MSc Thesis

Identification and evaluation of spatial pattern evolution and utilization efficiency of resource-based cities in China

Author: Yunqi Guo

Supervisor: Professor Yanling Zhao

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College of Geoscience and Surveying Engineering
China University of Mining and Technology (Beijing)

Beijing Haidian district Xueyuan Rd, D11.
Zonghe Building 312

Declaration of Authorship

„I declare in lieu of oath that this thesis is entirely my own work except where otherwise indicated. The presence of quoted or paraphrased material has been clearly signaled and all sources have been referred. The thesis has not been submitted for a degree at any other institution and has not been published yet."

Acknowledgement

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In the face of the epidemic, we are still trying our best to the end. This indomitable spirit will be brought to my future study and life. Moreover, the end of this project does not mean that I have reached the end of my study life, I think, I will usher in a new stage, with the knowledge, courage and spirit you taught me, to explore and climb to higher peaks.

Abstract

China's rapid urban development over the past few decades has been remarkable, but the early growth-oriented 'incremental planning' encouraged the disordered sprawl of China's urban land. The accelerated mobility of population in the wake of globalization and the rapid urbanization of China, which has provided a platform for more movement of people between cities, making urban shrinkage caused by this kind of sprawl a common phenomenon. Resource-based cities, facing unprecedented challenges due to resource depletion, over-exploitation and environmental degradation, are quite vulnerable to this disordered growth. Therefore, monitoring the extent of urban shrinkage, identifying and analyzing the evolution of urban spatial use efficiency will be conducive to proposing reasonable and scientific urban development guidelines, as well as to the transformation of resource-based cities.

This paper takes prefecture-level resource-based cities in China as the subject, combining the concepts of urban expansion and urban shrinkage in an urban system. The theoretical analysis of the urban expansion mode and the degree of urban shrinkage is conducted, followed by a discussion of the evolution of urban spatial use efficiency and its causes according to different stages of urban development, and finally, strategies to improve spatial use efficiency are proposed. The main findings of the study are as follows:

(1) The overall scale of spatial expansion of resource-based cities in China gradually becomes larger, with looser and more complex spatial forms.

(2) The urban shrinkage of resource-based cities in China also shows obvious geographical differences, with the eastern region having a high density of built-up areas but a low degree of overall shrinkage, while the northeastern and western regions have a lower density of built-up areas but a more severe degree of overall shrinkage.

(3) The overall spatial use efficiency of resource-based cities in China is not high. In different types of resource-based cities, there are differences in the impact of population, economy and land on urban spatial use efficiency, and it is of great practical significance for cities to monitor and assess these fluctuations.

Keywords: resource-based cities, urban expansion, urban shrinkage, space use efficiency

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1 Introduction

1.1 Background

Driven by the rapid industrialization and urbanization since the reform and opening- up, China is showing a momentum of vigorous development. In 2010 World Urbanization Prospects report, the United Nations noted that "China has been the fastest urbanizing country in the world over the past 30 years" (Li et al., 2020; Gao et al., 2016). And this rapid development first leads to the increasing expansion of urban population.

The latest criteria for city categories, as defined in The Notice on Adjusting the Criteria for the Classification of City Size issued on 21 November 2014, show that the minimum and maximum thresholds for each category of cities, based on the resident population of the city, have been significantly increased, i.e., the maximum threshold for the population of small cities has been raised from 200,000 initially to 500,000 today, the minimum and maximum thresholds for medium cities have been raised from 200,000 initially to 500,000 and 1 million respectively, and the minimum and maximum thresholds for large cities have been raised from 500,000 and 1 million to 500,000 and 5 million respectively. The minimum and maximum thresholds for medium-sized cities have risen from 200,000 and 500,000 to 500,000 and 1,000,000 respectively, while the minimum and maximum thresholds for large cities have risen from 500,000 and 1,000,000 to 1,000,000 and 5,000,000 respectively, and the minimum threshold for mega-cities has increased from 1,000,000 to 5,000,000. And it is expected that by 2025, more than 292 cities in China will have crossed the 500,000 threshold (684 cities in China in 2020). Furthermore, according to the results of the 7th Census in 2020, at least 902 million people will currently live in urban areas by 2020, representing 63.89% of the total number of people in China, an increase of almost 6 percentage points compared to the 6th National Census in 2010(Jiao et al., 2018; Liu et al., 2010).

When large numbers of rural people flocked into cities, it puts enormous pressure on the original urban infrastructure and thus directly and positively drives the continuous expansion of urban scale. According to the Ministry of Housing and Urban-Rural Development of the People's Republic of China, China's urban built-up area has increased tenfold in 30 years, from 12,462 square kilometers in 1989 to 40,058 square kilometers in 2009 and to 146,102 square kilometers in 2017 (Zhang et al., 2018; Zhao et al., 2015). On the one hand, gradually expanding cities bring more employment and innovation opportunities, more efficient use of resources and wider consumer markets, while on the other hand, people are subject to the negative effects of urban expansion.

Firstly, China's early land policy was oriented towards 'incremental planning' (Long et al., 2012), i.e., the government advocated the expansion of urban functions into the suburbs, creating new urban areas, industrial parks, special functional zones, etc. This was a philosophy that supported spatial expansion outwards. However, this rapid growth in urban area has come at the cost of annexing farmland around the city, and a large amount of available arable land has been encroached upon. The loss of large amounts of basic farmland has been accompanied by some planning failures, such as the actual rate of urbanization of the population being less than the rate of urbanization of the land, making the actual utilization of the occupied land low, sacrificing arable land resources and threatening China's food security. In addition, although cities are spreading outwards, they are showing high vacancy rates inside their bodies, i.e., 'urban hollowing' and 'urban shrinkage' (Dong et al., 2021; Tong et al., 2021). In some large and mega-cities, the actual affordability of the urban centers is excessive, with most people on low incomes unable to afford the high cost of living and those on high incomes seeking higher quality living conditions. In some second- and third-tier small and medium-sized cities, government subsidizes and land allocations have resulted in the construction of a large number of upscale neighborhoods and fine office buildings, but the supply of supporting facilities throughout the city exceeds demand, the population is severely underpopulated and the overall utilization of planned land in urban areas is low. Nowadays, these phenomena are commonplace in the urbanization process where urban boundaries are spreading, and are uniformly described as urban 'sprawl' (Zhang et al., 2022). Urban 'sprawl' is a huge waste of material and human resources, hindering the development of various industries, and in more serious cases, causing an overall decline in the city's economy.

The accelerated mobility of the population in the face of globalization and the rapid urbanization of China, which has provided a platform for greater mobility between urban and rural areas and between cities, has made urban shrinkage due to 'sprawl' a common phenomenon. This phenomenon is particularly evident in China's resource-based cities (He et al., 2017; Yu et al., 2016). Under the influence of the structural crisis of resource depletion and over-exploitation, most resource-based cities are in an awkward situation of "wanting to develop but not being able to do so", while resource-based cities with relatively rich resource reserves continue to suffer serious population loss due to their poor location and climate conditions. However, since the founding of the country, resource-based cities have been instrumental in promoting China's socio-economic development. According to records, from 1945 to 2013, China's resource-based cities produced 52.9 billion tonnes of coal, 5.5

billion tonnes of oil, 5.8 billion tonnes of iron ore and 2 billion cubic meters of timber (Li et al., 2021). Today, China is the world's second largest economy, the world's largest trading country and the world's largest foreign exchange reserve country. Therefore, as the country's resource and energy security base, resource-based cities should ensure the country's next high-quality and stable development.

In recent years, the Chinese government has begun to pay attention to the issue of resource-based cities and has introduced a series of policies to promote the sustainable development of resource-based cities, such as The Several Opinions on Promoting the Sustainable Development of Resource-based Cities issued in 2007, which emphaised the importance of resource-based cities in China. A few years later, The State Council promulgated the National Sustainable Development Plan for Resource-based Cities (2013-2020) in 2013. The plan states that governments at all levels should adopt practical and effective approaches to achieve transformation and high-quality development of resource-based cities. And, for the first time, 262 resource-based cities have been identified nationwide (Yu et al., 2016). At the same time, resource-based cities are classified into four types according to their current development status and problems: growing resource-based cities, grow-up resource-based cities, recessionary resource-based cities and regenerative resource-based cities (Sun et al., 2021). In 2014, the Ministry of Land and Resources and the Ministry of Housing and Urban-Rural Development defined the urban growth boundary to improve urban land use. Therefore, the task of constructing a robust framework for monitoring and assessing the evolution of urban spatial use efficiency under urban expansion and shrinkage is of great importance.

1.2 Current study

Many developed countries, with their earlier development and more mature urban systems, were the first to recognize the urban crisis caused by urban sprawl and the first to move from qualitative to quantitative and then to practical application of relevant research. Scholars were the first to notice the degradation of the natural urban environment and the unjustified urban planning that has led to sprawl changing the land use structure, destroying the surface microclimate, wasting and polluting water resources and causing serious imbalances in the urban carbon balance (Linard et al., 2013; Weber and Puissant, 2013) In order to better understand the impact of urban sprawl on cities and to formulate effective planning and management policies, a large number of scholars have used modelling to measure the characteristics of urban sprawl, to study the process of urban sprawl, urban land structure and urban growth boundaries, and to introduce geographic modelling systems to predict the trajectory of urban development (Carlson and Traci, 2000; Inostroza et al., 2013; Kuang et al., 2014; Wolfram, 1984). In the process, they found that most cities, especially the early industrialized cities, were gradually shrinking, and thus, under the guidance of the urban life cycle theory, the most distinctive characteristic of counter-urbanization arising from sprawl, 'urban shrinkage', began to enter the scholars' view, and its related definition criteria, formation causes, morphological characteristics, spatial heterogeneity, etc. have been widely discussed (Quan et al., 2014; Rifat and Liu, 2019; McCray et al., 2013; Stevens et al., 2007). In addition, as shrinking cities waste a lot of urban land and encroach on urban resources, and under the influence of the Sustainable Development Goals (SDG) and the strong sustainable development paradigm proposed by the United Nations, scholars are increasingly concerned about the improvement of urban spatial quality, hoping that the concept of "planning cities with fewer people, less land and fewer urban buildings" has been adopted. "The idea of smart shrinkage is being proposed, and these scholars are focusing more on the practical application of a single city than on large-scale forms of research, such as the efficiency of urban space use (Popper, 2002). For example, the city of Youngstown, USA, has converted a large amount of unused vacant land in the city into urban green gardens, abandoned factories and other areas into modern art corners, and the city center area has been rebuilt to enhance the vitality of the main city. In Germany, the municipality of Magdeburg directly allocated funds to demolish derelict houses on the fringes of the city and reshape the urban land space. In the UK, the heavy industrial city of Manchester has used strategies to raise the city's profile, such as bidding for the Olympics and Commonwealth Games, building light rail transit projects first, a new international airport, and financial, retail and entertainment center venues to stimulate the influx of people.

Compared with the relevant research progress abroad, such research in China started late. Moreover, there is no unified standard for measuring the extent of urban shrinkage, and no official document has been issued by the Chinese government to date (Jin et al., 2017). And the existing studies on domestic cities cover a relatively short time span and most of them stay in qualitative or quantitative research.

Scholars have mainly discussed three aspects of urban shrinkage: economic conditions, population size, and the rationality of urban planning. More specifically, some researchers have used census data to study the spatial characteristics of shrinkage in Chinese provincial capital cities, while others have quantified the current state of shrinkage in Dongguan in the Pearl River Delta, China, with the help of data on resident population, gross domestic product (GDP) and land use interviews (Du et al., 2020). Pan et al. (2020) have determined the vacancy rate in Changshu, Jiangsu Province, China based on urban water consumption. Nevertheless, statistical data usually lags behind the current urban situation and lacks spatial information and credibility, and the cost of obtaining data is also high. To optimize the shortcomings of statistical data, many scholars have integrated open data and applied Tencent population location data and Baidu community point of interest (POI) data to explore the spatial characteristics of the shrinking population in Chongqing, China and to identify shrinking cities in the Pearl River Delta, China by using information on recreational activities, commercial and residential data from web users (Zhao et al., 2021) . However, due to the large volume of data, it is quite time-consuming and laborious when there is a huge study population to evaluate, and there is also a lack of comprehensive studies that combine the three together.

In addition, the concept of the people-oriented city, which suggests that the city of the future should be people-oriented and that urban planning should be developed around its inhabitants, has become a hot topic in urban research. Scholars are beginning to focus on the spatial efficiency of cities under the influence of rapid urbanization. Input-output econometric models such as the DEA model and the Malmquist index are commonly used as quantitative measures of spatial efficiency (Chen et al., 2018; Chen et al., 2022; Long et al., 2021), but most of these models also use traditional panel data, which cannot avoid the limitations of statistical data (Wang et al., 2021).

With the booming development of satellite technology, remote sensing imagery, characterized by rich spatial information, wide monitoring areas and fast data collection, has entered the field of urban studies. In these studies, night-time light (NTL) imagery, which is closely related to human activities, has become a powerful and effective tool for demonstrating the economic vitality of urban areas (Jiang et al., 2020; Ge et al., 2018). However, in these studies, the selected subjects are mainly focused on small-scale or national scales, and there is a lack of studies directly targeting groups of resource-based cities. Also, in contrast, there are few studies that directly analyze the evolution of spatial use efficiency patterns based on inherent differences in urban expansion and shrinkage.

In summary, the main problems with the current study are as follows:

(1) Although foreign research systems are better, the application of research results will be hindered by the different national conditions, and there is an urgent need to establish a robust assessment framework that is appropriate to the actual level of development of Chinese cities.

(2) Existing research in China, mostly using traditional statistical panel data, has a cumbersome collection process, questionable accuracy of results, and poor spatial and temporal performance. Experiments based on big data often require huge amounts of confidential information, while the data are redundant, highly specialized and often time-

consuming. Today, with the rapid development of cities, fast, convenient and highly accurate research methods will become a research hotspot.

(3) Research on resource-based cities suffers from the shortcomings of small research areas and incomplete examination of dimensions. There are a large number of resource-based cities in China, with around 39% of all Chinese cities falling into this category, and the barriers encountered by these cities are diverse due to their different stages of development, economic and social foundations, necessitating a comprehensive analysis in relation to the resource-based city type.

1.3 Purpose, content and flow chart of the study

1.3.1 Purpose

Urban development is a dynamic evolutionary process, and cities are inevitably destined to shrink under external expansion, leading to serious waste of space and inefficient use of space in cities as a whole. In the post-modernization era, due to more and more accelerating urbanization, the development of Chinese cities frequently exhibits the aftermath of earlier extensive economic strategies. This trend of counter-urbanization is most likely to occur in resource-based groups of Chinese cities where resources are overexploited, and unreasonable spatial planning often further exacerbates the resource-based city crisis. Timely monitoring the spatial expansion and shrinkage of resource-based cities and identifying and assessing the evolution of urban spatial use efficiency are crucial to the healthy development of resource-based cities in China.

Taking 126 prefecture level resource-based cities as the research object, using open-source remote sensing data images, this study discusses the scale and form changes of spatial expansion of resource-based cities from 2000 to 2020, the actual shrinking degree of cities in 2020, and analyzes the evolution of spatial utilization efficiency under the influence of expansion and shrinkage of resource-based cities in different stages. Finally, some tailor-made suggestions are put forward according to different types of resource-based cities. The specific research purposes are as follows:

(1) Identify and analyze the spatial and temporal evolution characteristics of the spatial expansion of resource-based cities at the prefecture level in China. An index reflecting the scale and shape of urban expansion is selected to identify the spatial and temporal evolution characteristics of the spatial expansion of prefecture-level resource-based cities in 2000, 2010 and 2020, i.e., to discern the spatial expansion of different types of resource-based cities.

(2) Identifying and comparing the spatial shrinkage of resource-based cities at the prefecture level in China by constructing a shrinkage index for resource-based cities through three dimensions: population, land and economy. Analyzing the degree of shrinkage of cities in 2020 and their spatial differentiation, and finally, a classification of the degree of spatial shrinkage of resource-based cities and an evaluation of the severity of shrinkage of different types of resource-based cities is achieved.

(3) Identifying the modes in which China's prefecture-level resource-based cities expand and evaluating the evolution of urban spatial use efficiency. Following the coupling of the scale and form of urban expansion, the types of urban expansion are classified. Combining the spatial and temporal links between urban expansion and urban shrinkage in the sample, this study explores the differences between the expansion and shrinkage of resource-based cities and completes the identification and evaluation of the evolution of urban spatial use efficiency patterns based on these differences, analyzes the causes for the differences in spatial use efficiency of different types of resource-based cities and put forward practical and targeted planning recommendations.

