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Shrinkage and Expansion Mechanisms of Resource-based Cities: Analysis Based on Multidimensional Typology Definition Matrix

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K E Y W O R D S

urban shrinkage,
random forest,
resource-based cities

A B S T R A C T

The urban shrinkage phenomenon is increasingly common. However, at the same time, it is accompanied by local growth within the region, and its complex impact mechanism still lacks in-depth research. This paper takes Daqing, a resource-based city, as an example and constructs a multi-dimensional urban growth/shrinkage type definition matrix. The random forest classification model is used to quantitatively analyze the relevant factors affecting the classification matrix by comparing different models. The results show that: (1) The growth/shrinkage of Daqing City leads to a concentric structure of intensive growth—expansion growth—expansion shrinkage—intensive shrinkage that gradually changes from the center to the periphery in space. (2) The random forest classification model can better explain the cause mechanism of urban growth/shrinkage. (3) The growth/shrinkage of resource-based cities in the transformation stage is mainly affected by economic factors, such as traffic accessibility and urban morphology related to the resource economy. This study provides an evaluation framework from qualitative to quantitative, providing useful references for research and planning policy formulation in related fields.

1. Introduction

Urban shrinkage is a phenomenon that is becoming increasingly common, characterized by population loss, which first appeared at the end of the last century. With the development of globalization, the problems involved in urban shrinkage, such as inefficient land use, economic recession, etc., have become more complex and widespread (Shan et al., 2025; Shan & Gu, 2024). Moreover, urban shrinkage is gradually considered an inevitable outcome of the later stage of urban development (Bartholomae et al., 2017). Therefore, urban shrinkage has attracted widespread attention from scholars as a global phenomenon.

The definition of urban shrinkage is still controversial. Initially, people used population loss to judge whether a city was shrinking (Döringer et al., 2020). In recent years, the research on urban shrinkage has developed into a multi-dimensional perspective, and factors such as population, economy, and space are used to reflect the degree and type of urban shrinkage (Mallach et al., 2017). The classification method of urban shrinkage based on multi-dimensional definition further deepens the identification of urban shrinkage. Gao et al. classified shrinking cities by arranging and combining

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the measurement results of three dimensions: population, economy, and land use (Gao et al., 2021). Kim et al. refined the classification of shrinking cities in Korea by improving the traditional classification matrix of population and economy (Kim et al., 2022). The distilled research based on a category also provides more powerful support for discussing relevant impact mechanisms and formulating targeted policies.

Regarding relevant impact mechanisms, shrinking cities in different countries and regions have other main causes and characteristics. Shrinkage in Western countries mainly occurs in heavy industrial areas, and its main reasons are globalization, deindustrialization, and resource depletion. In Japan, factors such as aging and low fertility are the main factors leading to urban shrinkage (Döringer et al., 2020). In China, economic factors are important factors affecting shrinking cities (*Shrinking Cities in a Rapidly Urbanizing China - Ying Long, Kang Wu, 2016*). Therefore, when studying urban shrinkage in China, we must focus on economic factors, such as industrial transformation and economic structure adjustment. In addition, the continuous development of big data and computer technology provides more choices and possibilities for the research methods of relevant impact mechanisms. More sources and higher precision big data can be used to reflect and analyze urban shrinkage. For example, night light data can reflect the economic activity intensity and vitality of different locations in the same area from the perspective of spatial distribution. They thus can be used to study urban shrinkage (Jiang et al., 2020). The advancement of computer technology has also promoted the development and innovation of quantitative research methods. Empirical models such as the OLS and GWR models explore the linear correlation (Deng & Ma, 2015) and spatial distribution mechanism of urban shrinkage-related problems, respectively (Guan et al., 2021). In recent studies, nonlinear models have been used to explore the nonlinear relationship between the single measurement dimension of shrinking cities and possible related influencing factors (Peng et al., 2023), providing a new perspective for urban shrinkage research.

