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Assessment of Urban Resilience and Spatiotemporal Patterns in Small and Medium-Sized Chinese Cities

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Abstract

Amid the compounded impacts of climate change, economic volatility, and sudden shocks, small and medium-sized cities (SMSCs) have become a critical yet frequently overlooked weak link in urban resilience research. Objective assessment of resilience in SMSCs is essential for improving the design and effectiveness of resilience-building policies. Following China's official city-size classification criteria—i.e., using urban-district resident population as the statistical basis and defining SMSCs as cities with less than 1 million urban-district residents—this study examines 510 Chinese SMSCs from 2012 to 2023. An entropy-weighted Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method is employed to construct an urban resilience index. Subsequently, spatiotemporal disparities are characterized using nonparametric kernel density estimation and Dagum Gini coefficient decomposition. The results indicate that: (1) from 2012 to 2023, the resilience index of Chinese SMSCs rose from 0.1108 to 0.1121, with an average annual growth rate of 0.1067%. Overall resilience remains low, and the increase is modest, showing a clear regional gradient of Eastern > Central > Western > Northeastern China. (2) Spatiotemporal differentiation reveals the fastest growth in the Eastern region, a similar trajectory in the Central region, slower growth in the Western region, and a decline in the Northeastern region, reinforcing a pattern of gradient divergence. Within-region disparities generally converged, whereas between-region disparities expanded markedly; nonetheless, the transvariation (overlapping) component remained the primary contributor to overall inequality. (3) The resilience of Chinese SMSCs may face a potential Matthew-effect risk driven by the interaction of scale disadvantage and regional disadvantage. These findings provide evidence to support policies aimed at enhancing resilience in SMSCs and inform the development of differentiated resilience-building strategies across regions.



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1. Introduction

Against the backdrop of compounded global challenges—including climate change, public health emergencies, and geopolitical conflicts—cities, as the primary spaces for human activities and the central carriers of socio-economic development, are not only key drivers of global environmental change but also strategic arenas for addressing the climate crisis, ecological degradation, and systemic global risks. The ways in which cities are

governed, spatially configured, and technologically shaped will profoundly influence the future trajectory of the Anthropocene [1]. Meanwhile, as urban areas continue to expand and populations increasingly concentrate, a range of urban problems has become more visible, and cities are confronting unprecedented uncertainty and compound risks. In this context, the concept of “resilience” has emerged as a pivotal paradigm for urban safety and sustainable development. Accordingly, advancing urban resilience-building has become an urgent priority [2].

In response to these challenges and the imperative for transformation, the Chinese government—aiming to foster a virtuous interaction between high-quality development and high-level security—has proactively advanced the strategic agenda of urban resilience while promoting orderly urban development, thereby stimulating growing interest in urban resilience research and practice [3,4]. From the perspective of policy practice, since the concept of the “resilient city” was first introduced by the International Council for local environmental issues (ICLEI) in 2002 and subsequently gained broad international recognition, China has continued to explore resilience-oriented urban policies in recent years. In April 2020, an important policy signal was issued at the seventh meeting of the Central Commission for Financial and Economic Affairs, which highlighted building resilient cities as a key element of improving the national urbanization strategy. In October 2020, the Fifth Plenary Session of the 19th CPC Central Committee explicitly set the goal of developing “resilient cities” and characterized resilience as the capacity of a regional system to withstand shocks, reduce losses, and open new pathways for development. The 14th Five-Year Plan (2021–2025) further incorporated “resilient cities” into the national strategic agenda. Thereafter, the notion of “resilient cities” was included in the report of the 20th National Congress of the Communist Party of China (CPC), accelerating China’s policy momentum. The 2024 Government Work Report emphasized advancing urban renewal and building cities that are “livable, smart, and resilient,” and the 2025 Central Urban Work Conference identified “building safe and reliable resilient cities” as one of the key tasks for urban work. Taken together, China has formed an increasingly complete policy cycle—from conceptual introduction and strategic confirmation to institutional embedding and implementation—positioning resilient-city development as a critical lever for modernizing urban governance capacity in the new era.

As research on urban resilience continues to deepen, scholarly attention has gradually shifted from macro-level frameworks to micro-level mechanisms, and from coastal megacities to the vast inland hinterlands. As the most numerous and most widely distributed type of cities worldwide, small and medium-sized cities (SMSCs) play an essential carrier role in socio-economic activities and exhibit distinctive competitiveness within the urban hierarchy [5,6]. Therefore, it is necessary to examine the resilience of SMSCs in greater depth. Meanwhile, developing a scientific, replicable, and comparable framework for urban resilience assessment not only provides evidence for urban managers to identify critical vulnerable nodes, optimize resource allocation, and formulate adaptive strategies, but also serves as a “common language” for cross-scale and cross-sector collaborative governance. In this way, resilience can be translated into policy practices that are monitorable, accountable, and investable, ultimately enhancing urban sustainability and inclusiveness in an uncertain future. Accordingly, urban resilience assessment has attracted increasing scholarly attention [7–9]. Based on this line of reasoning, the literature on urban resilience assessment related to this study primarily covers the following aspects.

1.1. Conceptualizations of Resilience in Urban Resilience Assessment

As argued by Klein et al. (2003), one major challenge in resilience research lies in the existence of multiple definitions that can be operationalized into practical tools [10]. This

contributes to the complexity and uncertainty surrounding the conceptual content of urban resilience. To address this, Ribeiro and Gonçalves (2019) conducted a systematic review that identifies the main pillars, dimensions, and characteristics of urban resilience and develops a conceptual framework to facilitate understanding [11]. Meanwhile, studies on the conceptualization of urban resilience have continued to expand across perspectives and disciplines, and urban resilience increasingly appears in the literature as a “goal” [12,13], a “pathway” [14,15], or a “referent” [16,17].

1.2. Assessment Objects of Urban Resilience Assessment

Spaans and Waterhout (2017), in their evaluation of the Rockefeller Foundation’s definition of urban resilience, noted that urban resilience assessment encompasses a wide range of assessed entities and disturbance sources, providing an authoritative platform for assessment practice [2]. From the perspective of assessed entities, on the one hand, the urban system can be treated as a single complex adaptive system and assessed through case-based approaches [18], or evaluated as part of different types of urban clusters classified by cluster size, development type, locational conditions, and other criteria [19–24]. On the other hand, cities can be decomposed into multiple subsystems for separate assessments, which broadly fall into three categories. The first concerns the resilience of carrier-type subsystems, such as society, economy, ecology, and infrastructure [18,25–27]. The second concerns the resilience of urban spatial subsystems, including urban space, urban form, neighborhoods, and buildings [28–31]. The third concerns the resilience of urban functional subsystems, such as settlement, food, energy, water supply, sanitation, transportation, and related services [28,32–35].

From the perspective of disturbance sources, some studies do not distinguish specific hazards and instead construct an urban disaster resilience index to conduct spatiotemporal assessments, taking Chengdu, China as an example [36]. Other studies distinguish hazard types and numbers, assessing disaster resilience under single hazards or under compound hazards [37–39].

1.3. Dimensional Frameworks for Urban Resilience Assessment

In designing dimensional frameworks for urban resilience assessment, three main approaches can be identified. The first is the attribute-based (feature-based) approach, which starts from resilience-related perspectives such as “safety” and “emergency response,” either drawing on cross-domain applications of classical theories or conducting adaptive refinements based on existing studies [4,12,15,40,41]. This approach identifies the attribute characteristics of urban resilience and thereby constructs assessment dimensions with a strong theoretical foundation. The second is the component-based approach, which conceptualizes the city as a system and refines theoretical dimensions [3,42–44], or directly decomposes the system [45,46]—for example, into ecological, social, economic, engineering, and institutional resilience—to further realize the practical value of assessment and achieve the goal of framework design. The third is the process-/stage-based approach. For instance, Zhu et al. (2023) developed a PSR-SENCE model based on the Pressure–State–Response (PSR) framework and the theory of complex socio-economic-natural ecosystems, identifying factors of urban flood resilience along a dynamic process to complete the assessment [47].

