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Predicting and Improving the Waterlogging Resilience of Urban Communities in China—A Case Study of Nanjing

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Abstract: In recent years, urban communities in China have been continuously affected by extreme weather and emergencies, among which the rainstorm and waterlogging disasters pose a great threat to infrastructure and personnel safety. Chinese governments issue a series of waterlogging prevention and control policies, but the waterlogging prevention and mitigation of urban communities still needs to be optimized. The concept of "resilience" has unique advantages in the field of community disaster management, and building resilient communities can effectively make up for the limitations of the traditional top-down disaster management. Therefore, this paper focuses on the pre-disaster prevention and control of waterlogging in urban communities of China, following the idea of "concept analysis–influencing factor identification–evaluation indicators selection–impact mechanism analysis–resilience simulation prediction–empirical research–disaster adaptation strategy formulation". The structural equation model and BP neural network are used by investigating the existing anti-waterlogging capitals of the target community to predict the future waterlogging resilience. Based on this simulation prediction model, and combined with the incentive and restraint mechanisms, suggestions on corrective measures can be put forward before the occurrence of waterlogging.

Keywords: communities' resilience; waterlogging; BP neural network; systematic literature review; incentive and restraint mechanism

Citation: Cui, P.; Ju, X.; Liu, Y.; Li, D. Predicting and Improving the Waterlogging Resilience of Urban Communities in China—A Case Study of Nanjing. *Buildings* **2022**, *12*, 901. https://doi.org/10.3390/buildings12070901

Academic Editors: Jian Zuo, Hanliang Fu, Zezhou Wu and Tao Wang

Received: 18 May 2022
Accepted: 19 June 2022
Published: 25 June 2022

1. Introduction

Various disasters and unforeseeable extreme events, especially those related to climate change, have been occurring more and more frequently in recent years [1]. Over the last decade, China has experienced more than 500 natural disasters, most of which are hydrological and meteorological disasters [2]. For instance, the Super Typhoon Likima in 2019 passed through nine provinces and affected 14.024 million people. With the high concentration of population, economy, and infrastructure in urban areas, the intensity of the disaster-causing factor changed, which put great pressure on Chinese cities [3–5]. Especially, rainstorm and waterlogging have gradually become the main risk to urban development among various disasters [6]. Waterlogging does not mean the same thing everywhere. To better understand and reduce disputes, this paper defines waterlogging as a disaster in low-lying or flat areas, where long-term rainfall or instantaneous heavy rain leads to excessive water on the ground that cannot be drained in time. For example, in 2021, the rainstorm in Henan caused the death of 302 people and direct economic losses of RMB 88.534 billion. Nanjing suffered two heavy rainstorms in 2017 and 2019, resulting in severe waterlogging of the whole city.

With the pressure of urban rainstorm waterlogging increasing, building urban resilience has become a global consensus to achieve the sustainable development of cities [7]. All levels of the government in China always attach great importance to the prevention and control of rainstorm waterlogging and issue various documents such as "Implementation

Opinions of the General Office of the State Council on Strengthening Urban Waterlogging Control", "Emergency Plan for Flood Control and Drought Relief in Jiangsu Province", and "Nanjing's overall plan for establishing a national safe development model city". However, there are still shortcomings because of the lack of systematic theoretical support and community intervention. As the basic component of the city, the community is also the frontier of urban disaster prevention and mitigation (DPM) system [8]. By the end of 2020, the total number of disaster reduction model communities in China reached 14,511 [9]. Due to the fact that disaster reduction model communities begin to take shape, improving the anti-waterlogging ability from the community level is essential. One measure for resisting waterlogging is enhancing community resilience, which is a key index that more and more research points to [10,11].

Currently, a lot of research studies focus on theories and methods of DPM in urban communities. They start from various dimensions for many types of communities and adopt multiple evaluation methods. Most of them are post-disaster evaluations; however, once a disaster occurs, it is too late to remedy. To solve the above problems, this paper attempts to develop a predictive model for community resilience towards waterlogging based on structural equation model and BP neural network. The model is used to predict social, natural, and economic resilience before waterlogging occurs, and the corresponding improvement measures are proposed based on the predicted results.

2. Literature Review

2.1. Definition of Waterlogging Resilience

The concept of resilience has multidisciplinary origins and accepts various interpretations, thus posing challenges to understanding and defining [12]. Holling's pioneering research on ecosystem resilience in 1973 is often considered to be the origin of modern resilience theory [13]. In the 1990s, the concept of resilience was introduced into the field of urban planning, and it has quickly become popular [14]. Although the term "resilience" appears frequently in urban studies nowadays, scholars have not reached a consensus on the definition [15,16]. The focuses of research on resilience definition are not the same. Some scholars combine other related concepts to analyze and explain the meaning of resilience. For example, Xu et al. [10] and González et al. [17] define resilience as a system's capacity to absorb, adapt to, and recover from damage, which is different from vulnerability, an indicator that describes the exposure of the system. Roostaie et al. [18] studied the similarities between the definitions of sustainability and resilience. In addition, roughly half of scholars define urban or community resilience to all risks. Meerow et al. [19] believe that urban resilience is the capacity of an urban system and all its social–ecological networks to maintain or restore functions when facing disturbances. However, Brown et al. [20] propose a more positive definition of urban resilience, which is not only to maintain basic functions, but also to improve and develop. Rapaport et al. [21] argue that resilience determines the ability of a community to use its existing resources to resume daily work and even perform better than pre-disturbance situation. Meanwhile, the other half focuses on the definitions that are presented in the context of a specific disaster. Take flood resilience as an example; Miguez and Verol [22] define it as the ability to resist or recover from the impacts of flood and continue to perform a function. Wagner and Breil [23] define it as the ability to reduce losses and recover from a flood rapidly. Moreover, many researchers attempt to introduce the definition of resilience into flood management are limited to improve the stability of the drainage system. In general, waterlogging and flooding always accompany each other; waterlogging resilience in this paper refers to the ability to tolerate waterlogging, disperse risks, and maintain or restore stability.

2.2. Mechanisms and Characteristics of Urban Communities Waterlogging in China

Urban community waterlogging disaster is different from a flood, which is the result of the joint action of a rainstorm and the drainage system. A rainstorm is the sufficient condition for the occurrence of disasters, and the disaster bearing the body of the urban community is the necessary condition for the occurrence of disasters. The internal causes of waterlogging in urban communities generally include the following aspects: (1) Communities mostly use impermeable materials such as cement concrete, masonry, or asphalt to lay the ground or pavement, and the rainwater storage capacity is poor. (2) The construction of waterlogging-prevention facilities such as drainage pipes, canals, and pumping pumps in most old communities lags behind, and the pumping capacity is insufficient. (3) Due to improper construction and management, construction waste or residents' domestic waste blocks or silts the pipeline, resulting in poor drainage and local water accumulation on the ground. (4) There is a lack of public awareness and failure to deliver disaster information to citizens in time. In addition, the surface of coastal areas is flat. If the rainstorm coincides with strong winds and tides, the drainage capacity of the community is particularly affected, and waterlogging is more serious.

When the urban community suffers from a rainstorm and waterlogging, it accumulates rapidly on the community ground in a short time, resulting in community road blockage and traffic obstruction of vehicles and pedestrians; water inflow in the basement, garage, shop, and other places; and damage to walls, floors, and other indoor properties of ground floor residents. The residents on the top floor may have water leakage; Some infrastructure in the community is damaged or restricted. With the passage of time, the retention of sewage and garbage in the ponding pollute the community environment and accelerate the spread of diseases; furthermore, the people's mood is affected, they are dissatisfied with the community management, and the community quality and value and residents' harmony decline. The chain transmission of the impact of a rainstorm and waterlogging on the community is shown in Figure 1.

