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Classification and Planning Strategies of Multidimensional Resilience Units for Urban Waterlogging: A Case Study of the Old City District in Shijiazhuang, China

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Abstract: The frequency of urban disasters such as waterlogging has markedly increased, highlighting the urgent need to strengthen urban disaster prevention capabilities and resilience. This research, anchored in the resilience characteristics of robustness, redundancy, resource deploy ability, and rapid response, devised a resilience clustering factor system specifically designed for older urban districts. The old city district of Shijiazhuang, China, was selected as the empirical case study area. This research employs the K-Means++ clustering method to analyze the region's resilience units against waterlogging. Furthermore, it utilizes the method of pedigree classification to categorize the identified ten types of resilience. Secondly, these were subsequently divided into three primary categories based on a spectrum of strengths and weaknesses within each unit: dominant, mixed, and disadvantaged clustering. This categorization unveiled the unique resilience distribution patterns within the area. The findings of this study reveal a pronounced differentiation in resilience types among the units in Shijiazhuang's old city district. This spatial analysis highlighted a significant heterogeneity, with a tendency towards cluster formation. The spatial distribution of different resilience unit types was found to be uneven, leading to the emergence of clustered, patch-like, and zonal agglomerations. Combined with the unit clustering classification and the mean clustering performance of each factor, the response unit of waterlogging control resilience planning is determined for the study area, and the strategy of resilience waterlogging control and linkage is proposed. By mapping the spectrum of rainwater resilience types across the studied area, this research broadens the scope of resilience evaluation from a traditional vertical-level assessment to a more comprehensive horizontal typological analysis, offering empirical, theoretical insights for future resilience-building endeavors in older urban districts.

Keywords: rainstorm waterlogging; the old city; waterlogging resilience; cluster analysis; K-Means++; planning strategy

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1. Introduction

Urban waterlogging is a common disaster triggered by high-intensity, short-duration torrential rains caused by extreme climate changes, overwhelming the capacity of urban drainage systems and leading to extensive water accumulation [1]. With global warming, the frequency of extreme rainfall events is on the rise, exacerbating urban waterlogging issues and posing significant threats to urban environments and public safety [2]. For instance, in the summer of 2021, Zhengzhou city in China faced extraordinary torrential rains, resulting in waterlogging disasters that caused traffic paralysis, direct economic losses of 88.534 billion yuan, and 302 casualties [3]. In August 2022, the capital region of South Korea suffered historic extreme rainfall, with daily precipitation exceeding 380 mm,

leading to severe waterlogging and forcing over 7000 people to evacuate [4]. In 2023, Typhoon Dujuan affected 14 provinces and cities in China, causing extreme rainfall and urban waterlogging, with direct economic losses of 14.755 billion yuan in Fujian Province, affecting 8.142 million people. These cases highlight the severe threat of torrential rain and waterlogging disasters to urban development. Therefore, analyzing urban rainwater characteristics and enhancing urban resilience have become key strategies for addressing waterlogging issues.

The term "resilience", originating from the Latin "resilio", meaning 'to bounce back', refers to the capacity of a system to return to its original state after external shocks [5]. In 1973, Canadian ecologist Holling first introduced the concept of "resilience" to the field of ecology, interpreting it as the capacity of ecosystems to adapt, maintain, resist, and recover balance after disasters or other short-term impacts [6]. In the early 21st century, urban resilience, as a comprehensive and practical approach to climate disasters, gained widespread attention, gradually becoming a core principle guiding urban scientific and policy discussions [7]. In recent years, the application of the resilience concept in urban flood research has been growing. In 2007, Delft University of Technology in the Netherlands first proposed the concept of "rain flood resilience" [8], referring to the city's capacity to withstand the impacts of flooding despite infrastructure damage and economic losses and to rapidly reorganize its resources and return to its original state after the flood [9]. In 2012, Chinese scholar Liao G first proposed "flood-bearing resilience", focusing on the city's capacity to endure flood disasters, after which many domestic scholars began integrating resilience theory into urban planning and flood prevention research [10]. Unlike traditional urban flood risk studies, urban rain flood resilience and flood-bearing resilience place greater emphasis on the recovery capability of urban systems during waterlogging disasters, highlighting the dynamic nature of this process [11].

In studying urban and regional pluvial flooding issues, scholars have established resilience assessment systems to measure and categorize the study area, subsequently proposing optimization strategies [12,13]. In terms of indicator system selection, researchers have constructed an urban resilience assessment indicator system based on resistance, recovery, and adaptability dimensions, evaluating the urban resilience of Wuhan city from 2009 to 2015 [14]. Grounded in the "4R" resilience theory, which encompasses the robustness, rapid recovery, resourcefulness, and redundancy of cities facing flood disasters, the approach has offered new perspectives for urban planning [11]. Coupling urban rainfall models and utilizing the 4R theory to quantify flood elasticity values has enabled the quantification of the spatial distribution of flood resilience in the Xishan District of Kunming City [15]. Other research teams have embarked on assessments of urban flood resilience across natural, economic, social, and infrastructure dimensions, analyzing the resilience and its spatiotemporal changes in Zhejiang Province from 2011 to 2020 [16]. Moreover, the influence–pressure–state–response (PSR) model proposed by Xiao S and collaborators has been recognized as an effective tool for assessing urban pluvial flood resilience [17]. In the realm of research areas for urban flood and pluvial flood resilience assessments, Zhao R and others conducted a city-level resilience evaluation in the Yangtze River Delta region of Jiangsu Province using the socio-ecological system framework [18]. Zhang J et al. studied three communities suffering from waterlogging problems in Jingdezhen City, China, using a community-scale flood resistance assessment method [19]. Cui, P et al. identified indicators of community-level flood resilience involving social, natural, and economic aspects in Nanjing [20]. Conversely, other scholars have focused on urban resilience studies at various scales, including community, metropolitan, urban agglomeration, and regional levels [21].

Despite some progress in urban waterlogging resilience research, current methods often rely on qualitative analysis and subjective judgment, leading to limitations in data objectivity and scientific rigor. Existing issues include superficial explanations of resilience levels and an inadequate exploration of the resilience response methods and categorizations. Particularly in old urban districts, torrential rain and waterlogging disasters pose even more severe challenges. Old districts typically lag in infrastructure, drainage systems, and

urban planning, making them more prone to waterlogging during rainfall. Additionally, due to their unique geographical environment, urban form, land use, building density, and road networks, the characteristics of old districts differ significantly from modern cities. Therefore, directly applying modern urban resilience theories and assessment methods to old districts is often insufficient. Given this, it is necessary to conduct more detailed categorization and in-depth research on the waterlogging resilience of old districts to better address these challenges.

In light of these challenges, exploring new research methods becomes particularly important. In this regard, applying typological methods to the study of urban rainwater resilience offers a novel perspective. Typology, originating from French thinker Michel Foucault's theory, focuses on exploring the origins and evolutionary processes of objects or phenomena, revealing their uniqueness and specificity. This approach aids in understanding the interactions, developmental trajectories, and formation principles between entities. Through such an in-depth analysis, it accurately identifies complex relationships within a given group or category, grasping its transformative patterns and evolutionary laws. To date, typological research has laid some foundational work in the field of urban and rural planning [22–24]. This method, through a deep analysis of different urban areas and units, can uncover regional differences and specific issues, thereby providing precise improvement and management strategies for planners and decision-makers.

Therefore, this study, taking the old city district of Shijiazhuang as the empirical research object, constructs a rainwater resilience clustering factor system for old urban districts based on the four core resilience attributes of robustness, redundancy, resource deployability, and rapidity. Utilizing this system, we have opted for the K-means++ clustering algorithm and phylogenetic typological methods based on their unique advantages and complementarity in handling complex datasets. The K-means++ algorithm is particularly suited for rapidly partitioning large datasets into multiple similar groups, revealing the intrinsic structure and patterns within the data. The phylogenetic typological approach excels at dealing with subtle differences and hierarchical structures within data, enabling a more nuanced understanding of the relationships between data categories. By combining these methods, we can fully mine the potential information within the data, ensuring the breadth, depth, and accuracy of our research, thereby providing a solid foundation and reference for applying this method to other ecosystems in future research. The study incorporates typological theory and employs clustering analysis methods to categorize and generate spectra for rainwater resilience units. By analyzing the average attributes of the resilience factors among different types of units, this research reveals their specific strengths and existing issues in rainwater resilience, further exploring the diversity of these units in this aspect. Based on this, the study delineates planning response areas and proposes corresponding strategies for enhancing resilience. The entire process aims to improve the scientific rigor and comprehensiveness of urban rainwater resilience research, providing valuable references for future resilience practice optimization, especially in the specific urban context of old city districts.

2. Study Area and Data

2.1. Study Area

Shijiazhuang is located in the central part of the North China Plain, adjacent to the Taihang Mountains to the west. It is a typical plain city, situated between 37°27′ to 38°47′ north latitude and 113°30′ to 115°20′ east longitude. The city experiences a warm, temperate, semi-arid monsoon continental climate, with an average annual precipitation of 640.9 mm. The terrain is higher in the west and lower in the east, with stormwater runoff generated from heavy rains draining southeast into the Minxin River. As of the end of 2022, Shijiazhuang had a permanent population of 11.2235 million people, with 8.0179 million urban residents, indicating an urbanization rate of 71.44%. Significant differences exist between the old and new urban areas of Shijiazhuang in terms of rainwater inundation events. The old urban areas often face challenges from aging underground pipe networks,

impermeable surfaces, and dense roadways, resulting in serious waterlogging over the past decades. In contrast, new urban areas tend to adopt modern planning concepts, equipped with advanced rainwater management systems and infrastructure, focusing on the development of sponge cities and emphasizing redundancy and resilient design, thereby minimizing the risk of inundation. Despite these challenges in the old urban areas, they can still improve resilience through targeted enhancements, making them a more typical and demonstrative study subject.

The main urban area of Shijiazhuang includes Xinhua District, Qiaoxi District, Chang'an District, and Yuhua District. The old city district, which has been developed over several decades (Figure 1), is located in the central region of the main urban area. This study delineates the research area based on administrative divisions, road boundaries, river systems, and drainage zones. The boundaries of the study area are defined as Heping East Road to the north, Youyi North Street to the west, Qingyuan Street to the east, Huai'an East Road to the south, and Minxin River as the boundary. The study area, located at the administrative junction of the central four urban districts, covers a total area of approximately 23 square kilometers. Although its drainage system operates effectively, it is still vulnerable to heavy rains with a high return period. The region frequently experiences torrential rain events from June to September each year. For instance, the heavy rain on 22 July 2022 caused 14 waterlogging spots across the city, and the rainfall on 21 July 2023, led to waterlogging in 48 sections of roads, disrupting traffic on several roads and underpasses, resulting in significant property damage. Therefore, it is necessary to study the rainwater resilience of the old city district of Shijiazhuang, specifically addressing the unique needs posed by torrential rain and waterlogging disasters.