The current research on urban shrinkage mainly focuses on the definition and identification, cause mechanism, and other aspects of urban shrinkage. Although there are many studies on shrinking cities, due to the complexity of its agent, there is also local urban growth while shrinking. We also found some research perspectives and problems that need to be fully explored from the relevant research: (1) The multi-dimensional definition of shrinking cities based on classification types only qualitatively explains the classification causes and mechanisms through case analysis, lacking quantitative research. (2) The nonlinear relationship between the influencing factors of shrinking cities based on classification machine learning models still needs to be improved in research. (3) The coupling relationship between shrinkage and growth under the transformation of resource-based cities has yet to be discussed in detail. Therefore, based on these problems, this study conducts relevant research, taking Daqing, a typical resource-based city, as the research object, and explores the spatial distribution of urban growth and shrinkage types under the multi-dimensional definition from the perspective of resource-based city transformation. In addition, we also compare the interpretability and nonlinear relationship of different machine learning classification models for relevant influencing factors. This study aims to provide a comprehensive research framework from type evaluation to quantitative analysis of appropriate mechanisms. Based on this framework, we conduct in-depth research on the mechanism of shrinking cities under the background of resource-based city transformation.

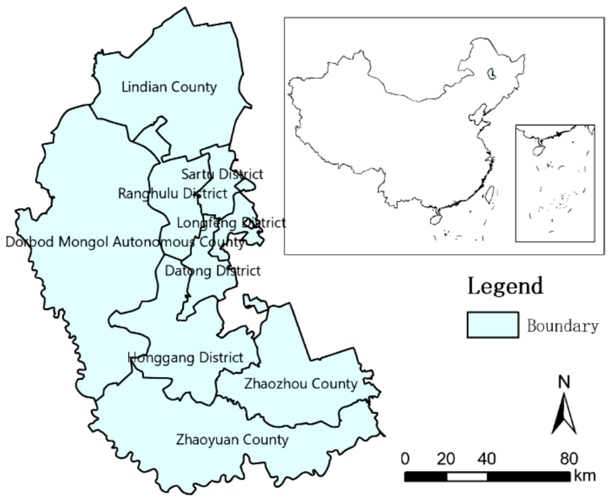

Fig. 1. Regions of Daqing City.

2. Materials and Methods

2.1. Study Area and Data

As shown in Fig. 1, this study takes Daqing City, Heilongjiang Province, Northeast China, as the research object, and the research period is 2015-2020. As an important resource-based city in China, Daqing faces problems such as ecological environment damage, complex social contradictions, industrial system transformation, resource depletion dilemma, etc. In recent years, it has continuously controlled the exploitation of oil and gas resources and explored new directions for industrial change. Since 2015, the output of Daqing Oilfield has begun to decline, with an average annual reduction of more than 1.3 million tons during the “13th Five-Year Plan” period. Daqing's urban and population structures based on primary oil development also face reorganization in the transition stage to adapt to industrial diversification. Daqing's special development stage also causes urban shrinkage and growth to coexist. This study aims to quantitatively identify and describe the characteristics of urban shrinkage in Daqing from 2015 to 2020 and analyze its cause mechanism.

This study collects and organizes data on the spatial pattern of urban growth and shrinkage subtypes and related possible influencing factors. To improve the research accuracy, this paper abandons panel data. It selects grid data with spatial resolution ≤1km for relevant research and classifies them according to type measurement and relevant influencing factors. All data are summarized in Table 1.

Among them, Population Density (PD) represents the population per km², reflecting the characteristics of population spatial distribution. Night-light data (NL) can reflect the intensity of economic activity, electricity consumption, and other energy consumption indicators, thus characterizing economic vitality. Artificial Impervious Areas (AIA) reflect the built-up area, thus reflecting the overall land use situation. Regarding relevant influencing factors, we explore the specific impacts from different perspectives, such as population age structure, economic level, land use subdivision data, etc. Among them, GDP reflects the specific economic output of each grid; AR and BR reflect the impact of population age structure; RD reflects traffic accessibility; and UL, RS, and OCL, respectively, represent the use of urban, rural, and special land. We use different normalization methods to process data and compare and select the better normalization method to eliminate the dimension difference.

