Research Paper

Study on the Evolutionary Characteristics of County Town Shrinkage and Planning Response Strategies under Multi-Dimensional Framework： Taking the Three Northeastern Provinces of China as an Example

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Abstract

With intensifying regional disparities, the number of shrinking cities in China has risen, particularly in areas facing not only population loss but also economic recession, structural challenges, and fiscal deficits. This threatens China's strategy to promote county towns as hubs of urbanization. This study analysed contraction patterns in northeastern county towns through a four-step framework: (1) constructing a multi-dimensional measurement system with an entropy-weighted index; (2) using correlation and grey relational analysis to examine inter-dimensional relationships; (3) developing a model of multi-dimensional shrinkage interactions; and (4) proposing targeted planning strategies. Key findings include: (1) Over 90% of the 178 county towns in the northeast have experienced population shrinkage, about 50% show economic contraction, and less than 10% exhibit social contraction; (2) Between 2006 and 2020, most counties faced ongoing population shrinkage, with equal parts experiencing deepening and stabilizing trends. Economic shrinkage progressed from initial growth to continuous contraction, with towns increasingly polarizing into "persistent shrinkage" or "persistent growth"; (3) Shrinkage remains largely single-dimensional, with two-dimensional shrinkage (mainly "population-economic") affecting about 20% of towns, while comprehensive shrinkage is rare; (4) There is a significant correlation between shrinkage dimensions in the early stages, which weakens over time. This study's multi-dimensional analysis of shrinkage in northeastern county towns offers insights into contraction patterns and proposes planning and policy recommendations.

Keywords

Shrinking city, Measurement, Evolutionary Characteristics, Response Strategies, County towns of China

1. Introduction

Urban shrinkage is a new challenge in China's push for urbanization. With growing regional disparities, shrinking cities in China have become more numerous, multidimensional, and severe in recent years(Guan, He and Hu, 2021; Zhang *et al.*, 2024). County-level towns, in particular, face greater shrinkage pressures due to their larger base numbers and weaker attraction for population inflows, leading to more diverse forms of urban decline. Population shrinkage in these areas is often accompanied by socio-economic recession, creating a "downward spiral" and "structural decay" that makes reversing the trend especially difficult(Lee, Won and Kim, 2016; Liu, 2022). In 2022, the country proposed a new deployment for county-level urbanization construction, clarifying that county towns will be the main body of future urbanization development. However, the phenomenon of urban shrinkage in county towns hinders the smooth progress of this deployment. Therefore, it is necessary to investigate and analyze the urban shrinkage situation in county towns, grasp the laws of county town shrinkage, and take targeted measures to respond(Tong *et al.*, 2022)..

The identification and measurement of urban shrinkage can be mainly divided into four methods: socio-economic indicators, spatial statistics, geographic landscape detection, and new data analysis (Jiang *et al.*, 2020; Lang, Deng and Li, 2020; Tan *et al.*, 2023). Most studies focus on national, regional, or prefecture-level scales, with limited research on county-level shrinkage. While some foundational research has examined multi-dimensional shrinkage—covering economic, social, and spatial aspects, while studies on the interrelations between these dimensions remain scarce(Lee, Hye-Jin and Jae-Su, 2018; Li and Mykhnenko, 2018; He *et al.*, 2023; Zhang *et al.*, 2024).

In light of this gap, this study focuses on the three northeastern provinces of China, which face the most severe urban shrinkage. Taking county-level towns in these provinces as the study subject, we aim to address the following questions: (1) What are the primary characteristics of urban shrinkage in population, economic, and social dimensions across the northeastern provinces? (2) What are the spatiotemporal evolution patterns of multi-dimensional shrinkage in these county towns? (3) What interrelationships exist among the different dimensions of shrinkage in these areas? (4) What policy recommendations can be made to improve governance in shrinking cities based on these findings?

To address these questions, this study develops a multi-dimensional measurement system for shrinkage, using correlation analysis and grey relational analysis to explore the patterns of interrelated shrinkage dimensions. Based on these findings, we propose practical strategies for urban governance.

2. Study Area and Research Methods

2.1. Study Area

The three provinces of Northeast China (TPNC) are collectively known as Heilongjiang Province, Jilin Province, and Liaoning Province, with a total of 34 prefecture level cities under their jurisdiction, including 141 municipal districts, 54 county-level cities, and 92 counties, totaling 287 county-level administrative units (as shown in the picture). They are important industrial bases, grain production bases, and foreign trade gateways in China, and also have abundant resources such as timber and minerals.

2.2. Measurement Methods and Data Collection

This study addresses the complexity of urban shrinkage by adopting a multidimensional framework that considers population, economic, and social dimensions. Following principles of scientific rigor and systematic analysis, and drawing on existing literature and county-level data, an 8-indicator measurement system was developed(Schetke and Haase, 2008; Wang *et al.*, 2021; Chen *et al.*, 2024).

For the population dimension, shrinkage is measured through population size and change rate. Population size reflects the total resident count and serves as the primary indicator of urban shrinkage, while the rate of population change captures the intensity of population fluctuations, indicating the speed and severity of shrinkage—key for assessing the depth and trajectory of urban decline(Turok and Mykhnenko, 2007, 2007).

In the economic dimension, shrinkage is reflected in low economic development (especially low per capita GDP), slowing growth, and an imbalanced economic structure. Indicators include per capita GDP and fiscal revenue (reflecting economic strength), GDP growth rate (indicating growth trends), and the proportion of secondary and tertiary industries in GDP, which suggests industrial and service sector vitality(Fleschurz and Pallagst, 2016).

The social dimension focuses on fiscal imbalances and the quality of public services. Indicators include hospital beds per 10,000 people (measuring public service quality) and local general budget expenditures (measuring social investment). Together, these indicators assess the capacity of social infrastructure to support urban development(Glaeser and Gottlieb, 2006; Cheshire and Magrini, 2009).

Based on this analysis, a multi-dimensional measurement system for urban shrinkage is constructed, as shown in Table 1.

Table 1. Multi-Dimensional Measurement System for Shrinkage in County-Level Town. Source: Self Drawing.

Goal Level	Criterion Level	Indicator Level	Formula	Unit
Population Dimension	Population Size	Total Population	Year-end population (permanent residents)	10,000 people
	Change Rate	Population Change Rate	(Population at end of period - Population at start of period) / Population at start of period * 100%	%
Economic Dimension	Economic Level	Per Capita GDP	GDP per capita	Yuan
		Per Capita Fiscal Revenue	Local fiscal budget revenue / Total population	Yuan
	Economic Growth	GDP Growth Rate	GDP growth rate	%
	Economic Structure	Industrial Structure Index	(Value added by tertiary sector + Value added by secondary sector) / GDP	%
Social Dimension	Social Services	Public Services	Hospital beds per 10,000 people	Beds
	Social Investment	Fiscal Expenditure	Local general budget expenditure	Yuan

This study takes a macro-level approach, primarily using government statistics or open data. Ultimately, the study covers 178 county-level or district-level units. The data spans from 2000 to 2020, sourced mainly from the China County Statistical Yearbook, Heilongjiang Statistical Yearbook, Liaoning Statistical Yearbook, Jilin Statistical Yearbook, China City Statistical Yearbook, and economic and social development statistical bulletins of various counties and cities.

2.3. Analytical Framework

The analysis of urban shrinkage evolution is divided into three main aspects: spatial evolution patterns, temporal evolution patterns, and multi-dimensional shrinkage correlations(Guo *et al.*, 2021; Song, He and Zeng, 2023; Zhang *et al.*, 2023).

