



A Resilience Assessment Model for Urban Gas Systems under Extreme Rainfall: Development and Empirical Analysis

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Abstract. Extreme rainfall increasingly threatens the safety and service continuity of urban gas systems by inducing flooding, secondary hazards, facility failures, supply disruptions and leakage risks. Existing risk-oriented approaches are insufficient for capturing the multi-stage resilience of gas systems under flood-disaster scenarios. This study develops an integrated resilience assessment model that links flood-disaster impacts with the functional maintenance, restoration, and adaptive improvement of urban gas systems. A three-dimensional indicator system is constructed from the perspectives of resistance, recovery, and adaptation. A combined weighting scheme integrating stochastic multi-criteria acceptability analysis, the analytic hierarchy process, and game-theoretic aggregation is then developed to balance data-driven variation and expert judgment, and the VIKOR method is used for compromise ranking. An empirical analysis of four administrative districts in a representative city in North China shows that resilience follows the order District C > District D > District A > District B, consistent with the SMAA-based ranking. The proposed model can identify regional resilience disparities and dimension-specific weaknesses, providing methodological support for flood-risk prevention, emergency resource allocation, and resilience enhancement in urban gas systems.

Keywords: extreme rainfall; urban gas system; flood disaster; resilience assessment; VIKOR method.

1 Introduction

Climate change and rapid urbanization have intensified urban flood risks, with extreme rainfall increasingly triggering waterlogging, flash floods, landslides, debris flows, and cascading failures across interdependent lifeline systems^[1,2]. Accordingly, urban infrastructure resilience research has shifted from structural resistance toward functional maintenance, post-disaster recovery, and adaptive emergency management, while flood-resilience assessment has become increasingly refined, dynamic, and process-oriented^[1,3,4]. As a critical component of urban energy supply, urban gas systems are

characterized by networked configuration, continuous operation, and high hazard potential. Under flood-disaster conditions, pipelines, pressure-regulating facilities, stations, and external support systems may be affected by scour, inundation, ground collapse, and secondary geological hazards, leading to supply disruption, leakage, fire, or explosion. However, existing studies mainly focus on cities, communities, or general infrastructure systems, with limited attention to the resilience of urban gas systems under extreme rainfall. To address this gap, this study develops a resilience assessment framework for urban gas systems by linking flood-disaster impact mechanisms with resistance, recovery, and adaptation processes, and proposes a combined weighting–VIKOR model for regional resilience evaluation.

2 Impact Mechanisms of Flood Disasters on Urban Gas Systems

2.1 Composition and Hazard-Bearing Characteristics of Urban Gas Systems

Urban gas systems are critical lifeline infrastructures for urban energy supply, comprising pipeline natural gas, CNG, LNG, and LPG systems across supply, transmission, storage, distribution, and end-use processes, as shown in Fig. 1. Their safe operation depends on both internal facility reliability and external infrastructure support, including power, transportation, communications, and drainage systems. Given their networked structure, continuous operation, and high hazard potential, failures of key nodes or supporting systems may cause supply disruption, gas leakage, fire, or explosion, thereby threatening urban energy security and public safety.

