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Temporal and Spatial Differences in the Resilience of Smart Cities and Their Influencing Factors: Evidence from Non-Provincial Cities in China

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Abstract: Based on the sample data of 81 non-provincial smart cities in China in 2017, the comprehensive evaluation index of the resilience of sample cities is calculated by using the entropy method, and the spatial differences of different factors on the resiliency are analyzed by using the geographical weighted regression (GWR) model. The conclusions are as follows: Firstly, the comprehensive evaluation index of the resilience of smart cities presents a spatial distribution characteristic of decreasing from the east to the west. At the same time, the resilience comprehensive index, the public infrastructure resilience capacity index, the economic development resilience index, the social security resilience index, and the ecological environment resilience index of smart cities have obvious agglomeration effects on their geographical spaces. Secondly, the public infrastructure resilience capacity index and the ecological environment resilience index are both low with a discrete distribution, while the economic development resilience index and the social security resilience index are both high with a concentrated distribution. Thirdly, different factors have significantly positive effects on the resilience of smart cities. In particular, the public infrastructure capacity resilience index decreases from the north to the south with the spatial distribution pattern of concentration, the economic development resilience index and the ecological environment resilience index of smart cities decrease from the east to the west with a concentrated spatial distribution pattern, and the social security resilience index of smart cities decreases from the southwest to the northeast with a concentrated spatial distribution pattern. Therefore, it is necessary to enhance awareness of smart cities, strengthen the driving force of science and technology innovation, strengthen public infrastructure and service construction, and continuously improve the rapid resilience of smart cities.

Keywords: resilience index; influencing factors; smart city; non-provincial city; GWR

1. Introduction

With the acceleration of the urbanization process in China, the problems of urbanization, such as water pollution, water shortage, urban haze, and urban flooding are becoming more and more prominent at the same time as benefits are provided by urban development. As traditional urban management has been difficult to use to meet the real needs of the environment and social development, this concept is facing a major challenge. Smart cities are the key means for modern urban governance [1–3]. However, cities that are smart do not necessarily effectively respond to rapid urbanization and their own growth.

This is because they also need additional resilience to help them withstand the impact of population growth, global economic crises, rapid population change, and environmental disasters.

Terrorists attacked New York City on 11 September 2001, which was an iconic urban systemic shock. However, the quick response of local residents, enterprises, communities, volunteer groups, and public institutions to the disaster was resilient. New York, which has been revitalizing for some time, remains an important global economic and cultural center. In short, it is a resilient city. In comparison, a devastating earthquake struck Wenchuan, China, on 12 May 2008, which destroyed a large amount of local infrastructure, causing devastating damage to the local social system and the city. After reassessing the possibility of reconstruction, the Chinese government gave up on redeveloping the city at its original site and decided to relocate the city. It is clear that Wenchuan did not withstand the impact of the 2008 earthquake and did not have adequate resilience. Therefore, the resilience of smart cities is crucial and deserves more attention.

In the past few decades, China has experienced rapid urbanization. The urbanization rate in China was 59.58% at the end of 2018 and is expected to reach 70% by 2030. With the further acceleration of urbanization, various kinds of urban problems will become increasingly prominent. In addition, the rapid development and in-depth application of cloud computing, big data, "Internet of things" (IOT), new generation mobile broadband networks, and other new rounds of information technology in China provide an important technical force for the construction of new smart cities in China. These trends have also made the construction of smart cities in China enter into a new major stage. At the same time, as the political and economic centers of the provincial administrative regions of China, provincial capital cities have a relatively obvious comparative advantage in the construction of smart cities compared with the non-provincial capital cities. Hence, analysis of the resilience of non-provincial smart cities can better reflect the disaster tolerance boundary of the construction of smart cities. Therefore, this paper constructs an evaluation index system of the resilience of smart cities by using the 81 non-provincial cities of China as the sample, and then analyzes their temporal and spatial differences in order to help urban managers to build smart cities more effectively and improve the resilience of their cities to prevent any adverse external impacts.

This paper is devoted to an analysis of the temporal and spatial differences of the comprehensive resilience index and the driving factors of non-provincial smart cities. The structure of the paper is as follows: the second section provides a theoretical background of the subject area; the third section introduces the data and methodology, the evaluation index system, and the evaluation method of the resilience of smart cities; the fourth section provides the results and cause analysis, the temporal and spatial differences of the evaluation index, and the driving factors of non-provincial smart cities; and the fifth section is the conclusion, where relevant suggestions are put forward. The conclusion of this paper provides a major contribution to the enrichment and development of related theories for the smart city and urban resilience. Through the analysis of the data from China, a comprehensive evaluation index of recovery capacity of 81 sample cities is calculated, and the spatial difference of the effect of different elements on urban resilience is used to provide ideas and reference for other countries and regions to help test urban resilience. The research results can also provide a practical reference to help governments enhance the resilience of their cities in the process of smart city construction.

