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Research on identification, classification, and policy development for urban shrinkage: A case study of Liaoning Province, China

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Abstract. Under the influence of economic globalization and the transformation of pillar industries, cities are facing phenomena such as slow economic growth and population outflow, which indicate urban shrinkage. However, the theoretical framework for this phenomenon remains incomplete, and measurement standards are inconsistent. Therefore, studying urban shrinkage is of significant importance. This paper analyzes the current status and causes of urban shrinkage in Liaoning Province, China, and proposes an accurate model for identifying shrinkage. It utilizes a two-step diagnostic method that incorporates both one-dimensional and multidimensional approaches to identify shrinking cities and applies systematic clustering methods to categorize urban population changes. By observing and analyzing the population and economic data of 30 cities over 12 years, this study assesses urban shrinkage from the perspectives of population change and multivariate indicators. It identifies five cities with significant shrinkage, categorized into mild, moderate, and severe levels. Based on multiple linear regression and grey relational analysis, the study examines the impact of socio-economic factors on population changes and offers corresponding development suggestions.

Keywords: Two-step diagnostics, Principal component analysis, Systematic clustering, Multiple linear regression, Grey relational analysis, Urban shrinkage

1. Introduction

Urban shrinkage is a global urban development and socio-economic issue that emerged in the mid-20th century [1], challenging the traditional notion of continuous urban growth. It redefines the evolutionary paths of cities, primarily involving urban population loss and economic stagnation. With economic globalization and urban industrial transformation, China also faces the pressures of urban shrinkage driven by slowing economic growth [2].

In China, Liaoning Province, as a typical resource-based and industrial support region, experienced dual growth in economy and population in earlier stages due to resource advantages and policy incentives. However, subsequent economic reforms and resource depletion led to economic decline and massive population outflow, resulting in urban shrinkage. Nevertheless, current theories on urban shrinkage in China remain incomplete, and the measurement standards for indicators are still unclear [3].

Thus, this paper aims to introduce a one-dimensional and multidimensional "two-step diagnostic method" for identification and classification models, supporting qualitative research on urban shrinkage. It also proposes an indicator weight analysis method based on multiple linear regression and grey relational analysis, offering suggestions for urban development.

The main contributions of this work include:

(1) Using the "two-step diagnostic method" to accurately identify and classify shrinking cities in Liaoning Province. Initially, cities experiencing a population loss exceeding 10% of the total population or an annual average population loss rate greater than 1% are identified as one-dimensional shrinking cities. Then, by considering economic and social indicators through principal component analysis, the development levels of cities are evaluated to identify multidimensional shrinking cities. Finally, systematic clustering methods are used to categorize changes in urban population.

(2) Analyzing the impact of socio-economic factors on population changes. For prefectural-level cities, a multiple linear regression analysis method is used, selecting socio-economic factors as independent variables and population change as the dependent variable, to progressively regress and choose the most suitable independent variables for analysis. For counties with less data, the grey relational analysis method is used to determine the degree of correlation between socio-economic factors and population changes.

(3) Based on analyzing the current status, causes, and development trends of urban shrinkage in Liaoning Province, this paper proposes accurate methods to identify urban shrinkage and offers suggestions for influencing factors.

The structure of this paper is organized as follows: Section 2 reviews the literature on urban shrinkage. Section 3 describes the model building process, followed by Section 4, which implements the model based on urban data from Liaoning Province, China. Section 5 discusses the findings based on this research.

2. Literature Review

The phenomenon of urban shrinkage has been extensively discussed by Martinez-Fernandez et al. [1], who used population decline as a core indicator while identifying multiple causes of urban shrinkage, providing a foundation for further in-depth exploration. Chen Dan and others [4] in their review articles, point out that urban shrinkage is not only a common phenomenon in the urbanization process but also a cutting-edge issue. Yu Shangkun and others [2] have delved into the impact of urban shrinkage in the three northeastern provinces of China on resilience, showcasing its characteristics across population, economic, and spatial dimensions.