2.2. Urban growth/shrinkage based on multi-dimensional definition

This study establishes a matrix of urban growth/shrinkage type definition based on three dimensions: population, economy, and land use, according to the Chinese context, to determine the subtypes of urban growth and shrinkage. First, we overlay the population density data and night light data of each grid to construct a comprehensive economic vitality (EV) indicator, which represented equation (1).

$$EV = DN \times PD \tag{1}$$

Where EV is the economic vitality index of each grid, DN is the night light intensity value, and PD is each grid's population number. A data overlay can avoid the brightness anomalies caused by high-brightness economic activities such as fishing and natural disasters such as fires and truly reflect the economic vitality.

Then, we construct the x-axis and y-axis by the positive and negative of the comprehensive EV index and land use index (AIA) and build a discrimination matrix of growth and shrinkage at the grid scale by the four-quadrant classification method (Table 2). The matrix divides the growth and shrinkage situation into four different spatial types,

Table 1. Multi-source data being applied

Application	Name	Sources
Type determination	Population Density (PD)	WorldPop (https://hub.worldpop.org/)
	Nighttime Light (NL)	(A Harmonized Global Nighttime Light Dataset 1992–2018 | Scientific Data, n.d.)
	Artificial Impervious Areas (AIA)	(Li et al., 2020)
Analyze Impact factors	GDP	(Zhao et al., 2017)
	Aging Rate (AR)	WorldPop (https://hub.worldpop.org/)
	Birth Rate (BR)	
	Road Density (RD)	https://www.openstreetmap.org
	Urban Land (UL)	https://www.resdc.cn
	Rural Settlements (RS)	
	Other Construction Land (OCL)	

and the four quadrants correspond to expansion growth, intensive growth, expansion shrinkage, and intensive shrinkage, respectively.

2.3. Multi-model comparison and selection and influencing factor analysis

This study first tests the multicollinearity between variables by Pearson correlation analysis and eliminates variables with high data correlation with 0.8 as the standard (Wilcox, 2009). Then, we explore the nonlinear relationship between classification types and relevant influencing factors by machine learning algorithms. Since there is no conclusive conclusion on the fitting effect of different models on type determination, we conducted a multi-model comparison analysis. Regarding the specific classification model selection, we chose several machine learning models such as random forest, xgboost, logistic regression, K-nearest neighbor (KNN), and support vector machine (SVM) from two perspectives of mainstream models and newer models. Then, we construct an 80% training set and 20% test set for each model and comprehensively compare each model's accuracy, recall, precision, F1 value, and other indicators to judge the fitting effect and interpretability (Goutte & Gaussier, 2005). Finally, based on the selected machine learning algorithm with a better comprehensive outcome, we further analyze the specific impact mechanism of relevant influencing factors on urban growth and shrinkage according to the indicator results, such as feature importance generated by the algorithm.

3. Results & Discussion

3.1. Spatial distribution of growth and shrinkage types in Daqing City

Through data analysis, we obtained the overall characteristics of urban development in Daqing City from 2015 to 2020 (Fig. 2), that is, dominated by intensive shrinkage space, accompanied by perforated intensive growth and expansion shrinkage space, and there are also local scattered growth spaces in the intensive growth space area. Specifically, 12046 grids show intensive shrinkage, 5800 grids show intensive growth, 2503 grids show expansion shrinkage, and 1411 grids show expansion growth. From the perspective of urban overall spatial distribution, intensive shrinkage is mainly distributed in the urban periphery areas of Lindian County, Dorbod Mongolian Autonomous County, Datong, Zhao Yuan, and other regions of the north, west, and south of the city. Intensive growth and expansion growth are mainly distributed in the core urban areas of Sartu, Longfeng, Honggang, Ranghulu, and other regions of the central and eastern parts of the city and Zhaozhou area in the southeast, as well as local scattered regions of the periphery urban areas. Expansion shrinkage is mainly scattered in Daqing's northwest and southeast regions, forming a concentric structure of intensive growth-expan-

