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Spatio-Temporal Analysis of Urban Emergency Response Resilience During Public Health Crises: A Case Study of Wuhan

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Abstract: In recent years, public health emergencies have severely disrupted city functions and endangered residents' health and lives, enhancing the emergency response capacity, a crucial aspect of building resilient cities. Based on the Wuhan Statistical Yearbook and local economic and social big data, this study constructed a resilience assessment system that covers resistance, adaptability, and resilience. Evaluate the resilience level of each region and analyze its spatiotemporal characteristics using the entropy weight method, Theil index, and natural breakpoint method. The central area exhibited higher resilience levels, while peripheral areas showed lower resilience, owing to location advantage and developmental disparities. The obstacle degree model revealed that scientific and technological innovation, social rescue capabilities, and population size are the primary weak links in building urban emergency response capacity. Based on these findings, this study aims to provide policy recommendations and improvement measures for multiple stakeholders, guide the construction of resilient cities, enhance the ability to respond to public health crises and recovery speed, and ensure urban functions and residents' well-being.

Keywords: urban resilience; emergency response capacity; public health emergencies; Wuhan city

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1. Introduction

Public health emergencies greatly impact population health and societal stability owing to their suddenness, uncertainty, and rapid spread [1]. From SARS to Ebola, public health emergencies have significantly impacted the society [2]. The coronavirus disease (COVID-19) outbreak has affected more than 200 countries and regions worldwide to varying degrees [3]. According to the World Health Organization, 760 million people have been diagnosed with COVID-19. Such public health emergencies significantly affect national security, social stability, and economic development, severely testing the emergency response capacity of human society [4]. When cities respond to these crises, they not only need short-term emergency capabilities but also long-term resilience to ensure recovery and sustainable development after the crisis [5]. In recent years, urban resilience has gradually become an important criterion for measuring the quality of urban development, and the ability to resist and recover from major disasters has become one of the core concepts of modern urban construction [6]. This concept is highly compatible with the initiatives proposed by international organizations, such as the United Nations and the Rockefeller Foundation, such as the “Building Resilient Cities Campaign” and the “100

Resilient Cities Initiative” [7,8], which have promoted research and practice on urban resilience construction around the world. This study aims to answer the following research questions: what are the spatio-temporal evolution characteristics of urban resilience in response to public health emergencies? What are the key factors influencing these changes? These issues provide a foundation for subsequent analysis and the proposal of response strategies. The research framework for evaluating the resilience of Wuhan is shown in Figure 1. Since Wuhan is the center of COVID-19, it provides a unique case to explore how the city’s response capacity to public health emergencies develops.

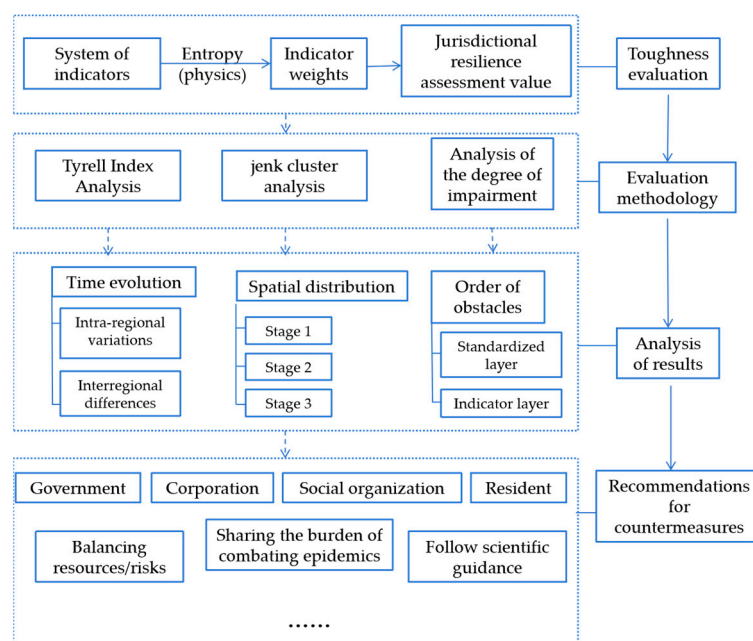


Figure 1. Research framework.

As a megacity with early concentrated outbreaks of COVID-19, Wuhan, China, has faced issues, such as insufficient medical resources, an aging infrastructure, and an imperfect social governance system. These problems severely tested the city’s emergency response resilience throughout different pandemic stages and provided valuable insights into building modern resilient cities. Wuhan was chosen not only as the epicenter of COVID-19 but also as a key economic hub that demonstrated remarkable resilience. By the third quarter of 2020, Wuhan’s GDP grew by 8.1%, outpacing the national average, with strong recovery in fixed asset investment and foreign trade. This highlights its economic resilience, which is of great significance for understanding the construction and evaluation of the overall resilience of cities, and helps to reveal the adaptability and resilience of cities in the face of major shocks [9]. This study analyzed the spatial and temporal evolution of emergency response resilience in 13 Wuhan districts during different COVID-19 stages. It constructs an assessment index system based on resistance, adaptability, and resilience using an obstacle degree model to diagnose the index factors and propose targeted improvement strategies. Using Wuhan’s situation during the COVID-19 pandemic as a case study, this study aimed to reveal the response mechanisms, existing issues, and future development directions for public health emergencies. The goal is to provide valuable insights for improving the city’s emergency response capacity. This research not only quantifies urban resilience in Wuhan but also provides a theoretical framework and empirical evidence for other cities worldwide facing similar public health emergencies. By identifying key resilience factors, the study offers practical recommendations to improve urban governance and emergency response strategies.

2. Literature Review

To better understand resilience and its role in the urban emergency response, reviewing existing literature on urban resilience frameworks and their application in crisis management is essential.

2.1. Urban Resilience

Research on urban resilience has gained significant attention, particularly in the context of natural disasters and public health crises. As globalization and urbanization intensify, cities face more frequent public health emergencies, making resilience a critical factor in enhancing urban response capabilities. Resilience [10,11] is a complex and abstract concept. Klein et al. (2003) define it as the ability to recover from significant impacts [12], while Pendall et al. (2010) describe it as a city's capacity to mitigate the adverse effects of shocks and implement measures for future resilience [13]. Despite varying definitions, resilience serves as a framework for assessing the survival, adaptation, and growth of urban systems, businesses, institutions, communities, and individuals under stress. The "4R" characteristics of urban resilience—robustness, speed, redundancy, and resourcefulness—proposed by Bruneau et al. (2003) [14], are widely used in evaluating resilience, especially in earthquake and emergency management research. However, there remains a lack of studies focusing on resilience in response to specific crises, like public health events.

2.2. Current Research Trends

Recent resilience research has expanded beyond physical infrastructure and technology to include Bruneau's four-dimensional urban resilience framework, "TOSE" [15], which encompasses technical, organizational, social, and economic resilience. Wang et al. (2022) studied the economic resilience of 286 prefecture-level cities in China during the COVID-19 outbreak and found a significant negative impact, with more confirmed cases leading to decreased economic resilience [16]. Alizadeh et al. (2021) examined social resilience in Tehran, identifying gender, age, occupation, and education as significant positive factors [17]. Ali (2020) highlighted that organizational resilience and early preparedness can mitigate COVID-19's effects on urban resilience [18]. Furthermore, the rise of "smart cities" has shifted research focus to the potential of intelligent technology and big data in enhancing urban resilience. Ayyoob et al. (2021) noted that the COVID-19 pandemic coincided with the evolution of modern smart cities, suggesting that advanced information technology can bolster technological resilience [19]. Baibarac (2017) emphasized developing digital tools for cross-site connectivity and knowledge sharing to maintain local resilience [20]. This trend shows a growing emphasis on integrating technology and socio-economic factors for an improved crisis response. Figure 2 illustrates recent research trends in urban resilience based on data from the Web of Science (2021–2023), showcasing keyword clustering analysis to highlight key themes in urban resilience research and further inform the study of urban emergency capacity.

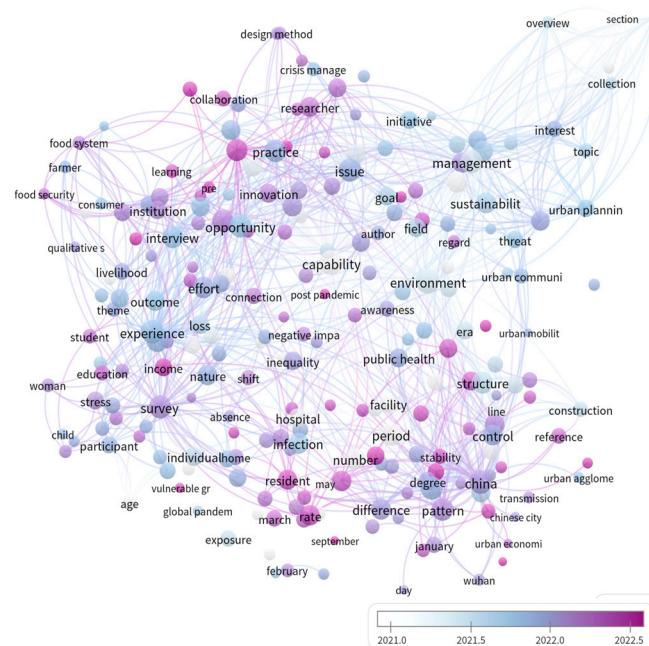


Figure 2. Network of urban resilience research hotspots, 2021–2023.