2. Theoretical Background

2.1. Smart Cities

The concept of the smart city was first proposed by Giffinger et al. of the center for regional scientific research at the university of Austria in 2007 in a report named, "Smart Cities: Ranking of European Small-Medium Sized Cities" [4]. They pointed out that smart cities should include six aspects: a smart economy, smart residents, smart governance, smart transportation, a smart environment, and a smart life. Those six aspects have become important indicators for academics, businesses, and governments to study, evaluate, and build smart cities. Then, in 2008, the International

Business Machines Corporation (IBM) came up with the idea of the "smart planet", which also included the concept of the "smart city". The cores of the concept are "perception", "interconnection", and "intelligence", which have attracted worldwide attention once the concept was put forward [5]. In the view of IBM, the "smart city" is consciously and actively controlling the trend of urbanization and combining advanced information and communication technology to integrate the core systems of the cities, such as people, commerce, transportation, communication, water, and energy, so as to make the whole city as a grand "system of the system" and operate in a smarter way, thus creating a better life for people in the city, and promoting the harmonious and sustainable growth of the city [6–8]. Caragliu et al. think that smart cities are meant to invest in human capital, social capital, and traditional and modern communications infrastructure through participatory governance, to promote sustainable growth in the economy, to improve the quality of life of the population, and to push forward the smart management of natural resources [9].

At present, there is no unified specific definition of smart city. For example, Anavitarte and Tratz-Ryan argue that the smart city is the government's use of "information and communications technology" (ICT) in different public service areas with urban function to provide sustainable and efficient services to citizens [10]; Batty et al. propose that the smart city mainly coordinates and integrates ICT and traditional infrastructure in cities through new electronic technology in cities [11]. However, the basic connotation of the smart city has been generally recognized, in which the use of a new generation of information technology manages the operation of the city in an integrated and systematic way, so that the functions of the city can be coordinated with each other and are beneficial to provide high quality development space for the enterprises in the city. In essence, the smart city is a complex system, which has the characteristics of adaptability. Besides, the smart city can interact with the environment and other subjects and constantly "learn" or "accumulate experience" in the process of continuous interaction and change to its own structure and behavior according to the experiences learned [12]. In the process of urban development, the most direct embodiment of this adaptive behavior is to repair itself in the process of resisting external interference, and finally to achieve sustainable development.

2.2. Urban Resilience

The concept of resilience stems from the field of engineering, which has been used by scholars in "risk and emergency management" in recent years [13]. In response to natural and human-made disasters facing human society, urban resilience has been used to measure the city's ability to withstand external "disturbances", with more emphasis on early preparedness and recovery. Meerow et al. believe that urban resilience is an ability of the urban system and all its social ecological and social technology networks on the temporal and spatial scales to maintain or quickly restore the required functions under interference, adapt to changes, and quickly change the systems that limit current or future adaptability [14]. The definition emphasizes that urban resilience focuses on managing and adapting to current conflicts and pressures.

Many scholars have carried out relevant research on urban resilience. Urban resilience mainly includes five aspects: the motivations and purposes [14], the resilience boundary of urban system [15,16], the time range of resilience [17–19], the content of resilience [20,21], and the subjects of the implementation of resilience [22,23]. These studies are all carried out around the connotations of urban resilience, while the problems of those five aspects will affect urban resilience. More importantly, how to judge the level of urban resilience is still pending. In addition, compared with ordinary cities, smart cities have their own unique features, for example, they are more dependent on information technology, and their response is faster in the process of external conflicts and crises. However, there is little research on the resilience of smart cities at present. Therefore, it is of great theoretical and practical significance to study the influencing factors of the resilience of smart cities and to build a systematic scientific evaluation model [24].

3. Data and Methodology

3.1. Data

Marana et al. argue that urban resilience should include critical infrastructure dependency, climate change, and social dynamics [25]. To achieve rapid recovery, Hernantes et al. constructed the resilience maturity model (RMM) with five divisions of starting, moderate, advanced, robust, and vertebrate [26]. Unlike ordinary cities, smart cities are driven by three factors, namely community, technology, and policy, which directly affect productivity, sustainability, accessibility, wellbeing, livability, and governance [27]. Different drivers may lead to risks with smart city development. Based on the case of five smart cities, Bunders and Varro argue that big data can also bring development risks to smart cities [28]. Further, based on the reality of China, Zhu et al. construct a disaster resilience evaluation index system including infrastructure, economy, society, the public, and the environment, and hold that the differences of above five aspects lead to the difference of disaster resilience capacity of smart cities in China [29].

Based on the research results of existing scholars, this paper divides the resilience evaluation index system of the smart city into urban public infrastructure capacity, urban economic development capacity, social security capacity, and ecological environment capacity, which are described as follows:

(1) The public infrastructural resilience capacity of smart cities. This is the underlying resilience capacity of the smart city, which can evacuate and assist quickly during catastrophes such as earthquakes, storms, and so on. It includes urban public transport resilience capacity, urban flood discharge capacity, and urban medical assistance capacity. In this paper, urban public transport resilience capacity is expressed by the number of buses and the urban road area, which reflects the capacity of smart cities to mitigate the disaster; the urban flood discharge capacity is expressed by the length of the urban drainage pipeline, which reflects the capacity of smart cities to deal with flood disasters; the urban medical assistance capacity is expressed by hospital beds and practitioners in the city, reflecting the medical resilience capacity of the city in disaster emergency.

