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Characteristics of Population Shrinkage in Inner Urban China and Correlations with Urban Growth Patterns

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Abstract

Urban shrinkage has led to urban decline and depopulation in Western countries. With the development of urbanization in China, urban shrinkage also appeared in China and gradually spread in many cities. The study of urban shrinkage helps to provide an important theoretical basis for the development of China's new urbanization and restore the vitality of urban development. This study used China's population data at a scale of 1 km from 2000 to 2015 to identify population increases and decreases over a long time series. Based on microscopic population changes in the city, the identification and characteristic analysis of urban shrinkage were performed, and the results were correlated with three modes of urban expansion in order to explore the relationship between the intensity of urban shrinkage and the pattern of spatial expansion. The results were as follows: (1) from 2000 to 2015, 80% of 366 cities in China experienced varying degrees of shrinkage, of which moderate and low shrinkage accounted for 64%. In addition, some regions such as northeast China, the Beijing-Tianjin-Hebei region, and southwest China have shown the spatial agglomeration of urban shrinkage phenomena. (2) Of the 291 cities where urban shrinkage has occurred in China, 99% experienced a weak shrinkage, while only 1% experienced a moderate shrinkage. In northern China, center shrinkage is the main pattern, while cities in southern China had an alternating distribution of marginal and central shrinkage. The type of urban shrinkage may be related to the speed of local economic development. Excessive speed of economic development and unreasonable mode of urban spatial expansion may lead to marginal shrinkage. (3) The expansion pattern of construction land in China from 2000 to 2015 was mainly outlying expansion, and population shrinkage was the most significant in this expansion mode. The compactness of the construction land expansion in China is inversely proportional to the intensity of the population shrinkage, and the lower the compactness, the stronger the intensity of the population shrinkage.

Keywords Urban shrinkage · Urban growth patterns · China

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Introduction

Although disputed, urban shrinkage is often related to the phenomenon of population decline and economic transformation with structural crisis (Richardson & Nam, 2014; Wang et al., 2020). Against the background of the shrinkage that occurred in some cities in Europe and the United States in the 1960s, it is the phenomenon widely discussed and studied in the planning and geographical areas (Popper & Popper, 2002; Hasse et al., 2014; Li & Mykhnenko, 2018; Wiechmann & Pallagst, 2012; Pallagst et al., 2021). With the continuous progress of urbanization in other countries and regions in the world, the phenomenon of urban shrinkage has gradually set off a research wave in the world. As the world's largest emerging economy, China's urban shrinkage is not uncommon. Since the reform and opening up, China has experienced an unprecedented urbanization process (Sun et al., 2020). With the continued concentration of population and industry in large urban agglomerations, metropolitan circles and megacities above the provincial capital, some cities in China are facing the development dilemma of declining economic vitality and population (Liu et al., 2020; Wang, 2019; Li et al., 2020).

In the academic community, Western scholars first conducted a series of studies on this phenomenon and produced a large number of academic achievements (Oswalt & Rieniets, 2006; Martinez-Fernandez et al., 2016; Wiechmann & Pallagst, 2012; Haase et al., 2014). In recent years, the Chinese scholars' research on urban shrinkage have been deepened and enriched, gradually forming the research context of urban shrinkage definition, identification, pattern characteristics analysis, driving mechanism research and planning response (Wu & Sun, 2017). Due to the complexity of the causes of urban shrinkage, the definition and identification standards of urban shrinkage have not yet reached a consensus. However, the phenomenon characterized by population decline has been widely studied around the world. For example, the more authoritative international organization for research on urban shrinkage (Shrinking Cities International Research Network, SCIRN) defined a "shrinking city" as a city with at least 10,000 residents, a dense urban area that has experienced population loss in most areas over a 2-year period and were going through an economic transition characterized by some sort of structural crisis (Hollander, 2009; Wiechmann, 2008). Other studies, including Karp et al., 2022, Iwasaki, 2021, Lym, 2021, and Long & Wu, 2016, also identified population decline as the first sign of urban shrinkage. Population census data and statistical yearbook population data are currently the most common indicators for identifying and defining changes in the urban population growth and decline. However, census data have a long-time span. Although the statistical yearbook data is refined to a single year, existing studies often examine only the population data of the first and last two years of the period, ignoring population changes in the middle years, which cannot reflect the overall trend of urban development and cannot demonstrate the persistence of population loss in the definition of urban shrinkage (Zhou et al., 2021). On the other hand, population census data take administrative districts as statistical units, which cannot reflect the differential distribution and changing trends of population within administrative districts. With the advancement of remote sensing, information and communication technology, large and highly accurate spatiotemporal big data provide more precise support for the analysis of urban shrinkage in inner space. For example, some scholars have conducted research on urban shrinkage using night light data (Zhou et al., 2021; Dong et al., 2021; Yang et al., 2021) and geospatial big data (Ma et al., 2020b; Meng et al., 2021a, b). The research on a refined classification of shrinking cities based on these emerging big data complements the shortcomings of statistical yearbooks and census data and represents an important direction for future research on urban shrinkage.

In the spatial dimension, current studies mainly focus on Northeast China, where resource-based cities are concentrated, and urban agglomeration areas such as Beijing-Tianjin-Hebei and the Pearl River Delta are used as research areas. Multiple regions with different spatial scales such as towns and streets (Li & Long, 2019; Tong et al., 2021; Long & Wu, 2016), districts and counties (Zhou et al., 2021), cities (Zhou et al., 2019) or urban agglomeration/region (Wu, 2019; Ma et al., 2020b) were selected to investigate the spatial distribution characteristics and formation mechanism of urban shrinkage. This kind of research based on administrative division ignores the "duality" of the separation between the administrative region (spatial scope corresponding to urban jurisdiction) and the physical region (scope of urban built-up areas) of Chinese "cities" (Zhang, 2011). Thus, these studies ignored changes in the number of people and their activities in a large number of cities outside statistical and administrative systems and in rural areas outside the boundaries of urban built-up areas (Long & Wu, 2016). On the other hand, most of the existing studies have abstracted the city (surface) as the analysis point, ignoring the heterogeneity within the point (city) (Wu & Qi, 2021), which is difficult to provide guidance and inspiration for the future city planning and development.