1.4. Methods and Models for Urban Resilience Assessment

A variety of methods can be used to measure urban resilience. The first category comprises composite indicator approaches, which construct an indicator system, assign weights subjectively or objectively, and derive a composite score for evaluation purposes [30,48]. The second category includes remote sensing and spatial modeling approaches, which employ remote-sensing raster data together with GIS-based spatial analysis to quantify

resilience-related characteristics [24]. The third category involves scenario simulation approaches, which model the evolution of resilience trends to enable dynamic assessments under different scenarios [49,50]. The fourth category uses machine learning and other data-driven approaches to build big-data models for disaster risk assessment and prediction [51]. In addition, some studies go beyond resilience measurement and further apply spatiotemporal models, causal inference methods, and related approaches for more in-depth analysis [52,53].

1.5. Expansion of Urban Resilience Assessment Results

To translate findings on urban resilience into policy practice, extending analysis beyond initial measurement is an important component of resilience assessment research. Some studies examine the spatiotemporal distribution of urban resilience across large geographic scales to derive policy implications in both temporal and spatial dimensions [54,55]. Others focus on resilience-building and investigate which factors affect urban resilience, through what mechanisms, and to what extent [13,56]. As resilience-oriented policies advance, resilience effects may also diffuse across space; understanding the magnitude and patterns of such spillover effects has become another focal point in recent evaluations [46,53].

Overall, the above literature provides important references and multi-dimensional perspectives for understanding urban resilience assessment, offering a robust methodological foundation. Nevertheless, several gaps remain. Firstly, existing research has not offered a conceptual definition or expounded on the intrinsic meanings of urban resilience within small and medium-sized cities (SMSCs). Similarly, in terms of research subjects, current studies have predominantly focused on individual cities, urban agglomerations, or urban systems, relatively limited attention paid to the macro-level aspects of urban resilience. More importantly, there is a scarcity of research that explicitly categorizes small and medium-sized cities and communities (SMSCs) as distinct subjects for evaluation, which restricts the generalizability of research findings for broader applications. Furthermore, most existing assessment frameworks tend to concentrate on a single dimension of either ‘urban’ or ‘resilience,’ and there is still a notable deficiency in the development of integrated assessment systems—particularly those frameworks that are tailored to specific types of evaluation objectives.

As key nodes linking large cities with their rural hinterlands, SMSCs perform multiple functions within China’s territorial spatial structure, including industrial relocation/absorption, population agglomeration, and the spatial diffusion of public services. Their resilience conditions therefore bear directly on balanced regional development and the stability of national security safeguards. Studying SMSC resilience can help address a “scale blind spot” in existing resilience assessment frameworks and support urban–rural integration as well as regional coordination. Meanwhile, cities are complex and evolving systems. When SMSCs face uncertain risks, their resilience is often more prone to pronounced spatial polarization and vulnerability due to limited resource endowments and weaker governance capacity, which are in turn shaped by factors such as administrative hierarchy, fiscal capacity, industrial diversity, and access to external support. Therefore, in the context of accelerating resilient-city development, quantitatively assessing resilience in SMSCs not only aligns with China’s strategic orientation of promoting urbanization with counties as important carriers, but also contributes to strengthening grassroots governance effectiveness and regional risk resistance.

Notably, existing studies suggest that SMSC resilience has substantial research value [57], yet it has not received adequate scholarly attention [58,59]. Accordingly, this study provides a definition of SMSC resilience, specifies SMSCs as the focus of urban

resilience assessment, constructs an assessment framework through theoretical reasoning, measures the resilience level of Chinese SMSCs, and investigates their spatiotemporal differentiation. This raises several key questions: What is the overall level of resilience in SMSCs? How does this resilience evolve dynamically over time? Do resilience levels exhibit spatial disparities across regions? Addressing these questions can help clarify the development patterns of SMSC resilience and fill the theoretical gap concerning the city size–resilience relationship. Moreover, it can provide empirical evidence for identifying key determinants of resilience in SMSCs and for designing differentiated resilience-enhancement strategies, thereby supporting more targeted resilience policies for SMSCs, optimizing resource allocation and governance arrangements, and promoting regional coordination and sustainable urbanization.

The marginal contributions of this study are twofold. (1) Focusing on SMSCs extends the analytical scale of urban resilience research to the level of individual small and medium-sized cities, which broadens the existing perspectives on urban resilience. (2) Based on urban resilience theory and prior studies, a comprehensive evaluation index system for SMSCs has been developed, incorporating both the general attributes of urban resilience and characteristics specific to SMSCs. The findings aim to help policymakers better understand SMSC resilience and formulate more fine-grained, differentiated strategies.

2. Materials and Methods

To achieve the aforementioned research objectives (i.e., to better understand the resilience of SMSC and develop differentiated strategies), this study develops an overall analytical framework, as illustrated in Figure 1. First, an assessment system for SMSC resilience is established by drawing on the general attributes of urban resilience and the distinctive characteristics of small and medium-sized cities (SMSCs). Second, an entropy-weighted TOPSIS approach is applied, based on the indicator system, to compute resilience levels for Chinese SMSCs. Third, nonparametric kernel density estimation is used to examine the time-varying evolution of SMSC resilience. Finally, the Dagum Gini coefficient decomposition is employed to quantify spatial disparities in SMSC resilience and to decompose the sources of these disparities.

2.1. Study Area and Data Sources

Following the regional classification scheme released by the National Bureau of Statistics of China (NBS) in 2011, China is divided into four major regions: Eastern, Central, Western, and Northeastern China [60]. In this study, the study area covers 28 provincial-level administrative units (23 provinces and 5 autonomous regions). Specifically, the Eastern region includes Hebei, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the Central region includes Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan; the Western region includes Inner Mongolia, Guangxi, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang; and the Northeastern region includes Liaoning, Jilin, and Heilongjiang. The specific distribution of the cities involved in this study is shown in Figure 2.

According to the State Council's official notice on adjusting the standards for city-size classification (issued in November 2014), city size is defined using urban-district resident population as the statistical basis [61]. Under this standard, cities with an urban-district resident population of less than 1 million are classified as small and medium-sized cities; accordingly, this study defines such cities as SMSCs. On this basis, the SMSC sample includes county-level cities nationwide and a subset of prefecture-level cities. The identification of SMSCs relies on the key results of the Seventh National Population Census, specifically China Population Census by County—2020.

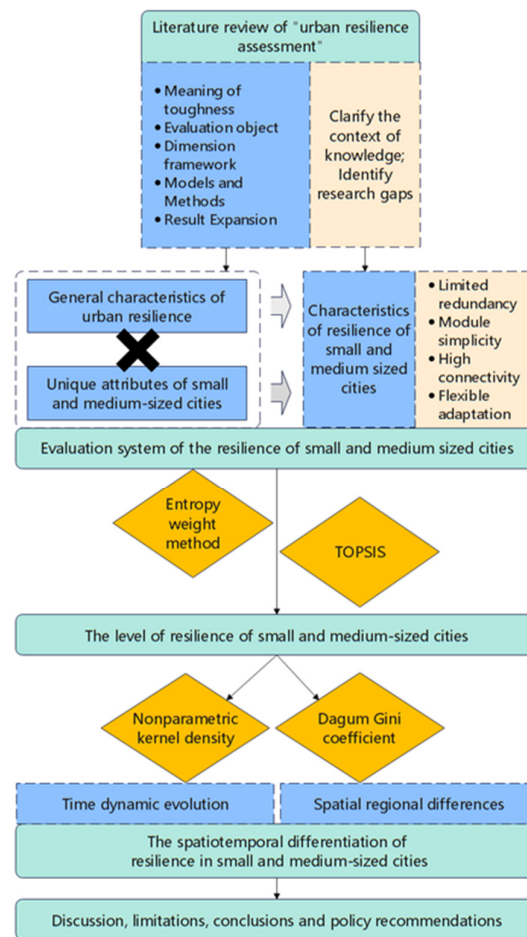


Figure 1. Research framework.