1.3.2 Content

The unreasonable urban growth strategy, which consumes the land and financial resources of the city, makes the city in crisis and makes the transformation of resource-based cities difficult. How to grasp the "degree" of urban expansion and urban shrinkage, achieve efficient use of urban space, effectively improve the quality of life of urban residents, and rejuvenate resource-based cities, is to reveal the law of the evolution of spatial expansion and efficiency of use in resource-based cities. To sum up, the research of this study is as follows.

(1) Identification of urban spatial expansion based on built-up areas. This study selects three time points, 2000, 2010 and 2020, and uses the land use dataset to calculate the scale of spatial expansion of urban built-up areas, i.e., expansion amount, expansion degree and expansion intensity, as well as the form of spatial expansion of urban built-up areas, i.e., spatial compactness and fractal dimension values, to analyze the evolution of urban spatial expansion. Based on the calculated expansion amount and spatial compactness, the Tapio decoupling model is used to carry out a coupling degree analysis to identify the specific forms of resource-based urban expansion.

(2) Identification of the degree of urban shrinkage based on a multidimensional perspective. Using images of built-up areas extracted from population raster data, nighttime light remote sensing images and land use data, urban shrinkage evaluation indices based on population,

economy and land are constructed and the indices obtained are classified using standard deviation classification. Spatial autocorrelation analysis is used to explore the spatial distribution of urban shrinkage in resource-based cities and to evaluate the severity of shrinkage in the sample cities.

(3) Identification of the evolution of urban spatial use efficiency patterns based on the differences between urban expansion and urban shrinkage. The evolution of the overall spatial use efficiency of resource-based cities is analyzed through the differences in the expansion mode and shrinkage degree of each city. By decomposing the urban shrinkage index and combining it with the actual situation of resource-based cities, we take different types of resource-based cities as the breakthrough point to explore the causes of the differences in urban spatial use efficiency and finally propose suitable development strategies.

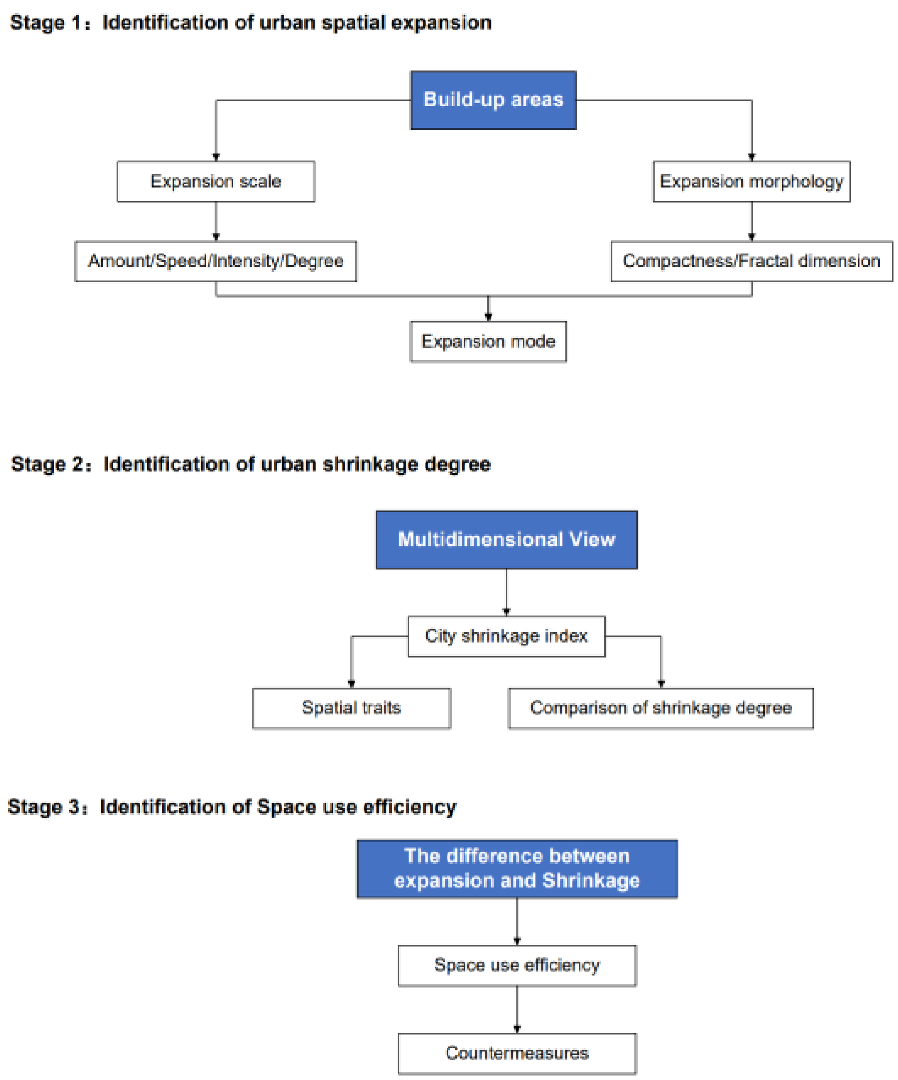

Figure 1 Research flow chart

2 Concepts

2.1 Resource-based cities

The creation and accumulation of human material wealth begins with the acquisition of natural resources. Therefore, natural resources are the indispensable material basis for human survival, economic construction and social development (Ruan et al., 2021; Tan et al., 2016). The degree of exploitation and utilization of resources directly reflects the economic strength and development potential of a region or country. Since ancient times, many human settlements have naturally been built around these resources in order to make efficient use of them, and as these settlements evolved from small to large into cities, the concept of resource-based cities was born.

Resource-based cities are cities that have been established and gradually developed through the exploitation and management of resources such as minerals and forests. Such cities provide a constant source of impetus for the advancement of human society (Gao et al., 2021; Li et al., 2021; Du et al., 2019). In developed countries in Europe and America, relying on coal and steel, the Ruhr region of Germany and the Lorraine region of France not only led their countries out of the gloom of war and achieved post-war economic recovery, but also laid a solid material foundation for the industrialization and modernization of their countries. For example, since the founding of the country, Anshan, as the backbone of China's steel, has provided Anshan Steel products that are widely used in defen ce, civil and commercial sectors. Meanwhile, the discovery of the Daqing oilfield has freed China from the situation of being an oil-poor country with large amounts of oil imports. And the Daxinganling, known as the green lung, has not only escorted the cause of carbon neutrality in China, but also delivered a constant flow of gold, timber and other valuable resources to the outside world.

As t resources contained in resource-based cities gradually decreases with large-scale exploitation, the industrial chain is relatively short and the industries are severely homogenized, the original pillar industries can no longer sustain the city's devel opment, and a large number of laborers have migrated to neighboring cities, resulting in a serious economic decline (Chen et al., 2018; Cheng et al., 2019). Moreover, the situation of resource-based cities at different stages of development is different. Based on the ability to secure resources and sustainable development, the State Council released The National Sustainable Development Plan for Resource-based Cities (2013-2020) in 2013, which divides China's resource-based cities into four categories: growing resource-based cities, grow-up resource-based cities, recessionary resource-based cities, and regenerative resource-based cities (Yu et al., 2016; Zheng et al., 2017). Therefore, it is not only a challenge for urban planners and policy makers to come up with practical strategies for the actual level of development and existing problems of each resource-based city, but also crucial for the future development of China.

2.2 Urban expansion

A city can be seen as a living organism, and the process of its development is the process of its growth, accordingly, the city grows from small to large. The growth of the city brings with it a rapid increase in economy, population, the size of the city, infrastructure, etc. The city begins to need more public space to accommodate these growing things (Zhang et al., 2016). As a result, cities began to show spatial expansion, i.e., an increase in the size of built-up areas and fluctuations in administrative boundaries outwards. Therefore, urban expansion is mainly manifested as changes in spatial scale and spatial form. This study determines the evolution of the spatial expansion of resource-based cities through the changes in the scale and form of built-up areas at different time points.

2.3 Urban shrinkage

The term "shrinking cities" originated in Germany in 1988 and refers to the economic downturn and social development of formerly densely populated cities affected by a structural crisis characterized by population loss (Häußermann and Siebel, 1988). As more and more European and American cities have fallen prey to urban shrinkage, the definition of the term is no longer limited to depopulation, but has begun to take on a richer connotation (Herrmann et al., 2016; Hospers, 2013). According to a large body of scholarship, there are now three main causes, namely persistent population loss, rising vacancy rates and sluggish or declining economies (Ma et al., 2018; Pan and Dong, 2021; Shan et al., 2021; Long and Shen, 2015). Shrinking cities are scattered around the world, but China, the largest developing country and the world's second largest economy, is a phenomenon that will have far-reaching implications for its national development and the world economy. Over the past few decades, China has been undergoing rapid urbanization, with cities exhibiting rapid outward expansion, and this irrational path of planning for 'quantity' over 'quality' has made it difficult for Chinese cities to escape the clutches of shrinkage. Resource-based cities, in particular, are more vulnerable to the adverse effects of urban shrinkage due to resource depletion, industrial homogeneity and environmental degradation (Cheng et al., 2019).

3 Study area and data

3.1 Study area

For decades, China's resource-based cities have made significant contributions to national economic growth, and the development of resource-based cities has been largely due to the exploitation of natural resources, such as forest and mineral resources. As a result, resource-based industries are an important part of the economic system of this type of city. However, with the depletion of natural resources during the exploitation process and the gradual decline of the pillar industries, the sustainable development of these cities faces serious challenges (Long et al., 2021).

To help resource-based cities get rid of their predicament and promote more stable, coordinated and sustainable economic growth in the cities, based on their ability to secure resources and develop sustainably, the Chinese State Council issued The National Sustainable Development Plan for Resource-based Cities (2013-2020) in 2013 classified China's Resource-based cities into four categories (Yu et al., 2016). As shown in Figure 2. Resource-based cities with strong resource security and sustainable development capacity, and with fewer obstacles to development at present, are in the growth stage and can be categorized as growing resource-based cities (G-RC); Resource security level has slightly decreased and a series of social and economic crises are gradually emerging in the urban development process, such resource-based cities are defined as grow-up resource-based cities (GU-RC); Resource-based cities with available resources close to depletion and serious obstacles to urban development are defined as recessionary resource-based cites (Rec-RC); Although the resources used to maintain urban development have been exhausted, the effect of urban transformation has begun to appear, such a resource-based city is a regenerative resource-based city (R-RC).

According to the above classification framework, there are 262 RCs in China (126 prefecture-level cities, 62 county-level cities, 58 autonomous counties and autonomous banners, and 16 open economic zones under municipal districts). In this study, considering the higher status of prefecture-level administrative regions, their more prominent political, economic and cultural influence than the rest of the levels, and the stronger concept of 'city', 126 prefecture-level resource-based cities are selected for this study, of which 20 are G-RCs, 66 are GU-RCs, 24 are Rec-RCs and 16 are R-RCs. The geographical distribution of the 126 cities is shown in Figure 3.

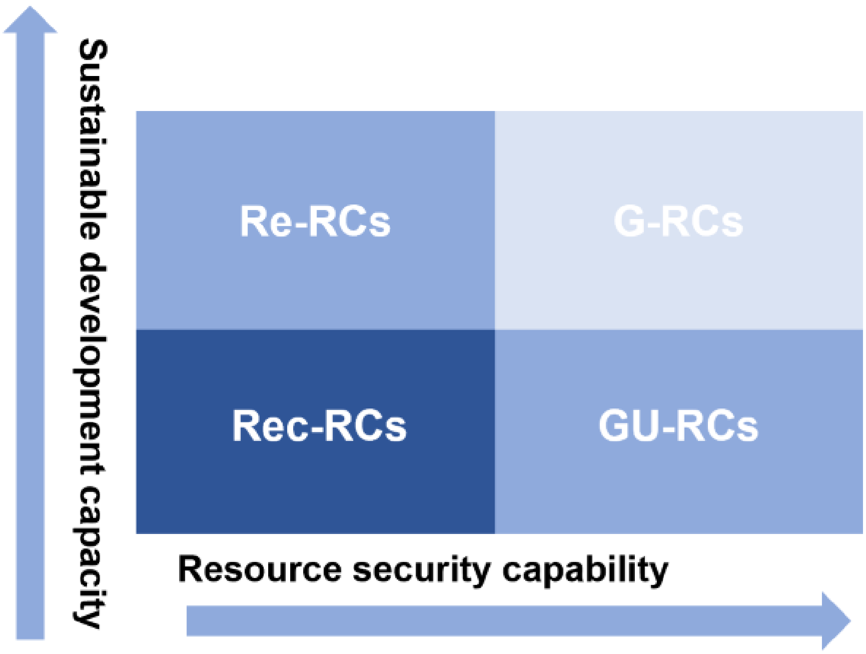

Figure 2 Concept map for the identification of different types of resource-based cities

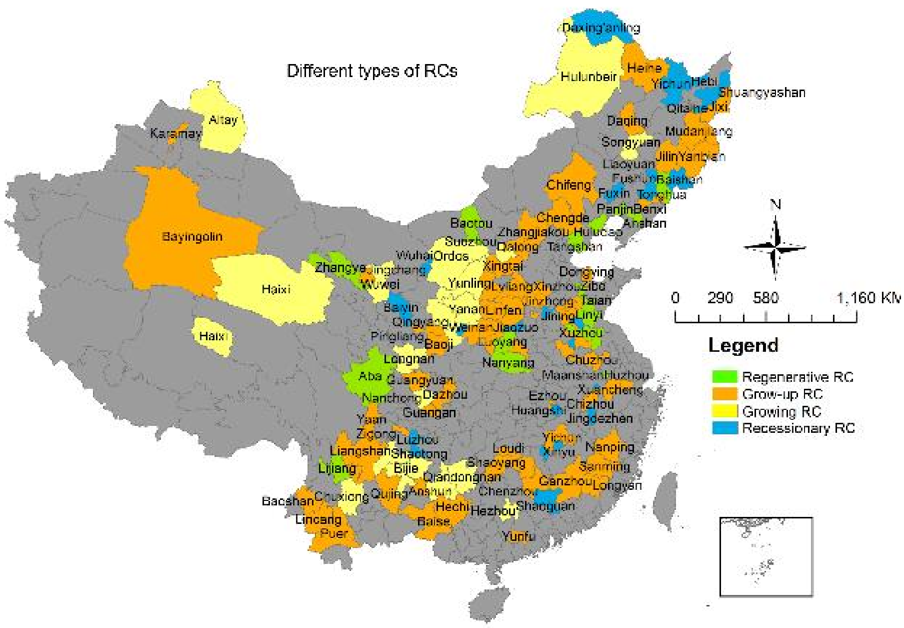

Figure 3 Geographical distribution of resource-based cities at the prefecture level in China

3.2 Data

3.2.1 Build-up areas

The built-up area data is extracted from the GlobeLand30 (GL30) dataset. This dataset is a global high-resolution land cover data product developed independently by the China National Geographic Information Center (http://www.globallandcover.com/). Based on a large amount of auxiliary data, and combining the Landsat TM5 ETM+ and OLI multispectral images, 30m resolution multispectral images collected by China's Environment and Disaster Mitigation Satellite HJ-1, and 16m resolution High-Fraction-1 (GF-1) multispectral images, the highly accurate land cover product is generated by adopting the methods of image element method classification, object filtering and human-computer interaction check. The raster open-source data has 10 land cover categories, i.e., arable land, woodland, grassland, shrubland, wetland, water, tundra, man-made surface, bare land, glacier and permanent snow. Zheng et al (2017) used this dataset of man-made surface to identify and evaluate "ghost cities" in the Pearl River Delta, China. Ma et al (2020) selected the dataset of man-made surface to establish an index to examine vacancy rate in Erdos City, China. Therefore, this dataset of artificial surfaces can simulate urban built-up areas to a certain extent. In this experiment, the artificial surface is used as the built-up area of sample cities.

The data for the study period, i.e., 2000, 2010 and 2020 GL30 images, are selected and the stitching process was completed on ERDAS IMAGINE 9.2; the man-made surface data with code 80 are extracted using ArcGIS 10.2;

3.2.2 Night-time lighting data

The Night-Time Light (NTL) images were collected from the Prolonged Artificial Nighttime-light Dataset of China (1984-2020), which is created independently by the China National Tibetan Plateau Data Center (http://data.tpdc.ac.cn/zh-hans/data/e755f1ba-9cd1-4e43-98ca-cd081b5a0b3e/) (Zhang et al., 2021). This dataset is based on images collected by the US Defense Meteorological Satellite (DMSP) and the Visible Infrared Imaging Radiometer (VIIRS) sensor of the US NPOESS Preparatory Project (NPP) satellite system, trained in a long and short-term memory neural network (NTLSTM) to generate an artificial nighttime light dataset for the Chinese region from 1984-2020. The results of the study show that the data accuracy and quality of the product is high. Compared to the original data, the new dataset has a coefficient of determination (R2) of 0.95, a root mean square error (RMSE) of 0.73 and a linear slope of 0.99 at the pixel point.