In studying the spatial characteristics of urban shrinkage, Western research generally divides shrinking cities into perforated and doughnut. The perforated type is the population shrinkage that occurs in different parts of the city, and vacant and abandoned buildings are highly mixed with other buildings in use. The doughnut type is a hollowing phenomenon in which a large number of people migrate from the inner city, and the population in the suburbs remains relatively stable (Blanco et al., 2009; Wiechmann & Pallagst, 2012). Due to the wide distribution and complex causes of shrinkage in China, the spatial distribution types of shrinkage cities are classified into several patterns. Meng et al. (2021a, b) divided China's shrinking cities into perforated, global, local, doughnut and marginal cities using big urban population data. Jiang et al. (2020) divided shrinking cities into scattered shrinkage, central shrinkage, local shrinkage, complete shrinkage, unilateral shrinkage and peripheral shrinkage using NPP-VIIRS night light data. In general, scholars have performed a limited number of studies on the spatial characteristics of urban shrinkage in China.

Meanwhile, in the context of China's economic development and urbanization, the paradoxical phenomenon of urban expansion and population shrinkage has emerged in China (Yang et al., 2015). Why is urban expansion associated with population shrinkage? How do they interact with each other? This is associated with differences in urban expansion patterns. affected by profit drive and cost constraints

(Meng & Si, 2022), Chinese cities as a whole are expanding but with different expansion patterns. The patterns of expansion can be classified as infilling, edge-expansion, and outlying type based on the spatial morphological characteristics of landscape expansion (Wilson et al., 2003; Forman, 1995). Infilling expansion occurs in the inner city, with the highest expansion density, which is closely related to the original construction land and relatively optimal spatial utilization efficiency, but it may cause traffic congestion, environmental damage, and other problems. Edge-expansion has the second highest density, which is spread out at the edge of the city and is the most common sprawl in China in recent decades, easily leading to wasteful and inefficient use of land resources and increasing the cost of urban development such as transportation expenses. Outlying expansion has the lowest density and is farther away from the old city, weakening the industrial agglomeration and scale economy effect, and posing the potential risk of energy and capital waste invested in construction. At the same time, urban expansion may bring inefficient use of public services, which is reflected in the shortage of public resources such as education and medical care under the infilling expansion, and the insufficient construction or low utilization of public resources such as infrastructure under the edge-expansion and outlying expansion.

According to the above theoretical analysis, different expansion patterns will affect the spatial efficiency of cities. The more compact urban expansion means more concentrated capital and talents, lower transportation and public services costs, higher spatial efficiency, and less population loss, despite the risks of ecological degradation and traffic congestion; the lower urban expansion density means more wasted land resources, poorer industrial clustering effect, and higher urban production and living costs, which may lead to economic depression and population loss. The low space utilization efficiency, the flagging economic development, and the gradual loss of population will reinforce each other, and eventually lead to the shrinkage of the city.

The above theories come from the analysis of existing studies on urban expansion and its consequences (Meng & Si, 2022) and the driving force of urban shrinkage (Zhou et al., 2021). We have established a connection between them (Fig. 1), but no research has been found to make a specialized quantitative analysis and comparison of the relationship between urban expansion and population shrinkage.

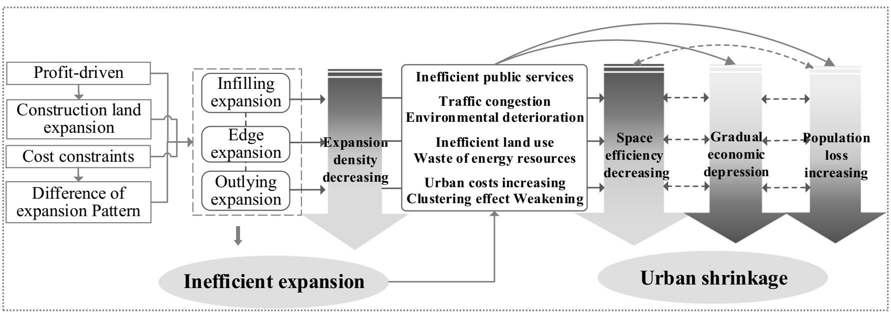

Fig. 1 Association between shrinking population and urban expansion

To fill the above mentioned research gaps, this study uses 1×1 km population grid data in China from 2000 to 2015 in order to calculate the population change trend, so as to identify and analyze the spatial characteristics of urban shrinkage in China. The study achieved long-term research on the dynamics of urban shrinkage, broke the administrative boundaries in the spatial dimension, refined spatial details and reflected more subtle local characteristics within the city. On this basis, in combination with the mode of urban expansion, this paper analyzes the correlation between the compactness of urban space development and the intensity of urban population shrinkage, so as to provide more accurate theoretical support for urban planning and policy making. Therefore, this paper focused on the following two issues: (1) the trend and spatial distribution of population shrinkage in Chinese cities from 2000 to 2015, and (2) the correlation between patterns of urban spatial expansion and the intensity of population shrinkage.

Data and Research Methods

Data Sources

In this paper, the period 2000–2015 was chosen as the research period, which represents an important stage of China's economic development. Since 2000, China's economic growth and urbanization have accelerated significantly. During this period, China's economy experienced rapid growth after joining the WTO and a cliff-like decline after the financial crisis. In 2015, China entered a new normal development, and economic growth has since changed from a high-speed growth to a medium–high growth rate. Research on this stage will help to further grasp the characteristics of China's economic development and urbanization and will provide a theoretical basis for the development of new urbanization.

The research data mainly includes China's population grid data from 2000 to 2015, China's administrative data, and urban construction land data. China's 1 km-resolution population grid data from 2000 to 2015 is derived from Landscan data of global kilometer grid population distribution produced by the Oak Ridge National Laboratory of the United States, which reflects the 24-h average population distribution within the city, and integrates various economic activities of the area, including employment, housing, and transportation (Desmet et al., 2020; Wang et al., 2021). Thus, it can reflect the distribution of population and economic activities within cities more precisely and can help to identify urban shrinkage in China more accurately. This dataset has been widely used by scholars in the field of urban economics (Meng et al., 2021a, b; Calka & Bielecka, 2019; Bhaduri et al., 2007). In these studies, LandScan data showed high accuracy and the superiority of micro-scale research. All data were coordinate-corrected before use and incorporated into unified WGS-1984 coordinates. Vector data of China's administrative regions and prefecture-level municipal government location are from the National Basic Geographic Information Center of China. Urban construction land data were extracted from the National Land-Use/Cover Database of China (NLUD-C) produced by the Chinese Academy of Sciences, which included data from 2000 and 2015. NLUD-C was produced based on Landsat TM image and China-Pakistan Earth Resources Satellite (CBERS) image data with a spatial resolution of 30 m. In the process of data production and updating, visual interpretation, geometric correction, field investigation and a large amount of auxiliary information were used. It is considered to be the most accurate classification data of China's land use types currently available to the public. The land use types include six categories of cultivated land, forest land, grassland, water area, construction land, and unused land.