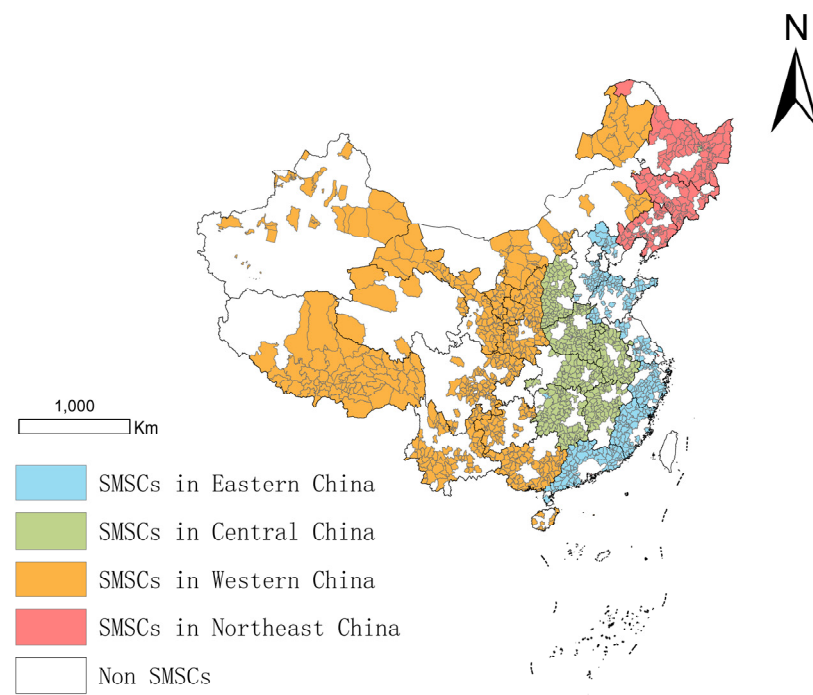


Figure 2. Map of Study Cities.

Data for the indicators in the SMSC resilience measurement system are mainly drawn from the China City Statistical Yearbook (2013–2024) and official local government websites, among other sources [62]. Data preprocessing was conducted to ensure panel integrity.

Specifically, cities whose city-type classification changed during the sample period were excluded. For observations with limited missingness, missing values were supplemented using annual work reports and statistical bulletins, together with linear interpolation. Observations with substantial missingness were removed. Outliers in the panel were cross-checked and corrected using the same sources and procedures. Ultimately, a balanced panel dataset of 510 SMSCs over the period from 2012 to 2023 was obtained.

2.2. Constructing the SMSC Resilience Indicator System

As an extension of the broader concept of urban resilience, SMSC resilience represents a scope-specific application rather than a simple “scaled-down” or “lower-specification” version of resilience. Instead, it constitutes a form of resilience that is re-coded under structural constraints. Accordingly, research on SMSC resilience not only broadens the theoretical spectrum of urban resilience but also offers an important methodological implication: resilience in SMSCs should be examined on the basis of established urban resilience research while fully accounting for the distinctive attributes of SMSCs. This perspective emphasizes transforming resource bottlenecks into triggers for institutional innovation, so that scale-related disadvantages can be converted into enabling conditions for resilience formation.

More specifically, the construction of an indicator system for SMSC resilience should build on the general attributes of urban resilience and treat core features—such as redundancy [63], diversity [14], robustness [64], and adaptability [65,66]—as a shared “resilience consensus.” At the same time, attributes distinctive to SMSCs—such as resource limitations [67], strong relational embeddedness [68], investment lag [69], development dependence [70], and regional peripherality [71]—should be incorporated as “city labels” into this resilience consensus. In doing so, SMSC resilience can be conceptualized as a nonlinear fit between resilience functions and structural constraints. Based on the above reasoning, SMSC resilience exhibits the following characteristics, which are used as the main dimensions of the SMSC resilience indicator system:

- **Constrained redundancy:** SMSCs, facing triple constraints in fiscal capacity, land availability, and human resources, are often unable to maintain conventional forms of physical backup. Instead, they seek a critical level of redundancy through redundancy reduction, functional repurposing, and digital substitution.
- **Modular simplicity:** By aggregating functions and compressing hierarchical layers, SMSCs decompose complex systems into units that are “few but integrated,” enabling fault isolation and rapid repair to be achieved at the smallest possible scale.
- **High connectivity:** Leveraging their scale-related advantages and regional governance agreements, SMSCs can be embedded in larger-scale networks of resource and information flows, allowing real-time access to external resources.
- **Flexible adaptability:** SMSCs capitalize on the advantages of small-scale experimentation and iterative learning, enabling the dynamic optimization of resilience strategies through low-cost, short-cycle loops. This allows cities to rapidly adjust their structures and functions when exposed to external shocks, rather than relying primarily on rigid infrastructure upgrades.

In summary, SMSC resilience exhibits a composite profile characterized by constrained redundancy, modular simplicity, high connectivity, and flexible adaptability. In essence, under structural constraints, SMSCs can transform scale-related disadvantages into adaptive advantages through regional collaboration and functional reconfiguration. These four feature dimensions are not independent; rather, they form a “constraint–response” feedback loop. Constrained redundancy lowers the resource threshold for resilience-building, modular simplicity compresses system complexity, high connectivity enables the inflow of

external resources, and flexible adaptability ensures that the first three mechanisms can still be recalibrated and corrected under shocks. Together, this configuration endows SMSCs with a resilience identity that differs from that of cities in a more generic sense. The specific indicator system is presented in Table 1.

Table 1. Indicator system for assessing resilience in small and medium-sized cities (SMSCs).

Resilience Dimension	Indicator	Interpretation and Resilience Logic	Indicator Type *
Constrained redundancy	GDP per capita	Economic output efficiency, reflecting “individual-level redundancy”	Positively oriented
	Balance of household savings deposits (urban and rural residents)	Private reserves, reflecting “societal redundancy”	Positively oriented
	Local government general public budget expenditure	Government-disposable resources, reflecting “governmental redundancy”	Positively oriented
Modular simplicity	Share of primary industry in GDP	Whether the economic structure is overly dependent on a single module (agriculture)	Negatively oriented
	Share of tertiary industry in GDP	Whether the industrial structure is diversified and service-oriented	Positively oriented
	Number of above-scale industrial enterprises	Complexity of the industrial module; an excessive number may imply inefficient redundancy	Moderately oriented
High connectivity	Outstanding loans of financial institutions at year-end	Capacity for financial-resource circulation, reflecting “capital connectivity”	Positively oriented
	General public budget revenue	Fiscal interactions between government and markets	Positively oriented
	GDP per unit area	Spatial economic density, reflecting “economic–spatial connectivity”	Positively oriented
Flexible adaptability	Enrollment in regular secondary schools (number of students)	Human-capital reserves and future adaptive potential	Positively oriented
	Administrative area per capita	Whether spatial resources are overly dispersed, affecting adaptive efficiency	Moderately oriented
	Registered population at year-end	Population scale, shaping the system’s “baseline capacity” for adaptation	Positively oriented

* Note. Positively oriented indicators imply that a larger value corresponds to better performance; negatively oriented indicators imply that a smaller value corresponds to better performance; moderately oriented indicators imply that performance is better when the indicator is closer to a certain “optimal” value. For the moderately oriented indicators used in this study, there is no universally accepted optimal value. Given that Deyang (Sichuan Province) was selected for the Rockefeller Foundation’s “100 Resilient Cities” program in December 2014 and was among the first batch of selected cities in China, and that Deyang is included in the sample under the present SMSC definition, Deyang’s corresponding indicator values are used as the reference (optimal) values for moderate-orientation transformation. In addition, given the limited comparability of the number of above-scale industrial enterprises across cities, an intermediary measure—value added per industrial enterprise (secondary-industry output divided by the number of above-scale industrial enterprises)—is introduced to obtain the moderate-orientation values for the sample cities.

2.3. Main Methods

2.3.1. Indicator Data Preprocessing

Because the indicator system includes positively oriented, negatively oriented, and moderately oriented (target) indicators, a positive-orientation transformation is first conducted before evaluation to ensure that larger values consistently indicate better performance.

For negatively oriented indicators, the transformation is implemented using Equation (1):

$$x' = \frac{x_{\max} - x}{x_{\max} - x_{\min}} \quad (1)$$

For moderately oriented (target) indicators, the transformation is implemented using Equation (2):

$$x' = \frac{1}{1 + |a - x|} \quad (a \text{ denotes the target/optimal value}) \quad (2)$$

where x is the original indicator value, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the indicator, and x' is the transformed value after positive-orientation processing.

2.3.2. Entropy-Weighted TOPSIS

This study applies the entropy-weighted TOPSIS approach to measure resilience levels in small and medium-sized cities (SMSCs) [72]. By assigning objective weights to indicators and integrating them into a multi-criteria evaluation, this method yields a composite resilience index for 510 Chinese SMSCs. Specifically, the entropy-weighting method quantifies the information entropy of each indicator, thereby reducing subjectivity in weight assignment and directly reflecting the amount of effective information conveyed by the data—an advantage that aligns well with practical assessment needs. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), also known as the distance-to-ideal-solution method, ranks a finite set of alternatives by their relative closeness to an ideal solution, and is widely used in multi-criteria decision analysis [73]. Combining entropy weighting with TOPSIS leverages the strengths of both methods and enhances the objectivity and plausibility of the resilience assessment for SMSCs.