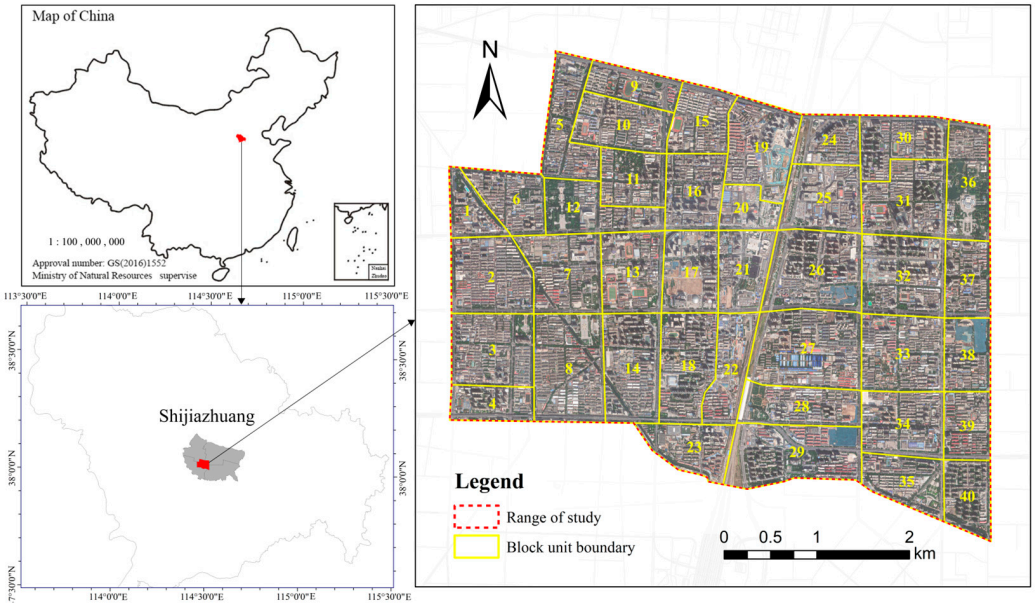


Figure 1. Location of the study area and statistical unit division.

2.2. Delimitation of Statistical Units

In this study, the boundaries for defining statistical units were determined using administrative divisions, water systems, road boundaries, drainage zones, and other criteria. The study area was divided into 40 statistical units, and each unit was assigned a unique code. Each code corresponded to a sample of each research unit (Figure 1). The red line represents the scope of the research area, the yellow line represents the boundary range of each statistical unit, and the number represents the serial number name of the statistical unit.

2.3. Data Sources

This study relied on data from multiple sources, encompassing four primary categories: terrain and landform, hydrological rainfall, municipal infrastructure network, and land use, as well as socio-economic data. For the terrain and landform data, a 10 m × 10 m digital elevation model (DEM) was generated using GIS's TIN (triangulated irregular network) methodology based on surveyed CAD elevation points. Rainfall data, spanning from 1950 to 2022, were obtained from the ERA5-Land dataset, which compiles information from organizations like the European Centre for Medium-Range Weather Forecasts, providing monthly average precipitation grid data for Hebei Province. The municipal infrastructure network data primarily included details regarding the distribution of stormwater pipes, including their lengths and diameters. Land use data were derived from Sentinel-2 satellite remote sensing imagery captured in October 2022 [25], obtained from the European Space Agency (ESA) website. This imagery underwent atmospheric correction and classification using the maximum likelihood method, categorizing the study area into four types: green spaces, water bodies, roads, and impermeable surfaces, crucial for the subsequent calculations using the Fragstats landscape index model. Socio-economic data covered a range of factors, including population statistics, economic indicators, public service details, administrative demarcations, and area measurements within the old city region. Both raster and vector data were meticulously organized at the unit or street level. Additionally, raster data underwent uniform resampling to achieve a consistent 10 m resolution, facilitating subsequent statistical analyses, spatial assessments, and data visualization using ArcGIS. For comprehensive data specifics, please consult Table 1.

Table 1. Data required for urban waterlogging toughness clustering research.

Data Name	Type	Accuracy and Range	Source
Digital Elevation Model (DEM)	Raster	10 m × 10 m	Geospatial Data Cloud website (https://www.gscloud.cn/, accessed on 10 July 2022)
Remote Sensing Imagery Data	Raster	24 October 2022, 10 m × 10 m	Sentinel-2 satellite remote sensing imagery dataset from the European Space Agency's Copernicus Data Space website (https://dataspace.copernicus.eu/, accessed on 20 August 2022).
Municipal Infrastructure Network Data	Vector	1 m × 1 m	The rainwater pipe network data were obtained from Comprehensive Planning of Urban Drainage (Rainwater) Flood Control in Shijiazhuang (2014–2020) and inversion of DEM elevation data
Land Use Data	Raster	24 October 2022, 10 m × 10 m	Obtained from the Chinese Academy of Sciences Resource and Environmental Science Data Center (https://www.resdc.cn/, accessed on 23 July 2022).
Hydrological and Road Data	Vector	2022, 1:25,000 scale	National Basic Geographic Database at 1:25,000 scale (https://www.webmap.cn/, accessed on 20 July 2022).
Rainfall Data	Raster	Monthly from 1950 to 2022	ERA5-Land dataset released by organizations, including the European Centre for Medium-Range Weather Forecasts (https://cds.climate.copernicus.eu/, accessed on 3 July 2022).
Public Services and Infrastructure Data	Vector	1 m × 1 m	OpenStreetMap open mapping data (http://www.osm.org/, accessed on 10 January 2023).
Socio-economic Data	Text	2022	Shijiazhuang City's 2023 National Economic and Social Development Statistics Report (https://www.sjz.gov.cn/, accessed on 11 January 2023).

3. Method

We developed a framework to comprehensively analyze the resilience of urban rainfall inundation. Firstly, statistical units for the study area were defined based on relevant criteria, and a factor system for urban rainfall inundation resilience was established according to the 4R attributes of resilience. Subsequently, data statistics for each factor of the factor system were conducted for each unit. The data were normalized using the range normalization method, and the weights of the factors were determined

using the equal-weight method. The characteristics' values for the 4R dimensions were calculated by combining the factor values with their respective weights. Finally, the optimal clustering value (k) for the four characteristic values was determined using K-Means++, the elbow method, and the silhouette coefficient method for cluster analysis, resulting in the classification of the units.

In the end, we utilized lineage analysis to classify the clustering results into ten categories of urban spatial rainfall inundation resilience. By summarizing the lineage types, we were able to analyze the distribution of superior and inferior clustering units, the 4R dimension characteristics of the unit clusters, and the mean values of the factors for each dimension. Combining these aspects allowed us to plan the zoning of rainfall inundation resilience units in the study area and propose corresponding strategies. The flowchart of the modeling framework is shown in Figure 2.

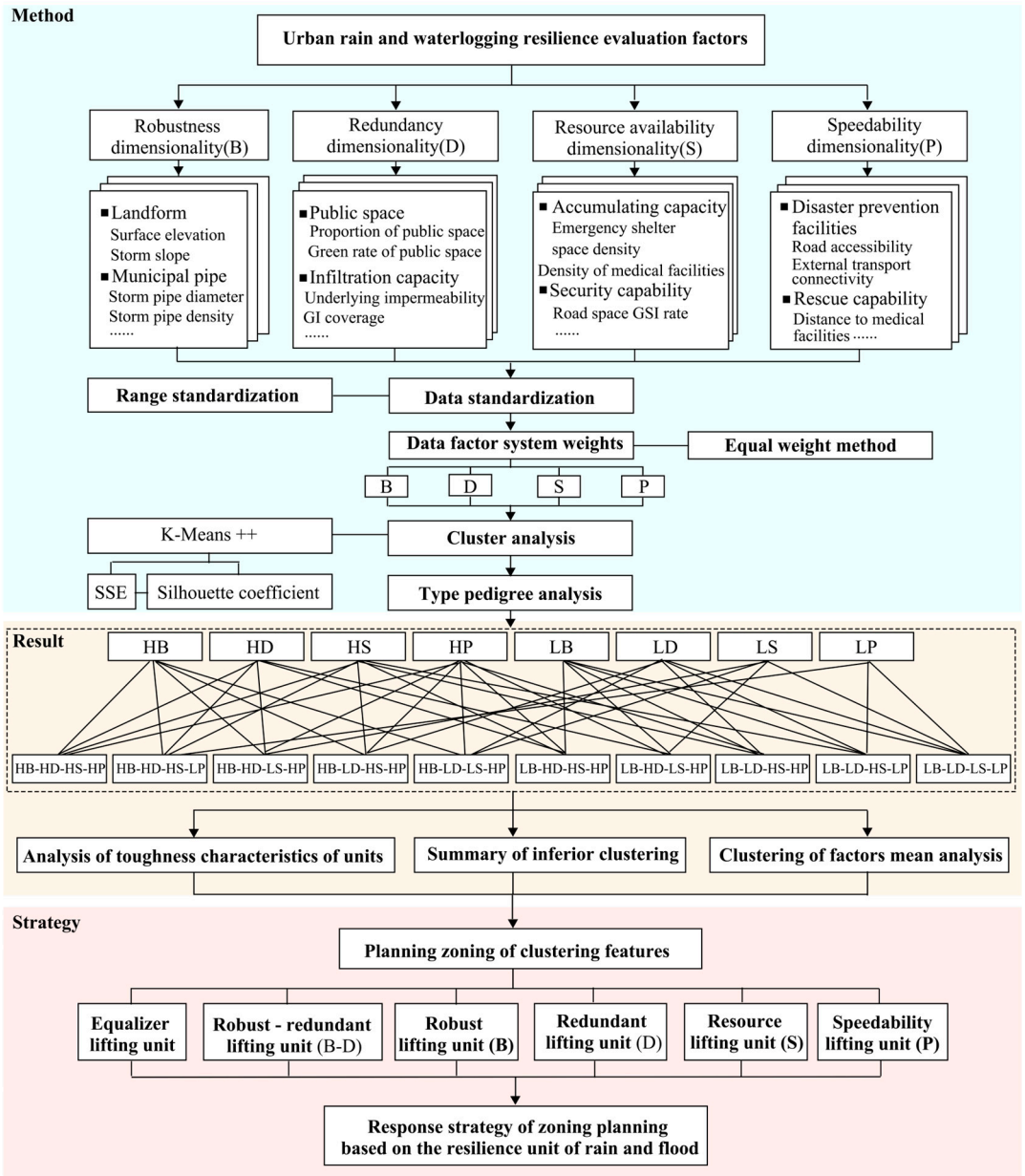


Figure 2. Research framework.