Research Methods and Data Processing

Based on the identification of city shrinkage phenomena, this paper explores the relationship between the intensity of urban shrinkage and the mode of spatial expansion in China. Therefore, this study is mainly conducted from three aspects (Fig. 2): (1) The 16-phase population grid layers are superimposed to obtain the K-value that represents the trend of population change on each grid, and then the construction land data layer and the K-value data layer are superimposed to obtain construction land patches with K-values. This is used to identify shrinkage and classify the degree of shrinkage; (2) Perform spatial autocorrelation analysis in ArcGIS and convert the shrinking patches into a format suitable for FRAGSTATS software, then conduct landscape pattern analysis; and (3) The newly added construction land patches from 2005 to 2015 are extracted and expansion patterns classification is performed. Then, the K-value patches that represent population change trends and construction land patches are superimposed and the correlation characteristics and spatial pattern of the two are analyzed. The specific research methods are as shown in Fig. 2.

Identification of City Shrinkage and Judgment of Shrinking Degree

Since the definition and identification indicators of urban shrinkage have not yet unified, the addition of socio-economic indicators may affect the accuracy of the identification results. In addition, the influence and indicative role of environmental and economic factors on population distribution often occur on a large scale (at the city

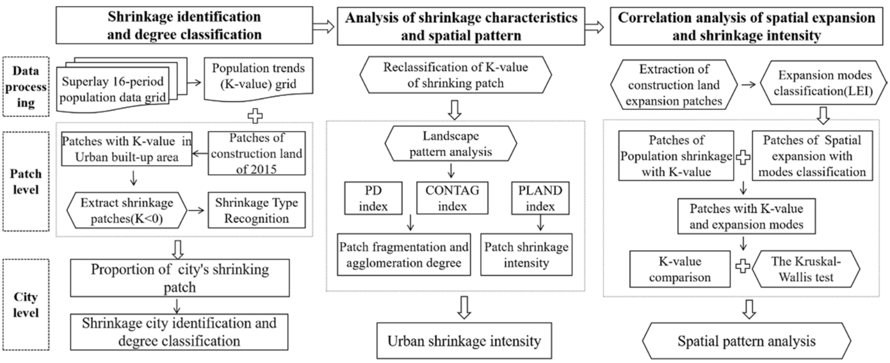

Fig. 2 Research framework

and county scales). At a finer scale (1 km), the correlation between population distribution and environmental and economic factors hardly exists. Therefore, this study starts from a narrower definition of urban shrinkage and uses only population data as an identification and classification marker of city shrinkage. According to the slope value of the population changes of the patch formed by the superposition of 16 periods of the 1 km population grid in China from 2000 to 2015, the increase and decrease of the population of the patch during this period were judged. Then the shrinkage or not and the degree of shrinkage of the 366 cities are judged according to the proportion of each city's shrinking patch in relation to the total patch.

The specific operations are as follows. In ArcGIS software, the 1 km population grid data of China from 2000 to 2015 are extracted from Landscan, and 16 layers are superimposed to form a new layer. Each 1 km patch of the layer has 16 values, representing the total annual population from 2000 to 2015 respectively. By calculating the trend of change of the 16 values of each patch, the population change slope (K) of the patch during the study period is obtained. A K-value less than 0 indicates that the population of the patch has a decreasing trend from 2000 to 2015, and the size of the K-value reflects the population change intensity of the patch. Based on this, the construction land was extracted from the 2015 China land use type map as an urban area, and the construction map layer and the patch layer with K-value were superimposed to obtain the population change on the patch scale in the urban built-up area. K-value shows the trend of population change during the study period (2000–2015), which compensates for the lack of traditional research by using data of two periods (last period—first period) and avoids the contingency of the research. On this basis, dividing the shrinking patches within the administrative boundaries of Chinese cities by the total number of patches in the cities gives the proportion of shrinking patches in each city. The results are divided into four categories: high shrinkage, medium shrinkage, low shrinkage and no shrinkage using the natural breakpoint method. Finally, city shrinkage and their degree of shrinkage are identified.

Determination of Shrinkage Type

Generally, the government of each city is located in its central area. Therefore, this study assesses whether the shrinkage type is central shrinkage or peripheral shrinkage by calculating the distance between shrinkage patches (patches with a K-value less than 0) and the location of the government. Here we calculate the average distance of all patches in each city from its government location in ArcGIS and set it as D1. Furthermore, we calculate the average distance of the shrinking patch from its government location and set it as D2. After eliminating the difference in the area of different urban regions by dividing D2 by D1, the results are divided into peripheral shrinkage and central shrinkage according to the natural breakpoint method.

Landscape Pattern Analysis

Landscape pattern refers to the spatial arrangement of landscape elements of different sizes and shapes (Han et al., 2005). Analyzing regional landscape pattern is an effective tool for revealing regional ecological status and spatial variation characteristics (Long et al., 2022). Landscape pattern analysis has a patch level, a class level and a landscape level. Since the research objects in this study are patches of 1 km size with uniform size and shape, the research was conducted at both the class Level and landscape Level. In this study, we selected one class level index named percent of landscape (PLAND) and two landscape level indices named patch density (PD) and contagion (CONTAG). The PLAND is one of the bases for determining the dominant landscape elements in the landscape. In this study, it can identify the dominance degree of patches with different shrinkage intensity in the city. When its value tends to 0, it means that this type of patch is very rare in the landscape; when its value is equal to 100, it means that the entire landscape is composed of only this patch type. The PD represents the density of a certain patch in the landscape, which can reflect the overall heterogeneity and fragmentation of the landscape and the degree of fragmentation of a particular type. The higher the patch density, the greater the fragmentation of the landscape. The CONTAG describes the degree of agglomeration or extension of different types of patches in the landscape. A high CONTAG value indicates that a certain dominant patch type in the landscape has formed a good connection; otherwise, it indicates that the landscape has a high degree of fragmentation and shows a dense pattern with multiple elements. Patch density and contagion can reflect spatial distribution characteristics (such as fragmentation and agglomeration) of shrinking patches at the overall landscape level.

