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Measuring the Urban Resilience Abased on Geographically Weighted Regression (GWR) Model in the Post-Pandemic Era: A Case Study of Jiangsu Province, China

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Abstract: Since China declared that the post-epidemic era would begin in April 2020, the prevention and control of epidemics have become routine. The capacity of cities to respond to future public health emergencies will be enhanced if the resilience of cities is accurately measured and an emphasis is placed on improving resilience levels. Under the 4R framework, this study quantifies and analyzes the level of resilience of the cities in Jiangsu Province from both subjective and objective perspectives. By selecting explanatory variables and developing a GWR model, the spatial distribution characteristics of the quantified scores of resilience and the spatial characteristics of the influencing factors are analyzed. The results indicate that cities in southern Jiangsu should invest more in economic development and medical resources in the post-epidemic period. Northern Jiangsu should prioritize boosting the health and social work sector's gross domestic product. Coastal cities must enhance their capacity for innocuous waste treatment.

Keywords: post-pandemic era; resilience quantification; GWR

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1. Introduction

In recent decades, frequent public health calamities have become a global phenomenon [1]. The outbreak of novel coronavirus pneumonia at the end of 2019 was a typical and significantly unexpected public health event [2]. COVID-19 has exerted a variety of social, economic, and environmental impacts on the global community since its emergence. Threats to the sustainable development of communities are also formidable obstacles. Wuhan was the first city in China to disclose the COVID-19 epidemic, and it also had the greatest number of cases [3]. China declared the post-epidemic era to have begun at midnight on 8 April 2020, when it lifted the quarantine of Wuhan city. The post-epidemic era refers to when people returned to normal life after COVID-19 had been contained, but we must still cope with its long-term effects. To prevent future epidemics, robust public health measures are required. In the post-epidemic era, the public cannot avoid the recurrence of low-intensity epidemics and the constant mutation of the virus, despite the fact that the peak of the epidemic has passed. As a result of the virus's ongoing mutation, its mortality and severity rates have decreased significantly. Based on this, on 8 January 2023, China announced that the new coronavirus has been re-classified from Class B to Class B2, a significant adjustment in China's epidemic prevention and control policy. Although this change denotes, to some extent, that the COVID-19 epidemic has been effectively controlled, there are still other known and unknown public health disasters such as monkeypox, malaria, etc., that will continue to pose new challenges to future medical and health services.

In the post-pandemic era, urban areas, as comprehensive systems with multiple interconnected elements, have become a propelling force for the nation's social and economic development. The length of the social and economic recovery process depends upon the resilience of the region [4]. Given the escalating threats posed by external factors, bolstering the capability of cities to recover has assumed paramount importance. This necessitates emergency healthcare systems, including medical facilities and other critical infrastructure, to pursue multidisciplinary solutions, thereby shortening the recovery time and enhancing levels of resilience [5]. Owing to urban characteristics, such as high population density, intricate building networks, and complex social frameworks, these areas are vulnerable to uncertainty and disruption from external risks as well as internal structural transformations [6]. In order for these areas to withstand the effects of natural disasters, it is crucial to enhance urban resilience in multiple dimensions.

Cities with weak resilience demonstrate less adaptability and a longer recovery process, necessitating substantial resource consumption for restoration to the original status, whereas cities with robust resilience can rapidly recover from unpredictable external interferences, restoring or even surpassing their original status [7]. Rotterdam, one of the Rockefeller Foundation's 100 Resilient Cities worldwide, has the potential to deal with future shocks more effectively [8]. New Orleans and Medellin, which are considered "pioneer cities" with regard to resilience, not only reduce vulnerability or mitigate a threat but also provide multiple groups with economic, social, and infrastructure benefits [9]. Cities with a high level of resilience can be targeted by identifying their strengths and using them to maintain that level. Reasonable positioning can improve the capacity of non-resilient regions to withstand public health emergencies [10]. Through precise quantification of urban resilience level, an evaluation of a city's disaster response capacity can be formulated, which provides substantial guidance and recommendations for future resilience enhancements.

The article is structured as follows. Section 2 provides an overview of the relevant literature. Section 3 introduces the methodology of quantifying urban resilience analysis through the combination of resilience assessment indicators' weighting and quantitative weighting. Section 4 shows the spatial characteristics of urban resilience based on the GWR. Section 5 presents the contributions, implications, limitations, and future work following this study.

2. Literature Review

2.1. The Definition and Characteristics of Resilience

Holling first applied the concept of resilience to the field of ecology, where he defined it as the capacity of an ecosystem to resist and absorb change and recover from a shock [11]. Although resilience originated in fields such as psychology, its definition has been expanded in recent decades and is now extensively applied to infrastructure systems and communities, particularly in the context of public health disasters [10,12]. This paper defines urban resilience as the ability to resist shocks and maintain normal operations, practice learning, and summarize existing disasters, and recover to its original state relatively quickly when a city experiences a sudden public health disaster.

Cui et al., argue that a resilient city must demonstrate four characteristics: robustness, redundancy, rapidity, and resourcefulness [13]. A multi-perspective resilience approach based on the 4R framework provides a holistic view of a city's resilience performance in response to public health disasters. The greater the significance of the aforementioned 4R characteristics in a city, the greater its resilience. Robustness and rapidity are considered to be the objectives of resilience, while diversity and redundancy are the means of achieving these objectives [10]. The basic level of urban resilience is determined by resourcefulness and redundancy, while the highest level is determined by the height of urban resilience. The greater the prominence of the 4R characteristics in a city, the greater its elasticity [14]. Robustness refers to the urban system's capacity to maintain its normal function and stability in the face of external pressure [15]. Redundancy refers to the ability to maintain the original functional state through backup or other alternative systems, in spite of the damage caused to systems and the community during, for example, an epidemic. The resourcefulness of a city refers to its capacity to mobilize other alternative systems or elements from other systems to preserve its original state and better cope with disasters [16,17]. Rapidity, which refers to the speed at which a city can recover its normal operating capacity after a disaster and reflects the ability to control disaster losses when achieving predetermined goals, is another factor that determines resilience [18].