(2) The economic development resilience capacity of smart cities. The economic development resilience capacity means that government and residents have more economic development capacity to resist catastrophes and can inherit resilience relying on the technological innovation capacity quickly. It includes three parts: economic resilience capacity, scientific and technological innovation resilience capacity, and employment resilience capacity. Among them, the economic resilience capacity is expressed by the registered population number at the end of the year, per capita GDP, and the proportion of tertiary industries by GDP, which reflects the realistic basis of economic development of smart cities. Scientific and technological innovation resilience capacity is expressed by the intensity of research and development (R&D), the number of general college students, and patent applications. Furthermore, employment resilience capacity is indicated by the registered unemployment rate in cities and towns.

(3) The social security resilience capacity of smart cities. This is the public economic security capacity of the smart city, reflecting basic economic protection during catastrophes. It includes three parts: pension resilience capacity, medical insurance resilience capacity, and unemployment insurance resilience capacity, which are expressed by the number of participants in basic old-age insurance, the number of participants in basic medical insurance, and the number of insured persons in unemployment insurance, respectively.

(4) The ecological environment resilience capacity of smart cities. This is the external protection capacity of the smart city, meaning that the higher the quality of the ecological environment, the lower the possibility of a catastrophe. The ecological environment resilience capacity includes urban greening potential and urban ecological cleaning capacity. In this paper, urban greening potential is expressed by the greening coverage rate of the urban built-up area, and urban ecological cleaning capacity is expressed by comprehensive utilization rate of general industrial solid waste, the centralized treatment rate of sewage treatment plants, and the harmless disposal rate of domestic waste.

From 2012 to 2015, the Ministry of Industry and Information Technology of China has released three lists of smart cities, and a total of 287 cities or counties (districts) were selected as pilot projects for the construction of smart cities; no list of smart cities has been released since 2016. Therefore, this paper took smart cities released in 2015 and before as the investigation sample. Considering the availability of data and the reality of non-provincial smart cities, 81 smart cities were selected. At the same time, considering the accumulation of the construction effect of smart cities, only the year of 2017 was selected as the investigation period. Without special explanation, all the data in this paper came from the China Urban Statistical Yearbook, the China Regional Economic Statistical Yearbook, and the China Urban and Rural Construction Statistical Yearbook (2018), all retrieved from the Easy Professional Superior (EPS) electronical database. The selection and description statistics of variables are shown in Table 1.

3.2. The Entropy Evaluation Method

Compared with other methods, the entropy method can effectively avoid the subjectivity of index weighting, and objectively conduct evaluations [30–32]. Therefore, referring to the literature above, the entropy method was used to calculate the comprehensive evaluation index of resilience of smart cities.

$$\begin{cases} x_i' = \frac{x_i - \min\{x_1,\ldots,x_n\}}{\max\{x_1,\ldots,x_n\} - \min\{x_1,\ldots,x_n\}} \\ p_i = (1 + x_i') / \sum\limits_{i=1}^{n} (1 + x_i') \\ e_j = -k \sum\limits_{i=1}^{n} p_i \times \ln(p_i), k = 1/\ln(n) \end{cases} \tag{1}$$

Where x_i' represents the standardized value of x_i, the negative standardized x_i only needs to change the molecule of x_i' into $(\max\{x_1, \ldots, x_n\} - \min\{x_1, \ldots, x_n\})$, p_i represents weight of index, e_j is the entropy of index j, and n is the sample size. Hence, we can get weights of different samples w_j as follows:

$$w_j = d_j / \sum_{j=1}^{m} d_j, d_j = 1 - e_j \tag{2}$$

In Formula (2), d_j is the utility value of the index j. Then we can get the composite index of the resilience capacity of smart cities, $\mathrm{SMRT_i}$:

$$SMRT_i = \sum_{j=1}^{m} w_j \times x_i' \tag{3}$$

3.3. The Geographical Weight Regression Model

The traditional econometric model can only reflect the statistical relationship among variables as a whole, but cannot reflect the regional effect among variables, while the spatial econometric model can make up for the shortcomings of the traditional econometric model and fully reflect the differences in spatial geographical impact among variables, and especially can show all variables' coefficients of the smart city in the sample [33–35]. Therefore, the geographical weighted regression (GWR) model was used to analyze the spatial differences of the influence of various factors on resilience capacity of smart cities.

$$y_i = \beta_0(m_i, n_i) + \sum_{i=1}^{k} \beta_j(m_i, n_i) x_{ij} + \mu_i \tag{4}$$

Table 1. Evaluation index system and descriptive statistics of resilience of 81 smart cities.