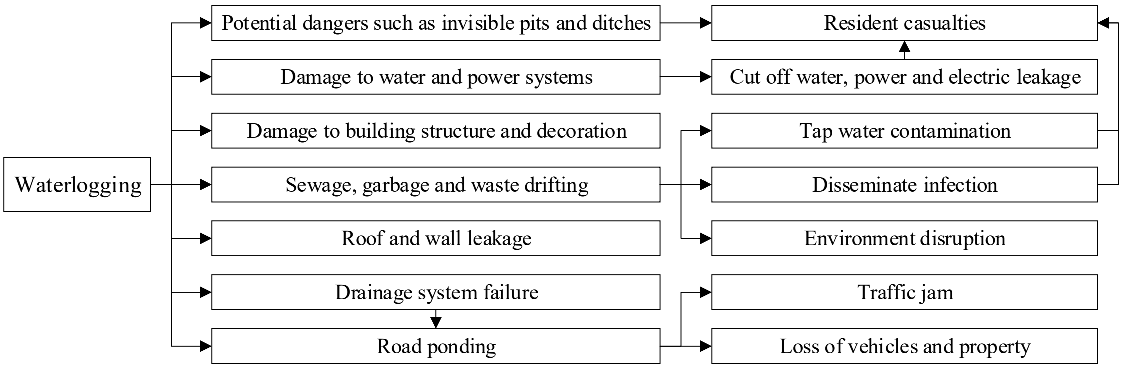

Figure 1. Community impact and chain transfer diagram of waterlogging disasters.

Studying the mechanisms and characteristics of urban waterlogging is helpful for revealing the urban waterlogging prone areas, so as to minimize the negative impact of waterlogging [24–26]. Some studies have investigated the occurrence and change mechanism of urban waterlogging. Sofia et al. [27] used multivariate statistical methods to analyze the change of various influencing factors, thereby revealing the basic mechanism of waterlogging. There are also some studies that have used hydrodynamic models such as SWMM and MIKE to simulate the process of urban waterlogging [28–30]. More and more scholars are establishing machine learning models such as SVM and ANN to study the susceptibility or impact mechanism of urban waterlogging [31–33]. For instance, Zhang et al. [34] combined SCAM with HPA, discovering that extreme rainfall, impervious surface, and vegetation abundance are the main driving factors of urban waterlogging mechanism. Since different types of rainfall often cause different characteristics of waterlogging, Ma et al. [35] took Zhengzhou as an example to analyze the characteristics and classification of rainstorm waterlogging. Ma et al. [36] utilized 25 years of records from the government to expound the characteristics of urban waterlogging in China.

2.3. Assessment and Measurement of Waterlogging Resilience

A lot of studies have been conducted on the assessment and measurement of urban resilience. Much of the literature recognizes that developing resilience evaluation tools and methods is a vital step to prepare for natural hazards [37–39]. In other words, resilience assessment tools can monitor the effectiveness of the mitigation plan after decisions and help allocate limited resources before decisions [40]. Before resilience theory is applied to the field of DPM in urban communities, scholars focus on disaster management based on enhancing the capital of urban communities. Sanyal and Routray [41] pointed out that strengthening the social capital and social network of the community can make up for the deficiencies in infrastructure and disaster management. Fu et al. [42] proposed to improve social education capital and promote urban pollution disaster management through sustainable environmental education. Onuma et al. [43] found that households with sufficient emergency material reserves (basic preparation, energy/heat preparation, and evacuation preparation) can effectively resist natural disasters. In summary, community capital affects disaster resilience to a certain extent, but few scholars have systematically studied the impact of community capital on community resilience in the field of community resilience assessment. Existing waterlogging-resilience assessment approaches can be broadly divided into the following categories. Some have analyzed resilience thresholds based on historical flood events [44], while some have taken urban social, economic, and environment into account, setting up an index system [45,46]. Many assessment methods are based on the subjective impressions of experts, so they do not have a higher accuracy [47]. Furthermore, to assess and measure the urban resilience against waterlogging, the evaluation indexes must be indispensable. Recent years have witnessed a proliferation of works focusing on this topic. Huang et al. [48] assess the resilience of Guangzhou in response to waterlogging and flooding, using historical flood data. Chen et al. [49] introduce a time-varying waterlogging resilience index to quantify the level of resilience during and after urban floods. Bottazzi et al. [50] apply a subjective index framework to assess and measure flood resilience after project intervention. However, the key points of these assessment indexes and methods are mostly around resilience after a disaster, not before. In fact, some experts in the field of disaster management have used various advanced technologies to conduct pre-disaster assessment. Munawar et al. [51] wrote an overview of the use of disruptive technologies to move towards automated disaster prediction and forecasting. Tahir et al. [52] created a satellite image dataset by using a convolutional neural network–based framework to perform object detection. Qadir et al. [53] analyzed various metaheuristic algorithms for pre-disaster assessment and realize the function of UAV path optimization. These papers also serve as a reminder that more scholars can use similar techniques to study the prediction mechanism of community pre-disaster resilience.

In summary, the existing studies have earned a certain achievement on the urban communities waterlogging resilience. However, there are significant knowledge gaps regarding the mechanisms of urban communities waterlogging, and the assessment of waterlogging resilience. First, there is still a lack of systematic mechanism, which specifies the whole process of urban waterlogging. Second, there are few studies that focus on the prediction of community resilience before waterlogging. In order to fill these gaps, this study aimed at identifying the influencing and evaluating factors, introducing the prediction model of waterlogging resilience, and improving resistance capacity before waterlogging.

3. Method and Data

3.1. Roadmap

This paper follows the overall idea of "community capitals–disaster indicators–qualitative relationship–Prediction Model–improvement measures". Based on the existing research status, we systematically identified and evaluated the impact indicators and evaluation factors of community disaster resilience, clarified the qualitative relationship between indicators, and built a pre-disaster prediction model. Finally, by applying the prediction model in Nanjing target communities, providing improvement measures and suggestions for community stakeholders before rainstorm and waterlogging may occur. The roadmap is shown as Figure 2.

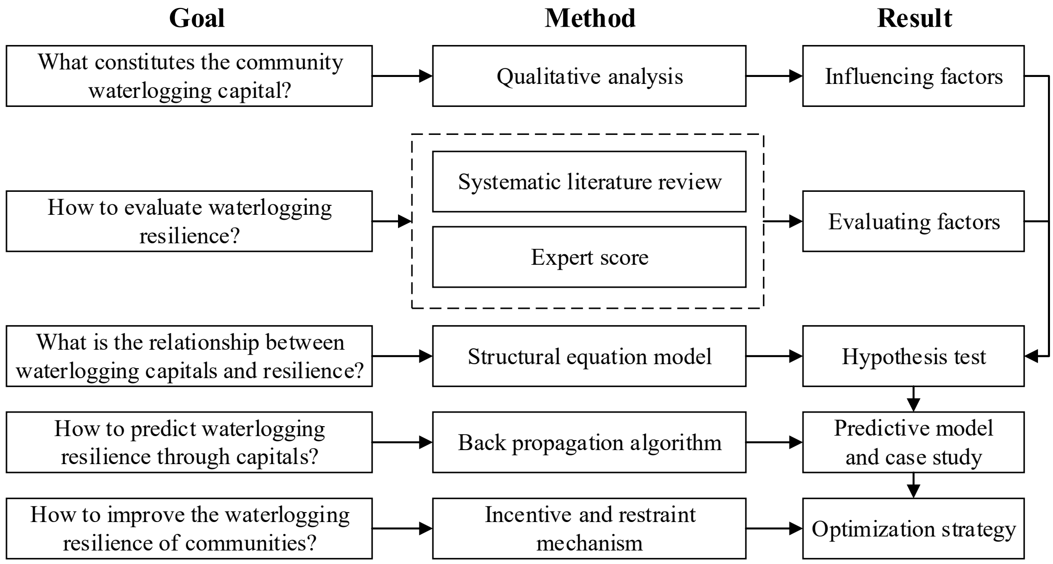

Figure 2. The roadmap of predicting and improving the waterlogging resilience.

