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Spatiotemporal Evolution and Influencing Factors for Urban Resilience in China: A Provincial Analysis

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Abstract: In the current era, as modern cities increasingly face environmental disasters and inherent challenges, the creation and enhancement of resilient cities have become critical. China's urban resilience exhibits significant imbalances and inadequacies at the provincial level. This study delves into the evolution of urban resilience in various Chinese provinces, offering valuable insights for building and nurturing resilient cities. Initially, a comprehensive evaluation system for China's urban resilience was established, incorporating 24 indicators across three key resilience aspects: resistance, adaptability, and recovery. The entropy weight method was used to develop an urban resilience evaluation model, and the Moran index and spatial cold-hot-spot analysis were applied to examine the spatiotemporal dynamics of urban resilience across China's 31 provinces from 2012 to 2021. Moreover, the geographically and temporally weighted regression model was employed to analyze the spatial distribution of factors affecting urban resilience. The results show a general upward trend in urban resilience across Chinese provinces, with notable regional differences and concentrations. A significant decrease in urban resilience is observed from southeastern coastal cities to inland regions. The regression model highlights spatial variations in the impact of different factors, with the same factor having varying effects in different provinces. This research provides a thorough understanding of the factors influencing urban resilience in China, contributing to both theoretical and practical discussions on the topic. It lays a strong scientific groundwork for the development and advancement of resilient cities in China.

Keywords: urban resilience; spatial correlation; influencing factors; spatial cold-hot spot



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1. Introduction

An alarming increase in environmental disasters profoundly affect urban systems worldwide. The continuous expansion and growth of urban areas has heightened their vulnerability and introduced greater uncertainty in urban governance when facing a range of disaster risks. Currently, frequent environmental disasters such as typhoons and floods are occurring globally, which pose great challenges for cities' safety [1]. Specifically, in 2022, China was hit with a series of environmental disasters, impacting an estimated 112 million people. The mainland endured 27 earthquakes with magnitudes of five or higher. Typhoon-induced disasters alone led to direct economic damages amounting to CNY 5.42 billion, and ten provinces suffered direct economic losses exceeding CNY 10 billion due to various disasters over the year [2]. This pattern of significant direct economic losses from environmental disasters in China is not an isolated incident of 2022 but has been a persistent issue over the years. Moreover, this challenge is not unique to China. The world is facing enormous economic losses due to disasters (refer to Figure 1). Consequently, the development and advancement of resilient urban areas have emerged as urgent worldwide issues.

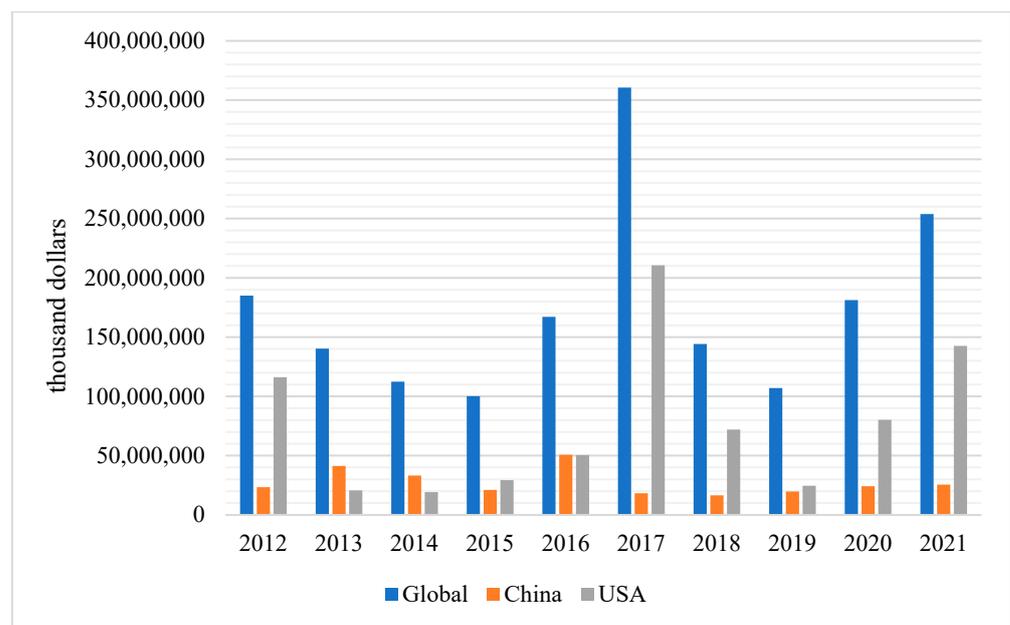


Figure 1. Yearly direct economic losses due to environmental disasters; date resource: <https://www.gddat.cn/newGlobalWeb/#/NationalScale> (accessed on 20 June 2023).

Beyond the increasingly challenging external environment, the ongoing march of industrialization and urbanization also leads to disparities in urban development which have emerged globally. These variations have led to numerous issues, including overpopulation, traffic congestion, insufficient infrastructure, and environmental pollution [3,4]. The resilience of cities is being tested by both internal challenges and external pressures [5]. The critical question is how cities can effectively counter these external forces and manage internal inefficiencies within their unique constraints and the unpredictability of external shocks, in pursuit of enhancing their resilience and achieving sustainable development. This remains a global challenge that all countries must confront [6].

Recently, China's economic boom and rapid urbanization have thrust its cities into a phase of accelerated development. However, this development has been uneven, leading to significant disparities in economic growth, infrastructure advancement, and environmental management across China's 31 provinces [7]. Consequently, a scenario of imbalanced and inadequate development prevails across these regions. Urban areas, increasingly interconnected and interdependent, face heightened vulnerability to a variety of risks, including environmental disasters and socioeconomic upheavals [8]. In light of this disparate development, it becomes imperative to tailor strategies at the provincial level [9]. By analyzing the temporal pattern of urban resilience and discerning the drivers behind its variability, policymakers and urban planners can formulate nuanced strategies to strengthen the resilience of specific regions. In the context of China, marked by its diverse regional development trajectories, investigating the spatial- and temporal-distribution characteristics of urban resilience and its determinants at the provincial level is crucial for formulating effective strategies that promote sustainable development and enhance the nation's overall resilience.

To achieve this goal, we first established a system of evaluation indicators for urban resilience, which were developed from three dimensions: resistance, adaptability, and recovery. We then conducted a spatial correlation analysis (SCA) to analyze the spatiotemporal-differentiation pattern of urban resilience in each province of China. Subsequently, this study identified six influencing factors and used the geographically and temporally weighted regression (GTWR) model to evaluate their different impacts on urban recovery within these provinces. Based on these findings, we proposed targeted recommendations that provide a detailed understanding of how to enhance urban resilience in different regions of China.

As China grapples with the complex interplay of urbanization, economic growth, and environmental sustainability, it is crucial to understand the current state of urban resilience across its provinces and the factors driving its development. This research aims to develop targeted strategies and interventions to enhance urban adaptability by investigating the differences and vulnerabilities at the provincial level. In turn, this fosters sustainable development and equips China's cities to better navigate the complexities of a constantly evolving urban landscape. Our findings offer valuable insights into the dynamics of urban resilience, highlighting varying growth patterns, challenges, and opportunities across different provinces, which contribute significantly to urban studies.

2. Literature Review

2.1. Concept of Urban Resilience

The concept of "resilience" initially rooted in physics, as the capacity of a material to withstand energy during plastic deformation and fracture, has evolved significantly over time [10]. Its application extended to modern urban research, first introduced in the context of ecology by ecologist Holling in 1973. This concept has since undergone a transformation, especially as urban economies and ecological environments have evolved. In 2002, the International Council for Local Environmental Initiatives pioneered the idea of "resilient cities", integrating it into the realm of urban disaster prevention research. Since then, related concepts like "economic resilience [11,12]", "ecological resilience [13,14]", and "industrial resilience [15,16]" have gained significant scholarly attention. In China, the establishment of the Research Center for Resilient Cities at Zhejiang University in 2012, as the country's inaugural research center focusing on urban resilience and disaster prevention, marked a milestone in this field. Currently, scholars and research institutions increasingly view urban resilience as a composite of various capabilities, encompassing a city's ability to resist, adapt, maintain, recover, and develop, as outlined by X. Luo et al. in 2022 [17].