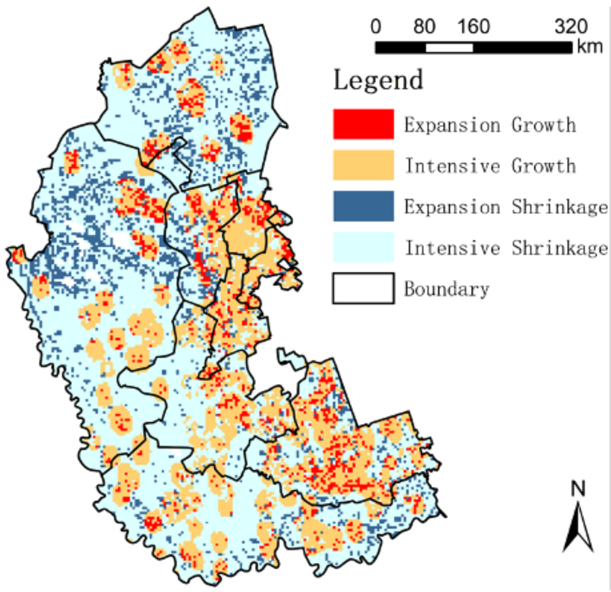

Fig. 2. Spatial Distribution of Urban Shrinkage/Expansion Types in Daqing City from 2015 to 2020

Table 2. Identification matrix of urban growth / shrinkage

Economic Vitality (EV)		Built-up Areas (AIA)		Space Type
Relative Relation	Type	Relative Relation	Type	
$R_{EV} > 0$	Growth	$R_{AIA} > 0$	Expansion	Expansion growth
		$R_{AIA} \leq 0$	Intensive	Intensive growth
$R_{EV} \leq 0$	Shrinkage	$R_{AIA} > 0$	Expansion	Expansion shrinkage
		$R_{AIA} \leq 0$	Intensive	Intensive shrinkage

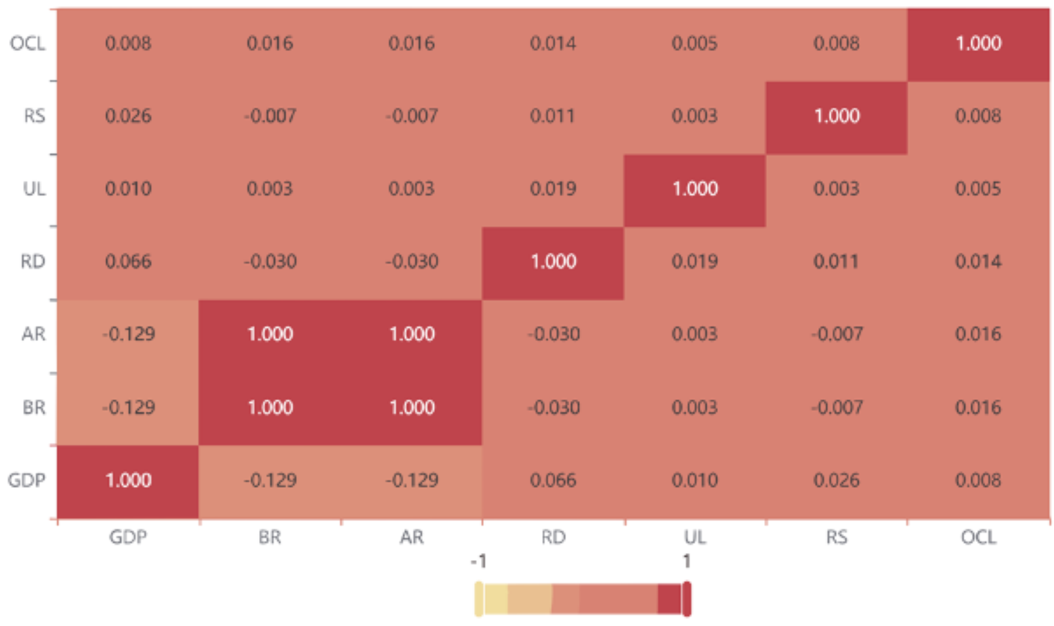

Fig. 3. Correlation Matrix of Influencing Factors Related to Urban Shrinkage from 2015 to 2020.

sion shrinkage-intensive shrinkage that gradually changes from the center to the periphery.