2.3. The Connection between Emergency Response and Resilience

Emergency response refers to the rapid and coordinated actions taken to mitigate the impact of public emergencies and restore normalcy. Cutter et al. (2008) defined it as measures implemented immediately after a disaster to protect life, property, and the environment, enabling communities to resume normal life quickly [21]. Emergency response capability is closely linked to urban resilience, which encompasses not only recovery after a crisis but also preparedness and adaptability to shocks. Godschalk (2003) highlighted that a city's emergency response capability is a key indicator of its resilience, as a robust system can mitigate disaster impacts and strengthen future shock resistance [22]. Recently, the concept of emergency response has expanded. Maziar Yazdani et al. (2023) emphasized that it involves coordination and planning throughout the mobilization of medical resources, including patient evacuation and efficient resource allocation [23]. Furthermore, the focus is shifting from traditional passive responses to more proactive, intelligent management models to enhance resilience and reduce the impact of future crises [24]. Many recent studies have integrated the emergency response with resilience frameworks to explore how optimizing management and policymaking can improve cities' response speed and resilience during public health emergencies.

2.4. Construction of Emergency Capability Resilience Evaluation Index System

In urban emergency management and resilience research, developing a scientific evaluation index system for emergency capability resilience is crucial. The World Resources Institute (2018) proposed a framework for assessing community resilience based on vulnerability, service access, and resilience, emphasizing the inclusion of local knowledge in decision-making to address the needs of marginalized communities [25]. Recently, studies have begun to integrate big data and intelligent technologies to enhance resilience evaluation systems through dynamic monitoring and data analysis, improving the real-time accuracy of emergency responses. Carneiro et al. (2024) explored the use of advanced data analysis, predictive models, and digital twin technologies to optimize urban resilience and the emergency response [26].

This study constructs a two-level evaluation index system comprising a criterion layer and an indicator layer [27]. The criterion layer includes three dimensions: resistance, adaptability, and resilience [28]. The resistance index measures the urban system's ability

to absorb disturbances and mitigate adverse consequences, the adaptability index assesses the capacity to adjust structures and functions in response to challenges, and the resilience index focuses on the ability to restore the affected area post-disturbance.

To ensure the scientific rigor and practicality of the indicators, this study adhered to three principles: systematicity, independence, and operability [29]. Systematicity ensures comprehensive coverage of urban public health emergency resilience, enhancing the evaluation accuracy. Independence requires indicators to be distinct, avoiding redundancy and ensuring objectivity. Operability ensures that indicators are easily obtainable and quantifiable, promoting feasibility and efficiency in the evaluation [30]. The design of the indicators also takes social vulnerability factors into account. Adhering to these principles laid the groundwork for a scientific, practical, and operable emergency resilience evaluation index system [31,32], as illustrated in Figure 3 or Table A1.

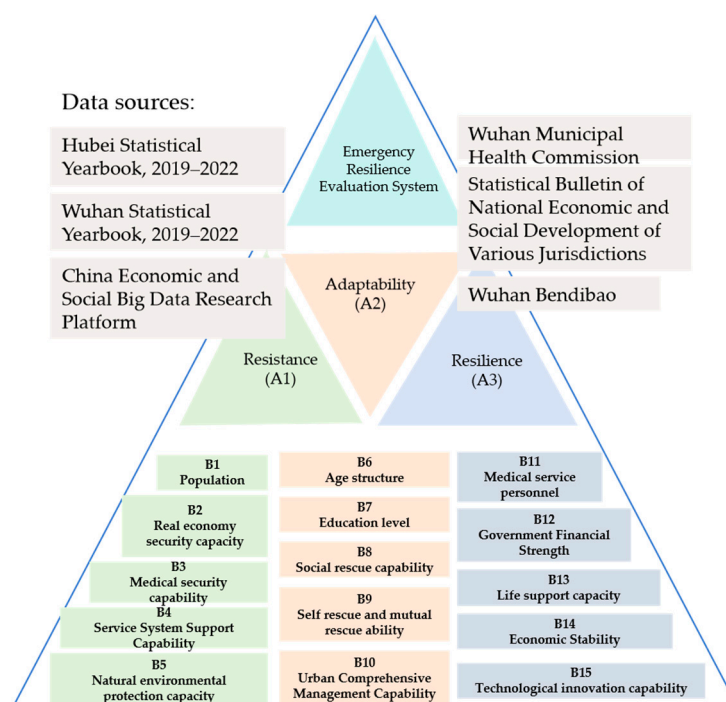


Figure 3. System of indicators for evaluating the resilience of emergency response capacity.

2.5. Research Gaps

Despite notable advancements in research, several key issues remain unaddressed. First, there is a lack of systematic studies on the interaction among different dimensions of resilience, particularly regarding public health emergencies, where the relationships among technological, organizational, and social resilience are not fully explored. Second, empirical research on regional differences in resilience levels is limited, especially concerning resource allocation imbalances and their impact on emergency management systems. Additionally, most existing studies focus on resilience post-crisis. For instance, Guo (2012) analyzed the resilience framework of Dujiangyan Irrigation Project City after the Wenchuan earthquake [33], and Campanella (2006) examined New Orleans' recovery from Hurricane Katrina through the lens of urban resilience [34]. However, there is insufficient emphasis on proactive measures to prevent and mitigate the impacts of crises.

2.6. The Significance of Studying Urban Resilience in the Context of Sudden Public Health Emergencies

The COVID-19 pandemic underscores the critical importance of urban resilience research. In the face of a global public health crisis, cities must quickly adapt and recover to mitigate long-term impacts. Studying resilience enables cities to identify vulnerabilities

and develop effective response strategies for future crises. Shi, C.C. (2023) notes that building resilient cities helps identify urban disaster risks and prepare preventive measures through modern governance [35]. In public health emergencies, resilience research not only optimizes emergency management but also informs policy-making, promotes equitable resource allocation, and enhances overall response capabilities [36]. Forman et al. (2022) highlight that the Pan European Commission on Health and Sustainable Development's final report offers evidence-based policy recommendations to achieve major goals, establish sustainable health systems, and enhance social resilience.

2.7. Summary

Existing research has extensively examined the importance of urban resilience in addressing sudden public health emergencies. However, gaps remain, particularly in empirical studies on how different dimensions of urban resilience—such as technology, society, economy, and organization—interact during crises. Chen et al. (2021) developed a comprehensive evaluation index system for urban resilience in the COVID-19 context, assessing four dimensions: economy, ecology, infrastructure, and social systems, with a quantitative evaluation in the Yangtze River Delta region of China [37]. Additionally, regional disparities in resource allocation and emergency management capabilities continue to pose challenges. As global public health crises become more frequent, future research should focus on enhancing resilience across different urban areas by integrating technological, social, and organizational resources to improve the adaptability and resilience of emergency management systems. This approach is crucial for strengthening cities' long-term risk resistance and optimizing responses to public health events. Miao et al. (2013) proposed strategies to improve emergency resource management by incorporating resilience perspectives to mitigate the impact of natural disasters [38].

3. Identification of Study Area and Data Sources

3.1. Study Area

Wuhan was the earliest confirmed diagnosis and outbreak area of the New Crown pandemic in China. A major city in Hubei Province, Wuhan is divided into 13 districts with a resident population of 13.774 million people, characterized by high building density, high population density, and high mobility [39]. The impact of sudden public health emergencies on cities is not only manifested in their strong impact and long duration but also exposes significant spatial inequality issues, such as significant differences in the distribution and access to medical resources in different regions of the city, abundant medical resources in the central area of the city, and residents being able to access services in a more timely manner with strong resilience; However, medical facilities in peripheral areas are scarce and resources are limited, resulting in a delayed response and uneven resilience. The impacts of public health emergencies on the city showed a high impact strength and long duration, especially during COVID-19. The city has demonstrated its ability to respond to distinct urban resilience challenges, such as complex management approaches [40]. In this study, 13 districts in Wuhan with the most cases of the outbreak—Jiangan, Jianghan, Qiaokou, Hanyang, Wuchang, Qingshan, Hongshan, East-West Lake, Caidian, Jiangxia, Huangpi, Xinzhou, and Hannan Districts—were selected as the study area (shown in Figure 4), and the resistance, adaptability, and resilience in the face of public health emergencies were considered comprehensively from the perspectives of urban resilience security and emergency management.

