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Urban Flood Resilience Evaluation Based on GIS and Multi-Source Data: A Case Study of Changchun City

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Abstract: With extreme rainfall events and rapid urbanization, urban flood disaster events are increasing dramatically. As a key flood control city in China, Changchun City suffers casualties and economic losses every year due to floods. The improvement of flood resilience has become an important means for cities to resist flood risks. Therefore, this paper constructs an assessment model of urban flood resilience from four aspects: infrastructure, environment, society and economy. Then, it quantifies infrastructure and environmental vulnerability based on GIS, and uses TOPSIS to quantify social and economic recoverability. Finally, based on k-means clustering of infrastructure and environmental vulnerability and social and economic recoverability, the flood resilience of Changchun City was evaluated. The results show that different factors have different effects on flood resilience, and cities with low infrastructure and environmental vulnerability and high socioeconomic recoverability are more resilient in the face of floods. In addition, cities in the same cluster have the same flood resilience characteristics. The proposed framework can be extended to other regions of China or different countries by simply modifying the indicator system according to different regions, providing experience for regional flood mitigation and improving flood resilience.

Keywords: urban flood resilience; analytic hierarchy process; remote sensing and GIS; TOPSIS; k-means; resilience evaluation

1. Introduction

Over the past few decades, urbanization has accelerated in countries around the world. At the same time, climate change, mainly characterized by global warming, has exacerbated the occurrence of extreme weather events [1]. In the past 30 years, the global economic loss caused by natural disasters was about USD 4 trillion, 75% of which were related to major hydrometeorological extreme weather events, and urban flood disasters accounted for 43.4% of hydrometeorological disasters [2,3]. China is one of the countries with a high incidence of waterlogging [4,5]. In the first half of 2020 alone, floods affected 11.22 million people and caused economic losses of USD 3.6 billion [6]. Considering the changes in precipitation patterns and the damage they have caused in recent years, traditional safety concepts and disaster prevention measures are no longer sufficient for China's current and future urban development. Therefore, in order to reduce the damage caused by floods and achieve sustainable urban development, it is important to strengthen the flood control capacity of urban communities [7].

Urban flood resilience is defined as the ability of a city and its constituent systems (society, economy, environment, infrastructure, etc.) to resist, cope with, recover from and adapt to urban flood disasters caused by rainstorms or heavy precipitation [8,9]. At present, scholars' research on flood disasters mainly focuses on the evaluation of flood resilience [10,11], the evaluation of flood vulnerability [12,13] and the evaluation of flood risk [14,15]. With the further development of flood disaster research, the study of flood resilience becomes increasingly important [16]. Flood resilience is mainly based on the

establishment of an index system based on the theoretical framework for evaluation [17]. For example, Siebeneck et al. assessed flood resilience in 76 Thai provinces and territories using 25 metrics [18]. Qasim et al. identified community flood disaster resilience indicators at four levels, i.e., social, economic, institutional, and physical, and calculated community resilience indices for three districts in Khyber Pakhtunkhwa province using expert scoring [19]. Bertilsson et al. proposed the urban spatial Flood Resistance Index (S-FRESI) to measure the changes in flood resistance obtained by different flood control measures [20]. Huiming Zhang et al. used the entropy weight method and the TOPSIS model to evaluate the flood resilience of flood control cities in major river basins in China [21]. Liu Gang et al. used the analytic hierarchy process to evaluate the urban flood resilience of Suzhou, Wuxi and Changzhou from the aspects of stimulation, sensitivity and adaptability, and concluded that Suzhou had the strongest resilience and Changzhou had the weakest resilience [22]. Orencio P et al. constructed a system of resilience indicators for coastal communities to cope with floods from seven aspects that affect their disaster resilience, and used the AHP to calculate an urban resilience index [23]. Lyu, H et al. compared the flood risk in the subway system based on AHP and evaluated the subway system in Guangzhou. In addition, they used GIS software to verify the flood injection risk in different areas of the subway based on the actual occurrence of a flood [24].

In addition to the above methods, recent studies have begun to consider the combination of vulnerability and resilience to consider flood resilience, which can better consider the interaction and connection between various factors, such as Ruirui Sun based on the quantitative model of the correlation between vulnerability and resilience, an urban flood resilience evaluation model from pre-disaster exposure, disaster sensitivity and adaptability, and post-disaster recovery ability to evaluate the resilience of flood disasters in Beijing [25]. However, the flood resilience evaluation index system established considering vulnerability and resilience is limited by the influence of the database, and only limited indicators can be considered. The data source is also single statistical data, and the accuracy of the data also determines the usefulness of the analysis results. Most studies only ranked the flood resilience of cities in the study area separately, unable to identify clusters of cities with similar characteristics, and cities with similar characteristics often have the same problems. Therefore, further research is required.

To sum up, this paper uses hierarchical analysis to determine indicator weights from the perspective of infrastructure and environmental vulnerability and socioeconomic recoverability. All indicator data of infrastructure and environment are based on remote sensing and GIS data, and GIS is used to determine the vulnerability of infrastructure and environment. The socioeconomic indicators are all based on statistical data, and the determination of socioeconomic recoverability is based on the TOPSIS method. Finally, based on the k-means method, a cluster analysis of cities with similar flood resilience in Changchun was conducted based on infrastructure and environmental vulnerability and socioeconomic recoverability to provide a theoretical basis for improving urban flood resilience in Changchun.