Regarding government intervention in urban shrinkage, research by Jaroszewska and Stryjakiewicz [5] in the context of Poland explores how to alleviate urban shrinkage, emphasizing the importance of effective policies. Research by Jin Yu and others [6], as well as Ma Zuopeng and others [7], shows that local government management and innovation levels are crucial to urban resilience, with urban shrinkage exhibiting heterogeneity and interactive effects at different scales.

From the literature summarized, it is evident that urban shrinkage is a complex, multidimensional field. A comprehensive approach is needed to fully understand its causes, impacts, and coping strategies, which can then provide scientific bases and guidance for urban planning and policy formulation.

3. Research Methods

This paper primarily collects socio-economic data from 30 prefecture-level and county-level cities in Liaoning Province, mainly sourced from the statistical yearbooks of various provinces and cities. The main research methods include:

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3.1. Principal Component Analysis (PCA)

Principal Component Analysis quantitatively utilizes indicators and data. The steps include data collection, standardization, calculation of the covariance matrix or correlation matrix, then computing eigenvalues and eigenvectors, selecting the number of principal components, calculating principal component scores, and finally interpreting and applying the results.

3.2. Systematic Clustering

Systematic clustering involves calculating the distances between data points and grouping close data together, iterating until all data are clustered into one group. The necessary number of clusters is selected for classification, and the clustering results are then interpreted and applied. The distance between samples is calculated using the Euclidean distance:

$$d_{ij} = \sqrt{\sum_{k=1}^{p} (x_{1k} - x_{2k})^{2}} \tag{1}$$

3.3. Multiple Linear Regression Analysis Model

The multiple linear regression model identifies the quantitative expression that best represents the relationship between independent variables and the dependent variable. The specific steps are as follows: set the dependent variable as y, and the independent variables as $x_1, x_2, \ldots, x_n$. $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon$. The regression constant is β_0 and the regression coefficients are $\beta_2, \ldots, \beta_k$ with random error terms ε_i (i=1,…,k)that satisfy:

$$\begin{cases} E(\varepsilon_i) = 0 \\ Var(\varepsilon_i) = \sigma^2 \\ \varepsilon_1, \varepsilon_2, \ldots, \varepsilon_k \ are\ independent\ of\ each\ other \end{cases} \tag{2}$$

The analysis starts with a correlation analysis to measure the closeness between explanatory variables and the dependent variable. A multiple regression model is then established, introducing independent variables one by one and conducting F-tests to select those variables that significantly impact the dependent variable. Finally, regression testing is done. Under the null hypothesis, a t-test is applied. If the observed value of the t-statistic is higher than the significance level, the independent variable should be removed.

3.4. Grey Relational Analysis Model

When the sample size is too small for regression analysis to be applicable, grey relational analysis is used instead. The process includes data preparation, serialization, standardization, constructing a relational degree matrix, determining the reference sequence, calculating the degree of relation, ranking the analysis results, and ultimately interpreting and applying them.

4. Results and Analysis

4.1. Data Preprocessing

In the population statistics of 30 cities in Liaoning Province, China, there are missing and outlier values. Outliers are first removed, followed by interpolation and fitting of missing values using cubic spline interpolation, considering the sparse amount of missing data.

4.2. Identification of Shrinking Cities

The criteria for identifying shrinking cities are established based on either a total population loss exceeding 10% or an annual average population loss rate greater than 1%. The formulas for calculating the proportion of population loss to total population, average population growth rate, or population loss rate are as follows:

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$$r = \frac{P_{early} + P_{late}}{P_{late}} \tag{3}$$

$$r = \sqrt[n]{\frac{P_1}{P_0} \cdot \frac{P_2}{P_1} \cdot \frac{P_3}{P_2} \cdot \dots \cdot \frac{P_n}{P_{n-1}}} = \sqrt[n]{\frac{P_n}{P_0}} \tag{4}$$

The end-of-period population is denoted by P_{late} and the initial population by P_{early};$P_i, i = 1,2,3, \cdots, n$, with each year's total population denoted by n.