(1) Spatial Evolution Analysis of Shrinking Towns

The study of spatial evolution focuses on two areas: spatial distribution and spatial pattern. The spatial distribution analysis identifies the changing spatial characteristics of shrinking towns across dimensions over time. Spatial pattern analysis, on the other hand, examines the shifting centers of shrinkage and clustering characteristics of shrinking towns.

(2) Temporal Evolution Analysis of Shrinking Towns

Temporal evolution is analyzed in terms of shrinkage intensity and shrinkage dimension patterns. Shrinkage intensity analysis categorizes towns based on the temporal patterns of their multi-dimensional shrinkage, capturing overall trends in urban shrinkage. Shrinkage dimension analysis examines the changes in the combinations of shrinkage dimensions, tracking the increase or decrease in shrinkage across dimensions to capture the general trends in multi-dimensional shrinkage.

(3) Multi-Dimensional Shrinkage Correlation Analysis

The multi-dimensional correlation analysis includes two parts: correlation testing and interaction analysis. The correlation test applies Spearman correlation to assess the relationships and trends among different shrinkage dimensions. The interaction analysis breaks down shrinkage indicators by dimension and uses grey relational analysis to examine the influence of each dimension on others, constructing a theoretical framework for understanding the interrelationships in multi-dimensional shrinkage.

2.4. Analytical Framework

(1) Measurement Calculation Method

First, the range method is used to normalize the indicators to eliminate units. Given n years and m indicators, X_{ij} represents the j-th indicator in year i (i= 1,2⋯,n; j= 1,2,⋯,m). Since all indicators are positive in this study, the normalization formula is as follows:

$$X_{ij}{}' = \frac{X_{ij} - minX_j}{maxX_j - minX_j} \tag{1}$$

Second, indicator weights are determined using the entropy method to ensure objectivity and accuracy. The steps are as follows:

Proportion of the j-th indicator in year i:

$$P_{ij} = \frac{X_{ij}{}'}{\sum_{i=1}^{n} X_{ij}{}'} \tag{2}$$

Entropy value of the j-th indicator:

$$E_j = -\frac{X_{ij}{}'}{\ln(n)} \sum_{i=1}^{n} P_{ij} \ln(P_{ij}) \tag{3}$$

Redundancy of the j-th indicator:

$$d_j = 1 - E_j \tag{4}$$

Weight of each indicator W_j:

$$W_j = \frac{1 - E_j}{\sum_{j=1}^{m}(1 - E_j)} \tag{5}$$

Finally, each dimension's development index and shrinkage index for each year are calculated.

Development Index Z_i for year i:

$$Z_i = \sum_{j=1}^{m}(W_j X_{ij}') \tag{6}$$

Shrinkage Index SK_i for year i, comparing with the previous year:

$$SK_i = (Z_i - Z_{i-1}) \times 100\% \tag{7}$$

A smaller SK_i indicates a greater level of shrinkage compared to the previous year, and vice versa. Equation (7) can also be applied to calculate shrinkage over longer time spans by comparing development indices over those periods.

(2) Classification of Shrinkage Levels

Using ArcGIS 10.5, the Natural Breaks (Jenks) method is applied to classify shrinkage levels for each dimension into six categories: high, moderate, and mild shrinkage, as well as mild, moderate, and high growth (Table 2). This classification allows for a comprehensive understanding of the shrinkage level, dimensional characteristics, and regional disparities across counties and towns in the three northeastern provinces of China.

Table 2. Thresholds for Shrinkage Levels in County-Level Towns. Source: Self Drawing.

Dimension	Thresholds					
	High shrinkage	Moderate shrinkage	Mild shrinkage	Mild growth	Moderate growth	High growth
Population	R≤-7.4%	-7.4%<R≤-3.2%	-3.2%<R≤0%	0% < R≤3.3%	3.3% < R≤9.7%	9.7% < R
Economic	R≤-17.1%	-17.1% < R≤-7.8%	-7.8% < R≤0%	0% < R≤7.1%	7.1% < R≤14.8%	14.8% < R
Social	R≤-6.6%	-6.6% < R≤-2.7%	-2.7% < R≤0%	0% < R≤6.1%	6.1% < R≤13.9%	13.9% < R

(3) Weighted Mean Center Calculation

Since higher negative values in the shrinkage index indicate greater shrinkage, and positive values indicate growth, the shrinkage index is inverted for use as a weight. The weight w_i for element i representing its shrinkage level is calculated as:

$$w_i = -SK_i \tag{11}$$

The weighted mean center coordinates $(\overline{x}, \overline{y})$ are then calculated as:

$$\overline{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \quad , \quad \overline{y} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \tag{12}$$

(4) Directional Distribution

Directional distribution (standard deviation ellipse) is used to observe clustering direction and degree. The standard deviation ellipse is centered on the weighted mean center, with calculations as follows:

$$\tan\theta = \frac{A+B}{C}$$
$$A = \sum_{i=1}^{n}(x_i-\overline{x})^2 - \sum_{i=1}^{n}(y_i-\overline{y})^2$$
$$B = \sqrt{\left(\sum_{i=1}^{n}(x_i-\overline{x})^2 - \sum_{i=1}^{n}(y_i-\overline{y})^2\right)^2 + 4\left(\sum_{i=1}^{n}(x_i-\overline{x})(y_i-\overline{y})\right)^2} \tag{13}$$
$$C = 2\sum_{i=1}^{n}(x_i-\overline{x})(y_i-\overline{y})$$
$$\sigma_x = \sqrt{2}\sqrt{\frac{\sum_{i=1}^{n}((x_i-\overline{x})\cos\theta - (y_i-\overline{y})\sin\theta)^2}{n}}$$
$$\sigma_y = \sqrt{2}\sqrt{\frac{\sum_{i=1}^{n}((x_i-\overline{x})\sin\theta + (y_i-\overline{y})\cos\theta)^2}{n}}$$

In the above formula, $x_i$and y_i,represent the coordinates of element i,while $(\overline{x},\overline{y})$ denotes the coordinates of the mean center. θ represents the angle between the major axis and true north, σ_x is the length of themajor axis, σ_y is the length of the minor axis, and n is the total number of elements.

(5) Spearman Correlation Coefficient

The Spearman correlation coefficient is used to examine the relationship between two variables, x and y. Its formula is:

$$p = \frac{\sum_{i=1}^{n}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\overline{x})^2\sum_{i=1}^{n}(y_i-\overline{y})^2}} \tag{14}$$

Where x_i and y_i are values for each object *i*, and $\overline{x}$ and $\overline{y}$ are the mean values of x and y, respectively.

(6) Grey Relational Analysis

Grey Relational Analysis (GRA) measures the similarity in geometric patterns between a reference data series and characteristic data series to assess correlation strength, often used for examining nonlinear relationships.

Step 1: Define reference and characteristic sequences and normalize data (e.g., using initial or mean values):

$$[X_1' \quad X_2' \quad \dots \quad X_n'] = \begin{bmatrix} x_1'(1) & x_2'(1) & \cdots & x_n'(1) \\ x_1'(2) & x_2'(2) & \cdots & x_n'(2) \\ \vdots & \vdots & & \vdots \\ x_1'(m) & x_2'(m) & \cdots & x_n'(m) \end{bmatrix} \tag{15}$$
$$X_0' = (x_0'(1), x_0'(2), \dots, x_0'(m))^T$$

In the above formula, X_0' represents the reference sequence (also called the parent sequence), and $x_0'(m)$ denotes the value of the parent sequence at point m. $[X_1' \quad X_2' \quad \dots \quad X_n']$ represents the n-th characteristic sequence.