The specific operations are as follows. In ArcGIS, the K-values of shrinking patches are divided into weak, moderate and strong shrinkage using reclassification. Then, the data format was transformed and exported, opened in FRAGSTATS software, and appropriate indices were selected for analysis.

Spatial Autocorrelation Analysis

The Global Moran's I index reflects the similarity degree of attribute values of regional units adjacent to the space. Its value range is between -1 and + 1. The closer to -1, the greater the difference between the units; the closer to 1, the more similar the properties between the units. Its calculation formula is as follows (Moran, 1950):

$$I = \frac{N}{S_0} \cdot \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \mu)(x_j - \mu)}{\sum_{i=1}^{n} (x_i - \mu)^2} \tag{1}$$

The Anselin Local Moran's I index corresponds to the specific geographic distribution of agglomeration areas based on the global Moran's I index analysis, and its formula is (Anselin, 1995):

$$L_{\mathrm{i}} = \frac{z_i}{m_2} \cdot \sum_{j=1}^{n} W_{ij} Z_i \tag{2}$$

Landscape Expansion Index

There are three main spatial modes of landscape expansion, namely infilling, edge-expansion, and outlying (Ellman, 1997; Forman, 1995; Wilson et al., 2003). Other modes of expansion can be seen as variants or mixtures of these three basic modes (Liu et al., 2014). Based on this, Liu et al. (2014) proposed the Land Expansion Index (LEI) that uses the buffer analysis function of GIS to determine the dynamic expansion type and analyze the spatial distribution of the landscape. The calculation formula is as follows:

$$LEI = \frac{A_o}{A_o + A_v} \times 100 \tag{3}$$

where, LEI is the expansion index of the new patch; A_o is the intersection area of the buffer zone of the new patch and the original patch; and A_v represents the intersection area of the buffer zone of the new patch and other areas other than the original patch. The numerical range of the LEI is [0, 100]. When LEI = 0, it is outlying expansion; when 0 < LEI ≤ 50, it is edge expansion; and when 50 < LEI ≤ 100, it is infilling expansion (Liu et al., 2014).

In this study, the LEI was used to classify the expansion patterns of new construction land in China from 2000 to 2015. The classification result layer was superimposed with the K-value population patch layer in order to obtain a new patch data with K-value and expansion pattern name. Then, the patch data were divided into prefecture-level cities, and the average K-value of population patches under different expansion modes of different cities were calculated. Based on the average K-value, correlation analysis and spatial pattern analysis of urban expansion mode and shrinkage intensity were conducted.

Spatial Distribution and Characteristic Analysis of City Shrinkage

Overall Distribution Characteristics of City Shrinkage

According to the proportion of shrinking patches (K-value less than 0) to the total number of patches in each city, the identification results of city shrinkage were obtained (Table 1). Between 2000 and 2015, 80% of the 366 cities in China

Table 1 Proportion of shrinking patches in Chinese cities from 2000 to 2015

Shrinking patches percentage	Degree of shrinkage	Number of cities	Proportion
0.000000—0.156522	Non-shrinkage	75	0.2
0.156523—0.287671	Low shrinkage	116	0.32
0.287672—0.418831	Medium shrinkage	117	0.32
0.418832—0.803419	High shrinkage	58	0.16
	Total	366	1

experienced varying degrees of shrinkage. Only 20% of cities did not shrink. In cities where shrinkage has occurred, low and medium shrinkage accounted for the main proportion, each accounting for 32%; the number of high city-shrinkage was the smallest, only 58 cities. Urban shrinkage has become a common phenomenon in China, but the degree of shrinkage has generally been mild.

Dividing the shrinkage results into economic zones (Fig. 3, Table 2), it could be seen that 35 of the 36 cities in the Northeast experienced a shrinkage. Only 6 cities experienced a low shrinkage, accounting for 17% in the Northeast region. Cities with medium and high shrinkage accounted for 81% in Northeast China. The degree of shrinkage in the eastern region was more evenly distributed, with 22% of cities experiencing no shrinkage, and 61% of the cities experiencing low (27%) and medium (34%) shrinkage. The western region had the highest proportion of non-shrinking cities among all regions which accounting for 30%, and 59% of cities experienced low and medium shrinkage, only 11% of cities had high shrinkage. In the central region, the proportion of non-shrinking cities was only 10%, which is lower than the national average of non-shrinking cities (20%). The low and medium city shrinkage phenomena accounted for the main proportion at 79%, indicating that urban population loss was more common in the central region. And a small number of cities (11%) developed a high degree of shrinkage with serious population loss in this region. Overall, the degree of shrinkage in the western region is the lowest, while medium and high shrinkage mainly occurred in the northeast and central regions. Among them, the proportion of highly city