3.2. Data Collection

Three kinds of online/offline data collection are conducted, including expert score, interview, and questionnaires. First, this study conducted in-depth interviews with 43 stakeholders of urban community DPM to obtain the influencing factors of community waterlogging resilience. The interviewees are from the Nanjing Fuguishan Community, Nanjing Southeast University Community, Nanjing Meiyuan Xincun Subdistrict Office, Shenyang Xita Police Station, Liaocheng Gulou Subdistrict Office, Shenzhen Jincheng Huating Community Property Centre, Shenzhen Huangbei Street Xinyi Community Committee, Chengdu Jinquan Community, and so on. Several interviews conducted in the early stage were mainly open-ended, gradually moving to semi-open-ended, semi-structured interviews, and finally structured interviews. Second, after summarizing the initial selection of evaluation indicators for community waterlogging resilience, this paper distributes expert scores (Supplementary Material) to screen and supplement indicators. Third, on the basis of identifying the influencing factors and evaluation indicators of community waterlogging resilience, the paper constructs a structural equation model to test the hypothetical relationship between factors and indicators, which requires a large number of sample data through the questionnaires (Supplementary Material) as support. This questionnaire is divided into three parts: The first part is the basic information of the respondents, which is used to analyze the group characteristics in different backgrounds. The second part contains 20 items, mainly to investigate the damage status of community after disasters. The results obtained in this part can be used for structural equation model verification. In the third part, there are 19 items on the community DPM capacity survey that examine the types and stocks of influencing factors of waterlogging resilience in the target communities.

4. Prediction of Waterlogging Resilience

4.1. Identifying the Influencing Factor by Using Grounded Theory

The interviews were conducted based on grounded theory to mine information from various stakeholders' practice and perceptions of community disasters to find the relevant concepts and categories needed in this paper, establish a system of anti-disaster capital indicators, and then construct models and theories.

Due to the limited theoretical basis and prior research, the questions and content were random, open-ended, and unstructured in the early stages of the interviews. Interviewers and interviewees talked freely, expanding on a particular topic or issue and, gradually, gridisolated issues. For example, common questions used in the early stages of the interviews include the following: "Have you ever experienced a community waterlogging?" "What steps would you take as a property company manager to protect your own and other people's lives and property when a disaster hits?" "What aspects of the community are most affected by a disaster?" "What materials, resources, and capitals do you think are available in the community to mitigate the impact of a disaster in a limited way?" "Who is the first person you think of asking for help after waterlogging?" "What government funding has been provided to combat waterlogging?" As the interviews and research progressed, the questions became more focused and fixed in scope. The relevant categories, characteristics, and order of questions also became clearer: "Please give an example of helping or being helped when you were in a disaster?" "Please describe your psychological changes and feelings during the whole disaster?" In summary, the outline of the interviews developed in this paper is shown in Table 1.

Table 1. Interview topics, outlines, and content.

Interview Topics	Specifics
Basic Information	Age, education, occupation, stakeholder affiliation, etc.
Community disaster identification: What aspects of the community (people, economy, physical facilities, environment, etc.) are affected by waterlogging?	➢ Has your current or previous community experienced waterlogging? ➢ What infrastructure or public services have been damaged by waterlogging in the community?
Mechanisms of disaster: How do disasters specifically affect the above aspects of the community?	➢ How are residents affected after waterlogging? How has it changed? ➢ How has your home, vehicle, other property been affected? ➢ How has the community environment been affected?
Anti-disaster capital identification: What capitals in the community can reduce and resist the impact of waterlogging?	➢ What disaster prevention items would you prepare for frequent waterlogging? ➢ What items are prepared by neighborhood committees and properties in case of waterlogging? ➢ What qualities should residents and communities have to face waterlogging better? ➢ What capital in your community is you most concerned about being damaged after waterlogging?
Mechanisms of anti-disaster capital: How do these capitals play the role of DPM?	➢ What kinds of traffic roads are effective in alleviating waterlogging? ➢ What transformations have the community carried out to effectively improve the ability of resisting waterlogging? ➢ What is the effect of community culture on uniting residents and working together to resist internal flooding?
DPM strategies: What measures and actions can stakeholders take to enhance or increase the anti-disaster capital in communities?	➢ What do you do in your daily disaster preparedness and mitigation efforts? ➢ What role did you play and what steps did you take when waterlogging hit? ➢ Is there any way to help quickly restore the capacity of the community in post-disaster reconstruction?

After organizing and extracting the interview data until all the interviews were completed, 35 randomly selected interviewees were coded and sorted, and the remaining 8 interview records were used for the saturation test of grounded theory.

(1) Open coding of impact factors

A continuous iterative approach was used in this study to open coding of resident interview data; that is, based on the coding results of the first interview material, we continued to compare with the coding results of other interviews and add new content until all the material was summarized. With NVivo software, this paper organizes, summarizes, browses, and codes the materials, eliminates the initial concepts with a repetition frequency ≤ 2 times, and selects only the initial concepts with a repetition frequency > 2 times. The causes of waterlogging in the community, the key locations and facilities affected in the community, and the measures and capitals in the community that contribute to DPM were extracted from the interview materials in turn, as shown in the Supplementary Material.

(2) Influence factor axial coding and selection coding

Axial coding aims to further refine and compare the initial categories formed in the open-coding stage to form higher-level main categories and analyze the logical relationships between the main categories and the initial categories in terms of cause and effect, process, similarity, and function. Selective coding, also known as three-level coding, aims to clarify the relationships among the main categories; refine and integrate them into a core category that can summarize all the above categories; and display the relationships among the core category, the main category, and the initial category in the form of a story line and integrate them into the same theoretical framework. In summary, the core category of this study is defined as "the influencing factors of anti-waterlogging resilience in Chinese urban communities". Ultimately, 108 concepts and 13 initial categories were obtained from the 195 statements in the original material. Four main categories were obtained by axial coding, in turn, and finally one core category was obtained by core coding. The qualitative analysis process using the software Nvivo 11.0 is shown in Figure 3.

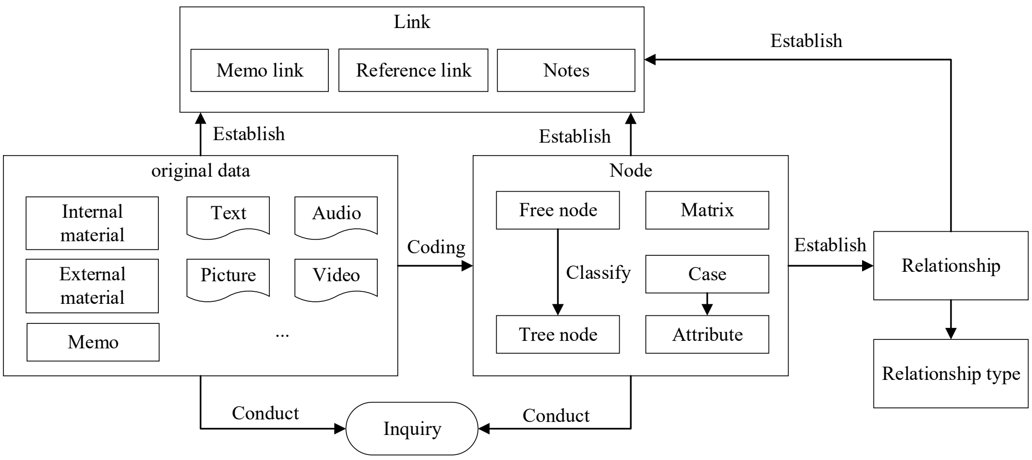

Figure 3. Qualitative-analysis flowchart.

(3) Theoretical saturation test

In the coding process, the theory reaches a "saturated" state when the newly added material and data can no longer generate new theoretical insights and new attributes of class genera. In this study, to ensure the reliability and validity of the grounded theory, the theory saturation test was conducted by using eight interviews reserved in advance. The results show that no new class and class attributes emerge, and the coding process is completed.

