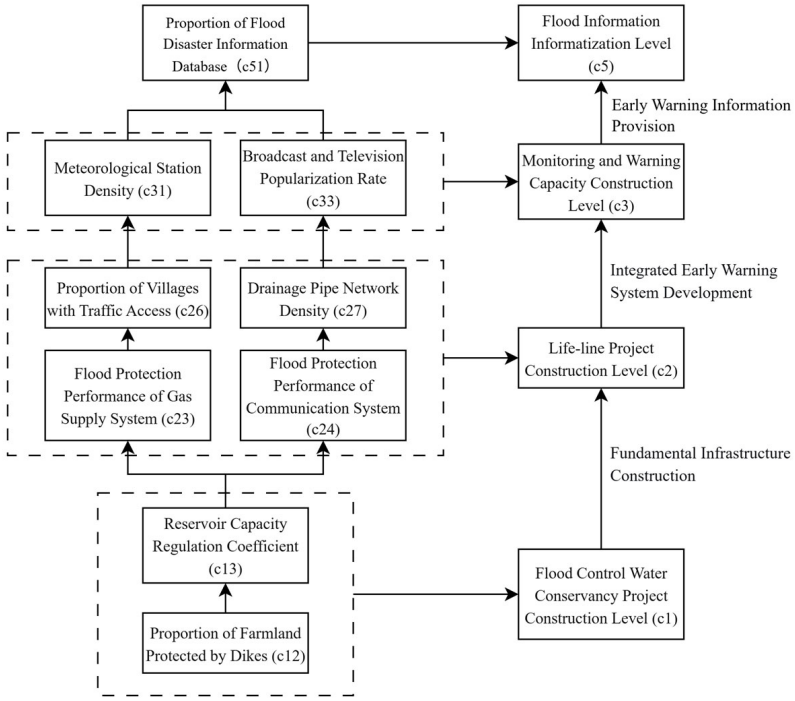


Figure 5. Hierarchical Topology of Factors in the Engineering Resilience Dimension.

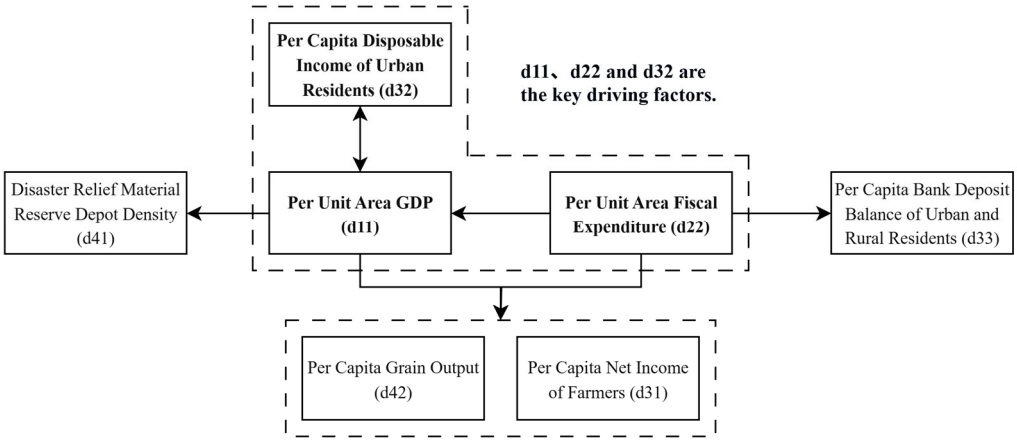


Figure 6. Hierarchical Topology of Factors in the Economic Resilience Dimension.

(5) Institutional Resilience Dimension

Within the institutional resilience dimension, the proportion of flood control laws and regulations (e21) and the proportion of flood emergency plans (e24) directly govern the standardization and effectiveness of flood prevention and mitigation by establishing a comprehensive legal and operational framework. The frequency of flood control awareness activities (e62) and flood disaster reduction drills (e61) significantly enhance public flood awareness and emergency response capabilities, thereby indirectly strengthening the overall regional capacity for flood disaster mitigation. Furthermore, the flood insurance claim ratio (e22) and the scale of mobilized personnel (e51) exert considerable influence on the practical outcomes of flood control and disaster reduction through economic compensation mechanisms and human resource investment, respectively. The hierarchical relationships and interactions among these institutional factors are depicted in Figure 7.