2.2. China's Urban Resilience Development

The increasing focus among Chinese scholars on advancing urban resilience extends beyond theoretical models. This shift is marked by a heightened emphasis on studying urban agglomerations, as evidenced in the research conducted by Tang [18], B. Wang [19], and Ye [20]. Additionally, there is a growing body of research exploring the resilience of cities within individual provinces, such as the studies by K. Zhao [21] and Cao [22]. These scholars are also delving into the differential development of resilience between provincial capitals and their surrounding urban areas, aiming to provide bespoke strategies that cater to the unique needs of each province. The scope of the research encompasses broader themes, including urbanization dynamics [3], carbon emissions [23], and high-quality development [24], with a particular focus on the provincial level. This body of work collectively examines China's overall developmental trajectory and the disparities across different provincial regions. However, there is a notable gap in the literature that specifically addresses urban resilience from a provincial perspective in China. Considering the uneven pace of development across provinces, enhancing urban resilience at this level is pivotal, aiming for comprehensive improvements in the resilience of Chinese cities. This targeted approach is essential for addressing the diverse challenges and needs of different regions, thereby contributing to a more balanced and sustainable urban development across the country.

2.3. Evaluation Index for Urban Resilience

Developing a comprehensive evaluation index system for urban resilience is critical for accurately gauging the resilience of cities or regions. However, currently, there is no consensus on a unified evaluation index system or assessment model for urban resilience. This lack of standardization in defining urban resilience indices stems from the diverse

perspectives held by various scholars such as urban composition [25,26], socioecological systems [27,28], and the stress-state-response model [29].

In the field of resilience research concerning natural ecosystems, the evaluation framework is considerably comprehensive and well-developed [30]. Contemporary studies have introduced the perspective that ecological resilience involves the capacity to recover from external shocks, encompassing preventative measures, responses, and recovery capabilities [31]. Subsequent researchers have refined the concept further by introducing socioecological resilience, emphasizing that systems confronted with external disruptions should possess proactive resistance, inherent adaptability, and post-event transformation capacity [32]. Ultimately, in the context of natural ecosystems, resilience, adaptability, and transformative capacity are regarded as the three fundamental elements of ecological resilience, embodying an ecosystem's ability to withstand shocks, adapt to external influences, and adjust based on both internal and external factors.

Based on the aforementioned research, the resilience of cities is defined as the ability to withstand disasters, reduce disaster losses, and allocate resources effectively in order to recover quickly from disasters and the ability to learn from past disaster incidents and continuously improve their adaptive capacity. Therefore, three core attributes are recognized in the context of urban resilience: resistance, adaptability, and recovery [33]. According to this evaluation framework, a total of 24 indicators were ultimately selected, as detailed in Table 1. Urban resistance is defined as a city's ability to diminish the impact of disasters through its infrastructure. Urban adaptability refers to the capacity of cities to maintain effective management and stability under various levels of disaster pressure. Urban recovery is characterized by the city's capability to rapidly re-establish equilibrium after experiencing the effects of disasters. This comprehensive framework aims to provide a holistic understanding of urban resilience, encapsulating its preparedness, responsiveness, and ability to bounce back from adverse events.

Table 1. Evaluation indicator system of urban resilience.

Index	Units	References	Directivity
<i>Group 1: Urban resistance</i>			
Per Capita Road Area	m ²	[34]	Positive
Total Electricity Consumption	1000 kWh	[35]	Positive
Natural Gas Supply Level	m ³ /person	[36,37]	Positive
Number of Urban Road Lighting Lights	1000 units	[38]	Positive
Density of Drainage Pipelines in Built-up Areas	km/km ²	[37]	Positive
Public Buses and Electric Vehicles Per 10,000 People	car	[39,40]	Positive
Number of Beds in Health Facilities Per 10,000 People	bed	[41]	Positive
<i>Group 2: Urban adaptability</i>			
Green Coverage Rate in Built-up Areas	%	[20]	Positive
Per Capita Park Green Area	m ²	[14,18]	Positive
Public Toilets Per 10,000 People	1000 units	[42]	Positive
Rate of Domestic Garbage Hamless Treatment	%	[43]	Positive
Centralized Treatment Rate of Sewage Treatment Plant	%	[44]	Positive
Per Capita Daily Water Consumption	liter	[39]	Positive
Population Density	person/km ²	[45,46]	Positive
Natural Population Growth Rate	%	[20]	Positive
<i>Group 3: Urban recovery</i>			
Per Capita GDP	CNY/person	[47,48]	Positive
Per Capita Disposable Income of Urban Residents	CNY	[13,25]	Positive
Per Capita Consumption Expenditure of Urban Residents	CNY	[49,50]	Positive
Fiscal Expenditure/Income Ratio	%	[45]	Negative
The Proportion of the Tertiary Industry in the GDP	%	[35]	Positive
Average Students Enrolled in Higher Education Institutions Per 100,000 People	person	[51,52]	Positive
The Number of Participants in Year-End Unemployment Insurance.	person/10,000 people	[53]	Positive
Registered Urban Unemployment Rate	%	[54,55]	Negative

Noted: When a city's development exerts a positive influence, the corresponding indicator is assigned a positive direction. Conversely, if the impact is adverse, the indicator is allocated a negative direction.

2.4. Factors Influencing Urban Resilience

In recent years, a growing number of scholars have been leveraging spatial econometric models to dissect the factors influencing urban resilience. Chen [56] utilized multi-scale geographically weighted regression to delve into the spatiotemporal dynamics of urban resilience in China and its driving factors. Similarly, Wang et al. (2022) [57] conducted comprehensive empirical surveys and a quantitative analysis to identify critical factors affecting urban community resilience, including marketization, urbanization, industrial structure, emergency facilities, and population resources. Moreover, various spatial detection methods, such as the Geographical Detector [58] and the Spatial Durbin Model [41], have been commonly utilized to analyze the influencing actors for urban resilience.

Based on previous studies, our research probes into the factors affecting urban resilience from six distinct perspectives: urban economic, social services, infrastructure improvement, urban digitization, urban ecology, and urban science and education, as detailed in Table 2. Urban economic development can provide additional resources to support urban resilience improvement. The GDP per capita is used to represent the economic level of a city. Social services' capability is crucial for a city's resilience, which can be represented by the proportion of public fiscal expenditure to GDP. Infrastructure improvement not only directly affects a city's daily resource supply capability, but also its ability to resist disasters. The total urban water supply is used to reflect the completeness of infrastructure. Urban digitization plays a crucial role in improving urban governance and future development. The percentage of internet users in each region to the whole country is used to represent a city's digital level. Urban ecology, as an important component of sustainable development for modern urban systems, is inseparable from the resilient cities' development. The per capita green space area is used to represent its ecological level. The level of scientific and educational development is an important indicator of a city's innovation capabilities, which can be represented by the percentage of its expenditure in fiscal expenditure.

Table 2. Influencing factors for urban resilience and corresponding variables.

Influencing Factor	Variable	Representation	References
Urban Economic	GDP per capita	X ₁	[52]
Social Service	Proportion of public fiscal expenditure to GDP	X ₂	[16,29]
Infrastructure Improvement	Total urban water supply	X ₃	[5]
Urban Digitization	Percentage of internet users in each region to the whole country	X ₄	[14,21]
Urban Ecology	Per capita green space area	X ₅	[52,56]
Urban Science and Education	Percentage of science and technology expenditure in fiscal expenditure	X ₆	[29,59]

2.5. Gap in Knowledge

In conclusion, while resilience has been integrated into urban management studies, a universally accepted definition remains elusive in academic discussions. This absence of a single, definitive concept has not impeded the progress of research in urban resilience. On the contrary, it has stimulated the field's continual growth and diversification. The development of urban resilience evaluation indicators predominantly focuses on cities themselves, with limited research adopting a resilience-centric viewpoint. In examining the factors influencing urban resilience, the existing body of literature recognizes the complex interaction of multiple elements. The influence of these diverse factors on urban resilience shows variation across different times and locations. However, most studies tend to adopt a global spatial perspective, with scant attention given to the spatial and temporal variances in factors that affect urban resilience. This gap highlights a potential area for future research, encouraging a more localized or temporally specific examination of urban resilience dynamics.