4.2. Selecting the Evaluating Factors Based on SLR

(1) SLR-based indicator selection

Previous studies fail to thoroughly distinguish the difference between the concepts, components, dimensions, evaluation indicators, and influencing factors of community resilience. This paper uses the systematic literature review (SLR) method to reorganize the evaluation indicators of community resilience. SLR is a method of scientifically summarizing and organizing the literature by avoiding errors in the selection of the literature and subjective factors [54]. Referring to the modified Cochrane evaluation proposed by Ahrentzen and Tural [55], this study used the terms "community", "resilience", "disaster", and "urban/city" in Chinese and English as keywords, searching in the Web of Science Core Collection (WOSCC), Elsevier, and CNKI database to verify the search results. In addition, the search was limited to the title, abstract, and keywords; the article type was limited to journal articles; and the publication time was set between 2006 and 2021. Articles that did not meet these restrictions were eliminated in the search results.

The results obtained from the search process are not always accurate; therefore, the following strategies were developed to screen existing articles multiple times. (1) Repeatability screening: An article may be affiliated with multiple databases. For example, an article published by Elsevier may be indexed by WOBCC. Therefore, a duplicate elimination process is required to ensure that there are no duplicate articles in the results. (2) Title filtering: Title filtering entails reading through the titles to filter those articles that are clearly not relevant to the community resilience evaluation indicators for disaster preparedness and mitigation. (3) Abstract filtering: In order to check whether the detailed objectives and conclusions of the research are related to the SLR rules, obtaining research information from the abstract is necessary; it was necessary to delete articles that do not mention community resilience and related content. (4) Full-text screening: In order to ensure the availability of articles that meet the above screening steps, downloading and reading the full text is an important part of the screening process. (5) Reference screening: Gathering missing articles from the references cited in the above screened articles provided additions to this study. From the above review of the literature, we can see that community resilience includes, but is not limited to, seven dimensions: social, economic, physical, natural/ecological/environmental, institutional/organizational, infrastructural, and human aspects.

(2) Results of evaluation indicators preliminary selection

After applying the aforementioned indicator selection method, we finally determined 92 articles related to evaluation indicators for community waterlogging resilience. The specific process is shown in Figure 4.

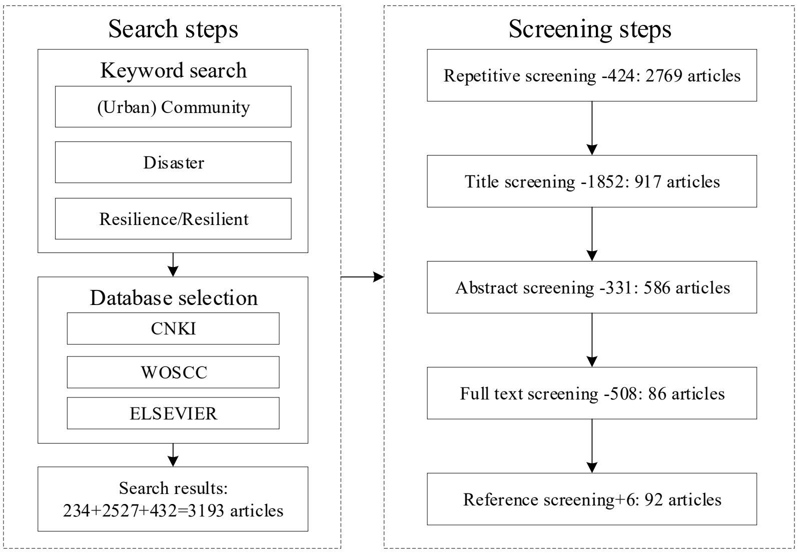

Figure 4. SLR searching and screening process.

Based on the above research, this study performed word frequency statistics on the community-resilience dimensions, primary indicators, secondary indicators, and representational indicators appearing in the above 92 papers by using Tuyet word frequency statistics software and extracting and sorting out the indicators with a frequency ≥ 3. Then we further organized the indicators. On the one hand, we deleted duplicate indicators and merged indicators with different expressions but the same content. On the other hand, the indicators were zoned according to the social, economic, and natural dimensions of the composite ecosystem theory. The initial community waterlogging resilience indicators that were obtained are shown in Table 2.

Table 2. Initial summary of community waterlogging-resilience indicators.

Dimensionality	Evaluation Indicators			
Societal	Elderly population	Innovative capacity	Disaster preparedness	Waterlogging detection and early warning
	Disabled population	Residents' ability to learn	DPM plan	Resident casualties
	Foreign population	Resident participation	Organizations in the community	Management system
	Healthy population	Trust and reciprocity	Nonprofit organizations	Dangerous exposure
	Single-person households	Sense of belonging	Religious organizations	Disaster response
	Mental health	Anti-waterlogging experience	Volunteer organizations	Disaster awareness and sensitization
	Educational level of residents	Residents' understanding of the community	Government actions	Emergency plan
	Educational equity for residents	Resident work occupation	Social structure function	Neighborhood relations
	DPM training and education	Stakeholder communication and collaboration	per capita housing area	Neighborhood committee capacity
	Disaster drills	DPM signs	Social network	Community promotion
	Awareness of waterlogging prevention	Social intercourse network	Leadership	Crime rate
Economy	Anti-waterlogging funds	Government budget for waterlogging prevention	Disaster insurance	Intelligent DPM
	Anti-waterlogging materials	Community assets	Health insurance	Food supply
	Income for residents	Community business	Social insurance	Energy supply
	Resident savings	Government financial input	Household assets	New technology applications
Natural	Community greening	Road traffic conditions	Ecological protection	Flood control standard
	Wetlands	Power system	Resource protection	House type
	Natural resources	Water supply system	Emergency facilities	Housing density
	Community water resources	Drainage system	Medical and health equipment	Space construction
	Resource accessibility	Gas system	Fire-fighting facilities	Facility protection
	Secondary disaster	Emergency shelters	Public service facilities	Bus
	Frequency of disasters	Building quality	Communication facilities	Evacuation routes
	Land	Building code standards	Community security	Flora and fauna

(3) Indicator simplification based on expert scoring method

The indicators in Table 2 may be cross, duplication, inclusion, redundancy between each other, and need to further screen and supplement. This study conducted a round of expert surveys through questionnaires to (1) ask about the rationality of the 92 indicators and (2) check if there are other indicators that needed to be added. Therefore, a total of 12 people, from college experts and doctoral students in relevant fields, heads of community committees, managers of street offices, and heads of property companies, were selected and distributed electronic questionnaires one by one (see Supplementary Material for details). The interviewees include two professors, one associate professor, two lecturers, four PhD students, and three undergraduates. The experts' opinions from 12 received questionnaires were organized, retaining the indicators that are endorsed by more than half of the experts and adding other key indicators suggested by the experts. In addition, the experts proposed a number of modifications to the existing indicators according to the characteristics of urban communities in China, and they added several new secondary indicators. Finally, three dimensions with 20 secondary indicators were chosen as evaluation indicators of waterlogging resilience in Chinese urban communities, as shown in Table 3.

Table 3. Evaluation indicators and influencing factors of the waterlogging resilience in China's urban community.

Influencing Factors				Evaluation Indicators			
Dimension		**Characterization Indicators**		**Dimension**		**Evaluation Indicators**	
A	Population capitals	A1	Age structure	E	Social resilience	E1	Personal safety
		A2	Educational level			E2	Resident participation
		A3	Disaster experience			E3	DPM awareness
B	Social capitals	B1	Trust and reciprocity			E4	Normative order
		B2	Social network structure			E5	Community response
		B3	External contact			E6	Social support
		B4	Regulation			E7	Emergency rescue
		B5	Pre-disaster preparations			E8	Recovery and reconstruction
		B6	Disaster warning	F	Economy resilience	F1	House status
C	Economic capitals	C1	Income for residents			F2	Government subsidies
		C2	Disaster insurance			F3	Community newsletter
		C3	DPM funds			F4	Community transportation
		C4	Emergency reserve			F5	Security system
		C5	Dedicated reconstruction			F6	Fire-fighting system
						F7	Public facilities
D	Natural capitals	D1	climate and meteorology	G	Natural resilience	G1	Water supply system
		D2	Energy supply			G2	Power system
		D3	Public services			G3	Road system
		D4	Transport			G4	Drainage system
		D5	Planning and siting			G5	Waste disposal system

4.3. Hypothesis Test on the Relationships of the Factors Using SEM

The evaluation indicators and influencing factors of waterlogging resilience in the urban community were obtained through SLR and grounded theory, as shown in Table 3. To further explore the relationship between the evaluation indicators and influencing factors, thus predicting the performance of non-affected communities when they experience waterlogging disaster through the influencing factors of anti-waterlogging capitals available in the affected communities, this section uses structural equation modeling to verify the relationship between the evaluation indicators and influencing factors.