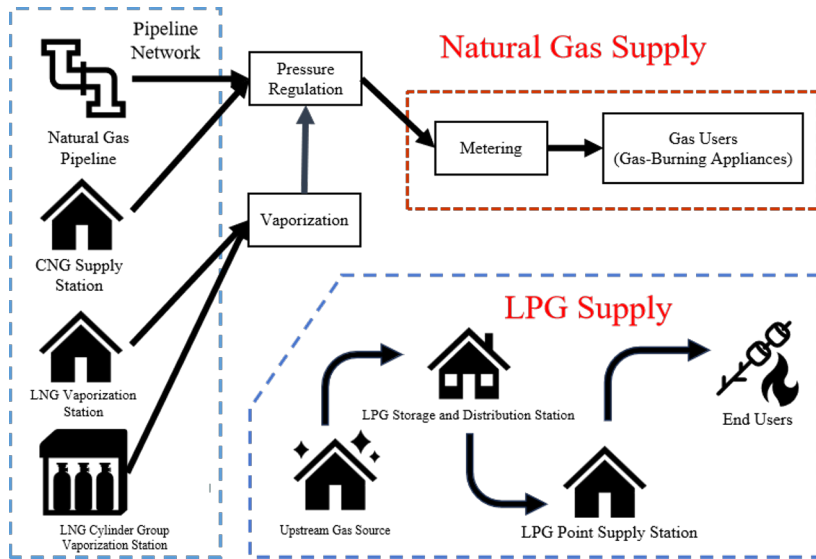


Fig. 1. Gas Supply Flow Diagram of the Urban Gas System

2.2 Formation and Impact Mechanisms of Flood Disasters

Flood disasters are compound processes shaped by extreme rainfall, topography, land-surface conditions, river conveyance, and urban drainage capacity. When intense or prolonged rainfall exceeds infiltration, river discharge, and drainage capacities, surface runoff accumulates, river levels rise, and low-lying areas become inundated^[5]. Rapid runoff concentration makes mountainous, valley, and riverine areas prone to flash floods and flood scour, whereas increased impervious surfaces, reduced retention space, and insufficient drainage aggravate waterlogging in built-up areas. Flood impacts extend beyond inundation and involve scour, prolonged immersion, soil disturbance, and secondary hazards. Flow erosion, foundation scour, and debris impact may undermine facility stability, while waterlogging can disable underground spaces, pipe trenches, valve chambers, and electrical equipment. Intense rainfall may further induce soil softening, ground collapse, slope instability, landslides, and debris flows. Owing to infrastructure interdependencies, flood disasters may propagate through critical infrastructure networks and trigger service disruptions or cascading failures^[6,7]. As shown in Fig. 2, the impacts of flood disasters can be conceptualized as a chain process of “extreme rainfall–runoff concentration–flooding/waterlogging–secondary hazards–facility damage–functional degradation”, which provides the basis for analyzing the disaster mechanisms affecting urban gas systems.

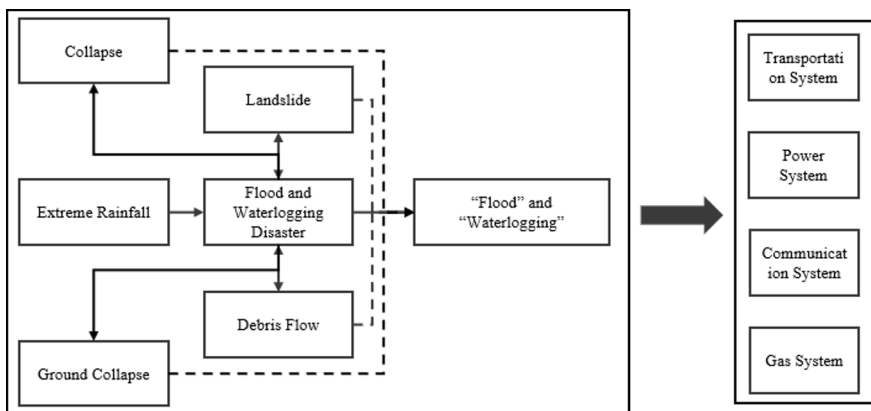


Fig. 2. Mechanism of Flood Disaster Impact

2.3 Resilience Analysis Framework for Urban Gas Systems under Flood Disasters

Based on the hazard-bearing characteristics of urban gas systems and the impact mechanisms of flood disasters, system safety under flood-disaster scenarios depends not only on the impact resistance of physical assets such as pipelines and stations, but also on pre-disaster protection, emergency response, post-disaster recovery, and subsequent adaptive improvement. Extreme rainfall-induced flood scour, urban waterlogging, and secondary hazards may affect key links, including gas sources, stations, transportation,

and end users, while failures of external supporting systems such as transportation, power supply, communications, and drainage may further amplify system impacts. To link disaster impacts with the maintenance, restoration, and enhancement of gas-system functionality, this study develops a resilience analysis framework for urban gas systems under flood disasters from the perspectives of resistance, recovery, and adaptation, as shown in Figure 3.