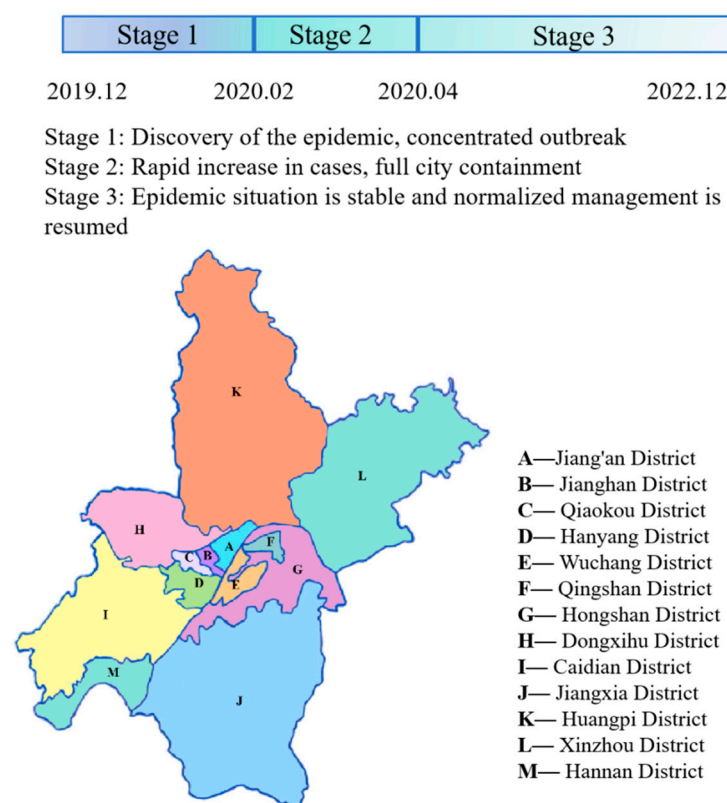


Figure 4. Study stages and regions.

3.2. Data Sources

This study adopted diversified data sources to ensure the accuracy and practicability of the evaluation index system. The primary data were obtained from the Hubei and Wuhan Statistical Yearbooks of previous years, supplemented by channels, such as the China Economic and Social Big Data Research Platform, Wuhan Local Treasure, Wuhan Municipal Health Commission, the National Economic and Social Development Statistical Bulletin of the districts, and the Baidu Index [41]. Interpolation was used to estimate missing values in the data to ensure completeness and continuity.

4. Research Methods

The entropy method was first used to conduct an objective evaluation of emergency response capacity resilience to analyze the changes in the importance of each indicator at different stages and the impact of these changes on the resilience of the city's emergency response capacity [42]. Then, on this basis, the uneven distribution of specific indicators among different regions within Wuhan was measured using the Theil index [43], revealing the differences in emergency response capacity resilience among regions and their evolutionary trends. Next, the natural breakpoint method was used to cluster districts with different resilience indices to analyze the overall characteristics of districts' resilience and the causes of spatial patterns [44]. Finally, by constructing an obstacle degree model [45], the impact of each index on the resilience of the 13 districts was analyzed at the criterion and indicator levels to propose targeted responses and improvement measures for each district.

4.1. Entropy Method of Empowerment

The entropy method, a widely used objective weighting technique, is based on information theory and quantifies the amount of uncertainty or unpredictability in a system. It helps in measuring the significance of indicators by analyzing their variability [46]. The

entropy method is primarily used to judge the randomness and disorder of events and the degree of dispersion of an indicator. If the degree of dispersion of an indicator is more remarkable, its influence on comprehensive evaluation is also greater. Compared with the subjective weighting method, the entropy method can effectively avoid the interference of human factors [47], thereby making the evaluation results more objective. In addition, the entropy value method assigns weights to the process of considering changes in the importance of the indicators of the corresponding development stages of different emergencies to ensure a more comprehensive and accurate evaluation of the research object. The weights of the indicators are listed in Table A1 in Appendix A. The specific data processing is as follows:

Step 1. Indicator homogenization and normalization

(1) Isotropic processing

$$\begin{cases} x'_{ij} = x_{ij} & (\text{Positive indicators}) \\ x'_{ij} = \frac{1}{x_{ij}} & (\text{Negativity indicators}) \end{cases} \quad (1)$$

(2) Normalization process

$$R_{ij} = \frac{x'_{ij} - \text{Min}(x'_j)}{\text{Max}(x'_j) - \text{Min}(x'_j)} \quad (2)$$

Step 2. Calculate the entropy value of each indicator

$$P_{\theta ij} = \frac{x'_{\theta ij}}{\sum_{\theta} \sum_i x'_{\theta ij}} \quad (3)$$

Then, find the entropy value E_j of the j^{th} indicator

$$E_j = -K \sum_{\rho}^r \sum_i^n [P_{\theta ij} \ln(P_{\theta ij})] \quad (4)$$

where $K > 0$, $K = 1/\ln(r \times n)$.

Step 3. Calculate the weights of the indicators

Calculate the information utility value D_j for the j^{th} indicator

$$D_j = 1 - E_j \quad (5)$$

Obtain the objective weight W_j for the j^{th} indicator

$$W_j = \frac{D_j}{\sum_j^m D_j} \quad (6)$$

Step 4. Find the weighted sum and draw conclusions

$$S_i = \sum_{j=1}^n w_j x'_{ij} \quad (7)$$

4.2. Theil Index Analysis of Regional Differences

To further analyze the spatial distribution of resilience levels, the Theil index is introduced as an evaluation tool. The Theil index, rooted in economic theory, is a statistical measure of inequality often applied to assess disparities in resource distribution or outcomes across groups. It provides a more nuanced view of inequality by breaking it down into within-group and between-group components [48]. The Theil index is commonly used to measure the uneven distribution of a given indicator across regions [49]. The calculation of the Theil index is based on the cumulative distribution function of the jurisdictional resilience indicator, which quantifies the degree of inequality between regions by comparing the difference between the cumulative share and cumulative percentage in different regions. The value of the Theil index ranges from 0 to 1 [50], with values closer to 1

indicating a higher degree of inequality and values closer to 0 indicating greater equality. In emergency management, the Theil index can be used to assess the degree of inequality between different regions in the fight against pandemics and, thus, the resilience and resistance of districts.

The jurisdictional resilience Theil index can be expressed as follows:

$$T_{\theta} = \frac{1}{n} \sum_{i=1}^n \left[\frac{y_{\theta i}}{\bar{y}_{\theta}} \ln \left(\frac{y_{\theta i}}{\bar{y}_{\theta}} \right) \right] = T_{\theta W} + T_{\theta B} \quad (8)$$

$$T_{\theta W} = \sum_{k=1}^e \left[\left(\frac{n_k}{n} \frac{\bar{y}_{\theta k}}{\bar{y}_{\theta}} \right) T_{\theta k} \right] \quad (9)$$

$$T_{\theta B} = \sum_{k=1}^e \left[\left(\frac{n_k}{n} \frac{\bar{y}_{\theta k}}{\bar{y}_{\theta}} \right) \ln \left(\frac{\bar{y}_{\theta k}}{\bar{y}_{\theta}} \right) \right] \quad (10)$$

where T_{θ} denotes the total Theil index for stage θ , with a larger T_{θ} denoting more enormous differences, $y_{\theta i}$ denotes the value of resilience for the i^{th} district of stage θ , and $\bar{y}_{\theta}$ denotes the mean value of resilience for all districts in stage θ .

All districts observed are divided into subregions: $T_{\theta W}$ denotes the difference within a subregion in stage θ , $T_{\theta B}$ denotes the difference between subregions in stage θ , $T_{\theta k}$ denotes the total Theil index of the k^{th} subregion in stage θ , e denotes the number of subregions divided, n_k denotes the number of districts within the k^{th} subregion, and $\bar{y}_{\theta k}$ denotes the mean value of jurisdictional resilience in the k^{th} subregion of stage θ .

4.3. Natural Breakpoint Method to Analyze the Spatial Distribution of Resilience

After completing the Theil index analysis, further analysis of the spatial distribution of resilience is conducted using the natural breakpoint method. The natural breakpoint method determines optimal classification breakpoints by minimizing variability within categories and maximizing variability between categories to appropriately group similar values in the data [51]. The specific data processing procedure is as follows:

Step 1. Calculate the sum of squared deviations of the array's mean (*SDAM*)

$$SDAM = \sum_{i=1}^n (x_i - \bar{x})^2 \quad (11)$$

Step 2. For each data stratification method, compute the sum of the squared within-group deviations based on each group G_i ; it stratifies and accumulates the results for all groups (*SDAM_{ALL}*).

$$SDAM_{ALL} = \sum_{i=1}^k \sum_{j=1}^{|G_i|} (G_{ij} - \bar{G}_i)^2 \quad (12)$$

Step 3. Calculate variance goodness of fit (GVF)

$$GVF = (SDAM - SDCM) / SDAM \quad (13)$$

The natural breakpoint method in ArcGIS software (version 10.7) was used to classify the resilience values of Wuhan districts in different stages of the pandemic into five classes [52,53]: low resilience, lower resilience, medium resilience, higher resilience, and high resilience to clearly demonstrate the spatial distribution characteristics of resilience levels [54], which can be used to analyze the reasons why the resilience levels of districts show regional differences according to the classification results.