Indicator	Implication	Variable	Unit	Mean	Std. Dev.	Min	Max
Public infrastructural resilience	Urban public transport resilience capacity	Number of buses	Vehicles/10,000	2.1320	5.3986	0.1682	47.4291
		Urban road area	Km/10,000	2.7473	2.5148	0.0000	15.4238
	Urban flood discharge capacity	Length of drainage pipeline	km	1657.3460	2464.4710	87.0000	13,815.0000
	Urban medical assistance capacity	Hospital beds	Beds/10,000 persons	23.7075	14.6794	2.7020	74.3510
		Ten thousand practitioners (assistants)	Doctors/10,000	13.2268	8.5399	2.0344	40.8834
Economic development resilience	Economic resilience capacity	Household registration population at the end of the year	10,000 persons	441.9506	235.1831	31.0000	1200.0000
		Per capita gross domestic product	10,000 CNY	7.5725	3.6594	2.3855	18.4068
		Proportion of tertiary industry to GDP	%	48.2547	10.3159	27.7100	77.2900
	Scientific and technological innovation resilience capacity	R&D intensity	%	3.1037	2.2361	0.0331	14.1109
		The number of general college students	College students/10,000 persons	79.8027	79.6312	4.9457	458.5934
		Number of patent applications	Files/10,000 persons	25.8666	52.0308	0.8321	407.1333
	Employment resilience capacity	Registered unemployment rate in cities and towns	%	5.7570	5.0986	0.5762	36.3857
Social security resilience	Pension resilience capacity	Number of participants in basic old-age insurance	Persons/10,000 urban workers	1432.5570	2056.6710	75.6265	15,847.0200
	Medical insurance resilience capacity	Number of participants in basic medical insurance	Persons/10,000 urban workers	1219.2770	1625.8990	144.8569	9116.7520
	Unemployment insurance resilience capacity	Number of insured persons in unemployment insurance	Persons/10,000 urban workers	740.0060	1138.2430	93.7457	7162.8730
Ecological environment resilience	Urban greening potential	Greening coverage rate of built-up area	%	41.4022	3.8207	27.0800	51.0100
	Urban ecological cleaning capacity	Comprehensive utilization rate of general industrial solid waste	%	78.9782	22.0040	19.0000	99.9900
		Centralized treatment rate of sewage treatment plant	%	92.4299	6.9003	59.5400	100.0000
		Harmless disposal rate of domestic waste	%	97.3614	8.4441	44.6200	100.0000

In Formula (4), y_i represents the resilience indexes of smart cities, and x_{ij} represents the driving factors; (m_i,n_i) represents the spatial position of sample i, and μ_i is the random error; β represents the regression coefficient, which is calculated as follows:

$$\beta(m_i, n_i) = (X^{\mathrm{T}} W_{ij} X^{-1}) X^{T} W_{ij} Y \tag{5}$$

In Formula (5), W_{ij} represents spatial distance weight between different sample points, which is determined by the following Gaussian function: $w_{ij} = \exp[-(c_{ij}/b)^2]$, where C_{ij} represents Euclidean distance between sample point *i* and sample point *j*; *b* is the bandwidth, which determines the weight of distance between any two smart cities and the optimal bandwidth determined by the cross confirmation method (CV): $CV = \min \sum_{i=1}^{n} [y_i - \hat{y}_i(b)]^2$; here, $\hat{y}_i(b)$ is the fitting value of y [29].

4. Results and Discussion

In this section, we first analyze the spatial distribution of the comprehensive evaluation index of resilience capacity of smart cities, and then reveal the spatial different characteristics of factors that affect the resilience capacity of smart cities.

4.1. The Spatial Distribution of Resilience Index

Figure 1a shows the spatial distribution of the comprehensive resilience index of smart cities. From the figure, we can see that in 2017, the comprehensive resilience index of sample smart cities decreased from east to west, and the resilience capacity of smart cities in the eastern coastal areas was significantly higher than that in the central and western regions and Northeast China.

First, the number of smart cities with the highest resilience index was small and relatively concentrated. Only seven smart cities were located in the first range of the highest comprehensive resilience index, and the order from large to small was Suzhou, Shenzhen, Qingdao, Wuxi, Ningbo, Dalian, and Nantong, most of which are developed cities along the eastern coast, among which, Suzhou, Shenzhen, Qingdao, and Wuxi have comprehensive resilience indexes of more than 60.

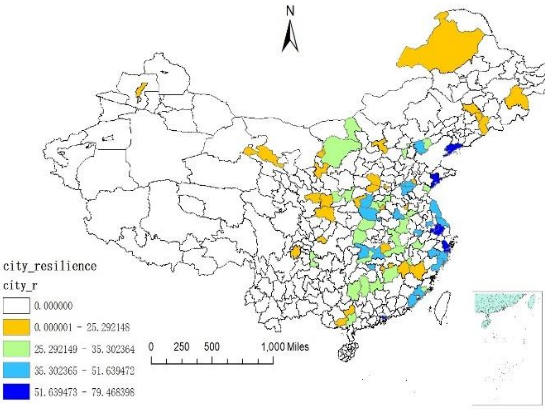
Second, the number of smart cities with the second highest resilience index was small and relatively concentrated. There were 18 smart cities located in the interval of the second highest value of the comprehensive resilience index, which were discretely distributed in the eastern and central regions, while most were in the east.