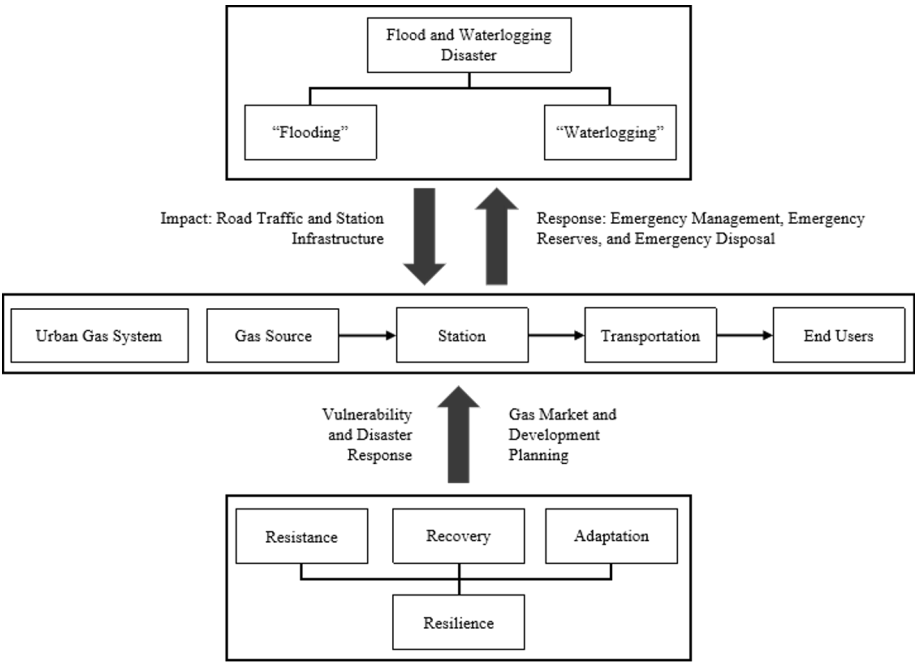


Fig. 3. Flood resilience framework for urban gas systems

3 Construction of the Indicator System

3.1 Conceptual Basis for Constructing the Indicator System

The resilience assessment indicator system should capture the full-process performance of urban gas systems under flood-disaster impacts. Based on the disaster-chain analysis, flood impacts on gas systems are reflected in facility exposure and protection before disasters, emergency response and gas supply assurance during disasters, and recovery and adaptive improvement after disasters. Following the resilience framework, this study divides flood resilience into three dimensions: resistance, recovery, and adaptation [8]. Resistance reflects the ability to reduce disaster impacts and maintain structural and functional stability; recovery reflects the ability to restore gas supply and operational order after disruption; and adaptation reflects the ability to improve future disaster response through planning, management, and technological enhancement.

3.2 Composition of the Indicator System

The indicator system consists of three dimensions—resistance, recovery, and adaptation—which together characterize the full-cycle resilience of urban gas systems under flood disasters. Resistance indicators reflect facility exposure, protection basis, and emergency preparedness. Existing flood-resilience studies identify resistance, early warning, and emergency response as key assessment components^[3,9], while infrastructure resilience research emphasizes the roles of exposure, vulnerability, and response capability in maintaining system functionality^[1,10]. Accordingly, this study uses the proportions of facilities located along rivers and in mountainous areas to characterize disaster exposure, annual average rainfall and rainfall variability to represent external flood pressure, and emergency plans, drills, and rescue teams to measure preparedness and response capacity.

Recovery indicators characterize post-disaster gas supply restoration and resource support. Infrastructure resilience depends not only on pre-disaster resistance but also on functional recovery, resource allocation, and emergency response capacity^[1,3,10]. Gas network resilience studies also emphasize repair resources, recovery processes, and service restoration^[11]. Therefore, gas supply structure and emergency material storage/allocation are used to represent alternative supply and repair-support capacity; profit margin, gas supply volume, and number of users reflect operational foundation, service scale, and sustained operation capacity; and insurance coverage rate represents economic compensation and risk-transfer capacity.