According to the criterion of a population loss rate greater than 10%, five cities meet this standard, as shown below:

Table 1. Initial Assessment of Shrinking City Populations

	Benxi	Linghai	Dengta	Diaobingshan	Beipiao
2009	95.54	57.36	51.54	24.15	59.56
2010	95.13	56.94	51.08	24.13	58.54
2011	94.93	56.85	50.52	24.10	58.23
2012	94.2	56.67	44.52	23.85	58.09
2013	93.61	56.33	44.54	23.77	57.56
2014	93.28	56.09	44.61	23.70	57.61
2015	92.54	51.49	44.44	23.50	57.24
2016	91.63	51.37	44.43	23.40	57.02
2017	90.24	50.51	43.80	22.92	55.80
2018	89.09	50.23	43.61	22.62	55.56
2019	87.89	49.90	43.42	22.25	55.19
2020	86.46	49.22	42.91	21.76	54.05
Population Loss Rate (%)	-0.10502	-0.16532	-0.20127	-0.1099	-0.10198

Linghai and Dandong have an annual average population loss rate exceeding 1%, meeting the criteria for shrinking cities, and are categorized together with the other three cities. Thus, Benxi, Linghai, Dandong, Diaobingshan, and Beipiao are identified as shrinking cities in Liaoning Province.

The evolution of urban shrinkage is influenced by multiple dimensions, complicating the analysis. However, due to the interrelation among indicators, a comprehensive evaluation model can be constructed, and Principal Component Analysis can be used to identify and assess urban shrinkage in Liaoning Province.

Due to some missing data, the analysis uses data from the years 2009 and 2018 for prefecture-level cities, and 2013 and 2016 for county-level cities, totaling 30 sample cities. The cities are denoted by i=1,2,3,…,30, with the indicators for city i recorded as [x_{i1},x_{i2},x_{i3},x_{i4}], forming a 30x4 sample matrix x. The specific indicators and sample matrix are shown below:

Table 2. Principal Component Analysis Evaluation Indicators Table

Objective Layer	**Economic Dimension**	**Fiscal Security Dimension**	**Investment Consumption Dimension**
Indicator Layer	Secondary and Tertiary Industry Employment X_1 Regional GDP Total X_2	General Public Budget Expenditure X_3	Total Retail Sales of Consumer Goods X_4

$$x = \begin{bmatrix} \mathbf{x_{11}} & \mathbf{x_{12}} & \cdots & \mathbf{x_{14}} \\ \mathbf{x_{21}} & \mathbf{x_{22}} & \cdots & \mathbf{x_{24}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{x_{301}} & \mathbf{x_{302}} & \cdots & \mathbf{x_{304}} \end{bmatrix} = (\mathbf{x_1}, \mathbf{x_2}, \dots, \mathbf{x_{30}})$$

First, the sample matrix is standardized. The elements of the matrix, i.e., the mean and standard deviation of the data from the 30 cities $\overline{x_j}$ and S_j, resulting in standardized data X_{ij}.

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$$\overline{x_j} = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \tag{5}$$

$$S_j = \sqrt{\frac{\sum_{i=1}^{n}\left(x_{ij} - \overline{x_j}\right)^2}{n-1}} \tag{6}$$

$$X_{ij} = \frac{x_{ij} - \overline{x_j}}{S_j} \tag{7}$$

After standardization, the matrix becomes: $x = \begin{bmatrix} \mathbf{x_{11}} & \mathbf{x_{12}} & \cdots & \mathbf{x_{14}} \\ \mathbf{x_{21}} & \mathbf{x_{22}} & \cdots & \mathbf{x_{24}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{x_{301}} & \mathbf{x_{302}} & \cdots & \mathbf{x_{304}} \end{bmatrix} = (\mathbf{x_1}, \mathbf{x_2}, \dots, \mathbf{x_{30}})$