2. Materials and Methods

2.1. Data and Methodology

2.1.1. The Study Area

Changchun is located at 43°05′–45°15′N and 124°18′–127°05′E. The relief is relatively gentle, and the height is mainly distributed around 300 m. The average annual temperature in the study area is 4.6 °C. Precipitation mainly occurs from June to September, with an uneven distribution and an increasing trend from west to east. The average annual precipitation is between 600 and 700 mm. The river systems in the study area include the Lalin River and the Songhua River. The main rivers are the Yitong River, the Wukai River and the Xinkai River. Due to the lack of data for Gongzhuling City, we excluded this city from the study area, as shown in Figure 1.
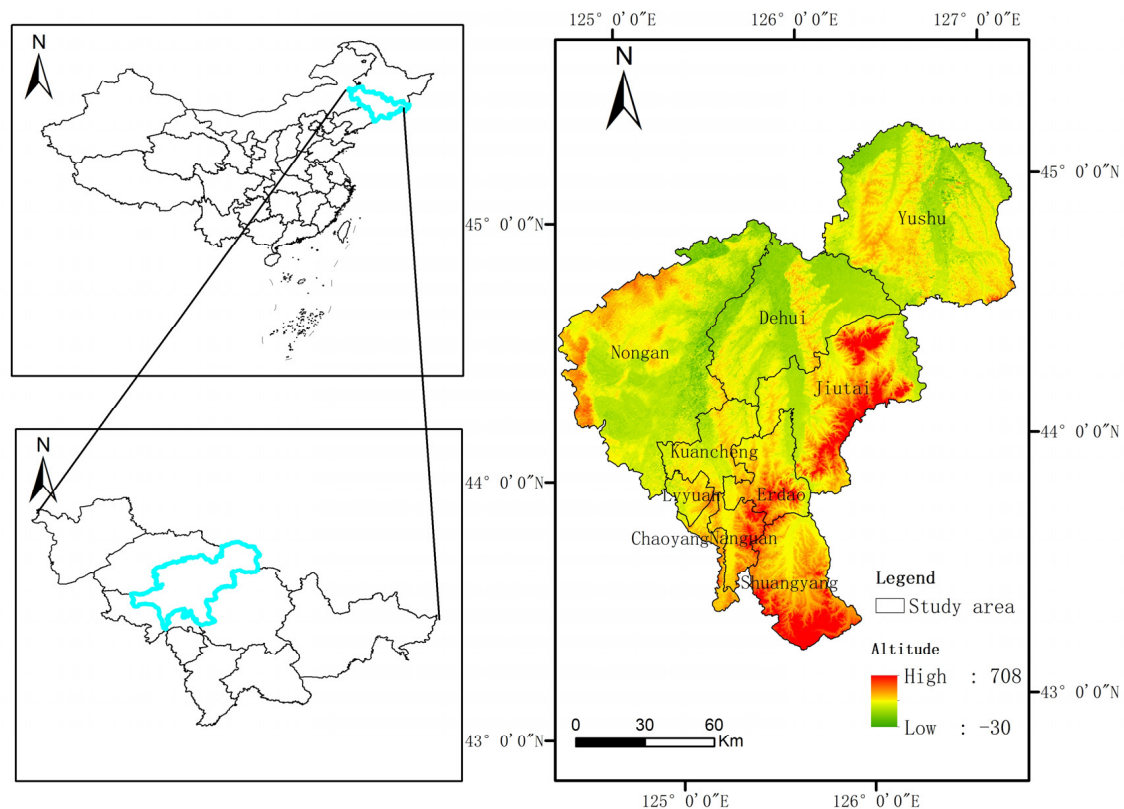
Figure 1. Location map of the study area.

2.1.2. Selection of Evaluation Index

Selecting and establishing a scientific index system and evaluation criteria is the key to evaluating urban flood resilience. The acquisition of indicators requires the further comprehensive extraction of a large amount of information, which is targeted to problems and risk-oriented. On the basis of referring to existing models, frameworks and index systems that are influential, such as the DROP model [26], the PEOPLE framework [27] and the urban resilience index framework [28], and following the principles of comprehensiveness, typicality, applicability, scientificity and feasibility, we divide urban flood resistance capacity into four dimensions: social dimension, economic dimension, infrastructure dimension and environmental dimension. On the basis of these four dimensions, following the principles of reliability, accessibility and operability, indicators that can accurately reflect the relationship between the social dimension, economic dimension, infrastructure dimension, environmental dimension and flood disaster are selected. Table 1 shows the specific index system and the basis of index selection.

Table 1. Urban flood resilience evaluation index system and selection basis.

Criterion Layer	Indicator Layer	Index Selection Basis
Environment	Altitude	Altitude will affect the pressure of urban storm flood system, and low-lying areas are more prone to rain and flood damage [29,30].
	LULC	In the event of flood, different land use types have different degrees of flood damage and different vulnerability. Compared with green space, impervious ground is less able to absorb water and more prone to flooding [31,32].
	Rainfall	Precipitation is an important cause of flood disaster, so precipitation as an evaluation index is important [33].

Table 1. *Cont.*

Criterion Layer	Indicator Layer	Index Selection Basis
	NDVI	NDVI is an important index of vegetation coverage, and vegetation has certain resistance to flood disaster [34].
	Slope	Slope determines the current flood velocity, so slope selection is also an important evaluation index [35].
	Distance to water bodies	The closer an area is to rivers and lakes, the more likely it is to flood [34].
Infrastructure	Road density	Road density also affects the evacuation of people during flood disasters, which helps improve resilience [36].
	Building density	The more built up an area is, the more vulnerable it is to flooding [37].
	Drainage density	Drainage pipe network can remove the flood as soon as possible when the flood disaster occurs, which is an important means of urban drainage [36].
	GDP per capita	In general, economically less developed areas are more vulnerable to flooding [36].
	Flood defense investment as a proportion of public expenditure	The higher the proportion of flood control investment, the lower the probability of flood disaster and the loss caused by flood disaster [37].
Economy	Proportion of health expenditure	Medical and health finance can provide important guarantees for people's safety after disaster [38].
	Fiscal revenue	Fiscal revenue represents the economic strength of local governments. The higher the fiscal revenue, the stronger the resilience to flood disasters [38].
	The number of industrial enterprises above designated size	Large companies are more resilient to flooding [38].
	Population density	The greater the population density, the greater the damage caused by flood disaster [39].
	Proportion of talents in higher education	Education can improve people's awareness and knowledge of disasters. People with higher education levels have stronger coping abilities when flood disasters happen [40].
	Proportion of water conservancy employees	The higher the proportion of water conservancy employees, the lower the loss caused by a flood disaster [38].
Society	Number of beds in health institutions per 10,000 people	Provide relief facilities during and after flood disasters. The more beds available, the better the first aid and recovery capacity [41].
	Health professionals per 10,000 population	Health workers can provide relief during and after floods [41].
	Unemployment rate	Unemployment rate is an important factor for social stability. The higher the unemployment rate, the greater the loss caused by the flood disaster [41].
	Coverage of basic medical insurance	As an important means of social security, basic medical insurance provides important medical security for the disaster-stricken people after the flood disaster [39].