3.1. Construction of Urban Waterlogging Resilience Factor System

Based on a comprehensive review and comparative analysis of the relevant urban resilience assessment literature, this study constructed a framework for urban spatial rainwater resilience clustering factors, utilizing the '4R attributes' theory of urban resilience [26]. The four attributes, namely robustness, redundancy, resource allocability, and rapidity, were employed as the target layer. A factor system for urban spatial rainwater resilience clustering was developed by selecting resilience clustering factors through the analysis of existing research. Indicators such as municipal drainage [27], disaster mitigation facilities, topography [28], public spaces, storage capacity, and safety capacity were included in the first-level indicator layer. Specific factors contained within various urban spatial elements constituted the second-level indicator layer. In total, the system consisted of 30 factors under four categories in the target layer (Table 2).

Table 2. Urban waterlogging resilience clustering factor system.

	Primary Indicator Layer	Secondary Indicator Layer	Indicator Description	Unit
Robustness	Terrain Landform	Surface elevation	Relative height of ground relative to sea level.	m
		Hydrogeological conditions	Adjustable storage volume of groundwater.	Cubic meters (m^3)
		Rainfall gradient	Surface runoff slope in the plot.	Degrees (°)
	Municipality Drainage	Drainage system	The forms of sewage and rainwater transportation and treatment inside the plot, such as diversion system and confluence systems.	-
		Rainwater pipe network density	The length of rainwater pipe/the total area of the plot represents the drainage capacity.	km/km^2
		Rainwater pipe diameter	Rainwater pipe diameter size.	M
		Density of rainwater storage facilities	The number of rainwater pumping stations and rainwater outlets/the total area of the plot.	$/km^2$
	Disaster Prevention Facilities	Lifeline system fortification level	Reflect the robustness of the lifeline system of disaster prevention facilities in the region.	-
		Development intensity of underground space	Underground space development area/total land area, underground space terrain low-risk level is higher.	km/km^2
		Status of hydropower communication facilities	Completeness and normal operation capacity of water supply, power supply, communications, and other infrastructure.	m
Redundancy	Public Space	Proportion of public space area	Public space area/total area in the unit.	%
		Public space surface elevation	Relative surface height of public space.	m
		Rainfall gradient in public space	Slope of surface runoff in public space.	Degrees (°)
		Green space rate of public space	Total area of green space in plot/total area of area.	Percentage (%)
		The proportion of public space area higher than rainstorm water level	It reflects that the vertical height of the block is above the elevation of the rainstorm water level, which affects the space of runoff path introduction and infiltration absorption capacity during the disaster.	Percentage (%)

Table 2. *Cont.*

	Primary Indicator Layer	Secondary Indicator Layer	Indicator Description	Unit
Redundancy	Penetration Ability	Impervious rate of underlying surface	The sum of impervious underlying surface area/total plot area.	Percentage (%)
		Surface water storage capacity	The water storage volume of natural and artificial water bodies in the plot.	m^3
		Surface water connectivity	The degree of connectivity between surface water bodies that can be used for storage and drainage.	-
		Vegetation type	Ground cover plants, trees, and shrubs have different infiltration capacities and reduction degrees to rainstorms.	-
		Green infrastructure coverage	It reflects the ability of green infrastructure in space to absorb and store rainwater in various forms.	Percentage (%)
Resource Allocability	Reserves Ability	Emergency shelter space density	Number of emergency shelters/total plot area.	/km^2
		Emergency standby facilities	Water, electricity, communications, and other emergency backup facilities.	-
		Density of regional medical facilities	The density of general hospitals and health centers that can be treated in the plot.	/km^2
	Safety Ability	Early warning ability of waterlogging disaster	Reflects the strategy and pre-allocation of urban waterlogging disaster responses.	-
		Waterproof evacuation ability	It reflects the safety and stability of urban space engineering systems in the event of disasters.	-
		Road space GSI rate	It reflects the rainwater diversion capacity of green infrastructure in road space.	Percentage (%)
	Adaptation Ability	Digestive capacity of affected persons	It reflects the scale and ability of post-disaster urban treatment of digestive casualties.	-
		Waterlogging storage capacity	It reflects the scale and ability of post-disaster urban self-regulation of rainwater and flood storage.	-
Rapidity	Infrastructure	Road accessibility	The degree of road connectivity in the plot.	km/km^2
		External traffic connectivity	External traffic road length/total plot area.	
		Urban maintenance and construction capacity	It reflects the disaster recovery ability and rapidity of post-disaster regional infrastructure.	-
	Rescue Ability	Emergency shelter space distance	The distance between the plot and the emergency shelter space, such as parks and square heights.	km
		Infrastructure communication capabilities	It reflects the responsibility of various communication infrastructures after a disaster.	-
		Distance of medical facilities	The distance between the area and the medical treatment places, such as general hospitals and health centers.	km

(1) Robustness refers to the ability of urban systems and infrastructure to resist, absorb, and mitigate disasters and stress events, with a focus on maintaining core services

and functions to minimize losses, protect lives and property, and sustain the stability of urban economies and social activities. This attribute mainly comes into play before heavy rain events, emphasizing the effectiveness of existing terrain conditions and municipal engineering measures. It was assessed using seven factors, including the terrain elevations within resilience units, rainfall slope, drainage system, rainfall pipe density, rainfall pipe diameter, and the density of rainwater storage facilities [29–33].

(2) Redundancy focuses on the degree of backup of internal elements within the urban system, ensuring resilience by guaranteeing the continuity of critical services when some system components fail. It increases the flexibility and fault tolerance of urban responses to rainwater-related disasters, shortening recovery times. This attribute is more oriented towards the rainwater carrying capacity and subsurface conditions within urban spaces. It was assessed using ten factors, including the green space ratio, the proportion of public space area, impermeability rate, surface water storage capacity, and green infrastructure coverage [34–40].

(3) Resource allocability refers to how efficiently a system can mobilize material and human resources to solve problems after a disaster occurs. It represents the city's ability to use existing resources effectively, formulate response strategies quickly, and efficiently organize their implementation. This ensures that sufficient resources can reach disaster points in a timely manner, expediting emergency responses and recovery processes. It emphasizes preparedness, safety, and adaptability and is assessed using seven factors, including emergency shelter density, regional medical facility density, road space GSI rate, and waterlogging evacuation capacity [41–43].

(4) Rapidity is the ability to complete tasks in a timely manner according to priorities to ensure the normal operation of the system. It is characterized by a swift urban system response, fast recovery, and the ability to promptly repair damaged infrastructure to mitigate disaster impacts and restore normal operation. A swift response is crucial for protecting lives, reducing property losses, and quickly restoring social operations. This attribute places greater emphasis on the completeness of disaster mitigation facilities and rescue capabilities. It was assessed using six factors, including regional road density, external traffic connectivity, urban maintenance and construction capacity, distance to emergency shelters, and distance to medical facilities [44–46].

3.2. Urban Waterlogging Resilience Clustering Method

3.2.1. Clustering Factor Standardization Processing

Given the availability of data, 22 quantifiable indicators were further selected from a system of 34 urban-built environment clustering factors aimed at addressing urban waterlogging. These indicators served as clustering factors for resilience typology. The indicator data comprised five metrics under the target layer for robustness (B), including ground elevation (a), rainfall slope (b), and stormwater network density (c). Eight metrics under the redundancy (D) layer, such as the proportion of public space area (f), green space rate (g), and impervious surface rate (h), among others, were also included. Five metrics tied to the resource mobilization (S) layer, including the emergency shelter space density (n) and regional medical facility density (o), were accounted for, along with four metrics under the rapidity (P) layer, like regional road density (s) and external traffic connectivity (t), as depicted in Figure 3.

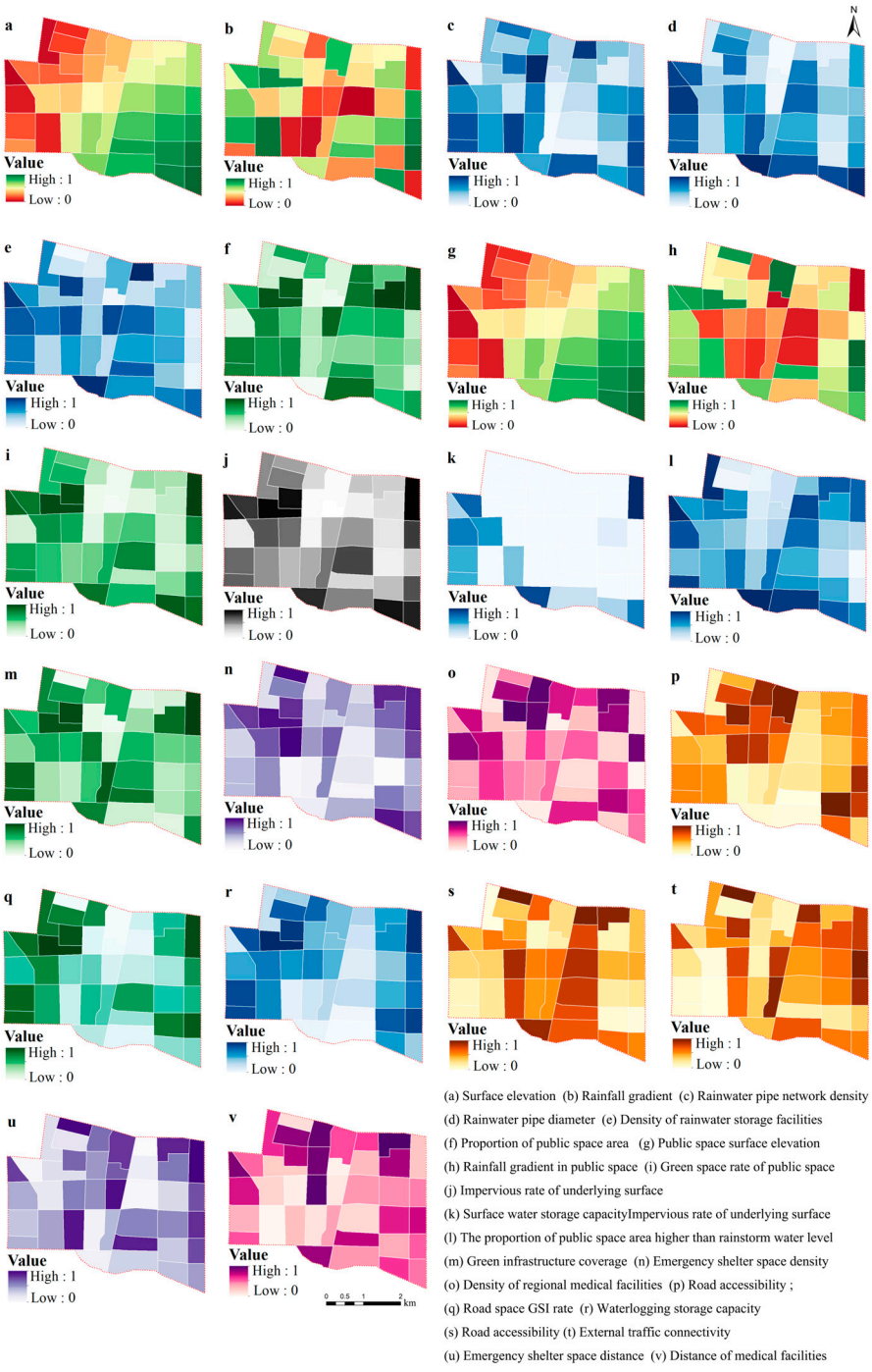


Figure 3. Study area's unit rainfall toughness factor statistics.