Subsequently, the sample correlation coefficient matrix for the standardized matrix is calculated:

$$R = \frac{\sum_{k=1}^{n}(x_{ki} - \overline{x_i})\left(x_{ij} - \overline{x_j}\right)}{\sqrt{\sum_{k=1}^{n}(x_{ki} - \overline{x_i})^2 \sum_{k=1}^{n}\left(x_{kj} - \overline{x_j}\right)^2}} \tag{8}$$

Next, the eigenvalues λ and eigenvectors a based on the urban shrinkage indicators' sample correlation coefficient matrix R are calculated using *MATLAB*, satisfying $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \lambda_4 \geq 0$, with corresponding eigenvectors $a_1, a_2, \dots, a_{30}$, among which $a_j = [a_{1j}, a_{2j}, \dots, a_{30j}]$.

The contribution rate of the principal components of the urban shrinkage matrix is then calculated.

$$contribution\ rate = \frac{\lambda_i}{\sum_{k=1}^{30}\lambda_k}\ (i = 1,2,\dots,4) \tag{9}$$

The eigenvalues, contribution rates, and cumulative contribution rates for each city $x_1, x_2, \dots, x_{30}$are shown in the following tables.

Table 3. Results for Prefecture-Level Cities in 2009 and 2018

Index	2009			2018		
	Eigenvalue	Contribution Rate	Cumulative Contribution Rate	Eigenvalue	Contribution Rate	Cumulative Contribution Rate
X1	4.9124	0.9825	0.9825	4.7291	0.9458	0.9458
X2	0.0557	0.0111	0.9936	0.2371	0.0474	0.9932
X3	0.0209	0.0042	0.9978	0.0214	0.0043	0.9975
X4	0.0093	0.0019	0.9996	0.0109	0.0022	0.9997
X5	0.0018	0.0004	1.0000	0.0015	0.0003	1.0000

Table 4. Results for County-Level Cities in 2013 and 2016

Index	2013			2016		
	Eigenvalue	Contribution Rate	Cumulative Contribution Rate	Eigenvalue	Contribution Rate	Cumulative Contribution Rate
X1	4.3682	0.8736	0.8736	4.1264	0.8253	0.8253
X2	0.3904	0.0781	0.9517	0.6901	0.1380	0.9633
X3	0.1519	0.0304	0.9821	0.1287	0.0257	0.9890
X4	0.0689	0.0138	0.9959	0.0331	0.0066	0.9957
X5	0.0206	0.0041	1.0000	0.0216	0.0043	1.0000

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For both prefecture-level and county-level cities, the first two principal components reach cumulative contribution rates of 99% and above 95% respectively, suggesting using only the first two principal components for effective summarization of original variables and comprehensive analysis.

The comprehensive evaluation model for the prefecture-level cities in 2009, 2018, and county-level cities in 2013, 2016 can be expressed as:

$$\begin{aligned} F_1 &= 0.9825X_1 + 0.0111X_2 \\ F_2 &= 0.9458X_1 + 0.0474X_2 \\ F_3 &= 0.8736X_1 + 0.0781X_2 \\ F_4 &= 0.8253X_1 + 0.1380X_2 \end{aligned} \tag{10}$$

Scoring results are calculated and normalized, and the scores for each city in different years are detailed below.