The structural equation model is a comprehensive statistical analysis method that integrates path analysis and factor analysis. SEM verifies the validity of a theoretical framework by establishing links between target data, including the following four important parameters: (1) endogenous variables, which are affected by other variables in the SEM, are pointed by a single arrow in the path diagram; (2) exogenous variables, which affect other variables but are not influenced by other variables; (3) latent variables, which cannot be directly measured but can be reflected by the corresponding observed variables; and (4) explicit variables, also known as observed variables, can be directly measured to obtain a definite value. Observed and latent variables can be both endogenous and exogenous in SEM. This study set population capitals, social capitals, economic capitals, and natural capitals as exogenous latent variables corresponding to 3–6 observed variables, respectively, and defined social resilience, economic resilience, and natural resilience as endogenous latent variables corresponding to 5–8 observed variables, respectively. A hypothetical model with 12 hypotheses was established, asserting that the stronger a community's anti-waterlogging capitals are, the stronger its DPM capacity is, and the more resilient the community is, as shown in Figure 5.

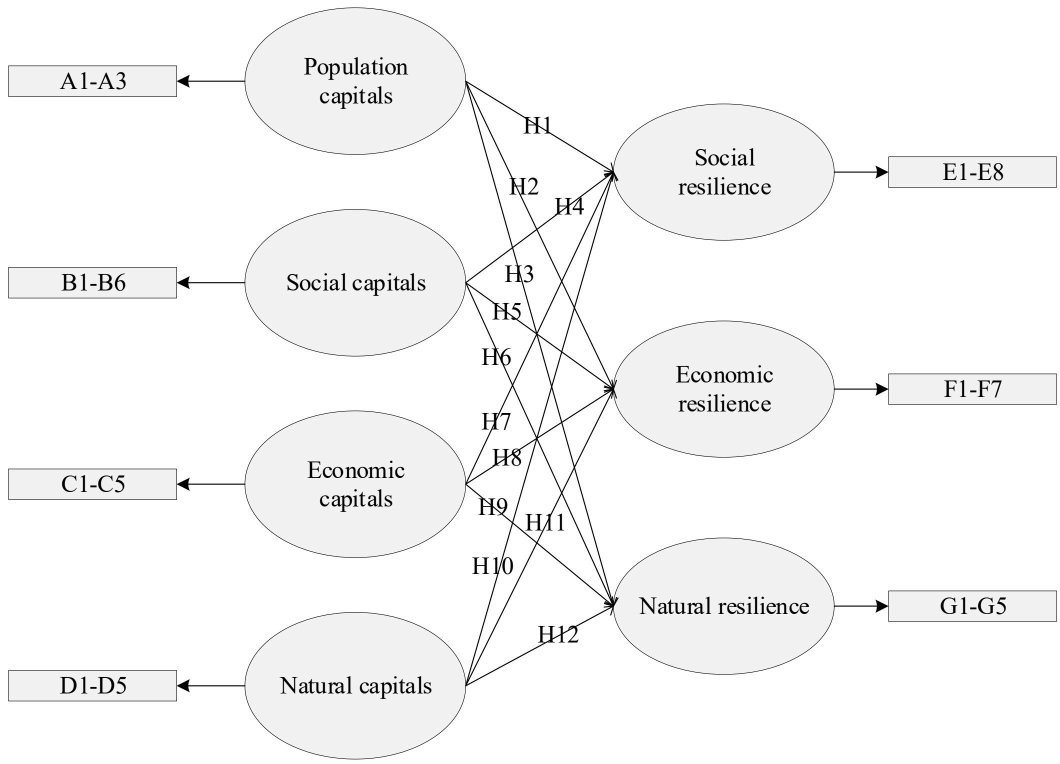

Figure 5. Model of waterlogging-resilience mechanism of urban community in China.

(1) Questionnaire distribution and data collection

The questionnaires were distributed to stakeholders of communities in more than ten cities, including Nanjing, Wuhan, Guangzhou, Shenyang, Shenzhen, etc. A total of 500 online/offline questionnaires were distributed, and 387 valid questionnaires were return. The basic information of these 387 interviewees and statistical analysis of the sample characteristics are detailed in Supplementary Material Survey S4 and are briefly introduced here. In the statistics of belonging stakeholders, there are 291 community residents, accounting for 75% of the total number of people in the study, and other stakeholders account for 2–6%. Respondents mainly came from Jiangsu Province, Sichuan Province, Guangdong Province, Hubei Province, and Fujian Province.

Based on AMOS software, this paper plots the path analysis of the structural equation model, as shown in Figure 6. The sample data obey more normal distribution in this paper, and the maximum likelihood estimation method is suitable for estimating the path coefficients. After the calculation of path coefficients by AMOS software, the direct-path test results of each hidden variable in the participating mechanism model are obtained (10 of the 12 hypotheses hold), and the corresponding standardized direct effect coefficients are shown in Table 4.

(2) Analysis of the relationships among factors

- Population capitals have a significant impact on social and natural resilience of communities and a generally significant impact on economic resilience. Hypotheses 1–3 were tested. For example, the more concentrated the age structure distribution of community residents is in young adults, the more efficient they are in DPM before and after disasters, and the stronger their role in maintaining the complex ecosystem within the community is. For example, the more experience stakeholders have in disasters through personal experience or theoretical learning, the better they handle the next disaster. The post-disaster status of various indicators such as DPM awareness, standardized order, and residents' participation is improved.

- Social capitals have a significant impact on the social resilience of communities. Hypothesis 4 was tested. In the in-depth interviews, most of the community stakeholders mentioned the role of social capitals, such as "regulations", "pre-disaster preparation and warning", and "external social support", in enhancing the performance indicators of "personal safety", "post-disaster order in the community", and "post-disaster recovery effectiveness" in relation to the waterlogging resilience of communities. For example, the installation of "disaster prevention information signs" in the community can efficiently guide people to prevent and evacuate, greatly reducing the risk to personal and property safety and improving the speed of community disaster response.
- Economic capitals have a significant impact on the social and natural resilience of communities. Hypotheses 7–9 were tested. Economic capitals mainly involve various funds and material inputs related to community DPM work, which may encourage stakeholders to invest more energy and capitals in normative order and community responsiveness. Moreover, upgrading security systems, retrofitting drainage systems, and replenishing emergency reserves can enhance the resilience of corresponding subsystems in a community. However, each community has a limited share of economic capitals, especially for DPM, so economic input should be allocated rationally to find the best balance of inputs and outputs.
- Natural capitals have a significant impact on social and natural resilience of communities and a generally significant impact on economic resilience. Hypotheses 10–12 were tested. Natural capitals refer to the natural ecological environment, including the climatic meteorology and hydrogeology around the community, as well as the manmade environmental conditions such as transportation and site selection, which have a significant impact on the community resilience. If a community is located in a coastal zone, a rainfall zone, or a low-lying region, it may be exposed to more severe rainstorms and waterlogging; furthermore, it may have more serious impacts on human safety, housing, utilities, and lifeline systems within the community. If the community is surrounded by well-developed transportation and public-service types, various rescue departments, and other social forces, and if various materials can be delivered to the community in the first instance when waterlogging occurs, then the community resilience is effectively enhanced.

Table 4. Structural equation model analysis results.