2.1.3. Data Collection

This paper establishes an index system of flood resilience in Changchun from four aspects: infrastructure, environment, society and economy. The data for the infrastructure index and environment index come from remote sensing and GIS data, while the data for the socioeconomic index come from statistical data. The data types and sources are shown in Table 2, and the technical route is shown in Figure 2.

Table 2. Data types and sources of urban flood resilience evaluation index.

| Evaluation Index	Data Type	Date Details	Data Source
Altitude	ASTER GDEM	30 m	Geospatial data cloud
LULC	Raster data	30 m	Data grain
Rainfall	Raster data	2017–2021	National Data Center for Meteorological Sciences
NDVI	Landsat 8 OLI/TIRS	30 m	Data grain
Slope	ASTER GDEM	30 m	Geospatial data cloud
Distance to water bodies	Vector data	2021	Geospatial data cloud
Road density	Road network shape file	2021	Geospatial data cloud
Building density	POI	2021	Planning cloud
Drainage density	Vector data	2021	Planning cloud
GDP per capita	Attribute data	2021	Changchun Statistical Yearbook
Flood defense investment as a proportion of public expenditure	Attribute data	2021	Changchun Statistical Yearbook
Proportion of health expenditure	Attribute data	2021	Changchun Statistical Yearbook
Fiscal revenue	Attribute data	2021	Changchun Statistical Yearbook
The number of industrial enterprises above designated size	Attribute data	2021	Changchun Statistical Yearbook
Population density	Attribute data	2021	Changchun Statistical Yearbook
Proportion of talents in higher education	Attribute data	2021	Changchun Statistical Yearbook
Proportion of water conservancy employees	Attribute data	2021	Changchun Statistical Yearbook
Number of beds in health institutions per 10,000 people	Attribute data	2021	Changchun Statistical Yearbook
Health professionals per 10,000 population	Attribute data	2021	Changchun Statistical Yearbook
Unemployment rate	Attribute data	2021	Changchun Statistical Yearbook
Coverage of basic medical insurance	Attribute data	2021	Changchun Statistical Yearbook
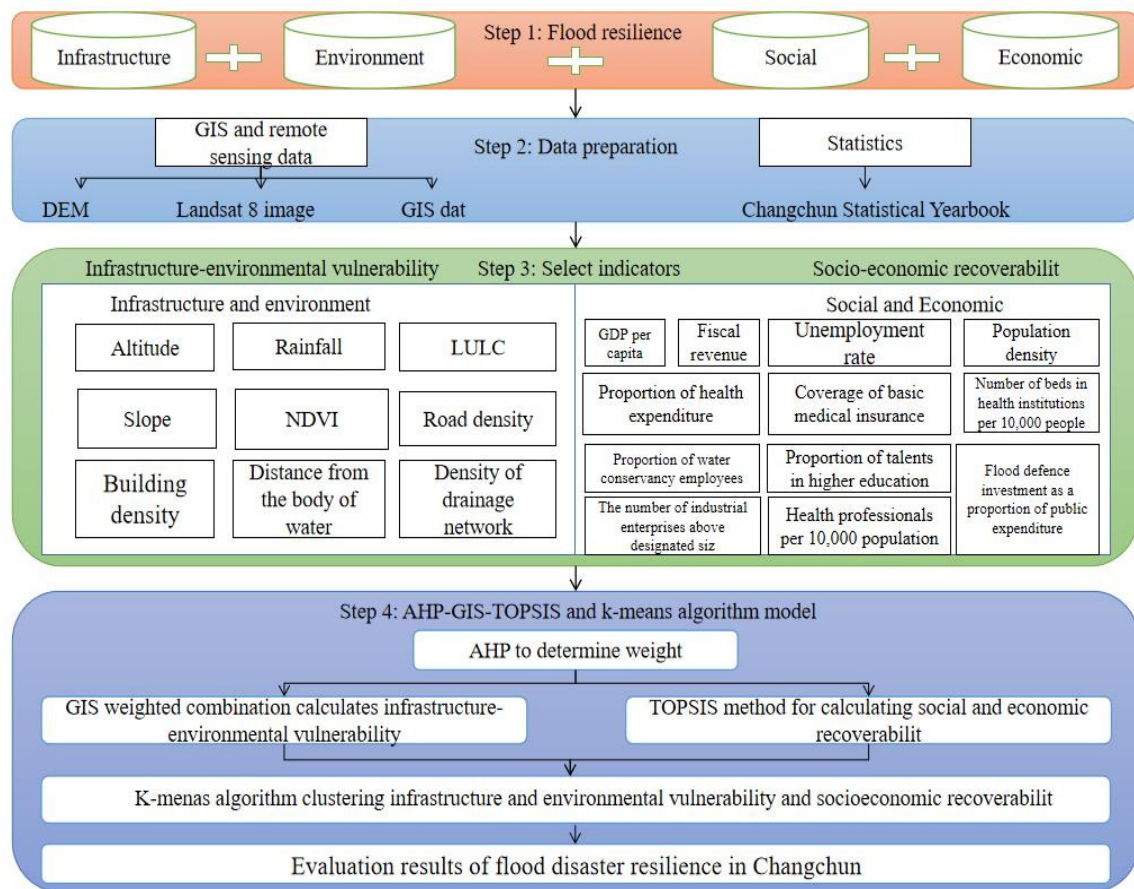
Figure 2. Flow chart of flood resilience evaluation.

2.1.4. Analytic Hierarchy Process (AHP)

The analytic hierarchy process (AHP) [42] is a subjective method to determine weight, proposed by T.L. Satty in the late 1970s. As one of the most widely used knowledge-driven methods, AHP is widely used to calculate the weight of the urban flood resilience evaluation index [20]. The specific steps are as follows:

(1)　Establish a hierarchical structure.

We take flood resilience as the overall target layer; infrastructure, environment, society and economy as the first-level target layer; and specific indicators as the final target layer.

(2)　Construct a pairwise comparison judgment matrix.

We gathered the opinions of five experts in disaster risk and civil engineering and evaluated the importance of the indicators of the same level compared with the indicators of the next level through the method of pairwise comparison. The comparison results between the indicators are represented by numerical scales from 1 to 9 [43] (Table 3).

Table 3. KScale and significance of judgment matrix.

Scale	Meaning
1	Equally important
3	Moderately more important
5	Strongly more important
7	Very strongly more important
9	Extremely more important
2, 4, 6, 8	Intermediate values

(3) Consistency check.