By standardizing the data through range normalization, we ensured that all indicators' values fell between 0 and 1. This approach not only maintained the positivity of the data, making subsequent clustering computations more straightforward and preventing the generation of negative values in the data processing phase, but it also made the comparison of the 4R attributes in unit clustering more intuitive. Especially in strategy formulation and resilience assessment, this method clearly displayed each unit's strengths and weaknesses, thereby simplifying the decision-making process and data interpretation and better guiding practical operations and decision-making.

The clustering factor data for the old resilient units of Shijiazhuang were standardized by statistical processing and normalization of the aforementioned data indicators. This

entailed a conversion of negatively correlated factors to positive expressions and an adjustment of all factor values to fall within a range of 0 to 1, eliminating the discrepancies resulting from the units and scales.

$$x_{i^*} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (1)$$

The normalized index value x_{i^*} represents the normalized indicator value, x_i is the indicator's original value, and x_{min} and x_{max} are the minimum and maximum values observed for the indicator, respectively. This process coincided with the numbering of the 40 resilience units in the old town of Shijiazhuang, designated as 1–40.

3.2.2. Index Factor System Weight

Currently, two common methods to determine the index weights include non-equal weighting and equal weighting. The former relies on expert scoring and analytic hierarchy process techniques, while the latter assigns equal importance to each indicator [47]. Lacking standardized variables for calculating waterlogging resilience, the current trend is to assign equal weight to all indicators [29]. Studies have shown that equal weighting is more objective and less influenced by subjectivity compared to non-equal weighting methods. Consequently, in this study, each indicator was normalized and conferred equal importance through equal weighting to calculate the urban waterlogging resilience.

3.2.3. Principle of K-Means Clustering Algorithm

As a typical unsupervised learning method, clustering algorithms play a crucial role in multiple research domains, facilitating the segmentation of datasets into cohesive clusters based on similarity. Among various clustering techniques, hierarchical clustering, K-means, as well as the EM algorithm [48] and DBSCAN algorithm [49] each has distinct advantages and is tailored for specific scenarios. Owing to the numerical nature of the chosen clustering factors and the effectiveness of K-means in managing large numeric datasets—its quick computation and ease of implementation for convex clusters [50]—this study primarily employed the K-means algorithm.

The advantage of utilizing the K-means++ clustering analysis in the field of urban block unit rainwater resilience or disaster resilience lies in its efficient sample grouping capability—it can divide the city into several groups with similar properties based on the different 4R characteristics of the urban block units. The key advantage of this method was that it minimized the variability within clusters while maximizing the differences between clusters, providing precise data support for urban rainwater resilience planning. With the K-means++ algorithm, it was possible to accurately identify the areas in the city that were most sensitive to rainwater events and in greatest need of intervention. Furthermore, K-means++, as an improved version of the K-means algorithm, reduced sensitivity to the selection of initial clustering centers, improving the stability and accuracy of the clustering results. Therefore, applying K-means++ clustering analysis in our research not only enhanced the efficiency and precision of the study but also improved urban rainstorm waterlogging resilience, reducing the negative impact of rainwater disasters.

The choice of K-means++ as our clustering method was primarily based on its optimization of the initial cluster center selection. In each iteration, the algorithm assigned data points to the nearest cluster center and recalculated the center of each cluster. This process iterated until the convergence criteria were met, such as minimal changes in cluster centers or reaching a predetermined number of iterations. This significantly enhanced the adaptability and accuracy of the clustering process for heterogeneous datasets. Subsequently, by showcasing the clustering results, this method effectively revealed the intrinsic connections between samples within the relevant clusters.

This method presumes clusters to be spherical, leading to comparatively low variance within each cluster—a natural fit with the inherent variance definitions of numerical data. Despite the requirement to define the number of clusters (k) a priori, this is usually informed

by domain knowledge or heuristic analysis [51], from which an optimal number can be inferred to enhance the algorithm's performance for the respective issue.

In the employed K-means clustering process, clusters were differentiated based on spatial proximity—with closer data points in the coordinate system exhibiting higher similarity [52]. The clustering commenced with the random selection of candidate center points and iteratively computed them to optimize these initial points, minimizing intra-cluster variance, thus ensuring the optimal clustering of all data points. The objective function stands as follows:

$$J = \sum_{j=1}^{k} \sum_{x_i \in w_i}^{k} ||xi - cj||^2 \tag{2}$$

$$Cj = \frac{1}{n} \sum_{xi}^{n} \binom{n}{k} x^k a^{n-k} \tag{3}$$

Here, J represents the K-means objective function, w_i is the sample dataset, x_i refers to the ith data sample in the dataset, and Cj denotes the center point of the jth cluster.

In this analysis, the objective function revealed the distances between the dataset points and the cluster centers. The K-means algorithm allocated groups based on the similarity between data points and centers so that points within a cluster are highly similar, with clear distinctions between different clusters. This aligned with our grouping objectives in the research, as it was a quantitative interpretation based on the natural classification features generated by the K-means algorithm [53]. The K-means clustering involved four consecutive stages: initially, the algorithm randomly selected k data points ($0 < k \leq n$) from n samples as initial cluster cores; then, in each iteration, each of the other data points was assigned to the nearest cluster based on proximity to these centers; subsequently, new cluster centers were determined by calculating and updating the mean of the newly formed cluster members; finally, this iterative process continued until one of two possible termination conditions was met—either convergence of the algorithm's objective function was achieved or the positions of cluster centers no longer changed.

3.2.4. Determination of the Best Clustering Value K

(1) Elbow Method SSE

The elbow method is a technique used to determine the optimal number of clusters, k, in K-means clustering based on the sum of squared errors (SSE). Graphically, the SSE decreases rapidly as the number of clusters increases, but after reaching a certain point, the decline in the SSE rate slows down, creating a turning point resembling an elbow in the curve. This specific k value represents the best cluster number [54]. The formula for the SSE is as follows:

$$SSE = \sum_{i=1}^{k} \sum_{p \in C_i} |P - m_i|^2 \tag{4}$$

In this formula, SSE is the sum of squared errors, C_i is the ith cluster, P is the sample data point within C_i, and m_i is the center of the ith cluster.

(2) Silhouette Coefficient Method

The silhouette coefficient method measures the cohesion and separation of clusters resulting from various k values by computing the distance between samples within a cluster [53]. Typically, the k value corresponding to the largest silhouette coefficient score indicates the most suitable number of clusters for that dataset. The silhouette coefficient for the i-th data sample point (X_i) in the dataset is calculated with the following formula:

$$S = \frac{b - a}{max(a, b)} \tag{5}$$

In this formula, (S) represents the silhouette coefficient; (C_i) is the ith cluster; (a) is the average distance of the sample point (X_i) to the other sample points within the same

cluster, indicating the degree of cohesion within the cluster; (b) is the average distance from the sample point (X_i) to all sample points within the nearest cluster, shedding light on the separation between different clusters [54]. The formula for determining the closest cluster is the following:

$$C_j = \arg min_{C_k} \frac{1}{n} \sum_{p \in C_k} |P - X_i|^2 \quad (6)$$

Here, (P) is any data sample point within the Kth cluster, and the average distance from the sample points within cluster (X) to the sample points in other clusters serves as the measure of distance to that cluster, with the smallest average distance indicating the nearest cluster.

In this study, the Python programming language, along with Sklearn.Cluster and Sklearn.Metrics modules were utilized to compute the SSE and silhouette coefficients for the standardized data. We then used Matplotlib.Pyplot for visualization. As depicted in Figure 4a, the *SSE* initially decreased rapidly with an increase in k but exhibited a noticeable rate change at k = 10, presenting an elbow-shaped inflection point. As depicted in Figure 4b, It was also observed that the silhouette coefficients peaked at k = 5 and k = 6, suggesting better clustering effects at these points. However, when compared to the left graph, the SSE remains high at these values. Nevertheless, considering the combined assessment of the SSE and silhouette coefficients, we discovered a relatively high silhouette score at k = 10, indicating a superior clustering effect. After evaluating the *SSE* inflection points via the elbow method and the results from the silhouette coefficient approach, the study designated k = 10 as the optimal clustering value. This will aid in better understanding the underlying structure of the dataset and yielding high-quality clustering outcomes consistent with the categorization demands and features of the 4R attributes (robustness, rapidity, reliability, and resilience).