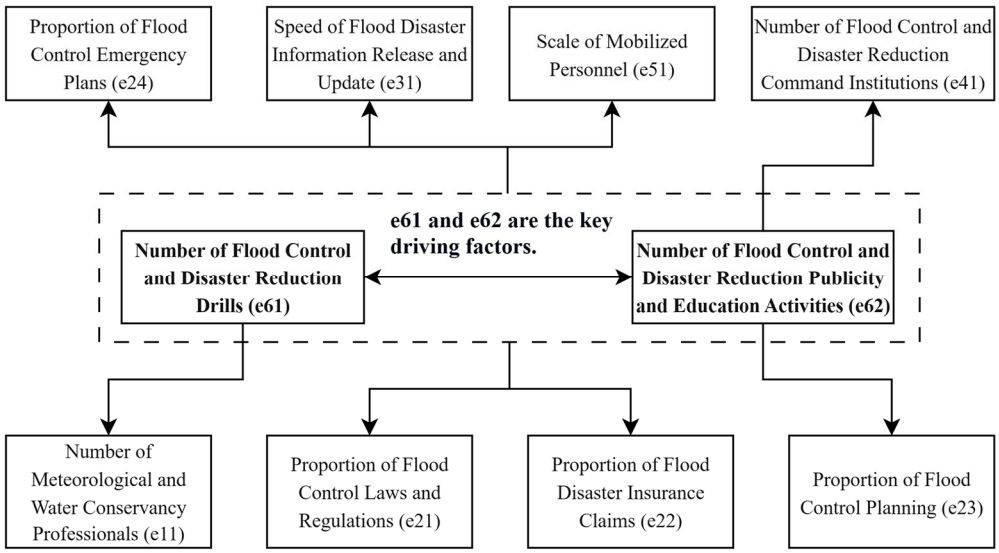


Figure 7. Hierarchical Topology of Factors in the Institutional Resilience Dimension.

Fangshan District demonstrates the strongest recovery capacity in economic resilience, a result attributable to multiple interacting factors. First, the district has benefited from robust policy support and efficient resource allocation during post-disaster reconstruction. The government's rapid restoration of infrastructure and enhancement of urban resilience has established a solid foundation for economic recovery. Second, Fangshan has actively promoted industrial structure optimization and upgrading, vigorously developing new quality productive forces, attracting high-quality investments, and improving its business environment, all of which have injected new momentum for rapid economic revitalization. Simultaneously, the district's focus on livelihood security and social stability—through improved public services and enhanced resident quality of life—has strengthened social cohesion and endogenous drivers for economic development. The synergistic effect of these factors has enabled Fangshan to demonstrate remarkable economic recovery capacity when confronting challenges.

Regarding infrastructure restoration, Fangshan has achieved significant results, successfully meeting the "one-year basic recovery" target. Damaged river channels, drainage systems, roads, and utilities (water, electricity, gas, heating) have all been repaired or reconstructed. Furthermore, the district has actively advanced the construction of "dual-use infrastructure for normal and emergency situations," enhancing its emergency response capabilities. These measures indicate relatively strong recovery capacities in both social and engineering resilience.

However, the notably low institutional resilience can be theoretically interpreted as a manifestation of the 'institutional and maintenance capacity gap' highlighted in life-cycle infrastructure studies, where long-term system performance is often defined not by initial construction but by sustained governance, funding, and adaptive management. Furthermore, this finding resonates with research on grey–green infrastructure, which identifies the integration of governance and institutional coordination across departments as a critical determinant for coping with climate uncertainty and achieving integrated hydrological performance. In Fangshan's context, this gap likely stems from insufficient inter-departmental coordination, fragmented policy implementation, and limited long-term institutional capacity for maintenance and adaptive learning, ultimately constraining the effectiveness of even robust engineering and economic investments.

5. Discussion

The findings of this study, derived from the integrated DEMATEL-TOPSIS-AISM model, provide more than a static assessment of resilience; they reveal the underlying architecture and dynamics of the flood resilience system in Fangshan District. The following discussion interprets these results by exploring the nature of key drivers, the paradox of dimensional performance, and the methodological implications of a hierarchical perspective.