Based on the established SMSC resilience indicator system, after transforming negatively oriented and moderately oriented indicators into positively oriented ones, the main computational steps of the entropy-weighted TOPSIS procedure are as follows:

Assume there are m evaluation units (cities) and n indicators for each unit. The decision matrix is constructed as:

$$X = (x_{ij})_{m \times n} \quad (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (3)$$

The decision matrix is then normalized as:

$$x'_{ij} = \frac{x_{ij} - \min_j(X)}{\max_j(X) - \min_j(X)} \quad (4)$$

where $\max_j$ and $\min_j$ denote the maximum and minimum values of indicator j across all evaluation units, respectively.

Next, the information entropy of indicator j is calculated as:

$$H_j = -k \sum_{i=1}^m p_{ij} \ln p_{ij} \quad (5)$$

where $P_{ij} = \frac{x'_{ij}}{\sum_{i=1}^m x'_{ij}}$; $k = \frac{1}{\ln m}$.

The weight of indicator j is defined as:

$$\omega_j = \frac{1 - H_j}{\sum_{j=1}^n (1 - H_j)} \quad (6)$$

where $\omega_j \in [0, 1]$, and $\sum_{j=1}^n \omega_j = 1$.

The weighted normalized matrix is then obtained as:

$$R = (r_{ij})_{m \times n}, r_{ij} = \omega_j \cdot x'_{ij} \quad (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (7)$$

The positive ideal solution S_j^+ and negative ideal solution S_j^- are determined by:

$$S_j^+ = \max(r_{1j}, r_{2j}, \dots, r_{nj}), S_j^- = \min(r_{1j}, r_{2j}, \dots, r_{nj}) \quad (8)$$

The Euclidean distances to the positive and negative ideal solutions are computed as:

$$sep_i^+ = \sqrt{\sum_{j=1}^n (s_j^+ - r_{ij})^2}, sep_i^- = \sqrt{\sum_{j=1}^n (s_j^- - r_{ij})^2} \quad (9)$$

Finally, the composite evaluation index is calculated as:

$$C_i = \frac{sep_i^-}{sep_i^+ + sep_i^-}, C_i \in [0, 1] \quad (10)$$

where a larger C_i indicates better performance of the evaluation unit.

2.3.3. Nonparametric Kernel Density Estimation

Kernel density estimation (KDE) is an important nonparametric technique and can be regarded as a smoothed version of a histogram [74]. By using a continuous density function, KDE characterizes the distributional properties of SMSC resilience levels. To further examine absolute disparities in SMSC resilience and the dynamic evolution of its distribution, this study applies KDE to explore features such as the central tendency, shape, range (dispersion), and polarization of the resilience distribution among Chinese SMSCs. The formula is given as follows:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^N K\left(\frac{X_i - x}{h}\right) \quad (11)$$

where X_i denotes the observed value for city i , x denotes the value at which the density is evaluated, $K(\cdot)$ is the kernel function, h is the bandwidth, and N is the number of cities in the sample.

With respect to kernel selection, although different kernel functions may affect the estimation to some extent, this study adopts the Gaussian kernel, which is the most widely used in practice. This choice is motivated by its broad applicability and good smoothing performance, making it a preferred option for kernel density analysis.

2.3.4. Dagum Gini Coefficient

The traditional Gini coefficient is a widely used tool for measuring overall inequality in a sample. Although it effectively captures aggregate disparity, it has limitations when one seeks to further analyze between-region differences and distributional features across subgroups. In particular, it does not provide a sufficiently informative decomposition of inequality sources, nor does it facilitate comparisons of distributional differences among different subpopulations. By contrast, the Dagum Gini coefficient proposed by Dagum is an inequality measure that explicitly accommodates subregional grouping [75]. It not only quantifies overall inequality, but also enables further decomposition into within-region inequality, between-region inequality, and the transvariation (overlapping) component, thereby addressing key shortcomings of the traditional Gini coefficient in subgroup decomposition and distributional comparison and offering a richer perspective for understanding inequality structures [76]. The Dagum Gini coefficient is computed as follows:

$$G = \frac{\sum_{j=1}^k \sum_{h=1}^k \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}|}{2n^2\mu} \quad (12)$$

In Equation (12), k denotes the number of regions, n is the total number of SMSCs, and j and h index regions. The indices i and r index cities within regions. $y_{ji}(y_{hr})$ denotes the urban resilience index of city $i(r)$ in region $j(h)$, and μ is the mean resilience index across all SMSCs. A larger G indicates a larger disparity in urban resilience.

The within-region Dagum Gini coefficient for region j , denoted G_{jj} , and the contribution of within-region inequality, denoted G_ω , are computed as:

$$G_{jj} = \frac{1}{2\mu_j n_j^2} \sum_{i=1}^{n_j} \sum_{r=1}^{n_j} |y_{ji} - y_{jr}| \quad (13)$$

$$G_\omega = \sum_{j=1}^k G_{jj} p_j s_j \quad (14)$$

The between-region Dagum Gini coefficient between regions j and h , denoted G_{jh} , and its contribution G_{nh} , are computed as:

$$G_{jh} = \frac{\sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}|}{n_j n_h (\mu_j + \mu_h)} \quad (15)$$

$$G_{nh} = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) D_{jh} \quad (16)$$

When decomposing regional groups, the contribution of the cross-term (i.e., the effect of distributional overlap between groups) to overall disparity is referred to as the transvariation (overlapping) contribution, denoted G_t , which is calculated as:

$$G_t = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) (1 - D_{jh}) \quad (17)$$

In Equation (17), $p_j = n_j/n$, $s_j = n_j \mu_j / n \mu_j$, $D_{jh} = (d_{jh} - p_{jh}) / (d_{jh} + p_{jh})$ captures the relative impact (or relative influence) of the resilience distributions between regions j and h . Here, $d_{jh} = \int_0^\infty dF_j(y) \int_0^y (y-x) dF_h(x)$ measures the expected positive difference in SMSC resilience between regions j and h , and $p_{jh} = \int_0^\infty dF_h(y) \int_0^y (y-x) dF_j(x)$ corresponds to the first-order moment of transvariation (overlap).

3. Results

3.1. Measurement Results

The average resilience level of SMSCs for China as a whole and for the four major regions is estimated using the methods described above. The year-by-year results are presented in Figure 3. To facilitate further interpretation and comparison, the estimation results are also visualized, as shown in Figure 4.

Overall, the resilience level of Chinese small and medium-sized cities (SMSCs) remains relatively low. The national average increased gradually from 0.1108 at the beginning of the sample period to 0.1121 by the end, with an average annual growth rate of 0.1067%. Regionally, Northeastern China exhibits the lowest level of SMSC resilience, with a within-sample mean of 0.0749, which is substantially lower than that of Western China (0.1125); both regions remain persistently below the national mean of 0.1192. In contrast, the annual mean values for Eastern and Central China are similar—0.1356 and 0.1331, respectively—and both are above the national average. In terms of average annual changes, resilience in the Eastern, Central, and Western regions increased at 0.409%, 0.133%, and 0.390% per year, respectively, whereas the Northeastern region experienced a decline of 1.810% per year.

Taken together, SMSC resilience in China displays a clear gradient pattern of Eastern > Central > Western > Northeastern. High-resilience SMSCs are concentrated mainly in the eastern coastal area and parts of Central China, and they often appear as spatially isolated “high-resilience enclaves” (i.e., an “island effect”).