3.2. Collinearity and multi-model comparison

As shown in Fig. 3, we first tested the collinearity between variables by Pearson correlation analysis. According to the results, except for AR and BR, the absolute values of correlation coefficients between other variables are all less than 0.2, meaning there is almost no multicollinearity problem between variables.

BR and AR have a collinearity overlap problem because they reflect population structure characteristics and come from the same data set. We eliminate variable BR and use the remaining variables as influencing factors for further analysis.

Then, this study compares different machine learning models and selects the model with a better comprehensive analysis of the effect on the urban growth/shrinkage classification problem and its relevant influencing factors. As shown in Table Ⅲ, we comprehensively compare the evaluation results of models such as logistic regression, random forest, xgboost, KNN, SVM, etc. From the perspective of preventing overfitting, the logistic regression model, random forest model, and SVM model perform better, with the difference between the training set and test set within 0.02, while the difference between the training set and test set of the other two models are more than 0.1. Among them, the best-performing model is the random forest model, with the difference between the training set and test set Accuracy, Recall, Precision, and F1 values within

Table 3. Comparison of Evaluation Results of Different Classification Models

Machine Learning Model		Model Evaluation Results			
		Accuracy	Recall	Precision	F1
Logistic Regression	Train	0.587	0.587	0.466	0.507
	Test	0.572	0.572	0.451	0.49
Random Forest	Train	0.624	0.624	0.505	0.55
	Test	0.619	0.619	0.501	0.546
xgboost	Train	0.783	0.783	0.81	0.76
	Test	0.602	0.602	0.533	0.543
KNN	Train	0.679	0.679	0.662	0.663
	Test	0.533	0.533	0.496	0.511
SVM	Train	0.557	0.557	0.462	0.401
	Test	0.544	0.544	0.443	0.387

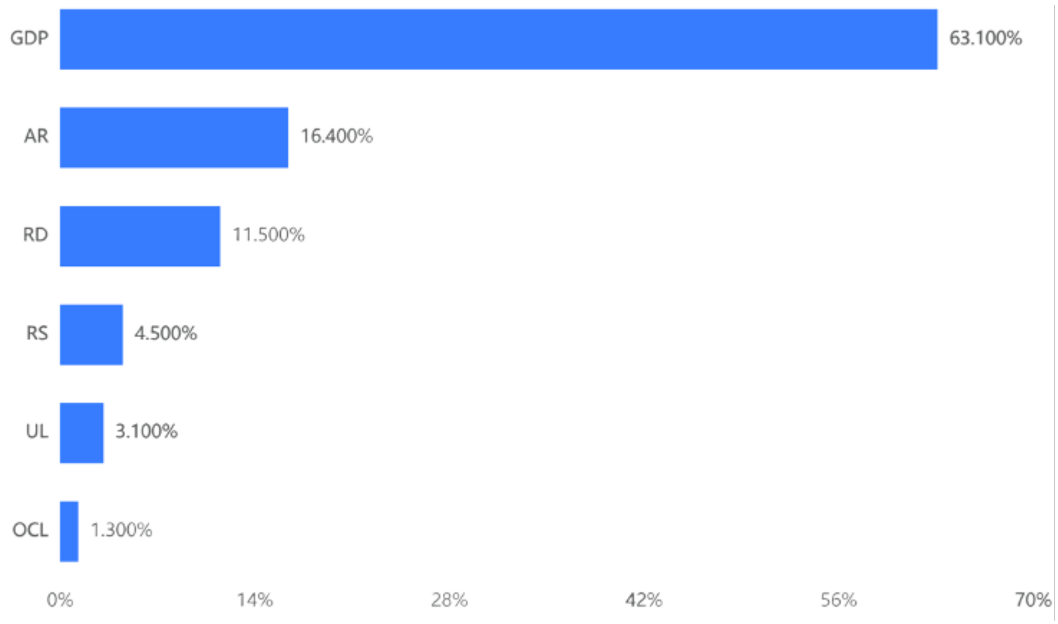

Fig. 4. Features importance of Influencing Factors Related to Urban Shrinkage from 2015 to 2020.