Path relationship			*p*	Support Hypothesis or Not
social resilience	←	Population capitals	0.007	support
social resilience	←	Social capitals	0.001	support
social resilience	←	Economic capitals	0.203	unsupported
social resilience	←	Natural capitals	0.311	unsupported
economic resilience	←	Population capitals	0.017	support
economic resilience	←	Social capitals	0.002	support
economic resilience	←	Economic capitals	***	support
economic resilience	←	Natural capitals	0.008	support
natural resilience	←	Population capitals	***	support
natural resilience	←	Social capitals	***	support
natural resilience	←	Economic capitals	***	support
natural resilience	←	Natural capitals	***	support

(***): $p < 0.001$. Path relationship has a very high level of significance.

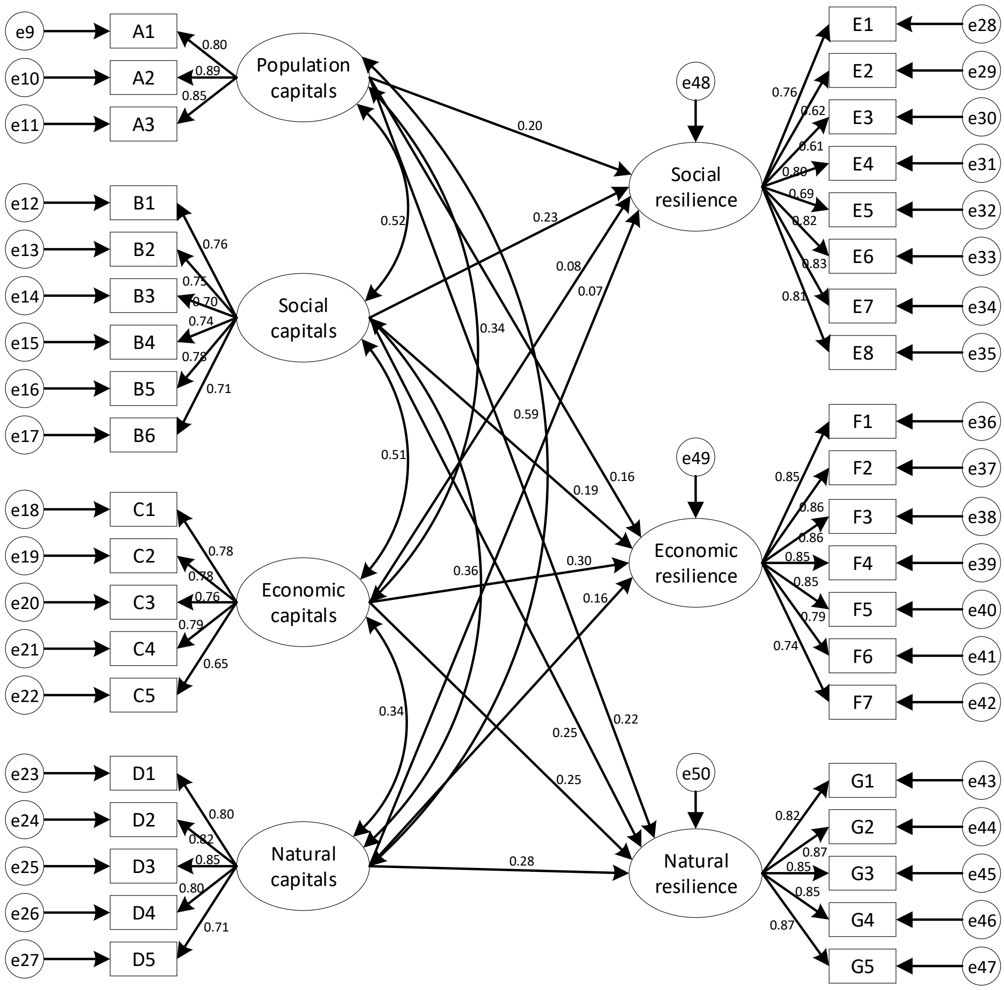

Figure 6. Equation model of structural equations for urban community waterlogging resilience in China.

4.4. Prediction Model of Waterlogging Resilience Using BP

Through the BP neural network prediction model, on the basis of the qualitative relationship between the influencing factors and evaluation indicators obtained above, a quantitative relationship based on large-scale sample data was established to realize the pre-disaster measurement function of community waterlogging resilience.

(1) Network structure design

Based on the results of the previous structural equation model, three sub-prediction models for social, economic, and natural waterlogging resilience were developed. Taking economic waterlogging resilience as an example, we were influenced by four aspects, namely population capitals, social capitals, economic capitals, and natural capitals, containing a total of 19 observed variables. The number of hidden layers is taken as 11, and the initialization of the weights follows a uniform distribution based on BP network characteristics. The model for waterlogging resilience in Chinese urban communities is shown in Figure 7.

(2) Data and processing

First, import 387 sets of original sample data of rainstorm and waterlogging disasters into MATLAB as input layer data and output layer target values and normalize the data. Second, randomly select 70% of the sample data as the training-set data, 15% of the sample data as the validation set data, and the remaining 15% of the sample data as the test set data.

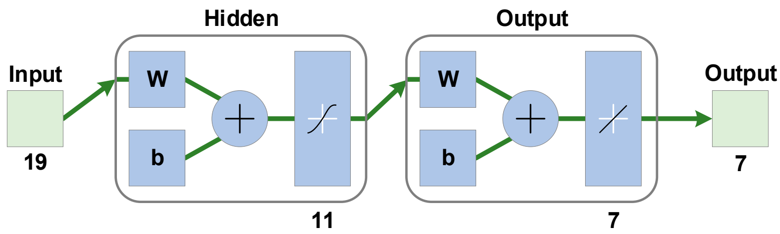

Figure 7. BP neural network interlayer coefficient setting.

(3) Training method development

Because the data sources in this study are research questionnaires and Likert five-level scale, the data volume and numerical range are small, and the degree of dispersion is high. Therefore, the hidden layer activation function of this paper selects the Sigmond function. In addition, the Bayesian regularization training method can effectively reduce the sample error and avoid the phenomenon of over-fitting, extreme weights, or thresholds. In this study, the maximum number of operations per training group was 1000, the operation time was not limited, the minimum optimization gradient was 10–7, the initial value of Mu was 0.005, and the maximum value was 1010 as the stopping condition of the function.

(4) Model training and testing

Based on the above network structure setup, data processing, and parameter setting, the training data are tested. Select the Neural Fitting module that comes with MATLAB to perform BP neural network operations. The training is run 438 times in 11 s and stopped when the Mu value reaches the maximum. After the above training, the predicted fit degree of economic waterlogging resilience in Chinese urban communities is obtained as R = 0.86, which is a good fit degree. In the same way, based on the above method, the social and natural waterlogging resilience levels of urban communities in China are predicted, and the training fit degree of both is obtained, as shown in Figure 8.

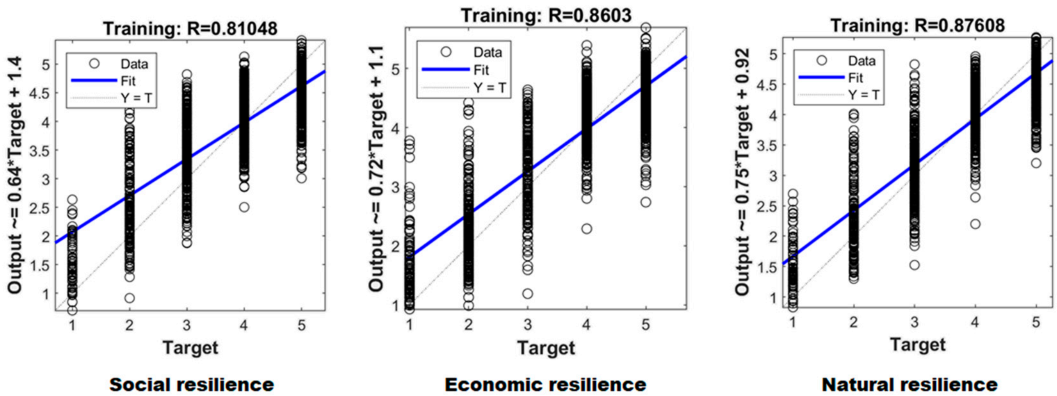

Figure 8. Training fit degree of social, economic, and natural resilience.