Considering these factors, our research aims to develop urban resilience indicators and an evaluation model, with a focus on the temporal patterns and spatial features of urban resilience in China. Utilizing the GTWR [60], our study explores the variability in regression coefficients of influencing factors across different provinces. This approach allows us to

provide targeted recommendations for enhancing urban resilience and lays a foundational basis for future research in this area. Our findings are intended to contribute significantly to China's ongoing efforts in urban resilience development, specifically in addressing and reducing the disparities in resilience levels among various provinces. Through this work, we hope to offer valuable insights and guidance for policymakers and urban planners in their pursuit of a more resilient urban future.

3. Methods and Data

3.1. Research Framework

Urban resilience evaluation employs a variety of methods, drawing on diverse disciplines, concepts, and theories. These methods encompass comprehensive index evaluation, resilience network analysis, remote sensing model evaluation, functional modeling, threshold methods, resilience maturity models, scenario analysis, and layer overlay techniques. Among these, the most prevalent is the comprehensive index evaluation. This method utilizes index weights determined by expert scoring [61], the Analytic Hierarchy Process method [44], and the entropy method [45]. In this study, the entropy evaluation method, with the advantage of providing a more objective evaluation, was selected for constructing an urban resilience evaluation model and providing comprehensive scores of urban resilience in the 31 provinces of China based on indices detailed in Table 1. In terms of exploring spatial characteristics, the use of Moran's index and spatial cold-hot spots can better investigate the agglomeration phenomenon of urban resilience in Chinese provinces and generate a spatial-distribution map. The influence of various factors on urban resilience, as detailed in Table 2, was quantified using a GTWR model. Spatial characterization, based on regression coefficients from the study period, aided in visualizing the results. The research framework and methodology are illustrated in Figure 2.

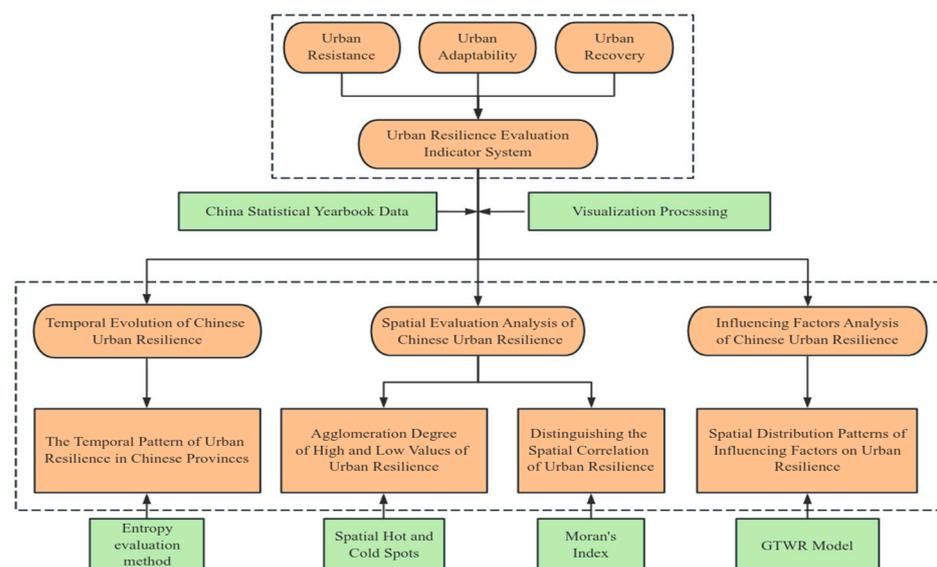


Figure 2. Research framework and workflow.

3.2. Model Building

3.2.1. Entropy Evaluation Method

As a measure of uncertainty, the greater the information, the lower the entropy. Conversely, with less information available, the uncertainty increases, resulting in higher entropy [46]. The entropy method is utilized for the allocation of weights to indicators of urban resilience, followed by the computation of an overall urban resilience score [47]. This method involves the following steps:

- (1) Construct the original data matrix

$$X = \{X_{ij}\} (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (1)$$

where i refers to the provinces being evaluated, of which there are m ; j represents the evaluation indicators, of which there are n .

- (2) Data normalization

The samples were normalized to eliminate the effect between the type of indicator and their dimensions, and dimensionless processing was, respectively, performed for both positive indicators and negative indicators.

Positive indicator:

$$x'_{ij} = \left\{ \frac{x_{ij} - \min(x_{1j}, x_{2j}, \dots, x_{mj})}{\max(x_{1j}, x_{2j}, \dots, x_{mj}) - \min(x_{1j}, x_{2j}, \dots, x_{mj})} \right\} \quad (2)$$

Negative indicator:

$$x'_{ij} = \left\{ \frac{\max(x_{1j}, x_{2j}, \dots, x_{mj}) - x_{ij}}{\max(x_{1j}, x_{2j}, \dots, x_{mj}) - \min(x_{1j}, x_{2j}, \dots, x_{mj})} \right\} \quad (3)$$

where x'_{ij} is the normalized value of the indicator j of the province i , and for convenience, we still denote $x'_{ij} = x_{ij}$. To prevent meaninglessness occurring in the data, the data is panned.

P_{ij} is the proportion of the province i in indicator j , as follows:

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^m X_{ij}} (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (4)$$

- (3) Information entropy value and information utility value of the indicator

The information entropy value e_j for indicator j is as follows:

$$e_j = -K \sum_{i=1}^m P_{ij} \ln P_{ij} \quad (5)$$

where the constant K is related to the number of system samples m . For a completely disordered system, the order degree is zero and its entropy value is maximum, $e_j = 1$. When m samples are in a completely disordered distribution state, $x_{ij} = \frac{1}{m}$, then $K = \frac{1}{\ln m}$.

The information utility value d_j depends on the difference between the information entropy e_j and 1, that is

$$d_{j=1-e_j} \quad (6)$$

- (4) Evaluation indicator weight

The weight w_j of the indicator j is as follows:

$$w_j = d_j \sum_{j=1}^n d_j \quad (7)$$

- (5) Calculate the comprehensive score

The comprehensive score F_i for the province i regarding urban resilience level is as follows:

$$F_i = \sum_{j=1}^n w_j x_{ij} \quad (8)$$

3.2.2. Moran's Index

Moran's index is categorized into two types [47]. The global Moran's index is primarily employed to ascertain the presence of spatial clustering in urban resilience across China.

Moran's index, following normalization, spans a range from -1 to 1 . A value below 0 indicates a spatial negative correlation, above 0 signifies a spatial positive correlation, and a value of 0 suggests randomness [43]. The local Moran's index, generates a cluster map for analyzing the local spatial dependencies among cities. These dependencies are categorized into four types: high–high clustering, low–low clustering, high–low clustering, and low–high clustering. The methodology is as follows:

$$\text{Moran's } I = \frac{\sum_{i=1}^m \sum_{j=1}^m W_{ij} (F_i - \bar{F})}{S^2 \sum_{i=1}^m \sum_{j=1}^m W_{ij}} \quad (9)$$

where m is the total number of provinces under study; w_{ij} is the spatial weight matrix, representing the spatial correlation between i and j ; \bar{F} and S^2 are, respectively, the mean and variance of attribute values; F_i and F_j represent regional attribute values.

3.2.3. Spatial Hot and Cold Spots

By examining the spatial-distribution patterns, hot-spot analysis explores the spatial evolution characteristics of urban resilience within China [57,62]. The specific formula is as follows:

$$G_I^*(d) = \frac{\sum_{i=1}^m W_{ij}(d) F_j}{\sum_{j=1}^m F_j} \quad (10)$$

where $G_I^*(d)$ is the Getis-Ord G_I^* statistic of each element.

3.2.4. GTWR Model

GTWR was proposed by Huang Bo in 2010, adding a temporal dimension to the geographic weighted regression (GWR), which incorporates the functions of geographic location and observation time into the linear regression equation [35]. The specific formula is as follows:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^p \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i; i = 1, 2, \dots, m \quad (11)$$

where X and Y represent the explanatory variable and the dependent variable, respectively; u_i and v_i represent the latitude and longitude coordinates of the centroids of each province; (u_i, v_i, t_i) represents the spatiotemporal coordinates of the province i ; p is the number of explanatory variables; $\beta_0(u_i, v_i, t_i)$ is the intercept term; $\beta_k(u_i, v_i, t_i)$ is the estimated coefficient of the explanatory variable k ; ε is the residual.