4.4. Diagnosis of Factors at the Indicator Level of the Obstacle Degree Model

Finally, the obstacle degree model was applied to enhance the evaluation and distribution analysis of emergency resilience levels. The degree of influence of each indicator on the resilience improvement of the emergency response capacity of 13 districts in Wuhan was measured using the obstacle degree model to find a way to improve the resilience level of the city [55,56], which is expressed by the following formula:

$$m_{\theta ij} = \frac{W_j^* (1 - x_{\theta ij})}{\sum_{j=1}^m W_j^* (1 - x_{\theta ij})} \quad (14)$$

$$M_{\theta ij} = \sum_{j=1}^m m_{\theta ij} \quad (15)$$

where $m_{\theta ij}$ denotes the degree of obstruction of district i by indicator j at stage θ , W_j denotes the value of the combined subjective and objective weighting weights of the j^{th} indicator, $x_{\theta ij}$ denotes the standardized value of the j^{th} indicator for district i at stage θ , $1 - x_{\theta ij}$ denotes the deviation of the j^{th} indicator for district i at stage θ from the development goal, and $M_{\theta ij}$ denotes the degree of obstruction of the guideline layer.

5. Results and Discussion

The following sections present the resilience evaluation results for Wuhan's districts, highlighting both general trends and specific insights into the city's emergency response capacity during the pandemic. According to the constructed resilience evaluation indices of emergency response capacity, the Wuhan Municipal Government evaluates the resilience level. It analyzes the obstacle factors to propose countermeasures and suggestions for improving the emergency response capacity of the city in the face of public health emergencies.

5.1. Evaluation of Resilience Levels

The resilience evaluation results of 13 districts in Wuhan were explored, starting from the resilience evaluation values and the overall and respective subsystem resilience evaluation means.

5.1.1. Jurisdictional Resilience Evaluation

In terms of the districts' resilience evaluation values (see Figure 5 or Table A2 in Appendix A), from stage 1 to stage 3, the resilience levels of the six districts, namely Jiangnan, Qiaokou, Wuchang, Qingshan, East-West Lake, and Caidian Districts, decreased, with the range of the decrease ranging from 0.16% to 10.20%; the three districts with the largest decreases in resilience levels were East-West Lake, Jiangnan, and Qiaokou Districts, with a decrease of 10.20%, 4.63%, and 4.19%, respectively. Qingshan District experienced the smallest decline in resilience (0.16%). The resilience level of the remaining seven districts increased, with an increase ranging from 1.95 to 64.24%. The three districts with the largest increase in resilience level were Caidian, Huangpi, and Jiangxia Districts, with an increase of 64.24%, 28.13%, and 27.59%, respectively.

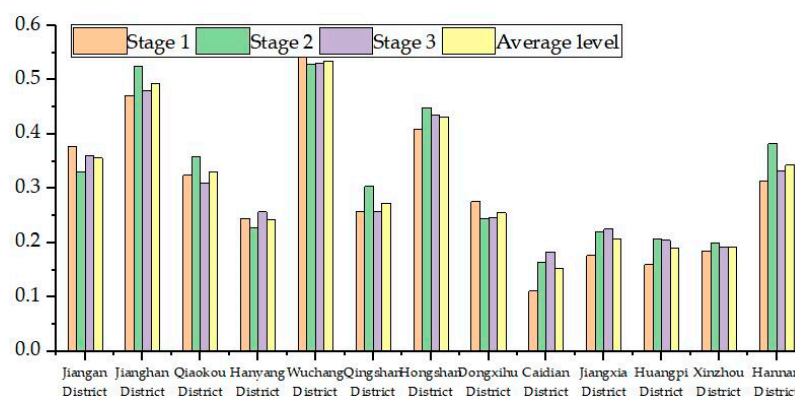
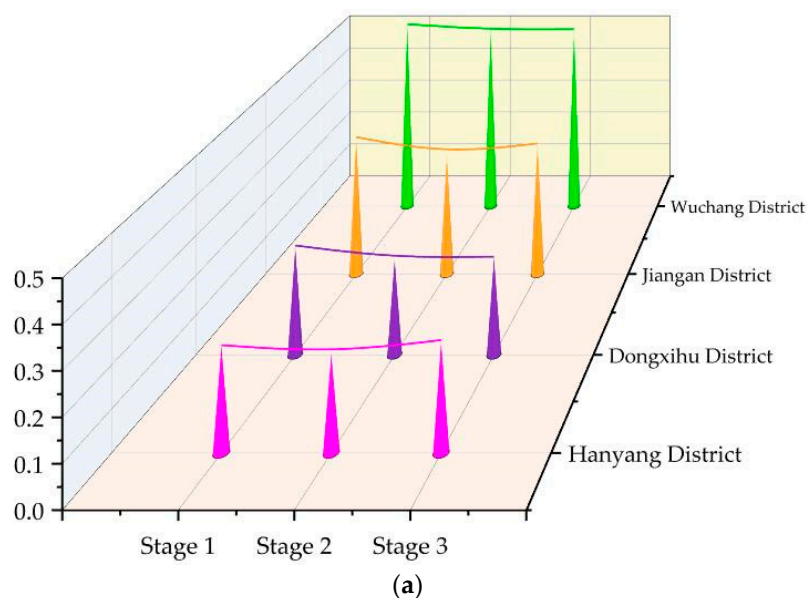


Figure 5. Resilience assessment of 13 districts in Wuhan.

The emergency response capacity resilience levels of Jiangnan, Wuchang, Hanyang, and East-West Lake districts showed a “decrease and increase” trend during the three developmental stages of the pandemic (Figure 6a). As per the official work summaries and news reports released by the three districts, this change mainly stemmed from the significant impact and pressure on the local emergency management system caused by the sudden outbreak of COVID-19 [57]. This downward trend was particularly evident in the early stages of the outbreak as the unknown and spreading nature of the virus, as well as the lack of information and resource constraints faced by the districts in their initial response to the outbreak, led to a decline in the level of resilience of emergency response capacity. With the continued development of the pandemic and the deepening of prevention and control efforts, the districts ultimately achieved resilience recovery and enhancement through the continuous adjustment and optimization of their emergency management systems, although with some shortcomings, such as the low prevalence of prevention and control knowledge and insufficient infrastructure reserves [58].



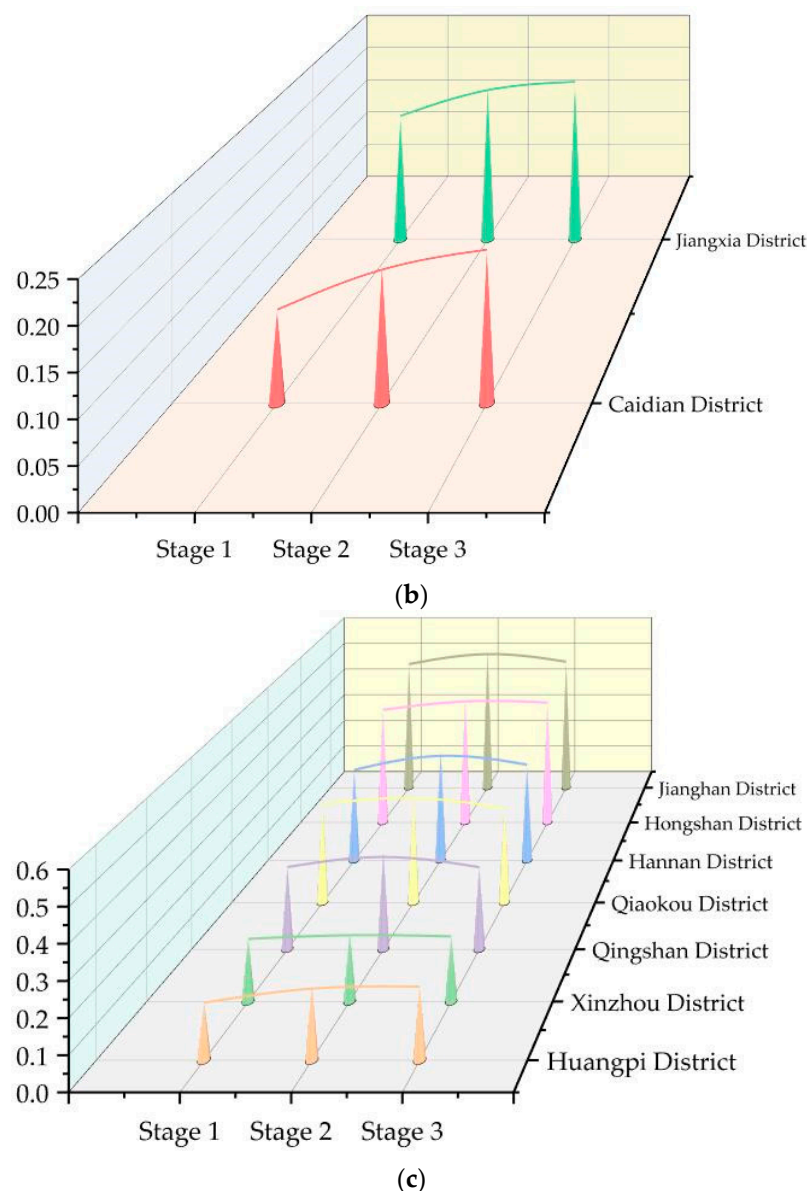


Figure 6. Comparison of resilience in the same trend districts. (a) “Decrease and increase” in jurisdictional resilience. (b) “Continuous enhancement” of jurisdictional resilience. (c) “Increase and decrease” in jurisdictional resilience.