In order to test whether the weight distribution is reasonable, the following formula should be used to test the consistency of the matrix:

$$CI = (\lambda_{max} - n)/(n - 1) \tag{1}$$

$$CR = \frac{CI}{RI} \tag{2}$$

where λ_{max} is the largest characteristic root, n is the number of indicators and CI is the consistency index. RI is the average randomness index, and its value is shown in Table 4. CR is the test coefficient root. If $CR < 0.1$, the matrix passes the consistency test. Table 5 shows the calculation results of index weights.

Table 4. Average randomness index.

Order	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Table 5. Weight of flood resilience index.

Target Layer	Criterion Layer	Criterion Layer Weight	Index Layer	Index Layer Weight
Flood resilience	Infrastructure	0.205	Road density	0.051
			Building density	0.051
			Drainage density	0.102
	Environment	0.169	Altitude	0.020
			Slope	0.013
			Rainfall	0.026
			LULC	0.046
			NDVI	0.038
			Distance to water bodies	0.026
	Economy	0.339	GDP per capita	0.089
			Flood defense investment as a proportion of public expenditure	0.109
			Proportion of health expenditure	0.038
			Fiscal revenue	0.055
			The number of industrial enterprises above designated size	0.048
	Society	0.288	Population density	0.066
			Proportion of talents in higher education	0.031
			Proportion of water conservancy employees	0.053
			Number of beds in health institutions per 10,000 people	0.030
			Health professionals per 10,000 population	0.036
			Unemployment rate	0.044
			Coverage of basic medical insurance	0.028

2.2. Quantifying Flood Resilience

2.2.1. GIS Weighted Combination Quantitative Infrastructure and Environmental Vulnerability

On the basis of collecting the data for infrastructure and environmental indicators, this paper uses ArcGIS 10.8 to process the evaluation indicators, makes each indicator a layer (Figure 3), and then uses the following 9 indicator layers to estimate infrastructure and environmental vulnerability areas: altitude, slope, rainfall, NDVI, distance from a water

body, road density, building density and drainage density. Nine maps are combined by weighted linear combination, in which the weighted average of the continuous standard is standardized into a common numerical range and combined [44], as shown in Equation (3). Finally, the results of infrastructure and environmental vulnerability are counted by region through the ArcGIS regional mean statistical tool. The weight of the index comes from the weight determined by the analytic hierarchy process.

$$S = \sum_{i=1}^{n} W_i X_i \tag{3}$$

where S is infrastructure and environmental vulnerability, n is the number of infrastructure and environmental indicators, W_i is the weight of each individual factor i at the infrastructure and environmental level and X_i is the value of each individual indicator i at the infrastructure and environmental level.
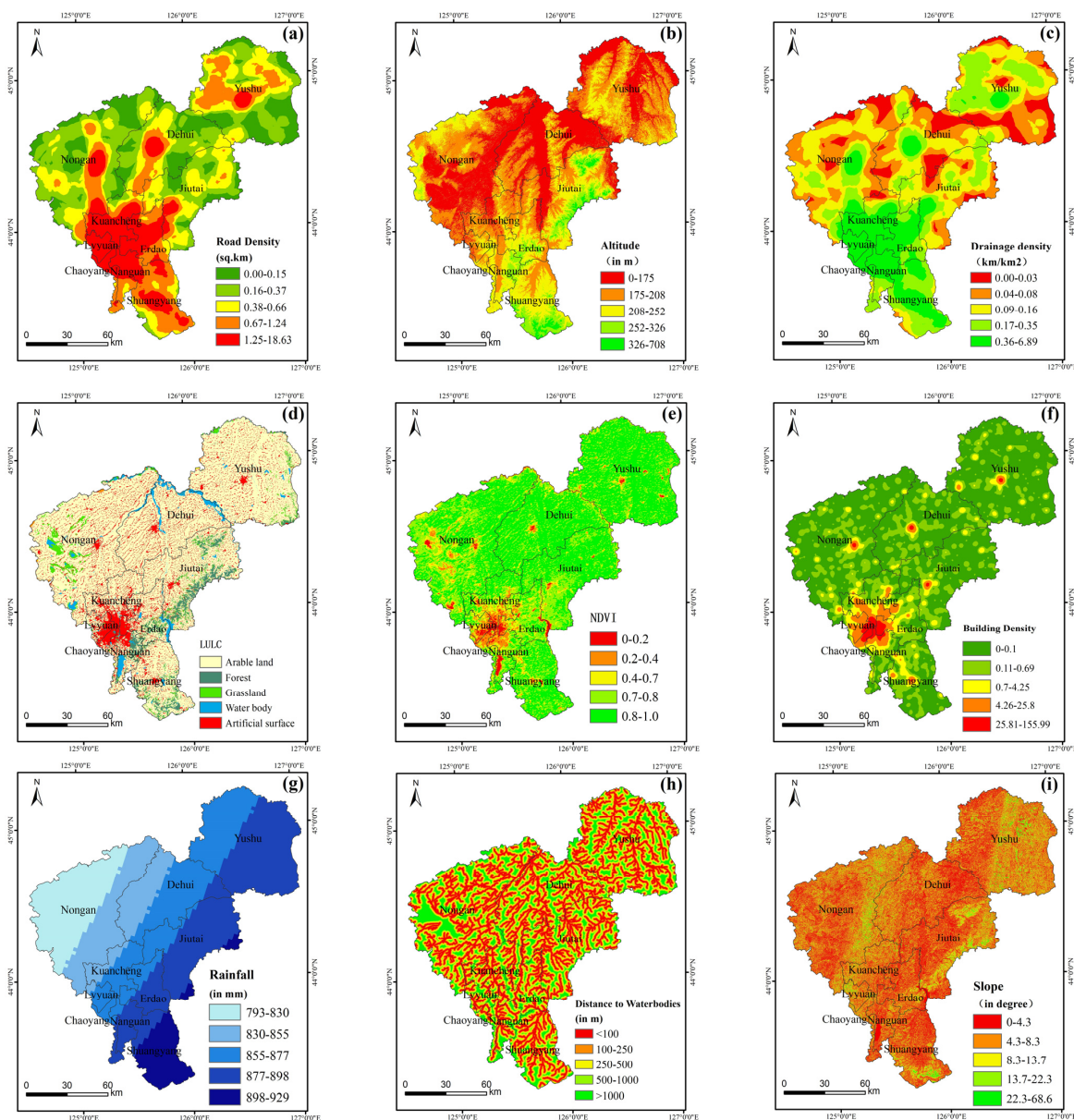

Figure 3. Spatial distribution map of infrastructure and environmental indicators: road density (**a**); altitude (**b**); drainage density (**c**); LULC (**d**); NDVI (**e**); building density (**f**); rainfall (**g**); distance to water bodies (**h**); slope (**i**).