Table 5. Shrinkage Analysis Results for Prefecture-Level and County-Level Cities

Prefecture-Level Cities					County-Level Cities				
City	2009 Development Score	2018 Development Score	Difference in Development Level	Shrinking Status	**City**	2009 Development Score	2018 Development Score	Difference in Development Level	Shrinking Status
Shenyang	0.325027	0.309675	-0.01535	Yes	**Xinmin**	0.067727	0.058285	-0.00944	Yes
Dalian	0.267704	0.327161	0.059457	No	**Wafangdian**	0.158349	0.227139	0.06879	No
Anshan	0.095541	0.052189	-0.04335	Yes	**Zhuanghe**	0.122739	0.149592	0.026853	No
Fushun	0.045864	0.04991	0.004046	No	**Haicheng**	0.131605	0.125932	-0.00567	Yes
Benxi	0.045039	0.032306	-0.01273	Yes	**Donggang**	0.076716	0.056381	-0.02033	Yes
Dandong	0.019278	0.013156	-0.00612	Yes	**Fengcheng**	0.068393	0.042758	-0.02564	Yes
Jinzhou	0.031976	0.038606	0.00663	No	**Linghai**	0.039843	0.038378	-0.00146	Yes
Yingkou	0.039942	0.046858	0.006916	No	**Beizhen**	0.021923	0.029913	0.00799	No
Fuxin	0.014243	0.012095	-0.00215	Yes	**Gaizhou**	0.034539	0.041571	0.007032	No
Liaoyang	0.029496	0.033085	0.003589	No	**Dashiqiao**	0.0771	0.066006	-0.01109	Yes
Panjin	0.038256	0.043299	0.005043	No	**Dengta**	0.03825	0.030193	-0.00806	Yes
Tieling	0.011224	0.007367	-0.00386	Yes	**Diaobingshan**	0.027009	0.021964	-0.00505	Yes
Chaoyang	0.012053	0.011742	-0.00031	Yes	**Kaiyuan**	0.049501	0.023498	-0.026	Yes
Huludao	0.024354	0.022552	-0.0018	Yes	**Beipiao**	0.034572	0.027547	-0.00703	Yes

To enhance the effectiveness of the evaluation system and results, cities identified by both one-dimensional and multidimensional indicators are determined as shrinking cities. The cities finally identified as shrinking include Benxi, Linghai, Dandong, Diaobingshan, and Beipiao.

Following the classification of shrinking cities, considering the annual population loss, similar cities are grouped together. Based on the population change data and charts from 2010-2020, it is found that Dandong's population loss rate reached 20%, Linghai's was 16%, with the rest around 11%. Systematic clustering methods are used for classification, with the dendrogram as shown below, dividing the shrinking cities into three categories: Dandong as a severely shrinking city, Linghai as moderately shrinking, and Diaobingshan, Beipiao, and Benxi grouped together as mildly shrinking cities.