According to the above steps, the goodness of fit between the actual output values and the expected values for each sample were calculated in MATLAB, as shown in Figure 9. The R values of social, economic, and natural waterlogging resilience are all greater than 0.8, which has a good fit degree. Using the BP neural network algorithm above, a set of corresponding waterlogging-resilience evaluation index predicted values can be calculated from a set of influencing factors in the target community. (Note: When an index value exceeds 5, the default is taken as 5.) Thus, the waterlogging-resilience performance of urban communities in China can be predicted before the disaster.

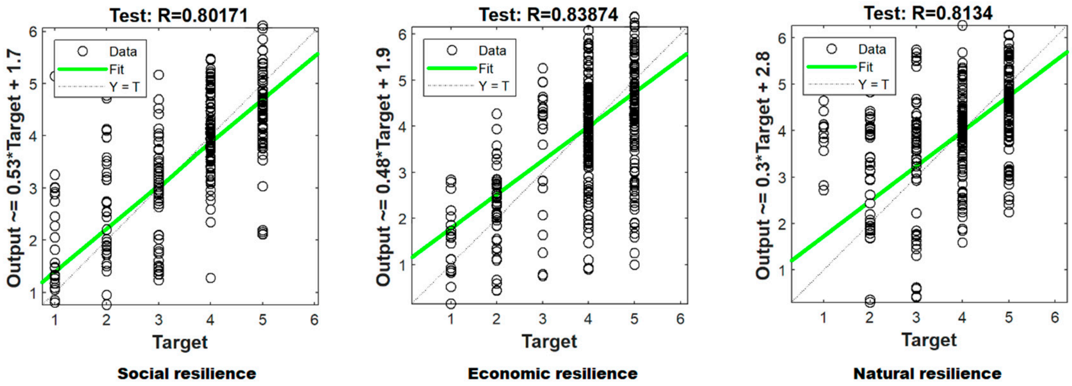

Figure 9. Test sample output value and expected value goodness of fit.

5. Case Study

5.1. Basic Information

Nanjing is located in Eastern China, belonging to subtropical monsoon climate. Influenced by climate and meteorological changes in coastal areas, Nanjing has been frequently hit by heavy rains and windstorms every year. When the rainy season comes in June to August, communities in Nanjing often suffer from waterlogging, which seriously affects the daily lives of citizens and the safety of their personal property. However, in the face of the same disaster, some certain communities are able to cope well and are less affected; in other words, these communities have better resilience against waterlogging. Accordingly, this study selected four different communities within Meiyuan Xincun Street, namely DXG, SEU, TPM, and FGS communities.

On 10 August 2019, Super Typhoon Lichima landed on the coastal areas of China. Nanjing may be affected by the typhoon, resulting in heavy or torrential rainfall, and urban communities may face waterlogging. Before typhoon Lichima made landfall, the waterlogging resilience of the above four communities were comprehensively evaluated. Data that came from the community key stakeholder included street office staff, community committee leaders, property service center supervisors, and some resident representatives. Question items 8–27 in the Supplementary Material were used as the community waterlogging resilience scoring under the waterlogging disaster in June 2017; and question items 28–46 in the Supplementary Material were used as the community anti-waterlogging capitals scoring in August 2019. Each item of the questionnaire still uses the Likert five-level scale method.

5.2. Results and Discussion

In recent years, nine communities have strengthened public awareness of DPM, added food and goods, and renovated houses and infrastructure. The overall waterlogging resilience of each community have improved significantly. Through the BP neural network prediction method, the predicted values of the future waterlogging resilience are calculated. Then the predicted value data are input into Visual PROMETHEE software, and the rankings of waterlogging resilience characterization indicators for the four communities are obtained in the following order: the DXG community (0.073), the SEU community (0.057), the TPM community (−0.004), and the FGS community (−0.126), as shown in Figure 10.

The distribution of the data shows that the DXG community performs best when the F indicators are used as the main basis for evaluating waterlogging resilience. The reason is that the commercial areas, attractions, and services within the DXG community create a good economic climate for the community. When the indicators in category E are used as the main measure, the SEU community performs well due to its good quality of residents, rich external connections, and strong awareness of DPM. The indicators in category G are more evenly distributed, but it can be seen that the TPM community has a higher score in the prediction of waterlogging resilience of the natural subsystem. The possible reasons for this is that the relevant units within and around military compound have more military personnel who have good organizational and implementation skills and are able to respond quickly to problems in water supply, power supply, drainage, roads, and garbage disposal.

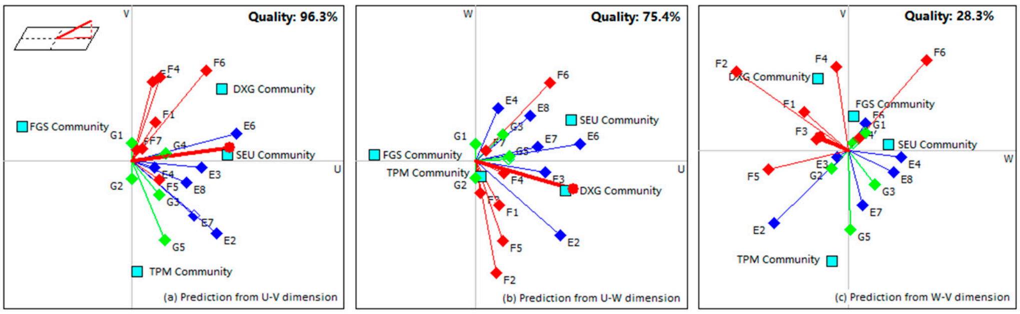

Figure 10. GAIA analysis of community waterlogging-resilience prediction.

5.3. Implements through IRM

Among the influencing factors of urban community resilience towards waterlogging in this paper are age structure (A1), education level (A2), resident income (C1), climate and meteorology (D1), and planning and siting (D5); they cannot be changed in a short time, and the corresponding anti-waterlogging strategy is difficult to find. This study focused on analyzing the potential improvement capabilities of the remaining indicators. Changes in the influencing factors (i.e., anti-waterlogging capital) of community resilience are actually caused by the behavior of stakeholders in community DPM. Generally, the stakeholders of urban community disaster prevention and reduction in China mainly include the following 10 parts: residents (S1), community committee (S2), property service center (S3), subdistrict office (S4), urban management department (S5), community police (S6), municipal government (S7), volunteers (S8), community organizations (S9), and emergency departments (S10) [56]. There may be no property center in some old communities, and some neighborhood offices do not have community service centers. Accordingly, the stakeholders corresponding to the specific impact indicators are shown in Table 5.

Table 5. The influencing factors of waterlogging resilience and the related stakeholders.

Serial Number	Influencing Factors	Stakeholders Involved
A3	Disaster experience	S2, S3
B1	Trust and reciprocity	S1, S2, S3
B2	Social network structure	S1, S2, S3
B3	External contact	S2, S4, S8
B4	Regulation	S2, S4, S6
B5	Pre-disaster preparations	S3, S4, S5
B6	Disaster warning	S6, S7, S10
C2	Disaster insurance	S1
C3	DPM funds	S4, S7
C4	Emergency reserve	S2, S3, S4
C5	Dedicated reconstruction	S2, S3, S4, S7
D2	Energy supply	S3, S5
D4	Transport	S3, S5

The incentive and restraint mechanism (IRM) is applied to enable community stakeholders to adopt a series of strategies before, during, and after the disaster to reduce the impact of waterlogging and improve the resilience. The incentive aspect classifies methods into moral incentive, pay incentive, honor incentive, work incentive, subsidy incentive, and so on [57–60]. The restraint aspect classifies methods into self-constraint, internal constraint, and external constraint. For the potential risks and deficiencies under waterlogging, stakeholders can connect and work together to enhance community resilience through different incentive and restraint mechanisms, as shown in Figure 11.