2.2. Resilience in the Face of Public Health Crises

Liu et al., note that in the context of frequent occurrences of natural disasters around the globe, resilience construction is imperative for risk reduction and modern emergency management [1]. Not only do resilient cities exhibit excellent post-disaster performance, but they also facilitate prompt prevention, control, and management in response to abrupt public health emergencies. Strong social networks have been found to make communities more resilient in the face of disasters, as they are better able to coordinate and respond to the crisis [19]. Bakkensen et al., emphasize the importance of focusing on the ability of cities and urban systems to recover and reconstruct after public disasters [20]. Fu et al., also contend, via the geographical detector model and geographic weighted regression model, that urban resilience is a key factor in enhancing preparedness for public health challenges [21]. Various factors influence the degree of urban resilience. For instance, the resilience of urban infrastructure can improve the city's ability to respond to natural disasters, while community participation and social networks can foster cooperation and support among urban residents [6]. Under the new normal brought by the pandemic, resilience is generally of utmost importance for urban sustainability. To increase the level of urban resilience, it is necessary to consider the impact of various factors, and to take measures that emphasize the variable effects of these factors.

Existing research articles indicate that urban resilience plays a critical role in reducing risks, enhancing the city's disaster resistance, promoting urban recovery, and achieving sustainable development in the face of public health emergencies. However, how to comprehensively and scientifically evaluate urban resilience is still an urgent problem to be solved. Therefore, we need multidisciplinary participation to build a comprehensive and reasonable evaluation system for urban resilience and select scientific, practical, and operational evaluation indicators.

2.3. Assessment of Urban Resilience

Based on the 4R evaluation system, cities have varying levels of resilience and resource utilization in the face of sudden public health incidents. In order to maximize resource utilization and provide decision-makers with valuable empirical evidence and guidance, it is necessary to use specific indicators and methodologies to quantify urban resilience.

The resilience triangle and performance-based engineering are the two common fundamental concepts upon which resilience quantification research is predicted. Bruneau et al. introduced the resilience triangle as a method for assessing urban resilience based on robustness and rapidity, which reveals the quality or performance of the urban system by integrating the curve underneath [17]. Bruneau and Reinhorn expanded resilience quantification from two to four dimensions by incorporating diversity and redundancy, resulting in a more scientific and precise approach [22]. Moreover, based on the available data, contexts, and urban dimensions, various methodologies are adopted in urban resilience assessments, such as qualitative methods, index approach, simulation models, and so on [23]. To determine the impact factors of urban resilience, qualitative methods such as content analysis and interviews are employed, and semiquantitative methods are used to identify the impact mechanism of urban resilience under external disruptions [24–26]. By selecting urban resilience indicators from both its dimensions and characteristics, the index approach is the standard method for determining the level of resilience [27,28]. In contrast to the aforementioned methods, simulation models can dynamically measure resilience to external shocks [29].

Despite the abundance of studies evaluating urban resilience in various disaster contexts and proposing methods to improve it, there is a lack of research on identifying the factors that influence urban resilience and assessing the significance of each factor in the post-pandemic era. Firstly, in the aftermath of a pandemic, a systematic framework to identify all the factors influencing urban resilience in the post-pandemic context is inadequate. Second, our understanding of the impact mechanisms of the various urban resilience factors remains limited. Without this information, it is challenging to conduct a systematic and quantitative assessment of the level of urban resilience, which impedes its overall improvement. To address these gaps, this study aims to systematically identify the main factors that influence urban resilience in the post-pandemic context, investigate the relationships between these factors, and systematically quantify the resilience of 13 cities in Jiangsu Province. This will assist Chinese localities in preparing for future public health crises and enhancing their resilience.

3. Materials and Methods

Jiangsu Province, which is situated on the eastern coast of China, has made significant development advances since the implementation of the reform and opening-up policy. Its communities are economically developed and have significant radiating effects on neighboring regions [30]. The thirteen urbanized regions of Jiangsu Province feature a high concentration of industry and a dense population [31]. The occurrence of public health disasters such as COVID-19 has had varying degrees of impact on the 13 cities and has also tested the resilience of each city. This paper selects the cities in Jiangsu Province of China as its research area to evaluate and analyze their urban resilience during the post-pandemic period. The purpose of this paper is to develop a comprehensive and reasonable evaluation system, so that the level of resilience of each city can be assessed scientifically and accurately, and so that practical recommendations can be made for future resistance to major public health disasters.

This paper combines resilience assessment indicators' weighting and quantitative weighting to quantify urban resilience analysis, given that the DEMATEL method can reflect the qualitative intentions of evaluators, and the entropy method can reflect true quantitative data [32].

Initially, a literature assessment is conducted to identify the influencing factors of urban resilience. The weight W_1 for the resilience assessment indicators can then be determined after the DEMATEL method is applied to calculate the resilience assessment indicators. The weight W_2 for the quantitative indicators can be determined using the entropy weighting technique. In current research, the additive synthesis and multiplicative synthesis methods for calculating the combined weights cannot assure the combined weights' validity [10]. Therefore, this paper employs the principle of minimal discrimination information to combine resilience assessment indicators' weight and quantitative weights, minimizing the difference between the desired combined weight and the qualitative weight in order to obtain the combined weight W [33]. In conclusion, geographically weighted regression (GWR) is used to analyze the spatial distribution of factors affecting urban resilience in Jiangsu Province, thereby providing recommendations for enhancing the overall level of urban resilience. Figure 1 depicts the evaluation system presented in this paper.