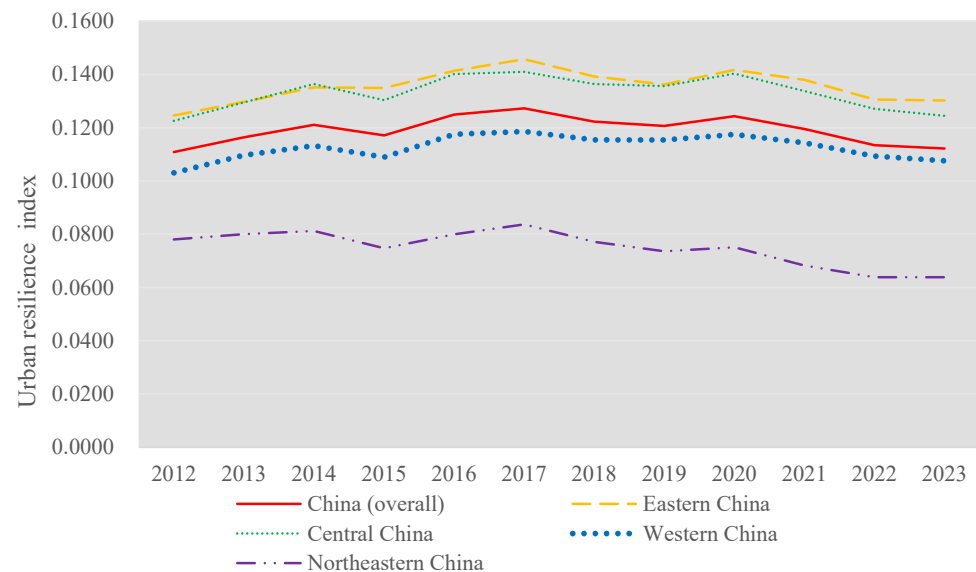


Figure 3. Year-by-year changes in the average resilience level of small and medium-sized cities (SMSCs) in China.

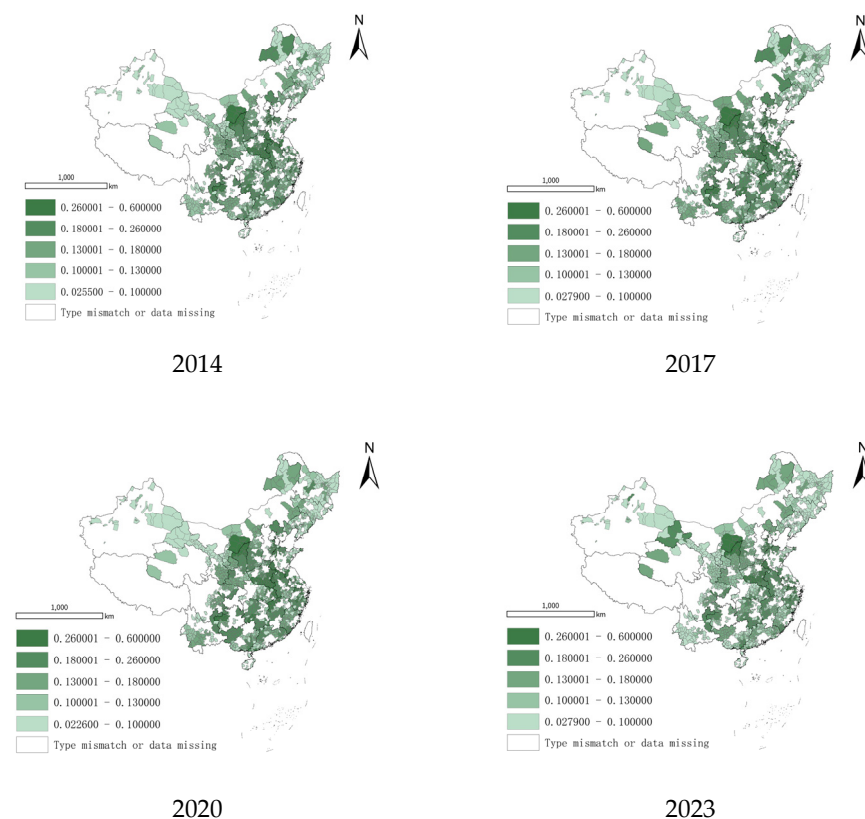


Figure 4. Spatiotemporal patterns of resilience in small and medium-sized cities (SMSCs) in China.

3.2. Spatiotemporal Disparities

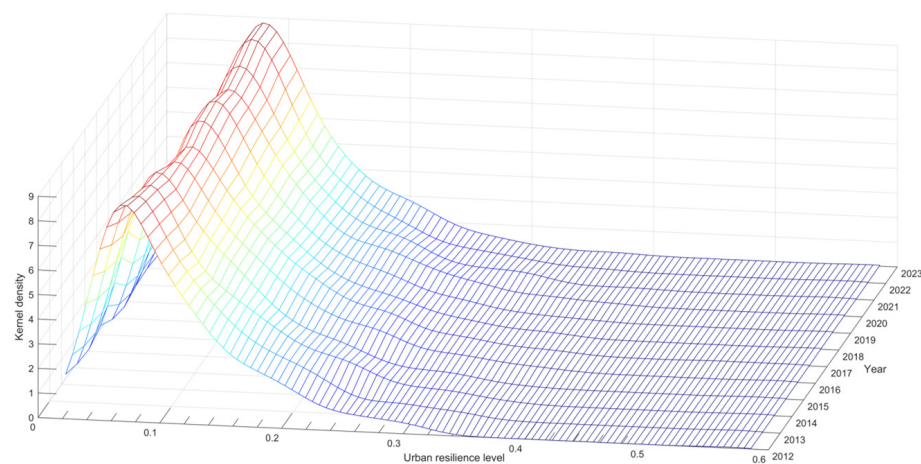
3.2.1. Dynamic Evolution

This study uses kernel density estimation (KDE) to characterize the distributional features of the sample, focusing on key properties of the corresponding density curves,

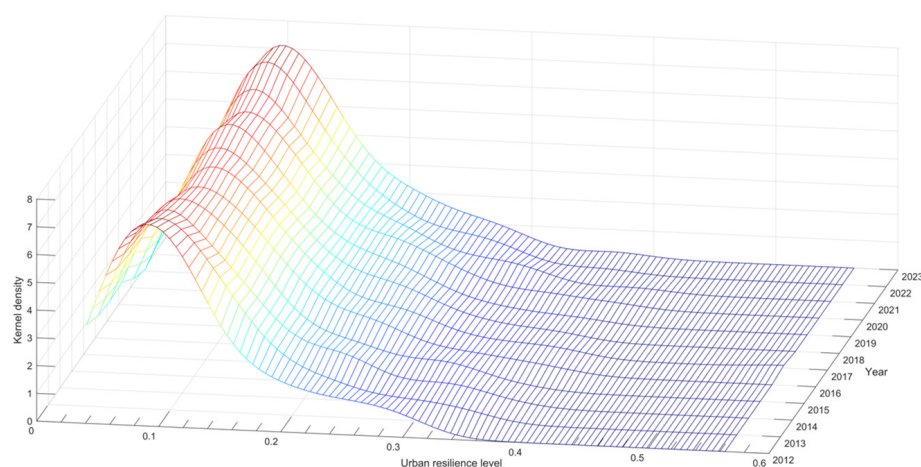
including location (central tendency), the shape of the main peak, distributional spread (dispersion/extension), and the number of peaks (multimodality). The dynamic evolution patterns are summarized in Table 2, and the KDE results are presented in Figure 5.

Table 2. Dynamic evolution characteristics of resilience in small and medium-sized cities (SMSCs).

Region	Location Shift	Main-Peak Shape	Distributional Spread	Number of Peaks
China (over all)	Slight rightward shift	Height unchanged; width increases	Right-skewed with a long right tail	Unimodal
Eastern China	Slight rightward shift	Height unchanged; width unchanged	Right-skewed with a long right tail	Unimodal
Central China	Slight rightward shift	Height increases; width increases	Right-skewed with a long right tail	Unimodal
Western China	Slight rightward shift	Height increases; width increases	Right-skewed with a long right tail	Unimodal
Northeastern China	Slight leftward shift	Height increases; width increases	Right-skewed with a long right tail	Unimodal or bimodal

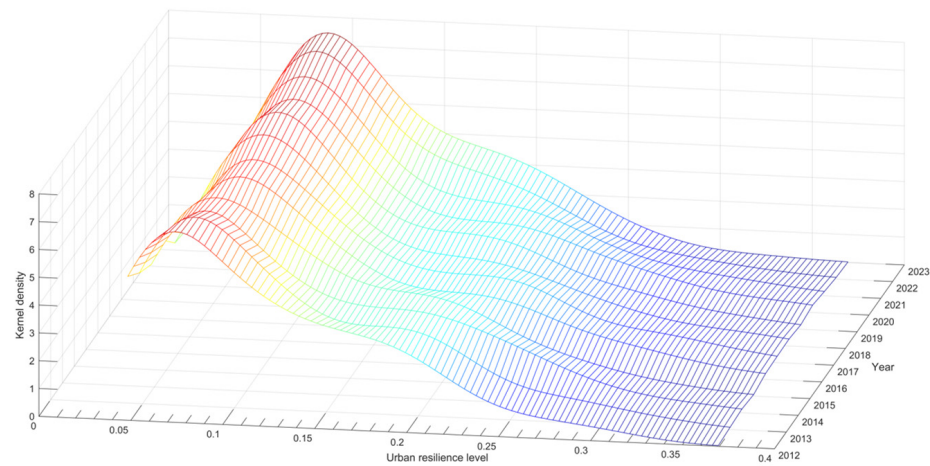


(a) China (overall)