Step 2: Calculate the grey relational coefficient between each element of the comparison series and the reference series:

$$\gamma_{0i}(k) = \frac{\Delta min + \rho\Delta max}{\Delta_{ik} + \rho\Delta max}$$
$$\Delta min = \min_i \min_k |x_0(k) - x_i(k)| \tag{16}$$
$$\Delta max = \max_i \max_k |x_0(k) - x_i(k)|$$
$$\Delta_{ik} = |x_0(k) - x_i(k)|$$

In the above formula, $x_i(k)$ represents the grey relational coefficient for the k-th sample of the i-th characteristic sequence. ρ is the distinguishing coefficient, with a range of (0, 1); a smaller ρ value enhances the differentiation of relational degrees between different indicators.Typically, ρ is set to 0.5, and this study adopts the same value.

Step 3: Calculate the overall relational degree as the weighted average of the grey relational coefficients:

$$r_{0i} = \frac{1}{m}\sum_{k=1}^{m} \gamma_{0i}(k) \tag{17}$$

This analysis helps determine the interdependencies among shrinkage dimensions, useful for identifying influencing factors in urban shrinkage dynamics.

3. Study Area and Research Methods

3.1 Spatial Evolution Analysis of Multi-Dimensional Shrinkage

(1) Spatial Distribution Patterns

To examine the spatial distribution patterns of multi-dimensional shrinkage in county-level towns across the three northeastern provinces of China, this study analyzes the distribution of shrinking towns in each dimension over four time periods: 2001–2005, 2006–2010, 2011–2015, and 2016–2020 (as shown in Figure 1&2&3).

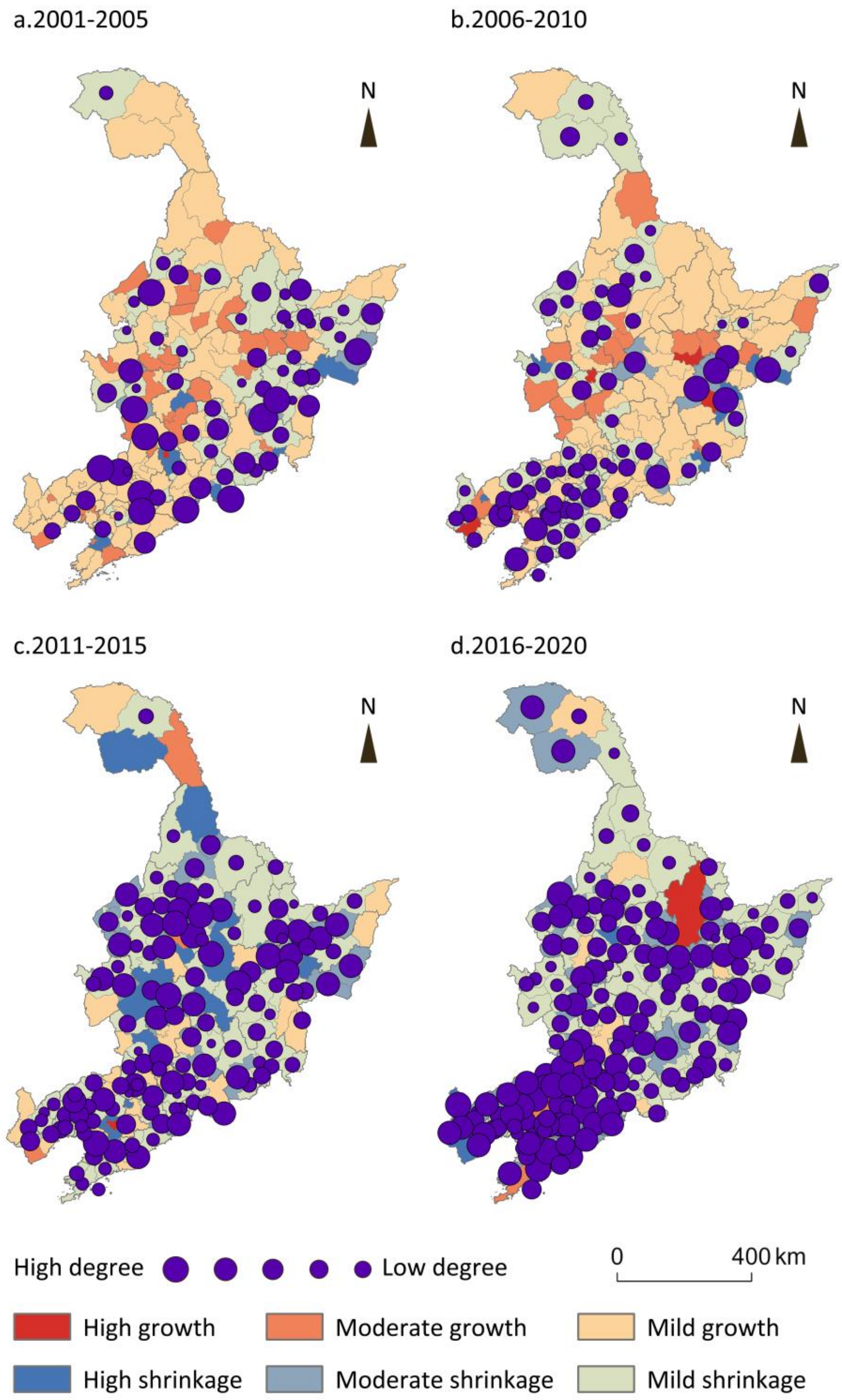


Figure 1. Analysis on the evolution of spatial distribution of towns in shrinking county. Source: Self Drawing