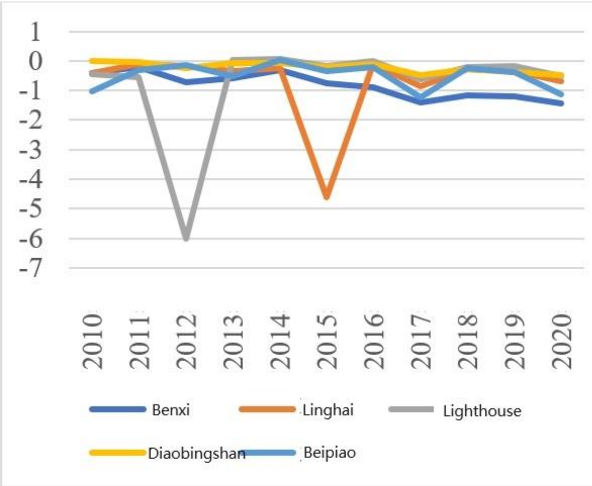

Figure 1. Population Loss Chart for Shrinking Cities

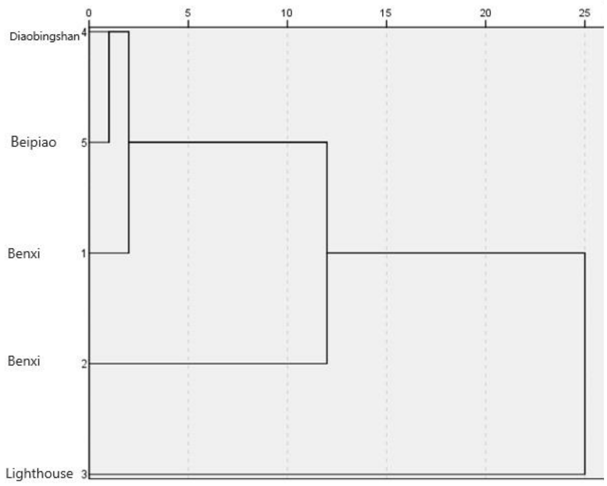

Figure 2. Systematic Clustering Classification Chart for Shrinking Cities

4.3. Analysis of Socio-Economic Factors on Population Change

Firstly, based on linear assumptions and multicollinearity, this paper selects four factors: GDP, public budget expenditure, fixed asset investment, and employment in the secondary and tertiary industries, to study the impact of socio-economic factors on population change. Descriptive statistics are provided below:

Table 6. Descriptive Statistics Results

Variable	Mean	Std. Dev.	Min	Max
GDP (ten thousand yuan)	6649101	1282711	5081110	8434548
Public Budget Expenditure (ten thousand yuan)	1066179	180371	740673	1304906
Fixed Asset Investment (ten thousand yuan)	3193817	1798092	1328359	6201696
Employment in Secondary and Tertiary Industries (ten thousand people)	20.4275	4.06032	12.42	27.02

The descriptive statistics reveal that the identified shrinking cities have an average GDP of 6,649,101 ten thousand yuan, with the highest reaching 8,434,548 ten thousand yuan; these cities' total GDP and other indicators are lower compared to expanding cities.

Next, an analysis of variance is conducted for this model, setting the null hypothesis as$H_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$. The results are presented below:

Table 7. Model Analysis of Variance Results

	df	SS	MS	F	Significance F
Regression	4	93.4691	23.36728	26.95456	0.00024
Residual	7	6.068395	0.866914		
Total	11	99.5375			

The joint significance test F-statistic is 26.95456, with a p-value of 0.00024, less than 0.05, leading to the rejection of the null hypothesis β_1、β_2、β_3、$\beta_4$suggesting that the coefficients are not all zero. A VIF test is conducted for the model in Benxi City:

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Table 8. VIF Test Results for Benxi City Model.

Variable	VIF	1/VIF
Fixed Asset Investment	24.83	0.04028
Employment Number	11.55	0.08655
GDP	8.74	0.114481
Public Budget Expenditure	1.7	0.587546

Fixed asset investment and employment numbers are affected by multicollinearity, whereas GDP and public budget expenditure are not affected. Therefore, stepwise regression is used to eliminate variables affected by multicollinearity. The stepwise regression results are as follows:

Table 9. Stepwise Regression Results

Population (ten thousand people)	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Employment~people	0.1637356	0.1450382	1.13	0.292	-0.170723	0.4981943
Public Budget~yuan	-0.0000121	2.27E-06	-5.33	0.001	-0.0000173	-6.88E-06
Fixed Asset~yuan	1.18E-06	4.63E-07	2.55	0.034	1.12E-07	2.25E-06
_cons	97.84538	4.008189	24.41	0	88.60248	107.0883

Public investment and fixed asset investment have p-values <0.05, considered significant, while the employment number in secondary and tertiary industries is not significant and is not suitable as an independent variable. The final selected variables for multiple linear regression analysis are public investment and fixed asset investment, with population as the dependent variable. The analysis results are as follows:

Table 10. Multiple Linear Regression Analysis Results.