2.2.2. TOPSIS Quantified Socioeconomic Recoverability

The TOPSIS method is an evaluation method proposed by C.L. Wang and K. Yoon in 1980s [45]. In this method, the target value of the evaluation object is taken as the evaluation basis. By comparing the close degree of the actual influence degree of the evaluation object in the criterion layer with the target impact degree, the evaluation object is ranked. The target value here is the influence degree produced by the object with the highest weight through the criterion layer under ideal circumstances, i.e., the best result, so this method is also known as the good and bad distance solution method. Among them, the evaluation is mainly based on the distance between the indicators under the criterion layer and the "positive and negative ideal solution". The closer the distance to the "positive ideal solution", the greater the importance of the evaluation index; similarly, the closer the distance to the "negative ideal solution", the smaller the importance of the evaluation index. The specific calculation steps are as follows:

(1)　Construct a decision matrix.

Constructing an original matrix with m objects and n indexes.

$$X = \left[x_{ij}\right]_{m \times n} \tag{4}$$

(2)　Calculate the weighted normalized matrix.

Because of the difference in the nature of different indicators, there are usually different dimensions. In this paper, the range method is used to standardize the index value so that it is between $[0-1]$.

For the positive index:

$$x'_{ij} = \frac{x_{ij} - min\left(x_{ij}\right)}{max\left(x_{ij}\right) - min\left(x_{ij}\right)} \tag{5}$$

For the negative index:

$$x'_{ij} = \frac{max\left(x_{ij}\right) - x_{ij}}{max\left(x_{ij}\right) - min\left(x_{ij}\right)} \tag{6}$$

In Equations (1) and (2), x_{ij} is the value of the jth index in the ith dimension of the original data, and x_{ij}' is the data after standardization.

A weighted normalized matrix is constructed by multiplying each element in each column of the normalized matrix by the weight obtained by the analytic hierarchy process.

$$Z = z_{ij} = w_j x'_{ij} \, for (i = 1, \ldots m)(j = 1, \ldots n) \tag{7}$$

where w_j is the weight coefficient of the jth factor in social and economic aspects.

(3)　Determine positive and negative ideal solutions.

$$A^+ = \left\{z_1^+, z_2^+ \ldots, z_n^+\right\}, where : Z_j^+ = \left\{\left(max_i(z_{ij}) if \, j \in J\right), \left(min_i z_{ij} if \, j \in J'\right)\right\} \tag{8}$$

$$A^- = \left\{z_1^-, z_2^- \ldots, z_n^-\right\}, where : Z_j^- = \left\{\left(min_i(z_{ij}) if \, j \in J\right), \left(max_i z_{ij} if \, j \in J'\right)\right\} \tag{9}$$

where J is related to the positive index, and J' is related to negative indices.

(4)　Calculate the geometric distance from positive and negative ideal solutions.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(Z_j^+ - Z_{ij} \right)^2} \ (i = 1, 2, \dots m) \tag{10}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(Z_j^- - Z_{ij} \right)^2} \ (i = 1, 2, \dots m) \tag{11}$$

(5)   Calculate the close degree between the evaluation object and the ideal solution.

$$C_i = \frac{S_i^-}{S_i^- + S_i^+} \ 0 \leq C_i \leq 1 \tag{12}$$

The greater the C_i value, the smaller the distance between the index value of the ith city and the positive ideal solution; that is, the better the flood toughness of the ith city.

2.2.3. K-Means Algorithm Clusters Flood Resilience

K-means belongs to unsupervised learning. Compared with clustering algorithms such as Mean-Shift, K-Medians and DBSCAN, it has two advantages. First, the principle of k-means is simpler than other clustering algorithms, and convergence is faster. Second, k-means tuning parameters only need to adjust one parameter. Therefore, k-means is currently a widely used clustering algorithm [46]. The principle of this algorithm is to take the mean value of all data samples in each subcluster as the central point and cluster the dataset by calculating the distance between each point in the class and the central point. The logarithmic data points were classified through the iterative process, and finally the evaluation function was optimized. This is because each subclass is independent of one another, and the characteristics of sample points in the class are more similar.