The emergency resilience of Caidian and Jiangxia Districts continued to improve (Figure 6b), mainly because these two districts have a relatively low population density, which reduces the risk of viral transmission by reducing interpersonal contact [59]. Moreover, they are located in the peripheral areas of Wuhan, which have a more expansive geographic space and favorable natural conditions, facilitating the installation of emergency facilities and improving emergency response capacity [60].

The resilience of seven districts, including Jiangnan and Qiaokou, declined after peaking in stage 2 (see Figure 6c) because at the beginning of the outbreak, the governments of the seven districts quickly activated their wartime mechanisms and took a series of extraordinary initiatives, such as intensive scheduling, setting up commands, and implementing the wartime mechanism, which effectively curbed the spread of the outbreak. As the outbreak continued, issues, such as virus mutations, increased difficulty in prevention and control and strained medical resources, and economic shocks gradually emerged, posing greater challenges to outbreak prevention and control and emergency management in these regions, and the level of performance resilience declined.

Different districts in Wuhan showed different resilience in response to public health emergencies owing to their geographic locations and economic and demographic differences [61]. The main urban areas, such as the Wuchang and Jiangnan Districts, were highly resilient owing to their muscular economic strength and social support. In contrast, peripheral areas, such as the Caidian and Jiangxia Districts, were relatively less resilient owing to resource and technological gaps in the healthcare system [62], coping experience, and resource constraints.

5.1.2. Overall Resilience Evaluation

Regarding the overall resilience evaluation mean (see Figure 7 or Table A3 in Appendix A), the overall resilience levels of the 13 districts in Wuhan City fluctuated during the study period. In stages 1 and 2, the overall resilience levels of the 13 districts showed an upward trend, with an increase of 7.52%. In stages 2 and 3, the overall resilience level of the districts decreased, with a decrease of 3.04%. Overall, the increase between these three stages was more significant than the decrease, based on which the overall resilience levels of the 13 districts in Wuhan showed an increasing trend during the study period, with an increase of 4.25%.

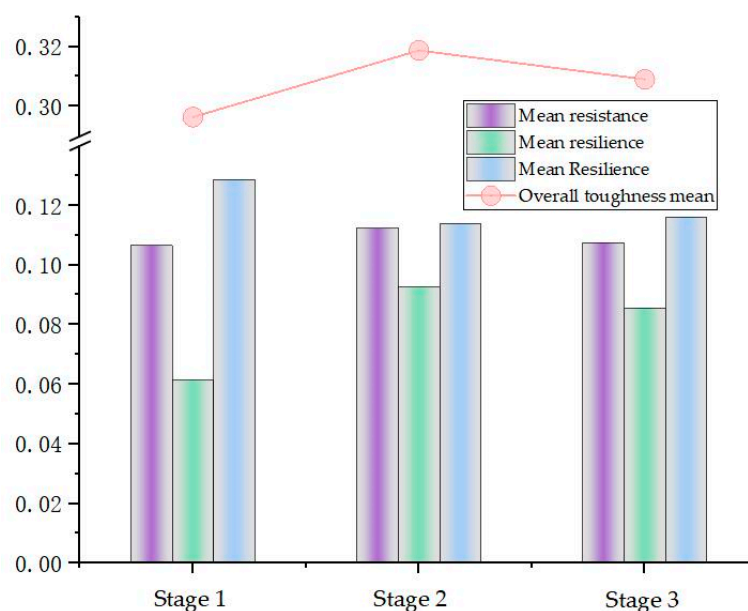


Figure 7. Average value of resilience evaluation of 13 districts and their subsystems in Wuhan.

The resistance, resilience, and overall resilience levels of the 13 districts in Wuhan city showed an overall increasing trend, with an initial increase and then a decrease. This is because in the early stage of the study (pandemic stages 1 and 2), the overall resilience level of the districts showed an increasing trend owing to the positive effects in a short period of the government's implementation of policies conducive to increasing urban resilience, such as strengthening pandemic publicity, distributing pandemic-preventive materials, and improving public services. With time (stages 2 to 3 of the pandemic), the policy effect gradually weakened, coupled with the relaxation of anti-pandemic measures and people's awareness of anti-pandemic measures, increased mobility of people in public places, and the normalization of the residents' life and work, leading to a slight decline in the resilience level of the district in stage 3. There is an interaction between the resilience level and severity of the pandemic, and when the pandemic was under control, the pressure on the city is eased, and the emergency level dropped to a normal state.

However, the overall level of resilience of the 13 districts in Wuhan declined and then increased during the pandemic, which was attributed to the fact that Wuhan, as the center of the outbreak, suffered a tremendous shock at the beginning. Factors, such as traffic

control and strained medical resources, led to almost stagnant socioeconomic activities, and the resilience level of each district dropped sharply. However, in the middle and late stages of the outbreak, the Chinese government implemented a series of solid measures [63], including the establishment of an efficient prevention and control mechanism and the deployment of national resources to support Wuhan, which provided a strong guarantee of the resilience level of the districts in Wuhan. In addition, the government introduced a series of economic stimulus policies, such as reducing taxes and fees and supporting enterprises to resume work and production, which strongly supported the economic recovery of the districts. Compared with China's response to the Tangshan and Wenchuan earthquake disasters, although there are similarities between the two in terms of rapid response, resource deployment, and social mobilization, the response to public health emergencies, such as pandemics, focuses more on the centralized deployment of medical resources and community management to control the spread of pandemics. In contrast, the response to an earthquake disaster focuses more on the reconstruction of infrastructure and the resettlement of residents. Together, these experiences reflect the country's efficient emergency management and a strong level of resilience in the face of different emergencies.

5.1.3. Subsystem Resilience Evaluation

From the mean value of the resilience evaluation of the districts (see Figure 5 or Table A3 in Appendix A), among the 13 districts, the highest mean value of water resilience was in Wuchang District (0.5351) and the lowest in Caidian District (0.1530), which indicates that the resilience level of the districts in Wuhan is unevenly developed, and there are large differences between individuals. This difference may stem from uneven urban location and development. As the central urban area, Wuchang District has demonstrated significant advantages in the transportation network, educational resources, medical conditions, and residents' quality of life. However, Caidian District is located on the edge, with a low economic level and limited resource investment, making it difficult to quickly allocate resources to maintain infrastructure and public service operations during the epidemic [64]. In addition, the changes in personnel activity trajectories directly affect regional resilience. With the advantage of intensive activities and smooth information flow, Wuchang District was able to quickly implement response measures during the epidemic. In contrast, areas, such as Caidian District have less regular activities, which further hinders information transmission during the epidemic and poses greater challenges to the normal operation of urban infrastructure and public services. In addition, the differences in industrial structure and innovation capability are also important factors affecting regional resilience differences. Wuchang District, with abundant educational resources, scientific research institutions, and modern service industries, has built a diversified industrial structure and high innovation capabilities, which can quickly respond to economic fluctuations, achieve transformation and upgrading, and maintain economic vitality. In contrast, areas, such as Caidian District, have a single industry, insufficient innovation, and are difficult to quickly adapt to changes, making them more fragile.

More importantly, for individual city residents, Wuchang District has a large number of young and middle-aged people with good education and awareness of pandemic prevention and hygiene, whereas Caidian District has many scattered residents and an older population. This implies that, in the face of emergencies, individual residents of Caidian District cannot make timely and effective responses in the same manner as those of Wuchang District. Moreover, this decentralization increases the difficulty of material rescue and medical resource services. This leads to a significant difference in resilience levels between the two districts, and this imbalance between the districts also contributes to the resilience differences in the other districts. However, in general, the closer the district is to the city center, the more pronounced the enhancement of resilience levels brought about by the location advantage to the district.

In summary, most cities in the 13 districts improved their resilience levels during the study period and the overall average resilience level showed an upward trend. However, there were differences in the resilience of individual districts.

5.2. Time Series Analysis of Resilience Evolution

To study the differences in resilience levels among the 13 districts in Wuhan and their time evolution patterns during the observation period more intuitively, the data were analyzed using the Theil index.

According to the regional development layout of Wuhan, 13 precincts are divided into the center precinct cluster (Jiangan, Jianghan, and Qiaokou Districts), the core precinct cluster (Hanyang and Wuchang Districts), the eastern precinct cluster (Qingshan and Hongshan Districts), the western precinct cluster (East-West Lake, Caidian, and Jiangxia Districts), and the suburb precinct cluster (Huangpi, Xinzhou, and Hanan Districts), and the analysis was performed by applying the Theil index and its decomposition formula to compute the process is shown in Equations (8)–(10).