Population (ten thousand people)	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Public Budget~yuan	-0.0000129	1.86E-06	-6.93	0	-0.0000171	-8.69E-06
Fixed Asset~yuan	1.55E-06	1.86E-07	8.33	0	1.13E-06	1.98E-06
_cons	100.8251	1.859302	54.23	0	96.61908	105.0311

The regression equation is as follows:

$$P = -0.0000129x_1 + 1.55 \times 10^{-6}x_2 + 100.8251 \tag{11}$$

After testing the goodness of fit of regression through the following table, it can be seen that the adjusted coefficient of determination is 0.9049, indicating that the regression model has a good fitting effect, and the sub-model can be used for analysis.

```
      Source |       SS           df       MS      Number of obs   =        12
-------------+----------------------------------   F(2, 9)         =     42.83
       Model |  90.0735737         2  45.0367868   Prob > F        =    0.0000
    Residual |  9.46392633         9  1.05154737   R-squared       =    0.9049
-------------+----------------------------------   Adj R-squared   =    0.8838
       Total |     99.5375        11  9.04886364   Root MSE        =    1.0254
```

Figure 3. Regression Goodness of Fit Test Chart

Due to the different scales of the variables, standardized regression analysis is conducted, with results as follows:

Table 11. Standardized Regression Analysis Results.

Population (ten thousand people)	Coef.	Std. Err.	t	P>t	Beta
Public Budget~yuan	-0.0000129	1.86E-06	-6.93	0	-0.7729276
Fixed Asset~yuan	1.55E-06	1.86E-07	8.33	0	0.928941
_cons	100.8251	1.859302	54.23	0	.

Fixed asset investment has the most significant impact on population change, followed by public budget inputs. As GDP is highly correlated with other investments, it was not used as an independent variable in the regression model. The impact of fixed asset investment on population change indirectly reflects the role of GDP. Higher GDP indicates more investment in public facilities or fixed assets, suggesting a vibrant local economy that attracts more investment, thereby prompting an increase in fixed asset investment.

These are the results of the multiple linear analysis for Benxi City. Next, the analysis will consider the other four county-level cities. As their data is limited, the above method is not applicable. Therefore, we first analyze the statistical charts of various socio-economic factors and population changes for each city. Initial statistics suggest a strong relationship between population changes and the four selected socio-economic factors, allowing for analysis using the grey forecasting model. After preprocessing the data, the correlation degree is calculated as follows:

$$y\big(x_0(k), x_i(k)\big) = \frac{a + \rho b}{|x_0(k) - x_i(k)| + \rho b} \tag{12}$$

$$y(x_0, x_i) = \frac{1}{n}\sum_{k=1}^{n} y\big(x_0(k), x_i(k)\big) \tag{13}$$

where a and b represent the maximum and minimum differences between levels, respectively; ρ is the distinguishing coefficient, set at 0.5; $y(x_0, x_i)$ is the correlation degree. The final correlation degrees for these four cities are as follows:

Table 12. Correlation Degree Results for Each City

City	GDP	Public Budget Expenditure	Total Retail Sales of Consumer Goods	Employment Numbers in Secondary and Tertiary Industries
Diaobingshan	0.5766	0.6286	0.854025	0.751975
Dengta	0.649125	0.83615	0.4011	0.75145
Linghai	0.553	0.800175	0.5334	0.741825
Beipiao	0.63135	0.7203	0.8175	0.648375

In these four shrinking cities, the main factors affecting population change are public budget expenditure and total retail sales of consumer goods. Although GDP is also important, its impact is less significant than the aforementioned factors because GDP primarily promotes the growth of other economic indicators rather than directly reflecting it. As GDP increases, public budget expenditures and total retail sales also rise, while the increase in fixed asset investment drives industry development and job opportunities, thereby reflecting in population growth.

Based on the impact of each indicator on population change, this paper suggests the following: (1) Population: Encourage the implementation of the “Two-Child Policy” to adjust the age structure of the population, attract migrants to improve population quality, and develop feasible policies to retain talent. (2) Economic: Actively adjust the industrial structure, increase secondary and tertiary industry positions to provide more high-income job opportunities. (3) Social: Strengthen infrastructure construction, improve the urban environment, and create livable cities, reflected in general public expenditure.