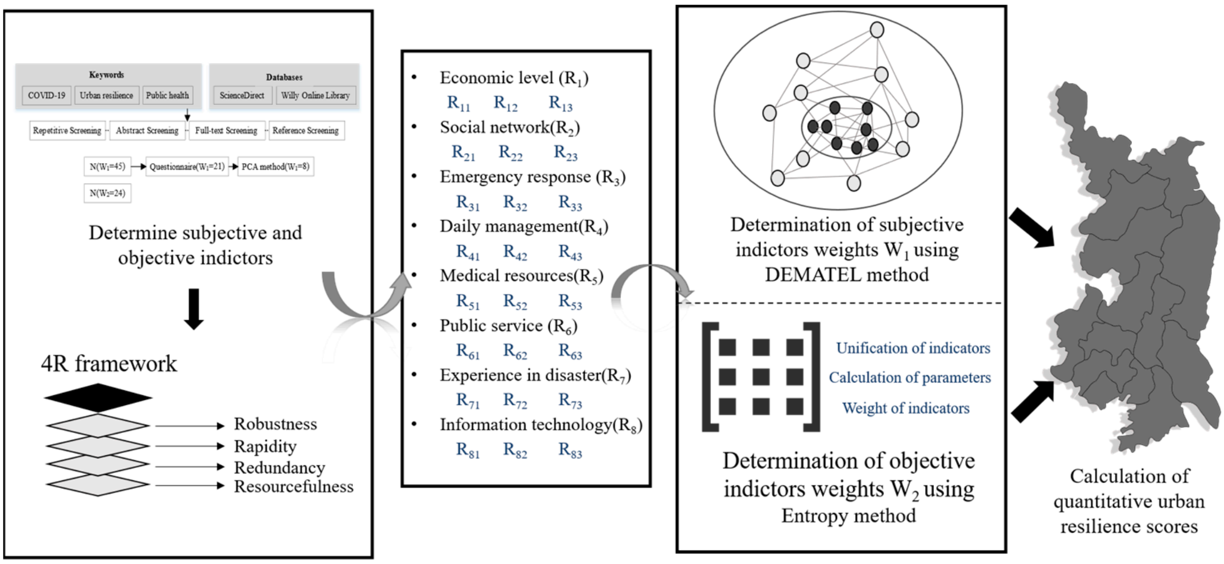

Figure 1. The flow chart of the evaluation system.

3.1. Identification of Influencing Factors

3.1.1. The Identification of Resilience Assessment Indicators

"Post-epidemic era", "Public health", and "Urban Resilience/resilient" are used as keywords to search ScienceDirect and Wiley Online Library, from which all English-language literature is screened and verified.

After consulting and organizing existing policies and research, this paper identifies eight resilience assessment indicators, including economic level, social network, emergency response, daily management, medical resources, public service resources, experience in disaster, and information technology, which are illustrated in Figure 2 [13,34–48].

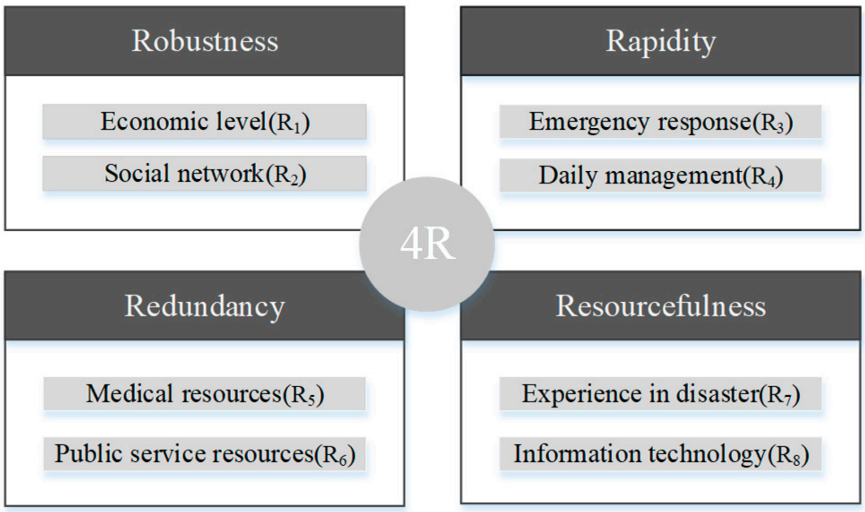

Figure 2. The identification of resilience assessment indicators.

Economic level and social network are regarded as constituting robustness. First, economic level has a significant impact on people's lives [49]. Economic policies aimed at enhancing resilience are, to some extent, conducive to enhancing recoverability [50]. In addition, economic conditions have a direct impact on the level of financial support provided by the government after a disaster as well as the ability of cities to recover [51]. Social network refers to the patterns of social interactions between individuals, which can provide a platform for individuals to communicate regardless of their geographical locations [52,53]. Social network has been identified as a crucial component of developing resilience. The role of social network in promoting resilience building within government institutions has been deemed crucial [54–56]. Emergency response and daily management are identified as two indicators of rapidity. By improving emergency response capacity, the speed with which urban systems can be restored to function can be increased, while daily management determines a city's ability to deal with public health emergencies [57–60]. Emergency response and daily operations collaborate to determine the rate of recovery to pre-disaster levels [61].

Two redundancy-related indicators are identified, namely, medical resources and public service resources. In the post-epidemic context, limited medical resources have sparked significant anxiety among patients, the general public, and health care providers [62]. Even the world's most developed economies have difficulty meeting the demand for medical services [63]. Medical resources ensure the availability of health services to some extent [64]. In the event that adequate public supplies and a well-organized emergency supply chain ensure the smooth operation of a city, the urban redundancy can be enhanced [65].

Two indicators of resourcefulness are identified, including experience in disaster and information technology. First, experience in disaster enables individuals to assess risks and plan for post-disaster supplies in advance [66]. It raises awareness among stakeholders of the potential hazards posed by disasters and the efficacy of alternative emergency measures [67,68]. Additionally, information technology enables daily communication and makes it convenient for people to obtain timely and reliable information about effective prevention and control measures [13].

3.1.2. The Identification of Quantitative Indicators

To accurately assess the resilience scores of the thirteen cities in Jiangsu Province during the post-epidemic period, this study extensively compares the sources of quantitative indicators data to ensure its accuracy and reliability. For readily available data, we rely on the Jiangsu Statistical Yearbook (2021) and provincial and municipal government work reports for readily accessible data. Data from these sources cover a wide range of indicators including population, employment, healthcare, culture, etc., ensuring the comprehensiveness of the data. For some data that are difficult to obtain, we employ web surveys and site visits to extract the required data. We ensure the reliability of these data by comparing data sources and consulting with experts.

Using the aforementioned methods, 24 sets of quantitative indicator data are obtained and categorized using the 4R framework. The data are presented in Table 1.

Table 1. Detailed Information about data of indicators.