Figure 8 or Table A4 in Appendix A shows that the degree of disequilibrium in the resilience of the 13 districts in Wuhan continues to decline. This is because, at the initial stage of the investigation, owing to the different development bases of each district, there is still a spatial “Matthew effect” in the development of the resilience of the district [65]. In the later period, owing to the government’s slanting regional policies and the active integration of Wuchang District, Dongxihu District and the surrounding areas of Huangpi District into the five major urban agglomerations [14], the spatial “trickle-down effect” gradually emerged, which reduced the degree of imbalance among various regions.

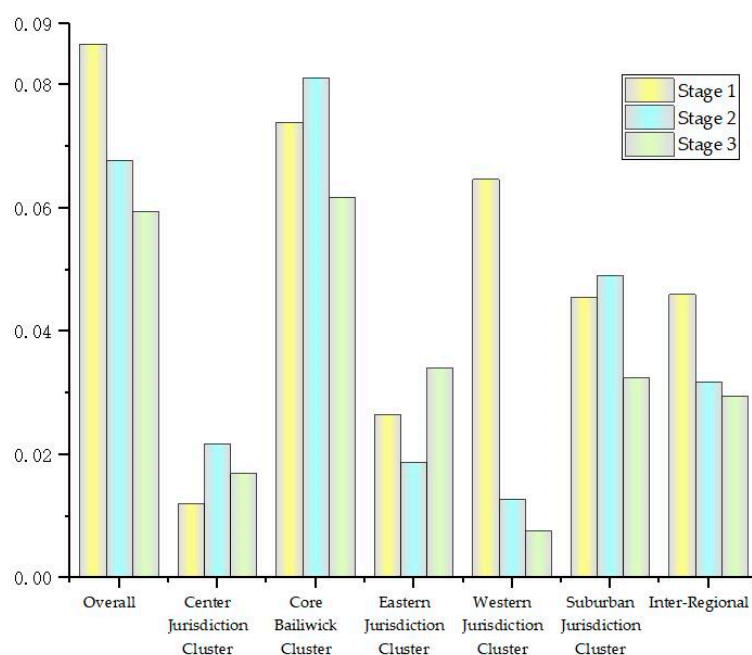


Figure 8. Theil index and its decomposition in 13 districts of Wuhan.

During the study period, urban resilience differences generally showed a decreasing trend, with the total Theil index decreasing from 0.0866 in stage 1 to 0.0594 in stage 3, a decrease of 31.41% [66]. The Theil index decreased from 0.0460 in stage 1 to 0.00295 in stage 3, a decrease of 35.87%, with an average contribution to the total Theil index of 49.89%, indicating that the variability in jurisdictional resilience mainly originates from inter-regional imbalances in the five major jurisdictional clusters. Among the five major jurisdictional clusters, unevenness in the level of jurisdictional resilience within the Core Jurisdictional Cluster had the highest average contribution to the total variance at 19.94%,

while the Eastern and Western jurisdictional clusters had an average contribution to the total variance of only 6.72% and 5.29%, respectively. It is worth noting that the bases of uneven levels of resilience within the Western, Core, and Suburban jurisdictional clusters are large but shrinking. In contrast, the base of uneven levels of resilience in the remaining two major jurisdictional clusters is small but widening.

5.3. Spatial Analysis of the Evolution of Resilience

The districts with different resilience indices were clustered using the Jenks' natural fracture method (Figure 9a–c)) and categorized into five classes.

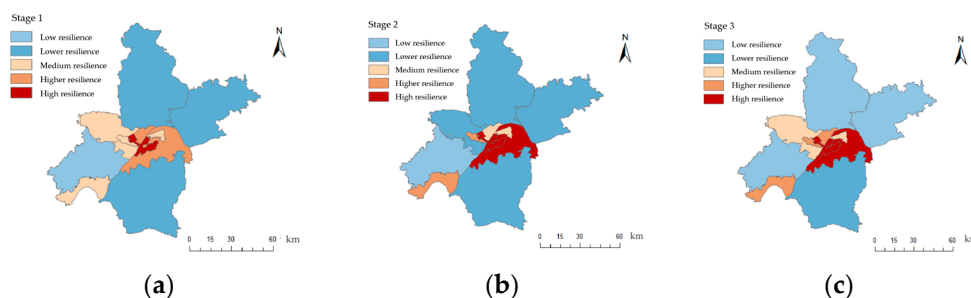


Figure 9. Resilience distribution pattern in different districts at different stages of the pandemic. (a) Distribution of stage 1. (b) Distribution of stage 2. (c) Distribution of stage 3.

The level of resilience in different stages of development shows the spatial distribution characteristics; the resilience is high in the center and low in the surroundings, and the formation of this locational advantage is directly related to the unbalanced development among cities. The center of the city, with its developed business, perfect infrastructure, dense population, etc., naturally has the advantage of resource enrichment; therefore, in the event of a public health emergency, it is able to make a timely response, deploy sufficient resources to maintain the functions of the city, and prevent further deterioration of the emergency, which is an inherent advantage that other types of districts cannot have. Research on other regions' responses to sudden public health emergencies shows that these areas exhibit uneven characteristics between regions, similar to Wuhan. Zhou et al. (2023) found that Ganzi Prefecture's disaster resistance capacity increased from 2011 to 2019, with higher capacity in the southeast and lower in the northwest [67]. Tang et al. (2022) observed that regions with high tourism economic resilience during COVID-19 were concentrated in the west, northeast, and east of China's coastal cities, while the eastern regions showed agglomeration and linkage [68]. Mengjie et al. (2022) noted significant regional imbalances in the disaster resistance of the Central Plains urban agglomeration, with higher levels in central areas and lower in surrounding regions [69].

During the entire time evolution process, the resilience level of each district increased, which changed the overall spatial distribution. In stage 1, only Wuchang and Jiangnan Districts were highly resilient areas, and the resilience indices of other districts were relatively low. In stage 2, owing to the implementation of prevention and control policies, the government and other social forces played a role in the centralized deployment of medical resources and support materials to supplement each district, which broadly strengthened the resistance of each district to the COVID-19 pandemic and helped urban functions slowly recover; thus, the number of highly resilient districts significantly increased in stage 2. However, it still exhibits the characteristics of a central distribution. Compared with stage 2, in stage 3, the main changes occurred in the low-resilience districts—their number decreased to 1, the number of high-resilience, moderate-resilience, and low-resilience districts increased to 3, and the number of high-resilience districts remained unchanged. This happened because the pandemic entered the stage of

normal prevention and control. With early vaccination and the popularization of pandemic prevention and control knowledge, people's immune resistance was effectively enhanced, and the malignant transmission of COVID-19 was blocked.

Cities continue to recover along with their normal functioning, thereby enhancing emergency resilience. However, such emergencies have also given way to new thinking. Location advantage is an inevitable aspect of the urban developmental process; sudden crises will undoubtedly be a severe blow to areas with an insufficient location advantage, and the imbalance of development could lead to an imbalance in emergency response capacity resilience, which further increases the difficulty of policy coordination and resource deployment. Therefore, to effectively improve the resilience of a city's emergency response capacity, balancing the development differences between regions is imperative and also a major focus of a city's future construction.

5.4. Problems and Responses

This study uses the obstacle degree model to analyze the main factors affecting resilience at the guideline and indicator levels and provides targeted suggestions for improving urban resilience.

5.4.1. Diagnosis of Handicap Degree Factors

The degree of obstacles at each stage of the resilience and the development guideline layer in Wuhan is shown in Figure 10 or Table A5 in Appendix A.

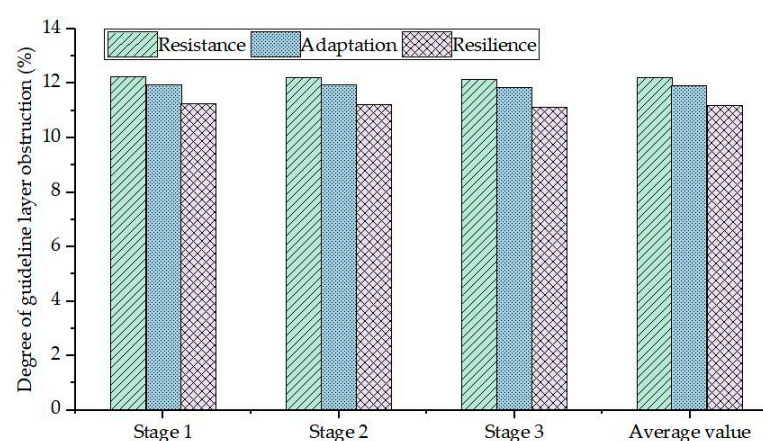


Figure 10. Obstacle levels of resilience development criteria in Wuhan City at various stages (unit: %).

From the time series, the obstacle degrees of resistance, resilience, and adaptability in Wuhan show a general decreasing trend, with decreases of 0.82%, 0.92%, and 1.24% from stage 1 to stage 3, which means that the level of urban resilience is increasing. Among the three subsystems, resistance had the most considerable obstacle degree, followed by adaptability, whereas resilience had the smallest. Therefore, the relevant indicators of resistance have a more significant impact on the resilience of Wuhan's emergency response capacity, so the focus should be on the resistance indicators, especially strengthening the reinforcement and renewal of urban infrastructure, improving disaster prevention and mitigation planning and the emergency response mechanism, to enhance Wuhan's resistance and ensure that the city can respond quickly and minimize the losses in the face of sudden-onset disasters.