We utilize 2020 nighttime light images and combined with the latest Chinese administrative boundary, the nighttime light of Chinese resource-based cities is acquired successfully.

3.2.3 Population data

WorldPop website provides a variety of global or regional population-related data, including population size, population density, age and gender structure, and population mobility. In this study, the 1km x 1km population density (PD) grid data was processed using ArcGIS 10.2 to obtain the corresponding regional data for China.

2020 population image is selected, and the snitching of China is completed on ERDAS IMAGINE 9.2; using the latest Chinese administrative boundary to finally generate the population density raster data for resource-based cities in China.

3.2.4 Ancillary data

The administrative boundary data is sourced from NewHorizon (http://horizon2021.xyz/), which provides the latest administrative boundary vector data at all levels, national railway data, world climate zone data and so on. The source data for this website comes from the SkyMap Administrative Data Interface API, which uses the inverse geocoding of Gaode Maps to complete the tagging of administrative name attributes. Additionally, some auxiliary data for validation were obtained from corresponding China City Statistical Yearbook and the Seventh Census.

To eliminate the influence of different spatial resolutions on the image calculation, based on the WGS-84 geographical coordinate system, Asia North Lambert Conformal Conic is selected as the projection coordinate system of all data in each period, and grids in all images are resampled to 1 km^2.

3.3 Summary

This chapter provides a detailed introduction to the basic overview of the selected study area, the data sources and the basic process of data pre-processing to guarantee solid data support for the research in the subsequent chapters.

4 Analysis of the spatial and temporal evolution of urban spatial expansion based on built-up areas

4.1 Introduction

After the 1970s, China's urban expansion is extremely rapid, which has directly led to great changes in regional land use. Cultivated land, forest land, grassland and wetland are heavily occupied, which not only threatens national food security, but also affects the regional climate, hydrology and ecological environment (Shan et al., 2020). In recent years, many RCs have faced environmental and social problems resulting from the large-scale exploitation of mineral resources as well as the lagging development of leading industries due to resource depletion. Therefore, under the impact of the urban expansion wave, when the social economy cannot keep pace with urban construction, the uncontrolled expansion of cities will further hinder resource-based cities from escaping the “resource curse”, resulting in a great waste of urban land resources, and greatly increasing the cost of urbanization and aggravating the deterioration of urban environment. Thus, to better explore the spatial expansion of resource-based cities, solve the problem of disorderly expansion of urban land, and speed up the task of urban transformation of resource-based cities, we must first identify the temporal and spatial pattern of urban expansion. It is of great significance to monitor and evaluate the spatial expansion of resource-based cities scientifically and accurately.

Currently, although there have been many studies targeted at urban expansion analysis, there are scarce researches on the characteristics of the spatial expansion of resource-based cities. Mostly of studies are limited to one or two typical cities to explore the evolution of urban expansion, which cannot meet the rapid and accurate standard of monitoring and evaluating spatial expansion of resource-based cities. In addition, The National Sustainable Development Plan for Resource-based Cities (2013-2020) delineates four different types of resource-based cities, making it clear that there are differences inside resource-based cities, but comparative studies on the spatial expansion characteristics of resource-based cities among different types are hard to find. In summary, given the need to address the shortcomings of current studies, this chapter analyses the spatial and temporal evolution patterns of urban expansion based on its most direct manifestation, i.e., the scale and the form of urban built-up areas. Furthermore, comprehensively identifies and evaluates the spatial expansion patterns of various types of resource-based cities. The focus of this study includes: (1) The scale of urban spatial expansion, including the amount, speed, intensity and degree of urban expansion; (2) The morphological evolution of urban expansion, including changes in the compactness of urban expansion and changes in the fractal dimensions of urban expansion.

4.2 Selection of urban expansion indictors

Starting from the evolution direction, scale and form of built-up area expansion, three types of related indicators are selected. Moreover, according to different time stages (first stage (2000-2010), second stage (2010-2020) and total stage (2000-2020)) and the types of resource-based cities, the in-depth analysis on urban expansion patterns in resource-based cities is conducted.

4.2.1 Spatial expansion scale

1) Built-up area expansion amount

The Expansion amount of build-up areas (EA) shows the change in the area of the built-up area (km^2) during the corresponding phase (Lu et al., 2022). The formula is exhibited in equation 4.4.

$$\text{EA}= A_{last} - A_{first} \qquad 4.1$$

A_{last} denotes the built-up area in the final year of each phase (km^2) and A_{first} is the built-up area in the initial year of each phase (km^2).

2) Built-up areas expansion speed

Expansion speed of built-up areas (ES) represents the ratio (%) of the final area of built-up areas in a given study period to the area of built-up areas in the initial year (Huang et al., 2021). It is used to describe the overall scale change of built-up area during the corresponding period. Its formula is shown in equation 4.5.

$$\text{ES}=\left[\left(\frac{A_{last}}{A_{first}}\right)^{\frac{1}{\text{N}}} \text{-1}\right]\times 100\% \qquad 4.2$$

A_{last} denotes the built-up area in the final year of each phase (km^2), A_{first} denotes the built-up area in the initial year of each phase (km^2) and N is the intervening year.

3) Built-up area expansion intensity

Expansion intensity of built-up areas (EI) represents the average annual growth rate of urban expansion over a given study period. It demonstrates the average annual ratio of urban built-up area growth to the total initial urban built-up area. The corresponding formula is shown in equation 4.6.

$$\mathrm{EI}=\frac{\left(A_{last}-A_{first}\right)}{A_{first}\times N}\times 100\% \qquad 4.3$$

A_{last} is the built-up area in the final year of each phase, A_{first} is the built-up area in the initial year of each phase, and N is the year between the corresponding phases.

4) Built-up area expansion degree

The degree of expansion of built-up areas (ED) indicates the degree of change in the expansion of built-up areas relative to the total area of the urban area during the corresponding period. It represents the annual average ratio of the growth of the built-up area to the total urban area. The corresponding formula is shown in equation 4.7.

$$\mathrm{ED}=\frac{\left(A_{last}-A_{first}\right)}{A_{sum}}\times 100\% \qquad 4.4$$

A_{Sum} is the total area of the city.

4.2.2 Spatial expansion form

1) Compactness of built-up areas

Compactness of built-up areas (CB) represents the concentration of elements within the built-up area at the corresponding stage and reflects the change in the morphology of the built-up area. Currently, there are three main methods of measuring CB: the long axis-based shape rate method, the perimeter-based circular rate method, and the minimum outer circle-based compactness method. In this study, considering that the area of the smallest external circle is difficult to determine and that the perimeter is a better indicator of the distribution and dispersion of entities in space than the longest axis, the most commonly used perimeter-based circular rate method is chosen to represent the compactness change in built-up areas. The corresponding equation is shown in equation 4.8.

$$\mathrm{CB}=\frac{2\sqrt{\pi A_{sum}}}{\mathrm{P}_{sum}} \qquad 4.5$$

P_{sum} represents the total circumference of the built-up area in the region. The more concentrated the built-up area is and the more compact it is; when the value of CB is equal to 1, the built-up area is in the form of a circle and shows extremely strong compactness; the smaller the value of CB, the greater the separation of elements within the built-up area and the less compact it is; when the value of CB is close to 0, the built-up area is distributed in a straight line and its spatial form tends to be loose.

2) Fractal dimension value of built-up areas

Fractal geometry was established in 1975 by the American scholar Mandelbrot through his study of the morphology of Britain's meandering coastline. Fractal geometry treats irregular geometric forms as objects of study, and the irregularity of objects' forms is so prevalent in nature that fractal geometry is also known as the geometry of nature. Fractal is a concept based on the self-similarity of objects themselves. Objects in nature often have complex forms, but they can be divided into an infinite number of small parts, which can be approximated as a reduced version of the whole.

Fractal dimension value of built-up areas (FD) is commonly used to describe the complexity and stability of urban boundaries. Based on the calculated value of fractal dimension, the characteristics of the spatial expansion pattern of cities in different periods can be inferred and can be further used for empirical analysis of urban expansion morphology (Chen et al., 2017). The specific formula is as follows.

$$\mathrm{FD} = \frac{2In\left(0.25\mathrm{P}_{sum}\right)}{In\left(A\right)} \quad 4.6$$

Where A is urban area. In general, the results of fractal dimension values range from 1 to 2. A larger fractal dimension value indicates a high complexity and irregularity of the resource-based urban fringe. If the fractal dimension value is less than 1.5, it indicates a low complexity of the resource-based urban fringe and a simpler shape of the urban built-up area. If the value is greater than 1.5, it indicates that the edge shape of the city is particularly complex.

4.3 Evaluation of the spatial and temporal evolution of urban spatial expansion

4.3.1 Analysis of spatial expansion scale of the built-up area

1) Built-up area expansion amount

As shown in Figure 5, the histogram distribution of EA shows that the second phase (2010-2020) of expansion is far greater than the first phase (2000-2010), with a wider range of values on the y-axis in EA. The overall phase (2000-2020) shows a rapid expansion of built-up areas in resource-based cities over the past two decades, although a small number of sample cities in the first phase (2000-2010) show negative growth.

As shown in Figure 4 and Table 1, regenerative resource-based cities maintain the largest expansion within all phases, and their EA means and medians are also the largest among all categories. In the first stage, 10 samples within regenerative resource-based cities are below the mean 148.56km^2, accounting for 62.5% of the total sample; In the second stage, 10 samples within regenerative resource-based cities are below the mean 926.98km^2, accounting for 62.5% of the total sample; In the total stage, 9 of its samples are below the overall mean 1075.54km^2, accounting for 56.3%.

The weakest expansion of the sample cities in all categories is concentrated in recessionary resource-based cities, with the smallest mean and median EA, except for the median value in the first stage, which is slightly larger than the median EA in growing resource-based cities. In the first stage, 12 samples of recessionary resource-based cities are below the mean EA of 20.03km^2, accounting for 50% of the total sample; In the second stage, 16 samples of recessionary resource-based cities are below the mean of 340.66km^2, accounting for 66.7% of the total sample; In the total stage, 20 of its samples are below the overall mean of 360.69km^2, accounting for 83.3% of the total sample. In the total stage, 20 samples are lower than the overall average, accounting for 83.3% of the total number of samples.

As can be seen from Table 1, EA is more strongly fluctuated in grow-up resource-based cities compared to growing resource-based cities. In the first stage, 42 samples in grow-up resource-based cities are below the mean of 49.60km^2, accounting for 19.7% of the total sample, and 14 samples in growing resource-based cities are below the mean of 38.79km^2, accounting for 70% of the total sample. In the second stage, 41 samples in grow-up resource-based cities are below the mean of 629.80km^2, accounting for 62.1% of the total sample. In the second stage, 41 samples are below the mean of 629.80km^2 and 13 samples are below the mean of 583.80km^2, accounting for 65% of the sample; In the total stage, 39 samples are below the overall mean of 679.40km and 13 samples are below the overall mean of 622.60km^2, accounting for 65% of all samples.

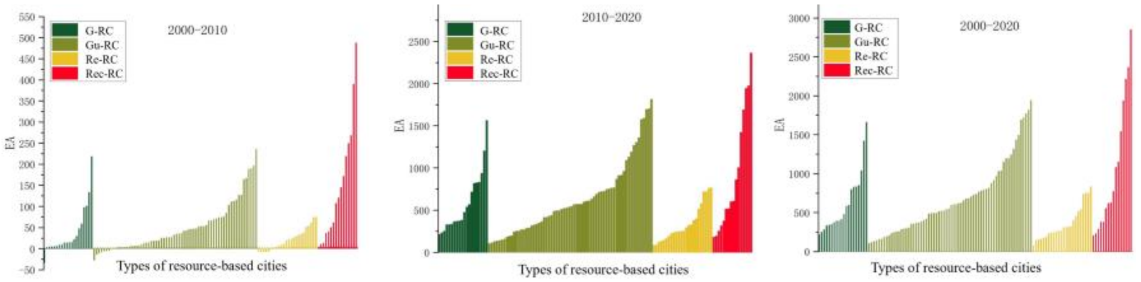

Figure 4 Distribution of EA in different resource-based city types (km^2)

Table 1 Statistical value of EA in different types of resource-based cities (km^2)

Type of resource-based city	Stage	EA Median	EA average
	Stage 1	14.59	38.79
G-RC	Stage 2	429.78	583.80
	Total stage	447.44	622.60
	Stage 1	33.81	49.60
GU-RC	Stage 2	541.23	629.80
	Total stage	573.31	679.40
	Stage 1	20.46	20.03
Rec-RC	Stage 2	252.17	340.66
	Total stage	289.13	360.69
	Stage 1	604.90	148.56
Re-RC	Stage 2	604.90	926.98
	Total stage	699.40	1075.54

2) Expansion speed of built-up areas

As shown in Figure 5, the histogram distribution of ES exhibits that the second phase (2010-2020) is expanding faster than the first phase (2000-2010) as a whole. The overall phase (2000-2020) shows that, although a small number of urban built-up areas expand at a negative rate in the first phase (2000-2010), in general, resource-based urban built-up areas are expanding dramatically.

As shown in Figure 5 and Table 2, in the first stage, regenerative resource-based cities expanded fast overall, with a maximum ES median of 8.86% and a maximum ES mean of 2.45% between classes, and their ES medians are much larger than those of the other three city groups, indicating that the cities in this category generally expanded fast; growing resource-based cities and grow-up resource-based cities had medium overall ES medians, but their ES The median ES of recessionary resource-based cities is much lower than that of the other categories, indicating that these cities are expanding at a slower pace.

In the second stage, growing resource-based cities have the largest inter-class median ES value of 15.07% and the largest ES mean value of 17.03%, with a faster overall expansion rate; grow-up resource-based cities and recessionary resource-based cities have the next highest expansion rates; regenerative resource-based cities have the smallest median ES and ES mean values, despite having the largest ES values, indicating that the low value component differs significantly from the high value component.

In the total phase, growing resource-based cities hold the largest ES median position among all categories at 9.50% and the largest ES mean at 9.21%; grow-up and recessionary resource-based cities continue to expand at the second and the third highest rate; meanwhile, regenerative resource-based cities have the smallest ES median and ES mean values.

From Table 2, it can be seen that among growing resource-based cities, 10 samples, 11 samples and 9 samples are below the mean threshold for each stage, accounting for 50.00%, 55% and 45% of the total sample respectively; 40 samples are below the mean value for all stages in grow-up resource-based cities, accounting for 60.61% of the total sample; in recessionary resource-based cities for each stage, there are 15 samples, 18 samples and 16 samples are below the average threshold, accounting for 62.50%, 75% and 66.67% of the total sample; regenerative resource-based cities have 8 samples, 13 samples and 13 samples below the mean value at all stages, accounting for 50.00%, 81.25% and 81.25% of the total sample.

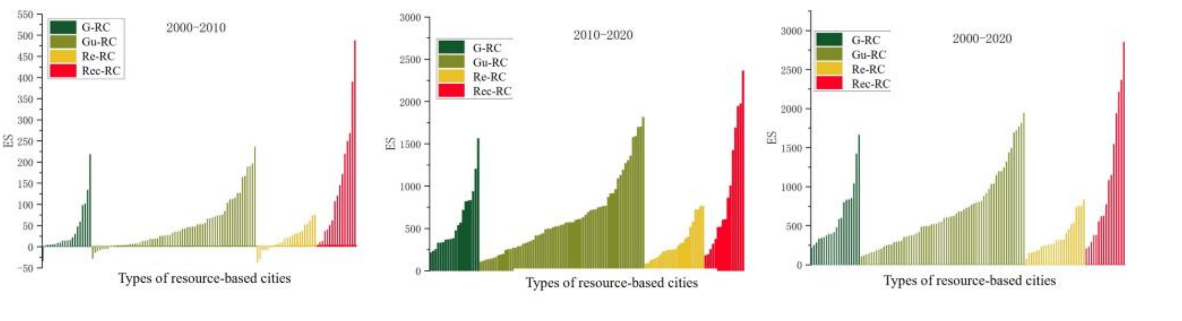

Figure 5 Distribution of built-up areas expansion speed in different types of resource-based cities (km^2)

Table 2 Statistical value of built-up areas expansion speed in different types of resource-based cities (km^2)

Type of resource-based city	Stage	ES Median	ES average
G-RC	Stage 1	1.95	2.00

	Stage 2	15.07	17.03
	Total stage	9.50	9.21
GU-RC	Stage 1	1.43	1.73
	Stage 2	12.52	13.31
	Total stage	6.93	7.34
Rec-RC	Stage 1	0.94	2.15
	Stage 2	11.26	11.52
	Total stage	6.53	6.69
Re-RC	Stage 1	8.86	2.45
	Stage 2	8.86	9.75
	Total stage	5.56	

(3) Intensity of built-up area expansion

As shown in Figure 6, the histogram distribution of expansion rates shows that the second phase (2010-2020) has a higher overall expansion intensity than the first phase (2000-2010). In terms of the total phase (2000-2020), the spatial expansion intensity of built-up areas in resource-based cities is generally higher, although a small number of cities in the first phase (2000-2010) have a negative expansion intensity.

