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Article

Evaluation of Factors Found to Influence Urban Flood Resilience in China

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Abstract: As one of the most frequently occurring natural hazards, flooding can seriously threaten global security and the sustainable development of our communities. Therefore, enhancing the resilience of cities and improving their ability to adapt to flooding have become issues of great significance. This study developed a new comprehensive evaluation model of flood resilience that includes an evaluation index system from the basis of four key dimensions of social resilience, economic resilience, ecological environment resilience and infrastructure resilience. Firstly, interpretative structural modelling (ISM) was applied to analyze the structural issues affecting urban flood resilience. Secondly, the analytic network process (ANP) was then used to calculate the importance of these indicators. Finally, taking three cities (Zhengzhou, Xi'an, and Jinan) in the Yellow River Basin of China as examples, the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) was used to evaluate their current levels of flood resilience using the findings from the earlier stages. The results show that the levels of rainfall and vulnerability of groups were the fundamental factors affecting urban flood resilience. Indicators such as average annual rainfall, fixed-asset investments, and emergency rescue capabilities were also found to have a greater impact on urban flood resilience. In the study area, Xi'an was found to have a higher level of resilience due to having strong ecological environmental resilience. These findings are expected to provide a useful reference for policymakers and stakeholders involved in the management of flooding events.

Keywords: urban flood resilience; influencing factors; resilience assessment; ISM-ANP-TOPSIS model

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1. Introduction

Due to the interaction of climate change, population growth, and rapid urbanization, the vulnerability of urban systems to natural disasters is increasing [1,2]. In recent years, natural disasters have occurred more frequently around the world, causing serious losses to lives, extensive damage to property, as well as wider-scale social and economic impacts. Flooding is one of the most serious and frequent natural disasters [3,4]. For example, in 2007, 55,000 properties in the UK were flooded, with an estimated economic loss of EUR 3.2 billion. In October 2022, catastrophic floods in Nigeria killed 363 people and forced the relocation of more than 2.1 million people. According to the statistics of the United Nations Office for Disaster Reduction, one-third of global natural disasters and economic losses are related to floods [5,6]. China is located in the eastern part of Asia, facing the Pacific Ocean and having clear continental climatic characteristics. This country has the most severe serious flood risks in Asia and possibly even the world [7]. Data from the 'China Flood and Drought Disaster Bulletin' show that there were increasing levels of flooding in China every year between 1990 and 2021 [8]. As global temperatures continue to rise, the number of extreme weather events will increase in the future. Hence, how to improve urban flood resilience and reduce the impact of floods has become an urgent challenge to be solved.

Traditional urban flood management concepts have focused on the use of various engineering measures to help prevent disasters. In the face of more serious and frequent flood events, questions have arisen about these traditional flood control approaches. In this context, in order to improve urban flood resilience and generate more effective water management, countries around the world are actively seeking methods and strategies to improve the status quo. For example, the United States proposed low-impact development (LID) and best management practices (BMPS) [9], Australia proposed water-sensitive urban design (WSUD) [10], and the United Kingdom proposed a sustainable drainage system (SUDS) [11]. Based on this, China has formed a sponge city theory and applied it to practice [12]. The Sendai Framework for Disaster Risk Reduction (2015–2030) [13] issued by the United Nations emphasizes the importance of resilience in disaster prevention and mitigation. "The CPC Central Committee's Recommendations on the Formulation of the 14th Five-Year Plan for National Economic and Social Development and the Vision for the Year 2035" emphasizes enhancing the resilience of urban systems and preventing and resolving major risks. Thus, it can be seen that improving resilience has now become the focus of the international community and is one of the main concerns of flood-prone cities and countries.

Hence, research in flood risk management has shifted from flood vulnerability analysis to flood risk identification and assessment; now, there is also a great focus on improving flood resilience. Holling [14] first introduced resilience into the field of ecology and the environment in 1973, believing that it is the ability of a system to discover and solve external shocks in the event of a crisis. The concept of resilience has been introduced into urban systems to contribute a new research perspective on urban flood control and disaster reduction [15]. Zheng integrated resilience into the urban flood risk assessment framework [16]. At present, there is no uniform standard for the definition of urban flood resilience [17]. Chen and Leandro pointed out that urban flood resistance refers to the ability to withstand a certain degree of disaster impact and restore the initial state after a flood occurs in the urban system [18]. According to Mehryar and Surminski, urban flood resilience refers to the ability to reduce flood risk in a timely and effective manner, resist potential flood impacts, and adapt to future floods [19].

Assessing the development level of urban flood resilience and then finding ways to enhance flood resistance will help to formulate long-term development plans and provide a useful reference for stakeholders. Based on this theoretical basis, some scholars have made attempts to assess resilience by selecting appropriate evaluation indicators. For example, Zhu considered the entire flood disaster cycle and selected indicators from three stages before, during, and after floods [15]. Moghadas et al. constructed an indicator system including social, economic, and institutional aspects, as well as infrastructure, the community, and the environment, and developed a multi-criteria decision-making (MCDM) tool to measure flood resilience in Tehran [20]. Chen et al. selected indicators according to the TOSE (technology, organization, society and economy) framework and proposed suggestions for flood management in Chongqing based on the results of a resilience assessment [21]. Other scholars have assessed urban flood resilience by developing new models. Miguez and Veról have developed an integrated flood resilience (FResI) tool for guiding flood control decisions and simulating future floods compared to current conditions; they tested it in a basin in the metropolitan area of Rio de Janeiro, Brazil, to improve flood resilience in future scenarios [22]. Muhammad Tayyab et al. developed the urban flood resilience model (UFResi-M) [23] and selected flood disasters, exposure, sensitivity, and response capacity as the main parameters of the model. After data processing and analysis, the urban flood resilience of two regions was compared.

In short, in the previous research, there are relatively few studies that quantify urban flood resilience while focusing on the social, economic and ecological mechanisms that also influence resilience. This is despite the fact that many studies have attempted to propose measures to improve flood mitigation capacity and explore urban flood risk factors [24]. However, urban flood resilience is affected by many aspects, and as the internal systems are very complex, there remain gaps in the research on the impact these have on levels of flood resilience. Therefore, the outstanding contribution of this study is to couple the structural aspects of flood resilience with a broader assessment of resilience levels. Furthermore, in developing countries with major flood-prone cities, such as China, further research is necessary to allow urban communities to coexist with flood threats [25]. In this research, the index system of urban flood resilience is further perfected, and a new comprehensive evaluation model is developed by integrating interpretative structural modeling (ISM), the analytic network process (ANP) and the technique for order preference by similarity to an ideal solution (TOPSIS), which is another contribution of this study. The model will help to understand the influence of key factors, assess the current level of urban flood resilience, and suggest improvements. The research results reveal the core influencing factors and mechanisms and provide a scientific basis for stakeholders to formulate targeted and feasible urban flood control and disaster reduction measures.

2. Research Method

2.1. Selection of Research Methods

The evaluation of urban flood resilience can be classified as part of the multi-criteria decision-making method (MCDM) [20,26], and MCDMs such as decision-making trial and evaluation laboratory (DEMATEL), data envelopment analysis (DEA), entropy weight method (EM), analytic network process (ANP), and grey relation analysis (GRA) have been widely used in flood studies [26]. Ning et al. applied the Fisher information (FI) and data envelopment analysis (DEA) to measure the sustainability of urban systems and also compared the advantages and disadvantages of the two methods [27]. Moghadas et al. used a hybrid AHP-TOPSIS approach to measure the resilience of Tehran and validated the reliability of the model [20]. Zheng and Huang quantified urban flood risk and flood resilience using the extension catastrophe progression method (ECPM) and analyzed the commonalities and differences between them [28]. Peng et al. used the structural equation model (SEM) to test the truth or falsity of the proposed hypotheses [29]. Chen ranked the disaster resilience of cities based on the VIKOR-GRA (VlseKriterijumska Optimizacija I Kompromisno Resenje, Grey Relational Analysis) method [21].

To justify the assessment method used, the currently available assessment methods were compared, as shown in Table 1. The decision-making trial and evaluation laboratory (DEMATEL) enables the causality analysis of indicators [30,31], and interpretative structural modeling (ISM) allows the analysis of causal relationships and considers direct and indirect relationships between subsystems [32]. It was proved that ISM is suitable for learning to understand systems with complex interrelationships [33]. Therefore, ISM was chosen to analyze the internal structure of urban flood resilience. ANP and AHP (analytic hierarchy process) are two common weighting methods. ANP considers the dependencies between factors based on AHP [34], and these dependencies can be obtained from the ISM model. Mousavi tested the effectiveness of several evaluation methods and found the TOPSIS method to be the most effective [35]. Therefore, the TOPSIS technique was introduced to quantify the level of resilience. However, the TOPSIS tool does not provide a weight reference [20], and ANP can exactly fill its gap. Based on the above analysis, these three methods can be closely linked and used to complement each other. Therefore, a new comprehensive evaluation model was developed using a combination of techniques: interpretative structural modelling (ISM), the analytic network process (ANP), and the technique for order preference by similarity to an ideal solution (TOPSIS).

Table 1. Comparison of evaluation methods.