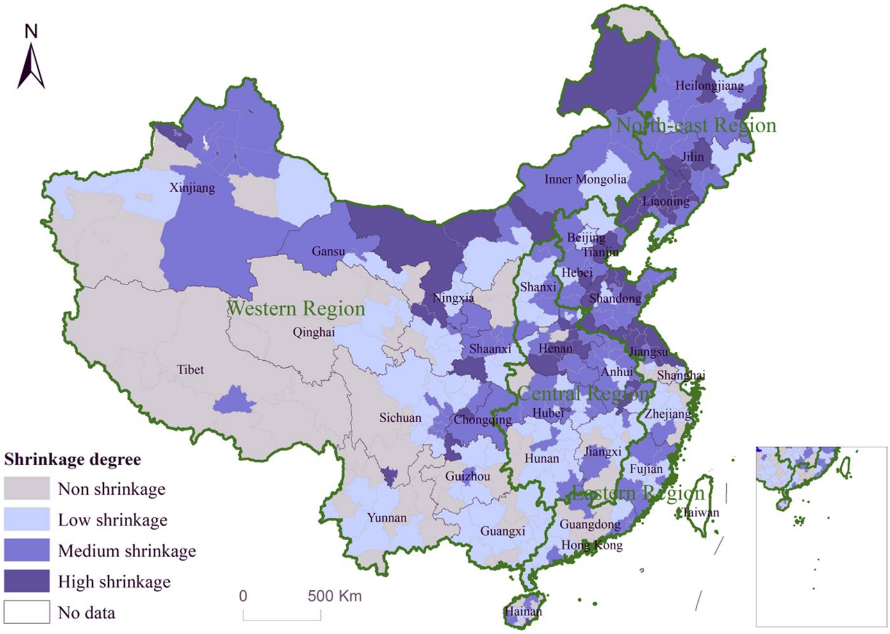

Fig. 3 Spatial distribution of urban shrinkage

Table 2 City Shrinkage by Region in China from 2000 to 2015

Economic zone division	Degree of shrinkage	Number of cities	Proportion	Representative city (shrinkage ratio)
North-east Region	Non-shrinking	1	0.03	Greater Khingan Mountains (0.12)
	Low shrinking	6	0.17	Dalian (0.26), Daqing (0.24)
	Medium shrinking	14	0.39	Harbin (0.33), Changchun (0.34)
	High shrinking	15	0.42	Jixi (0.46), Jilin (0.5)
	total	36	1	
Eastern Region	Non-shrinking	23	0.22	Xiamen (0.07), Nanjing (0.13)
	Low shrink	28	0.27	Beijing (0.25), Fuzhou (0.17)
	Medium shrinking	35	0.34	Putian(0.32), Shantou (0.35)
	High shrinking	18	0.17	Xuzhou (0.43), Tianjin (0.44)
	total	104	1	
Western Region	Non-shrinking	42	0.3	Liuzhou (0.15), Lijiang (0.13)
	Low shrink	51	0.37	Zunyi (0.2), Yinchuan(0.18)
	Medium shrinking	31	0.22	Jiayuguan (0.35), Xi'an(0.36)
	High shrinking	15	0.11	Lanzhou (0.43), Panzhihua (0.48)
	total	139	1	
Central Region	Non-shrinking city	9	0.1	Zhengzhou(0.14), Huaihua(0.14)
	Low shrink city	31	0.36	Hefei(0.17), Wuhan(0.26)
	Medium shrinking	37	0.43	Luoyang(0.36), Jingdezhen(0.3)
	High shrinking	10	0.11	Wuhu(0.61), Luohe(0.52)
	total	87	1	

shrinkage phenomena in the northeast is 42%, i.e., almost half of the cities experienced a high shrinking.

Regional Distribution Characteristics of City Shrinkage

From the perspective of spatial distribution (Fig. 4), the proportion of shrinkage increases roughly from west to east, and from south to north. There were large differences in the degree of shrinkage between cities in the south and north of China, which showed that the cities in the south generally experienced low shrinkage, while the cities in the north mainly suffered from medium shrinkage. Moreover, a continuous agglomeration of highly city shrinkage phenomena appeared in northeast China.

Among the three northeastern provinces, the degree of shrinkage weakened from south to north. In Jilin and Liaoning provinces, there were no non-shrinking cities. Liaoning Province had the most severe shrinkage, except Dalian (annotation "①" in Fig. 4), a sub-provincial city, which had a low shrinkage, Dandong (annotation "②"), Panjin (annotation "③"), and Yingkou (annotation "④") with a medium shrinkage (31%), and the remaining 10 cities shrunk severely (71%), including Shenyang

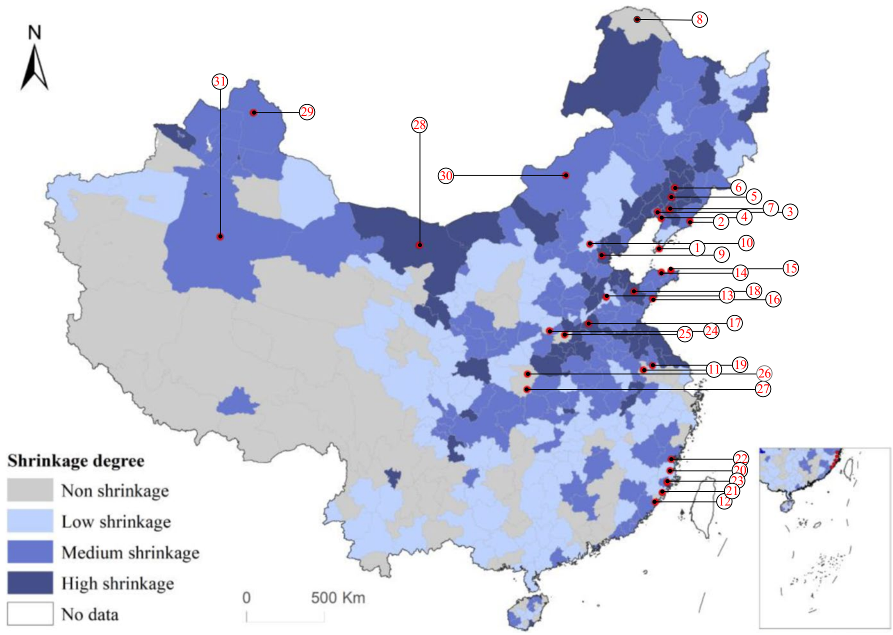

Fig. 4 Regional distribution of city shrinkage

(annotation ”⑤”), the capital of Liaoning Province, Tieling (annotation ”⑥”) and Anshan (annotation ”⑦”). Jilin Province was dominated by medium shrinkage (56%), followed by high shrinkage (33%). Low (31%) and medium shrinkage (46%) accounted for the main proportion in Heilongjiang Province, while the proportion of high city shrinkage phenomena was the smallest (15%), and the only non-shrinking city was Daxinganling (annotation ”⑧”).