As shown in Figure 6 and Table 3, in the first stage, regenerative resource-based cities expand fast overall, with the largest median EI among all categories of 13.36% and a higher mean EI of 2.82%, and their median EI is much larger than that of the other three categories of cities, indicating a generally high intensity of expansion in this category; growing resource-based cities and grow-up resource-based cities have an overall median EI in the middle, but their EI average values are lower than recessionary ones. The median EI of recessionary resource-based cities is much lower than that of the other categories, but their EI average value are the highest, indicating that the level of expansion intensity is extremely uneven within this category of cities.

In the second stage, growing resource-based cities have the largest inter-class median EI of 30.69% and the largest ES mean of 43.69%, with a higher overall expansion intensity; grow-up resource-based cities and recessionary resource-based cities rank the second and the third in expansion intensity; regenerative resource-based cities have the smallest median and mean EI, indicating that the expansion intensity of the sample cities in this category is decreasing. In the overall phase, growing resource-based cities maintain the largest EI median of 25.69% and the largest EI mean of 27.58% among all categories; grow-up and recessionary resource-based cities continue to occupy the middle position in terms of expansion intensity; regenerative resource-based cities have the smallest median and mean EI.

From Table 3, it can be seen that among the growing resource-based cities, 12 samples, 11 samples, and 11 samples are below the mean EI in each stage (first stage, second stage, and total stage), accounting for 60.00%, 55.00%, and 55.00% of the total sample; 41 samples, 42 samples, and 42 samples are below the mean EI in each stage in grow-up resource-based cities, accounting for 62.12%, 63.64%, and 63.64% of the total sample; in all stages of recessionary resource-based cities, 18 samples, 15 samples and 16 samples are below the mean EI, accounting for 75.00%, 62.50% and 66.67% of the total sample; in all stages of regenerative resource-based cities, 8 samples, 12 samples and 10 samples are below the mean, accounting for 50.00%, 75.00% and 62.50% of the total sample.

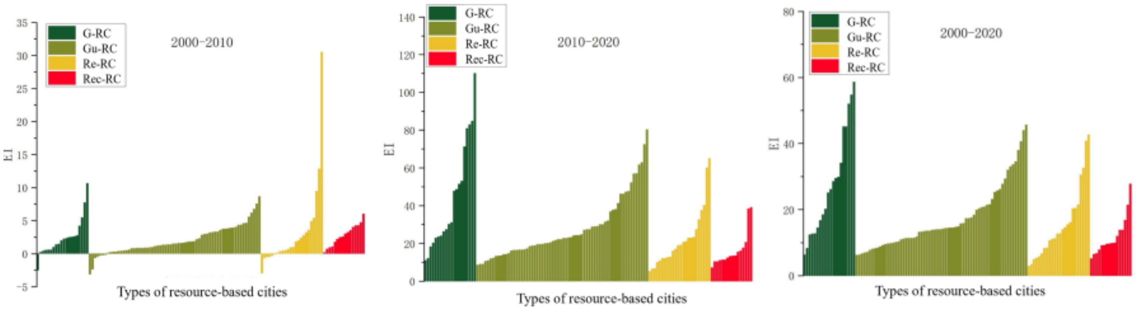

Figure 6 Distribution of built-up area expansion intensity in different resource-based city types (%)

Table 3 Statistical value of built-up areas expansion intensity in different types of resource-based cities (%)

Type of resource-based city	Stage	EI median	EI average
G-RC	Stage 1	2.13	2.44
	Stage 2	30.69	43.96
	Total stage	25.69	27.58
GU-RC	Stage 1	1.53	2.03
	Stage 2	22.52	27.34
	Total stage	14.11	17.18
Rec-RC	Stage 1	0.98	3.25
	Stage 2	19.06	22.3
	Total stage	12.73	15.57
Re-RC	Stage 1	13.36	2.82
	Stage 2	13.36	16.4

Type of resource-based city	Stage	EI median	EI average
	Total stage	9.77	11.85

4) Built-up area expansion Degree

As shown in Figure 7, the histogram distribution of expansion degree shows that the second phase (2010-2020) has a greater degree of overall expansion than the first phase (2000-2010). The overall phase (2000-2020) shows a higher degree of spatial expansion of built-up areas in resource-based cities in general, although a small number of cities in the first phase (2000-2010) have a negative degree of expansion.

As shown in Figure 7 and Table 4, in the first stage, regenerative resource-based cities have the greatest overall expansion, with a maximum inter-class median ED of 6.81% and a maximum mean ED of 1.83%, and their median and mean ED values are much greater than those of the other three city groups, indicating a generally high degree of expansion in this category; the ranking of median ED for recessionary resource-based cities and grow-up resource-based cities closely behind regenerative ones, and the median and mean values for growing resource-based cities are much lower than those for the other categories, indicating the lowest degree of expansion in this category.

In the second stage, regenerative resource-based cities maintain the highest median ED of 6.81% and the highest mean ED of 8.42%, with a significant increase in overall expansion, which followed by recessionary resource-based cities and grow-up resource-based cities; the median and mean ED of growing resource-based cities remain the lowest among all categories, indicating that the sample cities in this category are less expanded.

In the total phase, growing resource-based cities maintain a maximum median ED of 8.25% and a maximum mean ED of 9.79%; recessionary resource-based cities and grow-up resource-based cities come next; regenerative resource-based cities have a much smaller median ED and mean ED than the other three classes.

From Table 4, it can be seen that among the growing resource-based cities, there are 15 samples, 13 samples, and 13 samples below the mean threshold for each stage (first stage, second stage, and total stage), accounting for 75.00%, 65%, and 65% of the total sample; 45 samples, 45 samples, and 47 samples are below the overall mean value for each stage of grow-up resource-based cities, accounting for 68.18%, 68.18% and 71.21% of the total sample; 17 samples, 15 samples and 15 samples are below the average for all stages of recessionary resource-based cities, accounting for 70.83%, 62.50% and 62.50% of the total sample; 7 samples, 9 samples and 9 samples are below the average for all stages of regenerative resource-based cities, accounting for 43.75%, 56.25% and 56.25% of the total sample.

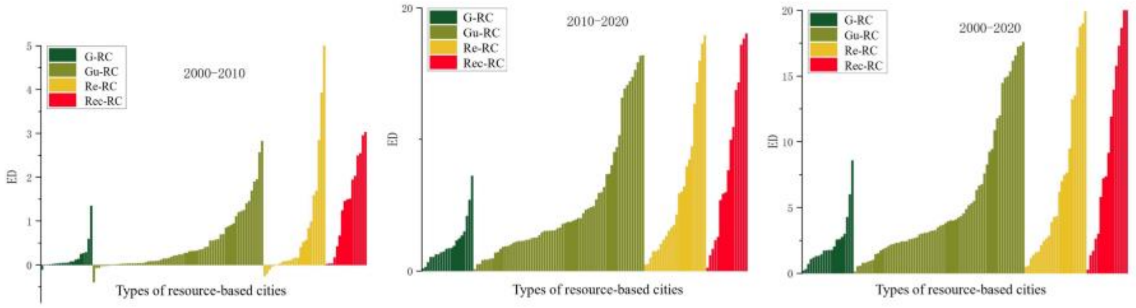

Figure 7 Distribution of the degree of built-up area expansion in different resource-based city types (%)

Table 4 Statistical value of built-up areas expansion degree in different types of resource-based cities (%)

Resource-based city type	Stage	ED median	ED average
G-RC	Stage 1	0.05	0.17
	Stage 2	1.70	2.15
	Total stage	1.75	2.31
GU-RC	Stage 1	0.22	0.47
	Stage 2	3.28	5.03
	Total stage	3.56	5.50
Rec-RC	Stage 1	0.15	0.77
	Stage 2	3.88	6.25
	Total stage	4.30	7.03
Re-RC	Stage 1	6.81	1.38
	Stage 2	6.81	8.42
	Total stage	8.25	9.79

Table 5 The expansion index of built-up areas in different types of resource-based cities lower than the average statistical value

Resource-based city type	Stage	EA number	EA ratio	ES number	ES ratio	EI number	EI ratio	ED number	ED ratio
G-RC	1	14	70.00%	10	50.00%	12	60.00%	15	75.00%
	2	13	65.00%	11	55.00%	11	55.00%	13	65.00%

Resource-based city type	Stage	EA number	EA ratio	ES number	ES ratio	EI number	EI ratio	ED number	ED ratio
	Total	13	65.00%	9	45.00%	11	55.00%	13	65.00%
	1	42	63.64%	40	60.61%	41	62.12%	45	68.18%
GU-RC	2	41	62.12%	40	60.61%	42	63.63%	47	71.13%
	Total	39	59.1	40	60.61%	42	63.63%	47	71.13%
	1	12	50.00%	15	62.50%	18	75.00%	17	70.83%
Rec-RC	2	16	66.67%	18	75.00%	15	62.50%	15	62.50%
	Total	20	83.33%	16	66.67%	16	66.67%	15	62.50%
	1	10	62.50%	8	50.00%	8	50.00%	7	43.75%
Re-RC	2	10	62.50%	13	81.25%	12	75.00%	9	56.25%
	Total	9	56.25%	13	81.25%	10	62.50%	9	56.25%

4.3.2 Analysis of the morphological evolution of the built-up area

1) Changes in compactness of built-up areas

From the histogram curves in Figure 8, the peaks of the histogram curves of the compactness distribution of all resource-based cities shift to the left during the study period. From 2000 to 2010, the curve of growing resource-based cities increases its width and height during the migration process, indicating that the compactness of the high value samples in the initial years has decreased while the compactness of the low value samples increases to some extent, thus the overall compactness of this category moves towards the middle. From 2010 to 2020, the shift of curves to the left is more significantly, with a much narrower width and a higher peak, indicating that the compactness of each city is more concentrated in the low value range. Meanwhile, the CB value of recessionary resource-based cities stays the highest at all stages.

As shown in Table 6, from 2000 to 2010, the most obvious declining trend of CB happens in growing resource-based cities, with a decline of up to 80% (number of cities in the sample:16), followed by grow-up resource-based cities and regenerative resource-based cities, with a decline of 53.03% (number of cities in the sample:35) and 50% (number of cities in the sample: 8) respectively; cities with the lowest decline in overall compactness from 2010 to 2020 are recessionary resource-based cities, with a decline of 41.67% (number of cities in the sample:10). From 2010 to 2020, the overall compactness of growing resource-based cities maintains the highest downward trend, and the decline proportion of CB reaches 100% (number of urban samples: 20), followed by grow-up resource-based cities and recessionary resource-based cities, with a decline rate of 89.39% (number of urban samples: 59) and 83.33% (number of urban samples: 20) respectively; The smallest decline in CB happens in the regenerative group, with a decline rate of 68.75% (number of urban samples: 11). In terms of the overall stage, the overall compactness of the built-up areas of growing resource-based cities is still not promising, and the CB decreased by 100% (number of urban samples: 20), followed by growing resource-based cities and recessionary resource-based cities, with a decline rate of 87.88% (number of urban samples: 58) and 79.17% (number of urban samples: 19) respectively; The smallest decline in the overall compactness of urban built-up areas is regenerative resource-based cities, with a decline rate of 68.75% (number of urban samples:11).

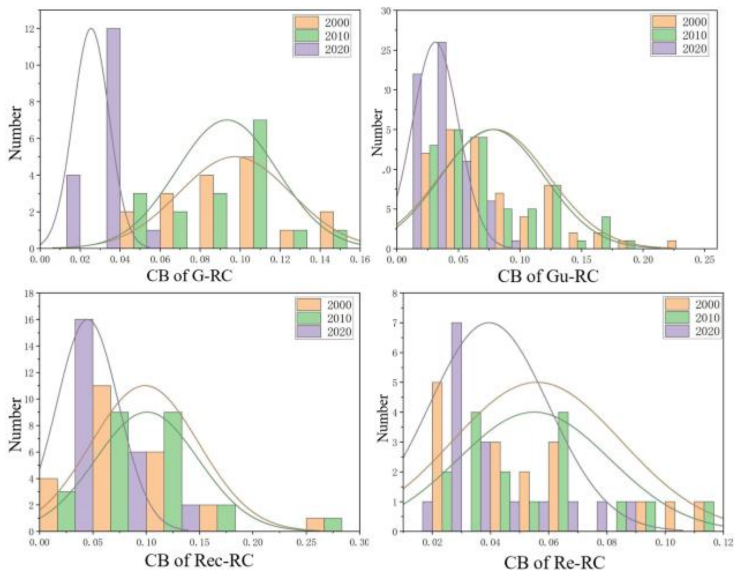

Figure 8 Comparison of compactness of the built-up area expansion in different resource-based city types

Table 6 Statistical values of decreasing compactness of built-up area expansion in different resource-based city types

Resource-based city type	Stage	Number of CB decline	CB decline in percentage
G-RC	Stage 1	16	80.00%
	Stage 2	20	100.00%
	Total stage	20	100.00%
GU-RC	Stage 1	35	53.03%
	Stage 2	59	89.39%
	Total stage	58	87.88%
Rec-RC	Stage 1	10	41.67%
	Stage 2	20	83.33%
	Total stage	19	79.17%
Re-RC	Stage 1	8	50.00%
	Stage 2	11	68.75%
	Total stage	11	68.75%

2) Change in fractal dimension values of urban built-up areas

From the histogram curve in Figure 9, except for regenerative resource-based cities, the peak of FD first moves to the left and then to the right during the study period, while the peak value of FD in regenerative resource-based cities keeps moving to the left, indicating that the complexity of spatial pattern in growing resource-based cities, grow-up resource-based cities and recessionary resource-based cities decreases in the first research period, but increases significantly in the following decade, while the complexity of the spatial pattern of regenerative resource-based cities is relatively stable. In all stages, the peak value of the histogram always lingers in the grow-up type.

As shown in Table 9, from 2000 to 2010, the overall FD of the built-up area of growing resource-based cities has the most obvious upward trend, with FD increasing by 20% (number of cities in the sample: 4); followed by grow-up resource-based cities and recessionary resource-based cities, with FD increasing by 16.67% (number of cities in the sample: 11) and 12.50% (number of cities in the sample: 3) respectively; the weakest growth trend of the overall FD is in regenerative resource-based cities, with an increase of only 6.25% (number of cities in the sample: 1). From 2010 to 2020, the overall FD of the built-up area in growing resource-based cities increases more significantly than in the previous period, with the FD growth rate increasing to 90% (number of cities in the sample: 18), followed by recessionary resource-based cities and grow-up resource-based cities. The smallest increase in the overall fractal dimension of the built-up area is in the regenerative resource-based cities, with an FD increase of 37.50% (number of cities in the sample: 6), which is much lower than the other three types of resource-based cities. In general, the growing resource-based cities maintain the highest level of growth in the overall fractal dimension of built-up areas, with a 90% increase in FD (number of city samples: 18), followed by grow-up and recessionary resource-based cities, with a 72.73% (number of city samples: 48) and 70.83% (number of city samples: 17) decrease respectively; The worst performer in terms of overall increase in FD is regenerative resource-based cities, with an increase of 37.50% (number of cities in the sample: 6).