5.1. The Ascendancy of Informational and Foundational Drivers

The DEMATEL analysis elevates two factors as paramount drivers: the frequency of heavy rainfall (a12) and the proportion of flood disaster information databases (c51). The prominence of a12 is expected, as climate stressors are fundamental external shocks to the system. However, the identification of c51 as a top driver is highly significant. It underscores a critical evolution in resilience thinking: informational infrastructure is not merely a supportive tool but a constitutive element of modern urban resilience. A comprehensive information database enables predictive analytics, streamlines resource allocation, and facilitates evidence-based policy-making, thereby amplifying the effectiveness of all other resilience dimensions. This finding aligns with emerging scholarship on "digital twins" and smart resilience, which posits that data is a critical infrastructure on par with physical networks [13].

Conversely, the fact that institutional factors, despite their importance, did not emerge as top-tier drivers in the DEMATEL model, yet the institutional dimension scored the lowest in the TOPSIS evaluation, points to a systemic challenge. It suggests that institutional elements often function as pervasive enablers or inhibitors rather than direct, active drivers. Their weakness does not initially propel the system into crisis but critically constrains its overall performance and capacity for adaptation, creating a "quiet crisis" that undermines more visible engineering or economic investments.

5.2. The Paradox of Performance: Decoupling Economic Capacity from Systemic Robustness

The TOPSIS results present a seeming paradox: Fangshan District exhibits its strongest resilience in the economic dimension. While this reflects a robust capacity for post-disaster financial mobilization and reconstruction, it may mask underlying vulnerabilities. A highly capable economic engine can fund a rapid "bounce back" to the pre-disaster state, but this does not necessarily equate to a transformative "bounce forward" that enhances long-term adaptive capacity.

This interpretation is supported by the AISM topology for the economic dimension, which shows a less complex, more direct hierarchy compared to the multi-layered structures of the ecological or institutional dimensions. This suggests that economic resilience in Fangshan is currently characterized by direct input-output relationships (e.g., fiscal expenditure leading to reconstruction) rather than being embedded in a deeply interconnected adaptive system. The stark weakness in institutional resilience further compounds this issue, indicating that the economic capacity is not yet fully harnessed by a sophisticated governance system to generate sustainable, long-term resilience. This decoupling highlights the risk of equating rapid recovery with genuine, systemic robustness.

5.3. The Hierarchical Lens: From Flat Indicators to a System of Causal Pathways

The primary methodological contribution of this study lies in applying the AISM model to move beyond a "flat" list of weighted indicators. The adversarial hierarchical topologies reveal the causal architecture of each resilience dimension, offering profound insights for targeted intervention.

For example, in the ecological dimension, factors like vegetation coverage (a43) and soil type (a42) are positioned as intermediate mediators. This clarifies that they are not ultimate drivers but are critical levers through which the impact of top-level drivers like rainstorm frequency (a12) is translated into hydrological outcomes. Therefore, policies enhancing green infrastructure are not just ecological goals but are strategic interventions to modulate the effect of climate stressors.

Similarly, in the institutional dimension, the hierarchy places foundational elements like flood control laws and regulations (e21) at the base, supporting higher-level activities like public drills (e61). This structure implies that institutional resilience is built sequentially: without a solid legal and planning foundation, awareness campaigns and mobilization efforts may lack coherence and legal authority. This hierarchical perspective challenges the effectiveness of ad hoc policy measures and advocates for a systems-engineering approach to building resilience, where strengthening the foundational layers is a prerequisite for effective performance at higher, more visible levels.

6. Conclusions

This study applied the DEMATEL-TOPSIS-AISM model to assess flood resilience in Fangshan District, Beijing, revealing economic resilience as the strongest dimension and institutional resilience as the weakest. Key causal pathways and hierarchical relationships among factors across the five resilience dimensions were systematically identified. Based on these findings, targeted strategies are proposed: (1) Strengthening meteorological early warning by upgrading monitoring networks; (2) Enhancing infrastructure resilience through optimized drainage systems and robust critical facilities; and (3) Optimizing institutional mechanisms via improved flood insurance, public awareness campaigns, and cross-departmental coordination. These recommendations directly address the specific weaknesses and leverage points identified in the analysis.