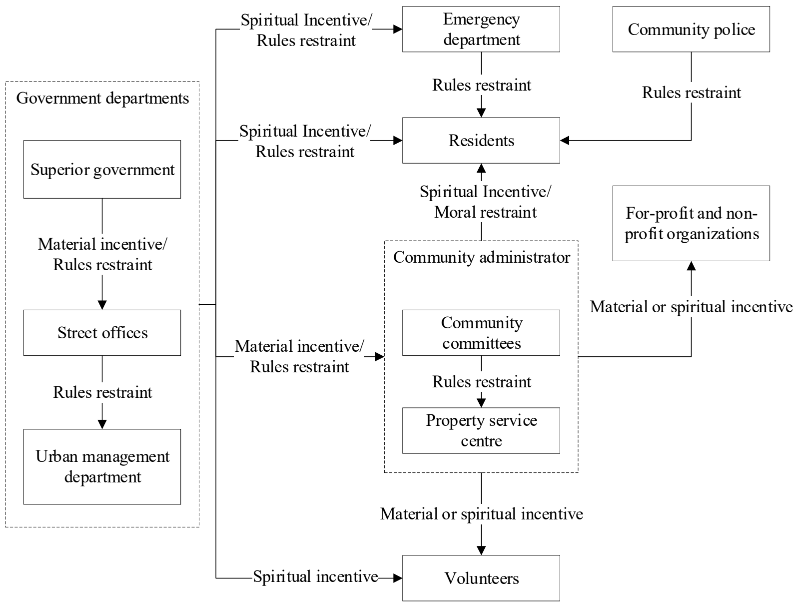

Figure 11. Division of incentive and restraint mechanisms for stakeholders in urban community DPM.

(1) Government departments

As the makers, promoters, and maintainers of anti-waterlogging policies, Chinese governments need efficient coordination to deal with the disaster. However, current government officials have limited tenure and are more concerned with short-term and immediate interests out of the pursuit of political achievements. Under the performance appraisal system, officials think that "waterlogging does not occur every day" and "is not serious every time", so the investment in DPM is relatively limited [61]. The incentives and restraint measures are as follows:

- The rules restraint is to develop a detailed and complete disaster emergency plan, establish a comprehensive disaster reduction leading group, and identify the relevant person in charge.
- Strengthen disaster resource inputs in communities and conduct the "sponge transformation" in the community through material incentives. Encourage communities to build disaster risk database and continuously learn from cases.
- Strengthen community outreach and activities through spiritual incentives and encourage communities to establish close ties with volunteer groups and individuals.

(2) Community Managers

Community committees and property service centers are the core link of anti-waterlogging work. However, as a resident self-governing organization, community committees cannot use administrative means to promote and regulate the development of community resilience, resulting in a series of problems such as great responsibility, small power, more affairs, less activity funds, and low salary. For example, in FGS community, the community committee even has to undertake the work of the property management company, and this seriously affects the motivation and efficiency of the community staff. Therefore, the following measures may help:

- Contact voluntary organizations and regularly hold drills and publicity lectures in the community.
- Through the rules and regulations of superior governments, strengthen daily disaster inspections in the community, maintain problem houses and facilities, replace old equipment, and update the list of anti-waterlogging reserves.
- Waterlogging-prevention information screens, emergency hedging maps, and publicity boards are established through material incentives from superior governments.

(3) Residents and other organizations in the community

When the waterlogging occurs, community residents and other organizations in the community are the protection objects. Whether they participate in the waterlogging control and how actively they cooperate with the community depend to a large extent on their own interests. Most community residents weigh the benefits and costs to make decisions [61]. Therefore, the following incentives and constraints should be considered on these two stakeholders:

- Encourage disaster-prone residents to purchase disaster insurance and increase resident's interaction and improve community cohesion through community activities.
- Enhance the disasters awareness and collective awareness through moral restraints.

(4) Volunteers

Volunteer groups can play an auxiliary role in the community anti-waterlogging work. Since the behavior of volunteers is public-spirited and spontaneous, their capacity should be enhanced mainly through incentive mechanisms. The immature cooperation makes volunteers deviate, resulting in problems such as volunteer failure, vicious competition among organizations, and loss of independence [62,63]. The incentives and constraints are as follows:

- Volunteers should be given more recognition and praise through spiritual incentives. Volunteer groups should contact the surrounding communities and set up alliances to provide support under waterlogging.
- Through material incentives of government departments and social forces, the institutionalization and legalization of volunteer organizations' behavior and identity can be promoted.

(5) Emergency department

The emergency response sector contains three main departments: fire station, police station, and first aid. The participation of them in community DPM work is a compulsory responsibility according to the laws. However, the motivation of the emergency department can also be enhanced through material and immaterial incentive strategies such as follows:

- Set red lines of minimum relief guidelines for emergency departments, clarify their respective responsibilities, and pay attention to regular pre-disaster inspections.
- Through material and spiritual incentives, trainers from various sectors are invited to communities for regular lectures, promotions, and consultations to establish permanent links with communities.

6. Conclusions

Taking the rainstorm and waterlogging in urban communities as an example, this study systematically explored the key problems of urban community resilience against waterlogging by using a variety of research methods. The main conclusions are as follows: (1) The definition of waterlogging resilience was analyzed from the urban or community resilience literature, combined with the organizational structure and disaster stakeholders of urban communities in China; the occurrence mechanism and impact chain of waterlogging disasters in urban communities were clarified. (2) Based on grounded theory and qualitative analysis, 19 key influencing factors of waterlogging resilience were determined. Combined with the SLR method and expert scoring, an evaluation index system of waterlogging resilience in complete dimensions was constructed. (3) The structural equation model can test the hypothetical linear relationship between indicators and clarify the mechanism of urban community resilience towards waterlogging. Taking this as the theoretical basis, according to the BP neural network modeling process, the sample data obtained from questionnaires are imported. Finally, a pre-disaster prediction model of waterlogging resilience was established, and the predicted value of target community resilience based on the anti-waterlogging capitals was obtained.

Previous studies on urban community resilience are mostly post-disaster evaluation based on certain indicators and often confuse the influencing factors and evaluation indicators of disaster resilience; research on pre-disaster resilience prediction is lacking. This study used a series of methods to solve the above problems in detail. Starting from the behavior and performance of community stakeholders, strategies for improving the waterlogging resilience were formulated based on the incentive and restraint mechanism to provide experience and reference for the sustainable development of urban communities in other countries.

Taking urban communities in China as the precondition, this paper established a resilience prediction model for the most common waterlogging. The lack of enough information, including the difficulties that different types of communities, such as rural, coastal, and mountainous areas, are affected by after different disasters may be the limitation of the current study.

In addition, the BP neural network is a black-box theoretical operation; thus, the specific quantitative relationship cannot be obtained. In future research, more independent variables, intermediary variables, and moderator variables should be added in the simulation model through the operation rules under the white/gray-box theory. While improving the calculation accuracy of urban community resilience in China, the logic and traceability of the calculation process can be enhanced.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/buildings12070901/s1, Survey S1: Screening of Evaluation Indicators for Urban Community Resilience towards Waterlogging in China, Survey S2: Investigation of Evaluation and Influencing Factors of Urban Community Resilience towards Waterlogging in China, Survey S3: Open Coding Examples of Impact Factors, Survey S4: Statistics of the Basic Situation of Respondents in the Waterlogging.

Author Contributions: Conceptualization, P.C. and X.J.; methodology, P.C. and D.L.; software, P.C.; validation, P.C. and X.J.; formal analysis, X.J.; investigation, X.J. and Y.L.; resources, P.C. and D.L.; data curation, Y.L.; writing—original draft preparation, P.C.; writing—review and editing, P.C., X.J. and Y.L.; supervision, D.L.; funding acquisition, P.C.; final revision and layout, X.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Humanities and Social Sciences Fund of the Ministry of education, (grant number: 21YJC630017) and Innovation and entrepreneurship training program for college students in Jiangsu Province (grant number: 2021NFUSPITP0602).

Data Availability Statement: The data presented in this study are available upon request from the corresponding author. The data are not publicly available due to privacy.

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

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