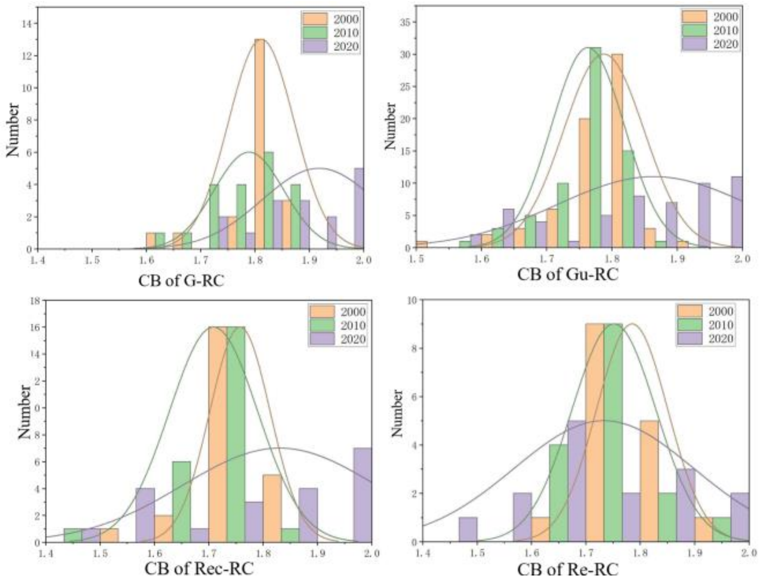

Figure 9 Comparison of fractal dimension values in different resource-based city types

Table 7 Statistical values of fractal dimension values in different resource-based city types

Resource-based city type	Stage	Number of FD growth	FD growth ratio
G-RC	Stage 1	4	20.00%
	Stage 2	18	90.00%
	Total stage	18	90.00%
GU-RC	Stage 1	11	16.67%
	Stage 2	52	78.79%
	Total stage	48	72.73%
Rec-RC	Stage 1	3	12.50%
	Stage 2	19	79.17%

	Total stage	17	70.83%
Re-RC	Stage 1	1	6.25%
	Stage 2	6	37.50%
	Total stage	6	37.50%

Throughout the study period, we can conclude that the spatial pattern of cities in the second phase is more complex, unstable and loose. Regenerative resource-based cities show relatively stable development in compactness and fractal dimension. Growing resource-based cities show lower and lower compactness, while higher and higher fractal dimension value is witnessed, grow-up resource-based cities and recessionary resource-based cities show relatively low compactness and relatively high fractal dimension value. Therefore, the complexity and looseness of the morphological evolution of cities are, in descending order: growing resource-based cities > grow-up resource-based cities > recessionary resource-based cities > regenerative resource-based cities.

4.4 Conclusion

Based on the data extracted from globeland30 remote sensing images at three-time nodes in 2000, 2010 and 2020, the spatial and temporal characteristics of urban expansion in different types of resource-based cities are identified. The results show that:

(1) Between 2010 and 2020, all cities experience dramatic spatial expansion, and the overall scale of cities are much greater than that of the cities between 2000 and 2010. Within all phases, according to the resource-based cities type, regenerative resource-based cities have the largest urban spatial expansion, followed by grow-up and growing resource-based cities, and expansion of recessionary resource-based cities rank the last, i.e., "regenerative resource-based cities > grow-up resource-based cities > growing resource-based cities > recessionary resource-based cities ". After considering the time dimension, growing resource-based cities have the fastest urban spatial expansion, followed by grow-up and recessionary resource-based cities, and regenerative resource-based cities expand in the lowest mode, i.e., "growing resource-based cities > grow-up resource-based cities > recessionary resource-based cities > regenerative resource-based cities".

(2) During the study period, the spatial expansion intensity and spatial expansion degree of all types cities show "high expansion intensity, low expansion degree", which to a certain extent indicates that the spatial expansion of resource-based cities still has great potential. The intensity and degree of expansion for all cities are as follows: Intensity of expansion: regenerative cities > growing resource-based cities > grow-up resource-based cities > recessionary resource-based cities; degree of expansion: growing resource-based cities >

grow-up resource-based cities > recessionary resource-based cities > regenerative resource-based cities.

(3) The spatial pattern of built-up areas in resource-based cities is slowly developing towards strong looseness and high complexity, as shown by the decreasing compactness and increasing fractal dimension values. The complexity and looseness of the spatial pattern from high to low: growing resource-based cities > grow-up resource-based cities > recessionary resource-based cities > regenerative resource-based cities.

5 Multidimensional-based identification and evaluation of the urban shrinkage degree

5.1 Introduction

The previous chapter has discussed the spatial and temporal evolution of urban expansion in built-up areas, which is characterized by a strong tendency of disordered sprawl and high complexity. Many studies have proved that with the impaction of the resource curse theory, resource-based cities in China have showed an increasing spatial growth, but due to population loss, economic decline and poor urban planning tactics, the phenomenon of “ghost cities” is becoming more and more common (Tong et al., 2021; Shi et al., 2020). Therefore, it is important to evaluate urban shrinkage degree in order to better adjust the overall urban planning, improve the efficiency of urban space utilization and maximize the potential of resource-based cities.

There have been many studies on urban shrinkage, mainly focusing on the three dimensions, i.e., economy, land and population. However, most of the existing studies are limited to statistical data or using only one or two dimensions, which cause problems such as poor timeliness and low accuracy. The emerging big data are generally difficult to obtain and rather cumbersome to process. Therefore, there is an urgent need to establish a comprehensive multi-dimensional, high-precision urban shrinkage evaluation model.

Based on the above three dimensions of urban shrinkage, i.e., population, land and economy, this study utilizes multi-source remote sensing data to construct a multi-dimensional comprehensive evaluation system of urban shrinkage in resource-based cities.

5.2 Establishment of an urban shrinkage evaluation system

5.2.1 Selection of evaluation indicators

Based on an in-depth analysis of the intrinsic characteristics of shrinking cities, the first and crucial step in building an evaluation system is to use remote sensing data to measure urban shrinkage from three dimensions i.e., population, land and economy.

Firstly, to eliminate unnecessary population movement interference, the population density under built-up areas is used as a population dimension factor in this study; secondly, night-time light data (NTL) is introduced to examine the efficiency of land use in the study area. Built-up areas which are poor-utilized or completely vacant usually lack light at night, resulting in a certain degree of difference between the built-up area data during the day and night. Therefore, by overlaying the NTL data on the original built-up area data and calculating the consistency of the built-up area in two statuses, the land use efficiency of the built-up area can be well described; at the same time, the lightness of the area is closely related to the economic level. Generally speaking, the higher the economic level means the stronger the light intensity, and the lower the economic level means the weaker the light intensity, therefore, light intensity can be selected as a strong tool to measure the economic level of the city.

5.2.2 Construction of the urban shrinkage index

According to the above ideas, the CSI is based on three dimensions (Zheng et al., 2017), i.e., population density, built-up area consistency and light intensity. When a city's population outflow is greater than its inflow, the vacancy of land will become quite obvious and its economy is persistently sluggish, it is evidence that the city is suffering from a serious urban shrinkage crisis. As resource-based cities in the plight of resource depletion and over-exploitation are vulnerable to environmental degradation, depopulation and economic decline, the urban shrinkage of such cities should be more closely monitored.

In summary, the index is constructed as follows：

$$RB = BA_{NTL} \big/ BA_{GL-30} \qquad 5.1$$

BA_{GL-30} represents the total number of pixels in the built-up area extracted by GL30. BA_{NTL} is the total number of pixels in the built-up area after superimposing NTL, and RB is the degree of the built-up area consistency.

$$PD = POP \big/ S_{GL-30} \qquad 5.2$$

PD denotes the result of intersecting the population density grid data with the corresponding built-up area i.e., the population density under the built-up area.

$$NI = NTL_{ave} \big/ NTL_{\max} \qquad 5.3$$

NTL_{ave} is the average luminance value of the NTL image, and $NTL_{\max}$ is the maximum luminance value of the NTL image.

$$\text{CSI=RB} \times \text{PD} \times \text{NI} \qquad 5.4$$

In this study, higher CSI values indicate relatively weaker urban shrinkage and lower CSI values indicate relatively stronger urban shrinkage, so as CSI values rise, urban shrinkage gradually decreases; as CSI values fall, urban shrinkage gradually deepens.

5.2.3 Identification of urban shrinkage types

1) Logarithmic transformations

The constructed CSI values follow a skewed distribution, in order to perform a more stable and accurate sample assessment, the calculated CSI is fitted to an approximately normal distribution using a logarithmic transformation method before further exploring the extent of urban shrinkage (Stine, 2017).

$$x = \log_a N \qquad 5.5$$

N is the original CSI value, x is the log-transformed CSI value, and a is the base of the logarithm.

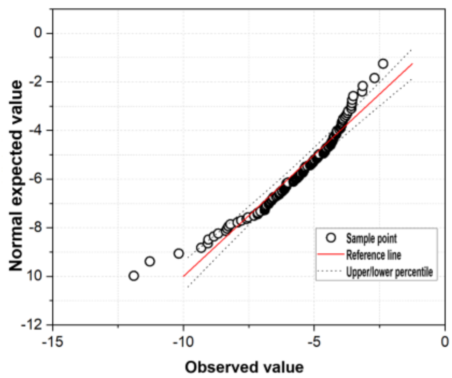

Figure 10 Sketch map of normal distribution test using Q-Q Plots method

In order to test the accuracy of the logarithmic transformation results, this study uses Q-Q plots to show the effect before and after the transformation. Q-Q plots, a popular method of testing whether the input dataset follows normal distribution. If the sample distribution is normal, then its predicted normal expectation value will be approximately the same as the actual observed value. According to this principle, in the scatter diagram, the actually obtained sample value is taken as the x-axis and the predicted expected value is taken as the y-axis. If the data meets normal distribution threshold, the points on its scatter plot are approximately a straight line, if the data does not have obvious normality, the data points will deviate from the straight line.

2) Classification and comparison of urban shrinkage indices

In order to better measure and compare urban shrinkage in resource-based cities, it is necessary to classify CSI for all the cities. Standard deviation is the arithmetic mean of variance. Compared with other classification methods, when the statistical sample is large, it can better reflect the dispersion pattern of samples. Therefore, the standard deviation classification method is chosen to classify the CSI of the study area into five types, i.e., Extremely Strong Shrinkage (ESS), Strong Shrinkage (SS), Moderate Shrinkage (MS), Relatively Weak Shrinkage (RWS), and Weak Shrinkage (RWS). The standard deviation classification (Zheng et al., 2017; Quan et al., 2014) is based on the following formula.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \qquad 5.6$$

σ is the final resulting standard deviation, N is the total number of samples, x is the sample corresponding CSI value, and μ indicates the sample CSI mean value.

In this study, the urban shrinking degree varies across resource-based cities. Therefore, in order to describe the differences in urban shrinkage in different resource-based city types, these inter-group variations are analyzed in the form of percentages. If a certain type of resource-based city has a higher proportion of WS and RWS and a lower proportion of ESS, SS and MS, this type of resource-based city is considered to have a relatively mild shrinkage problem. Conversely, if a certain type of resource-based city has a lower proportion of WS and RWS and a higher proportion of ESS, SS and MS, it would be considered that this type of resource-based city has a relatively heavy shrinkage problem.

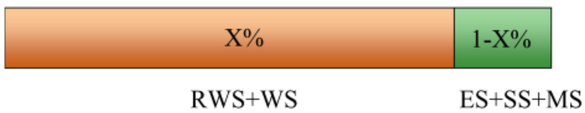

Figure 11 Schematic diagram of percentages

5.2.4 Identification of spatial distribution characteristics of urban shrinkage

Due to the vast territory of China and the wide distribution of resource-based cities, it is necessary to identify the spatial distribution characteristics of CSI. Based on the first law of geography proposed by Tobler, which states that geographical entities always exhibit certain spatial correlations regardless of their proximity, thus, this study uses spatial autocorrelation analysis to conduct an in-depth study of the spatial interrelationships of the CSI.

Spatial autocorrelation analysis is a powerful tool to test the relationship between the observed values of a point in space and its adjacent points. Therefore, in this experiment, we choose the commonly used spatial autocorrelation methods, i.e., global Moran's I and local Moran's I, to perform spatial analysis and visualize the spatial characteristics of geographical entities.

The global Moran's I is mainly used to describe the average correlation between all spatial units and their surrounding units in the whole region. During the study, the index can help infer the type of spatial relationship (Dong et al., 2021). The calculation formula of global Moran's I is as follows.

$$I_{GlobeMoran} = \frac{n}{s_o} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \overline{y})(y_j - \overline{y})}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \quad 5.7$$

$$s_o = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \quad 5.8$$

where y_i denotes the observations in region i, $\overline{y}$ is the average of all spatial cells, n denotes the total number of spatial cells and w_{ij} denotes the spatial weight matrix. The value of global Moran's I ranges from -1 to 1. When it is greater than 0, it indicates a positive spatial correlation between the data. The larger the value, the stronger the spatial correlation. When the global Moran's I is less than 0, it indicates that the data have negative spatial correlation. The smaller the value, the greater the spatial variation, and if Moran's I reaches 0, it indicates that the data are extremely weakly correlated and show a random distribution among the spatial elements.

The global Moran's I is the first step in checking for categories of spatial correlation; It cannot represent the spatial agglomeration or heterogeneity of local areas, and the advantage of local Moran's I can find the exact location of these spatial features. The calculation formula of local Moran's I is as follows.

$$I_{LocalMoran} = \frac{(y_i - \overline{y})}{s_o^2} \times \sum_{i=1}^{n} w_{ij}(y_i - \overline{y}) \quad 5.9$$

5.3 Results of the urban shrinkage evaluation

5.3.1 Logarithmic transformations

As shown in Fig 5.4, the dataset before log-transformation demonstrates a low fit to the red diagonal line, and after log-transformation the match-degree is greatly improved, indicating that the sample data basically conforms to the rules of normal distribution.

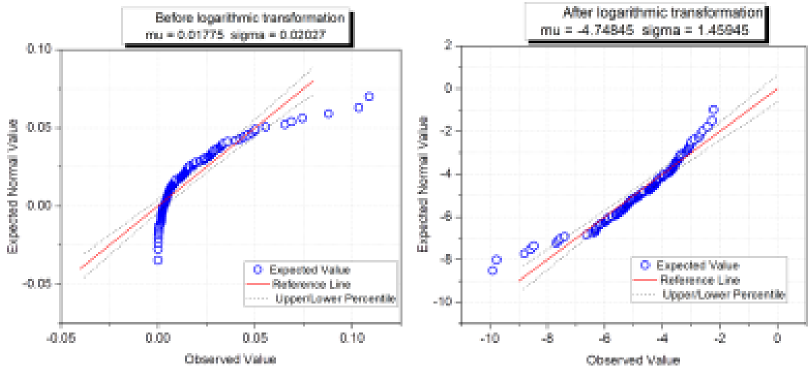

Figure 12 Normal distribution test using Q-Q Plots method

5.3.2 Comparison of the degree of urban shrinkage under different urban types

As the bar in Figure 13 implies, CSI values vary across the different types of resource-based cities. The rising trend in the bar is relatively smooth in the grow-up resource-based cities, with a merely slow climb. For the other three types, the CSI bar rises more rapidly, especially in the part of high values. In the comparison of CSI means, the average CSI value for growing resource-based cities is well below the overall mean of 0.009826, with recessionary resource-based cities having the highest average CSI value of 0.012618. In the comparison of the minimum value, recessionary resource-based cities fall to last place, with only 0.000004 in this category, followed by grow-up resource-based cities at 0.000031, both well below the mean of CSI value minima at 0.000143. In addition, regenerative resource-based cities show higher CSI values in the low value areas and thereby have the largest share in the semi-loop chart of the minimum CSI value. In the comparison of the maximum CSI value, growing resource-based cities and grow-up resource-based cities perform poorly at 0.029514 and 0.010375 respectively, both below the overall average of 0.041774, while regenerative resource-based cities are more dominant in this comparison, with 0.049348 well above the overall average. In the comparison of the median CSI value, although grow-up resource-based cities are not stand out in the previous comparison, they rank first in this category with a maximum CSI value of 0.038950. In addition, the median value of 0.009252 and 0.005219 for recessionary and growing resource-based cities respectively are well below the overall average of 0.016687.

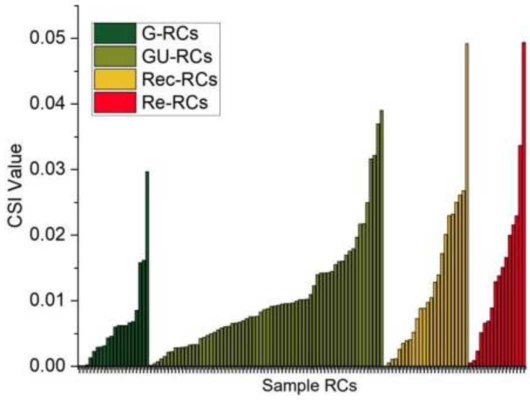

Figure 13 CSI distribution among different types of resource-based city

It is clear from Figure 14 supplied that urban shrinkage in China's resource-based cities is concentrated in the less shrinking categories of WS and RWS, with ESS and SS accounting for a relatively small number. More specifically, there are 42 WS and 56 RWS shrinking cities, 17 MS shrinking cities, and only 6 and 5 ESS and SS shrinking cities respectively.