Despite its contributions, this study is subject to several limitations. Regarding data, the reliance on statistical yearbooks and expert scoring, although standard practice, may not capture all real-time or qualitative aspects of resilience. Some indicators relied on proxy measures due to data unavailability. Methodologically, the DEMATEL and AISM models involve subjective elements, such as setting the threshold (γ) for constructing the adjacency matrix, which can influence the final structure. Contextually, the findings are based on a single case study of Fangshan District in Beijing. The district's unique socio-economic, geographical, and governance context implies that the specific hierarchy of factors and their relative importance may not be directly transferable to other cities with different developmental stages or environmental settings.

The limitations of this work point to several promising avenues for future research. First, applying the integrated DEMATEL-TOPSIS-AISM model to diverse urban contexts (e.g., coastal cities, inland metropolises, or cities in developing countries) would be valuable for testing its generalizability and identifying universal versus context-specific resilience drivers. Second, future studies could incorporate more dynamic and high-frequency data, such as social media analytics or remote sensing data, to create more real-time and spatially granular resilience assessments. Third, exploring advanced modeling techniques like Bayesian networks or system dynamics could complement our findings by simulating the dynamic evolution of resilience under different policy scenarios and shock intensities. Finally, qualitative investigations, such as in-depth interviews and participatory workshops with community stakeholders, could be integrated to triangulate and enrich the quantitative findings, providing deeper insights into the social and institutional barriers and enablers that our model highlights.

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References

1. Kurosaki, T. Household Level Recovery after floods in Tribal and conflict-ridden Society. *World Dev.* **2017**, *94*, 51–63. [CrossRef]
2. Rosselló, J.; Becken, S.; Santana-Gallego, M. The effects of natural disasters on international tourism: A global analysis. *Tour. Manag.* **2020**, *79*, 104080. [CrossRef]
3. Sutton, J.; Arku, G. Regional Economic Resilience: Towards a system approach. *Reg. Stud. Reg. Sci.* **2022**, *9*, 497–512. [CrossRef]
4. Ministry of Water Resources of the People's Republic of China. *China Flood and Drought Disaster Prevention Bulletin 2023*; China Water & Power Press: Beijing, China, 2024.
5. Leaning, J.; Guha-Sapir, D. Natural Disasters, Armed Conflict, and Public Health. *N. Engl. J. Med.* **2014**, *370*, 783. [CrossRef]
6. Lee, M.; Basu, D. An Integrated Approach for Resilience and Sustainability in Geotechnical Engineering. *Indian Geotech. J.* **2018**, *48*, 207–234. [CrossRef]
7. Berkes, F.; Ross, H. Panarchy and community resilience: Sustainability science and policy implications. *Environ. Sci. Policy* **2016**, *61*, 185–193. [CrossRef]
8. Klein, R.J.; Nicholls, R.J.; Thomalla, F. Resilience to natural hazards: How useful is this concept? *Glob. Environ. Change Part B Environ. Hazards* **2003**, *5*, 35–45. [CrossRef]
9. Liu, W.; Zhou, J.; Li, X.; Zheng, H.; Liu, Y. Urban resilience and its spatial correlation from multidimensional perspective: A case study of four province North-South Seismic Belt, China. *Sustain. Cities Soc.* **2024**, *101*, 105109. [CrossRef]
10. Holling, C.S. Resilience and Stability of Ecological Systems. *Annu. Rev. Ecol. Evol. Syst.* **1973**, *4*, 1–23. [CrossRef]
11. Amirzadeh, M.; Sobhaninia, S.; Sharifi, A. Urban resilience: Vague or not an evolutionary concept? *Sustain. Cities Soc.* **2022**, *81*, 103853. [CrossRef]
12. Shi, Y.; Zhang, T.; Jiang, Y. Digital economy, technological innovation and urban resilience. *Sustainability* **2023**, *15*, 9250. [CrossRef]
13. Zhu, C.H.; Xia, J.Q.; Chen, Q.; Hou, J.M. Simulation of Urban Flood Process and Risk Assessment Based on SWMM Model. *J. Catastrophol.* **2018**, *33*, 224–230.
14. Qin, P.C.; Zhou, Y.H.; Liu, H.S.; Xia, Z.H. Assessment of Crop Loss from Rainstorm and Flood Disasters Based on Hydrodynamic Model: A Case Study of Jianghan Plain. *Chin. J. Agrometeorol.* **2025**, *46*, 420–431.
15. Zhou, X.J.; Wang, B.J.; Fu, C.; Liu, W.C.; Liu, L.; Song, Q. Rainstorm Flood Risk Zoning in Taohe River Basin Based on Submergence Model. *Modern Agric. Sci. Technol.* **2016**, 178–180+189.
16. Li, J.Q.; Li, Y.; Huang, K. Annual Flood Disaster Assessment Model and Application Based on Critical-Weighted Grey Correlation Analysis. *China Rural Water Hydropower* **2024**, *36*, 21–29.
17. Li, M.Q.; Li, G.Q.; Xie, Z.H. Flood Disaster Assessment and Recovery Integrating Multi-Source Remote Sensing Data: A Case Study of the "7·20" Rainstorm Disaster in Henan Province. Remote Sens. *Nat. Resour.* **2024**, *36*, 250–266.
18. Sun, H.H.; Cheng, X.F.; Dai, M.Q.; Wang, X.; Kang, H.D. Study on the influence factors and evaluation index system of regional flood disaster resilience based on dematel method-taking chaohu basin as a case. *Resour. Environ. Yangtze Basin* **2015**, *24*, 1577–1583.
19. Qasim, S.; Qasim, M.; Shrestha, R.P.; Khan, A.N.; Tun, K.; Ashraf, M. Community resilience to flood hazards in Khyber Pukhthunkhwa province of Pakistan. *Int. J. Disaster Risk Reduct.* **2016**, *18*, 100–106. [CrossRef]
20. Huang, C.F. Discussion on the Basic Definition of Natural Disasters. *J. Nat. Disasters* **2009**, *18*, 41–50.
21. Li, Y.F. *Research on Natural Disasters and Emergency Management*; Economic Daily Press: Beijing, China, 2017.