No.	Description	Methods	Advantages and Disadvantages	Origin
1	Identifying factors influencing flood resilience	DEMATEL -ANP	Indicator causality and weights can be derived, but the evaluation results are more subjective and cannot reveal the structural problems of the indicators	[36]
2	The relationship between factors in the three dimensions of stress, state, and response was measured	Fuzzy -DMATEL	The results can show causal influence relationships between indicators, and the results rely on expert judgment and do not integrate objective data considerations	[37]
3	Explored how urban systems affect urban flood resilience	SEM	Clearly explains the strength of the relationship between the factors, but the evaluation results are too subjective	[29]
4	Quantitative analysis of sustainability assessment of urban systems, comparing the results of FI and DEA methods	FI, DEA	FI facilitates the assessment of dynamic changes in the system, DEA is suitable for comprehensive evaluation with many inputs and outputs, and both methods ignore the influence of indicator weights	[27]
5	Ranking cities for disaster resilience based on objective data	VIKOR -GRA	Objective data are fully utilized, but the results may deviate from reality due to the limited selection of indicators and ignoring the experience of experts	[21]
6	Link between flood risk and resilience through case studies	ECPM	Objective quantification of urban flood risk and resilience, but no analysis of structural issues	[28]
7	The resilience of urban road traffic network (URTN) was explored using the entropy method and G1 method	EM-G1	The combination of subjective and objective measures does not require consistency testing, but it cannot determine the impact of changes in a single indicator on the overall resilience of the URTN	[38]
8	The hierarchy of 13 influencing factors was analyzed	ISM-ANP	The analysis of indicator hierarchy and importance is more adequate, and the ISM-ANP model relies on the personal experience, knowledge, and professional judgment of decision makers and lacks objective and realistic analysis	[39]
9	The flood resilience of 31 key flood control cities was assessed	EM -TOPSIS	The assessment results are more objective and do not reflect the path of impact factors	[40]
10	Research on the influence mechanism and importance level of indicators of urban flood resilience to assess the level of urban flood resilience	ISM-ANP -TOPSIS	ISM can clearly reflect the influence mechanism of impact factors compared with other multi-objective decision making; ANP-TOPSIS combines subjective and objective data, and the evaluation results will not be detached from reality while making up for the defects of other methods, which are subjective	This research

The comprehensive evaluation model is shown in Figure 1. Firstly, the index system of urban flood resilience was screened based on an extensive review of the literature, questionnaires and surveys, and the Delphi method. Then, the structure of the complex system was analyzed by ISM so as to clarify the relationships and influences between the indicators. The hierarchical structure obtained by ISM and expert scoring results were input into the ANP model to determine the importance of the indicators. Finally, the flood resilience level of the three chosen study areas was evaluated by TOPSIS.

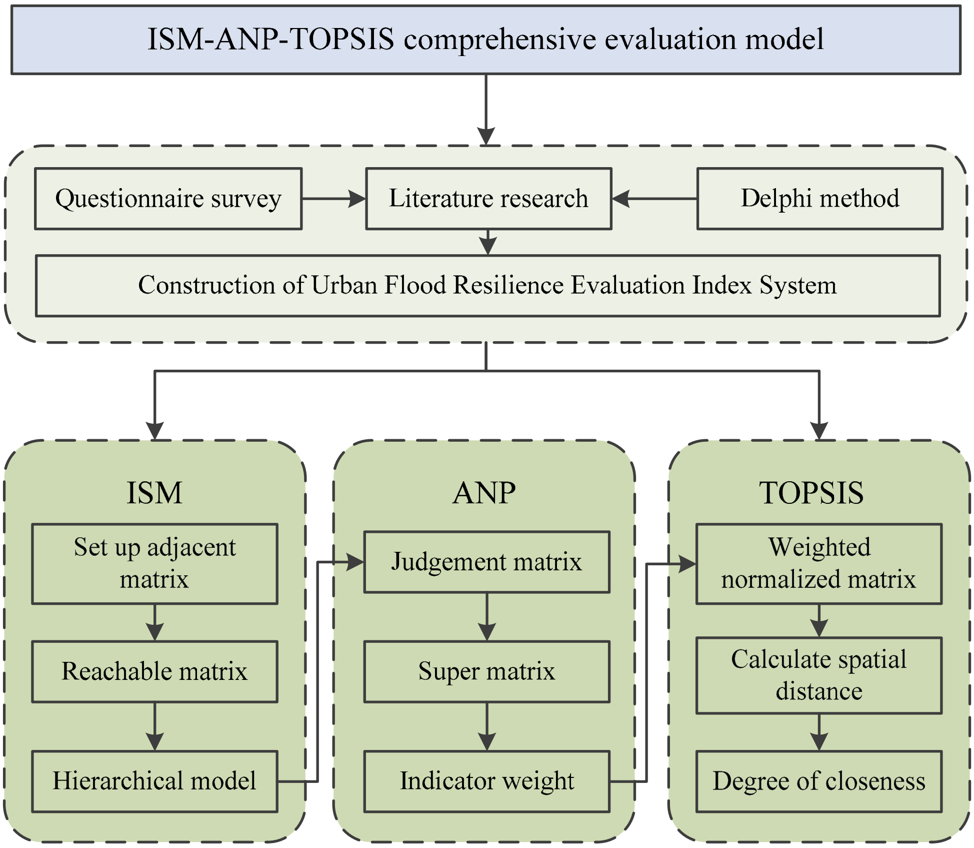

Figure 1. Comprehensive evaluation model.

2.2. Establishing an ISM Model

The principle of the interpretative structural model is to establish an adjacency matrix according to the direct correlation between the elements, calculate the reachable matrix, and finally form a hierarchical multi-level recursive structural model. Its core is to use tools such as directed graphs and matrices to perform mathematical operations, analyze complex structures, and transform fuzzy ideas and opinions into intuitive models with good structural relationships [39]. The final model is expressed in the form of a simple directed topology graph. This method is especially suitable for system analysis with many variables and complex relationships. This study uses the ISM method to obtain the relationship between factors and then uses the ANP method to obtain the importance of factors. The basic steps of ISM are as follows.

Step 1: Determine the correlation between indicators and establish the adjacency matrix M. Firstly, through literature analysis and expert investigation, the correlation between indicators is obtained, and the adjacency matrix that can reflect the correlation between indicators is established as M. Define $M = (a_{ij})_{mn}$, where a_{ij} is the influence of the index S_i on S_j.

$$a_{ij} = \begin{cases} 1, & S_i \; has \; an \; effect \; on \; S_j \\ 0, & S_i \; has \; no \; effect \; on \; S_j \end{cases} \tag{1}$$

Step 2: Calculate the reachable matrix T. According to the theory of system engineering, the Boolean logic operation is carried out after the adjacency matrix is established. Using Matlab version 2018 software calculations, until $(M+I)^k = (M+I)^{k+1}$ stops, the reachable matrix is $T = (M+I)^k$.

Step 3: Index factor level decomposition is performed, as is drawing ISM model diagram. Based on the reachability matrix, the reachable set $P(S_i)$ and antecedent set $Q(S_i)$ of each element are determined. The hierarchical division is carried out by the method of reason priority–result priority rotation, and finally, a multi-level hierarchical interpretative structural model is obtained.

2.3. ANP Method

The analytic network process (ANP) is a commonly used subjective weighting method derived from the analytic hierarchy process (AHP). This method takes into account the interaction between elements between groups and elements within groups, transforms complex problems into network structures for hierarchical and systematic analysis, and is suitable for internal complex decision-making systems with dependence and feedback. In this research, the Super Decisions 2.10 (SD 2.10) software was used to calculate ANP. The calculation steps are as follows.

Step 1: Construct the network structure of the evaluation index. In general, the main structure of the ANP model includes a control layer and a network layer. The control layer is composed of problem objectives and decision criteria. Each criterion is independent of each other and is not affected by other criteria at the same level. The network layer is extended and decomposed into different elements by the control layer criterion, and the elements influence and dominate each other to form a network structure of interdependence and feedback.

Step 2: Establish the judgment matrix. After completing the establishment of the network structure, it is necessary to compare the dependence and feedback relationship between the indicators to establish a judgment matrix. The expert research method is usually used to determine the judgment matrix, and the relative importance value is determined according to the Satty scoring table. It is worth noting that in this process, the consistency test should be carried out according to the formula $CR = CI/RI < 0.1$ to avoid logical errors.

Step 3: Determine the weight value of each index. The Super Decisions 2.10 software is used to input and test the judgment matrix, and then the unweighted super matrix shape, the weighted super matrix, and the limit weighted super matrix are obtained. Click the 'Priorities ' command to generate the weight values (W_j) of all indicators.

2.4. TOPSIS Method

The technique for order preference by similarity to an ideal solution is a common evaluation method in multi-objective decision-making [41]. The basic principle is to regard the evaluation value of a limited number of targets as a point in n-dimensional space and sort them by the relative distance between each point and the ideal solution to reflect the relativity between each evaluation object [42]. The calculation steps are as follows.

Step 1: Determine the positive and negative ideal solution. The initial matrix X_{ij} is non-dimensionalized, and the weighted normalized matrix $Y_{ij} = W_j \times X_{ij}$ is constructed. Formulas (2) and (3) compute the positive ideal solution Y^+ and negative ideal solution Y^-.

$$Y^+ = \left\{ \left(\max_i Y_{ij} | j \in Q_1 \right), \left(\min_i Y_{ij} | j \in Q_2 \right) \right\} \tag{2}$$

$$Y^- = \left\{ \left(\min_i Y_{ij} | j \in Q_1 \right), \left(\max_i Y_{ij} | j \in Q_2 \right) \right\} \tag{3}$$

Here, Q_1 represents the benefit attribute, and Q_2 represents the cost attribute.

Step 2: Calculate the spatial distance. The formula for the distance from the evaluation object to the positive and negative ideal solution is as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (y_{ij} - y_j^+)^2} \quad (1 \le i \le m, 1 \le j \le n) \tag{4}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (y_{ij} - y_j^-)^2} \quad (1 \le i \le m, 1 \le j \le n) \tag{5}$$

Step 3: Calculate the closeness. If the closeness S_i is close to 1, it indicates that its resilience level is high. If the closeness is closer to 0, the resilience level is low.