Adaptive indicators reflect the long-term capacity of gas systems to learn, adjust, and improve after disasters. Resilience assessment should consider learning feedback, planning optimization, and adaptive enhancement^[3,9], while long-term urban resilience also depends on economic vitality, population demand, human capital, and institutional improvement^[12]. Accordingly, per capita GDP and resident population are selected to reflect economic foundation and service demand, while safety education and system resilience/disaster-prevention planning are used to characterize adaptive improvement in safety management, disaster prevention, and engineering design. Based on the resilience framework, gas-system characteristics, and flood-disaster impact mechanisms, the final indicator system is shown in Table 1.

Table 1. Flood Resilience Indicators for Urban Gas Systems.

Criterion	Sub-criterion	Indicator	Unit	Indicator Direction
Resistance Capacity	Infrastructure Vulnerability	Percentage of gas system infrastructure located along rivers (A1)	%	Negative
		Percentage of gas system infrastructure located in mountainous areas (A2)	%	Negative
	Emergency Response Capacity	Completeness of emergency plans (A3)	-	Positive
		Emergency drill implementation (A4)	-	Positive
		Emergency rescue team capacity (A5)	-	Positive
		Annual average rainfall (A6)	mm	Negative

	Rainfall Conditions	Dispersion degree of rainfall over the past ten years (A7)	-	Negative
	Emergency Gas Supply	Gas supply structure of the gas system (B1)	-	Positive
	Recovery Capacity	Emergency material storage and allocation capacity (B2)	-	Positive
		Profit margin (B3)	%	Positive
Recovery Capacity	Enterprise Operation Status	Gas supply volume (B4)	100 million m ³	Positive
		Number of users (B5)	10,000 households	Positive
	Disaster Insurance	Insurance coverage rate (B6)	%	Positive
	Urban Attractiveness	Per capita gross regional product (C1)	10,000 yuan/person	Positive
		Permanent resident population (C2)	10,000 persons	Positive
Adaptive Capacity	Development Planning for Gas System Disaster Response	Safety education implementation (C3)	-	Positive
		Development plan for system resilience and disaster prevention design (C4)	-	Positive

4 Construction of the Evaluation Model

4.1 Selection of the Evaluation Model

Assessing flood resilience in urban gas systems involves multiple dimensions, including resistance, recovery, and adaptation, and requires indicators that combine objective data with expert judgment. A single weighting method may fail to capture data heterogeneity, disaster mechanisms, and domain knowledge simultaneously, thereby introducing information-source bias. To address this issue, this study adopts a combined subjective–objective weighting approach.

Specifically, Stochastic Multicriteria Acceptability Analysis (SMAA) is used to derive objective weights from the evaluation data under incomplete preference information and uncertainty^[13], while the Analytic Hierarchy Process (AHP) incorporates expert knowledge to quantify the relative importance of indicators^[14]. A game-theoretic aggregation model is then applied to reconcile the subjective and objective weights, yielding a balanced weighting scheme that reflects both data-driven variation and expert cognition.

For comprehensive evaluation, the VIKOR method is employed to rank regional gas-system resilience. As a multicriteria compromise-ranking method, VIKOR accounts for both group utility and individual regret relative to the ideal solution, making it suitable for evaluating alternatives with conflicting indicators. This enables a balanced assessment of overall resilience performance and critical weaknesses across regions^[15].

4.2 Weight Determination

Stochastic Multicriteria Acceptability Analysis.

Assume that there are (M) alternatives to be evaluated and (N) evaluation indicators, with an alternative set ($A = \{a_1, a_2, a_3, \dots, a_m\}$) and an original indicator data matrix ($X = (x_{ij})_{m \times n}$). Let the random attribute value of alternative (a_i) be represented by a stochastic variable with probability density function ($f(\xi)$). The indicator weight vector is represented as $w^s = (w^s_1, w^s_2, w^s_3, \dots, w^s_n)^T$.