3.3. Data Source

This study focuses on the dynamic nature of urban resilience, considering the data availability and local context, and it spans from 2012 to 2021. This particular timeframe was selected due to the availability of reliable data and significant economic growth and urbanization in various Chinese provinces during this period. Data were sourced from authoritative publications like "China Statistical Yearbook", "China Urban Construction Statistical Yearbook" and the provincial statistical yearbooks, covering 31 provinces in total excluding Hong Kong, Macau, and Taiwan (<https://www.stats.gov.cn/sj/ndsj/> (accessed on 20 June 2023)). To address any gaps in the data, interpolation methods were utilized to ensure a comprehensive and complete dataset.

4. Results

4.1. Temporal Evolution Analysis

By applying the entropy method to compute the comprehensive scores of urban resilience across China's 31 provinces, and visualizing these findings using Matlab R2018B, we gain insights into the temporal patterns of urban resilience from 2012 to 2021. As illustrated with the different yellow and blue colors in Figure 3, it can be observed that

Chinese provinces exhibit significant differentiation and agglomeration characteristics during research period in terms of their comprehensive scores for urban resilience.

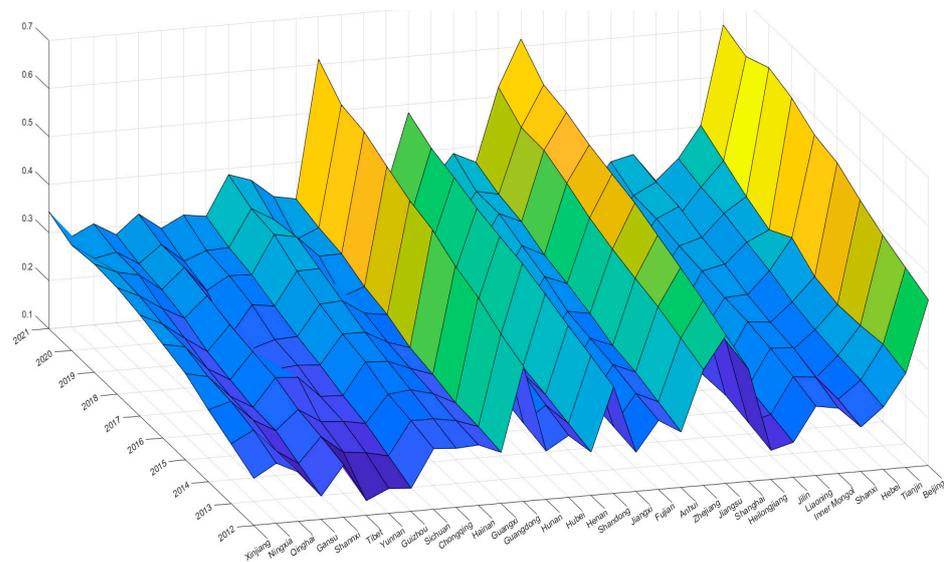


Figure 3. Temporal evolution of urban resilience in China's 31 provinces.

The feature of differentiation is strikingly evident in the substantial disparity observed between Beijing, Guangdong, and Jiangsu compared to other provinces from 2012 to 2021. This is visually underscored in Figure 3, where the comprehensive scores of urban resilience for these three provinces are distinctively highlighted in yellow. During the entire research period, the comprehensive scores of urban resilience across China's 31 provinces ranged from 0.1 to 0.7, with an average score of 0.3. It is evident that a majority of Chinese provincial scores of urban resilience are below 0.3, indicating a lower level of urban resilience in most provinces and a clustering phenomenon of low resilience values. This is marked by relatively minor variations among them, as denoted by the extensive blue area.

4.2. Spatial Evolution Analysis

4.2.1. Spatial Evolution Characteristics

To reveal the spatial evolution characteristics of urban resilience across China's provinces, we adopt the World Bank's regional economic classification method. During the study period, using thresholds at 50%, 100%, 150%, and 200% of the average comprehensive scores at 0.3, the 31 provinces are categorized into five resilience levels: Low, Lower-Middle, Middle, Upper-Middle, and High (see Table 3). Subsequently, ArcGIS 10.8 software was utilized for the visualization processing of the comprehensive urban resilience scores across China's 31 provinces for the years 2012, 2016, and 2021. Figure 4 provides a clear illustration of this.

Table 3. Classification of resilience levels.

Resilience Levels	Low	Lower-Middle	Middle	Upper-Middle	High
Dividing intervals	(0, 0.1500]	(0.1501, 0.3000]	(0.3001, 0.4500]	(0.4501, 0.6000]	(0.6001, 1]

In 2012, Beijing, Shandong, Jiangsu, Zhejiang, Shanghai, and Guangdong achieved a middle resilience level, while Tibet, Gansu, and Guizhou reached an upper-middle resilience level. However, the majority of the provinces in China exhibited lower-middle levels of resilience. This pattern indicates that, at this stage, spatial differentiation in urban resilience across the provinces was not markedly pronounced.

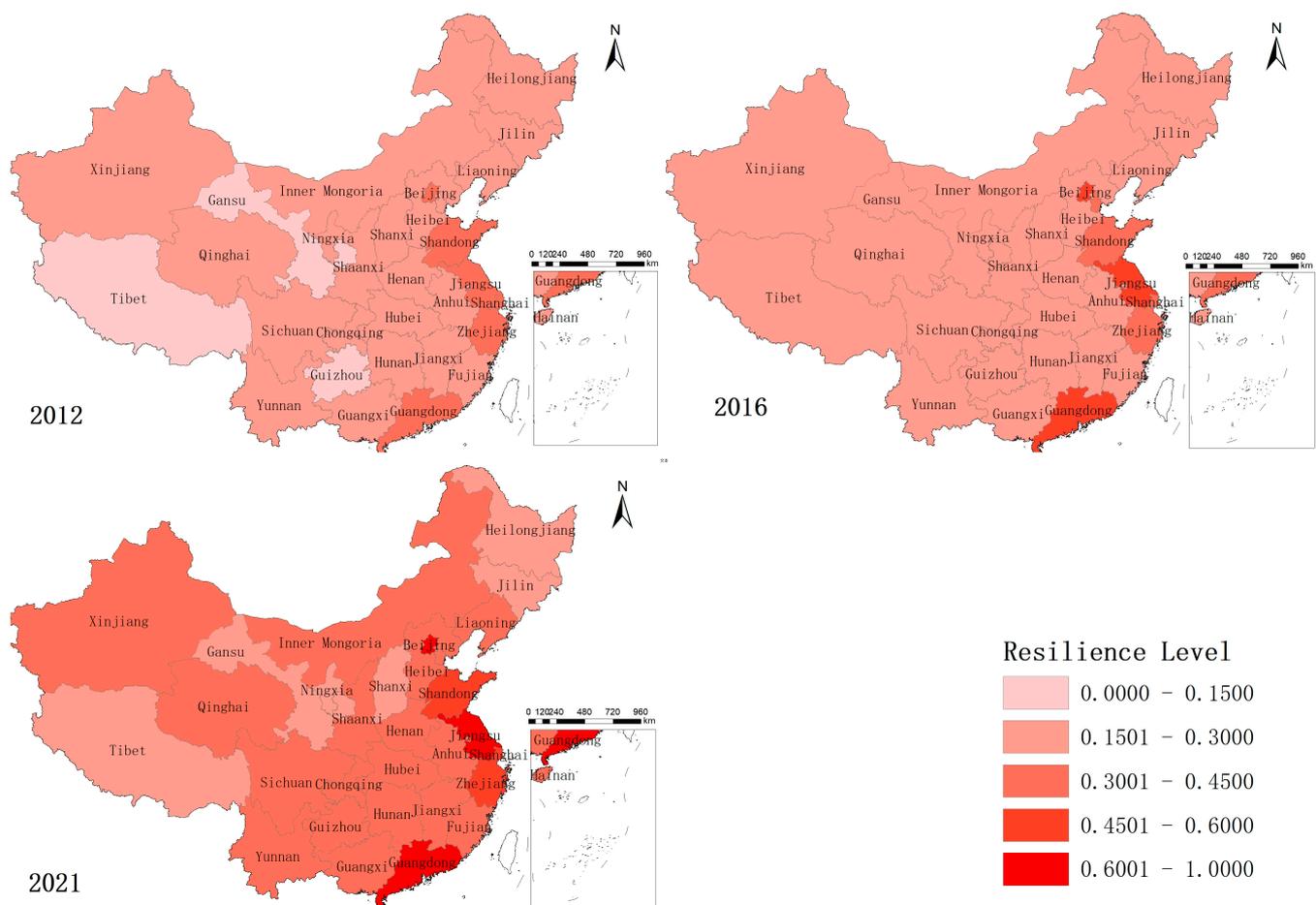


Figure 4. Spatial evolution of urban resilience in China’s 31 provinces.