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{6}$$

3. Case Study

3.1. Description of the Study Area

The three major cities of Zhengzhou, Xi'an, and Jinan were selected as the case studies for evaluating the applicability of the model. These three cities are economically well-developed and have high levels of urban agglomeration, and all are prone to severe urban flooding. In addition and according to previous studies, the flood exposure and vulnerability in these three regions are high [43]. The study areas are shown in Figure 2.

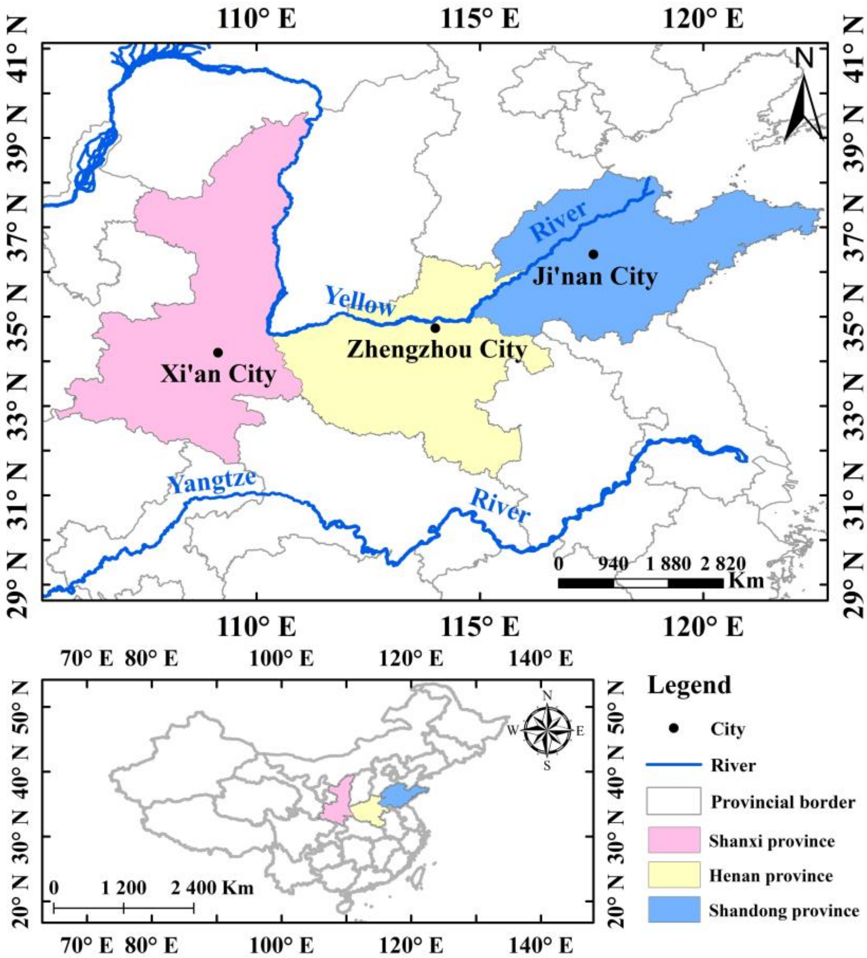

Figure 2. Study area.

Zhengzhou is the capital city of Henan, across the Yellow River and Huaihe River. The area has concentrated rainfall in the summer, with June and September accounting for about 60% of the annual rainfall. The pace of development in Zhengzhou has increased in recent years, placing extra demand on the drainage systems in the city. In the event of extreme precipitation events, such as on 20 July 2021, 380 people were killed, resulting in direct economic losses of CNY 40.9 billion and a huge loss of life and property.

Xi'an is located in the middle of the Yellow River Basin, with a temperate monsoon climate. The average annual precipitation is 740.4 mm. The rainfall has the characteristics of uneven spatial and temporal distribution, which is mainly concentrated in the summer and autumn. Short-term intense heavy rainfall is the main cause of urban flooding. For example, in July 2016, a short period of heavy rain caused Xi'an to be 'watching the sea' in many places, and the water accumulation in many areas was very serious, reaching above 1 m in depth in many populated areas.

Jinan is the capital city of Shandong Province, also known as 'Quancheng'. The southern part of the city is adjacent to Mount Tai, the north is dependent on the Yellow River, and the terrain is high in the south and low in the north. Jinan has a warm temperate continental monsoon climate zone with four distinct seasons. The average annual rainfall is about 700 mm, and the precipitation is mainly concentrated from June to September. The main rivers in the territory are the Yellow River and the Xiaoqing River. The northwest corner of Jinan City and the line along the Xiaoqing River are low-lying and often flooded. During heavy rain, it is easy for large-scale water accumulation and serious flood accidents to occur. For example, on 18 July 2007, Jinan City suffered a super rainstorm, resulting in more than 30 deaths, with more than 170 people being injured and approximately 330,000 people being affected; the city's direct economic losses were about CNY 1.32 billion.

3.2. Sources of Data

The data in this research were mainly derived from the 'Zhengzhou Statistical Yearbook', 'Xi'an Statistical Yearbook', 'Jinan Statistical Yearbook' and 'China Urban Statistical Yearbook' in 2022. In addition, the establishment of some data was based on the knowledge and experience of a range of experts who were consulted through multiple rounds of consultation, interviews, or questionnaires. To guarantee the validity of the results, the selected experts had been researching or working in the field of urban development and flood risk reduction for at least 5 years. The profile of the expert group is shown in Table 2. The questionnaire is shown in Appendix B.

Table 2. Introduction of expert group.

Background		Option	Number	Background	Option	Number
Experts (n = 28)	Age	30–39	5	Highest academic credentials	Undergraduate	3
		40–49	17		Master's	19
		≥50	6		Ph.D.	6
	Work unit	Colleges and universities	10	Expertise or research field	Urban resilience	8
		Government departments	6		Flood management	9
		State-owned enterprises	4		Risk assessment	6
		Research institutes	8		Flood control and disaster reduction	5

3.3. Establishing Evaluation Index System

This study selects indicators based on the pressure–state–response (PSR) conceptual framework, which was first proposed by Rapport and Friend in 1979 [44]. The PSR explains how human activities exert pressure on the environment, the environment self-regulates, and society responds to environmental regulation [45]. "Pressure" refers to the pressure faced by the urban system, such as the pressure caused by natural disasters or development and construction. "State" refers to the condition of the regional urban social environment, economic environment, ecological environment, and other subsystems. "Response" refers to the policies or measures to reduce flood risk, improve resilience, and promote sustainable urban development. The complex ecosystem theory holds that cities are composed of three different systems: social, economic, and natural [46]. Based on this theoretical perspective, the urban water and social systems, economic systems, ecological environment systems, and infrastructure systems are considered inseparable.

By reviewing a large number of articles related to flood resilience [37,42,45,47], the indicators affecting flood resilience were preliminarily identified, and some invalid indicators were eliminated, taking into account the actual situation of Chinese cities coping with flood disasters. Accordingly, a questionnaire was formulated (Appendix B), and the expert group was invited to evaluate and verify the indicators. When experts' opinions diverged, a second round of surveys was conducted to gradually obtain more consistent results. When the experts' combined views on an indicator exceeded 80%, it was considered a factor influencing the resilience to urban flooding. Based on the questionnaires filled out by experts, indicators that did not meet the criteria, such as internet penetration [29], public awareness of disaster prevention [48,49], etc., were removed. The final evaluation index system of urban flood resilience was constructed, which covers four dimensions: social resilience, economic resilience, ecological environment resilience, and infrastructure resilience, and thirteen secondary indicators, as shown in Table 3.

Social resilience refers to the ability of the urban system to maintain normal social order in the face of external interference [50]. The indicators selected in this dimension include vulnerable groups [49], population density [21,51], medical service capacity [20,29,40], and emergency rescue capacity [1,52]. Vulnerable groups can reflect the ability of the public to resist disasters [53]. The more children there are and the greater the elderly population, the higher the vulnerability is, and the more vulnerable to floods the population is. The population density reflects the concentration of the population. The more concentrated the population, the more urban areas need to take disaster prevention and mitigation measures in advance and make emergency plans [54]. Medical service ability reflects whether the casualties can be quickly and effectively rescued after the disaster and whether the number of hospital beds and medical and health staff can meet the basic needs after the emergency. Emergency rescue capability reflects the speed and quality of urban system rescue and disaster relief [54,55].

Economic resilience is a dimension that cannot be ignored. The construction of urban flood control facilities and the investment of disaster prevention funds are inseparable from economic factors [2]. Economic resilience refers to the ability of the economic system to maintain the original economic capacity in the face of disasters. This incorporates three indicators: fixed-asset investment [29], per capita disposable income [21,56], and disaster prevention capital investment [40]. Fixed-asset investment can promote economic prosperity and development. Per capita disposable income is the sum of residents' consumption and savings, which can reflect the economic situation of local residents [21]. A good economic situation means that there is a good material basis for resisting various disasters. The more investment in disaster prevention funds, the more funds the city has for disaster prevention and mitigation, and the stronger the ability to cope with disturbances [40].

Ecological resilience refers to the ability of the ecological environment system to resist, adapt, and restore the original structure by its own resilience when it is damaged [39]. The indicators selected in this dimension include the green coverage rate of built-up areas [18,57], the average annual rainfall [40,58], and the spatial structure of land use [59]. The higher the green coverage rate in the built-up area, the better the urban greening and the higher the ecological environment resilience. Extreme rainfall can sometimes cause the collapse of urban flood control and drainage systems, leading to flooding [60]. Reasonable spatial structures of land use can reduce flood risk to a certain extent.