1. Standardization of the original indicator data matrix. For positive indicators $x_{ij}' = \frac{x_{ij} - \min_j x_j}{\max_j x_j - \min_j x_j}$. For negative indicators $x_{ij}' = \frac{\max_j x_j - x_{ij}}{\max_j x_j - \min_j x_j}$, where $\max_j x_j$ and $\min_j x_j$ denote the maximum and minimum values of the j -th evaluation indicator, respectively. $\hat{x}_{ij}$ represents the normalized value, and the normalized indicator data matrix is expressed as $X' = (x_{ij}')_{m \times n}$.
2. Calculation of utility values. For each weight combination (w^s), the utility value is calculated using Eq. (1).

$$u_i(x_i, w^s) = \sum_{j=1}^n x_{ij}' w^s_j \quad (1)$$

3. Ranking of utility values. The utility values are ranked according to Eq. (2).

$$\text{rank}(a_i, x, w^s) = 1 + \sum_{k=1, k \neq i}^m \rho[u_k(x_k, w^s) > u_i(x_i, w^s)] \quad (2)$$

In the equation, $k = 1, 2, 3, \dots, m$, $\text{rank}(x_i, w^s) \in (1, 2, 3, \dots, m)$, and $\rho(\dots)$ is a logical function satisfying $\rho(\text{true}) = 1$ and $\rho(\text{false}) = 0$. According to the ranking position, the vector space corresponding to alternative a_i occupying a specific rank r can be obtained.

$$W_i^r(a_i) = \{w^s \in W : \text{rank}(a_i, x, w^s) = r\} \quad (3)$$

4. Calculate the acceptability index

$$b_i^r = \int_{x \in X} f(x) \int_{w \in W_i^r} f_w(w) dw dx \quad (4)$$

where b_i^r denotes the acceptability index of alternative a_i being ranked in the r -th position, with $b_i^r \in [0, 1]$. The sum of the acceptability indices of alternative a_i over all ranking positions in the entire weight space is equal to 1, namely, $\sum_r b_i^r = 1$.

5. Calculate the central weight vector

$$w_i^1 = \frac{\int_{x \in X} f(x) \int_{w \in W_i^1} f_w(w) dw dx}{b_i^1} \quad (5)$$

where w_i^1 represents the central weight vector that makes x_i rank first, and W_i^1 denotes the vector space in which x_i ranks first.

6. Calculate the confidence factor

$$p_i^c = \int_{x \in X: w \in W_i^1} f(x) dx \quad (6)$$

where p_i^c denotes the probability that an alternative actually becomes the best choice when the central weight vector representing the preference information of that alternative is used.

7. Weight determination: The confidence factor reflects the reliability of the acceptability results. The vector space with high first-rank acceptability and confidence is selected to calculate the central weight vector, while alternatives with low acceptability are excluded.

Analytic Hierarchy Process.

The major advantages of AHP lie in its intuitiveness and flexibility in dealing with complex, multi-level decision-making problems. In addition, AHP has strong extensibility and can be combined with other methods such as fuzzy logic and TOPSIS. Nevertheless, AHP also has certain limitations: it places relatively high requirements on the consistency of expert judgment, and its computational complexity increases as the number of levels and elements grows.

When AHP is used in combination with expert experience to determine the weights of resilience assessment indicators for urban gas systems under flood disasters, the specific procedure is as follows: experts are invited to perform pairwise comparisons of the importance of factors using a 1–9 scale judgment matrix; a comparison matrix is then obtained, from which the specific weight of each indicator is determined

Combination Weighting.

The SMAA method is used to obtain the objective weight vector W_1 , while the AHP method is used to obtain the subjective weight vector W_2 . A game-theoretic aggregation model is then adopted to optimize these weights and derive the most satisfactory combined weight vector ω^* . The core idea is to minimize the deviation between ω^* and each basic weight vector. The calculation steps are as follows.