In 2016, a considerable number of Chinese provinces retained lower-middle resilience levels, though some experienced an uptick in urban resilience. Notably, Beijing, Jiangsu, and Guangdong emerged as the first group of provinces to reach upper-middle resilience levels. This trend was also observed in the southeastern coastal provinces, which demonstrated a resilience radiating inward towards the inland provinces.

By 2021, there was a general increase in urban resilience levels across China’s 31 provinces, with most attaining middle resilience levels. High resilience levels continued to be exclusive to Beijing, Jiangsu, and Guangdong. The southeastern coastal provinces maintained their upper-middle resilience levels, while the northern and northeastern provinces predominantly exhibited middle resilience levels. This period marked a significant spatial differentiation in urban resilience, characterized by a gradual decrease from southeast coastal areas to inland areas.

From 2012 to 2021, only about 37% of China’s provinces had urban resilience levels above average; they were mostly categorized as middle resilience. The disparity in urban resilience between provinces gradually widened over time. By 2021, a clear spatial-differentiation pattern emerged, with the southeastern coastal provinces at upper-middle and high resilience levels, and a gradual decrease in resilience levels moving inland.

This trend can be attributed to the initial higher resilience levels in the southeastern provinces, which over time influenced the inland regions, elevating their resilience levels. The communication between provinces has become more intensive. The high-resilience urban management models of coastal provinces in Southeast China have started to spread inland. At the same time, the improvement of economic, cultural, and social levels in inland provinces has led them to shift towards the goal of sustainable development. As a result,

provinces across the country have begun to learn from new urban management models to establish and develop resilient cities. However, the northern and northeastern provinces further from these developed areas have not improved significantly in urban resilience.

4.2.2. Spatial Autocorrelation

Utilizing the comprehensive scores of each province and an adjacency matrix as the spatial weight file, we calculated the global Moran's index for urban resilience in China's 31 provinces from 2012 to 2021 using ArcGIS software, as detailed in Table 4. The findings reveal that, throughout 2012 to 2021, the global Moran's index consistently exhibited positive values, with most years passing the 5% significance test. This phenomenon indicates that the comprehensive scores of urban resilience among Chinese provinces exhibit strong spatial clustering during the study period. Notably, the global Moran's index displayed a distinctive 'W'-shaped trend, characterized by an initial decline, followed by a rise, another decline, and a concluding rise. Such a trend implies that urban resilience in various Chinese provinces exhibited fluctuating trend in spatial aggregation and the agglomeration of urban resilience in Chinese provinces did not increase significantly, during the study period.

Table 4. Global Moran index of urban resilience in China's 31 provinces.

Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Moran's I	0.3535	0.3382	0.2940	0.2948	0.2879	0.3254	0.3058	0.2858	0.3153	0.3539
Z value	3.3189	3.1790	2.8088	2.8369	2.767	3.0716	2.9076	2.7369	2.9867	3.3135
p value	0.0009	0.0014	0.0049	0.0045	0.0056	0.0021	0.0036	0.0062	0.0028	0.0009

Between 2012 and 2016, the global Moran's index observed a marginal decrease, indicating a reduction in the concentration of urban resilience in China. In 2017, this trend reversed as the index began to ascend, signifying a notable escalation in China's urban resilience agglomeration. However, between 2018 and 2019, the index experienced a moderate downturn, reflecting a diminished trend in China's urban resilience concentration. From 2020 to 2021, the global Moran's index reached an apex, marking the zenith of urban resilience agglomeration in China.

By developing the local Moran's index, we analyzed the spatial concentration patterns of urban resilience across China's 31 provinces for the years 2012, 2016, and 2021 (refer to Figure 5). Overall, the low–low agglomeration type demonstrated the most pronounced spatial variability, while the high–high and high–low agglomeration types remain relatively stable and exhibit clear regional divisions. The southeastern coastal provinces predominantly exhibited high–high agglomeration, and the northwestern and northern provinces demonstrated low–low agglomeration, while the inland provinces were characterized by high–low agglomeration.

In 2012, China's urban resilience was primarily characterized by the low–low agglomeration type, encompassing provinces such as Xinjiang, Qinghai, and Yunnan, all exhibiting low levels of urban resilience. Conversely, the high–high agglomeration regions, comprising Beijing, Tianjin, Jiangsu, Shanghai, and Guangdong provinces, demonstrated elevated urban resilience levels both within these provinces and their adjacent regions. The occurrence of high–low agglomeration regions was less frequent, with only Sichuan and Inner Mongolia falling into this category. Notably, Sichuan displayed a relatively high urban resilience level but with lower levels observed in its surrounding provinces. Consequently, the prevailing trend in 2012 was the dominance of low resilience levels across China's urban resilience landscape.

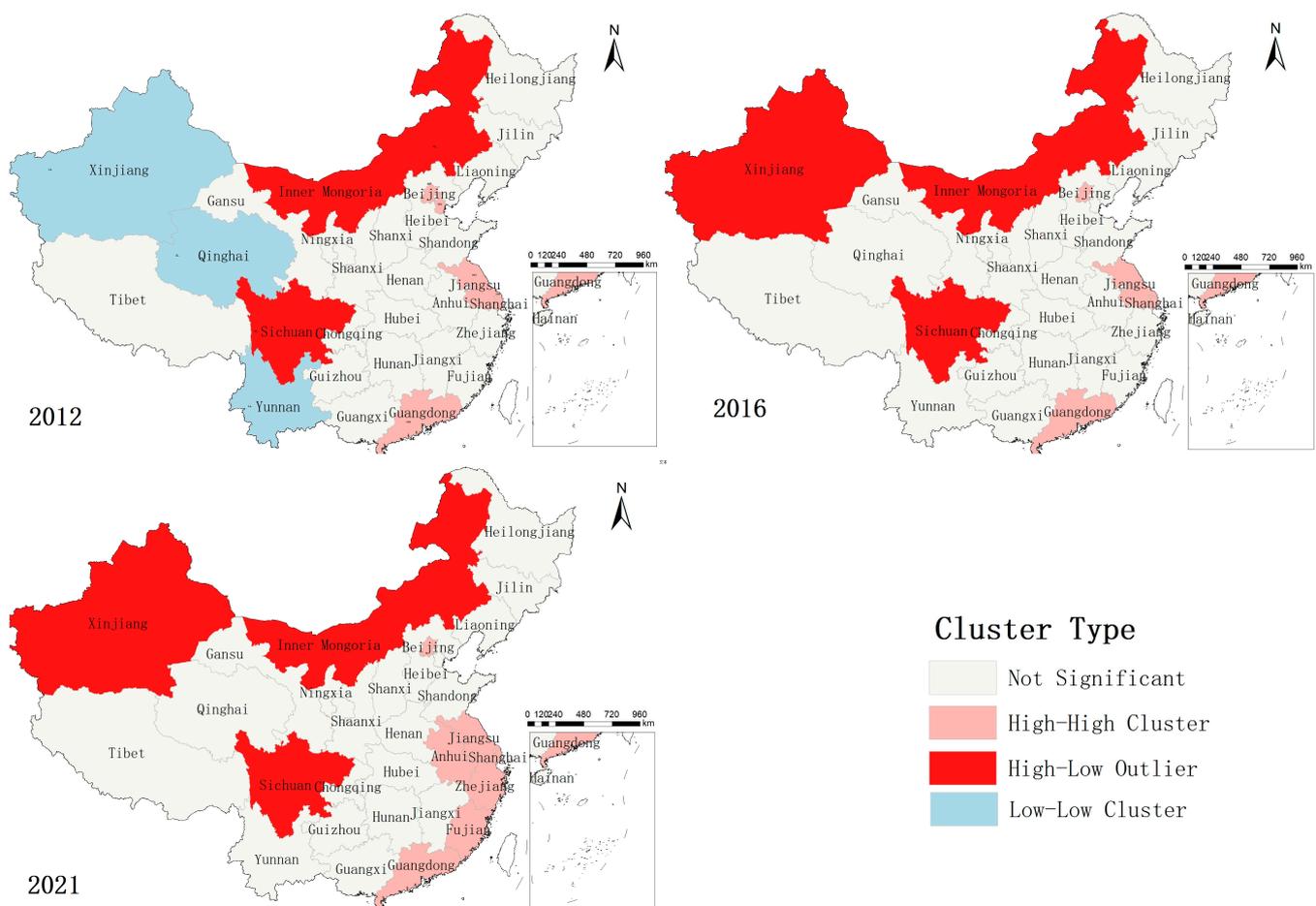


Figure 5. Local Moran's index of urban resilience in China's 31 provinces.