First-Level Indicator	Code	Second-Level Indicator	Code	Nan Jing	WuXi	Xu Zhou	Chang Zhou	Su Zhou	Nan Tong	Lian YunGang	Huai An	Yan Cheng	Yang Zhou	Zhen Jiang	Tai Zhou	Su Qian
Economic level	R_1	GDP per capita	R_{11}	174,520	166,672	113,844	166,964	158,586	150,584	99,846	106,144	11,154	151,879	169,648	149,365	84,652
		Disposable income per inhabitant	R_{12}	66,140	63,014	34,217	56,897	68,191	46,882	32,295	34,731	36,764	42,287	50,360	43,777	29,122
		Disposable expenditure per inhabitant	R_{13}	39,118	39,820	21,278	34,079	41,818	29,705	21,038	19,857	21,982	26,083	30,780	27,712	18,041
Social network	R_2	Per capita expenditure on transport and communication	R_{21}	5657	6669	3185	5905	7485	4851	2527	3136	3371	3195	4618	4166	2232
		Number of tourist arrivals	R_{22}	10,830	8800	5196	6999	11,248	4314	3619	3293	2672	6060	5563	2336	1801
		Number of travel agents	R_{23}	790	267	208	213	540	218	124	124	156	163	120	144	93
Emergency response	R_3	Number of medical beds per 10,000 population	R_{31}	64.2	59.3	62.3	54.7	58.1	62.3	57.7	60.1	61.9	52.5	46.2	61.3	65.8
		Number of physicians per 10,000	R_{32}	41.7	34.2	32.3	29.8	30.7	29.5	28.8	31.6	32.0	28.6	28.2	30.8	30.4
		Tourism income	R_{33}	2112.25	1646.79	629.96	1052.02	2262.31	614.96	495.84	403.9	291.09	810.41	774.51	290.03	209.83
Daily management	R_4	Engel's coefficient	R_{41}	26	27.1	29.4	27.4	25.8	28.9	32.9	30	28.8	29	28.9	29.5	30.6
		Research expenditure as a proportion of GDP	R_{42}	3.54%	3.18%	1.80%	3.30%	3.91%	2.60%	2.37%	1.78%	2.12%	2.26%	2.39%	2.65%	1.84%
		Daily treatment capacity of environmentally friendly treatment plants	R_{43}	9660	9390	4296	5190	13250	0	3390	300	2850	4690	1590	1220	1600
Medical resources	R_5	Number of health care facilities	R_{51}	3451	3107	4580	1667	4027	3494	2729	2316	3343	1899	1094	2140	2600
		Number of beds in health care facilities	R_{52}	6.61	5.16	6.12	3.19	7.76	5.06	2.83	3.01	4.36	2.7	1.77	2.94	3.35
		Number of staff in health care facilities	R_{53}	12.89	8.10	9.40	4.97	12.72	6.94	4.03	4.47	6.18	3.90	2.80	4.19	4.75
Public service resources	R_6	Number of general higher education schools	R_{61}	51	13	12	11	26	9	5	7	6	9	9	7	3
		Number of invention patents per 10,000 people	R_{62}	95.42	49	22.81	44.8	66.9	41.9	37.32	9.59	17.87	22	48.46	23.94	5.17
		Number of postgraduate graduates	R_{63}	41,495	2348	4926	970	5269	936	226	91	0	2516	3843	0	0
Experience in disaster	R_7	General public budget revenue	R_{71}	1729.5	784.17	319.81	600.78	1358.2	416.56	192.28	224.63	240.05	231.72	160.84	213.49	142.05
		Health and social work GDP	R_{72}	361.15	214.38	148.52	105.04	392.88	213.15	56.43	107.55	121.2	118.06	67.61	128.48	73.55
		Health care expenditure per capita	R_{73}	2632	2501	1764	2566	2425	2350	1514	1409	1843	1450	1768	2376	1294
Information technology	R_8	Number of 5G base stations	R_{81}	3.02	1	0.6	1	2.6	1.2	0.7	0.6	0.4	0.4	0.6	0.68	0.2
		Whether a Gigabit city	R_{82}	1	1	1	1	1	1	1	0	1	0	1	1	0
		Mobile phone penetration rate	R_{83}	139.67	131.09	110.5	124.91	140.8	113.63	104.11	106.29	104.54	115.75	117.91	108.79	100.17

3.2. Analysis of Resilience Assessment Indicators by DEMATEL

The DEMATEL method was first proposed by Gabus and Fontela in 1973 and is an important multi-criteria decision-making method. Its primary purpose is to identify key influencing factors [69]. The method has been widely utilized in numerous fields for risk assessment. This paper employs DEMATEL to determine the weight of qualitative indicators. It consists primarily of four major steps: constructing the direct influence matrix, normalizing the direct influence matrix, constructing the comprehensive influence matrix, and analyzing centrality and causal relationships [70].

(1) Construct the matrix of direct influence. In past studies, the classical influence degree of R_i on R_j is R_{ij}, which is divided into five levels: very high, high, moderate, low, and none. The five levels are then coded into corresponding scores as 4, 3, 2, 1, and 0. However, due to the limited number of evaluation levels in classical DEMATEL, it may result in insufficiently detailed evaluation results that cannot reflect subtle differences between influencing factors, thereby reducing the accuracy and sensitivity of the results. Therefore, in order to improve the accuracy of the DEMATEL method in evaluation, this study proposed an improvement to the classical DEMATEL. The degree of influence of R_i on R_j, denoted as R_{ij}, is divided into eight levels, with five levels of very high, high, moderate, low, and none corresponding to scores of 7, 5, 3, 1, and 0, respectively. The values 2, 4, and 6 correspond to the intermediate judgment scales.

Eight experts from higher education institutions in related fields are tasked with rating the eight resilience assessment indicators to generate the direct influence matrix R, as depicted in Equation (1), of whom five are male and three are female, accounting for 62.5% and 37.5%, respectively. These experts conduct their own research in this field, and their evaluations are fairly reliable.

$$R = \begin{pmatrix} 0 & 1 & 1 & 2 & 0 & 1 & 2 & 1 \\ 1 & 0 & 1 & 1 & 0 & 2 & 3 & 3 \\ 4 & 3 & 0 & 3 & 2 & 2 & 4 & 5 \\ 2 & 1 & 1 & 0 & 1 & 1 & 3 & 4 \\ 6 & 7 & 2 & 3 & 0 & 3 & 4 & 5 \\ 3 & 2 & 1 & 1 & 1 & 0 & 2 & 5 \\ 2 & 1 & 1 & 1 & 1 & 2 & 0 & 3 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{1}$$

(2) Construct the B matrix of direct influence. Normalizing the original relation matrix yields the normalized influence matrix B, as shown in Equation (2).

$$B = \frac{R_{ij}}{\max(\sum_{j=1}^{8} R_{ij})} \tag{2}$$

(3) Construct the comprehensive influence matrix T. Since the direct influence matrix can only express the direct influence relationship between resilience assessment indicators, it is necessary to obtain the comprehensive influence matrix, as shown in Equation (3), which can express both the direct and indirect influence relationships between resilience assessment indicators.

$$T = (B + B^2 + \ldots + B^k) = \sum_{k=1}^{\infty} B^k = B(I - B)^{-1} \tag{3}$$

I is unit matrix.