1. The linear combination of L weight vectors is expressed as:

$$\omega = \sum_{h=1}^L k_h \cdot W_h^T, k_h > 0, h=1, 2, \dots, L \quad (7)$$

2. The deviation between ω and each basic weight vector is minimized:

$$\min \left\| \sum_{h=1}^L k_h \cdot W_h^T - W_g^T \right\|_2, g = 1, 2, \dots, L; h = 1, 2, \dots, L \quad (8)$$

3. The first-order optimality condition is obtained as:

$$\sum_{h=1}^L k_h \cdot W_g \cdot W_h^T = W_h \cdot W_h^T \quad (9)$$

4. The coefficient vector $k_h = (k_1, k_2, \dots, k_L)$ is calculated and normalized as k_h^* . The combined weight vector is then given by:

$$\omega^* = \sum_{h=1}^L k_h^* \cdot W_h^T \quad (10)$$

VIKOR Method.

The VIKOR method is a multi-criteria decision-making approach based on compromise ranking, which is suitable for evaluating and ranking alternatives under conflicting indicators in complex systems. Based on the Lp -metric, it constructs a multi-criteria ranking index to measure the closeness of each alternative to the ideal solution, thereby deriving a compromise solution that balances group utility and individual regret. The calculation procedure is as follows:

1. Standardization of the original indicator data matrix.

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (11)$$

2. The positive and negative ideal solutions are determined as:

$$z^+ = \left\{ \left(\max_j y_{ij} \mid j \in Q_+ \right), \left(\min_j z_{ij} \mid j \in Q_- \right) \right\} \quad (12)$$

$$z^- = \left\{ \left(\min_j z_{ij} \mid j \in Q_+ \right), \left(\max_j z_{ij} \mid j \in Q_- \right) \right\} \quad (13)$$

where $\max_i z_{ij}$ and $\min_i z_{ij}$ denote the maximum and minimum values of the j -th indicator across all alternatives, respectively.

3. Calculate the group utility and individual regret

The group utility value S_i and individual regret value R_i are calculated as follows:

$$S_i = \sum_{j=1}^n \omega_j \frac{z_j^+ - z_{ij}}{z_j^+ - z_j^-} \quad (14)$$

$$R_i = \max_j \omega_j \frac{z_j^+ - z_{ij}}{z_j^+ - z_j^-} \quad (15)$$

where ω_j is the weight of the j -th indicator.

4. Calculate the compromise value

The decision coefficient ν reflects the preference between group utility and individual regret. In this study, $\nu = 0.5$, indicating equal importance. Alternatives are ranked in ascending order of Q_i , with smaller Q_i values indicating better performance.

$$Q_i = \nu \frac{S_i - S_i^-}{S_i^+ - S_i^-} + (1 - \nu) \frac{R_i - R_i^-}{R_i^+ - R_i^-} \quad (16)$$

where $S_i^- = \min_i S_i$, $S_i^+ = \max_i S_i$, $R_i^- = \min_i R_i$, and $R_i^+ = \max_i R_i$.

5. Calculate the flood resilience of the urban gas system

$$U_{Ri} = 1 - Q_i \quad (17)$$

6. Verify the compromise solution

Let A^1 and A^2 denote the district-level administrative units ranked first and second, respectively, and let Q_1 and Q_2 be their corresponding compromise values. The optimal compromise solution A^1 should satisfy the following two conditions.

Condition 1: Acceptable advantage

$$Q_2 - Q_1 \geq \frac{1}{n-1} \quad (18)$$

Condition 2: Acceptable stability

Alternative A^1 should also rank first according to either S_i or R_i .

7. Determine the final ranking

If both conditions are satisfied, A^1 is identified as the unique optimal compromise solution with the highest resilience level. If only Condition 1 is satisfied, A^1 and A^2 are both accepted as compromise solutions. If only Condition 2 is satisfied, Condition 1 is tested sequentially along the Q_i ranking, and all alternatives from A^1 to A^t are accepted once A^t satisfies the condition.

5 Empirical Validation

5.1 Study Objects and Data

To evaluate the applicability of the proposed resilience assessment model, four administrative districts in a representative city in North China were selected and denoted as Districts A–D. The city is characterized by a high level of urbanization, dense population and infrastructure, and a large and diversified urban gas system. It is also increasingly exposed to urban waterlogging, flash floods, and rainfall-induced geological hazards under extreme rainfall, making it suitable for assessing gas-system resilience under flood-disaster scenarios.