Table 8 City shrinkage index grading results

Category	Standard deviation interval	Number	Ln (CSI)	CSI
Extremely Strong Shrinkage (ESS)	< -1.5 Std. Dev	6	< -8.8167	0.000004~0.000255
Strong Shrinkage (SS)	-1.5 Std.Dev~ -0.5 Std.	5	-8.8167 ~ -7.3426	0.000386~0.000633
Medium shrinkage (MS)	-0.5 Std.Dev~0.5 Std.	17	-7.3426 ~ -5.8685	0.000867~0.002806
Relative Weak Shrinkage (RWS)	0.5 Std.Dev~ 1.5 Std.	56	-5.8685 ~ -4.3944	0.003066~0.012183
Weak Shrinkage (WS)	> 1.5 Std. Dev	42	-4.3944 ~ -3.0089	0.01247~0.04935

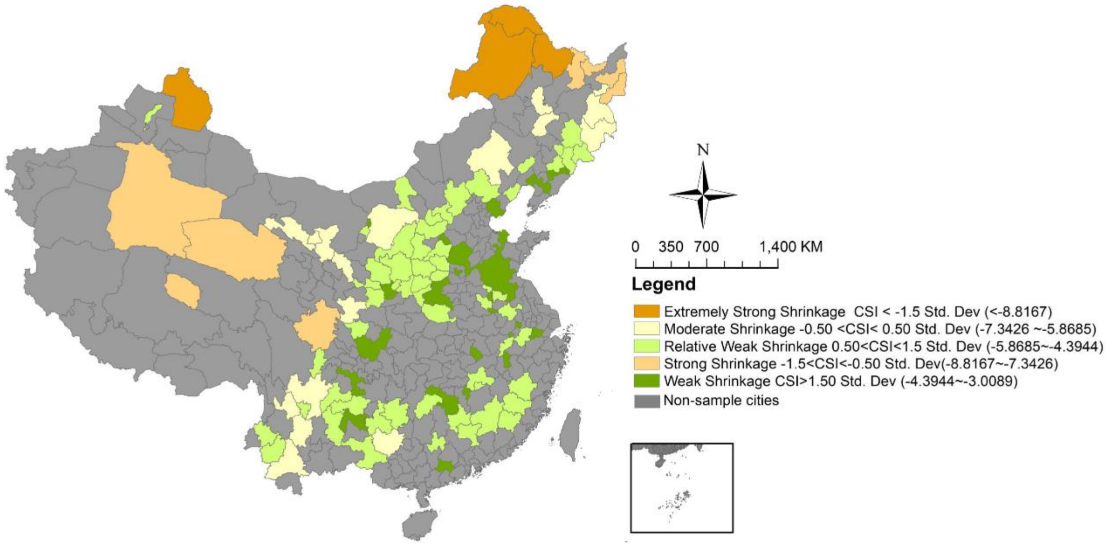

Figure 14 Spatial distribution of CSI classifications

In addition, as shown in Table 9, in-depth statistics on CSI according to the category of resource-based cities to obtain the details not noticed in the geographical distribution map are conducted. Among the light shrinking types MS, RWS and WS, the proportion of grow-up resource-based cities is 47.1% (number of cities: 8), 62.5% (number of cities: 35) and 47.6% (number of cities: 10) respectively, and they are the largest of the three categories. The number of growing resource-based cities rank second in MS and RWS, with 29.41% (number of cities: 5) and 16.07% (number of cities: 9) respectively, however, they rank last in WS, with only 7.14% (number of cities: 3). The recessionary resource-based cities are in the middle of the MS and RWS rankings, and in the comparison of WS, it accounts for 23.8% (number of cities: 10) which exceeds 7.14% (number of cities: 7) of growing resource-based cities, but less than 47.62% (number of cities: 20 cities) of grow-up resource-based cities. In addition, regenerative resource-based cities have the least share in MS and RWS, accounting for 11.76% (number of cities: 5) and 7.14% (number of cities: 9) respectively, but their proportion in WS has increased slightly, accounting for 21.43% (number of cities: 9) in WS. In the comparison of severe shrinking type, i.e., ESS and SS, as shown in Table 9, number of this type of resource-based cities in SS is very small, and ESS does not exist in them. The cities that account for a large proportion of ESS and SS are mainly concentrated in recessionary resource-based cities and growing resource-based cities, while the distribution of grow-up resource-based cities in ESS and SS is relatively stable, with 25% (number of cities: 1) and 28.57% (number of Cities: 2) respectively.

Table 9 Relationship between the number of each type of resource-based city in different categories of CSI

Type		G-RCs	Gu-RCs	Rec-RCs	Re-RCs	Total
ESS	Number	2	1	1	0	4
	Percentage	50.00%	25.00%	25.00%	0.00%	100.00%
SS	Number	1	2	3	1	7
	Percentage	14.29%	28.57%	42.86%	14.29%	100.00%
MS	Number	5	8	2	2	17
	Percentage	29.41%	47.06%	11.76%	11.76%	100.00%
RWS	Number	9	35	8	4	56
	Percentage	16.07%	62.50%	14.29%	7.14%	100.00%
WS	Number	3	20	10	9	42
	Percentage	7.14%	47.62%	23.81%	21.43%	100.00%

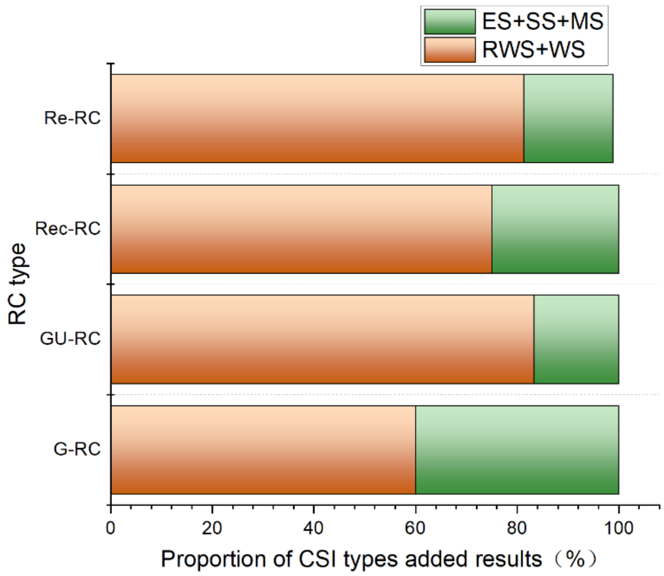

Figure 15 Comparison of the severity of urban shrinkage in different resource-based cities

Table 10 CSI classification results for different resource-based city types

Type	ESS	SS	MS	RWS	WS	Sum
Growing Resource-based cities	2	1	5	9	3	20
grow-up resource-based cities	1	2	8	35	20	66

Recessionary resource-based cities	1	3	2	8	10	24
Regenerative resource-based cities	0	1	2	4	9	16
Total	4	7	17	56	42	126

Given the different sample sizes for resource-based city types, bar charts in percentage form are used to compare and describe the severity of shrinkage for each resource-based city type. In Fig 5.8, although grow-up resource-based cities have the largest number, they have the smallest proportion of the ESS, SS and MS, denoting they have the lowest severity of shrinkage. For regenerative resource-based cities, the proportion of severe urban shrinkage types ESS, SS and MS lags slightly behind that of grow-up resource-based cities. Meanwhile, performances of the growing resource-based cities and the recessionary resource-based cities are not promising, with a larger proportion of cities in these two types staying in the green areas, i.e., areas which mean severe urban shrinkage. Therefore, based on the position of the black vertical lines in the bar chart, the severity of urban shrinkage can be ranked from the bottom to the top: grow-up resource-based cities < Regenerative Resource-based cities < Recessionary resource-based cities < Growing Resource-based cities.

5.3.3 Identification of spatial distribution characteristics of urban shrinkage

After examining the geographical distribution of CSI for 126 prefecture-level resource-based cities in China (Fig 5.7), there are clear geographical discrepancies in the shrinkage degree of resource-based cities. Severe urban shrinkage problems tend to concentrated in the northeast and west, and those with lighter severe shrinkage problems gather in the center and east.

To reveal the spatial agglomeration and heterogeneity of urban shrinkage, this study applies global Moran's I and local Moran's I to describe and visualize the spatial distribution pattern of shrinkage in resource-based cities. In subsequent experiments, using GeoDa software, Moran's I of 0.3048 is acquired, with a z-value of 11.9694 (greater than the prescribed 1.96) and a p-value of 0.001, which indicates that the rejection of the original hypothesis and data is significantly below the 1% level, and thereby CSI data exhibit significant positive spatial correlation. Positive spatial correlation means that sample cities with similar CSI (high value-high value or low value-low value) tend to be spatially distributed in clusters. More specifically, areas with higher CSI are adjacent to areas with higher CSI (high value-high value) and low CSI areas tend to close to similar low value areas (low value-low value). As shown in Figure 16, overall, the CSI distribution is poorly balanced spatially and the spatial correlation are not significant for most of sample cities in this study. The high value-high value sample cities (Number of cities: 36) are only found in the eastern region, while the low value-low value sample cities (Number of cities: 16) extend westwards from the northeast. This result is highly consistent with the current state of China's regional economic development. Cities in the east are economically stronger, while the north-eastern and western regions are relatively weaker. This phenomenon of geographical disparity suggests that China should take a good heed to this unbalanced distribution and accelerate the pace of urban development in inland areas.

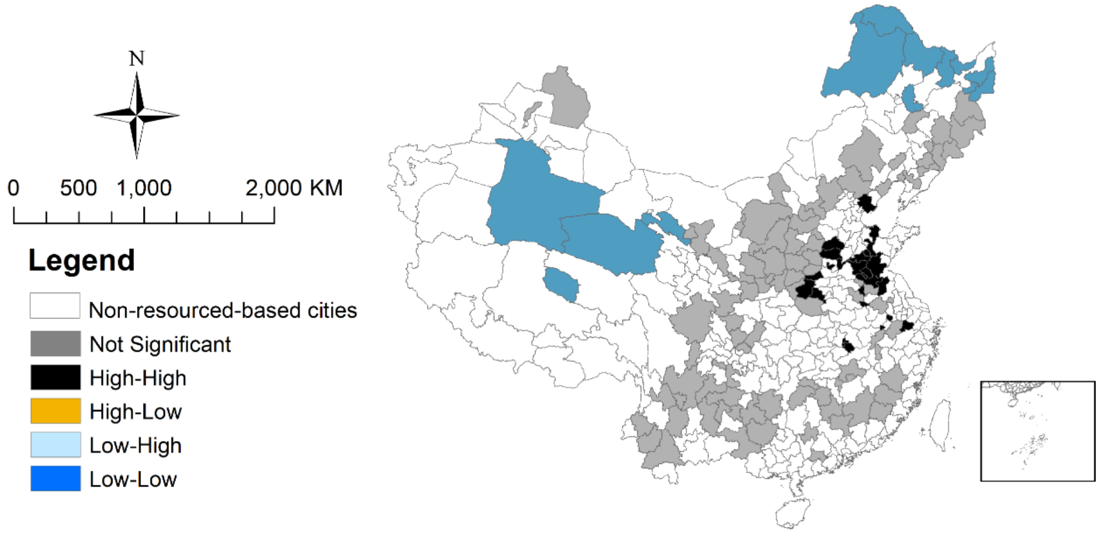

Figure 16 Local Moran index results for urban shrinkage in resource-based cities

5.4 Conclusion

Based on a multidimensional perspective of population, land and economy, this chapter realizes the task of identifying and evaluating the degree of urban shrinkage in 126 resource-based cities in China using a series of remote sensing spatial data such as NTL, GL30 and Worldpop. Firstly, the urban shrinkage index (CSI) is constructed by combining the three most significant characteristics of urban shrinkage in resource-based cities; the calculated CSI values are transformed into data obeying normal distribution by using logarithmic transformation; then the CSI of the study area is classified into five categories according to the doubled standard deviation classification method, i.e., ESS, SS, MS, RWS and WS; the commonly used spatial autocorrelation analysis methods are selected, i.e., global Moran's I and local Moran's I to analyze the spatial heterogeneity of shrinkage in all sample cities. The results show:

(1) Overall, the urban shrinkage of resource-based cities in China shows clear geographical differences, with high CSI values concentrated in the eastern region and low values clustered in the northeastern and western regions; resource-based cities in the western and

northeastern regions show stronger spatial shrinkage, while those in the central and eastern regions show weaker spatial shrinkage.

(2) According to the classification result, growing resource-based cities have the greatest degree of spatial shrinkage, followed by recessionary and regenerative resource-based cities, and grow-up resource-based cities have the least spatial shrinkage problem. In the end, it can be summed up as: growing resource-based cities > recessionary resource-based cities > regenerative resource-based cities > grow-up resource-based cities.

6 Analysis of the evolution pattern of urban spatial use efficiency based on differences between urban expansion and shrinkage

6.1 Introduction

The previous chapters have identified and evaluated the urban spatial evolution pattern of all samples, i.e., the expansion mode and shrinking degree, and realized the comparison of the severity of urban shrinkage according to different types of resource-based cities. However, in the empirical research, the detailed analysis which focuses on small-scale is more conducive to actual urban plan-making strategies. Therefore, the spatial expansion and shrinkage of each resource-based city in different sample groups still need to be further discussed in order to put forward tailor-made suggestions.

In the existing researches, a body of them consider the urban space utilization efficiency from the perspective of various input-output models based on conventional statistical data. However, these habitual methods are difficult to avoid the inherent defects of statistical data. It is worth noting that using remote sensing technology combined with urban expansion and shrinkage can greatly reduce the limitations of statistical data, thus, achieving analysis of urban space utilization efficiency in a more accurate way.

Based on above ideas, in this study, firstly, using the relationship between expansion scale and expansion morphology, the evolution pattern of urban built-up areas as well as the urban expansion mode are analyzed in all rounds; combining characteristics of urban expansion and spatial shrinkage, the evolution process of urban spatial use efficiency is identified; at the same time, to give better insight into the cause of spatial use efficiency changes, the ternary map method is used to decompose CSI; Finally, according to the stage of urban development, some practical suggestions are put forward.

6.2 Methodology for evaluating the efficiency of space use

Firstly, based on the Tapio method, the coupling analysis of urban area change and compactness is carried out to identify whether the city is expanding intensively or extensively, and these results in conjunction with urban shrinking degree, the space use efficiency of samples can be evaluated successfully.

In more details, if the extensive characteristics of spatial expansion are becoming more and more obvious from the first stage to the second stage, and the degree of spatial shrinkage positions in the serious shrinking type, it all indicates that the urban spatial utilization efficiency is gradually declining. Similarly, if the intensive characteristics of spatial expansion of the sample cities from the first stage to the second stage are becoming more and more prominent, and the degree of spatial shrinkage is a relatively mild shrinking type, then the urban spatial utilization efficiency in such city can be defined as the high-usage type. Finally, from the perspective of different development stages of resource-based cities, through the decomposition of the three factors constituting the urban shrinkage index, this study analyzes the causes of spatial utilization efficiency changes in resource-based cities, and then some constructive suggestions were put forward.

6.2.1 Identification of the urban expansion pattern based on the Tapio decoupling model

The decoupling index (Li et al., 2021) is originally applied to World Organization for economic cooperation and development (OECD) in 2002 and has subsequently been extended with a series of innovative ideas, i.e., Tapio decoupling index, IGT decoupling model, ZM decoupling model, etc.

The Tapio decoupling index (TDI) is developed by Tapio, a Finnish scholar, to measure the link between CO_2 emissions from road traffic and regional GDP in UK cities from 1970-2001. This TDI improves the original OECD Model and subdivides the decoupling relationship of spatial entities into 8 categories (Recessive coupling, Expansive coupling, Weak negative decoupling, Strong negative decoupling, Expansive negative decoupling, Weak decoupling, Strong decoupling, Expansive decoupling). Currently, TDI is widely used in the fields of greenhouse gas emissions and environmental pollution, energy use and economic development, ecological pressure and urbanization, population and land use. In this study, TDI is applied to a measure of how disorderly urban spatial expansion is, i.e., the coupling relationship between the urban expansion scale and the compactness of spatial form, calculation functions are as follows:

$$\Delta EA = EA_{last} - EA_{first} \tag{6.1}$$

$$\Delta EC = EC_{last} - EC_{first} \tag{6.2}$$

$$\text{DI}=\frac{\Delta EA / EA_{first}}{\Delta EC / EC_{first}} \tag{6.3}$$

EA is the urban expansion area, EA_{last} and EA_{first} are the final expansion area and the initial urban expansion area for each stage respectively; EC is the urban compactness, EC_{last} and EC_{first} are the final urban compactness and the initial urban compactness for each stage respectively; DI is the decoupling index for each stage of the city.

In the empirical study, in order to avoid over-interpreting problems, as shown in Figure 17, the TDI divides the area near the decoupling index 1.0, i.e., the dotted line in the first quadrant, into three categories according to the proportion of 20%. Therefore, this method provides more accurate and more comprehensive classification than the original OECD decoupling method.