Infrastructure resilience refers to the ability of infrastructure systems to withstand disasters, absorb losses, and restore their normal functions after a disaster occurs [52,61]. The indicators selected in this dimension include the density of drainage pipelines in built-up areas [62,63], per capita road area [56], and sewage treatment capacity [58,62]. The density of drainage pipelines in the built-up area can ensure the timely discharge of rainwater or sewage [64]. Per capita road area can ensure the smooth flow of traffic when disaster comes [38]. Floods can often cause the rapid spread of non-point-source pollution, underground sewage and industrial waste, and other large-scale diffusion, which brings great harm to the health of urban residents [58]. Sewage treatment capacity reflects the positive effects of human activities on urban systems.

3.4. Index System Structure Division

According to the 13 indicators identified above, 28 experts with rich experience in studying urban flood resilience were invited to participate in a survey to collect their opinions. After summarizing the findings, the results were fed back to each expert. Through three rounds of comprehensive collation of opinions, more consistent results were gradually obtained. Finally, the relationship between all index factors was obtained, and the adjacency matrix M was established as follows:

$$M = \begin{bmatrix}
0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\
0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 1 \\
0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}$$

Table 3. List and explanation of each selected indicator.

Goal Layer	First-Level Indicators	Secondary Indicators	Labels	Explanation	References
Evaluation index system of urban flood resilience	Social resilience	Vulnerable groups	N1	The proportion of people over 60 years old and under 15 years old indicates vulnerable groups.	[49]
		Population density	N2	Population per square kilometer. Reflects the density of population distribution.	[21,51]
		Medical service capacity	N3	Reflects the efficiency and level of medical services. It can be measured by the number of health institutions per 10,000 people, the number of health technicians, and the number of hospital beds.	[20,29,40]
		Emergency rescue capability	N4	The capability of emergency rescue and disaster relief under emergencies.	[1,52]
	Economic resilience	Fixed-asset investment	N5	The workload of construction and purchase of fixed-asset activities.	[29]
		Per capita disposable income	N6	The sum of final consumption expenditure and savings.	[21,56]
		Disaster prevention capital investment	N7	Total capital investment against various disasters.	[40]
	Ecological environment resilience	Green coverage rate of built district	N8	The proportion of green areas and built-up areas.	[18,57]
		Average annual rainfall	N9	The average annual rainfall in a region.	[40,58]
		Spatial structure of land use	N10	The spatial location of various types of land in the region and their combined pattern.	[59]
	Infrastructure resilience	Drainage pipe density in built-up area	N11	The density of drainage pipeline distribution.	[62,63]
		Per capita road area	N12	The per capita road area occupied by urban population is expressed by the ratio of the total area of urban roads to the total urban population.	[56]
		Capability of sewage treatment	N13	The capacity of a sewage treatment plant (or treatment plant) to treat sewage volume every day and night.	[58,62]

The reachable matrix T was calculated by Boolean logic operation rules and Matlab 2018 software programming. According to the reachable matrix, the reachable set and the antecedent set (Table 4) were obtained, and finally, the explanatory structure model of the influencing factors of urban flood resilience was obtained, as shown in Figure 3.

$$T = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Table 4. Reachable set, antecedent set, and intersection set.

Reachable Set $P(S_i)$	Antecedent Set $Q(S_i)$	$P(S_i) \cap Q(S_i)$
1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12, 13	1	1
2, 4, 6, 7, 8, 10, 11, 12, 13	1, 2	2
3, 7, 8, 10, 11, 12, 13	1, 3, 5, 9	3
4, 7, 8, 10, 11, 12, 13	1, 2, 4, 5, 9	4
3, 4, 5, 6, 7, 8, 10, 11, 12, 13	1, 5, 9	5
6, 7, 8, 10, 11, 12, 13	1, 2, 5, 6, 9	6
7, 8, 10, 11, 12, 13	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	7, 8, 10, 11, 12, 13
7, 8, 10, 11, 12, 13	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	7, 8, 10, 11, 12, 13
3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	9	9
7, 8, 10, 11, 12, 13	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	7, 8, 10, 11, 12, 13
7, 8, 10, 11, 12, 13	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	7, 8, 10, 11, 12, 13
7, 8, 10, 11, 12, 13	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	7, 8, 10, 11, 12, 13
7, 8, 10, 11, 12, 13	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	7, 8, 10, 11, 12, 13

Note: Numbers represent certain elements, such as 2 for N2.

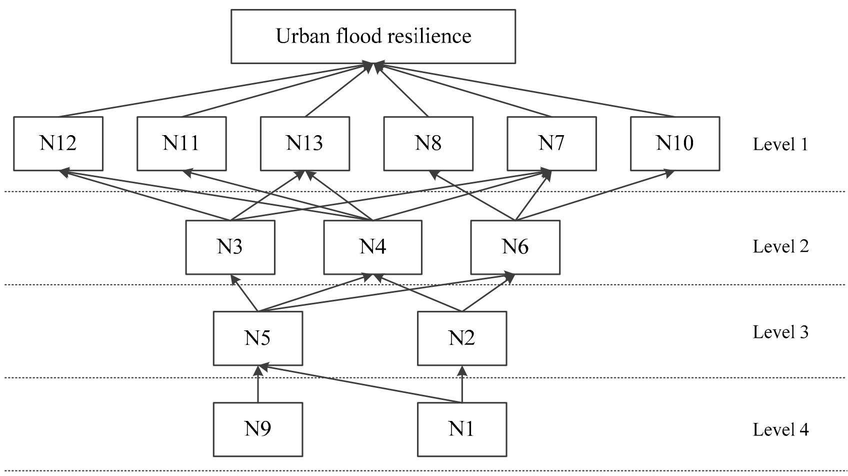

Figure 3. Explanatory structural model diagram.

4. Results and Analysis

4.1. Analysis of Index Level Results

It can be seen from the explanatory structure model of the influencing factors of urban flood resilience (Figure 3) that the thirteen evaluation indicators can be divided into four levels, and the underlying-level factors can affect the upper-level factors. Here, the first layer represents those factors that have a direct impact, while the second and third layers play a transitional role and are the factors influencing the middle layer. The fourth layer is located at the bottom, with the longest action path, which can be considered fundamental factors affecting flood resilience.

In this model, the first layer's direct influencing factors include the per capita road area (N12), drainage pipeline density (N11), sewage treatment capacity (N13), green coverage rate of built-up areas (N8), disaster prevention investment (N7), and the spatial structure of land use (N10). When a flood event occurs, the surface or direct factors will come into effect. For example, effective land-use spatial structures can ensure the preservation of people's lives. The built infrastructure and ecological environment, such as road area per capita, drainage pipeline density, green coverage of built-up areas, and sewage treatment capacity, can help reduce the impact of flooding. The investment in disaster prevention funds provides a material basis for urban disaster prevention and mitigation. Therefore, improving these indicators has a direct role in enhancing urban flood resilience.

The factors located in the middle layer include medical service capacity (N3), emergency rescue capacity (N4), per capita disposable income (N6), fixed-asset investment (N5), and population density (N2). These factors are affected by rainfall and vulnerable groups and, at the same time, act as a medium. Among them, medical service level, emergency rescue ability, and per capita disposable income are affected by fixed-asset investment and population density. The factors of the middle layer can link the factors of different levels and are also very important in improving the influence of factors in the middle layer.

The underlying factors include average annual rainfall (N9) and vulnerable groups (N1). In general, short-term heavy rainfall and extreme weather are the root causes of urban floods. Vulnerable groups can reflect the age composition of the population and the degree of human vulnerability and have a link to the impacts on society, the economy, infrastructure, and the ecological environment.

4.2. Analysis of ANP Results

The weighted scores of the influencing factors of urban flood resilience are shown in Table 5. Based on this, a histogram of index weight scores was drawn (Figure 4). The calculation processes are shown in Tables A1 and A2 in Appendix A. It can be seen from Table 5 that in the criterion layer, the weights of social resilience and economic resilience are higher, followed by ecological resilience and infrastructure.

Table 5. Index weight.

First-Level Indicators	Weight	Secondary Indicators	Intra-Group Weight	Index Weight	Ranking
Social resilience	0.285	Vulnerable groups	0.317	0.090	4
		Population density	0.239	0.068	8
		Medical service capacity	0.121	0.034	12
		Emergency rescue capability	0.322	0.092	3
Economic resilience	0.267	Fixed-asset investment	0.480	0.128	2
		Per capita disposable income	0.194	0.052	11
		Disaster prevention capital investment	0.326	0.087	5

Table 5. *Cont.*

First-Level Indicators	Weight	Secondary Indicators	Intra-Group Weight	Index Weight	Ranking
Ecological environment resilience	0.243	Green coverage rate of built-up districts	0.335	0.081	6
		Average annual rainfall	0.540	0.131	1
		Spatial structure of land use	0.125	0.030	13
Infrastructure resilience	0.205	Drainage pipe density in built-up area	0.310	0.064	10
		Per capita road area	0.316	0.065	9
		Capability of sewage treatment	0.374	0.077	7

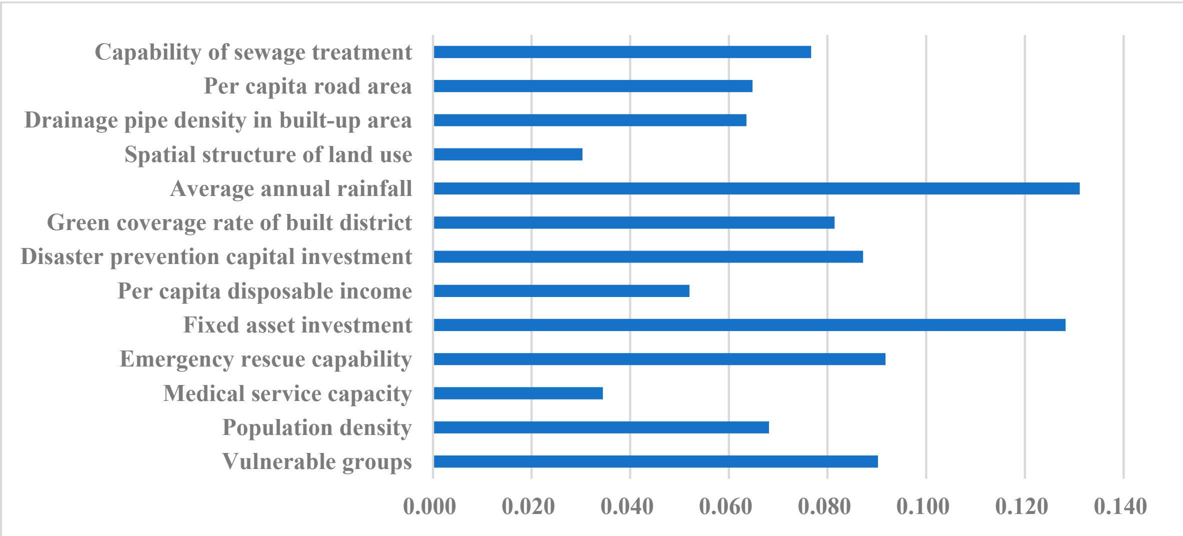

Figure 4. Index weight score histogram.