The four districts were selected to capture typical intra-city heterogeneity in flood exposure, urban development, and gas-system characteristics. They represent a rapidly urbanizing plain district, a highly modernized industrial-development district with a relatively concentrated gas supply structure, a mountainous district exposed to rainfall-induced geological hazards, and a district with mixed urban–rural development and transportation-related infrastructure. Their differences in topography, river distribution, development intensity, gas facility layout, user scale, supply structure, and emergency resources provide a representative basis for testing the model's ability to distinguish regional resilience heterogeneity under extreme rainfall.

Data were collected from statistical yearbooks, sectoral management records, gas enterprise operational data, field surveys, and expert questionnaires. Statistical and enterprise operational data were aligned to 2023 to ensure temporal consistency, while field surveys and questionnaires supplemented indicators unavailable from official or operational records. The questionnaire involved 12 respondents, with each district represented by one industry authority official, one gas-sector expert, and one gas operating enterprise representative. Scores for qualitative indicators were averaged across respondents to reduce individual judgment bias. All indicators were processed and standardized according to the proposed indicator system (Table 2), and sensitivity analysis was conducted to examine the robustness of the assessment results.

Table 2. Standardized Results of Evaluation Indicators for Each District

Indicator Code	Administrative District			
	District A	DistrictB	District C	District D
A1	1.0000	0.0000	0.4000	0.8000
A2	1.0000	0.0000	1.0000	1.0000
A3	1.0000	1.0000	0.5000	0.0000
A4	0.0000	0.5000	1.0000	1.0000
A5	1.0000	0.5000	1.0000	0.0000
A6	0.3083	0.0000	0.6690	1.0000
A7	0.9113	0.0000	0.7715	1.0000
B1	1.0000	1.0000	0.0000	0.5601
B2	0.5000	1.0000	0.5000	0.0000
B3	0.4375	0.0000	1.0000	0.7500
B4	0.6216	0.0000	0.4066	1.0000
B5	0.6189	0.2220	0.0000	1.0000
B6	0.0000	0.7000	1.0000	0.5000
C1	0.4095	0.0509	1.0000	0.0000
C2	0.6549	0.0000	0.0639	1.0000
C3	1.0000	0.0000	1.0000	0.5000
C4	0.0000	0.5000	1.0000	0.5000

5.2 Weight Calculation

Objective weights were derived using SMAA with Monte Carlo simulation based on 1×10^8 random weight vectors. Subjective weights were obtained from AHP scoring by nine experts, including four with senior professional titles, and all judgment matrices satisfied the consistency criterion ($CR < 0.1$). The final weights were generated through game-theoretic aggregation, as shown in Table 3.

Table 3. Weight Results of Evaluation Indicators

Indicator	SMAA (W_1)	AHP (W_2)	Combined Weight
A1	5.330%	5.474%	5.345%
A2	5.840%	5.024%	5.756%

A3	5.880%	6.071%	5.900%
A4	6.300%	6.308%	6.301%
A5	6.400%	9.903%	6.761%
A6	5.820%	9.005%	6.148%
A7	5.640%	5.320%	5.607%
B1	5.840%	6.425%	5.900%
B2	6.120%	4.686%	5.972%
B3	6.240%	3.210%	5.928%
B4	5.400%	6.671%	5.531%
B5	4.970%	5.289%	5.003%
B6	6.600%	8.761%	6.822%
C1	6.690%	3.403%	6.352%
C2	5.020%	3.238%	4.837%
C3	6.110%	4.922%	5.988%
C4	6.600%	6.291%	6.568%

5.3 Resilience Assessment

Based on the standardized indicator data for the four selected districts, the positive and negative ideal solutions were first determined. The group utility (S_i), individual regret (R_i), and compromise value (Q_i) of each district were calculated. The results are shown in Table 4.

Table 4. Resilience assessment results and ranking of each district.