Third, the number of smart cities with median resilience index was large and relatively concentrated. There were 27 smart cities in the middle and third range of the comprehensive evaluation index, which were scattered in the central area and Inner Mongolia, while mainly located in the central area.

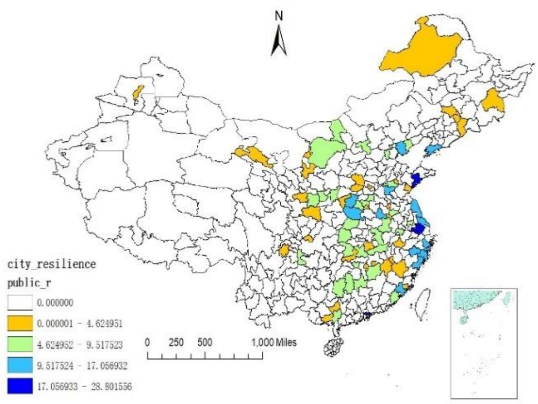
Fourth, the number of smart cities with low resilience index was large and relatively concentrated. There were 29 smart cities in the fourth range of the comprehensive evaluation index, which were discretely distributed in the western, northeast, and central regions, and mainly in the western regions.

Furthermore, we analyze the spatial distribution of public infrastructural resilience index of smart cities.

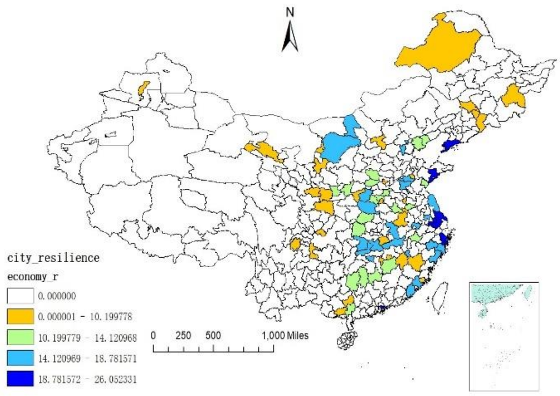
First, the public infrastructure resilience index of smart cities was small and discrete. In Figure 1b, smart cities located in the highest value range of infrastructure resilience index were few and scattered in the eastern area. Smart cities with the second highest value were few and discrete in the eastern, central, and northeast regions. There were many smart cities with medium values, which were scattered in the southeast and northeast, and were relatively concentrated in the central region. There were also many smart cities in the lowest value range, which were relatively concentrated in the central and northeast regions and scattered in the western region.



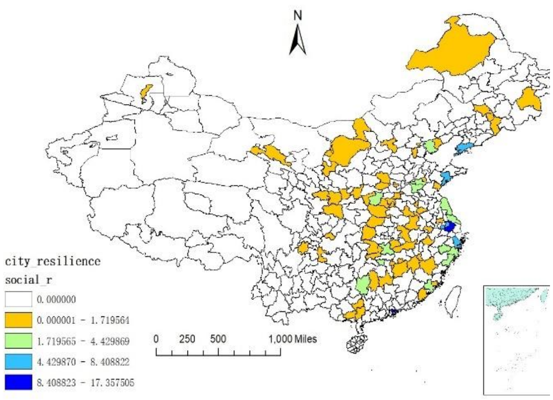
(**a**) Resilience composite index of smart city



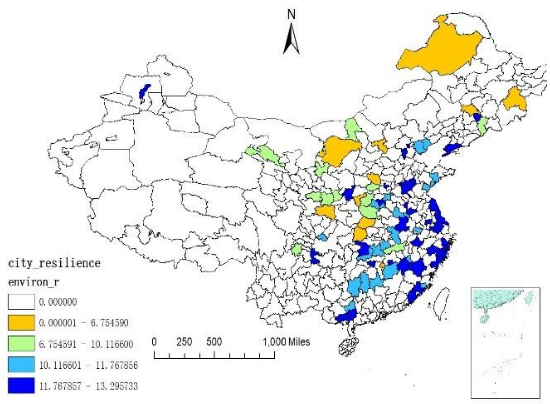
(**b**) Public infrastructure resilience index



(**c**) Economy development resilience index



(**d**) Social security resilience index



(**e**) Ecological environment resilience index

Figure 1. The spatial distribution of index.

Second, values of economic development resilience index of smart cities were high, and the distribution of those cities was relatively concentrated. In Figure 1c, smart cities, which were located in the highest value of the economic development resilience index, were small and discrete in the east, and a few in northeast and central regions; there were relatively more smart cities in the sub high-value range, and they were concentrated in the eastern and central regions; smart cities with median values were more abundant and relatively concentrated in the central and western regions; and smart cities with the lowest values were less abundant and were distributed in the western, central, and northeast regions.