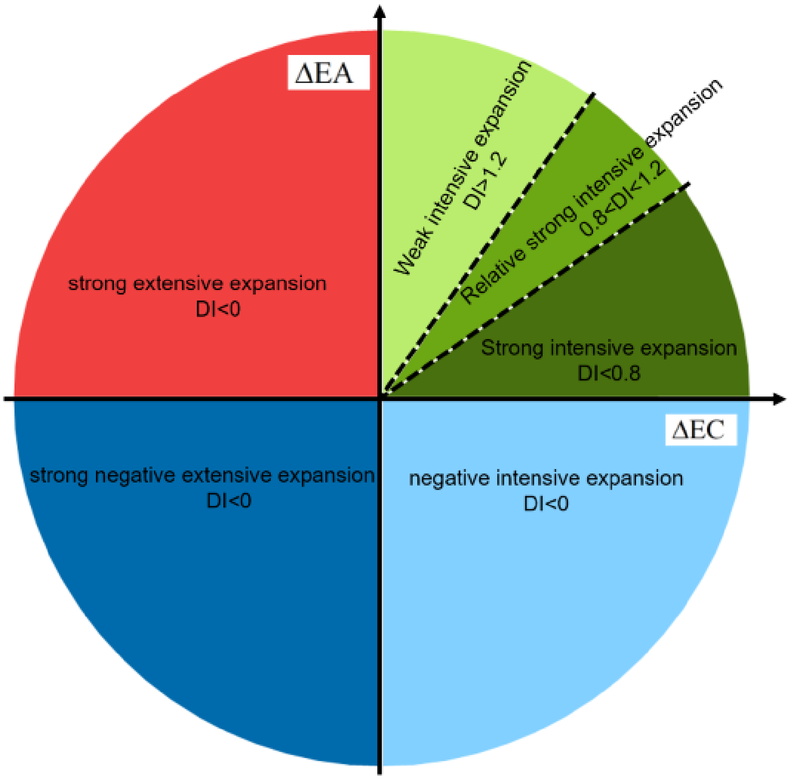

Figure 17 Schematic diagram of Tapio decoupling model analysis (TDI)

Table 11 Tapio decoupling status classification

Decoupling categories	Eigenvalue		
	△EA	△EC	DI
Strong intensive expansion	>0	>0	<0.8
Relative strong intensive expansion	>0	>0	0.8 - 1.2
Weak intensive expansion	>0	>0	>1.2
Strong extensive expansion	>0	<0	<0
Strong negative extensive expansion	<0	<0	>0
Negative intensive expansion	<0	>0	<0

When △EA and △EC are both greater than 0 and the DI value is greater than 1.2, it shows that the increasing rate of compactness of built-up areas is much greater than the expansion rate of built-up areas, and the sample cities are in the strong intensive expansion mode; when △EA and △EC are both greater than 0, and the DI value ranges between 0.8 and 1.2, it shows that the increasing rate of compactness of built-up areas is similar to the expansion rate of built-up areas, and the sample cities are in the relative strong intensive expansion mode; when both △EA and △EC are greater than 0, and the DI value is greater than 1.2, indicating that the compactness increase rate of the built-up area is lower than the expansion rate of the built-up area, and the sample cities are in the weak intensive expansion mode; when △EA is greater than 0 but △EC is less than 0 and the DI value is less than 0, it indicates that although the city is expanding to the outside, its compactness is decreasing, and the sample city has the characteristics of strong extensive expansion; When the city is expanding negatively, △EA and △EC are both smaller than 0, and the DI value is higher than 0, indicating that the built-up area is shrinking and the compactness of the built-up area is also decreasing, i.e., the sample city is expanding in a strong negative extensive expansion way; △EA is smaller than 0 but △EC is higher than 0, and the DI value is lower than 0, indicating that although the built-up area is shrinking but its compactness is increasing, and the sample city is expanding in a negative intensive expansion path.

6.2.2 Urban shrinkage index decomposition

China's resource-based cities are numerous and widely distributed, and each city has different economic strengths and development potential. As a result, the three factors that make up the CSI, i.e., population, land and economy, vary with the characteristics of these different cities themselves, and even cities with similar CSI values often have widely varying NI, PD and RB. Therefore, identifying differences in the constituent factors within the CSI of resource-based cities is an essential task that can provide valuable technical support for studying the urban development process.

In different periods, the pulling power of three factors within CSI of different RCs' types is constantly changing. However, solely relying on stiff numbers to demonstrate the impact of corresponding factors are far from enough. Therefore, many scholars have come up with a variety of methods to address this problem. The radar map was used to show the dynamic fluctuation of environmental efficiency from first-tier cities to fifth-tier cities in China from 2003 to 2016 (Zhang, et al., 2019). A mechanical equilibrium model was established to give better insight into the evolution direction of the industrial land structure (Yuting, et al., 2019).

The ternary-plots method, which has gained wide popularity in the soil microbe region (Zgadzaj, et al., 2016; Kumar, et al., 2017), achieved success in identifying the ghost cities in China (Zheng, et al., 2017). Based on previous ideas, in this study, we selected the well-developed ternary-plots diagram to discern the trace of CSI determinants.

At the very beginning, three factors are sorted internally according to their values (Each category, from the lowest to the highest, is labeled 1 to 126). Then ranking of each factor is standardized as follows:

$$N_{CI} = \frac{R_{CI}}{R_{CI} + R_{PD} + R_{RB}} \quad 6.4$$

$$N_{PD} = \frac{R_{PD}}{R_{CI} + R_{PD} + R_{RB}} \quad 6.5$$

$$N_{RB} = \frac{R_{RB}}{R_{CI} + R_{PD} + R_{RB}} \quad 6.6$$

where R_{RB}, R_{PD} and R_{CI} indicate the ranking value of sample cities in RB, PD and CI. N_{RB}, N_{PD} and N_{CI} represent the final standardized value in each factor.

Furthermore, as shown in Fig 6.2, starting from point A, imagine there is a parallel line to BC corresponding to the factor of PD, and they intersect at point a, then Ba is the proportion of A in PD factor. Thus, through the position of plots, the distribution trend of all samples can be revealed. The closer the sample bubble is to the vertex of a corner, the higher the share in the corresponding factor. Under this circumstance, if each end exerts the same force of pulling, then all objects will be squeezed in point O. Conversely, when the contribution of each factor varies, all the research plots will be scattered in an irregular area.

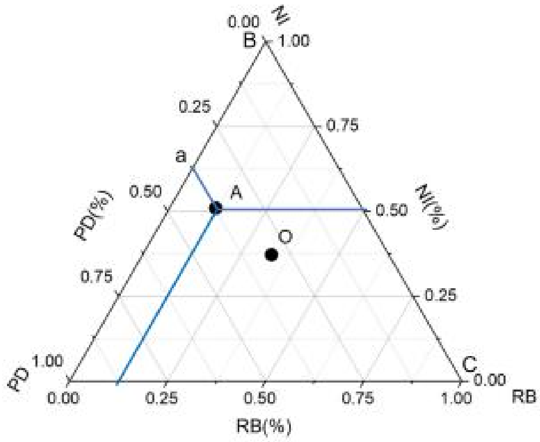

Figure 18 Schematic diagram of the CSI decomposition ternary map

6.3 Analysis of space use efficiency

6.3.1 Analysis of urban expansion patterns

As shown in Figure 19, it can be clearly seen that the form of urban expansion in the second stage is more extensive than that in the first stage, especially in the growing resource-based cities, where the weak intensive expansion in the first stage turns to the red area type in the second stage, i.e., strong extensive expansion, this finding is consistent with the findings of Chapter 4 (the complexity and looseness of the spatial pattern of the morphological evolution of urban built-up areas are as follows: growing resource-based cities > grow-up resource-based cities > recessionary resource-based cities > regenerative resource-based cities). For the remaining three types of cities, as shown in Figure 19, the urban expansion mode also has the trend of developing to the extensive mode, and many green strips in the first stage turn red in the second stage.

As can be seen from Table 12 and Figure 19, a small number of cities in the first stage, mainly concentrated in growing resource-based cities, grow-up resource-based cities and recessionary resource-based cities, have negative sprawl traits. This negative expansion is more serious in grow-up and recessionary cities, with 6 grow-up resource-based cities characterized by negative intensive expansion, accounting for 9.09% of the total number of such cities, 1 grow-up resource-based city characterized by negative extensive expansion, accounting for 1.52% of the total number of such cities, and while 4 recessionary resource-based cities characterized by negative intensive expansion, accounting for 16.67% of the total number of such cities, and 2 grow-up resource-based cities are characterized by negative intensive expansion, accounting for 8.33% of the total. The negative expansion of these cities is partly due to the fact that in the first phase, i.e., between 2000 and 2010, the concepts of "resource-based city transformation", "depleted resource-based city" and "sustainable urban development " and other concepts were more vague, and a small number of sample cities with poor geographical conditions, harsh climatic environments and weak economic foundations were directly affected by the original incremental planning oriented policies, thus, the trend of reverse development was observed. For example, since the mid - and late 1990s, Wuwei city in Gansu Province, China has had a serious desertification problem. Ya'an city in Sichuan Province, China locates on the western edge of the Sichuan Basin, has a predominantly high mountain valley within its jurisdiction, making it difficult to expand the urban framework, at the same time, with poorly planned transport facilities, the transport network can hardly meet the needs of urban development. Qitaihe city, Heilongjiang Province, China in the northeast was founded late, and has a poor economic base of its own, facing with "Dutch disease" brought by the single industry. In the second stage, i.e., between 2010 and 2020, the Chinese government began to pay attention to the internal problems of resource-based cities and promulgated a series of policies. In 2008, 2009 and 2012, the official identified 69 resource-depleted cities in a row. In 2013, the National State Council proposed *The National Sustainable Development Plan for Resource-based Cities (2013-2020)*, and in 2015, *The Overall plan for the reform of ecological civilization system* and other documents have facilitated the further development of these cities to some extent, and the problem of negative expansion in these cities has been greatly alleviated.

Table 12 Statistical values of Tapio decoupling types of various resource-based cities

Expansion mode	Stage	Resource-based city type							
		G-RCs		Gu-RCs		Rec-RCs		Re-RCs	
		Number	Ratio	Number	Ratio	Number	Ratio	Number	Ratio
Strong intensive expansion	Stage 1	0	0.00%	1	1.52 %	2	8.33 %	0	0.00%
Relative strong intensive expansion		0	0.00%	1	1.52 %	0	0.00 %	0	0.00%
Weak intensive expansion		3	15.00 %	23	34.8 5%	9	37.50 %	8	50.00 %

Expansion mode	Stage	Resource-based city type							
		G-RCs		Gu-RCs		Rec-RCs		Re-RCs	
		Number	Ratio	Number	Ratio	Number	Ratio	Number	Ratio
Strong extensive expansion		16	80.00%	34	51.52%	7	29.17%	8	50.00%
Negative intensive expansion		1	5.00%	6	9.09%	4	16.67%	0	0.00%
Strong negative extensive expansion		0	0.00%	1	1.52%	2	8.33%	0	0.00%
Strong intensive expansion		0	0.00%	0	0.00%	0	0.00%	0	0.00%
Relative strong intensive expansion		0	0.00%	1	1.52%	0	0.00%	0	0.00%
Weak intensive expansion		0	0.00%	6	9.09%	4	16.67%	4	25.00%
Strong extensive expansion	Stage 2	20	100.00%	59	89.39%	20	83.33%	12	75.00%
Negative intensive expansion		0	0.00%	0	0.00%	0	0.00%	0	0.00%
Strong negative extensive expansion		0	0.00%	0	0.00%	0	0.00%	0	0.00%

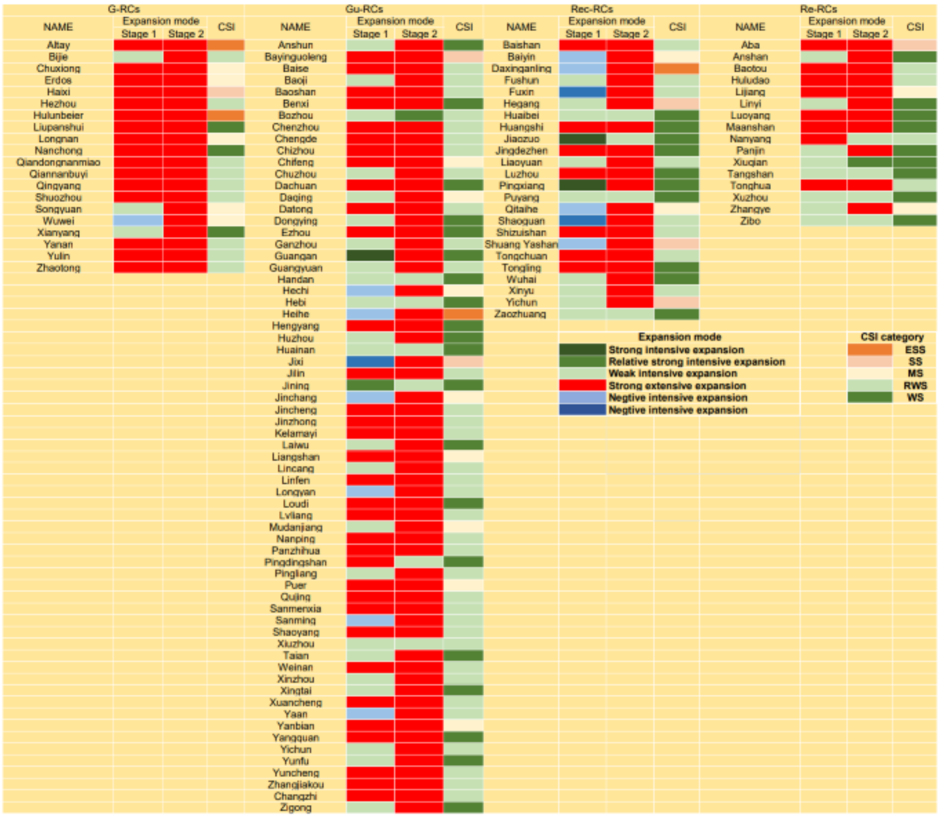

Figure 19 Comparison of urban expansion and shrinkage

6.3.2 Analysis of differences in urban spatial expansion and shrinkage

1) Growing resource-based cities

These cities are still in the early stage of development, the common problems of RCs have not yet completely appeared. However, this type does not demonstrate well in their efforts against urban shrinkage. As shown in Figure.20(a), cities in lighter shrinking modes follow a more evenly distribution pattern than their counterparts, while severe shrinking types gather in the lower part of triangle. For instance, according to the Chinese seventh census, Hulun buir had a permanent resident population of 2.24 million, which ranked in the top middle in Inner Mongolia Province, while haixi and Altay had fewer permanent residents, only 0.49 million and 0.69 million. Furthermore, when it comes to GDP of 304 Chinese prefecture-level cities in 2020, Hulun buir, haixi and Altay demonstrated poor performances, ranking 207th, 266th and 295th respectively. It is noted that all these cities have special geographical locations, Hulun buir and Altay located in the Chinese border and haixi is in the far West, making it difficult to generate economic benefits by relying on surrounding cities. Meanwhile, fragile ecology dues to disadvantageous climatic conditions also should be blamed. In these cases, cities need to issue corresponding response policies to hinder population loss and vigorously improve transportation facilities. Utilize their abundant resources scientifically and rationally, making sure mining develops in harmony with the ecological environment. In addition, learning success experiences from the same growing group shall be another good choice. Nanchong, with the highest CSI value in this RC type, has rich oil and natural gas resources, it has been striving to uphold the strategy of constructing energy and chemical industry base, meanwhile, developing advanced manufacturing and service industry agglomeration areas, constantly introducing talents and strengthening regional communications have ensured the high-quality and stable development of the city to a certain extent.

Therefore, taking traditional resources as the pillar industry, standardizing the order of resource development, reasonably planning the intensity of resource exploitation, improving the supporting facilities of upstream and downstream industries, continuously preparing and cultivating of successor industries can alleviate the phenomenon of urban shrinkage to a certain extent.

2) Grow-up resource-based cities

From the above analysis, it can be witnessed that the grow-up cities showed the most positive picture in the anti-shrinking tide. To a large extent, this kind of RCs is in a stable urban development stage and have strong resource guarantee ability. However, three sample cities, Heihe, Jixi and Bayingol, seem to be reluctant to go with the stream. All three are weakly attracted by NI, and occupying 286th, 289th, and 213th of 2020 GDP list. Instead, Ezhou, also owns a low-ranking, 234th, but it is grouped into the green zone. This city is one of the smaller cities in China, and is benefit from the role of being an important part of transportation hub in the middle reaches of the Yangtze River. Traditional heavy industry is no longer the only choice for this RC, relying on its vicinity of new first-tier city, it vigorously develops biomedicine and other high cutting-edge technologies, meanwhile, a mature e-commerce base has been built in this area. In contrast, the geographical location of Heihe, Jixi and Bayingol, is not very ideal, and industrial structure is single, and the connection of high and new technologies is not in place. Thus, these cities should pay attention to the efficient utilization of advantageous resources, change from primary resource mining to deep processing, diversify industrial structure and extend to corresponding high-tech fields.