The eastern region also showed a weakening trend from north to south, and the shrinkage degree of Tianjin city (annotation ”⑨” in Fig. 4) reached 0.44. Beijing (annotation ”⑩”), the capital of China, located in the Beijing-Tianjin-Hebei urban agglomeration, has a higher shrinkage percentage (0.25) than sub-provincial cities such as Nanjing (annotation ”⑪”) and Fuzhou (annotation ”⑳”). Hebei Province, a member of the Beijing-Tianjin-Hebei urban agglomeration, recorded 100% city shrinkage, of which 82% in medium and high levels of shrinkage. Except for Jinan (annotation ”⑬”), the capital of Shandong Province, which experienced low shrinkage, 56% of the remaining cities experienced medium shrinkage, including Yantai (annotation ”⑭”), Weihai (annotation ”⑮”) and sub-provincial city Qingdao (annotation ”⑯”); 38% experienced high shrinkage, including Heze (annotation ”⑰”) and Weifang (annotation ”⑱”). From the spatial distribution perspective, the highly city shrinkage phenomena in Shandong Province were concentrated in the northern part, i.e., cities close to the Beijing-Tianjin-Hebei region. Jiangsu province, located in the north of the Yangtze River Delta Urban agglomeration, saw obvious differences in the degree of shrinkage of central, northern and southern Jiangsu. Among the 13 prefecture-level cities in Jiangsu, the city shrinkage phenomena were mainly concentrated in the central and northern regions. Among them, 5 cities in northern Jiangsu experienced high shrinkage, and three cities in central Jiangsu experienced high shrinkage (two cities) and medium shrinkage (one city). Only one city in southern Jiangsu is experiencing low shrinkage (Zhenjiang, annotation ”19” in Fig. 4), and the remaining 4 cities (Suzhou-Wuxi-Changzhou region and the provincial capital Nanjing) (annotation ”11”) were non-shrinking cities. In Fujian Province, only Xiamen city (annotation ”12”) did not shrink, while the remaining three cities, including Fuzhou (annotation ”20”) and Quanzhou (annotation”21”) experienced mild shrinkage and five cities, including Ningde (annotation ”22”) and Putian (annotation ”23”) experienced medium shrinkage. Population shrinkage and growth in Guangdong Province, where the urban agglomeration of Pearl River Delta is located, also showed large internal differences. These differences are reflected in the steady population growth in the Pearl River Delta region, while cities with low and medium shrinkage were mainly concentrated in eastern and western Guangdong.

The distribution of shrinkage in the central region is strong in the north and weak in the south. Shanxi and Henan provinces, located in the urban agglomeration in the middle reaches of the Yellow River, had some city shrinkage phenomena, but the degree of shrinkage was slightly different. Shanxi Province was dominated by low and medium shrinkage, while Henan Province had a more severe shrinkage. In Henan Province, except for Jiyuan City (annotation”24” in Fig. 4) and Zhengzhou City (annotation ”25 ”), which were non-shrinking cities, the remaining 16 cities shrank to varying degrees (accounting for 89%), with medium and high shrinkage accounting for 33% and 39%, respectively. The three provinces in the urban agglomeration in the middle reaches of the Yangtze River showed shrinkage differences in the north–south direction. Except for the Shiyan (annotation ”26”) and Shennongjia forest areas (annotation ”27”) in Hubei Province, which were non-shrinking areas, the remaining 88% of cities experienced varying degrees of shrinkage. Cities with medium shrinkage accounted for 53%, showing characteristics of contiguous and massive distribution in this province. However, Hunan and Jiangxi provinces saw mainly low city shrinkage phenomena, and there were no high city shrinkage phenomenon.

The western region had a slight degree of shrinkage, and there were a considerable number of non-shrinking cities mainly concentrated in Tibet and Qinghai provinces. The eastern side of the region was mainly characterized by a low degree of shrinkage, but a medium and high degree of shrinkage occured in the north of Xinjiang, Gansu and Inner Mongolia.

The spatial autocorrelation analysis of the shrinkage ratio of each city showed that its Moran’s I was 0.3471, and the Z value was 13.6534, which passed the significance test at the 0.01 level. These results indicate that there is a significant positive correlation between the spatial distribution of the degree of urban shrinkage in China’s 366 prefecture-level cities. The results of the Anselin Local Moran’s I (Fig. 5) showed that the spatial distribution of the shrinkage degrees of 366 cities in China had a significant clustering feature from 2000 to 2015. A high-high agglomeration was formed in Northeast China and the Beijing-Tianjin-Hebei region. A low-low aggregation appeared in western and southwest China, which indicated that the proportion of shrinking urban patches in this region was relatively low, the shrinkage phenomenon was not obvious, and the surrounding cities did not shrink significantly.

Analysis of Shrinkage Characteristics

Landscape pattern analysis

Based on the identification of city shrinkage and their shrinking degree, a landscape pattern analysis method was used to analyze the shrinking intensity and spatial distribution patterns of shrinking patches in China. Through the analysis of the PLAND index, the results of the shrinkage intensity of each city were obtained (Table 3). On the patch level, among the 26,651 shrinking patches, 25997 had weak shrinkage intensity, 574 patches had moderate shrinkage, while only 80 patches had strong shrinkage, indicating that the shrinkage phenomenon occurs with weak intensity at the patch level. From a city-level perspective, after excluding the 75 non-shrinking cities, out of the remaining 291 cities, 287 (98.63%) cities showed a weak shrinkage intensity, and 4 (1.37%) cities showed a moderate shrinkage, namely Ala Shanmeng (in Inner Mongolia province, annotation "㉘" in Fig. 4), Beitun City (in Xin Jiang province, annotation "㉙" in Fig. 4), Xilin Gol League (in Inner Mongolia province, annotation "㉚" in Fig. 4), and Bayingoleng Mongolian Autonomous Prefecture (in Xin Jiang province, annotation "㉛" in Fig. 4). It was shown that the number of patches with their K-values in the range -3.781818 ~ -0.905244 of these four cities occupied the main proportion, and the population loss in the patch was severe. At the same time, combined with the proportion of the shrinking patches in the total patches (i.e., classification results of shrinkage degree), it was found that the