3. Results

3.1. Infrastructure and Environmental Vulnerability

The overall infrastructure and environmental vulnerability diagram is shown in Figure 4. It can be seen from the diagram that there are obvious differences in infrastructure and environmental vulnerability among different regions of Changchun. Chaoyang District has the highest infrastructure and environmental vulnerability, mainly due to its high rainfall, high road density, gentle topography and low vegetation coverage. Moreover, as the main urban area of Changchun, Chaoyang District has high building density, many land types and many impervious surfaces, which makes it difficult for excessive precipitation to pass through. Earlier sewers were not designed to meet the new demands. Nongan County has the lowest infrastructure and environmental vulnerability due to its high terrain, low road density and high vegetation coverage. Shuangyang District, Jiutai District, Dehui City and Yushu City have low infrastructure and environmental vulnerability. Although the rainfall levels in Shuangyang District, Jiutai District, Dehui City and Yushu City are high, the drainage pipe network density, vegetation coverage and topography of these four areas are relatively high, so they have low infrastructure and environmental vulnerability. Nanguan District, Erdao District and Lvyuan District have high infrastructure and environmental vulnerability due to high building density, gentle terrain and high road density. It is worth noting that although the road density and building density are higher in the wide urban area, the region has higher terrain and a higher drainage network density, so its infrastructure and environmental vulnerability are lower. In conclusion, the infrastructure and environmental vulnerability in the southern city of Changchun is higher than that in the northern city.
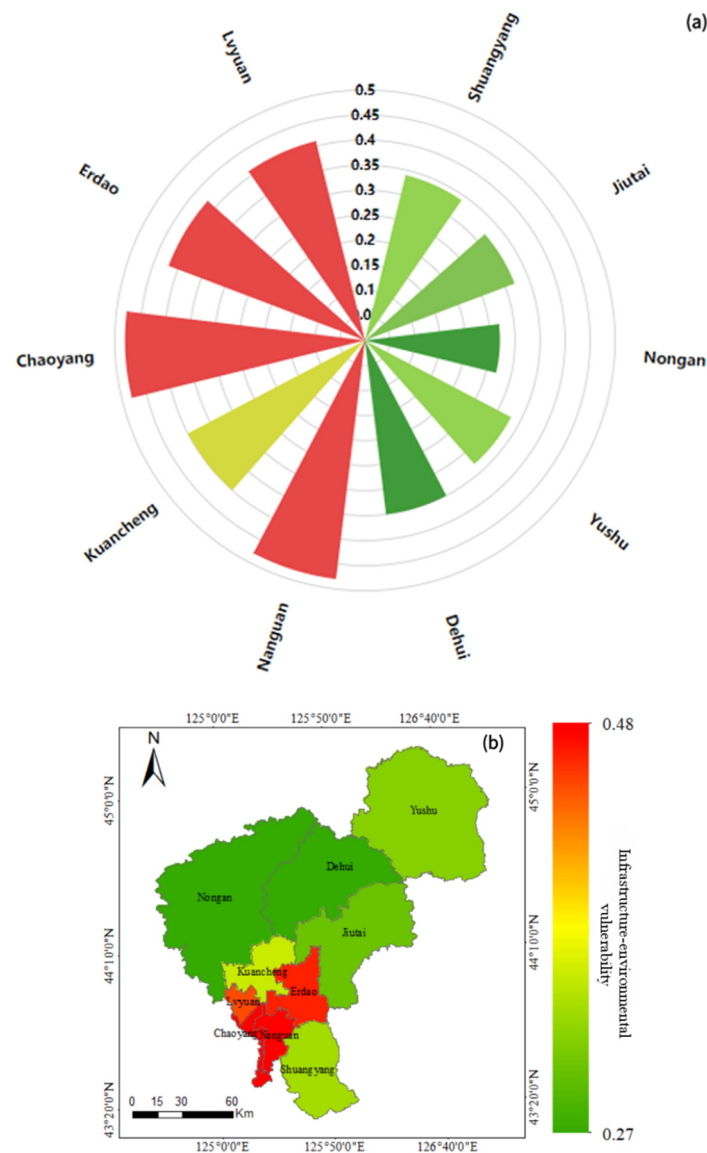
Figure 4. Infrastructure and environmental vulnerability map: vulnerability value (**a**); spatial distribution of vulnerability (**b**).

3.2. Socioeconomic Recoverability

The overall socioeconomic recoverability chart is shown in Figure 5. It can be seen from the chart that there are obvious differences in socioeconomic recoverability among different regions of Changchun. With the highest per capita GDP, flood control investment and fiscal revenue, Chaoyang District ranks first among the ten districts under Changchun in terms of socioeconomic recoverability. The socioeconomic recoverability of Nongan County is the least, because the index values of the coverage of basic medical insurance, the proportion of higher education talents, the proportion of flood control investment in public expenditure and the proportion of water conservancy workers in Nongan County are the smallest among the ten subordinate districts of Changchun City. Lvyuan District, Shuangyang District, Nanguan District and Kuancheng District have basic medical insurance coverage and flood control investment, and the social and economic recovery level is high. Jiutai District, Yushu City and Dehui City, due to the low proportion of water conservancy workers and low investment in flood control, have low socioeconomic recovery. It is worth noting that although flood control investment in Erdao District accounts for a high proportion of public expenditure, its socioeconomic resilience is low due to high population density, a

low GDP per capita and low investment in health care. In conclusion, the socioeconomic recoverability of the southern city of Changchun is higher than that of the northern city.
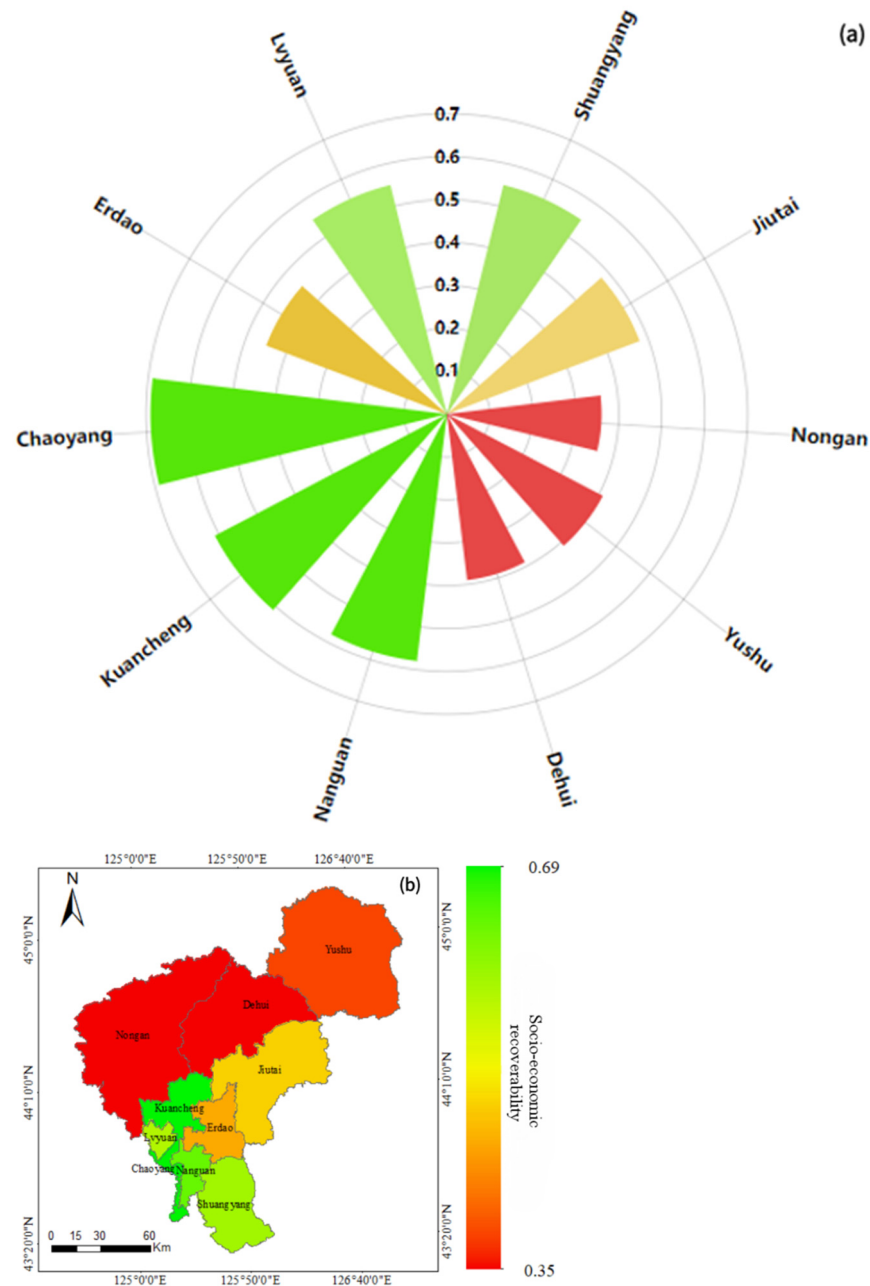