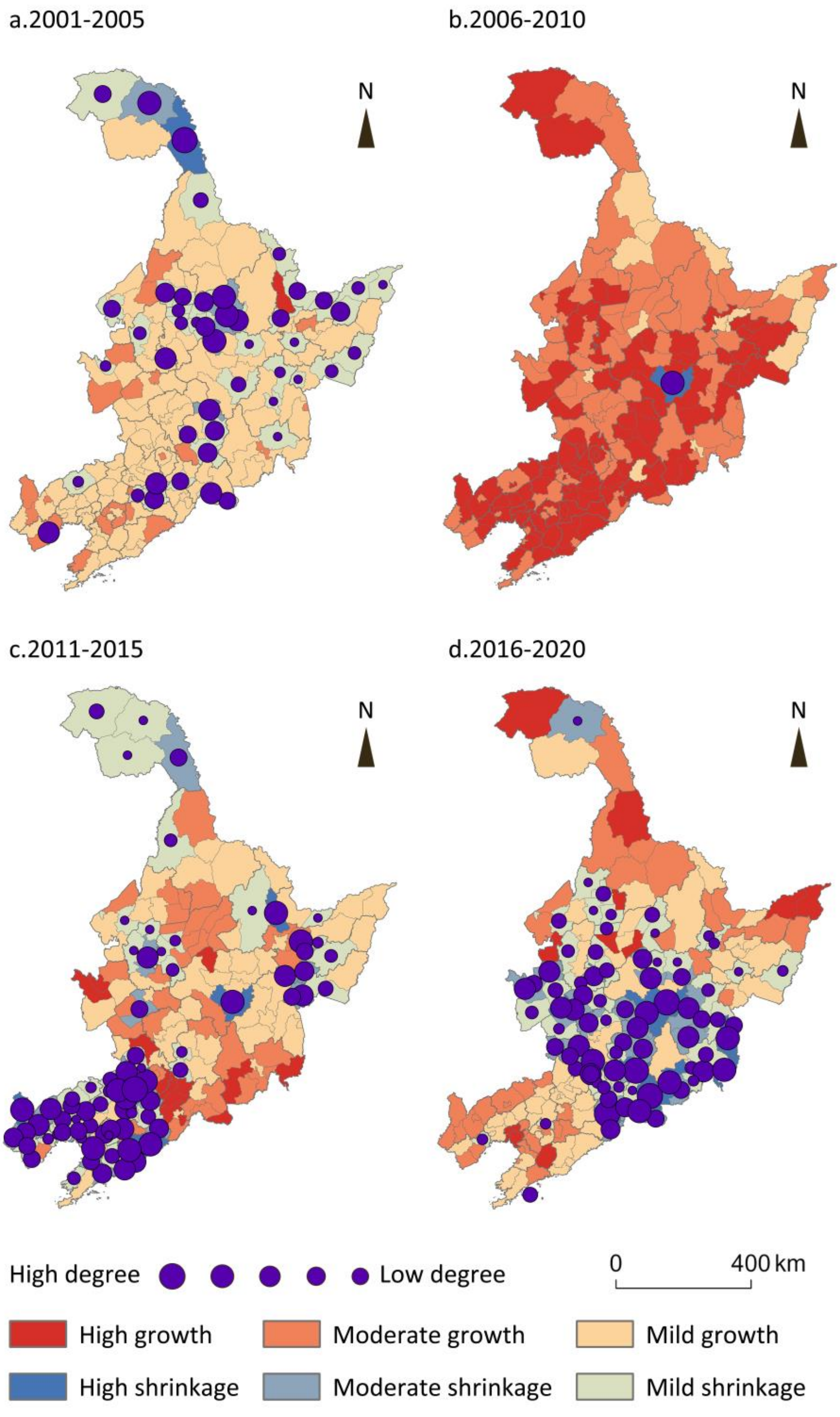


Figure 2. Analysis on the evolution of spatial distribution of cities and towns in counties with economic shrinking. Source: Self Drawing

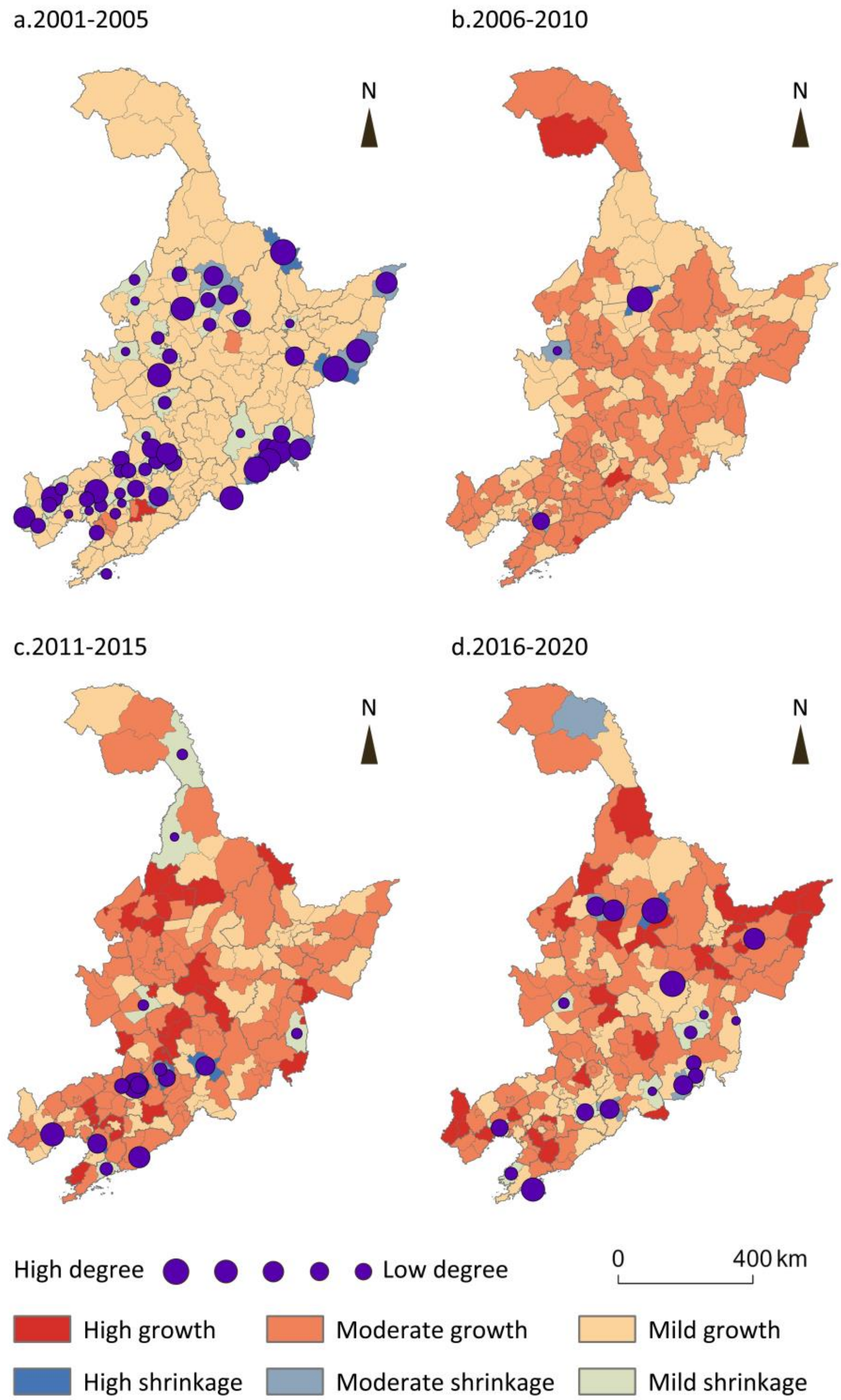


Figure 3. Analysis on the evolution of spatial distribution of towns in counties with social shrinking. Source: Self Drawing

In the population dimension, from 2001–2005, shrinkage was scattered across different regions of the three provinces, with no significant clustering of high-shrinkage towns. By 2006–2010, shrinkage became more concentrated in southeastern and western Heilongjiang and much of Liaoning, showing some spatial clustering. During 2011–2015, while shrinkage spread more widely, the northern and eastern borders of Heilongjiang experienced a slightly lower degree of shrinkage, and clustering remained weak. By 2016–

2020, most towns had fallen into shrinkage, especially in the southern regions, with high-shrinkage areas still concentrated mainly in Liaoning. Overall, the spatial distribution of population shrinkage evolved from a scattered pattern to partial clustering and eventually to widespread shrinkage, though clustering was generally weak.

In the economic dimension, economically shrinking towns initially appeared sporadically in the northern and eastern border areas of Heilongjiang from 2001–2005. However, from 2006–2010, most towns across the three provinces experienced economic growth, leaving only Shangzhi City in economic decline. During 2011–2015, shrinking towns were primarily concentrated in most of Liaoning and parts of Heilongjiang, showing significant clustering. By 2016–2020, economically shrinking towns were centered in the three provinces' central areas, particularly southern Jilin and southern Heilongjiang, while northern border areas showed strong growth. Economic shrinkage demonstrated consistent clustering, with shifting regional centers, indicating volatility in economic conditions.

In the social dimension, socially shrinking towns were evenly scattered across all four periods, with no significant clustering or distinct spatial distribution patterns.

In summary, population shrinkage in northeastern county-level towns evolved from scattered to widespread distribution, with weak clustering overall. Economic shrinkage showed clearer clustering across periods but with shifting centers, reflecting its volatility. Social shrinkage remained uniformly scattered, with no prominent clustering throughout the study period.