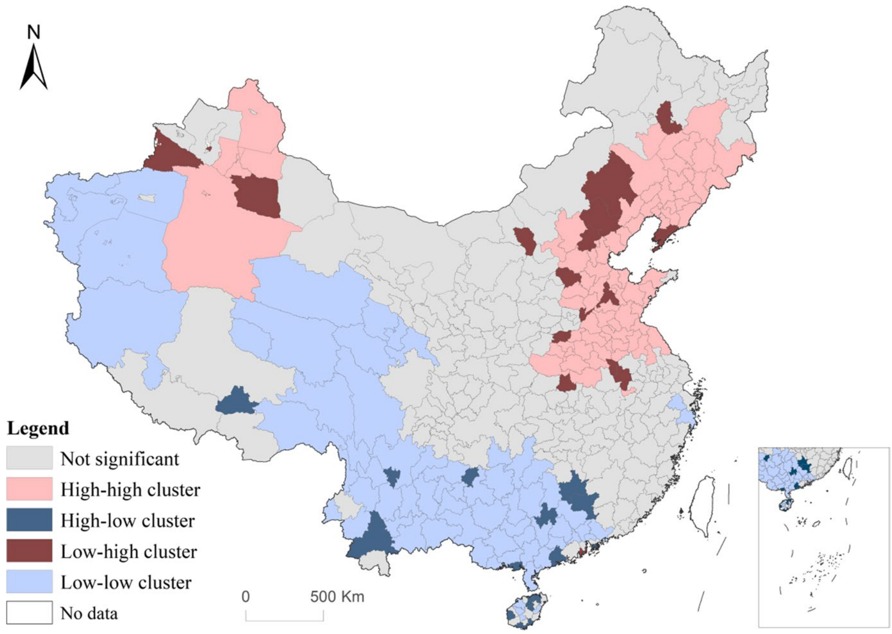

Fig. 5 Spatial distribution of clusters

Table 3 Results of shrinkage intensity based on landscape pattern analysis

K-value	Classification	Shrinkage intensity	Number of patches	Number of cities	Proportion
-8—-3.781818	cls_1	Strong	80	0	0
-3.781818—-0.905244	cls_2	Moderate	574	4	0.0137
-0.905244—0	cls_3	Weak	25997	287	0.9863
		Total	26651	291	1

shrinkage degree of Ala Shanmeng and Beitun City was high, and the shrinkage degree of Xilin Gol League and Bayingoleng Mongolian Autonomous Prefecture was medium, indicating that when the rate of population loss in the patches was high in these four cities, the number of shrinking patches of these cities was also relatively large. Overall, the shrinkage intensity of Chinese cities was relatively weak, with 99% of the population shrinking slightly and only 1% experiencing a more significant shrinkage.

Using ArcGIS to visualize the results of the PD index and the CONTAG index, we obtained the spatial pattern characteristics of K-values of shrinking patches in each city (Figs. 6 and 7). It can be seen from the figures that the areas with high PD index and low CONTAG index were mainly concentrated in the Beijing-Tianjin-Hebei to the Yangtze River Delta urban agglomeration and its hinterland. As the PD index increases, the landscape fragmentation degree increases, the CONTAG value is smaller, and more smaller patches exist in the landscape. It means that in these areas, the patches with population shrinkage had a high degree of fragmentation and general connectivity. However, the remaining regions have PD index values close to 0 and the CONTAG index tends to 100, indicating that weakly shrinking patches existed in most areas of China with the advantage of extremely high connectivity.

Identification of Shrinkage Types

The results of shrinkage types were obtained by calculating the mean distance between shrinking patches and the location of the city government (Fig. 8). As the distance value is smaller, the shrinkage phenomenon occurs closer to the central city area (central shrinkage). The higher the distance value, the closer the shrinkage is to the city edge (peripheral shrinkage). It can be seen from the Fig. 8 that central shrinkage was dominant in northern China. The central shrinkage appeared in economically backward regions, such as the northeastern and northwestern regions, which indicates that the shrinkage of these regions mainly occurred in old urban areas, i.e., the urban hollowing occurred. An alternate distribution of center and peripheral shrinkage occured in the south and the southeastern coastal cities had a tandem distribution of peripheral shrinkage.