(4) Calculate the influence degree D_i, affected degree C_i, and centrality degree M_i based on Equations (4)–(6).

$$D_i = \sum_{j=1}^{8} R_{ij}, (i = 1, 2, 3, \ldots, 8) \tag{4}$$

$$C_i = \sum_{j=1}^{8} R_{ji}, (i = 1, 2, 3, \ldots, 8) \tag{5}$$

$$M_i = D_i + C_i \tag{6}$$

By normalizing the centrality degree M_i, the weight W_1 of resilience assessment indicators can be obtained. Table 2 shows the results of calculating the weight W_1 for resilience assessment indicators using the DEMATEL method.

Table 2. Urban resilience indicator weights for Jiangsu Province.

Indictor	Weight of Resilience Assessment Indicators W_1	Indictor	Weight of Quantitative Indicators W_2	Portfolio Weight W
R_1	0.11	R_{11}	0.0119	0.0222
		R_{12}	0.0337	0.0374
		R_{13}	0.0343	0.0377
R_2	0.117	R_{21}	0.0328	0.0380
		R_{22}	0.0364	0.0401
		R_{23}	0.0671	0.0544
R_3	0.13	R_{31}	0.0130	0.0252
		R_{32}	0.0484	0.0487
		R_{33}	0.0498	0.0494
R_4	0.104	R_{41}	0.0000	0.0000
		R_{42}	0.0415	0.0404
		R_{43}	0.0428	0.0410
R_5	0.169	R_{51}	0.0206	0.0362
		R_{52}	0.0289	0.0429
		R_{53}	0.0385	0.0495
R_6	0.106	R_{61}	0.0588	0.0485
		R_{62}	0.0317	0.0356
		R_{63}	0.1411	0.0751
R_7	0.12	R_{71}	0.0778	0.0593
		R_{72}	0.0479	0.0466
		R_{73}	0.0310	0.0375
R_8	0.144	R_{81}	0.0479	0.0510
		R_{82}	0.0288	0.0395
		R_{83}	0.0350	0.0436

3.3. Analysis of Quantitative Indicators Using Entropy Method

Shannon first proposed the entropy weighting method in 1948; it is more reliable and accurate than qualitative weighting methods [71]. It determines the weight of each quantitative indicator by taking into account the utility value of the indicator's information entropy [72]. Entropy in information theory is a measure of uncertainty [71]. It is affected by the probability and frequency of events, with the effect increasing as system uncertainty increases [73]. As the amount of information decreases and the level of uncertainty rises, the entropy also decreases. Therefore, the greater the data disparity between cities for a given indicator, the greater the indicator's weight. Using the entropy weighting method, the quantitative indicator weight is calculated as follows.

(1) Assuming that n independent quantitative indicators are applied to evaluate m cities, the matrix of quantitative indicators is shown in Equation (7).

$$R = (R_{ij})_{n\times m} = \begin{pmatrix} R_{11} & R_{12} & \cdots & R_{1m} \\ R_{21} & R_{22} & \cdots & R_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ R_{n1} & R_{n2} & \cdots & R_{nm} \end{pmatrix}_{n\times m} \tag{7}$$

(2) Unification of indicators. As shown in Equations (8) and (9), the extreme value method is used to remove the scale and standardize the indicators in order to unify the 24 quantitative indicators and eliminate the influence of different units.

$$x_{ij} = \frac{R_{ij} - Min_i\{R_{ij}\}}{Max_i\{R_{ij}\} - Min_i\{R_{ij}\}} \tag{8}$$

$$x_{ij} = \frac{Max_i\{R_{ij}\} - R_{ij}}{Max_i\{R_{ij}\} - Min_i\{R_{ij}\}} \tag{9}$$

For Formulas (8) and (9), the higher the value of the positive indicator and smaller the value of the negative indicator, the better.

(3) The entropy of the indicator e_i, coefficient k, and coefficient p_{ij} are calculated as shown in Equations (10)–(12).

$$e_i = -k\sum_{j=1}^{m} p_{ij} \bullet \ln p_{ij} \tag{10}$$

$$k = \frac{1}{\ln m} \tag{11}$$

$$p_{ij} = \frac{x_{ij}}{\sum_{j=1}^{m} x_{ij}} \tag{12}$$

(4) Weight of quantitative indicators is calculated as shown in Equation (13).

$$w_i = \frac{1 - e_i}{\sum\limits_{i=1}^{n} (1 - e_i)} \tag{13}$$

Table 2 displays the weights of quantitative indicators W_2 according to the above formulas.

3.4. Calculation of Evaluation Indicator Combinations

After calculating the quantitative weight and the resilience assessment indicators' weight of the evaluation indicators using the DEMATEL method and the entropy method, a combined weighting model of the DEMATEL method and the entropy method is constructed based on the principle of minimum discriminative information entropy. The principle of minimum discrimination information entropy can avoid the one-sidedness of single-index evaluation, fully consider the interdependence and weight of multiple indicators, and evaluate the advantages and disadvantages of different schemes more comprehensively and objectively [33]. W_1 represents the weights calculated by the DEMATEL method, while W_2 represents the weights calculated by the entropy method.

The quantitative function is established as follows:

$$\min F = \sum_{i=1}^{24} w(i) \ln \frac{w(i)}{w_1(i)} + \sum_{i=1}^{24} w(i) \ln \frac{w(i)}{w_2(i)}$$
$$s.t. \sum_{i=1}^{24} w(i) = 1, w(i) > 0$$

Using the Lagrange multiplier method to find the minimum value, we can obtain:

$$w(i) = \frac{[w_1(i) w_2(i)]^{0.5}}{\sum\limits_{i=1}^{24} [w_1(i) w_2(i)]^{0.5}} \tag{14}$$

The magnitude of the combination weights can then be calculated, and the results are shown in Table 2.