In the indicator layer, average annual rainfall (N9) and fixed-asset investments (N5) account for a higher proportion, indicating that these two indicators are the key factors in improving urban flood resilience. Fixed-asset investment drives regional economic development and is important for urban infrastructure development and post-disaster recovery [15].Therefore, it is necessary to continue to increase investment in fixed assets so as to promote urban development and lay a foundation for improving urban resistance to floods. Secondly, emergency rescue capability (N4), vulnerable groups (N1), disaster prevention capital investment (N7), the green coverage rate of built-up areas (N8), and sewage treatment capacity (N13) are indicators that are more important and are the focus of improving flood resilience. Therefore, urban flood resilience can be enhanced by improving emergency rescue capabilities and paying attention to vulnerable groups. Further increasing investments in disaster prevention funds, taking disaster prevention and mitigation measures in advance, and regularly inspecting flood control materials and equipment are also beneficial measures. In addition, it is also necessary to expand the green area, enhance the sewage treatment capacity, adopt an ecologically friendly way of production and life, and consolidate the construction of an urban ecological environment.

4.3. Analysis of Flood Resilience in the Three Cities

Taking into account the weights obtained by the ANP model, a weighted normalized matrix was constructed, and the flood resilience levels of the three cities were calculated by Formulas (2)–(5). The closer the closeness value is to 0, the lower the urban flood resilience level is. The closer the value is to 1, the higher the urban flood resilience level is. The results are shown in Table 6. It can be seen from Table 6 that the resilience score is Xi'an > Jinan > Zhengzhou. Among the three research areas, Xi'an has the best resilience level, followed by Jinan, with Zhengzhou having the weakest flood resilience level.

Table 6. Regional flood resilience.

Research Object	D_i^+	D_i^-	S_i	Ranking
Jinan city	0.189	0.194	0.506	2
Zhengzhou city	0.213	0.183	0.463	3
Xi'an city	0.189	0.212	0.529	1

The study found that the resilience levels of the three research areas of Zhengzhou, Xi'an, and Jinan were not much different as a whole. In order to track the reasons, the resilience levels of each dimension are compared. According to Figure 5, Xi'an's social resilience and ecological environment resilience are the best, while Zhengzhou's social resilience and ecological environment resilience are the worst, and the resilience level of Jinan's four dimensions fluctuates relatively little.

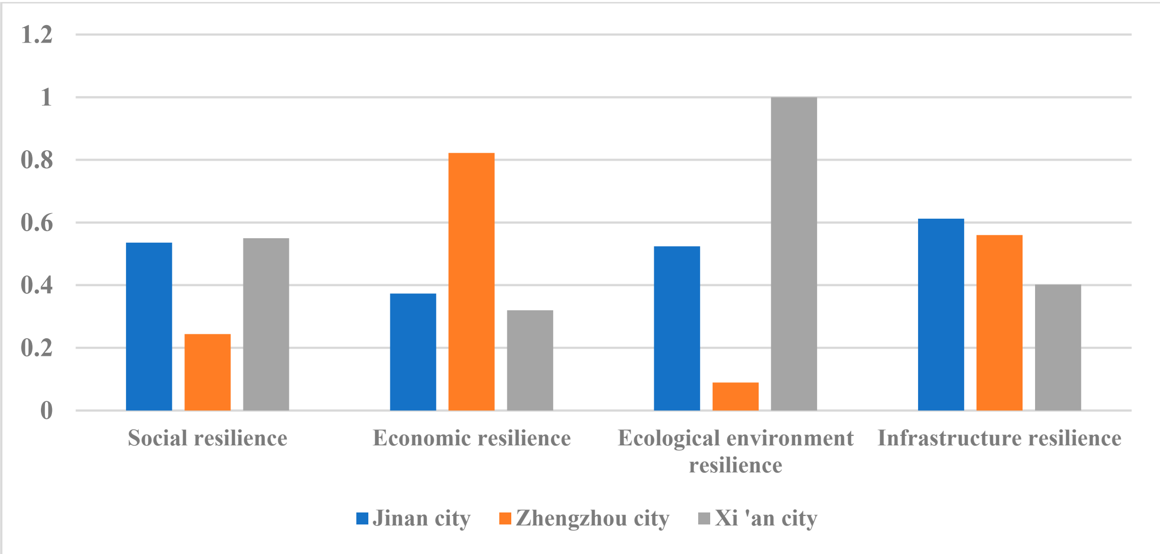

Figure 5. Comparison of resilience levels in each dimension.

In the dimension of social resilience, the resilience levels of Jinan and Xi'an are very close, whereas Zhengzhou is weak, and there is much room for improvement. From the dimension of economic resilience, Zhengzhou scored higher, which can reflect its faster economic growth rate, higher fixed-asset investment, investment in disaster prevention, and total per capita disposable income. From the perspective of ecological environment resilience, Xi'an scored much higher than the other two cities, reflecting Xi'an's emphasis on ecological environment protection. The ecological vulnerability of Zhengzhou City is relatively the highest among the three cities, and the impact of floods may be the largest. Therefore, Zhengzhou should give priority to the development of the ecological environment and increase environmental protection. From the perspective of infrastructure resilience, the gap between the three cities is small. Jinan and Zhengzhou have high infrastructure resilience and can effectively cope with sudden flood disasters. Xi'an's infrastructure resilience is slightly lower, so Xi'an can improve its ability to cope with flood disasters by accelerating the construction of infrastructure.

4.4. Suggestions and Measures

The cities of Zhengzhou, Xi'an, and Jinan all need to monitor and forecast heavy rainfall in a timely manner and regularly inspect urban drainage facilities to ensure that they can respond and recover quickly in the event of a flood disaster. In addition, the three cities should develop measures to improve urban flooding resilience according to local conditions.

Zhengzhou should focus on building an environmentally friendly city while developing its economy. There is a need to improve the planning process and improve the efficiency of urban space utilization while expanding green areas and enhancing the environmental capacity. Furthermore, there is a need to promote the development of green industries according to the requirements of sustainable development. In addition, Zhengzhou is characterized by high population density and "crowding", with a population density of 1683 people per square kilometer in 2021, more than twice that of Jinan. Therefore, the ecological impact of population growth can be mitigated by promoting the movement of people to other small and medium-sized cities.

The economic resilience of Xi'an is lower than the other two cities, and for Xi'an, the first consideration should be to increase the per capita disposable income of residents, increase investments in fixed assets, and build the economic structure system of a resilient city. The population density under the social resilience dimension is also higher, so it is also necessary to manage the agglomerated population and increase the construction of infrastructure such as transportation road networks, drainage facilities, and sewage treatment facilities.

Jinan City's economic, ecological and social resilience are all at the lower-middle level. Therefore, economic development can be promoted by encouraging young people to work and start their own businesses and by developing industrial support policies. Community-based organizations can organize greening activities for residents to increase greening coverage. Government departments can develop a system to protect ecological resources such as wetlands and water sources for the purpose of enhancing the ecological resilience of the city. Jinan has a high percentage of vulnerable groups, so it can consider setting up relevant institutions to protect vulnerable groups, promote flood mitigation methods, and enhance self-help awareness. Medical and health departments should strengthen the level of medical services and the capacity to undertake emergency rescue work, such as transfers and treatment, when disasters occur.

5. Discussion

Resilience considers the whole cycle of natural hazards, including preventive measures that can be undertaken before flooding, such as considering population density and reasonable spatial structures of land use in urban construction and improving drainage and sewage treatment according to the reality of urban development and construction. In the event of a flood, effective response measures can help speed up and support emergency rescue efforts and disaster relief. Recovery measures after floods enable cities to quickly return to normal order after being impacted. This study considers the characteristics of the whole process of the occurrence of floods, and the evaluation index selected according to the PSR framework and the structure of the urban system has a high degree of reliability. However, there is no unified index system to evaluate flood resilience at present. Among the many factors found to influence resilience, only those indicators with the greatest influence were selected, and those with less influence were eliminated. In future research, a paradigm for assessing urban flood resilience can be gradually formed.