0.005 or 0.01, which is the smallest compared with other models. Based on this, we choose the model with the highest comprehensive evaluation score among the models with a good fitting degree. The model with the highest overall score is also a random forest model, with its training set and test set Accuracy, Recall > 0.6, Precision, and F1 values > 0.5 are the highest compared with other models. Therefore, we choose the random forest model to analyze influencing factors further.

3.3. Resource-based city influencing factor analysis based on random forest classification model

As shown in Fig. 4, the feature importance chart generated by the random forest model shows the degree of influence of different influencing factors on urban shrinkage/growth. Among them, the GDP score accounts for more than 60%, the main influencing factor, while AR and RD's feature importance exceeds 10%, respectively, which has a certain impact. The scores of the three land use modes are low, and the related effects are small. By comparison, economic factors dominate urban growth/shrinkage in Chinese resource-based cities. At the same time, traffic accessibility and population structure also promote or inhibit urban growth/shrinkage to a certain extent. This reflects the current situation faced by resource-based towns in China, that is, the impact of the original urban pattern and traffic network based on resource exploitation on industrial transformation and economic development. Daqing City, as a typical resource-based city formed and grew with the development of oil fields and oil field economy, has a development mode of "city-mine integration." Its urban and rural distribution is sparse and uneven, with dense urban areas and light peripheral counties.

In addition, its original urban spatial distribution is based on the exploitation and transportation of oil and gas resources, that is, relying on the construction of traffic trunk lines and extending along them, forming a city shape with traffic trunk lines as the axis, and the core old urban area and the railway transportation intensive eastern area highly overlap. However, the distribution of resources leads to a loose connection between different metropolitan areas; each region has its system, showing a dispersed multi-center group structure. Generally speaking, this urban structure pattern cannot meet the needs of urban transformation and development. The overly dispersed urban layout pattern is not conducive to forming a regional center with strong attraction and radiation force. It is not conducive to transforming urban economic development from extensive to intensive. According to specific analysis types, scattered regional centers attract market, population, and other elements flow and aggregation by relying on oil field resources.

In the stage of urban industrial transformation, they change from large-scale expansion growth to intensive growth combined with local expansion growth to reduce resource consumption and dependence and optimize the existing resource industry mode. These areas spread from the eastern core urban area to other directions, showing a radiative scattered distribution. The peripheral regions of scattered centers show an intensive shrinkage pattern, which replaces inefficient stock and redundant space with retreatment and smooths over the economic transformation stage. Expansion shrinkage-type scattered areas are mostly located in the northern part of Daqing City, which is also the main traffic line away from the main urban area side area. The main reason is that there is a mismatch between the government's strategic advancement policy and the actual market element flow in the stage of transformation and development, resulting in excessive spatial supply and an imbalance of population and economic structure. At the same time, due to the exploration of new industries and the consumption of original resources leading to the downturn of the actual industry economy, the city's development expectation decreases. This leads to the outflow of labor population and local population aggregation, reflecting the population structure change represented by a high aging rate.

4. Conclusions

This study establishes an identification framework for urban growth and shrinkage from population, economy, and land use. It compares different machine learning models to explore the degree and mechanism of influence of relevant influencing factors under the context of resource-based city transformation from 2015 to 2020. The research results are: (1) Daqing City is dominated by intensive shrinkage space, accompanied by perforated intensive growth and expansion shrinkage space. At the same time, there are local scattered expansion growth spaces in the intensive growth space area, forming a concentric structure of intensive growth—expansion growth—expansion shrinkage—intensive shrinkage that gradually changes from the center to the periphery. (2) Compared with other models, the random forest classification model has better interpretability for urban growth/shrinkage type influencing factor analysis. (3) Economic factors are the main factors leading to urban growth/shrinkage in Chinese resource-based cities, such as traffic accessibility and urban layout determined by the resource economy. In summary, by providing a comprehensive research framework from type evaluation to quantitative analysis of relevant mechanisms, this study can provide useful supplements for urban shrinkage-related research based on type evaluation and applicable sustainable planning policy formulation.

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