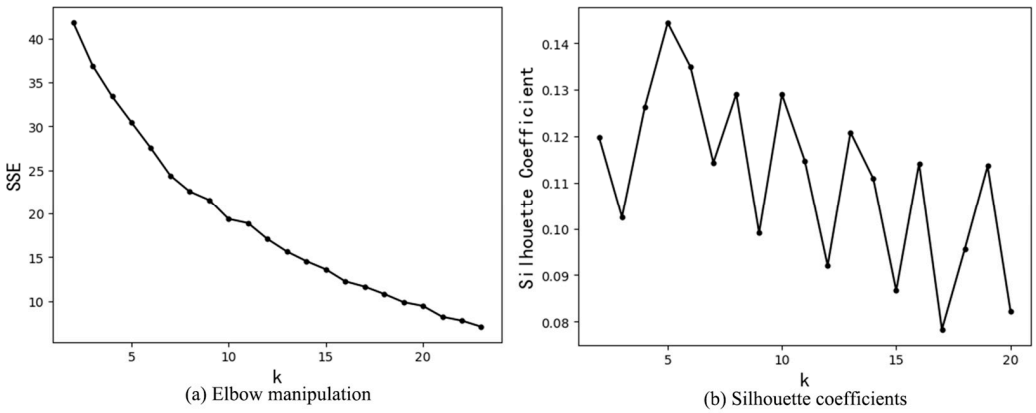


Figure 4. The optimal clustering value k calculated by the elbow method and contour coefficient method.

3.3. Clustering Pedigree-Type Summary Method

The pedigree method is an attribute-based analysis method. The content of genealogy has been introduced in the previous introduction. In view of the urban waterlogging resilience studied in this paper, the clustering data of waterlogging resilience can not only be analyzed. The clustering results can be summarized by using the pedigree classification method, which can reveal the characteristics and attribute arrangement of the clustering distribution, but can also be named for different clusters and reveal the meaning of their resilience attributes. Through an in-depth analysis of the data, this method enables us to fully and accurately understand the characteristics of different clusters and their advantages and disadvantages in terms of resilience. The summary of this method includes the following aspects:

Firstly, we can reveal the distribution characteristics of different clusters by analyzing the polyline trend of clustering data and the arrangement of the index values. For example, by combining different robustness, redundancy, resource allocation, and speed attributes,

different types of resilient units are formed. Then, by combining different resilience attributes, each cluster is named to reflect its resilience characteristics. By further analyzing the clustering results, we can obtain the distribution of the toughness unit-type lineage in the region so as to better understand the diversity and complexity of different toughness attributes. For example, high robustness–high redundancy–high resource redeployment–high speed (HB-HD-HS-HP) indicates that the cluster has high robustness, redundancy, resource allocability, and speed attributes. Finally, by visualizing the distribution of different types of ductile units in the region, intuitive information is provided to help better evaluate and improve the resilience of the region. These genealogical types provide key information for decision-makers to better evaluate and improve the resilience and adaptability of the region and provide an important basis for more targeted planning and decision-making for future waterlogging resilience.

4. Results and Discussion

This study adopts the research logic framework depicted in Figure 2, segmenting the study area into urban block units and establishing a resilience factor system for urban waterlogging, as outlined in Table 2, based on the '4R' theory of resilience. Following the collection and standardization of data related to these factors, the K-means++ algorithm was employed for cluster analysis. Additionally, phylogenetic classification methods were applied to categorize the resilience types of urban block units. These methodologies culminated in the significant findings and discussions presented below.

4.1. Cluster Analysis of Urban Waterlogging Resilience Units

4.1.1. Application of K-Means Clustering Algorithm

The present study implemented the K-Means++ algorithm written in Python language and applied it using the relevant modules from the Sklearn library in Jupyter Notebook. The computation yielded normalized values for clustering factors' SSE (sum of squared errors) and silhouette coefficients. Data visualization was accomplished through the Matplotlib.Pyplot module. Taking into account the results from the elbow method for the SSE and the silhouette coefficient approach, the study eventually selected $k = 10$ as the most suitable number of clusters. By continuously adjusting the random seed value in the code, this research successfully partitioned 40 urban units of Shijiazhuang's old city district into 10 distinct clusters, labeled Cluster1 through Cluster10, as indicated in Table 3.

Table 3. K-means resilience unit clustering results.

Cluster	Unit Number	Cluster	Unit Number
Cluster1	01, 24	Cluster6	23, 28, 29
Cluster2	10, 15, 16, 17, 19	Cluster7	02, 03, 04, 06, 07, 08, 11, 12
Cluster3	36	Cluster8	05, 20, 21, 22, 25, 27, 32
Cluster4	35, 40	Cluster9	09, 13
Cluster5	30, 31, 33, 34, 37, 38, 39	Cluster10	14, 18, 26

4.1.2. Verification of Clustering Results

To delve deeper into the data analysis and unveil the potential relationships between the indicators, the study aligned the ten clustering results with the four core dimensions of waterlogging resilience—robustness (B), redundancy (D), resource adaptability (S), and rapidity (P). Each cluster type underwent meticulous data verification and statistical analysis. This yielded a distribution characteristic map (Figure 5) of the resilience performance of Shijiazhuang's old city district in waterlogging disasters, with the resilience dimensions represented on the horizontal axis and the corresponding values on the vertical axis, while the resilience of the 40 units was depicted through a line chart with different colors.. The analysis indicates a consistent trend within each cluster across all four resilience attributes, demonstrating a high level of internal consistency within clusters.

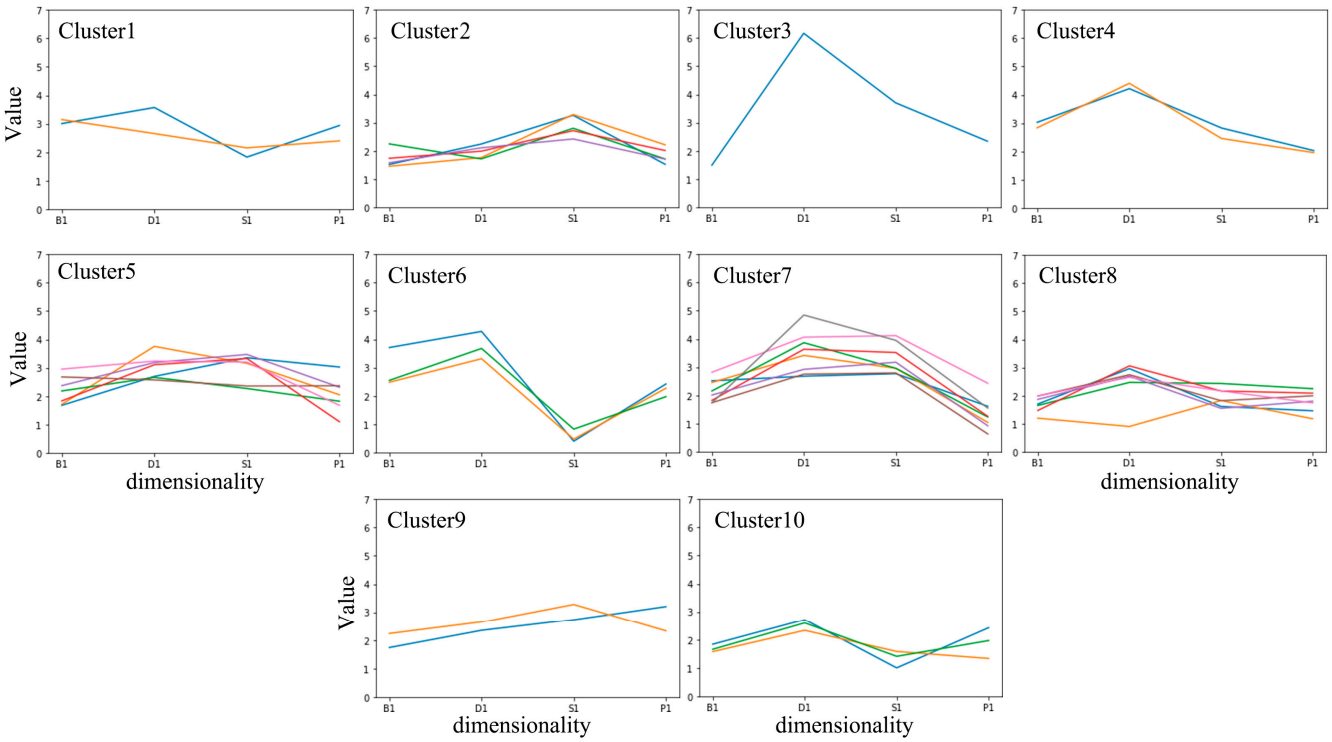


Figure 5. The clustering effect of waterlogging units in the old urban area of Shijiazhuang.

Comparative analysis of the characteristic values of different cluster centers aids in interpreting the practical significance of these clusters, revealing significantly different resilience attribute features. For instance, all indicators of Cluster4 are generally high, while those of Cluster8 are consistently low; Cluster1 scores high in robustness and rapidity but low in redundancy and resource adaptability, exhibiting a distinctive Z-shaped characteristic, whereas Cluster16 scores low across all attributes. Therefore, through evaluating the values of the 4R attributes, the study was able to categorize the types of resilience units accurately.

4.1.3. Analysis of Clustering Results

The post-verification outcomes revealed cluster distribution characteristics based on the 4R resilience attributes analysis, which informed the naming of each cluster. Analysis of the cluster data trends and the arrangement of cluster indicator values elucidated the resilience attribute implications of each cluster. For example, by combining attributes such as high robustness, high redundancy, high resource adaptability, and high rapidity (HB-HD-HS-HP) or high robustness, high redundancy, high resource adaptability, and low rapidity (HB-HD-HS-LP), ten different types of resilience unit categories were formed, as shown in Table 4.

Table 4. Resilience pedigree types of urban rain and flood toughness cluster units.

Cluster	Unit Pedigree Type	Cluster	Unit Pedigree Type
Cluster1	HB-LD-LS-HP	Cluster6	HB-HD-LS-HP
Cluster2	HB-LD-HS-HP	Cluster7	HB-HD-HS-LP
Cluster3	LB-HD-HS-HP	Cluster8	LB-LD-LS-LP
Cluster4	HB-HD-HS-HP	Cluster9	LB-LD-HS-HP
Cluster5	LB-LD-HS-LP	Cluster10	LB-HD-LS-HP

A summary of the cluster results revealed that the resilience unit typology in Shijiazhuang's old city district encompasses 10 of the 16 possible resilience types. The results

were visualized using ArcGIS 10.8 software developed by the Environmental Systems Research Institute (ESRI), USA, resulting in a resilience unit type spectrum distribution map of the old city area of Shijiazhuang (Figure 6), with different colors used for differentiation.The analysis indicated that the most prevalent types in the study area include high robustness–low redundancy–low resource allocation–high rapidity (HB-LD-LS-HP), high robustness–low redundancy–high resource allocation–high rapidity (HB-LD-HS-HP), low robustness–low redundancy–low resource allocation–low rapidity (LB-LD-LS-LP), and low robustness–low redundancy–high resource allocation–low rapidity (LB-LD-HS-LP).