After calculating the indicator weights, the combined weighting results are applied to the evaluation model of the DEMATEL-entropy weighting method in order to conduct comprehensive evaluation calculations. The final urban resilience score for the thirteen post-epidemic cities is determined by calculating the weighted standardized matrix and adding the scores for each indicator. According to Table 3, the resilience levels of the thirteen prefecture-level cities are divided into four categories: low-resilience city, medium-resilience city, slightly higher-resilience city, and high-resilience city. The resilience scores of the cities are then represented graphically for easy interpretation. Figure 3 demonstrates the results.

Table 3. The classification of urban resilience levels.

The Level of City Resilience	High-Resilience City	Slightly Higher-Resilience City	Medium-Resilience City	Low-Resilience City
Interval's division	(0, 0.15]	(0.15, 0.3]	(0.3, 0.45]	(0.45, 1]

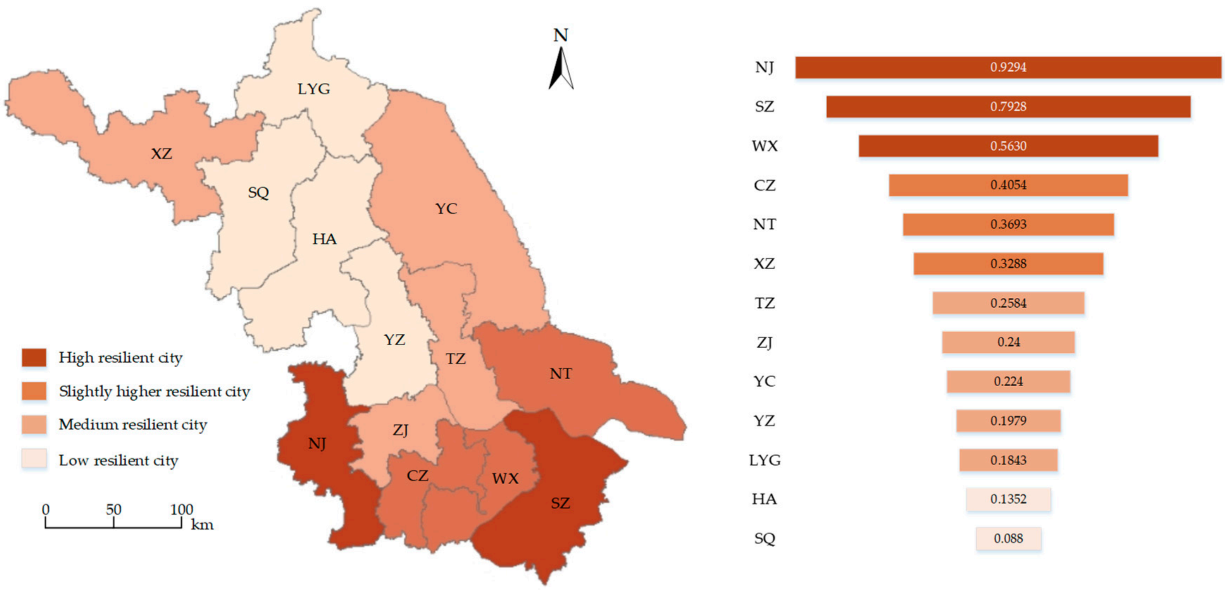

Figure 3. Map of spatial variation in urban resilience and resilience scores.

According to Figure 3, the overall resilience level of Jiangsu Province is relatively high, with 11 cities having resilience levels that are medium or higher. However, the number of cities with a high level of resilience is limited, with only three cities, namely, NJ, WX, and SZ, located in the southern portion of Jiangsu Province and radiating outward to neighboring cities. Influenced by the radiation of high-resilience cities in the surrounding areas, CZ and NT have the second-highest level of resilience after the three cities listed above. The majority of cities, covering the north, central, and south regions and accounting for 38.46% of all cities, have a medium resilience level, making it the most widespread of the four levels. With only SQ and HA, the number of cities with low resilience is the smallest.

Based on the score distribution depicted in Figure 3, there are still distinctions between cities with high and relatively high resilience levels, whereas the gap between cities with medium resilience levels is relatively small. Cities with a low level of resilience have low scores and a large gap compared with cities with medium or higher level of resilience.

4. Discussion

4.1. GWR Modeling

This study employs the geographically weighted regression (GWR) model to investigate the spatial characteristics of resilience and the contribution of influencing factors to the resilience of cities in Jiangsu Province in greater detail. GWR investigates the spatial variability and associated drivers of the dependent variable by establishing a local regression equation for every point in the spatial domain [74]. GWR is more accurate and powerful than OLS, because it takes into account the spatial heterogeneity of geographic factors [75,76]. However, GWR method requires high quality spatial distribution and spatial autocorrelation of data. If the data quality is poor or the spatial distribution is uneven, it may affect the results of the GWR method.

This study selects four influencing factors, namely, GDP per capita, number of physicians per 10,000, daily treatment capacity of environmentally friendly treatment plants, and health and social work GDP, as the research objects for the effect of urban resilience. The results of correlation and collinearity conducted on these four factors are presented in Table 4.

Table 4. Correlation and covariance tests.

Name of Variable	Representation of Variable	Relevance	VIF
GDP per capita	X_1	0.0468 *	1.2491
Number of physicians per 10,000	X_2	0.0384 *	1.6633
Daily treatment capacity of environmentally friendly treatment plants	X_3	0.0098 *	2.6444
Health and social work GDP	X_4	0.0073 *	3.4194

* Significantly correlated at the 0.01 level (two-tailed).

All the influencing factors are significantly correlated, and the model's VIF values are all less than 7.5, indicating that there is no collinearity issue. Therefore, it is possible to conclude that there is no correlation between the sample data, and the model yields satisfactory results.

To demonstrate the suitability of the GWR model, the fitness of the GWR model is compared to that of the OLS model, which is also used for spatial regression analysis. The influencing factors are computed using the GWR plug-in in the ArcGIS 10.7 software package, and the regression model is constructed with an automatically optimized bandwidth. The fitness of the OLS model is 0.956303, while the fitness of the GWR model is 0.956341, indicating an increase in the fitness of the model and, consequently, a better fitting effect as resilience level increases. In consideration of spatial heterogeneity, the GWR model is more suitable than the OLS model for analyzing the spatial variation characteristics of the influencing factors urban resilience.