Third, values of the social security resilience index were low, and the distribution of those cities was relative concentrated. As seen in Figure 1d, the number of smart cities located in the highest-value section of social security resilience index was small and discretely distributed in the eastern region; the number of smart cities in the sub-high-value section was also small and concentrated in the east and scattered in the northeast area; smart cities with medium value were distributed in the central and eastern regions; smart cities in the lowest-value section were large and distributed in western, central, and northeast China.

Fourth, values of the ecological environmental resilience index of smart cities were high, and the distribution was relatively concentrated. As seen in Figure 1e, smart cities with the highest ecological environmental resilience index were the most numerous and relatively concentrated in the eastern and central regions and scattered in the western region. Smart cities in the sub-high value range were more abundant, and most of which were concentrated in the central region and scattered in the eastern region. Smart cities in the medium value region were few and scattered in the western and central regions, as well as the northeast region. Smart cities in the lowest value range were the least abundant and were confined to the west, central, and northeast regions.

4.2. The Spatial Differences of Factors Affecting the Resilience of Smart Cities

Table 2 shows the spatial Moran I index of the resilience capability of smart cities. From Table 2, we can see that the Moran I index of the resilience capability of smart cities, the public infrastructure resilience index, the economic development resilience index, the social security resilience index, and the environmental ecological resilience index were significantly positive at a confidence level of 1%, indicating that all of those indices had obvious agglomeration effects in geographical space.

Table 2. Moran I index of resilience capability of smart cities.

Variable	City_re	Basement_re	Economy_re	Social_re	Environ_re
Moran I	0.1308	0.1059	0.1063	0.0649	0.1033
Z score	7.8751 ***	6.5346 ***	6.4473 ***	4.5695 ***	6.3029 ***

Note: *** stand for significance at 10%, 5%, and 1%, respectively.

Furthermore, based on Formula (4), spatial differences in the impact of influencing factors on the resilience capacity of smart cities were analyzed. The robustness results of the model are shown in Table 3. Except for the ecological environment resilience index, the R^2 values for the public infrastructure resilience index, economic development resilience index, and social security resilience index were all greater than 0.6, indicating that the estimated results could reflect the statistical relationship among variables well.

Table 3. The estimate results of the geographical weighted regression (GWR) model.

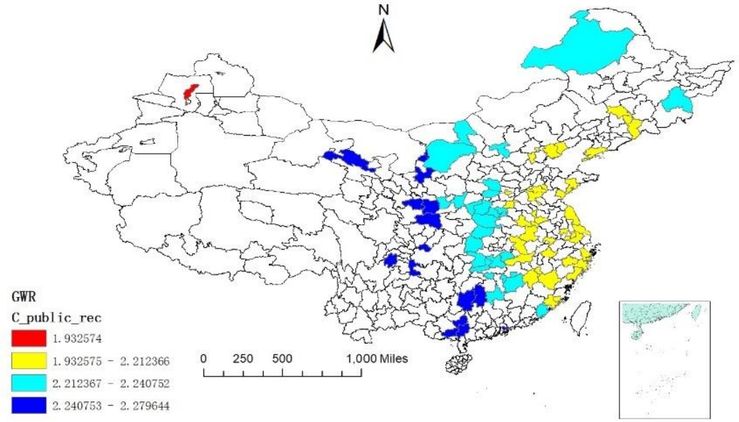
Variable	R2	AICc	Sigma	Bandwidth
Cr_Basement_re	0.9196	453.8966	3.8676	16.0344
Cr_economy_re	0.8662	492.5152	4.9108	16.0343
Cr_social_re	0.7790	532.9249	6.3032	16.0343
Cr_environ_re	0.2257	634.7021	11.8087	17.1392

Figure 2a shows the spatial distribution of the influence of public infrastructure resilience index on the resilience capability of smart cities. From Figure 2a, we can see that the coefficient of public infrastructure resilience index was significantly positive, and the mean value was 2.22, which indicates that improvement of public infrastructure is beneficial to promote the resilience capacity of smart cities. The better the public transport infrastructure, the easier it is to promote the rapid restoration of order in smart cities. In the event of natural disasters such as earthquakes and floods, we rely on the construction of big data central systems of smart cites to smartly improve the passage of urban traffic and the accuracy and timeliness of medical assistance, and to enhance the flood discharge capacity of the city. In space, the coefficient of public infrastructure decreased from west to east and had a concentrated spatial distribution pattern, which indicated that the positive influence of public infrastructure of smart cities in western China on urban resilience was higher than that in other areas. In western China, the population of smart cities was generally smaller than that in other areas, the urbanization rate was low, and the public transport infrastructure was relatively weak, which led to the marginal effect of public infrastructure on urban resilience capability being higher than that in other areas.