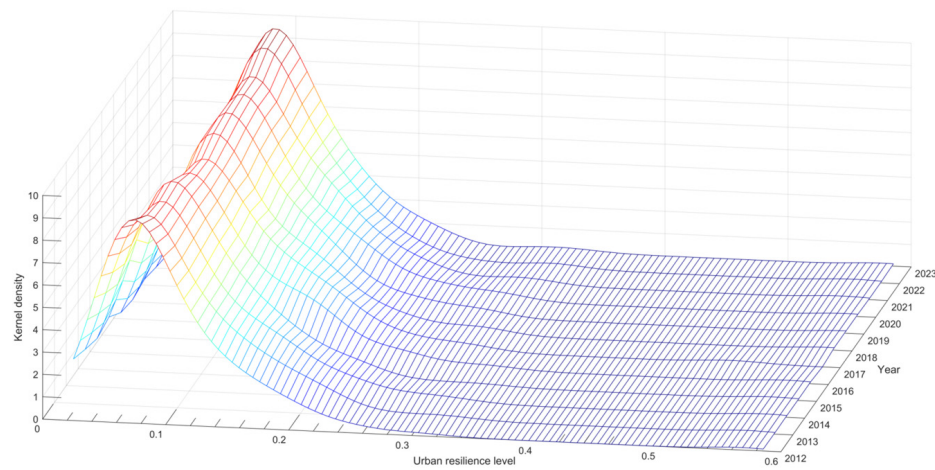


(b) Eastern China

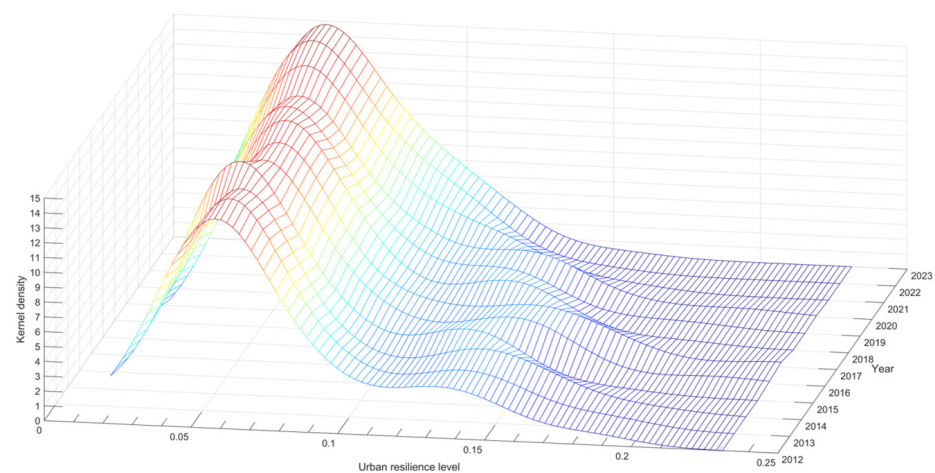
Figure 5. Cont.



(c) Central China



(d) Western China



(e) Northeastern China

Figure 5. Dynamic evolution of resilience level of small and medium-sized cities (SMSCs) in China.

Location Shift

During the sample period, the kernel density curve of SMSC resilience at the national level shows a slight rightward shift, indicating a modest overall improvement in resilience among most Chinese SMSCs. At the regional level, Eastern, Central, and Western China exhibit a similar rightward shift, suggesting gradual progress in resilience-building in these three regions. In contrast, the kernel density curve for Northeastern China shows a slight leftward shift, implying a year-by-year decline in resilience among SMSCs in the Northeast and greater difficulty in advancing resilience-building.

Main-Peak Shape

At the national level, the KDE curve is characterized by an unchanged main-peak height but an increasing peak width, indicating that the “middle” of the resilience distribution remains relatively stable while internal differentiation is gradually emerging. In Eastern China, the KDE curve shows an unchanged peak height and unchanged width, suggesting no marked changes in local density around the center or in dispersion—i.e., resilience among SMSCs in this region remains broadly stable. In Central, Western, and Northeastern China, the KDE curves exhibit higher peak heights together with increasing widths, indicating a rising share of SMSCs clustered around intermediate resilience levels.

Distributional Spread

For China overall, as well as for each of the four regions, the KDE curves display a pronounced right-tail elongation, implying that a subset of cities within each region attains resilience levels substantially higher than those of other SMSCs in the same region.

Number of Peaks

Over the sample period, China overall and the Eastern, Central, and Western regions are predominantly unimodal, indicating no clear polarization of SMSC resilience within these regions and a relatively stable distribution over time. By contrast, Northeastern China exhibits both unimodal and bimodal patterns; bimodality appears more frequently in the early years of the sample period and gradually evolves into unimodality toward the end. This suggests that polarization in the Northeast weakens over time, primarily because the mode associated with higher resilience levels diminishes.

3.2.2. Regional Disparities

While the KDE analysis reveals the time-varying evolution of absolute disparities in SMSC resilience, it does not quantify the overall level of inequality, identify the sources of disparities, or trace changes in relative differences across regions. Therefore, an inequality decomposition analysis is further conducted using the Dagum Gini coefficient decomposition.

Within-Region Disparities in SMSC Resilience

The within-group (within-region) disparities in resilience across the full sample of 510 Chinese SMSCs and within each of the four major regions are estimated using the Dagum Gini coefficient. The year-by-year results are reported in Figure 6.

At the national level, the overall Gini coefficient of SMSC resilience remains relatively stable, with a mean value of 0.2960 over the sample period. Except for a slight increase in the early years, it shows a steadily declining trend thereafter, indicating that resilience levels across Chinese SMSCs are relatively balanced and that the degree of balance has continued to improve. From a regional perspective, the within-group Gini coefficients in all four regions are below the national level, suggesting that within-region inequality is

comparatively limited and that the overall disparities in the sample are driven mainly by between-region differences.

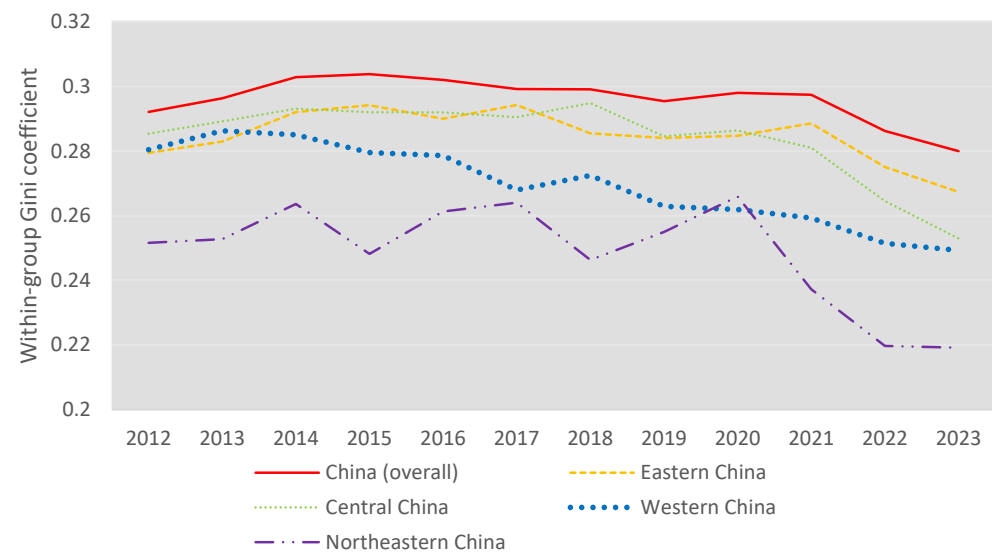


Figure 6. Changes in within-group disparities in resilience among small and medium-sized cities (SMSCs).