Using the GWR model, the quantification scores of resilience for each city serve as the dependent variable, while the four selected influencing factors serve as the explanatory variables to conduct regression analysis on the resilience-influencing factors for each city in Jiangsu Province. Figure 4 demonstrates the visualization outcomes.

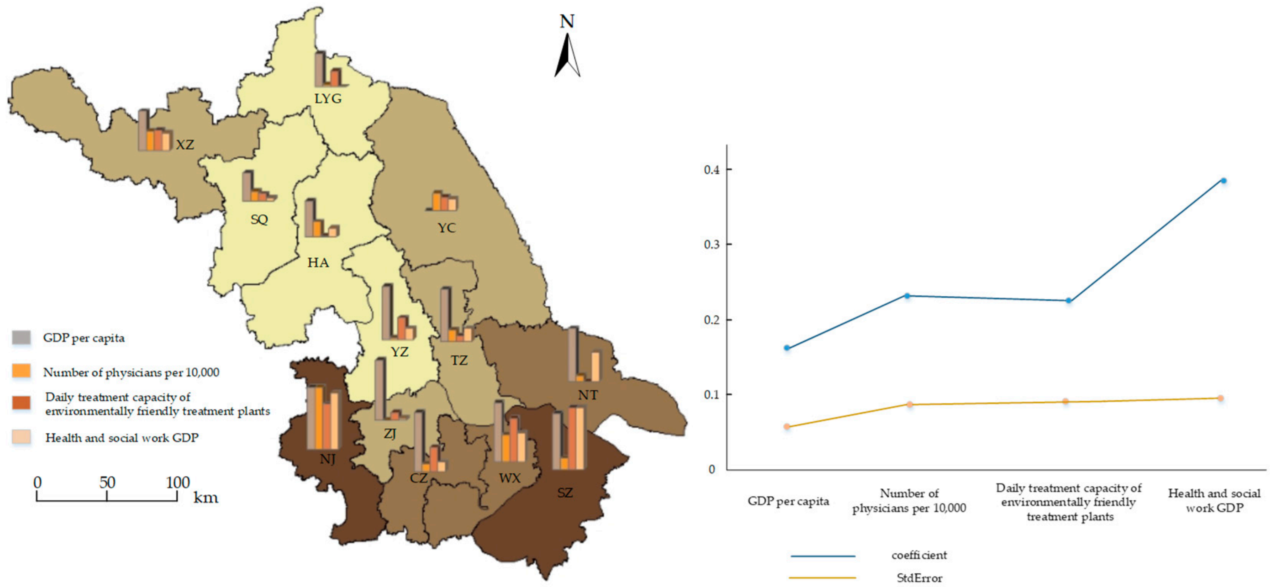

Figure 4. Spatial visualization of regression.

In Figure 4, the colors of the blocks corresponding to each city differ in intensity, with darker colors indicating higher urban resilience and lighter colors indicating lower urban resilience. The coefficient denotes the extent to which the independent variable influences the dependent variable, i.e., the resilience level of the city. The GWR model's standard error value (StedResid) is used to indicate its accuracy. If the geographically weighted regression model for a particular region is more accurate, the error value for that region will be smaller. The fact that the standard error values for the four factors fall within the range of (0.07, 0.11) demonstrates the model's relative precision.

4.2. *Spatial Characterization of Influencing Factors*

(1) Spatial characterization of GDP per capita

All of the regression coefficients of GDP per capita in the GWR model are positive, indicating a positive correlation between GDP per capita and urban resilience scores in the region (Figure 5). The enhancement of economic vitality has a positive effect on urban resilience. Generally, the regression coefficients indicate a decreasing trend from south to north. The high-value areas are concentrated in the central and southern regions of Jiangsu, primarily due to their advantageous location in the Yangtze River Delta economic belt, adjacent to Shanghai, with a more open market that is conducive to attracting foreign investment and expanding market scale. Shanghai, as the economic center of the Yangtze River Delta region and even China's financial, import–export, and shipping industries, can radiate and drive the economic development of Jiangsu, Zhejiang, and even the entire Yangtze River Basin, providing opportunities for capital, talent, and commodity flow. In the central and southern parts of Jiangsu, the industrial base is relatively robust, and a relatively complete industrial chain and industrial clusters have been formed. Considering GDP per capita, (1) for high-value areas, it is necessary to maintain the high level of economic development in the region and gradually shift to new urbanization construction in order to drive the economic development of neighboring cities and enhance urban resilience. (2) For low-value areas, the direction of economic development should be shifted gradually, and the government and businesses should invest more in ecological environmental protection while focusing on improving the urban aesthetic and the happiness of residents.