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5. Conclusion

This study conducted an in-depth analysis of urban shrinkage in Liaoning Province and successfully established an identification model for urban shrinkage based on a one-dimensional and multidimensional “two-step diagnostic method”, effectively classifying shrinking cities. The research shows that there are five cities within Liaoning Province that exhibit significant shrinkage, which were categorized into three classes—mild shrinkage, moderate shrinkage, and severe shrinkage—using systematic clustering methods. Additionally, this paper employed multiple linear regression and grey relational analysis to thoroughly explore the impact of socio-economic factors on urban population changes, thus providing a scientific basis for urban management and policy formulation.

Through this research, we have provided not only a precise model for assessing and classifying urban shrinkage specific to the characteristics of Liaoning Province and China at large, but we have also revealed the main socio-economic factors driving urban shrinkage, offering important references for related decision-making. Future research could further explore how to effectively utilize these factors to formulate effective policy measures aimed at slowing or reversing the trend of urban shrinkage, thereby promoting sustainable urban development.

References

[1] Martinez-Fernandez, C., Audirac, I., Fol, S., & Cunningham-Sabot, E. (2012). Shrinking cities: Urban challenges of globalization. International journal of urban and regional research, 36(2), 213-225.

[2] Yu, S., Wang, R., Zhang, X., Miao, Y., & Wang, C. (2023). Spatiotemporal Evolution of Urban Shrinkage and Its Impact on Urban Resilience in Three Provinces of Northeast China. Land, 12(7), 1412.

[3] Liu, G., Xie, F., Hong, J., & Chen, C. (2019). Urban Shrinkage in China Based on the Data of Population and Economy. Economic Geography, (07), 50-57.

[4] Chen, D., Fang, C., & Liu, Z. (2023). Progress and major themes of research on urban shrinkage and its eco-environmental impacts. Journal of Geographical Sciences, 33(5), 1113-1138.

[5] Jaroszewska, E., & Stryjakiewicz, T. (2020). Drivers, scale, and geography of urban shrinkage in Poland and policy responses. Journal of Urban Planning and Development, 146(4), 05020021.

[6] Jin, Y., Zhou, G., Liu, Y., Sun, H., & Fu, H. (2022). Resilience difference between growing and shrinking resource-exhausted cities and its influencing factors. Journal of Urban Affairs, 1-17.

[7] Ma, Z., Zhou, G., Zhang, J., Liu, Y., Zhang, P., & Li, C. (2024). Urban shrinkage in the regional multiscale context: Spatial divergence and interaction. Sustainable Cities and Society, 100, 105020.

[8] He, S. Y., Lee, J., Zhou, T., & Wu, D. (2017). Shrinking cities and resource-based economy: The economic restructuring in China’s mining cities. Cities, 60, 75-83.

[9] Fu, H., Zhou, G., Sun, H., & Liu, Y. (2022). Life satisfaction and migration intention of residents in shrinking cities: Case of Yichun City in China. Journal of Urban Planning and Development, 148(1), 05021062.

[10] Hu, Y. C., Liu, Y. J., & Sun, H. R. (2020). The Evolution Process and Influencing Factors of Urban Growth and Shrinkage: A Case Study of Coal Resource-Based Cities in Heilongjiang Province. Geographical Sciences, 40(9), 1450-1459.

[11] Li, Y., & Chen, Z. (2023). Does transportation infrastructure accelerate factor outflow from shrinking cities? An evidence from China. Transport Policy, 134, 180-190.

[12] Du, Z., Zhang, H., Ye, Y., Jin, L., & Xu, Q. (2019). Urban shrinkage and growth: Measurement and determinants of economic resilience in the Pearl River Delta. Journal of Geographical Sciences, 29, 1331-1345.