Among the four regions, Eastern China has the highest within-group Gini coefficient, with a sample mean of 0.2848; it increases in the early period and declines slightly in the mid-to-late period. Central China follows closely, with a mean of 0.2838; it remains relatively stable in the early-to-mid period but declines markedly in the mid-to-late period. Western China has a mean of 0.2695 and exhibits a relatively steady downward trend overall. Northeastern China has the lowest mean (0.2487); after relatively modest fluctuations in the early-to-mid period, it declines sharply in the later period, showing an overall pattern of fluctuation followed by a pronounced decrease.

Between-Region Disparities in SMSC Resilience

Dagum's between-group Gini coefficient is further used to measure disparities in SMSC resilience across China's four major regions. Estimates for selected benchmark years are reported in Figure 7.

In terms of overall trends, the shaded area in Figure 6 gradually narrows, suggesting that the degree of differentiation in SMSC resilience across regions has weakened over time. Regarding the magnitude of between-region disparities, differences among the Eastern, Central, and Western regions are relatively small. Specifically, the smallest disparity is observed between the Eastern and Central regions, with a sample mean of 0.2854, followed by the Central–Western pair (0.2874) and the Eastern–Western pair (0.2889). Larger between-region disparities mainly arise from comparisons involving the Northeastern region: the mean differences for Eastern–Northeastern, Central–Northeastern, and Western–Northeastern are 0.3571, 0.3525, and 0.3052, respectively. All three pairs reach their maximum disparities in 2021, and the Eastern–Northeastern pair attains the largest value across all between-group pairs (0.3820) in that year. In terms of temporal dynamics, disparities among Eastern–Central, Eastern–Western, and Central–Western show an overall declining trend, with average annual decreases of 0.206%, 0.177%, and 0.304%, respectively. By contrast, disparities involving the Northeastern region exhibit a stage-wise pattern: prior to 2021, the Eastern–Northeastern, Central–Northeastern, and Western–Northeastern gaps increase at average annual rates of 0.652%, 0.535%, and 0.357%, respectively, but after 2021 they decline at 0.384%, 0.736%, and 0.482% per year.

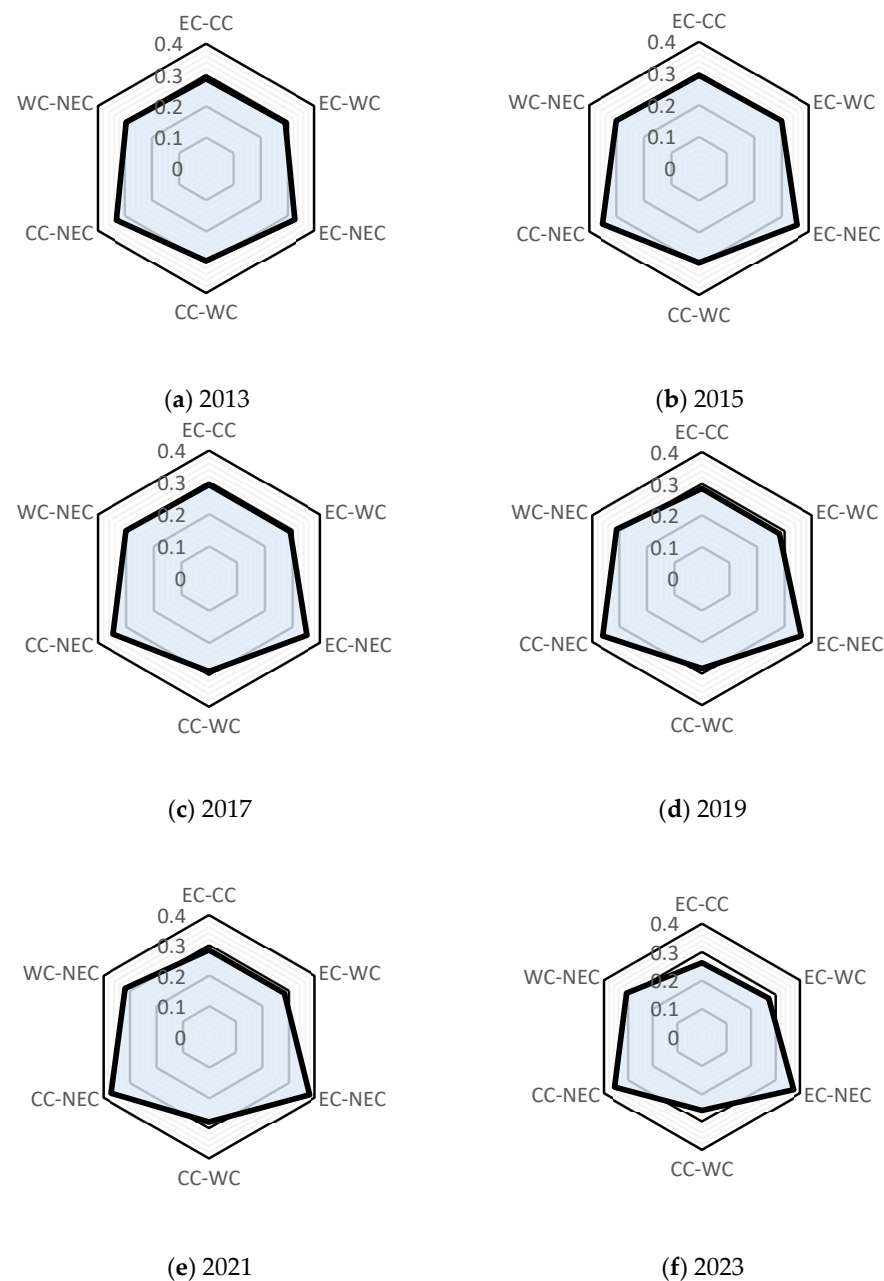


Figure 7. Changes in between-group disparities in resilience among small and medium-sized cities (SMSCs).

Overall Inequality and Decomposition of SMSC Resilience

Using the above method, overall inequality in the sample can be decomposed into three components: the within-group contribution, the between-group contribution, and the between-group transvariation (overlapping) contribution. The absolute values of these components and their relative shares are reported in Figure 8.

As shown in Figure 7, the within-group component of the Gini decomposition is 0.0753 in the early sample period and 0.0695 at the end of the sample period, with an average annual contribution of 0.0753 and a very small average annual change of 0.053%, indicating a slow convergence trend. Its contribution share decreases from 25.780% at the beginning to 24.819% at the end, with an average annual share of 25.435% and an average annual decline of only 0.087%. This suggests that the role of within-group disparities in explaining overall inequality in SMSC resilience has been weakening.

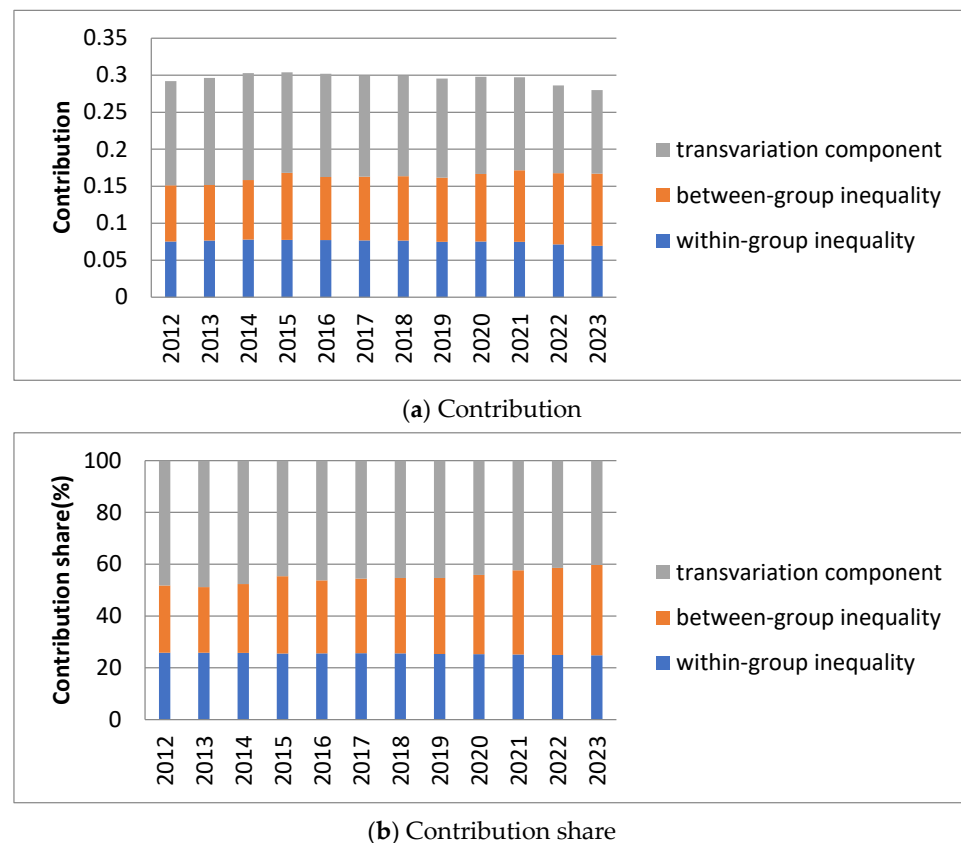


Figure 8. Spatial differences and sources of resilience in small and medium sized cities (SMSCs).