Figure 5. Socioeconomic recoverability map: recoverable value (**a**); spatial distribution of recoverability (**b**).

3.3. Flood Resilience

For the number of clustering k, the value of k needs to be set before the clustering starts. Using the elbow method to select k values can meet the requirements, while reducing the running time and the number of iterations. We determined from the elbow points in the elbow diagram that k = 4 is ideal. Therefore, we divided flood resilience into four groups, as shown in Figure 6, with each point representing a city in Changchun.
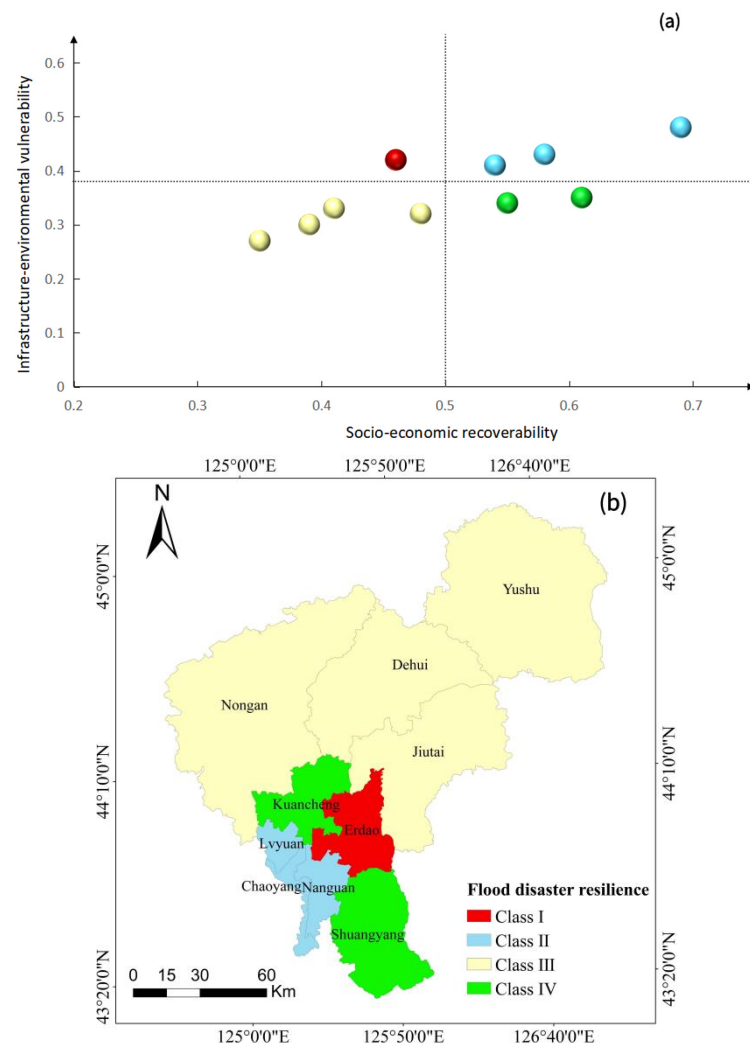
Figure 6. Changchun flood resilience cluster: cluster classification (**a**); spatial distribution of clusters (**b**).

Cluster I includes the second district, which has high infrastructure and environmental vulnerability and low socioeconomic recoverability. Cluster II includes Green Park, Chaoyang District and Nanguan District, which have high infrastructure and environmental vulnerability, and also high social and economic recoverability. Cluster III includes Dehui City, Yushu City, Nongan County and Jiutai District, which have low infrastructure and environmental vulnerability and socioeconomic recoverability. Cluster IV includes Kuancheng District and Shuangyang District, which have lower infrastructure and environmental vulnerability, and higher socioeconomic recoverability.

When floods occur, it is expected that the communities in Cluster I will need more recovery time than the communities in Cluster IV because their infrastructure and environmental vulnerability are higher and their socioeconomic recoverability is lower. Therefore, the flood resilience of the communities in Cluster I is lower than that in cluster IV, so Cluster I is identified as having low flood resilience. Cluster IV is considered to have high flood resilience. Although Cluster II has high vulnerability and resilience, Cluster II is considered to be more resilient to flood disasters because socioeconomic recoverability is more important than infrastructure and environmental vulnerability. Cluster III has moderate flood resilience. The figure shows that the flood resilience of northern areas of Changchun City is generally lower than that of southern areas of Changchun City, except for Erdao District. Different factors have different effects on flood resilience. Cities with low infrastructure and environmental vulnerability and high socioeconomic recoverability have higher flood

resilience, while on the contrary, cities with high infrastructure and environmental vulnerability and low socioeconomic recoverability may suffer more severely in the face of floods. In addition, cities in the same cluster have similar flood resilience characteristics.