The research of Hu et al. shows that the central and northern parts of Shandong Province, the northern part of Henan Province, and the central part of Shaanxi Province have high hazard exposure and vulnerability, and the flood risk of these locations is high, leading to frequent flood disasters [43]. However, the flood risk is also reduced to a certain extent by virtue of its high recoverability, and the final outcome is that these areas have a moderate flood risk. On the other hand, the cities in these regions are located in the Yellow River Basin and are also more vulnerable to floods. Therefore, the case study selected the capital cities of these three regions, namely Zhengzhou City, Jinan City, and Xi'an City. Further research on the flood resilience of these three areas was carried out, and the mechanism of action of the factors of flood resilience was analyzed. The weight was also considered when evaluating the resilience level. Xu et al. investigated three different types of communities in China through a network structure model. TOPSIS can be used to evaluate flood resilience [65]. Ji and Chen used this method to evaluate the resilience of Suzhou, Wuxi, and Changzhou [45]. Zhang et al. used the entropy-weighted TOPSIS method to evaluate the flood resilience of 31 key flood control cities in China [40]. Based on the existing research, this study developed a comprehensive evaluation model, ISM-ANP-TOPSIS, to evaluate urban flood resilience.

According to the research results, rainfall and vulnerable groups are the deep fundamental factors affecting flood resilience and also the factors with the highest weighting. In general, most urban floods are caused by heavy rain [60]. Short-term heavy rainfall is the most common cause of flooding. For example, the 2021 '7.20' event in Zhengzhou, Henan Province, was triggered by heavy rainfall. Similarly, in 2019, Houston, Texas, experienced unprecedented heavy rains, resulting in catastrophic floods [66]. Vulnerability reflects the ability of the population to cope with such events. The greater the total population of the elderly and children, the more people there will be waiting for rescue in emergencies, which is likely to cause more casualties. Therefore, managers need to pay attention to the underlying factors that influence urban flood resilience. To address the problem of heavy rainfall, rainwater flooding can be collected and utilized through measures to enhance flood control and drainage capacity and by expanding green areas to protect the ecosystem. For vulnerable groups, attention needs to be paid to raising awareness and the co-development of appropriate protection measures, such as establishing community help groups.

Decision makers and stakeholders involved in flood event management need to have a comprehensive understanding of the factors that influence urban flood resilience, as well as a good knowledge of the current situation, so as to support the basis on which scientific and rational decisions can be made. The National Development and Reform Commission (NDRC) and the Ministry of Housing and Construction (MOHURD) have proposed to build climate-resilient cities, and the program integrates the concept of resilience into the whole process of urban planning and construction [67,68]. Similarly, the Sponge City Plan (SCP) aims to maximize the use of precipitation [69], realizing a rainfall and flood cycle system that puts water resources to use on the one hand and enhances the stability of urban systems on the other. The perspective of this study fits with these plans and helps cities to adapt to the threats and challenges posed by floods and mitigate the impact of flooding on urban systems.

6. Conclusions

In this research, by considering the factors affecting flood resilience in four dimensions, social flood resilience, economic flood resilience, ecological and environmental flood resilience, and infrastructure flood resilience, through a search of the literature and consulting expert opinions, an index system for evaluating the flood resilience of Chinese cities was constructed. The system includes 13 indicators: vulnerable groups (N1), population density (N2), medical service capacity (N3), emergency rescue capacity (N4), fixed-asset investment (N5), per capita disposable income (N6), disaster prevention capital investment (N7), green coverage of built-up areas (N8), average annual rainfall (N9), the spatial structure of land use (N10), drainage pipeline density (N11), per capita road area (N12), and sewage treatment capacity (N13). An ISM-ANP-TOPSIS comprehensive evaluation model was developed to evaluate the level of flood resilience and the influence of factors across four dimensions in three cities (Zhengzhou, Xi'an, and Jinan) in China, providing a scientific reference point for the future management and decision-making involved in urban flood disasters. According to the results of this study, we can draw the following conclusions:

1. There are many factors that affect the resilience of urban flooding, and each factor also affects each other. The explanatory structural model diagram intuitively reflects the influence mechanism of indicators. In this study, the direct influencing factors include per capita road area (N12), drainage pipeline density (N11), sewage treatment capacity (N13), green coverage rate of built-up areas (N8), disaster prevention capital investment (N7), and the spatial structure of land use (N10). The influencing factors of the middle layer include medical service capacity (N3), emergency rescue capacity

(N4), per capita disposable income (N6), fixed-asset investment (N5), and population density (N2). The average annual rainfall (N9) and vulnerable groups (N1) are the deep and fundamental influencing factors and the root causes of urban flood problems.
2. The importance of correctly identifying indicators is of great significance for evaluating flood resilience. The ANP method used in this study scores the importance of indicators with the help of experts' knowledge and experience, ensuring the results are more in line with reality. The results of the ANP model show that the key indicators affecting urban flood resilience are average annual rainfall (N9), fixed-asset investments (N5), emergency rescue capability (N4), vulnerable groups (N1), and disaster prevention funding (N7).
3. The levels of flood resilience of Zhengzhou, Xi'an, and Jinan were evaluated. According to the research results, the resilience level of Xi'an is the best, followed by Jinan, and the flood resilience of Zhengzhou is relatively weak. The economic resilience and infrastructure resilience of Xi'an need to be enhanced; for Jinan City, the resilience performance of the four dimensions is moderate, and there is no particularly poor dimension. However, Zhengzhou's social resilience and ecological environment resilience levels are poor and need to be consolidated and improved urgently.

The initial data of ISM and ANP are derived from the opinions of the expert group, which makes the evaluation results more consistent with the actual situation. The assessment results of the ISM-ANP-TOPSIS integrated evaluation model were relatively reliable. Nevertheless, there are still areas to be improved in this study: the selection of indicators considering the availability of data was limited; when there were disagreements among expert groups, only the generally accepted valid data were retained, which may lead to some inaccuracies. These issues need to be further enhanced and improved through further research.

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Data Availability Statement: Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Weighted Supermatrix.

	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12	N13
N1	0.0000	0.1629	0.2053	0.1650	0.0000	0.1375	0.1375	0.0000	0.0000	0.0000	0.1667	0.2222	0.1667
N2	0.1387	0.0000	0.0815	0.1650	0.0000	0.1092	0.0000	0.0000	0.1465	0.0000	0.0000	0.0000	0.1667
N3	0.0000	0.0646	0.0000	0.0000	0.1250	0.0866	0.1092	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
N4	0.2774	0.1026	0.1293	0.0000	0.1250	0.0000	0.0866	0.0000	0.1465	0.0000	0.0833	0.1111	0.0000
N5	0.1818	0.0000	0.3635	0.0000	0.0000	0.1667	0.0000	0.2929	0.1294	0.2761	0.2500	0.0000	0.3333
N6	0.1818	0.1922	0.0000	0.0000	0.1250	0.0000	0.0000	0.0000	0.0494	0.0000	0.0000	0.0000	0.0000
N7	0.0000	0.0961	0.0000	0.2883	0.1250	0.1667	0.0000	0.0000	0.0283	0.1381	0.0000	0.3333	0.0000
N8	0.0000	0.2068	0.0000	0.0000	0.0777	0.3333	0.0000	0.0000	0.1953	0.1953	0.0000	0.0000	0.1111
N9	0.0000	0.0000	0.0000	0.2068	0.1234	0.0000	0.3333	0.2761	0.0000	0.3905	0.2500	0.0000	0.2222
N10	0.0000	0.0000	0.0000	0.0000	0.0490	0.0000	0.0000	0.1381	0.0976	0.0000	0.0000	0.0000	0.0000
N11	0.1469	0.0583	0.1102	0.0454	0.0650	0.0000	0.0000	0.1465	0.1381	0.0000	0.0000	0.0000	0.0000
N12	0.0000	0.0583	0.0000	0.0721	0.1032	0.0000	0.3333	0.1465	0.0000	0.0000	0.0000	0.0000	0.0000
N13	0.0735	0.0583	0.1102	0.0572	0.0819	0.0000	0.0000	0.0000	0.0690	0.0000	0.2500	0.3333	0.0000

Table A2. Limit Supermatrix.

	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12	N13
N1	0.09024	0.09024	0.09024	0.09024	0.09024	0.09024	0.09024	0.09024	0.09024	0.09024	0.09024	0.09024	0.09024
N2	0.06813	0.06813	0.06813	0.06813	0.06813	0.06813	0.06813	0.06813	0.06813	0.06813	0.06813	0.06813	0.06813
N3	0.03446	0.03446	0.03446	0.03446	0.03446	0.03446	0.03446	0.03446	0.03446	0.03446	0.03446	0.03446	0.03446
N4	0.09177	0.09177	0.09177	0.09177	0.09177	0.09177	0.09177	0.09177	0.09177	0.09177	0.09177	0.09177	0.09177
N5	0.12825	0.12825	0.12825	0.12825	0.12825	0.12825	0.12825	0.12825	0.12825	0.12825	0.12825	0.12825	0.12825
N6	0.05201	0.05201	0.05201	0.05201	0.05201	0.05201	0.05201	0.05201	0.05201	0.05201	0.05201	0.05201	0.05201
N7	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872
N8	0.08144	0.08144	0.08144	0.08144	0.08144	0.08144	0.08144	0.08144	0.08144	0.08144	0.08144	0.08144	0.08144
N9	0.13113	0.13113	0.13113	0.13113	0.13113	0.13113	0.13113	0.13113	0.13113	0.13113	0.13113	0.13113	0.13113
N10	0.03032	0.03032	0.03032	0.03032	0.03032	0.03032	0.03032	0.03032	0.03032	0.03032	0.03032	0.03032	0.03032
N11	0.06356	0.06356	0.06356	0.06356	0.06356	0.06356	0.06356	0.06356	0.06356	0.06356	0.06356	0.06356	0.06356
N12	0.06481	0.06481	0.06481	0.06481	0.06481	0.06481	0.06481	0.06481	0.06481	0.06481	0.06481	0.06481	0.06481
N13	0.07669	0.07669	0.07669	0.07669	0.07669	0.07669	0.07669	0.07669	0.07669	0.07669	0.07669	0.07669	0.07669

Appendix B

Part I. Basic information.