In 2016, the configuration of high–high agglomeration regions remained stable, whereas the number of low–low agglomeration regions decreased, and high–low agglomeration regions showed an increase. Notably, Xinjiang province transitioned from low–low agglomeration to become a high–low agglomeration region. Meanwhile, Qinghai and Yunnan provinces shifted from low–low to not significant agglomeration. Interestingly, despite being in close proximity, Qinghai and Yunnan did not benefit from the high resilience level of Sichuan.

In 2021, a notable surge in the high–high agglomeration type was observed, while the high–low agglomeration type experienced a decline. Specifically, in the majority of southeastern coastal provinces, there was a significant transition to the high–high agglomeration type. Noteworthy shifts occurred in Anhui, Zhejiang, and Fujian provinces, which moved from their 2016 classification to the high–high agglomeration type. The year 2021 marked the highest global Moran's I value, indicating a peak level of regional resilience clustering among Chinese provincial cities. A discernible spatial-differentiation pattern began to take shape. The increase in the high–high agglomeration type, particularly in the southeastern coastal region, signifies the strengthening interconnectivity in this area.

The spatial pattern exhibited distinctive differentiation characteristics, with the southeastern coastal region notably surpassing other regions. Sichuan and Inner Mongolia have consistently maintained a “high–low” agglomeration type, in contrast to the pronounced increase in the “high–high” agglomeration type observed in the southeastern coastal region. In other regions, while urban resilience has generally improved, it still lags significantly behind the level of resilience in high-agglomeration areas.

4.2.3. Hot-Spot Analysis

Hot-spot analysis using Getis-Ord G_i^* in ArcGIS software was employed to calculate hot and cold spots of comprehensive urban resilience scores for the 31 provinces in China for the years 2012, 2016, and 2021. The natural breaks method was applied for visual analysis (see Figure 6). Notably, the southeastern coastal provinces consistently emerged in hot-spot and sub-hot-spot regions. In contrast, over the study period, Inner Mongolia and Sichuan provinces gradually transitioned into cold-spot and sub-cold-spot regions. The spatial distribution of hot and cold spots in urban resilience across the 31 provinces reveals a “persistent hot” phenomenon, with cold-spot areas exhibiting more scattered patterns and displaying a certain degree of randomness.

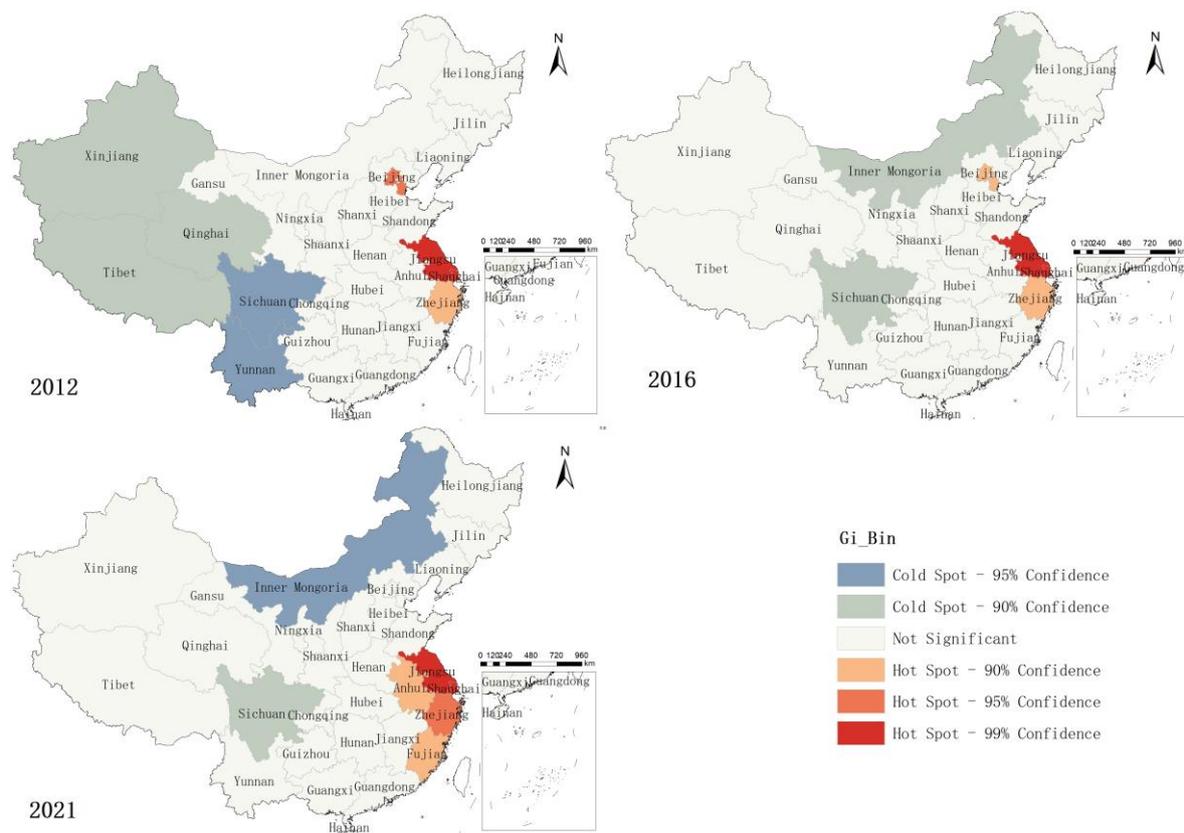


Figure 6. Spatial hot-spots and cold-spots of urban resilience in China’s 31 provinces.

Throughout the study period, Sichuan and Inner Mongolia provinces have consistently remained in the cold-spot and sub-cold-spot regions, indicating significantly low urban resilience levels for both the provinces and their surrounding areas. In contrast, provinces along the southeast coast, such as Jiangsu and Zhejiang, have consistently stayed in the hot-spot and sub-hot-spot regions, signifying consistently high urban resilience values.

Notably, Anhui province transitioned from an insignificant region to a sub-hot-spot region in 2021, while Yunnan province shifted from a sub-cold region to an insignificant region. Simultaneously, Inner Mongolia moved from a sub-cold region to a cold-spot region. These transitions emphasize the imbalanced development among provinces in China. While the southeastern coastal provinces have experienced rapid growth and successfully stimulated development in their adjacent regions, their influence has not extended throughout the entirety of China. In contrast, Inner Mongolia has remained in a low-value zone during the study period, with virtually no change in its urban resilience level. The western regions have not exhibited any significant high- or low-value zones. These findings suggest that urban resilience levels in the southeastern coastal provinces continued to rise, while resilience levels in other provincial regions remained largely unchanged. This spatial

pattern is expected to further exacerbate disparities in urban resilience levels across Chinese provinces as time progresses, leading to increased spatial polarization.

4.3. Factors Influencing Urban Resilience

4.3.1. Comparison of Models

To investigate the factors influencing urban resilience at the provincial level, the GTWR was employed. The results of correlation and collinearity tests are presented in Table 5. All influencing factors exhibit significant correlations. When assessing multicollinearity within the model, it was determined that all Variance Inflation Factor (VIF) values are less than 10, indicating the absence of collinearity issues [63]. This implies that there is no significant association among the sample data, supporting the model's reliability.