22. Saptono, Y.; Rustiadi, E.; Barus, B.; Pravitasari, A.E. Systematic Literature Review: Research Development of Urban Resilience in Metropolitan Areas. *Sustainability* **2025**, *17*, 7380. [CrossRef]
23. Xiao, J.; Boschma, R.; Andersson, M. Resilience in the European Union: The effect of the 2008 crisis on the ability of regions in Europe to develop new industrial specializations. *Ind. Corp. Change* **2017**, *27*, 15–47. [CrossRef]
24. Peng, C.; Yuan, M.; Gu, C.; Peng, Z.; Ming, T. A review of the theory and practice of regional resilience. *Sustain. Cities Soc.* **2017**, *29*, 86–96. [CrossRef]
25. Dalziell, E.P.; McManus, S.T. *Resilience, Vulnerability and Adaptive Capacity: Implications for Sistems Performance*; International Forum for Engineering Decision Making (IFED): Switzerland, 2004.
26. Rockefeller Foundation and Arup. City Resilience Index: Research Report Volume 1 Desk Study. New York and London: The Rockefeller Foundation: With Ove Arup & Partners International. April 2014. Available online: https://www.arup.com/globalassets/downloads/insights/city-resilience-index.pdf (accessed on 5 August 2024).
27. Olson, M. *The Logic of Collective Action: Public Goods and the Theory of Groups*; Chen, Y.; Guo, Y.; Li, C., Translators; Gezhi Publishing House: Shanghai, China, 2008.
28. Wildavsky, A. *Searching for Safety*; Transaction Books: New Brunswich, NJ, USA, 1988; p. 253.
29. Rose, A. Defining and Measuring Economic Resilience to Disasters. *Disaster Prev. Manag.* **2004**, *13*, 307–314. [CrossRef]
30. Adger, W.N. Social and ecological resilience: Are they related? *Prog. Hum. Geogr.* **2000**, *24*, 347–364. [CrossRef]
31. Obrist, B.; Pfeiffer, C.; Henley, R. Multi-layered social resilience: A new approach in mitigation research. *Prog. Dev. Stud.* **2010**, *10*, 283–293. [CrossRef]
32. Paton, D.; Johnston, D. Disasters and communities: Vulnerability, resilience and preparedness. *Disaster Prev. Manag.* **2001**, *10*, 270–277. [CrossRef]
33. Chen, M.R.; Fu, J.; Wang, T. Exploring Policy Instruments for Micro-Regeneration in Guangzhou from the Perspective of Resilient Cities. *Planners* **2023**, *39*, 117–123.
34. Juan-García, P.; Butler, D.; Comas, J.; Darch, G.; Sweetapple, C.; Thornton, A.; Corominas, L. Resilience theory incorporated into urban wastewater systems management. State of the art. *Water Res.* **2017**, *115*, 149–161. [CrossRef]
35. Chen, C.K.; Chen, Y.Q.; Shi, B.; Xu, T. Urban Resilience Assessment Model under Rainstorm Flood Disaster Scenarios. *China Saf. Sci. J.* **2018**, *28*, 1–6.
36. Pimm, S.L. The complexity and stability of ecosystems. *Nature* **1984**, *307*, 321–326. [CrossRef]
37. Shi, Y.; Jiang, Y. Knowledge mapping and emerging trends of urban resilient infrastructure research in urban studies: Precedent work, current progress and future perspectives. *Sustain. Cities Soc.* **2024**, *107*, 105455.