By contrast, the between-group component increases from 0.0760 at the beginning of the sample period to 0.0977 at the end, with an average annual contribution of 0.0874 and an average annual change of 0.198%. In terms of contribution share, the between-group component rises from 26.006% initially to 34.905% by the end, with an average annual share of 29.575% and an average annual increase of 0.809%. This indicates that between-group disparities have become increasingly important in shaping overall inequality in SMSC resilience.

The between-group transvariation (overlapping) component declines from 0.1408 in the early period to 0.1128 in the late period, with an average annual contribution of 0.1332 and an average annual change of 0.255%. Its contribution share falls from 48.214% at the beginning to 40.277% at the end, with an average annual share of 44.990% and an average annual decrease of 0.722%. Nevertheless, this component remains the largest source of overall inequality in SMSC resilience.

4. Discussion

With the advancement of urbanization, urban resilience has become a prominent research topic in the field of urban sustainability, and scholars have investigated and theorized it from diverse perspectives. Based on indicator data on the resilience of Chinese small and medium-sized cities (SMSCs) over 2012–2023, this study measures resilience levels in SMSCs and examines their temporal evolution and spatial disparities. The central finding is that resilience in Chinese SMSCs remains generally low and improves only slowly, exhibiting a clear gradient pattern of Eastern > Central > Western > Northeastern China. This result is consistent with, and provides further support for, previous evidence [77].

Comparative evidence based on our results indicates that the efficiency of resilience-building in SMSCs lags markedly behind that of large cities over the same period [78]. This lag reflects the dual constraints of economies of scale and the allocation of administrative

resources: because of scale-related disadvantages, SMSCs tend to face lower resilience levels [79]. If disparities across cities are not accurately identified, policy design may become less precise or even biased, potentially exacerbating a more severe Matthew effect. From the perspective of temporal dynamics, the Eastern region is the most stable: the shape of the main peak in its kernel density curve shows no substantial change over the sample period. As China's coastal belt, the Eastern region is among the most densely populated and economically developed areas and is also more frequently exposed to marine-related hazards [80]. Despite facing more complex disturbances, it maintains a steady improvement in resilience, highlighting the resilience capacity of SMSCs in Eastern China [81]. By contrast, the kernel density curve for Northeastern China exhibits atypical patterns: the distribution shifts leftward and displays bimodality in certain years. This suggests that SMSC resilience in the Northeast declines over the sample period and experiences pronounced internal differentiation. The findings of Jin provide a plausible explanation: Northeastern China has been confronting some of the most severe urban shrinkage in the country, which can undermine urban resilience but may also, under certain conditions, create opportunities for resilience enhancement—thereby contributing to the anomalous evolution observed for SMSCs in the Northeast [82]. Finally, from the perspective of spatial disparities, overall inequality in SMSC resilience shows a gradual reduction, while between-region gaps expand as resilience levels diverge across regions, indicating a pronounced regional Matthew-effect tendency in SMSC resilience. Such resilience disparities reflect regional differences in baseline conditions, development prospects, spatial planning, and urban challenges [83–85]. Meanwhile, decomposition results indicate that the between-group transvariation (overlapping) component remains the largest contributor to regional inequality, although its share declines year by year; in contrast, the contribution of between-region inequality rises, suggesting that regional differences are increasingly shaping SMSC resilience and that the spatial heterogeneity of SMSC resilience is correspondingly intensifying [86,87]. In this sense, conventional urban form-centered perspectives may offer decreasing explanatory power for SMSC resilience. As urban resilience research moves beyond its traditional “margins,” SMSC resilience is likely to assume a more prominent place in future urban studies.

Our findings carry important policy implications for understanding the development patterns of SMSC resilience, balancing efficiency and equity in resilience-building, and promoting regional coordination. Although our empirical setting focuses on China, the results may also offer useful insights for strengthening resilience in small and medium-sized cities in other countries. This study nevertheless has several limitations that may inform future research. First, the proposed assessment framework is primarily derived from theoretical reasoning and a synthesis of prior studies. Although each dimension has clear theoretical grounding, the framework has not yet been validated through large-sample empirical tests or extensive cross-case comparisons; its effectiveness should be further examined using multi-source data and comparative case-based evidence. Second, the study focuses on Chinese SMSCs. After excluding 61 cities whose city type changed during the study period or that contained substantial missing data, the final sample includes 510 SMSCs; this treatment may introduce potential sample-selection bias. Third, because SMSCs often have lower administrative status and limited statistical capacity, many key indicators exhibit systematic missingness in standard yearbooks and departmental reports. Although the issue was addressed using proxy variables and imputation methods, these treatments may introduce measurement error. Fourth, this study concentrates on measuring resilience levels and characterizing spatiotemporal disparities, but it does not systematically model the driving mechanisms behind resilience differences or conduct causal identification.

Future research could combine multi-case process tracing with more rigorous empirical strategies to uncover underlying mechanisms and contextual conditions.

5. Conclusions

This study innovatively constructs a resilience assessment indicator system for small and medium-sized cities (SMCs), using data from the China City Statistical Yearbook to measure the urban resilience levels of 510 SMCs in China from 2012 to 2023. The study applies non-parametric kernel density estimation and the Dagum Gini coefficient to explore the dynamic evolution and regional disparities in resilience across the nation and the four major regions. The key findings are as follows:

From 2012 to 2023, the overall resilience level of China's small and medium-sized cities remained relatively low, with a gradual but slow upward trend. The eastern, central, and western regions exhibited steady improvements, while the northeastern region showed fluctuating declines, leading to a gradient pattern of "East > Central > West > Northeast lagging." Furthermore, significant regional disparities in resilience were observed, with the overall gap between regions and intra-regional differences narrowing over time. However, the resilience gap between regions continued to widen, and SMCs face the "Matthew effect" risk arising from both "scale" and "region."

This study offers important policy implications for clarifying and optimizing the resilience of small and medium-sized cities in China.

- (1) Promote and dynamically optimize resilience enhancement plans nationwide, with resilience baseline standards as a precondition. For small and medium-sized cities (SMCs) with significantly low resilience levels, it is crucial to systematically draw on the best practices of coastal cities in the eastern region, particularly in areas such as infrastructure redundancy and emergency governance mechanisms. Tailored, practical implementation plans should be developed based on local factors, including population size, industrial structure, and fiscal capacity, to avoid simple replication of existing models.
- (2) Future urban development of SMCs must integrate resilience enhancement with urban transformation, upgrading, and renewal. While strengthening critical infrastructure, parallel development projects such as distributed energy systems, sponge cities, and low-carbon transportation should be advanced to achieve synergies between safety and development.
- (3) The design and implementation of resilience strategies for SMCs must consider city size and regional economic conditions, adhering to the principle of context-specific approaches. Given that existing policy tools are more suited to larger cities with higher population and economic scales, there is a risk of exacerbating the "Matthew effect" for SMCs. It is recommended to establish a "SMC Resilience Compensation Fund" within the central-provincial-city fiscal framework. This fund would provide targeted transfer payments and preferential green finance support to smaller, financially weaker cities. The fund should operate under a PPP framework, following the logic of "planning guidance—functional positioning—capital linkage—market operations," clearly defining the roles and responsibilities of government, enterprises, and social capital, minimizing administrative intervention, and promoting a more balanced evolution of resilience across small and medium-sized cities nationwide.

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