(2) Spatial Pattern Evolution

The spatial distribution analysis above shows that the 2011–2015 and 2016–2020 periods had the most significant shrinkage in population and economic dimensions. This section explores the evolution of spatial patterns for towns experiencing shrinkage in these two dimensions, by analyzing the average center of shrinkage and using the shrinkage degree as a weight to plot standard deviation ellipses for 2011–2015 and 2016–2020. The results are shown in Figures 4, while the coordinates of the average centers and the parameters of the standard deviation ellipses are listed in Table 3 and Table 4.

Table 3 . Average center and standard deviation ellipse for population shrinkage in county-level towns. Source: Self Drawing

Period	Center Longitude	Center Latitude	Short Axis Length	Long Axis Length	Orientation Angle
2011–2015	126.162034	44.832756	2.915568	4.817849	50.702558
2016–2020	125.179684	43.768928	2.904518	5.335846	53.804972

Table 4. Average center and standard deviation ellipse for economic shrinkage in county-level towns. Source: Self Drawing

Period	Center Longitude	Center Latitude	Short Axis Length	Long Axis Length	Orientation Angle
2011–2015	126.732861	44.703729	2.436813	5.468996	55.283068
2016–2020	126.753215	44.054627	2.571538	3.186308	104.770424

In terms of population, from 2011-2015 to 2016-2020, the center of population contraction shifted towards the southwest, indicating that the population outflow in the southwest direction was more severe than in the northeast direction. Geographically, this is consistent with the location of the inland border, and the closer the cities are to the inland area, the more severe the population outflow becomes. According to the distribution ellipse of the standard deviation of population shrinkage, the length of the short axis in 2016-2020 is slightly less than that in 2011-2015, while the length of the long axis is greater than that in 2011-2015. This indicates that the centripetal distribution of population shrinkage towns in the short axis direction is more obvious, and the spatial distribution clustering has been improved. However, the directional distribution of population shrinkage towns in the long axis direction is more obvious. In other words, the distribution range and dispersion degree of population shrinkage towns in the southwest and northeast directions are expanding, and overall, the ellipticity has decreased, and the distribution of shrinkage towns is more scattered. However, the direction of the major axis of the ellipse did not change significantly during the two time periods, so the concentrated axial distribution of shrinking towns did not change much, roughly fitting a straight line passing through the centers of Harbin, Changchun, and Shenyang.

In summary, with the development of time, the population shrinkage of counties and cities in the three provinces of Northeast China has become increasingly severe from the border to the inland. The overall distribution shows a clustering of the northeast and southwest axes, and the degree of dispersion is gradually increasing. The population shrinkage is becoming more uniform.

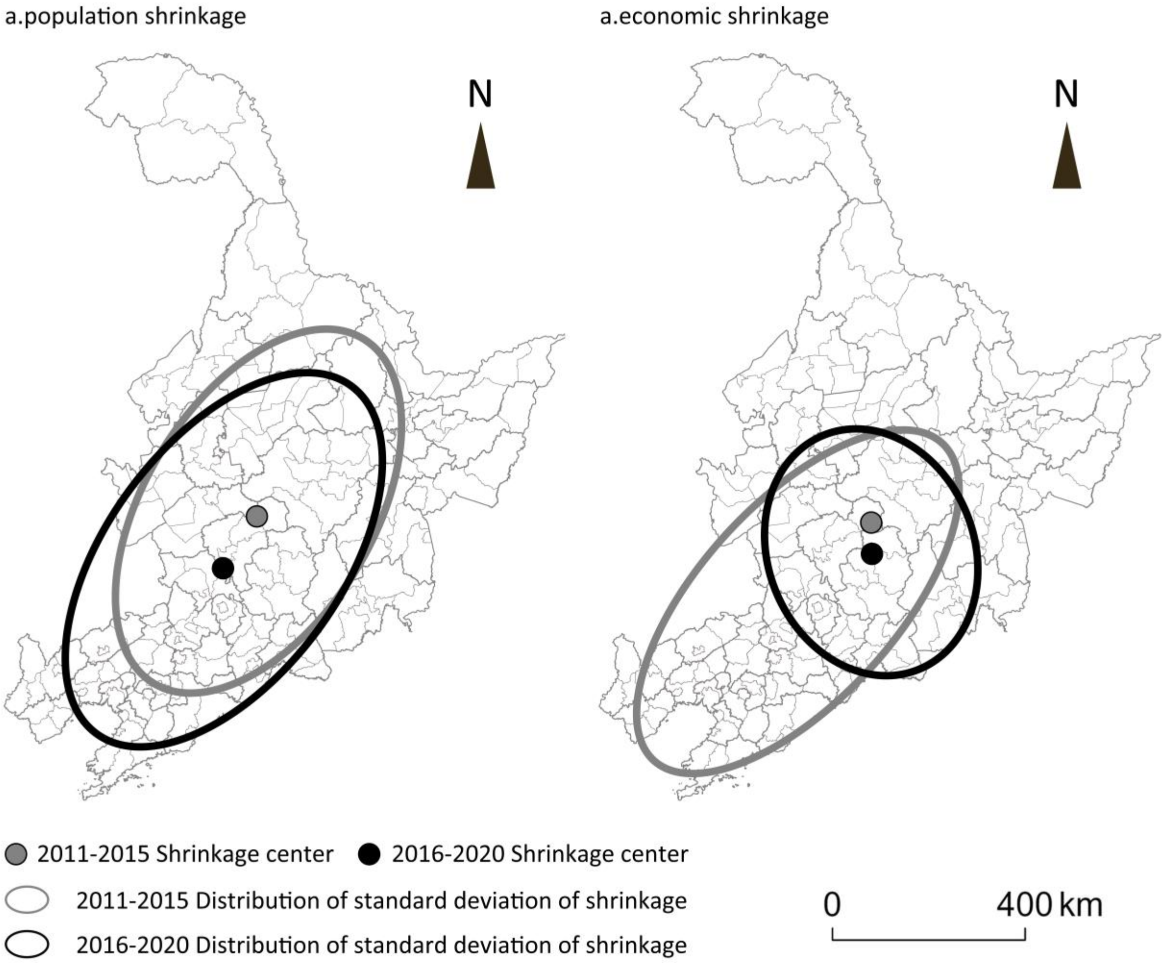


Figure 4. Analysis of the spatial pattern evolution of population shrinkage and economic shrinkage in county-level towns. Source: Self Drawing

In the economic dimension, from 2011-2015 to 2016-2020, the center of economic contraction shifted towards the southeast direction, indicating a stronger trend of economic recession intensification in the southeast direction. According to the distribution ellipse of the standard deviation of economic contraction, the length of the short axis in 2016-2020 is slightly greater than that in 2011-2015, while the length of the long axis is much smaller than that in 2011-2015. This indicates that the directional distribution of population shrinking towns in the short axis direction is more obvious, and the spatial distribution dispersion has improved. However, the clustering of population shrinking towns in the long axis direction is more obvious. That is to say, the distribution range of shrinking towns in the northwest and southeast directions is shrinking, and the degree of clustering is increasing. Overall, the ellipticity has increased, and the distribution of shrinking towns is more clustered. The direction of the major axis of the ellipse changed dramatically during the two periods, shifting from southwest and northeast to northwest and southeast, indicating that the economically contracted towns in the northwest and southeast directions were more concentrated and distributed. In summary, with the development of time, the main clustering direction of economically contracted towns in the counties of the three northeastern provinces has shifted from the northeast and southwest axes to the northwest and southeast axes, and the degree of clustering is gradually increasing. Economically contracted towns tend to appear more concentrated.