38. Ahern, J. From fail-safe to safe-to-fail: Sustainability and resilience in the new urban world. *Landsc. Urban Plan.* **2011**, *100*, 341–343.
39. Soz, S.A.; Kryspin-Watson, J.; Stanton-Geddes, Z. *The Role of Green Infrastructure Solutions in Urban Flood Risk Management*; World Bank: Washington, DC, USA, 2016.
40. Aldrich, D.P. *Building Resilience: Social Capital in Post-Disaster Recovery*; University of Chicago Press: Chicago, IL, USA, 2012.
41. Norris, F.H.; Stevens, S.P.; Pfefferbaum, B.; Wyche, K.F.; Pfefferbaum, R.L. Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *Am. J. Community Psychol.* **2008**, *41*, 127–150. [CrossRef]
42. Mileti, D.S. *Disasters by Design: A Reassessment of Natural Hazards in the United States*; Joseph Henry Press: Washington, DC, USA, 1999.
43. Adam, R.; Dongsoon, L. Business interruption losses from natural hazards: Conceptual and methodological issues in the case of the Northridge earthquake. *Glob. Environ. Change Part B Environ. Hazards* **2002**, *4*, 1–14. [CrossRef]
44. Hallegatte, S. *Economic Resilience: Definition and Measurement*; World Bank Policy Research Working Paper; World Bank: Washington, DC, USA, 2014; p. 6852.
45. Cutter, S.L.; Barnes, L.; Berry, M.; Burton, C.; Evans, E.; Tate, E.; Webb, J. A place-based model for understanding community resilience to natural disasters. *Glob. Environ. Change* **2008**, *18*, 598–606. [CrossRef]
46. Tierney, K. *The Social Roots of Risk: Producing Disasters, Promoting Resilience*; Stanford University Press: Redwood City, CA, USA, 2014.
47. Proag, V. The concept of vulnerability and resilience. *Procedia Econ. Financ.* **2014**, *18*, 369–376. [CrossRef]
48. Chen, W.; Wang, W.; Huang, G.; Wang, J. An XGBoost–SHAP approach to quantifying morphological impact on urban flooding susceptibility. *J. Hydrol.* **2023**, *617 Pt B*, 129085.
49. Liu, Z.; Wang, T.; Perera, A.T.M.; He, B.J.; Huang, Z.; Wang, L.; Hong, B. Multi-objective optimisation of integrated grey-green infrastructure in response to climate change from a life cycle perspective. *J. Clean. Prod.* **2023**, *430*, 139699.
50. Wang, W.T.; Qian, P.B.; Gan, Y.L.; Song, T.X.; Xie, Y.Q. The Correlation Mechanism and Transmission Path of University Library User Experience Influencing Factors: Evolution Based on ADSM-MICMAC Model. *Libr. Sci. Res.* **2022**, 54–66.

51. National Commission for Disaster Reduction. The 14th Five-Year Plan for National Comprehensive Disaster Prevention and Reduction [EB/OL]. 21 July 2022. Available online: https://www.mem.gov.cn/gk/zfxxgkpt/fdzdgknr/202207/t20220721_418698.shtml (accessed on 28 December 2024).
52. China Meteorological Administration; National Development and Reform Commission. The 14th Five-Year Plan for National Meteorological Development [EB/OL]. 24 November 2021. Available online: https://www.cma.gov.cn/zfxxgk/gknr/ghjh/202112/t20211208_4295610.html (accessed on 28 December 2024).

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