4. Discussion

4.1. Verification by Example Analysis

With the progress of urbanization in Changchun, the original natural underlying surface has been gradually replaced by various impervious surfaces. In addition, the drainage pipe network was constructed a long time ago and the diameter of most pipes is small, and the drainage function of part of the pipe network has been lost due to aging and serious disrepair. As a result, there are many waterlogged areas in the city after heavy rainfall in the summer, which seriously affects the normal life of residents. The higher the number of waterlogged spots in a city, the lower the level of flood resilience of that city. In order to verify the reliability of the model results, 266 waterlogged points in Changchun from 2017 to 2021 were collected in this paper. The data of waterlogged points were obtained from field investigations and news information. The waterlogged points are shown in Figure 7.
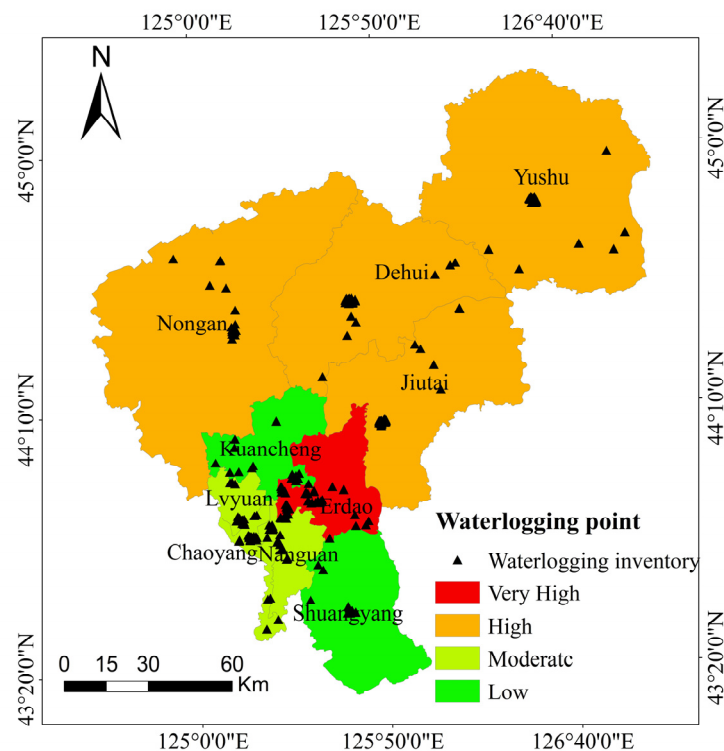

Figure 7. Waterlogging point verification map.

According to the results shown in Figure 7, most of the waterlogged points were concentrated in Erdao District, and Kuancheng District and Shuangyang District had the lowest number of waterlogged points. The calculation results of the model also showed that the urban flood toughness in Erdao District was the lowest, while Kuancheng District and Shuangyang District had the highest flood toughness. Therefore, it was considered that the evaluation results of the model on flood toughness were reasonable.

4.2. Comparison with Other Evaluation Methods

The existing evaluation methods for flood resilience are mainly divided into two categories. The first type of evaluation method is based on resilience curves, but this method requires considerable time to conduct surveys, and the resilience curves vary greatly from region to region. The second type of evaluation method is based on the resilience index,

which is also the most commonly used method for flood resilience evaluation, but the gap between the selected indicators and the existing database makes the acquisition of indicator data mostly from statistical data, which limits the number of indicators available for model evaluation and affects the reliability of the results. Additionally, most of the studies did not further analyze cities with similar flood resilience. Compared with the CORC model [47], this study is characterized by the combination of GIS data, remote sensing data and statistical data based on the flood resilience index, taking into account the important environmental components of the urban system and considering the dynamic relationship between the urban systems more comprehensively, and then using mathematical methods to process the index data to obtain urban clusters with similar flood resilience.

4.3. Measures to Improve Flood Resilience

According to the above results, there are spatial differences in flood toughness in Changchun, and the overall flood toughness needs to be further improved. Erdao District, Nongan County, Yushu City, Dehui City and Jiutai District are the areas that policy makers need to focus on to improve flood resistance. Depending on the situation in each region, policy makers should adopt appropriate policies to help the region strengthen its flood resistance capacity.

Erdao District needs to reduce the proportion of impervious ground, strengthen the level of urban health care and improve the per capita income level to improve the urban flood resistance ability. Nongan needs to increase the coverage of basic medical insurance, the proportion of flood control investment to public expenditure and the proportion of water conservancy workers. It should also enhance education to improve flood resilience. Yushu City, Jiutai District and Dehui City should increase their capital investment in flood control construction and strengthen the training of talents in the water conservancy industry to improve their flood resistance ability.

5. Conclusions

Measuring the resilience of cities to floods can help formulate flood control policies. Because of the inherent characteristics of Changchun City and the temporal and spatial variability of floods in this region, it is important to evaluate the flood resilience of Changchun City. To this end, we designed a set of flood control capacity evaluation processes.

By referring to relevant literature, we first determined a set of evaluation index system composed of 21 indicators to quantify the multifaceted concepts of urban flood resilience, including four basic dimensions: infrastructure, environment, society and economy. Considering the collection of evaluation index data, we used remote sensing and GIS data for infrastructure and environmental indicators, and statistical data for socioeconomic indicators. Secondly, after collecting the opinions of local experts, the AHP method was adopted to synthesize the experts' judgment and determine the index weight. Based on GIS weighted quantification of infrastructure and environmental vulnerability, TOPSIS was used to quantify social and economic recoverability. Finally, based on k-means clustering of infrastructure and environmental vulnerability and social and economic recoverability, the flood resilience of Changchun City was evaluated. The results show the influence of different factors on flood resilience and the characteristics of flood resilience as reflected by infrastructure and environmental vulnerability and socioeconomic recoverability. Furthermore, cities in the same cluster have the same flood resilience characteristics.

The proposed framework can enhance the understanding of infrastructure and environmental vulnerability as well as socioeconomic recoverability. Cluster analysis of the two can identify urban clusters with similar flood resilience, and provide guidance for further upgrading and improvement of cities in the same cluster and learning from different urban clusters. The proposed model is simple to operate and can be used to evaluate the flood resilience of different regions by simply adjusting the indicator bodies according to different regions. On this basis, the key points that need to be improved in urban planning at all levels are clarified, and the strategies to improve the institutional system are proposed

from the perspective of policy and public participation, which can provide new ideas for improving urban flood resistance ability and help decision makers determine the key points for improving urban flood resistance ability.

However, there are some challenges in developing composite indicators and measuring elasticity in this study. Due to the lack of previous flood impact information, it is impossible to build a flood scenario model to integrate the actual flood results in Changchun into the flood resilience evaluation index model. In the future, the actual flood scenario model and flood resilience evaluation index model can be combined to reflect the urban flood resilience more objectively and accurately.

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