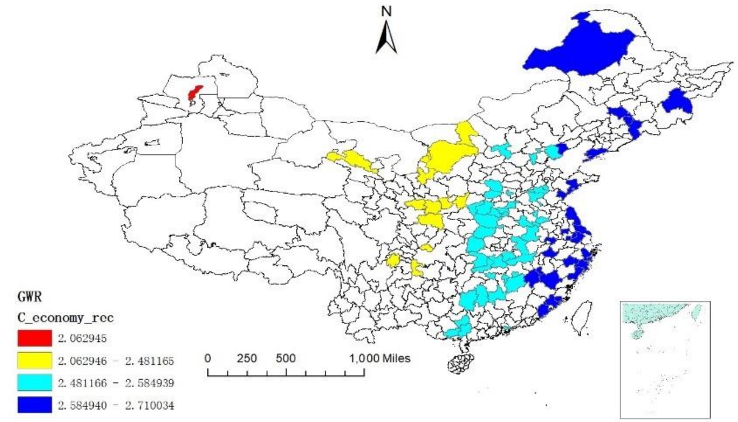
In Figure 2b, the coefficient of economic development resilience index of smart cities was generally significantly positive, and the mean value was 2.55, indicating that economic development resilience ability has a significant positive impact on the resilience of smart cities. The better the economic development, especially the stronger the scientific and technological innovation foundation and the innovation driven development capacity, the easier it is to realize the rapid economic recovery of disaster cities. In space, the coefficient of economic development resilience decreased from east to west and has a relatively concentrated spatial distribution pattern, which indicated that positive influence of economic resilience of smart cities in the eastern region was higher than that in other areas. In the eastern region, especially in the smart cities along the eastern coast, such as Suzhou, Shenzhen, Ningbo, and Wuxi, the intensity of R&D and per capita patent applications were significantly higher than those in other regions. The foundation of urban economic development driven by R&D was solid. At the same time, per capita GDP in these areas was also significantly higher than that in other areas, and the quality of economic resilience was therefore high. Furthermore, the promoting effect of economic development on urban resilience in this kind of area was higher than that in other areas.

In Figure 2c, the coefficient of social security resilience index of smart cities was generally significantly positive, and the mean value was 4.12, indicating that social security had a significant positive effect on the resilience capacity of smart cities. After disasters, smart cities with strong social security resilience capacity can guarantee life safety of residents in time through the convenient and rapid response of medical assistance system. At the same time, through the big data system of complete pension, medical care, and employment security, it can timely distribute living, medical, and unemployment security benefits to residents to ensure them basic needs, and quickly restore the order of smart city. In space, the coefficient of social security resilience capability decreased from north to south and had a relatively concentrated spatial distribution, which indicated that the positive influence of social security of smart cities in northern China on urban resilience was higher than that in other areas. Due to the restriction of economic development and fiscal income, the level of social security of smart cities in the northern and northeastern areas, such as Jinchang, Zhangye, Liaoyuan, Siping, and Tonghua, was lower than that in the south, especially in the coastal economically developed areas, which led to the marginal effect of social security on urban resilience being higher than that in other areas.

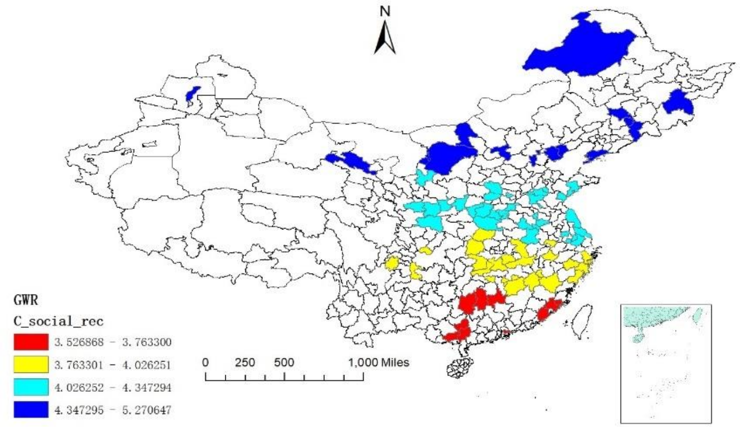
In Figure 2d, the coefficient of ecological environment resilience index of smart cities was significantly positive, and the mean value was 2.16, indicating that the ecological environment had a significant positive effect on resilience capacity of smart cities. Smart cities with good ecological environments, especially with more greening space and higher air quality, provide a better ecological basis, and by using the internet of things, can speed up the restoration of smart cities in catastrophes. In space, the coefficient of ecological environment decreased from east to west and had a relatively concentrated spatial distribution, which indicated the positive influence of the ecological environment on urban resilience in smart cities in eastern China was higher than that in other areas. The main reason was that ecological environment level of the eastern region was obviously lower than that of other areas, due to previous overdevelopment, especially the problems of urban greening and air quality, which led to the marginal effect of ecological environment of smart cities on the urban resilience in the eastern region being higher than that in other areas.