Figure 11 or Table A6 in Appendix A further shows the ranking of obstacles by district. The ranking of resistance, adaptability, and resilience obstacles for the 13 districts did not change at all stages, similar to the distribution of overall resilience obstacles in Wuhan.

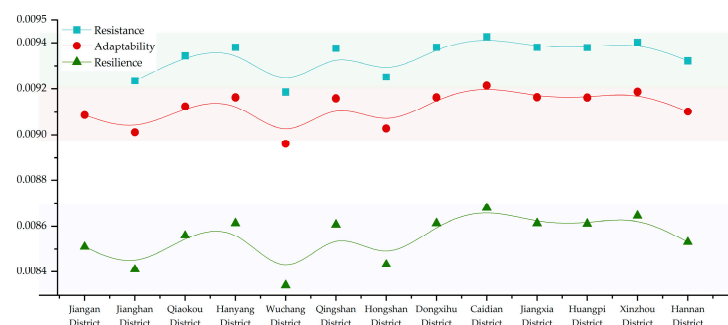


Figure 11. Ranking changes of obstacle degree in 13 districts of Wuhan.

As the above guideline-level obstacles do not accurately reflect the differences between the internal indicators, the obstacles at the secondary indicator level for each district were further calculated and ranked, as shown in Figure 12 or Table A7 in Appendix A.

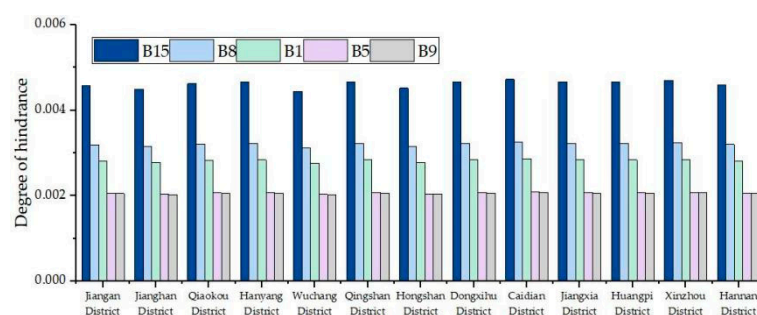


Figure 12. Ranking of obstacles at the stage 3 indicator level in 13 districts of Wuhan City.

In the ranking of the top five obstacle degree factors in stage 3, all 13 districts showed the same characteristics, from highest to lowest: B15 (scientific and technological innovation capacity), B8 (social rescue capacity), B1 (population size), B5 (natural environment security capacity), and B9 (self-help and mutual aid capacity). This is mainly because normal scientific research activities were hindered or even interrupted during the outbreak. The environment for the mobility of scientific research personnel and innovation was impacted, which had a serious effect on the pace of scientific and technological development in the districts, which in turn, had a detrimental effect on the resilience of the districts in the recovery process. In addition, the insufficient number of vaccination sites could not prevent the infection risk of residents in a timely and effective manner, and it was difficult to cut off the transmission of the virus and ensure the effective distribution of medical resources in districts with a high population density [70]. Compared with other indicators, the above five obstacles significantly negatively impacted Wuhan's resistance, resilience, and adaptability, which limited its rapid recovery and resilience during the pandemic.

5.4.2. Responses and Recommendations

Owing to the development imbalance between regions and changes in government emergency response measures at different stages of the pandemic, the resilience level of districts' emergency response capacity shows a trend of "rising and falling" in time and "high in the middle and low in the surroundings" in space. Furthermore, this study explored the influence of different indicators on the spatial and temporal evolution of jurisdictional resilience by analyzing the ranking of obstacle factors.

The results showed that B15 (scientific and technological innovation capacity), B8 (social relief capacity), and B1 (population size) were the leading indicators affecting the resilience of emergency response capacity of the 13 districts. The recommendations to deal with these indicators are as follows. (1) Vaccine research and development is an essential part of the pandemic prevention and control process, which is of great significance for the

rapid and effective control of pandemics. The government should increase its support for scientific research activities and provide researchers with a stable working environment and a favorable innovation environment; simultaneously, it should strengthen the cultivation and introduction of scientific and technological talents to enhance the city's scientific and technological innovation capacity. (2) A higher social rescue capacity can improve the efficiency of deploying resources and executing emergency response measures when responding to a pandemic. To enhance social rescue capacity, the construction of rescue teams should be optimized, and the training of professional rescuers should be intensified to ensure that rescue work can be performed quickly and effectively in emergencies. Concomitantly, the mechanism for stockpiling and deploying emergency supplies should be strengthened to ensure that the required rescue supplies can be provided in time in the event of a disaster, and an efficient emergency communication system should be established to enable the rapid transmission and sharing of information during the rescue process. (3) Higher population density can exacerbate the impacts of a pandemic on the quality of life of a city. Hence, cross-regional employment and the updating of transportation facilities should be encouraged to enhance the overall resistance of the city by promoting the logical flow of labor and resources, while appropriately adjusting the population policy and optimizing the population structure.

As for the diversified social entities in the city, there are also targeted measures to cope with their different social functions. The government should increase investments in urban infrastructure construction, improve the reliability and stability of urban infrastructure to promote sharing and communication between districts, and respond to the challenges of public health emergencies by balancing resources and risks. For example, the government can promote smart city projects, build cross-departmental management platforms, and foster data sharing for collaborative governance among the government, social organizations, and enterprises. An emergency response alliance can quickly allocate resources during crises. Additionally, innovative governance projects should be encouraged, with feedback and evaluation mechanisms to optimize performance and enhance multi-party collaboration and efficiency. Enterprises and social organizations can actively participate in public affairs, such as social rescue activities, to share the pressure of the pandemic. Urban residents should improve their quality by following scientific and reasonable anti-pandemic guidance measures to protect their health and safety; by contributing their small capacity, they are ultimately contributing to the collective positive effect. Through the joint participation of multiple urban subjects, the resilience of the city's emergency response capacity can be improved. Simultaneously, a positive feedback effect is generated, benefiting each participant.

6. Conclusions

This study constructs a resilience evaluation system for urban emergency response capacity by considering the three guideline layers of resistance, adaptability, and resilience. It also analyzes the spatial and temporal evolution characteristics of the resilience level and inter-regional differences of the 13 districts of Wuhan in different stages of COVID-19 as an example, while proposing targeted improvement suggestions based on the obstacle degree model. The main conclusions are as follows.

- (1) The resilience level in the Wuhan District fluctuated over time. During the early stages of the pandemic, an active pandemic prevention policy significantly improved the resistance and resilience of the city. In the later stage, the resilience level slightly decreased owing to the relaxation of pandemic prevention measures and the reduction in public awareness of pandemic prevention.
- (2) The analysis of the Theil index revealed significant differences in the spatial distribution of emergency response capacity resilience. The resilience level is higher in the central city and lower in the fringe areas and is mainly affected by the distribution of

resources, economic level, and residential structure. However, with policy adjustments, regional integration, and the participation of social forces, inter-regional differences show a decreasing trend, indicating that regional cooperation and coordination are key to future urban emergency response capacity building.

- (3) The diagnosis of the obstacle degree factor indicated that the obstacle degrees of resistance, resilience, and adaptability decreased with time. The main obstacles are scientific and technological innovation capacity, social rescue capacity, and population size. To enhance the urban emergency response capacity, the government, enterprises, social organizations, and residents need to participate together. The government should support scientific research, optimize the investments in pandemic prevention resources, promote resource sharing and exchange through social organizations, enhance residents' awareness of prevention and control, and regulate public mobility.
- (4) COVID-19 has revealed the weaknesses of a city's emergency response capacity-building and has provided an opportunity for improvement in building resilience. It is recommended that measures, such as diversified strategies, site-specific adaptation, and regional coordination, be adopted to optimize the system dynamics mechanism and enhance the resilience of the urban emergency response capacity. Regional cooperation and exchange are promoted by combining the characteristics of each district to form a development pattern of sharing resources and complementing each other's strengths to jointly meet the challenges of emergencies. Simultaneously, it is important to mobilize the enthusiasm of all parties to build together, formulate scientific policies, strengthen the social rescue capacity, optimize the population size and structure, improve the quality of personnel, and jointly enhance the urban emergency response capacity.

In summary, this study provides valuable insights into the improvement of urban emergency response capabilities by focusing on the resilience evolution of Wuhan city, despite the limitations of data geography and the lack of long-term resilience research. The data for this study are sourced from the Wuhan Statistical Yearbook and the local economic and social big data platform. Although it has historical comprehensiveness, there are limitations, such as insufficient spatio-temporal resolution of second-hand data storage and incomplete matching of collection methods and classification standards with demand. Future research should focus on fine first-hand data collection, especially real-time social surveys and perception data, to enhance analysis accuracy and depth. The practice in Wuhan has revealed the core role of technological innovation and social assistance capabilities in responding to sudden public health emergencies, setting an example for other cities. Looking ahead to the future, expanding comparative research across multiple cities and deepening the exploration of long-term resilience mechanisms will further enrich the theory and practice of urban emergency management. At the same time, the Wuhan experience has enlightening significance for achieving the United Nations Sustainable Development Goals' urban resilience construction, emphasizing the importance of economic, social, and technological resilience in building inclusive, safe, disaster-resistant, and sustainable cities. Therefore, urban development planning should integrate resilience concepts, strengthen disaster response and recovery capabilities, in order to promote the achievement of global sustainable development goals.