3.2 Spatial Evolution Analysis of Multi-Dimensional Shrinkage

(1) Analysis of Shrinkage Intensity Evolution

In order to further study the temporal evolution of shrinkage intensity in different dimensions of county-level towns in the three provinces of Northeast China, this section examines the changes in shrinkage intensity from 2006 to 2010, 2011 to 2015, and 2016 to 2020. The analysis focuses on the evolution of shrinkage intensity between consecutive periods and the relationships between these changes. The primary method involves plotting scatter diagrams with shrinkage intensity from the previous period on the horizontal axis and shrinkage intensity from the following period on the vertical axis. These scatter diagrams are divided into eight zones, representing eight types of shrinkage evolution. The classification criteria for each type of evolution pattern between periods i and j are shown in Table 5, and the zoning method is illustrated in Figure 5.

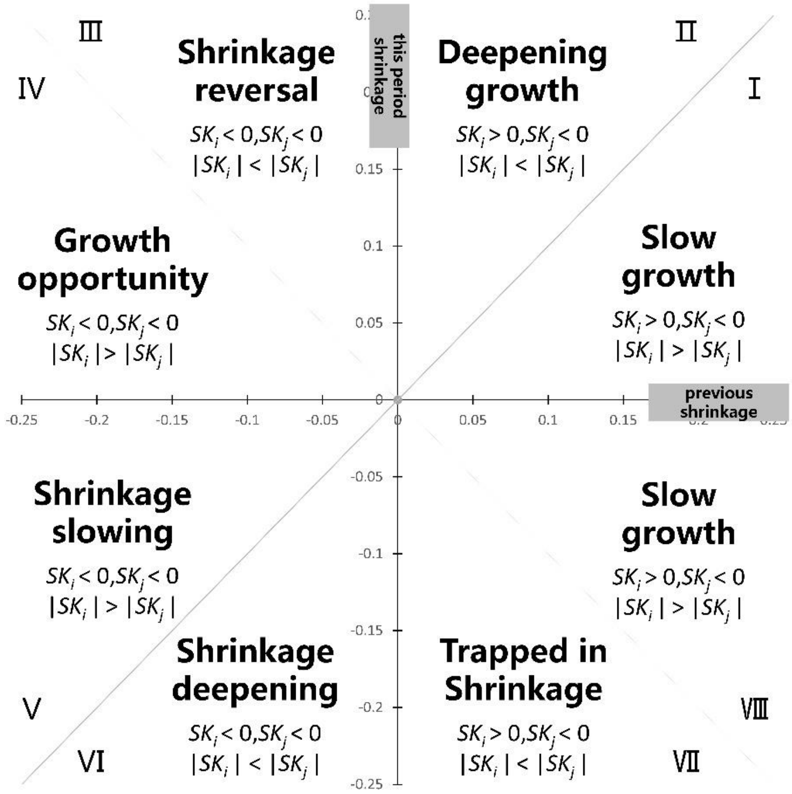
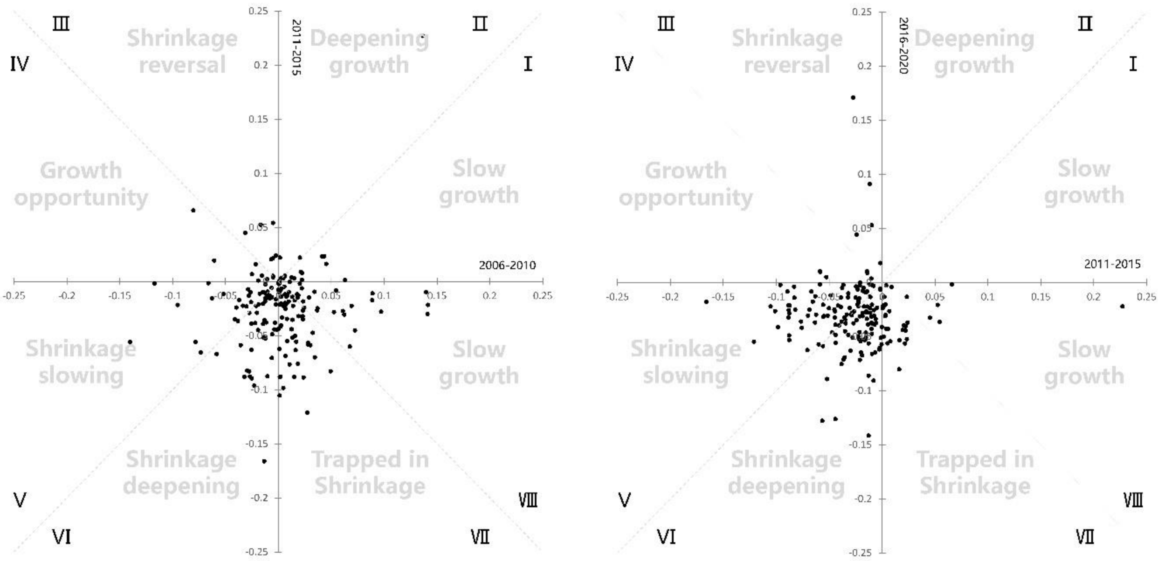


Figure 5. Schematic diagram of classification standard of shrinking evolution mode. Source: Self Drawing

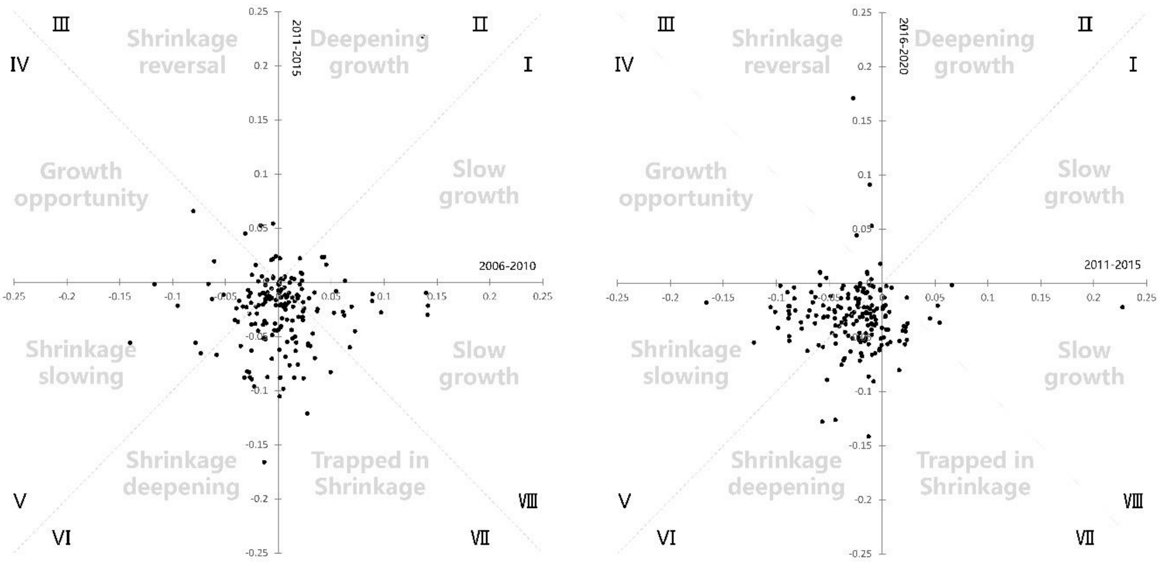
Table 5. Classification Criteria for Shrinkage Evolution Patterns. Source: Self Drawing.