1. Your gender is ( )

a. Male b. Female

2. Your age is ( )

a. 30–39 years old b. 40–49 years old c. 50 years old and above

3. Your job category is ( )

a. Colleges and universities b. Government departments c. State-owned enterprises d. Research institutes

4. Your area of expertise or research is ( )

a. Urban resilience b. Flood management c. Risk assessment d. Flood prevention and mitigation

Part II. The following evaluation indicators were initially established in this research, and you are invited to score them according to the level of importance. If you have additional information, please fill in the last column.

Table A3. Questionnaire.

First-Level Indicators	Secondary Indicators	Score Column					Supplementary
		Extremely Important	Important	General Importance	Not Important	Least Important	
Social resilience	Vulnerable groups	☐	☐	☐	☐	☐	
	Population density	☐	☐	☐	☐	☐	
	Medical service capacity	☐	☐	☐	☐	☐	
	Public awareness of disaster prevention	☐	☐	☐	☐	☐	
	Emergency rescue capability	☐	☐	☐	☐	☐	
Economic resilience	Fixed-asset investments	☐	☐	☐	☐	☐	
	Per capita disposable income	☐	☐	☐	☐	☐	
	Local revenue	☐	☐	☐	☐	☐	
	Disaster prevention capital investment	☐	☐	☐	☐	☐	
Ecological environment resilience	Green coverage rate of built-up district	☐	☐	☐	☐	☐	
	Average annual rainfall	☐	☐	☐	☐	☐	
	Harmless disposal rate of domestic waste	☐	☐	☐	☐	☐	
	Spatial structure of land use	☐	☐	☐	☐	☐	
Infrastructure resilience	Drainage pipe density in built-up area	☐	☐	☐	☐	☐	
	Internet penetration	☐	☐	☐	☐	☐	
	Per capita road area	☐	☐	☐	☐	☐	
	Capability of sewage treatment	☐	☐	☐	☐	☐	

References

1. Kotzee, I.; Reyers, B. Piloting a social-ecological index for measuring flood resilience: A composite index approach. *Ecol. Indic.* **2016**, *60*, 45–53. [CrossRef]
2. Ruan, J.; Chen, Y.; Yang, Z. Assessment of temporal and spatial progress of urban resilience in Guangzhou under rainstorm scenarios. *Int. J. Disaster Risk Reduct.* **2021**, *66*, 102578. [CrossRef]
3. Kellens, W.; Terpstra, T.; De Maeyer, P. Perception and Communication of Flood Risks: A Systematic Review of Empirical Research. *Risk Anal.* **2013**, *33*, 24–49. [CrossRef] [PubMed]
4. Jha, A.K.; Bloch, R.; Lamond, J. *Cities and Flooding: A Guide to Integrated Urban Flood Risk Management for the 21st Century*; World Bank Publications: Washington, DC, USA, 2012.
5. Liao, K.-H. A Theory on Urban Resilience to Floods—A Basis for Alternative Planning Practices. *Ecol. Soc.* **2012**, *17*, 48. [CrossRef]
6. Sun, H.; Cheng, X.; Dai, M. Regional flood disaster resilience evaluation based on analytic network process: A case study of the Chaohu Lake Basin, Anhui Province, China. *Nat. Hazards* **2016**, *82*, 39–58. [CrossRef]
7. Han, G.; Kasperson, R.E. Dilemmas and pathways to dealing with flood problems in twenty-first century China. *Int. J. Disaster Risk Sci.* **2011**, *2*, 21–30. [CrossRef]
8. China Flood and Drought Disaster Bulletin. Available online: http://www.mwr.gov.cn/ (accessed on 15 March 2023).
9. Darnthamrongkul, W.; Mozingo, L.A. Toward sustainable stormwater management: Understanding public appreciation and recognition of urban Low Impact Development (LID) in the San Francisco Bay Area. *J. Environ. Manag.* **2021**, *300*, 113716. [CrossRef]
10. Rodriguez, C.N.A.S.; Ashley, R.; Gersonius, B.; Rijke, J.; Pathirana, A.; Zevenbergen, C. Incorporation and application of resilience in the context of water-sensitive urban design: Linking European and Australian perspectives. *WIREs Water* **2014**, *1*, 173–186. [CrossRef]
11. Wilson, S.; Bray, R.; Cooper, P. *Sustainable Drainage Systems. Hydraulic, Structural and Water Quality Advice*; Ciria: London, UK, 2004.
12. Lashford, C.; Rubinato, M.; Cai, Y.; Hou, J.; Abolfathi, S.; Coupe, S.; Charlesworth, S.; Tait, S. SuDS & Sponge Cities: A Comparative Analysis of the Implementation of Pluvial Flood Management in the UK and China. *Sustainability* **2019**, *11*, 213. [CrossRef]
13. Center, A.D.R. *Sendai Framework for Disaster Risk Reduction 2015–2030*; United Nations Office for Disaster Risk Reduction: Geneva, Switzerland, 2015.
14. Holling, C.S. Resilience and stability of ecological systems. *Annu. Rev. Ecol. Syst.* **1973**, *4*, 1–23. [CrossRef]
15. Zhu, S.; Li, D.; Huang, G.; Chhipi-Shrestha, G.; Nahiduzzaman, K.M.; Hewage, K.; Sadiq, R. Enhancing urban flood resilience: A holistic framework incorporating historic worst flood to Yangtze River Delta, China. *Int. J. Disaster Risk Reduct.* **2021**, *61*, 102355. [CrossRef]
16. Zheng, J.; Huang, G. Integrating resilience into an urban flood risk assessment framework: A case study of the Minzhi region, Shenzhen City. *Stoch. Environ. Res. Risk Assess.* **2023**, *37*, 1183–1197. [CrossRef]
17. Sen, M.K.; Dutta, S.; Kabir, G. Modelling and quantification of time-varying flood resilience for housing infrastructure using dynamic Bayesian Network. *J. Clean. Prod.* **2022**, *361*, 132266. [CrossRef]
18. Chen, K.-F.; Leandro, J. A Conceptual Time-Varying Flood Resilience Index for Urban Areas: Munich City. *Water* **2019**, *11*, 830. [CrossRef]
19. Mehryar, S.; Surminski, S. Investigating flood resilience perceptions and supporting collective decision-making through fuzzy cognitive mapping. *Sci. Total Environ.* **2022**, *837*, 155854. [CrossRef]
20. Moghadas, M.; Asadzadeh, A.; Vafeidis, A.; Fekete, A.; Kötter, T. A multi-criteria approach for assessing urban flood resilience in Tehran, Iran. *Int. J. Disaster Risk Reduct.* **2019**, *35*, 101069. [CrossRef]
21. Chen, X.; Guo, Z.; Zhou, H.; Qian, X.; Zhang, X. Urban Flood Resilience Assessment Based on VIKOR-GRA: A Case Study in Chongqing, China. *KSCE J. Civ. Eng.* **2022**, *26*, 4178–4194. [CrossRef]
22. Miguez, M.G.; Veról, A.P. A catchment scale Integrated Flood Resilience Index to support decision making in urban flood control design. *Environ. Plan. B: Urban Anal. City Sci.* **2017**, *44*, 925–946. [CrossRef]
23. Tayyab, M.; Zhang, J.; Hussain, M.; Ullah, S.; Liu, X.; Khan, S.N.; Baig, M.A.; Hassan, W.; Al-Shaibah, B. GIS-Based Urban Flood Resilience Assessment Using Urban Flood Resilience Model: A Case Study of Peshawar City, Khyber Pakhtunkhwa, Pakistan. *Remote Sens.* **2021**, *13*, 1864. [CrossRef]
24. Liu, Z.; Jiang, Z.; Xu, C.; Cai, G.; Zhan, J. Assessment of provincial waterlogging risk based on entropy weight TOPSIS–PCA method. *Nat. Hazards* **2021**, *108*, 1545–1567. [CrossRef]
25. Khadka, A.; Kokkonen, T.; Niemi, T.J.; Lähde, E.; Sillanpää, N.; Koivusalo, H. Towards natural water cycle in urban areas: Modelling stormwater management designs. *Urban Water J.* **2020**, *17*, 587–597. [CrossRef]
26. Khiavi, A.N.; Vafakhah, M.; Sadeghi, S.H. Flood-based critical sub-watershed mapping: Comparative application of multi-criteria decision making methods and hydrological modeling approach. *Stoch. Environ. Res. Risk Assess.* **2023**. [CrossRef]
27. Ai, N.; Kjerland, M.; Klein-Banai, C.; Theis, T.L. Sustainability assessment of universities as small-scale urban systems: A comparative analysis using Fisher Information and Data Envelopment Analysis. *J. Clean. Prod.* **2019**, *212*, 1357–1367. [CrossRef]
28. Zheng, J.; Huang, G. Towards flood risk reduction: Commonalities and differences between urban flood resilience and risk based on a case study in the Pearl River Delta. *Int. J. Disaster Risk Reduct.* **2023**, *86*, 103568. [CrossRef]