3) Recessionary resource-based cities

In Rec-RCs, resources tend to be exhausted, economic development lags behind, people's livelihood problems are prominent, and ecological environment pressure is under great pressure. Three typical Rec-RCs, Shuangyashan, Hegang, Yinchun, as shown in Figure. 20(c), all suffer from low NI. This comes no surprise, because these cities are all enveloped by gloomy economic status in the Northeast, the declining pillar industries has taken away a large number of young labors, and the demographic dividend has disappeared, facing a tricky problem of ageing population. In addition， the industrial structures are uncompetitive and they fail to grasp the emerging markets, and ballooning costs of against inclement weather may all lead to an overwhelming plight. Nevertheless, the situation has been ameliorated in Tongling. This city uses to be the ancient copper capital of China, but most of the mine resources have been exhausted. In the past ten years, the government has spared no efforts to close down and restructure a number of mining enterprises, sought breakthroughs in extending the industrial chain, replaced the traditional mining industry with corresponding regions with less pollution and high added value, such as intensive processing, electronics and fine chemicals, and devoted to the introduction, cultivation and development of emerging successor industries.

Thus, for this type RC, their further developments require a fundamental transformation, which needs to unswervingly abandon traditional industries and find appropriate successor industries according to their local conditions. For example, the cold Northeast region can make use of rich ice and snow resources and unique natural scenery to create characteristic tourism and breeding industries. Moreover, government needs to pay attention to the sustainability of policies, meanwhile the exchange and cooperation among regions should not be absent.

4) Regenerative resource-based cities

Re-RCs have basically got rid of their dependence on resources, and their economy and society have begun to enter a benign development track. However, it is noted that performance of Aba is quite unsatisfied, RB and PD are not predominant. According to statistics, the number of permanent residents in this city ranks last in Sichuan Province in 2020. It is mainly because the city has vast grasslands and the mountainous terrain, which exacerbate the situation of disharmony between population and land. Although the substantial reserves of gold, lithium pyroxene, marble and other resources, Aba is vigorously developing tourism and animal husbandry. However, the total output of animal husbandry is not promising. In addition, there are signs of over development of scenic spots. Therefore, Aba should aim at building a modern characteristic agricultural and animal husbandry base, expand production and improve animal husbandry deep processing. And carry out policies to promote multi-level and multi structure development of tourism to avoid damaging the fragile environment. Maanshan, as the least shrinking city in this category, deserves further discussion. It is a famous steel base in China, and it has been actively upgrading its industry, the urban innovation capability index ranked 39th among the 72 innovative cities in China in 2020. Now, Bowang 5D manufacturing Valley in Maanshan has become an advanced intelligent manufacturing demonstration base, and it provides sustained impetus for economic growth.

In general, Re-RCs have a relatively good economic foundation, and some industrial and technological innovations have been witnessed. Therefore, further promoting the development of strategic emerging industries and characteristic industries will be conducive to the more stable development of such cities.

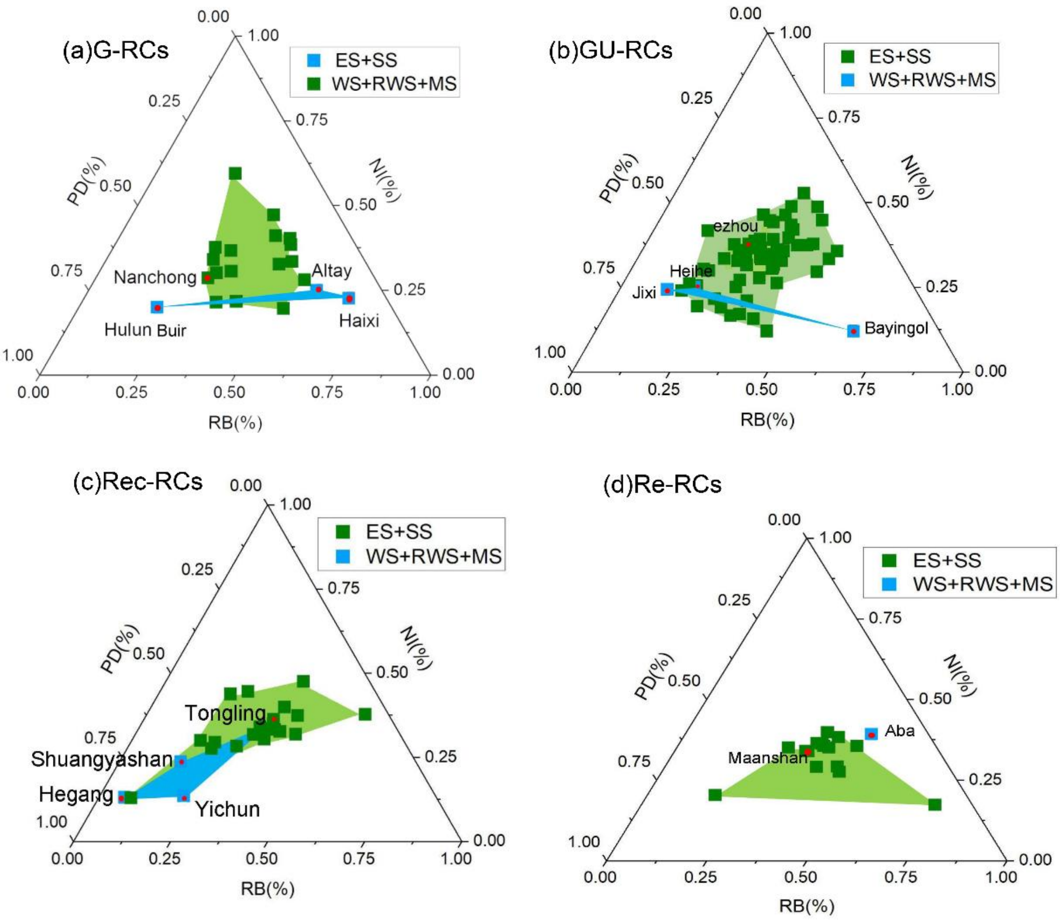

Figure 20 Ternary map results

6.4 Introduction

Based on the Tapio decoupling model, this chapter identifies the forms of spatial expansion in each stage of resource-based cities, and analyzes the spatial utilization efficiency and its causes of various resource-based cities by using the differences between urban expansion and shrinkage. The results show that:

(1) The second phase of urban expansion, although on a larger scale than the first phase, tends to be more disorderly in its overall expansion.

(2) A comparative analysis of urban expansion and urban shrinkage shows that the spatial efficiency of most cities is gradually declining, and that while outward expansion is

becoming stronger, there is a serious spatial shrinkage inside, which is particularly evident in growing and recessionary resource-based cities. This spatially inefficient phenomenon, which is declining year by year, should be monitored to ensure stable and sustainable urban development.

(3) To curb urban shrinkage, urban planners and policy makers should promote a balanced development of the three factors i.e., land, population and economy in all resource-based cities to improve CSI values.

7 Conclusion and future research directions

7.1 Conclusion

As the country with the largest population carrying capacity in the world, China has experienced rapid national economic and social development since the implementation of the reform and opening-up policy in the late 1970s. On the one hand, driven by the demographic dividend and the influx of foreign capital, China's urban built-up areas have shown a rapid expansion outwards. This has led to a crisis within the city and to a shrinkage of the city. This paradox of expansion and shrinkage is particularly evident in China's resource-based cities. Under the influence of over-exploitation and resource depletion, the sprawl of China's resource-based cities will put enormous pressure on the cities and seriously hinder their subsequent development and urban transformation. Therefore, in order to effectively prevent the adverse effects of sprawl on resource-based cities and promote their healthy and sustainable development, close monitoring and accurate assessment of the spatial expansion, degree of urban shrinkage and spatial utilization efficiency of resource-based cities are required.

In this study, firstly, a series of basic indicators of urban spatial expansion were selected, including the volume of urban expansion, the speed of expansion, the intensity and degree of expansion, changes in urban compactness and changes in the fractal dimension of urban expansion to identify and analyze the evolution pattern of spatial expansion of resource-based cities from 2000 to 2020; based on a multidimensional perspective, i.e., population, economy and built-up areas, the urban shrinkage index (CSI) was constructed, and a series of spatial data, NTL, GL30 and WorldPop were combined to measure the degree of urban shrinkage in resource-based cities in 2020; finally, the coupling relationship between the scale and form of urban spatial expansion and the results of urban shrinkage identification were used to achieve a qualitative evaluation of the spatial use efficiency of resource-based cities, and according to the urban The differences in the spatial use efficiency of various resource-based cities are analyzed in detail according to the link between the expansion mode and shrinkage. This study finds that.

(1) Between 2010 and 2020, China's resource-based cities experienced dramatic spatial expansion, and the overall scale, speed, intensity and degree of spatial expansion of all cities was much greater than the spatial expansion of cities between 2000 and 2010.

(2) The expansion of the various types of resource-based cities is extremely uneven, especially for regenerative resource-based cities, and there is a significant difference

between the expansion rate of cities with high expansion and those with low expansion. Within all phases, the amount of urban spatial expansion: "Regenerative resource-based cities > Grow-up resource-based cities > Growing resource-based cities > Recessionary resource-based cities". Within all phases, the rate of urban expansion: "Growing resource-based cities > Grow-up resource-based cities > Recessionary resource-based cities > Regenerative Resource-based cities".

(3) The spatial expansion intensity and degree of spatial expansion of resource-based cities are characterized by "high expansion intensity and low expansion degree". Regenerative resource-based cities have great potential for spatial expansion; the spatial expansion of recessionary resource-based cities is more impeded. The intensity of urban expansion and the degree of expansion are as follows: "Regenerative type resource-based cities > Growing resource-based cities > Grow-up resource-based cities > Recessionary resource-based cities; Growing resource-based cities > Grow-up resource-based cities > Recessionary resource-based cities > Regenerative resource-based cities". .

(4) The spatial pattern of built-up areas in resource-based cities is slowly developing towards strong looseness and high complexity. The complexity and looseness of the spatial pattern of urban built-up areas are in descending order: growing resource-based cities > grow-up resource-based cities > recessionary resource-based cities > regenerative resource-based cities.

(5) The urban shrinkage of resource-based cities in China shows obvious geographical differences, with cities with low shrinkage distributed in the eastern region and cities with more severe shrinkage clustered in the northeastern and western regions; according to the types of resource-based cities, growing resource-based cities have the greatest spatial shrinkage, followed by declining and regenerative resource-based cities, and grow-up resource-based cities have the least spatial shrinkage problem, i.e. "Growing Resource-based cities > Recessionary resource-based cities > Regenerative resource-based cities > Grow-up resource-based cities"; the impact of the three factors (NI, PD, RB) that make up the CSI are different in different types of resource-based cities. In general, PD, NI and RB in resource-based cities with severe urban shrinkage lag behind and are in urgent need of improvement. While RB is relatively high in cities with less severe urban shrinkage, PD and NI are rather unstable. Therefore, resource-based cities not only need to fill in the corresponding shortfalls according to the actual situation, but also need to ensure a stable and balanced growth of these three factors.

(6) Through the difference between urban expansion methods and urban shrinkage, it is clear that most cities have low spatial use efficiency, showing increasingly strong outward

expansion while actually having a more serious spatial shrinkage phenomenon. Compared with the rest of the cities, the low spatial use efficiency phenomenon is particularly obvious in growing resource-based cities and recessionary resource-based cities, and there is an urgent need to formulate reasonable, scientific urban planning and policies that are in line with the stage of urban development and strengthen land use efficiency.

In summary, the urban expansion and shrinkage of resource-based cities shows regional and urban type differences, with urban spatial expansion becoming increasingly rapid against the backdrop of increasingly loose and complex urban forms, and urban spatial shrinkage becoming more prominent, leading to inefficient spatial use in most cities. In order to get rid of the problem of inefficient spatial use in sprawling cities, attention to and correction of these imbalances can alleviate the pain of resource-based cities to a certain extent. Urban planners and policy makers should take into account the different stages of urban development and spatial locations of resource-based cities, and enact and implement planning schemes and policies tailored to the needs of small, medium and large resource-based cities. The expansion and shrinkage of cities is not exactly a bad event, it is a necessary cycle of urban development, however, how to turn the disadvantage into a stimulant to urban development and maintain the advantages of the original expansion is a serious challenge for all resource-based cities.

7.2 Shortcomings and outlook

This study reveals the characteristics of spatial expansion, spatial shrinkage and spatial use efficiency in China's prefecture-level resource-based cities from the perspective of space and different resource-based city development stages. However, there are some shortcomings in the data used and the model constructed that should be given some attention, including:

(1) The criteria for defining urban boundaries are controversial in China. There are three mainstream definitions of urban boundaries, namely the urban boundary by administrative division, the urban boundary by physical territory and the urban boundary by functional perspective. However, in recent years, China has been undergoing rapid urbanization and industrialization, and the phenomenon of urban sprawl in particular can cause the actual development of cities to exceed the official definition of urban boundaries, in which case the precise delineation of urban boundaries deserves subsequent exploration.

(2) There are some unavoidable limitations to the data used in the study. For example, the satellite used to acquire the raw nighttime light data transited the Chinese region in the early hours of the morning, and the timing of the shots did not coincide with the regular resting

time of urban residents, which may have somewhat weakened the calculated light intensity as well as the consistency of the built-up area.

(3) The CSI constructed by the three factors (NI, PD, RB) has some degree of room for improvement to construct a more robust urban shrinkage index. Firstly, built-up areas extracted with a DN value of 0 as a threshold cannot keep pace with the rapid urbanization of some sample cities, thus leading to a high value CSI with RB tending to be close to 1, somewhat narrowing the RB differences within each type of resource-based cities. Therefore, finding a reasonable threshold of DN values before extracting built-up areas will effectively reduce this adverse effect; the inclusion of some innovative modelling factors in the study can also enhance the model accuracy. For example, from a demographic perspective, although some cities exhibit high population density, the exodus of young people to the surrounding metropolitan areas has led to a significant ageing of these cities. Therefore, starting from a demographic perspective, relevant population vitality indicators are introduced to optimize the model, such as mobile phone signal data, mobile phone application data, point-of-interest (POI) data, transport accessibility and house prices; in addition, urban ecology is directly linked to the quality of life of residents. Modern cities should be people-oriented, and poor ecological quality will reduce people's happiness in life, leading to a decline in the resident population and eventually generating serious population loss. In recent years, the Chinese government has been emphasizing the importance of building an 'ecological civilization', so data on the ecological environment and urban resource reserves can be used to greatly improve the validity of the model.

(4) This study only evaluates the spatial expansion, shrinkage and spatial use efficiency phenomena of prefecture-level resource-based cities, and the evaluation of spatial use efficiency is only qualitative, lacking more powerful quantitative analysis; therefore, the quantitative evaluation of spatial use efficiency and the study of county-level resource-based cities will also be carried out subsequently; as the level of urban development varies under different types of resource-based cities, it may be necessary to adopt Economic zoning may be needed to better characterize urban spatial expansion, shrinkage and spatial utilization efficiency.

(5) The urban shrinkage model has certain limitations and is currently only applicable to the determination of shrinking cities in a single year, so only the degree of urban shrinkage of resource-based cities in 2020 has been assessed, and a measurement model that can be applied in different years will be explored in the future.

Based on these shortcomings, future research on spatial expansion, shrinkage, and spatial use efficiency of resource-based cities can be improved by using more accurate data sets, more factors and indicators to construct a more robust and long-term assessment framework.

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9 List of Figures

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11 List of Abbreviations

SDG	Sustainable Development Goals
GDP	gross domestic product
POI	point of interest
NTL	night-time light
G-RC	growing resource-based cities
GU-RC	grow-up resource-based cities
Rec-RC	recessionary resource-based cities
Re-RC	regenerative resource-based cities
GL30	GlobeLand30
DMSP	Defense Meteorological Satellite
VIIRS	Visible Infrared Imaging Radiometer
RMSE	root mean square error
NPP	NPOESS Preparatory Project
PD	population density
RB	degree of the built-up area consistency.
NI	night-time light intensity
SDE	standard deviation ellipse
EA	Expansion amount
ES	Expansion speed
EI	Expansion intensity
ED	Expansion degree
CB	Compactness of built-up areas
FD	Fractal dimension value of built-up areas
CSI	City shrinkage index
ESS	Extremely Strong Shrinkage
SS	Strong Shrinkage
MS	Moderate Shrinkage
RWS	Relatively Weak Shrinkage
WS	Weak Shrinkage
TDI	Tapio decoupling index

中国矿业大学(北京)
CHINA UNIVERSITY OF MINING & TECHNOLOGY-BEIJING

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Author: Yunqi Guo

Supervisor: Yanling Zhao Grade: 90 Signature: Yanling Zhao

Co-supervisor: ________ Grade: ______ Signature: ______