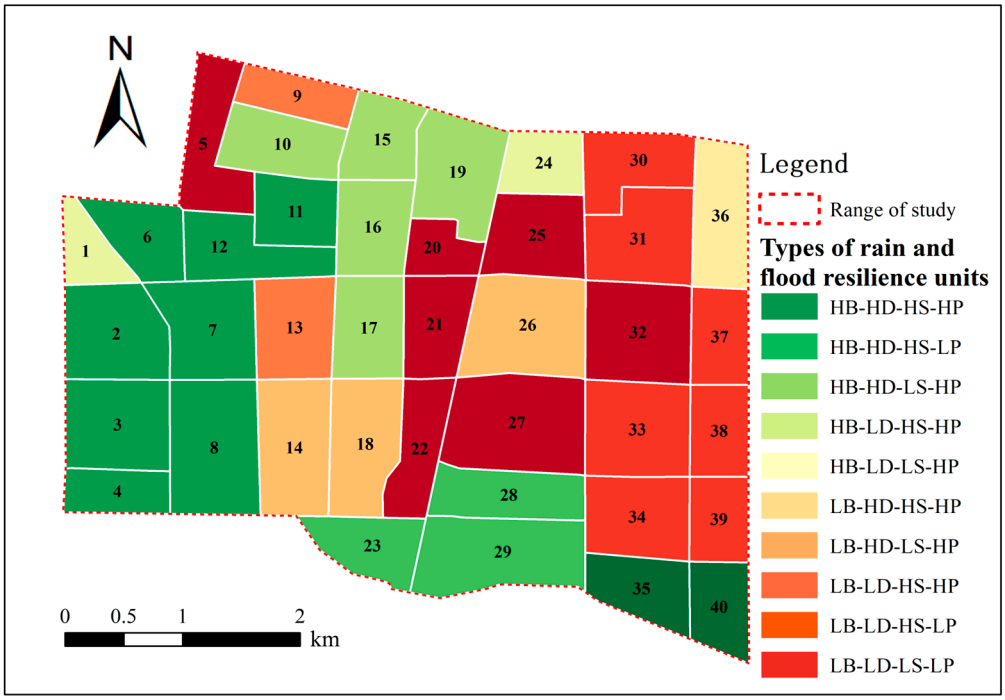


Figure 6. Pedigree of waterlogging toughness unit types in the old urban area of Shijiazhuang.

4.2. Characteristic Analysis of Resilience Clustering Factors in Shijiazhuang Old Town

By summarizing the phylogenetic spectra of urban spatial pluvial resilience clusters, we can analyze the mean characteristics of each factor in individual clusters (Figure 7). This enables the identification of the resilience vulnerabilities of the clusters and provides a reference for subsequent research into waterlogging response strategies for public spaces.

Figure 7a illustrates that, in terms of robustness, the northern (units 10, 11, 15, 16, 19, and 24) and western (units 1, 2, 3, 4, 6, 7, and 8) areas outperform other regions. This superiority is attributed primarily to the elevated terrain within these units, which reduces the likelihood of water accumulation. Additionally, the presence of large-diameter stormwater networks allows for rapid and effective rainwater removal, consequently strengthening the drainage system's processing capabilities. These sectors are, therefore, more capable of withstanding significant rainfall events, diminishing the risks associated with standing water and waterlogging. In contrast, the eastern region's vulnerability chiefly stems from its topographic features, marking it as the least robust concerning this variable.

As shown in Figure 7b, regarding redundancy, the northern and central areas show more vulnerability (units 19, 20, 21, 22), mainly due to the high density of buildings and roads, which leaves little public space available for water infiltration. On the other hand, other areas, such as units 5, 11, 8, 10, 7, and 13, display higher to moderate levels of recoverability. Public spaces and green infrastructure within these units ensure persistent infiltration during surface water accumulation, thereby mitigating the duration of waterlogging and reducing the risk of waterlogging. Units 2 and 3 in the west and 23 and 29 in the south, with their higher greenery coverage and better water system connectivity, demonstrate robust infiltration and rainwater conveyance capabilities.

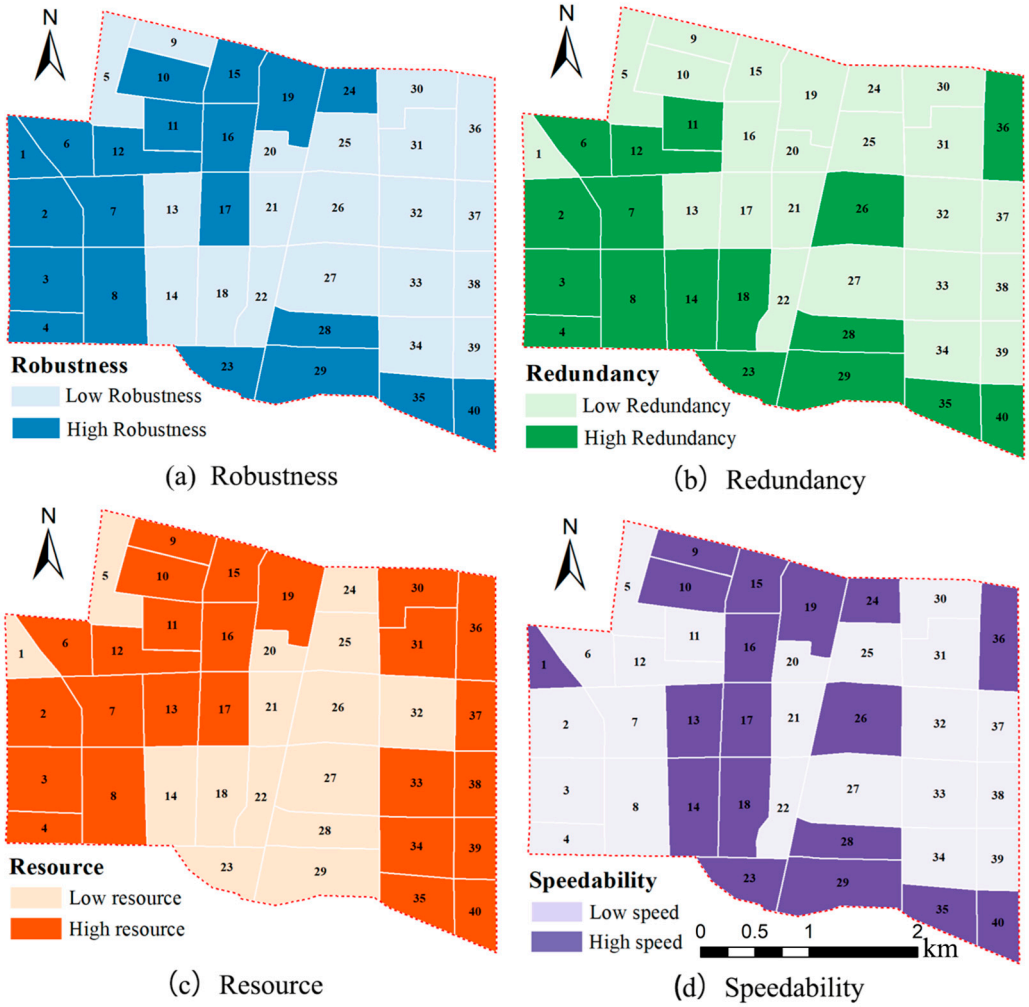


Figure 7. Analysis of toughness characteristics of units in the old urban area of Shijiazhuang.

As shown in Figure 7c, in terms of resource adaptability, the central areas of the old town exhibit poorer performance compared to the peripheral areas, primarily due to a north–south railway line that impacts the distribution of available resources and emergency facilities. The issue arises from dense urban structures and buildings that limit emergency response spaces or because resource allocations do not fully cover areas where the demand is concentrated.

As shown in Figure 7d, in the dimension of rapidity, the central areas of the old city (units 15, 16, 17, and 40) and the areas extending to the Minxin River in the south show favorable performance. However, the rapidity is notably weak in the western and eastern parts (units 2, 3, and 4), potentially due to outdated infrastructure, a scarcity of human resources, or insufficient response plans.

The numerical radar distribution map of the urban waterlogging resilience factor represents the difference between 22 resilience factors and their variables in 10 clustering-type units in the old city of Shijiazhuang (Figure 8). According to these different clustering features and the mean value analysis results of each unit factor, we can differentiate and systematically plan for the characteristics of each unit combined with the clustering situation. This means that for different types of regions, we can formulate differentiated planning programs, focus on strengthening their weak links, and enhance the overall urban waterlogging resilience. This differentiated planning provides a practical basis and standard for the subsequent planning response zoning and strategy according to the different characteristics and needs of clustering categories.