District	Compromise Value (Q_i)	Rank	Group Utility (S_i)	Rank	Individual Regret (R_i)	Rank
District A	0.6260	3	0.4018	3	0.0682	4
District B	0.6342	4	0.6692	4	0.0615	2
District C	0	1	0.3117	1	0.059	1
District D	0.5874	2	0.3982	2	0.0676	3

The overall resilience level of each district was further assessed from three dimensions: resistance capacity, recovery capacity, and adaptive capacity. The results are presented in Table 5.

Table 5. Evaluation results of resilience subdimensions for each district.

District	Resistance Capacity	Recovery Capacity	Adaptive Capacity
District A	0.5251	0.0324	0.261
District B	0.0862	0.4849	0.1322
District C	1	0.5288	1
District D	0.3931	0.9609	0.2935

District C > District D > District A > District B

5.4 Robustness Check

To validate the robustness of the proposed combined assessment model, the final ranking obtained using the VIKOR method was compared with the SMAA-based ranking probabilities calculated from the original data, as presented in Table 6.

Table 6. Comparison of rankings obtained by different methods

District	VIKOR ranking	SMAA ranking
District A	3	3
District B	4	4
District C	1	1
District D	2	2

The rankings generated by the two methods were completely consistent, and District C showed a markedly higher SMAA acceptability index than the other districts. These results indicate that the proposed model can produce stable and reliable rankings under different weighting conditions.

5.5 Results and Discussion

The results reveal pronounced regional heterogeneity in flood resilience across the four districts. District C shows the highest overall resilience, mainly due to lower infrastructure exposure, stronger emergency preparedness, and better adaptive capacity, although its recovery capacity remains constrained by a relatively concentrated gas supply structure. District D ranks second, with the strongest recovery capacity supported by emergency gas supply, enterprise operation, and post-disaster resource support, while its resistance and adaptation remain insufficient. District A exhibits moderate resilience, characterized by relatively strong resistance but weak recovery capacity. District B has the lowest overall resilience, largely due to mountainous terrain, higher facility exposure, weaker economic foundation, and limited adaptive capacity.

Subdimension results further show that District C performs best in resistance and adaptation, District D has a distinct advantage in recovery, and District B remains weak in both resistance and adaptation. These results indicate that resilience enhancement should adopt differentiated strategies. District C should strengthen backup gas sources and recovery support; District D should improve infrastructure resistance and adaptive planning; District A should enhance post-disaster recovery and risk-transfer capacity; and District B should prioritize facility protection, emergency resource allocation, and long-term resilience building. Overall, the proposed framework not only provides an integrated ranking of regional gas-system resilience but also identifies dimension-specific weaknesses, supporting targeted resilience enhancement under extreme rainfall.

6 Conclusions and Prospects

This study developed an integrated framework for assessing the flood resilience of urban gas systems under extreme rainfall by combining a three-dimensional resilience

indicator system, SMAA–AHP–game-theoretic weighting, and the VIKOR method. The framework was validated using four administrative districts in a representative city in North China. The main conclusions are as follows.

First, a resilience indicator system was established from the dimensions of resistance, recovery, and adaptation, capturing the performance of urban gas systems in pre-disaster protection, emergency response, post-disaster recovery, and long-term adaptive improvement. Second, SMAA-derived objective weights and AHP-derived subjective weights were integrated through game-theoretic aggregation, and the VIKOR method was used to achieve compromise ranking under multiple conflicting indicators while incorporating both data-driven variation and expert judgment. Third, the empirical results show that the resilience ranking is District C > District D > District A > District B, and the consistency between the VIKOR and SMAA rankings confirms the robustness and applicability of the proposed model. The framework can support flood-risk prevention, emergency resource allocation, and targeted resilience enhancement for urban gas systems under extreme rainfall.

Future research should extend the application to more cities and disaster scenarios, and incorporate dynamic monitoring, simulation-based hazard exposure, and post-disaster recovery data to improve the temporal resolution and generalizability of urban gas-system resilience assessment.

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Disclosure of Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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