Major categories	Subclass	Partition principle
Continuous growth	**Deepening growth**	Both periods growth, and the growth rate in the later period is higher
	Slow growth	Both periods growth, and the growth rate in the later period is lower
Continuous shrinking	**Shrinkage deepening**	Both periods shrinking, and the growth rate in the later period is higher
	Shrinkage slowing	Both periods shrinking, and the growth rate in the later period is lower
First increase and the n decrease	**Trapped in Shrinkage**	Growth followed by shrinking, and the degree of shrinking is higher
	Shrinkage risk	Growth followed by shrinking, and the degree of shrinking is lower
Shrink first and then e nlarge	**Shrinkage reversal tr ansformation**	Shrinking followed by growth, and the degree of shrinking is higher
	Growth opportunity	Shrinking followed by growth, and the degree of shrinking is lower



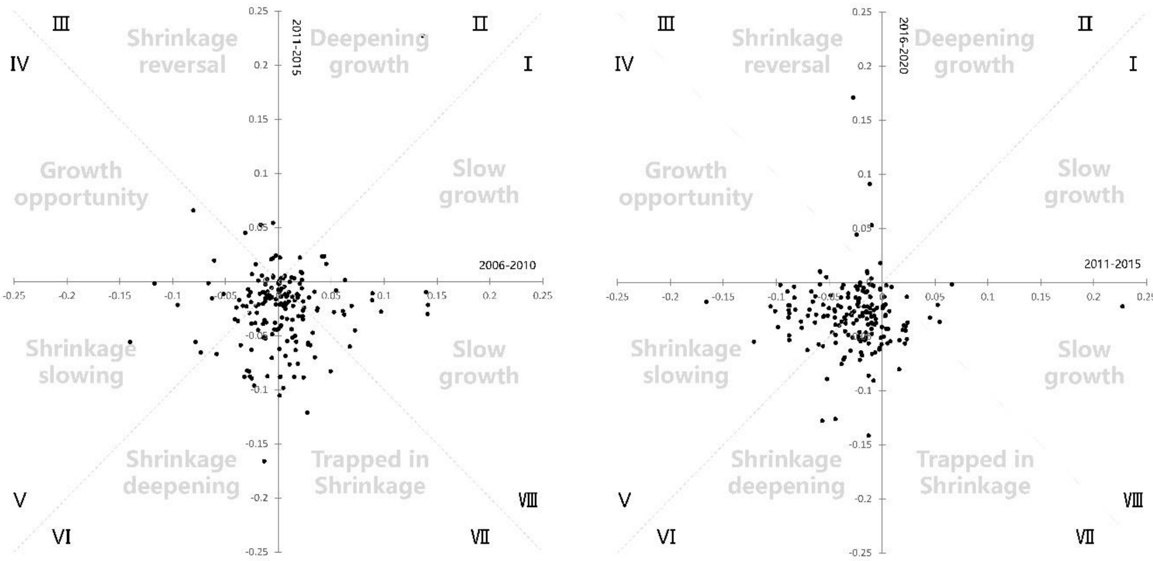
a. From 2006-2010 to 2011-2015 b. From 2011-2015 to 2016-2020

Figure 6. Analysis on the evolution of shrinking degree: population dimension



a. From 2006-2010 to 2011-2015 b. From 2011-2015 to 2016-2020

Figure 7. Analysis on the evolution of shrinking degree: economic dimension



a. From 2006-2010 to 2011-2015 b. From 2011-2015 to 2016-2020

Figure 8. Analysis on the evolution of shrinking degree: social dimension

In the population dimension (Figure 6), most towns experienced shrinkage between 2011–2015, with many of the towns that had grown from 2006–2010 shifting to shrinkage. The degree of shrinkage often exceeded the previous growth levels. Towns that were already shrinking in 2006–2010 generally continued to shrink, with half showing deeper shrinkage and the other half slowing down. A few towns even displayed potential for population shrinkage reversal. From 2011–2015 to 2016–2020, shrinkage intensified; all towns that had grown in the previous period fell into shrinkage, with most experiencing more severe shrinkage than their previous growth. In summary, the most common patterns are transitions from growth to sustained shrinkage or from initial shrinkage to continued shrinkage, showing a trend toward consistent and widespread population decline.

In the economic dimension (Figure 7), most urban areas saw economic growth between 2006–2010, followed by a mixed pattern of shrinkage and continued growth from 2011–2015. Towns with sustained growth often experienced slowing growth rates, while towns with shrinkage faced relatively mild declines, indicating a risk of future shrinkage without severe downturns. From 2011–2015 to 2016–2020, a marked polarization occurred, with towns either in "sustained growth" or "sustained shrinkage" categories. Towns switching between growth and shrinkage were few, indicating a trend where economic trajectories are becoming increasingly fixed. Overall, economic development across the periods resembles a process of "peeling off" towns from growth into shrinkage, eventually leading to persistent economic decline in many areas.

In the social dimension (Figure 8), from 2006–2010 to 2011–2015, most towns continued to grow socially, with variations in growth rate; only a few towns faced mild social shrinkage, posing minimal risk. From 2011–2015 to 2016–2020, towns that experienced social shrinkage mostly returned to growth, with only two towns facing deepening shrinkage. Overall, the social dimension maintained a stable growth trend across the three periods, with most towns showing increased growth levels. Towns in zones I and II were more dispersed and farther from the origin, suggesting overall growth momentum.

In summary, population and economic shrinkage showed increasing polarization and consistency toward decline, while the social dimension remained relatively stable, continuing on a growth trajectory throughout the study period.

(2) Analysis of Shrinkage Dimension Evolution

To understand the overall patterns of shrinkage across dimensions in county-level towns of the three northeastern provinces, a statistical analysis was conducted on the combinations of shrinkage dimensions across the three time periods (2006—2010, 2011—2015, and 2016—2020). The results are shown in Table 6.

Table 6. Classification Criteria for Shrinkage Evolution Patterns. Source: Self Drawing.

Shrink dimension combination type	2006 to 2010		2011 to 2015		2016 to 2020		Total	
	Count	%	Count	%	Count	%	Count	%
Only population shrinkage	71	39.89%	78	43.82%	71	39.89%	220	41.20%
Only economic shrinkage	7	3.93%	10	5.62%	10	5.62%	27	5.06%
Only social shrinkage	3	1.69%	7	3.93%	11	6.18%	21	3.93%
Unidimensional shrinkage	81	45.51%	95	53.37%	92	51.69%	268	50.19%
Population economic shrinkage	37	20.79%	26	14.61%	32	17.98%	95	17.79%
Population social shrinkage	5	2.81%	6	3.37%	6	3.37%	17	3.18%
Economic social shrinkage	0	0.00%	2	1.12%	7	3.93%	9	1.69%
Dual dimensional shrinkage	42	23.60%	34	19.10%	45	25.28%	121	22.66%
Population economy social shrinkage	6	3.37%	7	3.93%	5	2.81%	18	3.37%

Across the three time periods, single-dimension shrinkage is the most common, accounting for over 50% of shrinking towns in the northeastern provinces. Among these, population shrinkage is the most prevalent, comprising over 40% of single-dimension cases, followed by economic shrinkage, with social shrinkage being the least frequent.

Towns with two-dimensional shrinkage represent nearly 25% of cases, with the "population and economic" combination being the most common (17.8%). The combination of population and social shrinkage is less frequent, and economic-social shrinkage is the least common. Only about 3.4% of towns experience full-dimension shrinkage (population, economic, and social), indicating that comprehensive shrinkage is rare.