Table 5. Examination results of factors influencing urban resilience.

Variable Representation	Correlation	VIF
X1	0.773 **	3.041
X2	−0.210 **	1.493
X3	0.857 **	7.229
X4	0.731 **	6.075
X5	0.279 **	1.237
X6	0.801 **	3.776

** Significant correlation at 0.01 level (bilateral).

To evaluate the goodness-of-fit of the GTWR model, a comparative analysis was conducted in comparison to the GWR model and OLS model, both of which are employed for spatial regression analysis. The GTWR plugin in ArcGIS software was used to calculate the regression coefficients of influencing factors, automatically optimizing the bandwidth and constructing the regression model. The goodness-of-fit statistics for the GTWR model are as follows: $R^2 = 0.9950$, Adjusted $R^2 = 0.9951$, and $ALC = -1653.64$. When compared to the other models, the GTWR model demonstrates an improved R^2 and reduced ALC, indicating its strong fit and suitability for spatial variation analysis of influencing factors (see Table 6). Therefore, the GTWR model is adopted for exploring the spatial distribution of factors influencing urban resilience.

Table 6. Comparison of fitting results among GTWR, GWR, and OLS models.

Model	GTWR	GWR	OLS
R^2	0.995021	0.987695	0.753
Adjusted R^2	0.995128	0.987424	0.747
ALC	−1653.64	−1538.95	−1275.840191

4.3.2. Spatial Characteristics Analysis of Influencing Factors

Using the GTWR model, a regression analysis was conducted for identifying the spatial characteristics of influencing factors. As shown in Figure 7, the general spatial distribution of influencing factors reveals significant spatial imbalances and inconsistent patterns, with high-value areas clustering together and low-value areas clustering together. Additionally, the same influencing factor can either promote or inhibit the development of urban resilience in different provinces. This phenomenon may be attributed to the substantial variations in influencing factors across different regions, causing underdeveloped areas to lag behind in terms of overall urban resilience development in China, thereby appearing to restrict local urban resilience development.

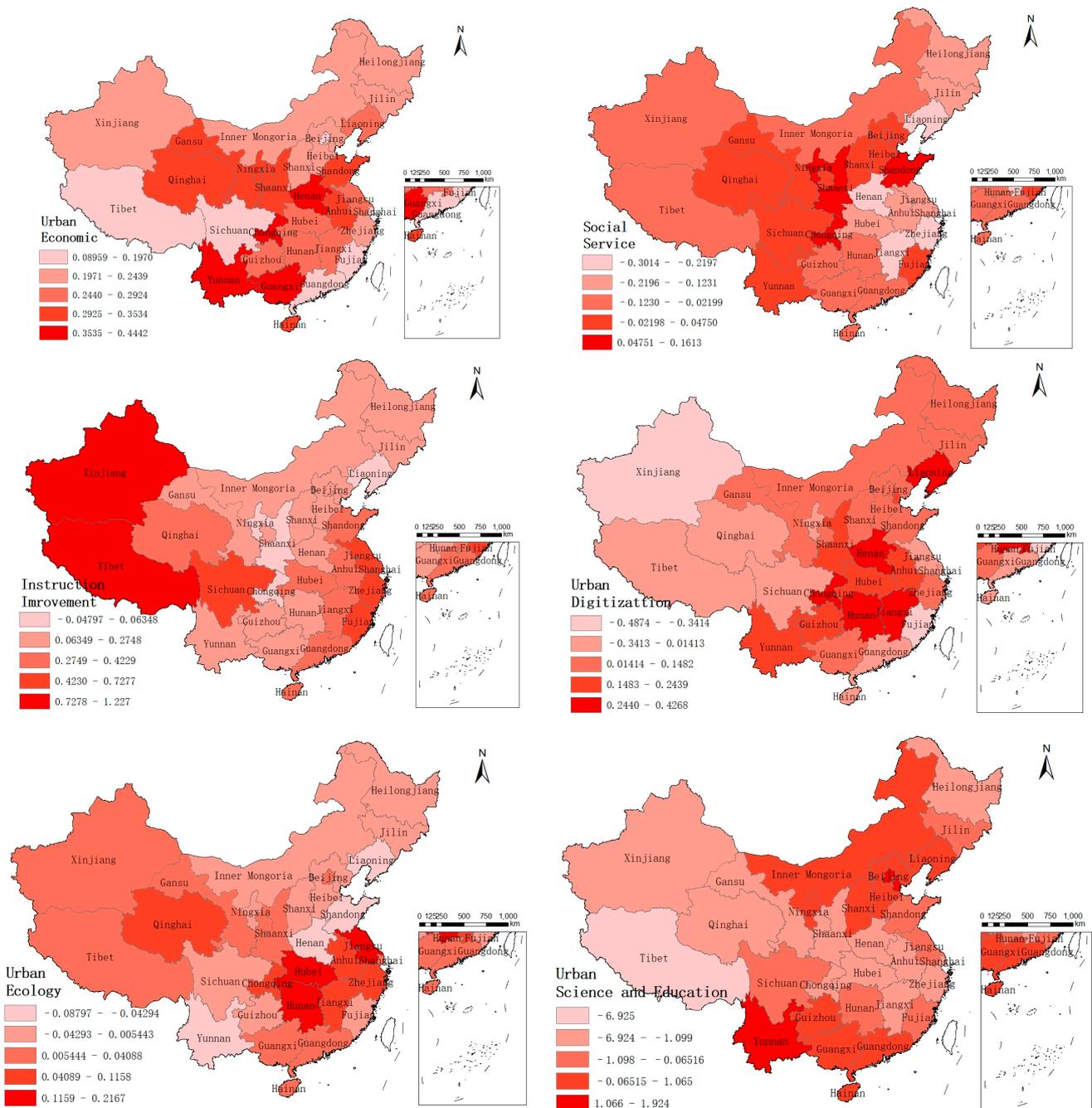


Figure 7. Spatial distribution of influencing factors in China's 31 provinces.

The spatial distribution and impact of these factors contribute to an intricate pattern of urban resilience development across China, as follows:

1. *Urban economy.* Distinct spatial-differentiation characteristics emerge with a gradual decline from north to south, while the regression coefficients in the central region significantly exceed those in the surrounding areas. The regression coefficients of all provinces are positive, which indicates that economic strength fosters urban resilience. There is a relative difference in regression coefficients for urban economic level, with the highest value being 0.4442 and the lowest value 0.089589. The low-value areas are regarded as Tibet, Sichuan, Guangdong, and Fujian provinces, while the high-value areas are regarded as Yunnan and Guangxi provinces. For high-value areas, economic development plays a crucial role in promoting urban resilience.

2. *Social services.* The spatial pattern is completely opposite to that of the economic level. The regression coefficient ranges from its highest at 1.226850 to its lowest at -0.047967 . Most provinces across the country exhibit negative regression coefficients, signifying that social services, to some extent, has hindered the development of urban resilience in Chinese provinces. For high-value areas, the level of social services promotes the construction of resilient cities.
3. *Infrastructure improvement.* The regression coefficient ranges from its highest at 1.227 to its lowest at -0.04797 , with a spatial pattern decreasing from the central region toward the periphery.
4. *Urban digitization.* The spatial characteristics exhibit a decreasing pattern from the East China region to the Northwest and North China regions. Notably, there exists a substantial gap between the regression coefficients of areas with positive and negative values, with the maximum reaching 0.426834 and the minimum dropping to -0.487433 .
5. *Urban ecology.* The regression coefficient demonstrates a transition from a positive value in the south to negative values in the north, ranging from a maximum value of 0.216740 to a minimum value of -0.087970 .
6. *Urban science and education.* It is apparent that the majority of provinces in China fall into the negative value category. Moreover, the level of science and education stands out as the most significant influencing factor among the six factors affecting urban resilience, ranging from a maximum value of 1.923984 to a minimum value of -6.925434 . This underscores the considerable impact of science and education levels on urban resilience, revealing noteworthy disparities across diverse regions.