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

Appendix A

Table A1. Urban public health emergency response resilience assessment index system

Primary Indicators	Secondary Indicators	Description of Indicators	Stage 1 Weights	Stage 2 Weights	Stage 3 Weights
Resistance (A1)	Population (B1)	Jurisdictional population density (persons/km ²)	0.1103	0.1051	0.0997
	Real economy security capacity (B2)	Number of industrial units above the large-scale (units)	0.0709	0.0771	0.0731
	Medical security capability (B3)	Number of non COVID-19 designated hospitals opened	0.0561	0.0492	0.0699
	Service System Support Capability (B4)	Regional tertiary sector GDP (billion yuan)	0.0412	0.0426	0.0368
	Natural environmental protection capacity (B5)	Soil erosion rate (%)	0.0808	0.0783	0.0685
Adaptability (A2)	Age structure (B6)	Urbanization rate of resident population (%)	0.0345	0.0389	0.0386
	Education level (B7)	Total number of students allocated to model senior high schools (number)	0.0766	0.0754	0.0761
	Social rescue capability (B8)	No. of vaccination points (number)	0.0001	0.0525	0.0438
	Self rescue and mutual rescue ability (B9)	Cumulative number of confirmed cases reported (number)	0.0605	0.0863	0.0824
	Urban Comprehensive Management Capability (B10)	“Big City Management” assessment (scores)	0.0352	0.0376	0.0358
Resilience (A3)	Medical service personnel (B11)	Health technicians (persons)	0.0512	0.0557	0.0495
	Government Financial Strength (B12)	GDP per capita (10,000 yuan per person)	0.0852	0.0617	0.0585
	Life support capacity (B13)	Urban per capita disposable income (yuan/people)	0.0528	0.0422	0.0415
	Economic Stability (B14)	Unemployment rate (%)	0.0796	0.0193	0.0505
	Technological innovation capability (B15)	State-level science and technology business incubators (number)	0.165	0.1783	0.1754

Table A2. Wuhan's 13 districts' resilience assessment values.

Districts	Stage 1	Stage 2	Stage 3	Average Score
Jiangan District	0.3776	0.3314	0.3601	0.3564
Jiangnan District	0.4714	0.5259	0.4806	0.4926
Qiaokou District	0.3243	0.358	0.3107	0.3310
Hanyang District	0.2453	0.228	0.2567	0.2433
Wuchang District	0.5456	0.5289	0.5307	0.5351
Qingshan District	0.257	0.304	0.2566	0.2725
Hongshan District	0.4096	0.449	0.4362	0.4316
East-West District	0.2754	0.2438	0.2473	0.2555
Caidian District	0.1113	0.1649	0.1828	0.1530
Jiangxia District	0.1765	0.2197	0.2252	0.2071
Huangpi District	0.1596	0.2072	0.2045	0.1904
Xinzhou District	0.1848	0.1992	0.1923	0.1921
Hannan District	0.3143	0.3827	0.3323	0.3431

Table A3. Mean values of resilience assessment for 13 districts in Wuhan in general and for their respective sub-systems.

Evaluation Mean	Stage 1	Stage 2	Stage 3
Resistance Mean	0.1065	0.1123	0.1075
Resilience Mean	0.0613	0.0926	0.0855
Mean Resilience	0.1286	0.1138	0.1160
Overall resilience Mean	0.2964	0.3187	0.3090

Table A4. Theil index of 13 districts in Wuhan and its decomposition.

Stages	Total Theil Index	Center District Cluster Theil Index	Core District Cluster Theil Index	Eastern District Cluster Theil Index	Western District Cluster Theil Index	Suburban District Cluster Theil Index	Inter-Regional Theil Index
Stage 1	0.0866	0.0120 (4.20%)	0.0739 (17.52%)	0.0264 (5.28%)	0.0647 (10.92%)	0.0455 (8.98%)	0.0460 (53.09%)
Stage 2	0.0678	0.0218 (9.41%)	0.0812 (21.88%)	0.0187 (5.00%)	0.0128 (2.86%)	0.0490 (13.77%)	0.0318 (46.93%)
Stage 3	0.0594	0.0169 (8.17%)	0.0618 (20.41%)	0.0340 (9.87%)	0.0076 (2.10%)	0.0324 (9.91%)	0.0295 (49.66%)

Table A5. Degree of obstacles at the guideline level of resilience development in Wuhan at each stage (unit: %).

Primary Indicators	Stage 1	Stage 2	Stage 3	Average Value
Resistance	12.24	12.21	12.14	12.20
Adaptability	11.96	11.94	11.85	11.92
resilience	11.26	11.23	11.12	11.20

Table A6. Changes in the ranking of guideline layer obstacles in 13 districts of Wuhan City.

Districts	Resistance	Adaptability	Resilience
Jiangan District	1→1 (0.9307%)	2→2 (0.9087%)	3→3 (0.8510%)
Jiangnan District	1→1 (0.9236%)	2→2 (0.9012%)	3→3 (0.8410%)
Qiaokou District	1→1 (0.9343%)	2→2(0.9125%)	3→3 (0.8560%)
Hanyang District	1→1 (0.9380%)	2→2 (0.9164%)	3→3 (0.8613%)
Wuchang District	1→1 (0.9187%)	2→2 (0.8960%)	3→3 (0.8342%)
Qingshan District	1→1(0.9376%)	2→2 (0.9160%)	3→3 (0.8607%)

Hongshan District	1→1 (0.9252%)	2→2 (0.9028%)	3→3 (0.8432%)
East-West District	1→1 (0.9380%)	2→2 (0.9164%)	3→3 (0.8613%)
Caidian District	1→1 (0.9427%)	2→2 (0.9214%)	3→3 (0.8679%)
Jiangxia District	1→1 (0.9380%)	2→2 (0.9165%)	3→3 (0.8613%)
Huangpi District	1→1 (0.9379%)	2→2 (0.9163%)	3→3 (0.8611%)
Xinzhou District	1→1 (0.9403%)	2→2 (0.9188%)	3→3 (0.8645%)
Hannan District	1→1 (0.9322%)	2→2 (0.9103%)	3→3 (0.8531%)

Before “→” is the beginning-of-period ordering; after “→” is the end-of-period ordering; the end-of-period obstacle value is in parentheses.

Table A7. Ranking of obstacles at the stage 3 indicator level in 13 districts of Wuhan City.

Districts	Arrange in Order				
	1	2	3	4	5
Jiangan District	B15 (0.4578%)	B8 (0.3189%)	B1 (0.2807%)	B5 (0.2060%)	B9 (0.2047%)
Jiangnan District	B15 (0.4494%)	B8 (0.3150%)	B1 (0.2777%)	B5 (0.2044%)	B9 (0.2031%)
Qiaokou District	B15 (0.4620%)	B8 (0.3209%)	B1 (0.2822%)	B5 (0.2068%)	B9 (0.2054%)
Hanyang District	B15 (0.4664%)	B8 (0.3229%)	B1 (0.2838%)	B5 (0.2076%)	B9 (0.2062%)
Wuchang District	B15 (0.4437%)	B8 (0.3124%)	B1 (0.2757%)	B5 (0.2033%)	B9 (0.2021%)
Qingshan District	B15 (0.4660%)	B8 (0.3227%)	B1 (0.2836%)	B5 (0.2075%)	B9 (0.2062%)
Hongshan District	B15 (0.4513%)	B8 (0.3159%)	B1 (0.2784%)	B5 (0.2047%)	B9 (0.2035%)
East-West District	B15 (0.4665%)	B8 (0.3229%)	B1 (0.2838%)	B5 (0.2076%)	B9 (0.2063%)
Caidian District	B15 (0.4720%)	B8 (0.3255%)	B1 (0.2857%)	B5 (0.2086%)	B9 (0.2073%)
Jiangxia District	B15 (0.4665%)	B8 (0.3229%)	B1 (0.2838%)	B5 (0.2076%)	B9 (0.2063%)
Huangpi District	B15 (0.4663%)	B8 (0.3229%)	B1 (0.2837%)	B5 (0.2076%)	B9 (0.2062%)
Xinzhou District	B15 (0.4691%)	B8 (0.3241%)	B1 (0.2847%)	B5 (0.2081%)	B9 (0.2067%)
Hannan District	B15 (0.4596%)	B8 (0.3197%)	B1 (0.2813%)	B5 (0.2063%)	B9 (0.2050%)

Outside parentheses are the Stage 3 obstacle factor codes; inside parentheses are the obstacle degree values.

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