29. Wang, P.; Li, Y.; Zhang, Y. An urban system perspective on urban flood resilience using SEM: Evidence from Nanjing city, China. *Nat. Hazards* **2021**, *109*, 2575–2599. [CrossRef]
30. Shang, X.; Song, M.; Huang, K.; Jiang, W. An improved evidential DEMATEL identify critical success factors under uncertain environment. *J. Ambient. Intell. Humaniz. Comput.* **2020**, *11*, 3659–3669. [CrossRef]
31. Zhou, X.; Shi, Y.; Deng, X.; Deng, Y. D-DEMATEL: A new method to identify critical success factors in emergency management. *Saf. Sci.* **2017**, *91*, 93–104. [CrossRef]
32. Wang, L.; Cao, Q.; Zhou, L. Research on the influencing factors in coal mine production safety based on the combination of DEMATEL and ISM. *Saf. Sci.* **2018**, *103*, 51–61. [CrossRef]
33. Haleem, A.; Sushil; Qadri, M.A.; Kumar, S. Analysis of critical success factors of world-class manufacturing practices: An application of interpretative structural modelling and interpretative ranking process. *Prod. Plan. Control.* **2012**, *23*, 722–734. [CrossRef]
34. Parkouhi, S.V.; Ghadikolaei, A.S. A resilience approach for supplier selection: Using Fuzzy Analytic Network Process and grey VIKOR techniques. *J. Clean. Prod.* **2017**, *161*, 431–451. [CrossRef]
35. Mousavi, S.M.; Ataie-Ashtiani, B.; Hosseini, S.M. Comparison of statistical and MCDM approaches for flood susceptibility mapping in northern Iran. *J. Hydrol.* **2022**, *612*, 128072. [CrossRef]
36. Cheng, X.; Sun, H. Study on Influence Factors of Regional Flood Disaster Resilience Based on DEMATEL-ANP. In Proceedings of the 7th Annual Meeting of Risk Analysis Council of China Association for Disaster Prevention, Changsha, China, 4–6 November 2016.
37. Zhu, S.; Li, D.; Feng, H.; Zhang, N. The influencing factors and mechanisms for urban flood resilience in China: From the perspective of social-economic-natural complex ecosystem. *Ecol. Indic.* **2023**, *147*, 109959. [CrossRef]
38. Li, D.; Zhu, X.; Huang, G.; Feng, H.; Zhu, S.; Li, X. A hybrid method for evaluating the resilience of urban road traffic network under flood disaster: An example of Nanjing, China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 46306–46324. [CrossRef] [PubMed]
39. Xu, W.; Cong, J.; Proverbs, D.; Zhang, L. An Evaluation of Urban Resilience to Flooding. *Water* **2021**, *13*, 2022. [CrossRef]
40. Zhang, H.; Yang, J.; Li, L.; Shen, D.; Wei, G.; Khan, H.U.R.; Dong, S. Measuring the resilience to floods: A comparative analysis of key flood control cities in China. *Int. J. Disaster Risk Reduct.* **2021**, *59*, 102248. [CrossRef]
41. Hwang, C.-L.; Yoon, K. Methods for multiple attribute decision making. In *Multiple Attribute Decision Making*; Springer: Berlin/Heidelberg, Germany, 1981; pp. 58–191.
42. Birgani, Y.T.; Yazdandoost, F. An integrated framework to evaluate resilient-sustainable urban drainage management plans using a combined-adaptive MCDM technique. *Water Resour. Manag.* **2018**, *32*, 2817–2835. [CrossRef]
43. Hu, L.; Zhang, Q.; Wang, G.; Singh, V.P.; Wu, W.; Fan, K.; Shen, Z. Flood disaster risk and socioeconomy in the Yellow River Basin, China. *J. Hydrol. Reg. Stud.* **2022**, *44*, 101272. [CrossRef]
44. Rapport, D.J.; Friend, A.M. *Towards a Comprehensive Framework for Environmental Statistics: A Stress-Response Approach*; Statistics Canada: Ottawa, ON, Canada, 1979.
45. Ji, J.; Chen, J. Urban flood resilience assessment using RAGA-PP and KL-TOPSIS model based on PSR framework: A case study of Jiangsu province, China. *Water Sci. Technol.* **2022**, *86*, 3264–3280. [CrossRef]
46. Ma, S.J.; Wang, R.S. The social-economic-natural complex ecosystem. *Acta Ecol. Sin.* **1984**, *4*, 1–9.
47. Lianxiao; Morimoto, T.; Siqin, T.; An, C.; Yuhai, B.; Fei, G. Evaluating Regional Flood Disaster Resilience Based on the DROP Model and TOPSIS Method: A Case Study of the Katsushika Ward, Tokyo. *Nat. Hazards Rev.* **2022**, *23*, 04022018. [CrossRef]
48. Berndtsson, R.; Becker, P.; Persson, A.; Aspegren, H.; Haghighatafshar, S.; Jönsson, K.; Larsson, R.; Mobini, S.; Mottaghi, M.; Nilsson, J.; et al. Drivers of changing urban flood risk: A framework for action. *J. Environ. Manag.* **2019**, *240*, 47–56. [CrossRef] [PubMed]
49. Oliver, M.-C.; Jesús, L.-D.l.C.; Ian, P.; Ma, M.-P.; Manuel, U.-R.J.; Ivan, R.-L.C.; Pedro, R.-A. Disaster Risk Resilience in Colima-Villa de Alvarez, Mexico: Application of the Resilience Index to Flash Flooding Events. *Int. J. Environ. Res. Public Health* **2019**, *16*, 2128. [CrossRef] [PubMed]
50. Zhang, X.; Song, J.; Peng, J.; Wu, J. Landslides-oriented urban disaster resilience assessment—A case study in ShenZhen, China. *Sci. Total Environ.* **2019**, *661*, 95–106. [CrossRef] [PubMed]
51. Kablan, M.K.A.; Dongo, K.; Coulibaly, M. Assessment of Social Vulnerability to Flood in Urban Côte d'Ivoire Using the MOVE Framework. *Water* **2017**, *9*, 292. [CrossRef]
52. Haque, M.M.; Islam, S.; Sikder, M.B.; Islam, M.S. Community flood resilience assessment in Jamuna floodplain: A case study in Jamalpur District Bangladesh. *Int. J. Disaster Risk Reduct.* **2022**, *72*, 102861. [CrossRef]
53. Sarmah, T.; Das, S.; Narendr, A.; Aithal, B.H. Assessing human vulnerability to urban flood hazard using the analytic hierarchy process and geographic information system. *Int. J. Disaster Risk Reduct.* **2020**, *50*, 101659. [CrossRef]
54. Sundaram, S.; Devaraj, S.; Yarrakula, K. Modeling, mapping and analysis of urban floods in India—A review on geospatial methodologies. *Environ. Sci. Pollut. Res.* **2021**, *28*, 67940–67956. [CrossRef]
55. Nayeri, S.; Asadi-Gangraj, E.; Emami, S. Metaheuristic algorithms to allocate and schedule of the rescue units in the natural disaster with fatigue effect. *Neural Comput. Appl.* **2019**, *31*, 7517–7537. [CrossRef]
56. Sun, R.; Shi, S.; Reheman, Y.; Li, S. Measurement of urban flood resilience using a quantitative model based on the correlation of vulnerability and resilience. *Int. J. Disaster Risk Reduct.* **2022**, *82*, 103344. [CrossRef]

57. Yang, Y.; Guo, H.; Wang, D.; Ke, X.; Li, S.; Huang, S. Flood vulnerability and resilience assessment in China based on super-efficiency DEA and SBM-DEA methods. *J. Hydrol.* **2021**, *600*, 126470. [CrossRef]
58. Zhang, Y.; Xue, W.; Wen, Y.; Wang, X. Sustainability Assessment of Water Resources Use in 31 Provinces in China: A Combination Method of Entropy Weight and Cloud Model. *Int. J. Environ. Res. Public Health* **2022**, *19*, 12870. [CrossRef] [PubMed]
59. Chen, J.; Chen, W.; Huang, G. Assessing urban pluvial flood resilience based on a novel grid-based quantification method that considers human risk perceptions. *J. Hydrol.* **2021**, *601*, 126601. [CrossRef]
60. Chen, A.B.; Goodall, J.L.; Chen, T.D.; Zhang, Z. Flood resilience through crowdsourced rainfall data collection: Growing engagement faces non-uniform spatial adoption. *J. Hydrol.* **2022**, *609*, 127724. [CrossRef]
61. Fekete, A. Critical infrastructure and flood resilience: Cascading effects beyond water. *WIREs Water* **2019**, *6*, e1370. [CrossRef]
62. Qiao, H.; Pei, J. Urban Stormwater Resilience Assessment Method Based on Cloud Model and TOPSIS. *Int. J. Environ. Res. Public Health* **2022**, *19*, 38. [CrossRef]
63. Bertilsson, L.; Wiklund, K.; Tebaldi, I.D.M.; Rezende, O.M.; Veról, A.P.; Miguez, M.G. Urban flood resilience–A multi-criteria index to integrate flood resilience into urban planning. *J. Hydrol.* **2019**, *573*, 970–982. [CrossRef]
64. Wang, Y.; Meng, F.; Liu, H.; Zhang, C.; Fu, G. Assessing catchment scale flood resilience of urban areas using a grid cell based metric. *Water Res.* **2019**, *163*, 114852. [CrossRef]
65. Xu, W.; Zhong, M.; Hong, Y.; Lin, K. Enhancing community resilience to urban floods with a network structuring model. *Saf. Sci.* **2020**, *127*, 104699. [CrossRef]
66. Trepanier, J.C.; Tucker, C.S. Event-based climatology of tropical cyclone rainfall in Houston, Texas and Miami, Florida. *Atmosphere* **2018**, *9*, 170. [CrossRef]
67. Albert, C.; Rufat, S.; Kuhlicke, C. Five principles for climate-resilient cities. *Nature* **2021**, *596*, 486. [CrossRef]
68. Liang, Z. Assessment of the Construction of a Climate Resilient City: An Empirical Study Based on the Difference in Differences Model. *Int. J. Environ. Res. Public Health* **2021**, *18*, 2082. [CrossRef] [PubMed]
69. Zeng, C.; Aboagye, E.M.; Li, H.; Che, S. Comments and recommendations on Sponge City—China's solutions to prevent flooding risks. *Heliyon* **2023**, *9*, e12745. [CrossRef] [PubMed]