5. Discussion

From the analysis of temporal evolution, the comprehensive scores of urban resilience in Chinese provincial cities showed significant differentiation and agglomeration characteristics during the study period. There is an obvious gap between high-scoring regions such as Beijing, Jiangsu, and Guangdong and low-scoring regions such as Heilongjiang, Tibet, and Jinlin, and they tend to cluster together. The characteristics of differentiation and agglomeration are also reflected from spatial evolution analysis, manifesting with spatial distance from each other. The provinces with high levels of resilience in China are mostly concentrated in the southeast coastal areas. In addition, high-high agglomeration clusters and hot-spot areas are also concentrated in southeastern coastal areas. It is worth noting that, low-resilience provinces do not exhibit spatial clustering characteristics, which is evidenced by the disappearance of low-low agglomeration clusters and the dispersed nature of cold-spot areas.

The results of influencing factors analysis showed that each influencing factor had a unique spatial pattern, and the same influencing factor had positive and negative effects on different provinces.

1. *Urban economy.* In regions where the regression coefficient is relatively low but remains positive, economic development still contributes to the advancement of urban resilience, but has a relatively limited impact. In regions where the regression coefficient is negative, the economic development has not increased urban resilience levels. In such cases, cities should shift their focus to other aspects for promoting resilient cities. Conversely, for regions where the regression coefficient is high, the focus of economic development should gradually shift towards new urbanization and ecological environment enhancement, thereby bolstering urban recovery capabilities.
2. *Social services.* The substantial variance in regression coefficients can be attributed to the growing prominence of the concept of modern cities across all provinces in the nation. Numerous provinces are beginning to prioritize social services to enhance residents' living standards and quality of life. In regions characterized by negative values, improvements in the social service levels might potentially impede urban resilience development. These provinces amplify their social services by transforming

the external environment, sometimes inadvertently neglecting the intricate connection between the external environment and the urban landscape. It is imperative to shift this perspective towards a dual focus on elevating residents' living standards and fostering sustainable development.

3. *Infrastructure improvement.* As contemporary cities continue to evolve, an increasing number of them emphasize the enhancement and modernization of infrastructure. Comprehensive infrastructure equips cities to mitigate the impact of external shocks, providing both residents and the city itself with more buffer time for rescue operations. However, the disparity in disaster impacts experienced across different regions in our country leads provinces facing severe weather conditions, such as typhoons, droughts, and sandstorms, to exhibit significantly superior infrastructure compared to others. In regions marked by negative values, each province should identify the prevailing types of disasters in their vicinity and enhance the construction of corresponding infrastructure.
4. *Urban digitization.* The significant variance in regression coefficients highlights profound spatial disparities in the level of digitization among Chinese provinces. More developed cities tend to prioritize the advancement of urban digitization, while cities with a moderate development level may inadvertently neglect the progress of digitization. These provinces should enhance their awareness of digitization and initiate the process of digital transformation, thereby establishing resilient cities founded on modern urban management principles [64].
5. *Urban ecology.* Provinces with notably high values, such as Guangdong and Fujian, highlight a dedicated focus on fostering urban ecological civilization and implementing thoughtful urban ecological development planning. This emphasis contributes significantly to the enhancement of urban resilience in these provinces. On the contrary, provinces with negative values, like Inner Mongolia and Heilongjiang, indicate a lack of acknowledgment regarding the importance of ecological construction in urban development. These particular regions, often operating within high-density population environments, impede the cultivation of urban resilience.
6. *Urban science and education.* Regions with high values are mainly concentrated in southern coastal provinces. The progress of science and technology in these areas supports the development of modern information network cities. In the event of disturbances or impacts on these cities, a robust information network can efficiently establish a post-disaster reconstruction and repair system. In contrast, regions with negative values are predominantly found in central areas with comparatively weak government investment in science and technology. As a result, these regions lack the capacity to leverage advanced modern urban systems for constructing resilience networks in urban development.

The existing research outcomes align with previous studies on urban resilience in China, particularly regarding temporal- and spatial-distribution attributes [65]. The degree of agglomeration in high-value and low-value areas closely parallels earlier research conclusions by Y. Chen et al. (2021). However, an enhanced focus on temporal factors in the analysis of influencing factors reveals distinct findings related to the spatial distribution of these factors compared to previous studies. This research introduces a framework for the evaluation and analysis of urban resilience in areas marked by pronounced disparities, incorporating temporal elements into the spatial influence regression model, which provides precise policy recommendations and suggestions.

6. Conclusions

In the face of escalating uncertainty related to external shocks impacting urban areas and with the goal of establishing sustainable and resilient cities, this study delves into the spatiotemporal-distribution characteristics of comprehensive urban resilience scores across China's 31 provinces from 2012 to 2021, and examines the spatial attributes of influencing factors utilizing a GTWR model. Overall, the resilience level of cities in Chinese provinces

resides at a moderate level. Cities in the southeastern coastal provinces demonstrate higher resilience levels, gradually declining as we move inland. In addition, urban resilience in China displays distinct variations, marked by a pronounced agglomeration of low resilience in certain provinces. The overall agglomeration of urban resilience in China has not shown significant changes. The southeastern coastal provinces are predominantly characterized by high–high agglomeration and high-value areas, while the central region is mainly marked by high–low agglomeration and low-value areas.

Through analyzing the influencing factors of urban resilience, the development disparity between provinces becomes more apparent. The spatial characteristics of each factor vary, and regression coefficients for the same influencing factors exhibit both positive and negative values across different provinces. In the southeastern coastal provinces, the principal affecting factors emerge as the level of social services, urban ecology, and urban science and education. In contrast, in the central regions, the influencing factors prioritizing urban resilience include the urban economic, infrastructure completion, and urban digitization. Similarly, in the Northwest and North China regions, significant roles are played by social services levels, urban science, and education levels.

Given the complexity, challenges, and long-term nature of building urban resilience, constructing resilient cities over a short span is a formidable task. Tailored strategies must be devised to enhance urban resilience and optimize risk response strategies, taking into account the distinct characteristics and resource advantages of various Chinese provinces, alongside their social and economic development conditions.

1. *Promoting resource and spatial complementarity between provinces*: Acknowledging the imbalances in development among Chinese provinces, particularly in regions with high resilience levels like Shanghai and Jiangsu in the southeastern coastal provinces, there is a need to foster spatial complementarity based on their unique resource attributes [66]. The development levels across provinces vary significantly, and developed provinces should play a pivotal role as central hubs, actively supporting the construction of urban clusters. These clusters can act as bridges for resource exchange among cities, fostering resource complementarity.
2. *Coordinating efforts in ecological safeguarding and conservation*: It is important to cultivate key ecological function areas and enhance ecological space management for natural reserves in each province. Furthermore, it is important to increase endeavors in establishing forest parks, wetland parks, and urban parks to bolster water source conservation and soil–water preservation [58].
3. *Strengthening inter-provincial regional cooperation and coordinated development*: It is necessary to deepen cooperation in industrial transfer, acquisition, technological innovation, and talent cultivation between provinces by capitalizing on the distinctive strengths within each province's industries and integrating advanced technologies and urban management experiences. Leveraging the radiation effect of developed provinces can foster synergy in infrastructure, industrial development, and ecological protection among city clusters.
4. *Advancing coordinated diversity*: Instituting a resilient urban collaborative governance system, that operates across multiple scales, entities, and processes [67], can ensure a rational and efficient swift response to various emergencies.
5. *Enabling digital governance for future urban development*: Urban digital governance represents an innovative “integration” model that unifies urban governance with digital governance. Each province should highlight the crucial role of information technology and information systems for urban governance in the digital era, such as big data, AI, and BIM [68].

Undoubtedly, urban resilience is of great significance for establishing and improving urban management and residents' quality of life. Although this study has made efforts to establish an evaluation index system for urban resilience from various aspects, there are still certain limitations that prevent a comprehensive assessment of urban resilience. Furthermore, a spatiotemporal geographically weighted regression model with a temporal

dimension was employed in this study, which dynamically demonstrates the effects of influencing factors on urban resilience. However, the underlying mechanisms and efficiency of these factors was not clear. Understanding the influencing mechanisms can intuitively reveal how these factors directly or indirectly affect urban resilience, while efficiency analysis can determine how resources should be allocated to these factors for maximizing the urban resilience level. Future research should focus on revealing the influencing mechanisms and efficiency evaluation of influencing factors. It could also consider longer time spans and utilize predictive models for urban resilience.

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