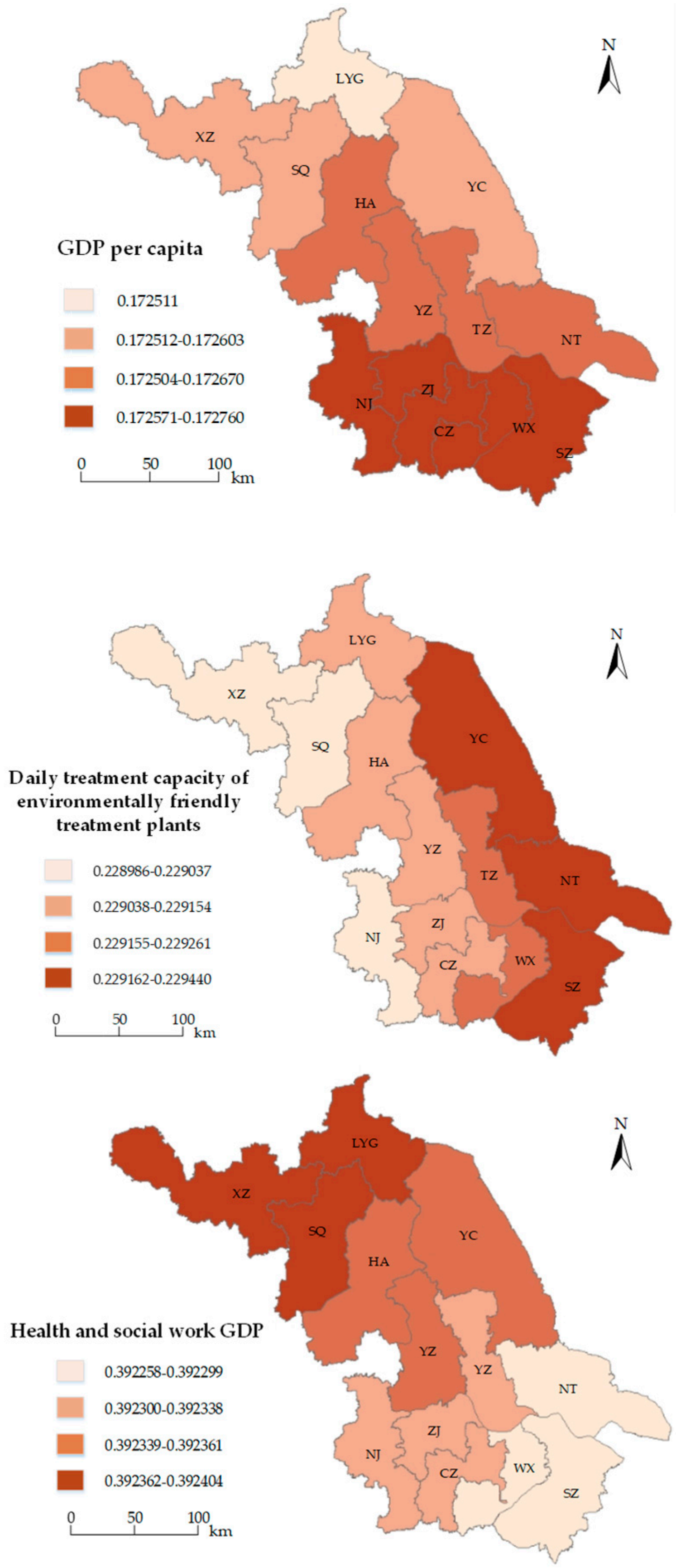

Figure 5. Spatially varying values of GWR model regression coefficients.

(2) Spatial characterization of the number of physicians per 10,000

In the GWR model, the difference between the presentation effect of the number of physicians per 10,000 and the GDP per capita on urban resilience scores is relatively small and generally shows a decreasing trend from south to north. Jiangsu's central and southern cities have a disproportionately high concentration of high-value areas, indicating that more emphasis is placed on investing in medical resources by those cities. Jiangsu's central and southern regions have relatively high population densities, and as urbanization continues to advance, so does the demand for medical services. The increase in urbanization and development also increases the demand for high-quality medical services and advanced medical technology among urban residents. Therefore, the focus of attention should vary between low-value and high-value regions. (1) Investments in medical personnel and resources should be increased in high-value areas, and special attention should be paid to the cultivation of high-level medical talents and the continuous improvement of the medical service network system to assure the accessibility and equity of medical resources. (2) For low-value areas, such as LYG and YC, focusing on investment in medical resources to enhance urban resilience may not have a significant impact and may result in an unreasonable utilization of resources.

(3) Spatial characterization of the daily treatment capacity of environmentally friendly treatment plants

The daily treatment capacity of environmentally friendly treatment plants decreases progressively from coastal cities to inland cities, as measured by their spatial distribution. After innocuous treatment, treated wastewater can be discharged directly into the natural environment via physical, chemical, and other mechanisms, with rivers and oceans serving as the primary discharge sites. In the post-epidemic era, the treatment of medical waste is a crucial component of innocuous treatment. (1) Coastal cities such as YC and NT discharge the most sewage into the ocean, and more efforts are required to increase their capacity for innocuous treatment. (2) A series of techniques, such as high-temperature sterilization and microwave treatment, can remove harmful substances or convert them into harmless ones, increase the efficacy of harmless treatment and the recycling rate of medical waste, and are effective means of enhancing urban resilience in high-value areas.

(4) Spatial characterization of health and social work GDP

In terms of spatial pattern, the factor of health and social work GDP is opposite to the factor of GDP per capita, with an upward trend from south to north. In the northern cities of Jiangsu, high-value regions are concentrated. (1) Given that cities such as LYG and SQ have relatively underdeveloped medical resources, increasing investment in health and service work during the post-epidemic period can significantly improve the city's resilience. (2) In cities with excellent medical conditions, such as SZ and WX, enhancing the production value of health and social work has little effect on the overall level of urban resilience. (3) Such cities should focus on enhancing the level of health services and training senior-level emergency personnel, as well as bolstering the emergency capabilities of management personnel and increasing public awareness of public health, which will increase urban resilience accordingly.

5. Conclusions

Using a combination of subjective and objective methods based on the 4R resilience theory, this study quantitatively and analytically evaluates the resilience level of various cities in Jiangsu Province and graphically displays the resilience scores for each city. The GWR model is used to assess the spatial distribution characteristics of cities' comprehensive resilience scores and the spatial distribution characteristics of influencing factors. During the post-epidemic period, cities in southern Jiangsu with improved development, such as NJ, SZ, and WX, can improve their urban resilience by increasing economic development and investment in medical resources while shifting towards new urbanization construction. Priority should be given to enhancing the production value of health and social work in relatively underdeveloped regions of northern Jiangsu by promoting digital health services and establishing intelligent health management systems. Increasing the capacity of coastal cities for harmless treatment is essential for urban resilience. The objective of enhancing the operational efficacy and treatment capacity of harmless treatment can be attained by improving the management system and supervision mechanism of the harmless treatment process, as well as by increasing social engagement.

Jiangsu Province has experienced sustained economic growth, accelerated urbanization, and effective disaster management in the post-pandemic era, but the issue of uneven urban resilience development persists. In order to improve the resilience levels of various cities in Jiangsu Province, it is essential to implement region-specific measures. This study not only fills a theoretical gap regarding urban resilience in the post-pandemic era, but also recommends critical actions to enhance urban resilience. Even though the scope of this study is limited to cities in the province of Jiangsu in China, it has implications for other Chinese cities. For other regions in China, the same research methodology can be adopted to evaluate urban resilience from a combined qualitative and quantitative perspective, and to provide rational recommendations for sub-regional development of the studied cities, based on spatial heterogeneity.

There is still a great deal of future work to be conducted in this field. This study identifies and analyzes a limited number of influencing factors; in the future, the range of influencing factors can be expanded to make the evaluation of resilience more exhaustive and objective. Future research can validate the proposed improvement path for urban resilience by examining its performance during other public health disasters to determine its efficacy.

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