Over time, from 2006–2010 to 2016–2020, the proportions of single-, two-, and three-dimension shrinkage towns have remained relatively stable. There is no significant decrease in single-dimension shrinkage or increase in multi-dimensional shrinkage, suggesting that shrinkage in one dimension does not necessarily lead to additional dimensions over time.

In summary, single-dimension shrinkage—especially population decline—is the dominant form of urban shrinkage in county-level towns in the northeastern provinces. While multi-dimensional shrinkage occurs, there is no clear trend that shrinkage expands across dimensions as it progresses.

3.3 Multi-Dimensional Shrinkage Correlation Analysis

(1) Correlation Analysis

To quantify the correlations between different dimensions of shrinkage, Spearman correlation analysis was conducted using shrinkage data from the three time periods (2006 - 2010, 2011 - 2015, and 2016 - 2020). The results are presented in Table 7.

Table 7. Classification Criteria for Shrinkage Evolution Patterns. Source: Self Drawing.

Time Period	Population-Economy	Population-Social	Economy-Social

2006–2010	-0.233 (0.001***)	-0.187 (0.011**)	0.306 (0.000***)
2011–2015	-0.182 (0.014**)	-0.127 (0.086*)	0.187 (0.011**)
2016–2020	-0.171 (0.021**)	-0.118 (0.111)	0.282 (0.000***)

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Between 2006 and 2010, there was a significant correlation between population and economic shrinkage, as well as between economic and social shrinkage. Although population shrinkage also correlated with social shrinkage, the correlation coefficients for population-economy and population-society were relatively low, indicating weaker links, while the economic-social correlation was somewhat stronger.

As shrinkage progressed, the correlation between population and economic shrinkage weakened, though it remained statistically significant. By the third period, the correlation between population and social shrinkage had further declined and was no longer significant. In contrast, the correlation between economic and social shrinkage remained strong and consistently significant across all periods.

In summary, during the early stages of shrinkage, all three dimensions showed significant correlations. Over time, however, the correlations between population-economic and population-social shrinkage declined, while the economic-social correlation persisted, indicating a closer and more stable relationship between economic and social dimensions.

(2) Grey Relational Analysis

The correlation analysis above provides an understanding of the general relationships between dimensions over time, but it does not reveal the specific influence of individual factors on each dimension. To further explore the mutual influences of factors within each shrinkage dimension over time, grey relational analysis was conducted for the three time periods (2006–2010, 2011–2015, and 2016–2020). The grey relational degrees are shown in Table 8.

Table 8. Classification Criteria for Shrinkage Evolution Patterns. Source: Self Drawing.

Dimension	Factors	Correlation	Ranking
Population	Public financial expenditure	0.974	1
	Number of hospital beds	0.971	2
	GDP	0.963	3
	Revenue	0.961	4
	GDP growth rate	0.792	5
	Industrial Structure Index	0.712	6
Economic	Public financial expenditure	0.829	1
	Number of hospital beds	0.775	2
	Total population	0.745	3
	Population change rate	0.737	4
Social	Total population	0.977	1
	GDP	0.976	2
	Revenue	0.972	3
	Population change rate	0.965	4
	GDP growth rate	0.789	5
	Industrial Structure Index	0.709	6

In the population dimension, four factors have correlation coefficients above 0.9 with population shrinkage, highlighting that the key to retaining residents lies in high-quality urban infrastructure and public services, followed by economic development.

In the economic dimension, urban infrastructure is strongly linked to economic levels, while social services, population size, and population change show a slightly lower correlation with economic performance.

In the social dimension, four factors are also highly correlated (above 0.9) with population shrinkage. Population size is the primary factor affecting social shrinkage, as it determines demand for social infrastructure, followed by economic development, which influences funding for social projects, and population change rate, which impacts the pace of social development.

In summary, correlations between factors across dimensions show a hierarchical pattern, with stronger links between population and social factors. Per capita fiscal revenue, hospital beds, GDP, and fiscal revenue are significantly correlated with population shrinkage.

4. Conclusions and Recommendations

4.1 Conclusions

This study analyzes the status and evolution of urban shrinkage in counties of the China's three northeastern provinces from a multidimensional framework, explores the correlation between multidimensional shrinkage, and proposes policy recommendations for planning response. The main conclusions are as follows:

(1) Spatial Evolution: the shrinkage of population dimension has gone through a process from scattered distribution to regional aggregation, and then to comprehensive deployment, with the aggregation gradually becoming less significant; The economic dimension has shifted from a scattered distribution to a clustered distribution, and spatial clustering remains significant; Over time, the population loss of cities located closer to inland areas in the counties and cities of the three northeastern provinces has become increasingly severe;

(2) Temporal Evolution: Population shrinkage remained steady across most towns, with an even split between intensifying and slowing trends. Economic shrinkage followed a clear path from growth to decline, leading to polarized outcomes of "persistent shrinkage" or "persistent growth." Shrinkage in multiple dimensions is not inevitable; single-dimension shrinkage predominates, with around 20% of towns experiencing two-dimensional shrinkage (primarily "population-economy"), and few experiencing comprehensive three-dimensional shrinkage.

(3) Multi-Dimensional Correlation: Significant correlations exist between shrinkage dimensions in the early stages, but these weaken over time. Multi-dimensional shrinkage can lead to a vicious cycle, where shrinkage in one dimension triggers others, potentially leading to comprehensive urban decline.

4.2 Recommendations

(1) Enhance Shrinkage Assessment and Develop Specialized Response Plans

According to the research findings, there are differences in the dimensions, degree, and duration of urban shrinkage in the three provinces of Northeast China. The impact and driving factors of urban shrinkage also vary among different cities. Therefore, the most effective coping strategies for urban shrinkage should also differ among different cities. Combining the contraction response thinking of the systematic treatment of "acupuncture and moxibustion - whole therapy", exploring the key problems of urban contraction and identifying the negative impact of contraction is an important basis for accurate response to contraction. The special plan for contraction response combined by "acupuncture and moxibustion" to address the key problems and "whole therapy" to eliminate the overall impact is an important means to achieve effective treatment of contraction. Therefore, it is necessary to have a clear understanding of the important impact of shrinkage background on urban development, strengthen the status of urban shrinkage examination work, and carry out special planning for shrinkage response.

(2) Optimize Spatial Patterns and Leverage Regional Gateway Advantages

According to the research findings, the distribution pattern of shrinking cities in the three provinces of Northeast China is significantly characterized, and some regions have significant clustering, especially in terms of economic dimension clustering and outliers. Therefore, solving the problem of shrinking from a regional perspective is crucial. Combining the coping strategy of "internal supplementation external adjustment" penetrative therapy, contraction physical examination and special planning are the urban "repair" to cope with contraction, while leveraging regional linkage advantages and building urban cooperation patterns are the regional "regulation" to cope with contraction. Only by combining the two can a new trend of regional growth be constructed. Therefore, it is important to recognize the importance of contraction in response to urban cooperation, and to construct a coordinated approach for urban contraction areas. Combining the characteristics of lighter contraction in border towns and significant growth in contraction areas, we should optimize the urban spatial pattern and leverage the advantages of regional external windows.

(3) Promote Compact Urban Development and Enhance Town Development Quality

According to research findings, the process of sustained and highly contracted urban shrinkage, as well as the trend of polarized development, tells us that irreversible shrinkage has become a certainty for some cities. Therefore, we should transform our growth mindset and develop the correct scale for these cities. Combining the coping strategy of "reducing fat and increasing muscle" strengthening treatment, intensive development, rational disposal of inefficient land and redundant facilities, restoration of vitality in the central area, and improvement of urban construction quality are the correct paths.

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