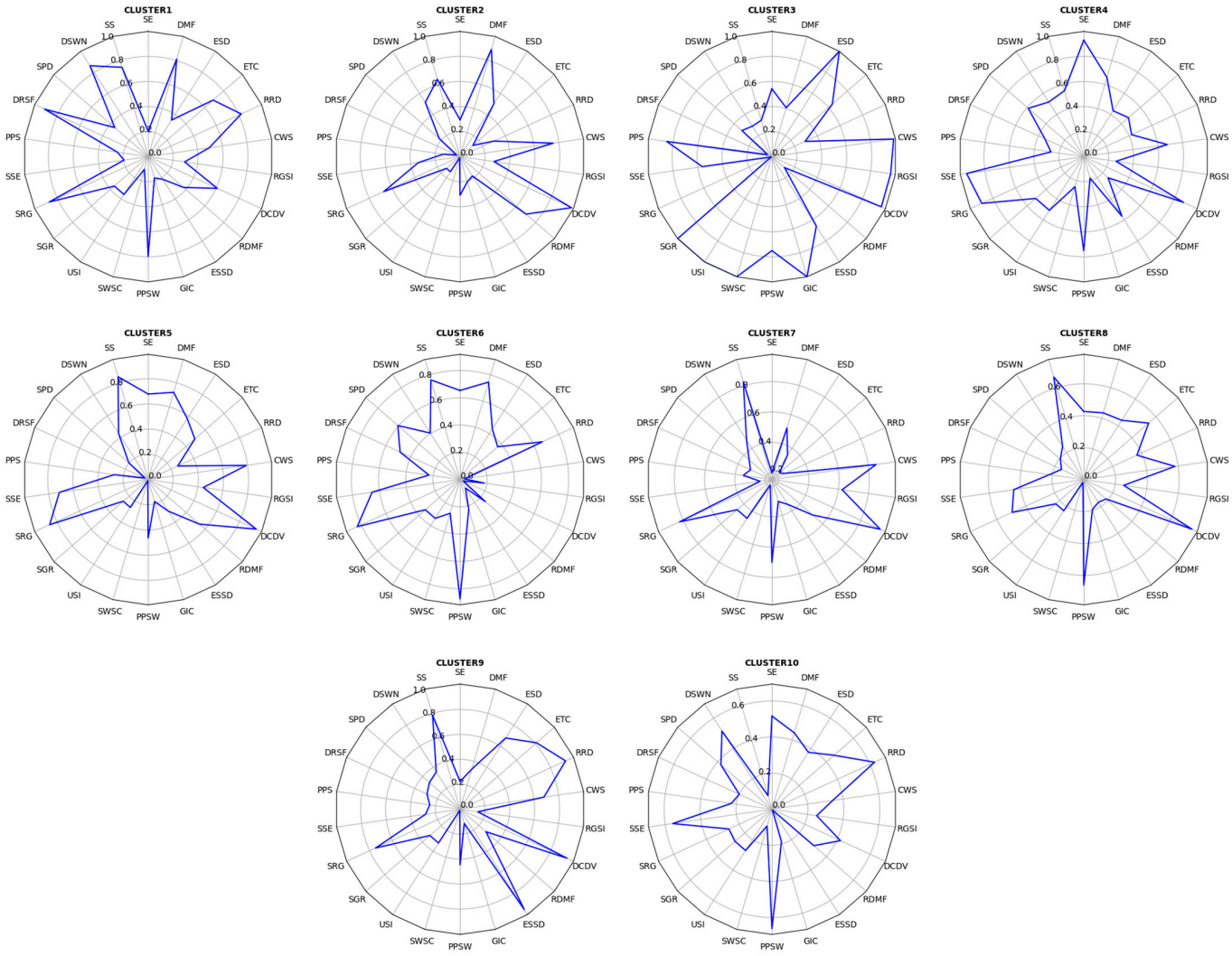


Figure 8. The average value of each factor of unit waterlogging toughness clustering in the old urban area of Shijiazhuang City.

4.3. Resilience Unit Spectrum Distribution Characteristics in the Old Town of Shijiazhuang

Based on the division into ten resilience spectra, the clusters of dominance, mixed, and disadvantage were identified by summarizing according to the 4R attributes of resilience. Clusters with more than two high attributes were defined as dominant clusters, while those with fewer than two high attributes were termed disadvantaged clusters [54]. Clusters with an equal number of high and low attributes were identified as mixed. This categorization led to a map of resilience unit clusters depicting the differential roles and distribution characteristics within the old town's urban waterlogging resilience context (Figure 9).

Upon analyzing the typology of the resilience spectra across typical areas of the Shijiazhuang old town, a distinct pattern of divergence was observed in the unit resilience types. Of all unit types, none exhibited a high robustness–low redundancy–low resourcefulness–low rapidity (HB-LD-LS-LP) or low robustness–low redundancy–low resourcefulness–high rapidity (LB-LD-LS-HP) cluster. Synthesizing the spectrum typologies with the dominance-disadvantage categorization, we discerned a pattern characterized by regions of coexisting dominance and disadvantage. A statistical breakdown of these clusters revealed the number and proportion of advantageous versus disadvantageous units, as outlined in the corresponding Table 5.

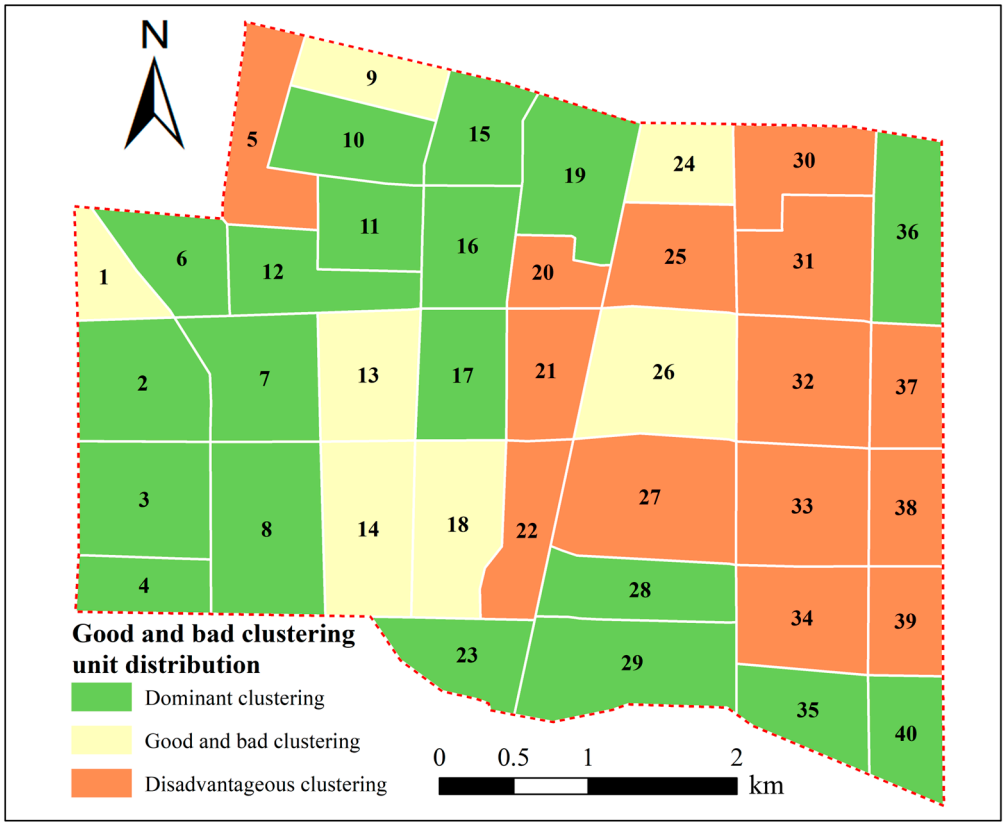


Figure 9. The spatial distribution of clustering advantages and disadvantages of waterlogging resilience units in the old urban area of Shijiazhuang City.

Table 5. Cluster unit statistics of good and bad in Shijiazhuang old city.

Dominant Type	Number	Proportion
Good clustering	19	47.5%
Bad clustering	14	35%
Good and bad combination clustering	7	17.5%

The spatial distribution of urban waterlogging resilience in Shijiazhuang reveals significant geographical clustering, highlighting the variability in regional capabilities to counteract waterlogging challenges. Specifically, units within the city exhibit distinct cluster formations, with patterns of both concentration and dispersion evident in the spatial distribution and similar resilience units tending to group within specific geographic locales. These units manifest spatially in various forms, including block clusters of varying sizes, elongated belts, or scattered dots.

Dominant resilience units are widespread throughout the old town of Shijiazhuang, occupying a relatively large area with a higher presence in the west compared to the east. These units are primarily consolidated in the western districts of Qiaoxi, Xinhua, and Yuhua along the Minxin River. With superior infrastructure, topographical advantages, and mature response mechanisms, these areas exhibit a higher level of resilience and reflect superior performance in withstanding and recovering from waterlogging disasters. In contrast, mixed resilience clusters within the old town are more sporadically distributed, forming a pattern of scattered points, mainly centered on the urban core and extending east and west along the central axis. This distribution reveals disparities in waterlogging resilience, highlighting areas in need of focused developmental efforts. Disadvantaged resilience clusters are predominantly found in the eastern regions of the old town. These clusters not only form dense groupings within certain districts but also extend linearly along

urban transport routes both longitudinally and transversely, indicating possible significant deficiencies in the geographical environment, infrastructural support, or resource allocation.

The observed spatial patterns prompt considerations for an uneven distribution of urban waterlogging resilience characteristics and suggest clear directionality for future targeted enhancements in urban waterlogging response mechanisms and overall resilience levels. These insights offer partitioning standards for subsequent planning measures, ensuring optimized resource distribution and precise execution of risk management strategies.

4.4. Planning Partition and Response Based on Resilience Unit Clustering

4.4.1. Planning Partition Based on Resilience Unit Cluster Characteristics

Given the varied cluster characteristics of urban waterlogging resilience units, encompassing dominant, disadvantageous, and mixed clusters, an inclusive assessment allows for systematic and differentiated planning tailored to each unit's features (Figure 10). An initial categorization of the urban units can identify differences in robustness, redundancy, resourcefulness, and rapidity (the 4Rs) in the face of waterlogging disasters. Differentiated zoning criteria should be applied across the three cluster categories as follows:

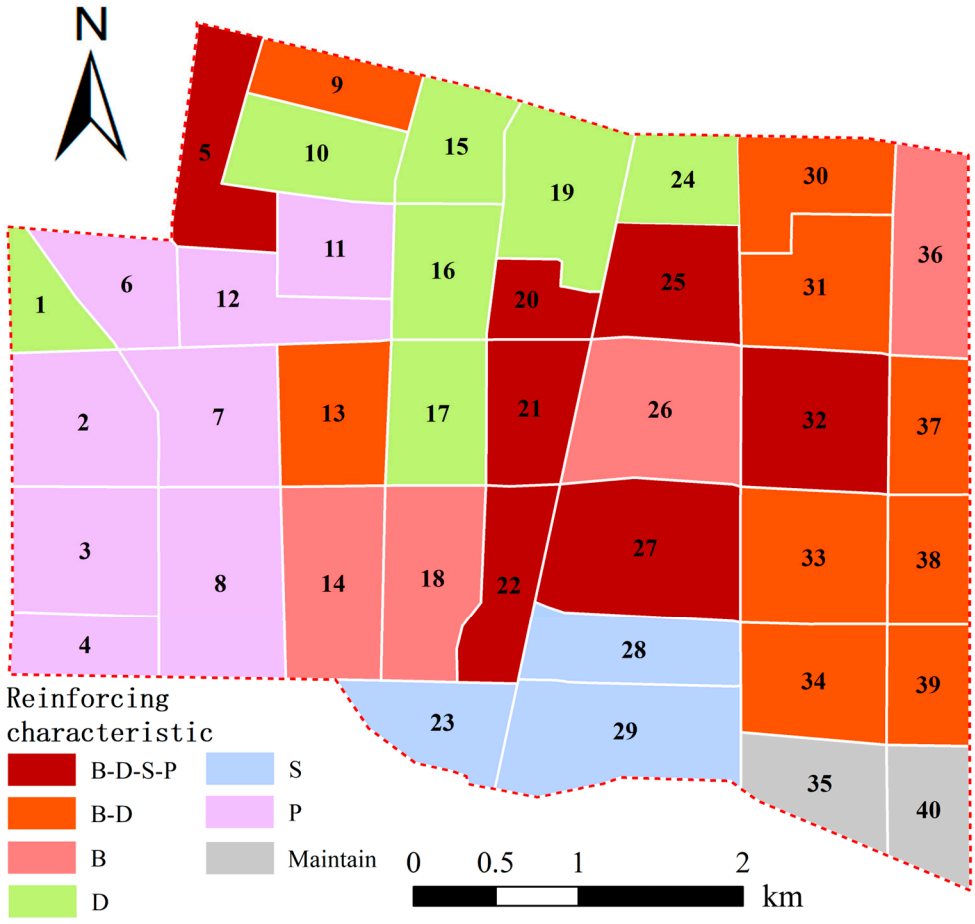


Figure 10. Planning response zoning based on clustering characteristics of waterlogging resilience units.