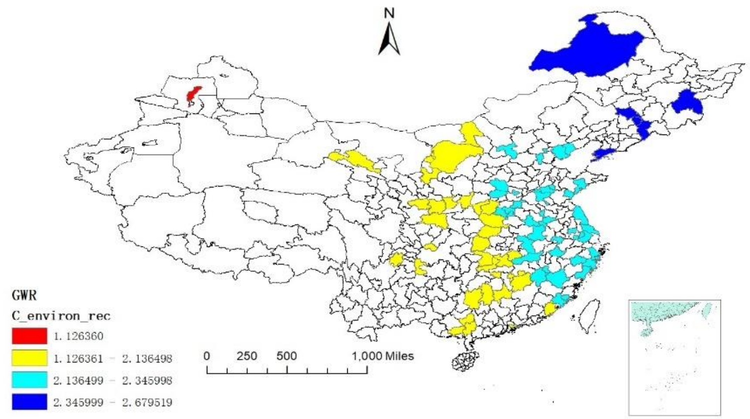
(**a**) coefficient distribution of public infrastructure resilience capacity index



(**b**) coefficient distribution of economy development resilience capacity index



(**c**) coefficient distribution of social security resilience capacity index



(**d**) coefficient distribution of ecological environment resilience capacity index

Figure 2. The spatial distribution of GWR coefficients.

5. Conclusions

Based on the sample data of 81 non-provincial smart cities in China in 2017, the comprehensive resilience indexes of smart cities were calculated by the entropy method, and spatial differences of influencing factors on urban resilience were analyzed by the GWR model. The conclusions are as follows:

First, the comprehensive resilience indexes of smart cities show the spatial distribution characteristics of decreasing from east to west, which are consistent with Zhu et al. [29]. The resilience capacity of smart cities in the eastern coastal area is significantly higher than that in the central, western, and the northeast regions. At the same time, in geographical space, smart city resilience capacity index, public infrastructure resilience capacity index, economic development resilience capacity index, social security resilience capacity index, and environmental ecological resilience capacity index have obvious agglomeration effects.

Second, spatial distributions of influencing factors of different smart cities are obviously different. The index of public infrastructure resilience capacity in smart cities is small and discrete, the index of economic development resilience capacity of smart city is high and relatively concentrated, the index of social security resilience capacity of smart city is small and relatively concentrated, while the index of ecological environment resilience capacity of smart city is high and relatively concentrated.

Third, different influencing factors have significant positive influences on resilience capacity of smart cities, and the spatial distribution of influence coefficients is quite different [36]. Coefficients of public infrastructure resilience capacity index are significantly positive and show a decreasing spatial distribution pattern from west to east, indicating that the positive influence of public infrastructure resilience capacity of smart cities in western China on urban resilience is higher than that in other areas [37]. Coefficients of economic development resilience capacity index of smart cities are significantly positive and show a decreasing spatial distribution pattern from east to west, which indicates that the positive influence of economic development resilience capacity of smart cities on urban resilience in the eastern region is higher than that in other areas. Coefficients of social security resilience capacity index of smart cities are significantly positive and show a decreasing spatial distribution pattern from north to south, which indicates that the positive influence of social security resilience capacity of smart cities on urban resilience in northern China is higher than that in other areas. Coefficients of the ecological environment resilience capacity index of the smart city are significantly positive and show spatial distribution patterns of decreasing from east to west in turn and concentration, indicating that the positive influence of ecological environment resilience capacity on urban restoration capacity of the smart city in the eastern region is higher than that in other areas [38].

6. Implications

Recently, earthquakes, flood disasters, and air pollution have occurred frequently in China, and construction of smart cities gives us a meaningful and practical method to predict and solve these catastrophes using smart tools. Based on the above conclusions, in order to continuously improve the resilience capacity of smart cities, this paper puts forward three suggestions:

First, the government should continue to strengthen the construction of big data central systems in smart cities. By increasing the data integration of smart cities in smart transportation, smart fire, and social security, smart brains of cities covering a variety of disaster recovery information can be constructed, and big data and cloud computing can be used to improve the resilience capacity of smart cities [39].

Second, the government should continue to strengthen the role of scientific and technological innovation in the resilience and development of smart cities. The investment in scientific and technological R&D needs to be continuously improved, and the training of scientific and technological talents should be strengthened [40]. Especially, the northeast and mid-western regions should make up for the shortcomings of scientific and technological innovation and attach importance to the supporting role of scientific and technological innovation in economic resilience of smart cities. At the same time, the eastern region needs to increase investment in major basic science and technology to consolidate the foundation driven by scientific and technological innovation.

Third, the government should step up efforts to withstand disasters in social security and infrastructure construction [41]. The construction of public infrastructure and public medical service facilities in the central and western regions, and also Northeast China, should be strengthened, and the capacity of smart cities to fight risks should be improved so rapid recovery can be achieved. In addition, it is necessary to improve the coverage of social security such as medical care and unemployment and constantly enhance the social security resilience capacity of smart cities in the central and western regions, and also Northeast China.

7. Limitations and Further Research

There are the following limitations: first, not all the smart cities in China were used in this paper due to lack of data availability. Second, we did not use panel data, since the construction year was 2015. Third, we did not analyze the influence with microscopic variables but focused on macroscopic variables.

In the future, we can continue to study from the following two aspects: The first is to further collect time series data for spatiotemporal analysis. The second is to try to add more variables from different angles to analyze the relevant problem of smart cities in multi-dimensional ways.

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