Dominant Clusters: These are typically referring to those units with relative strengths in robustness and redundancy. Planning strategies should maintain and enhance the proven strengths while considering augmenting other dimensions of resilience. For instance, units 10, 15, 16, and 17, while dominant, may be designated as Redundancy Enhancement Zones (D) due to insufficient redundancy.

Disadvantaged Clusters: Represent areas with notable vulnerabilities to urban waterlogging. Planning in these areas should fundamentally seek to improve robustness and increase redundancy. For units like 20, 21, and 22, which manifest weaknesses in three or

more 4R characteristics, such sections may be allocated as Equally Strengthened Zones (B-D-S-P) across all deficient attributes.

Mixed Clusters: Exemplify regions with mixed performance, meriting a balance of enhancing strengths and mitigating weaknesses. For units 14, 18, and 26, deficiencies in robustness and resourcefulness may result in a Robustness Enhancement Zone (B), coupled with emphases on improving resourcefulness.

4.4.2. Resilience Countermeasure Strategy for Cluster Response Units

Clustered response unit resilience strategies primarily refer to the adoption of personalized disaster prevention, mitigation, and response measures for different urban pluvial planning units aimed at enhancing the resilience of these units in the face of pluvial disasters. Each control unit needs to strengthen its pluvial resilience through targeted strategies that optimize resource allocation and enhance the capacity to resist disasters. These strategies rely on the precise identification and categorization of urban areas based on their pluvial resilience, as well as an in-depth understanding of the internal structure, functionality, and needs within these areas. Dividing the city into multiple pluvial resilience response units and tailoring specific waterlogging prevention and resilience measures for each unit can enhance the city's overall disaster response capability while ensuring flexibility and efficiency.

(1) Response for Unit Bs with Weak Robustness

For units with weaknesses in robustness, it is crucial to fortify the urban topography and municipal infrastructure capabilities. This includes improving the topography of low-lying areas within the unit, enhancing the waterlogging prevention standards of the rainwater pipeline network, maintaining and strengthening the existing drainage system, and increasing the waterlogging protection thresholds of key facilities to improve their efficiency and stability [19]. Planning responses should prioritize key areas based on the differences in robustness among units, ensuring these regions are better equipped to withstand pluvial waterlogging in future rainfall events. For example, in the central area of the old city, the unit's characteristics for coping with pluvial waterlogging show weak robustness. Investigations reveal that the local rainwater pipeline network's design life standard is below par. Precise positioning through the detection of specific causes of urban pluvial overflow nodes can allow for targeted improvements in the pipe network's drainage capacity within existing conditions by expanding pipe diameters [27]. The eastern unit of the old city district shows weaker robustness, yet the rainwater pipeline network's design standards are high. Considering the local terrain, constructing overflow retention tanks in underground pipelines near prone waterlogging areas or strategically placing retention tanks at bottleneck segments can alleviate network system overload and serve waterlogging prevention functions.

(2) Response for Unit Ds with Weak Redundancy

In planning for units with weaknesses in redundancy attributes, emphasis should be placed on increasing the alternative solutions and redundant elements within the unit, such as adding multifunctional water storage public spaces, enhancing the coverage rate of green infrastructure, and diversifying vegetation to improve water storage and permeability capabilities [55]. The enhancement of redundancy in planning units can be achieved by establishing rain gardens and multifunctional green spaces with flexible water management facilities so that, even if the primary drainage system fails, there are auxiliary means to alleviate the waterlogging impact. Spatially, low-redundancy central units can relieve pluvial waterlogging toward high-redundancy peripheral areas: (i) For low-redundancy units, internal high-resilience public spaces collaborate with other lower-resilience spaces to mitigate pluvial waterlogging, such as strengthening the connectivity of public spaces, transformation of road space to permeable surfaces, etc. [56]. (ii) High-redundancy units primarily assist neighboring low-redundancy units by undertaking surrounding low-redundancy high-risk units' water accumulation risks and enhancing the

continuity of green infrastructure within the unit [40], guiding rainwater runoff into inner high-redundancy areas through linear green belts to store water and mitigate waterlogging.

Unit resilience clustering analysis reveals that in the old city center, the railway line and surrounding green public spaces are linearly distributed, yet both the unit and adjacent units are low in redundancy. Consequently, these railway-adjacent green spaces can be used as typical pluvial potential spaces, developing linkage potentials with surrounding unit areas, primarily adopting strategies for waterlogging acceptance by connecting units and enhancing regional green infrastructure continuity, in line with the "sponge city" and low impact development (LID) concepts [57]. Additionally, partial LID measures may be adopted to link different parcels within the area, creating a disconnected high-low-high spatial pattern to disrupt the connectivity between surface buildings, thereby increasing surface runoff permeation and reducing the risk of urban waterlogging [58].

(3) Response for Unit Ss with Weak Resource Allocation

Enhancing resource allocability involves primarily optimizing resource distribution and dispatch efficiency. Planning units should fully utilize the existing resources, such as improving infrastructure distribution and the mobilization capability of disaster prevention resources. Moreover, by maximizing community resource mobilization, community members can be encouraged to respond collectively, thus dispersing risk. Strengthening the early warning and evacuation capabilities can enhance the prevention and response efficiency to pluvial waterlogging disasters. Increasing the number of emergency shelters and backup facilities, as well as the density of emergency shelters and medical facilities' layout within the region, can strengthen the rapid evacuation and sheltering capacity for people affected by disasters [59]. For instance, in the densely constructed central area of the old city, a dispersed emergency shelter space network should be established, with reasonably distributed densities for each gathering point, ensuring sufficient refuge spaces for every area [60]. Establishing emergency backup facilities to ensure rapid deployment during disasters, enhancing the density of regional medical facilities, perfecting the pluvial disaster monitoring and early warning system, and formulating clear emergency evacuation plans are crucial.

(4) Response for Unit Ps with Weak Responsiveness

To address the weaknesses in responsiveness, the delineation of planning units should enhance the city system's response speed to pluvial waterlogging events. Maintaining good road accessibility and external traffic connectivity, optimizing early warning systems and emergency response mechanisms, ensuring that information can be quickly transmitted to each unit before pluvial waterlogging occurs, and ensuring that emergency resources can be swiftly provided are key considerations [61], for example, by ensuring that rescue teams and supplies can quickly reach affected areas and optimizing the transportation network to guarantee efficiency in emergencies. For areas on the periphery of the old city, which show weak responsiveness, enhancing road accessibility can ensure that the main roads and bridges remain passable during pluvial events [62]. Strengthening connections between the city and external transportation hubs to ensure rapid mobilization of external rescue forces and supplies, enhancing the city's maintenance and construction capabilities, regularly maintaining and caring for urban infrastructure, and improving their waterlogging resistance and operational efficiency are essential.

Through the aforementioned planning unit responses and delineations based on urban pluvial resilience characteristics, the city's potential planning weaknesses during pluvial disasters can be effectively identified and reinforced in advance, increasing the city's response capacity to pluvial disasters and reducing potential losses.

5. Conclusions

In this study, we delved into the core components of urban resilience—robustness, redundancy, resourcefulness, and rapidity—and successfully developed a novel clustering factor analysis framework specifically designed to assess and understand the resilience

characteristics of urban spaces during waterlogging events. By selecting the old-town district of Shijiazhuang as a case study and employing the K-Means++ algorithm to process the resilience factor data, we meticulously categorized the urban spatial units of the old town into 10 distinct resilience types. Through comprehensive analysis and phylogeny construction, this research delineates the strengths and vulnerabilities of the Shijiazhuang old town in facing waterlogging disasters.

Building upon this, we further refined the cluster types into three major categories—dominant, disadvantaged, and combined types—and delved into the primary issues and characteristics of different types by integrating the average performance of each resilience unit within the categories. The methodologies and findings proposed in our research not only guided the formulation of relevant planning and measures but also provided valuable references for urban managers to tailor their strategies to strengthen the resilience of cities in response to waterlogging disasters.

The outcomes of this research underscore the importance of recognizing the heterogeneity among various urban units when confronted with waterlogging threats, and the extensive analysis of the unit types and their details within the "4R" dimensions of urban resilience significantly enhances our understanding of the weak links. Ultimately, this study not only bolstered the adaptability of individual urban units but also vigorously advanced the construction of an overall more resilient urban space against waterlogging disasters.

The case study of Shijiazhuang's old urban area illustrates the application of clustering and phylogenetic studies in addressing the multidimensional characteristics and complexity of urban resilience, thereby offering an innovative methodological framework for assessing urban resilience. This research contributes new insights into the robust development of increasingly complex urban environments, which are pertinent to the current studies and practices in urban resilience. Moreover, it encompasses a comprehensive analysis of various dimensions and types of disaster resilience, thereby laying a foundation for further optimization in other urban contexts and providing theoretical and methodological support for urban rainwater resilience research and prevention planning across diverse regions.

Looking forward, future studies are anticipated to continually validate the effectiveness of clustering methods in the domain of urban rainwater resilience research. There is also a pressing need to deepen our understanding of the phylogenetic-type division within urban resilience frameworks, aiming to bolster urban defenses against rainwater disasters and foster healthier, more sustainable urban development. Presently, this research encounters limitations in data sampling, most notably, the restricted scope of unit samples primarily concentrated in old urban districts. Subsequent research endeavors should extend their focus to newer urban areas to achieve a more comprehensive outlook. Furthermore, considering the potential influence of seasonal and temporal variations on urban rainwater resilience, forthcoming studies are encouraged to investigate the direct links and impacts of these factors on regional rainwater resilience. Venturing into these new areas of research will pave the way for a more thorough comprehension and enhancement of urban adaptability and recovery capabilities in the face of rainwater disasters, ultimately contributing to the promotion of healthier and more sustainable urban development.

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