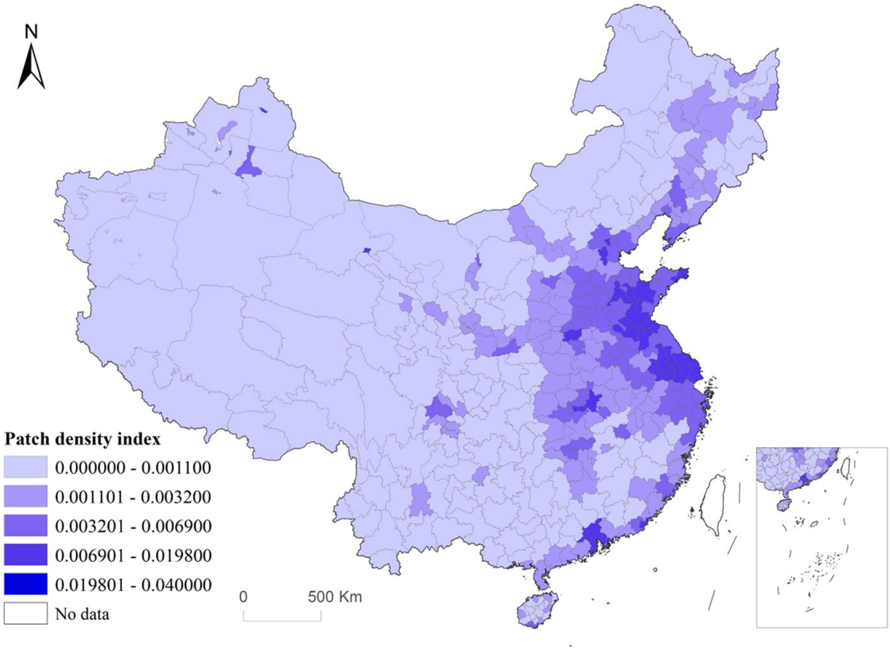

Fig. 6 Results of spatial visualization of the PD index

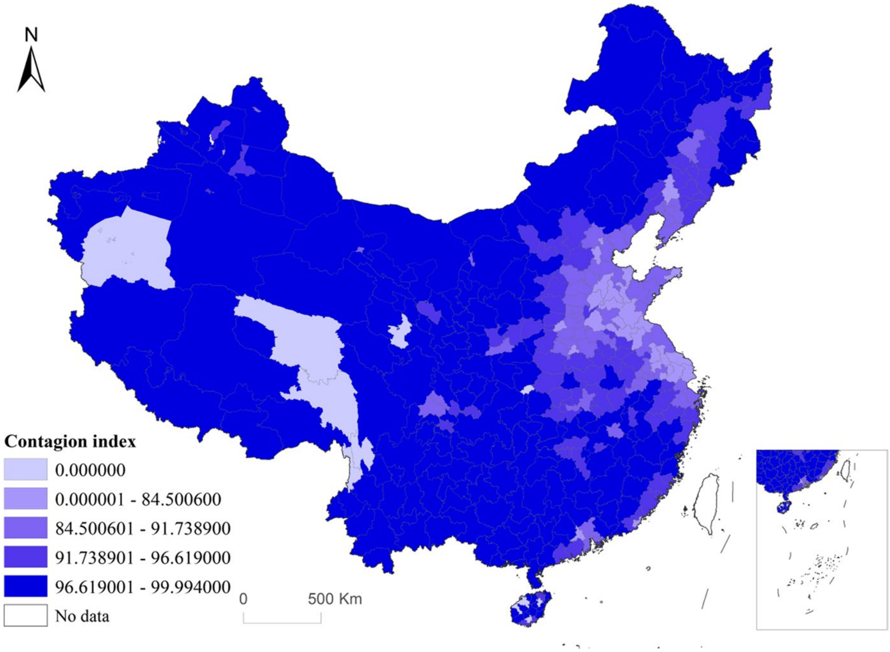

Fig. 7 Results of the spatial visualization of the CONTAG index

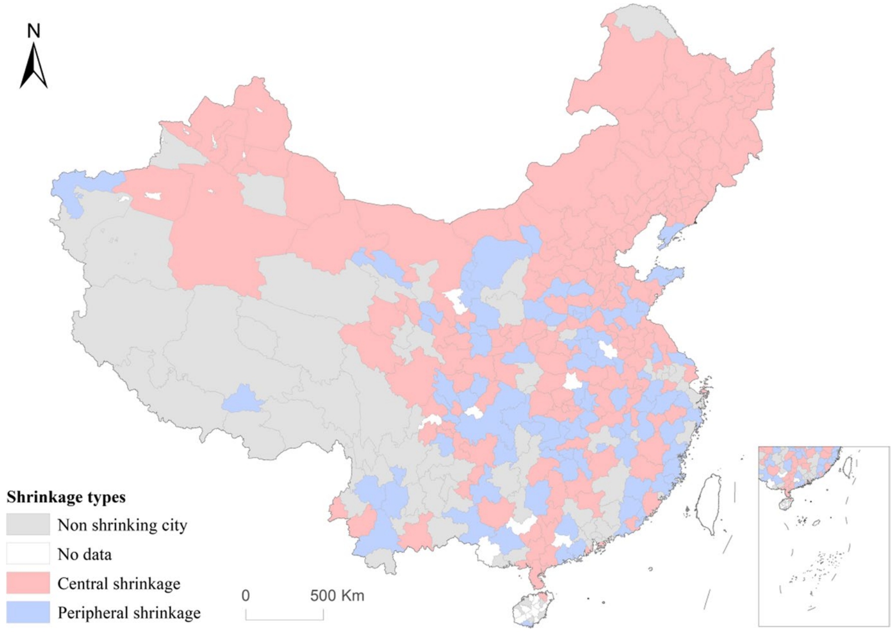

Fig. 8 Mean distance between the shrinking patches and the location of the city government

Correlation Analysis between Spatial Expansion Mode and Shrinkage Intensity

Comparative Analysis of the Population Shrinkage Intensity under Different Modes of Expansion

Using the landscape expansion index and ArcGIS technology, we obtained the classification results of the patch expansion patterns of construction land (Table 4) and the comparison of K-values of different expansion patches (Table 5). It was found that the mean and standard deviation of the K-value of the infilling and edge expansion patches were relatively small, indicating that the population shrinkage intensity of the two expansion modes was relatively small, and the difference in shrinkage intensity was not significant and close to the average. The mean value and standard deviation of the K-value in the outlying expansion patches were larger, and its maximum and minimum ranges were wider, indicating that the population shrinkage intensity of the outlying expansion was stronger, and the shrinkage intensity of each patch varied greatly. Overall, population shrinkage in areas with infilling and edge expansion was relatively mild and there was little difference in shrinkage intensity. The population shrinkage in the outlying expansion area was more serious, and the shrinkage difference was more significant.

To further verify whether there is a significant difference in the K-values of the patches under different expansion modes, three groups of data were tested

Table 4 Results of the classification of construction land patch expansion patterns

Patches expansion pattern	Number of patches	Proportion
infilling	4492	6.41%
edge-expansion	15757	22.50%
outlying	49781	71.09%
total patches	70030	1

Table 5 Comparison of K-values of different expansion patches

	Average value	Standard deviation	Maximum	Minimum
Infilling patches	−0.028968	0.137861	0.079716	−1.351318
Edge-expansion patches	−0.087271	0.253076	0.51566	−2.123678
Outlying patches	−0.3067	0.59687	0.916571	−5.027524

Table 6 Results of the significant difference test

Sample1-Sample2	Check statistics	Standard error	Standard test statistical data	Significance	Adjusted significance
1–2	−275.682	23.568	−11.697	0.000	0.000
1–3	−435.042	23.568	−18.459	0.000	0.000
2–3	−159.359	23.568	−6.762	0.000	0.000

Asymptotic significance is shown (bilateral test). The significance level was 0.05

for significant differences. After the SPSS software analysis, it was found that the three groups of data do not meet the normal distribution and that the variance is uneven, so the non-parametric statistical method (Kruskal–Wallis test) was chosen. This method uses the rank sum of multiple samples to infer whether the population positions represented by each sample are different, and finally makes inferences according by the test level. This test assumed that the overall distribution position of each group was the same. The test results were as follows: H = 348.860, $P < 0.001$, according to the test standard $\alpha = 0.05$, the hypothesis was not established, and the results showed that there are differences in the data of the three groups. The study further compared the three groups of data in SPSS software (Table 6), and found that there were significant differences between group 1 (outlying) and group 2 (edge-expansion), between group 1 (outlying) and group 3 (infilling), and between group 2 (edge-expansion) and group 3 (infilling) ($P < 0.001$ after adjustment).

In addition, in the three expansion modes, the degree of expansion compactness from large to small is infilling type > edge expansion type > outlying type (Liu et al., 2014). While the average of the K-values from large to small is outlying type > edge expansion type > infilling type in this study, which indicated that the compactness of spatial expansion in China is inversely proportional to the intensity of population shrinkage. The smaller the compactness of the expansion, the stronger the intensity of population shrinkage. For example, the outlying expansion type, which accounted for the main proportion of the expansion modes(71%, Table 4) during the study period, as the least compact mode of expansion, its population shrinkage intensity was the largest(Average value is -0.3067, Table 5).

The Spatial Distribution Difference of Urban K-values under Different Modes of Expansion

A separate visual analysis of the average K-values of the three expansion modes in each city (Figs. 9, 10 and 11) showed that the K-value map of the outlying expansion was dominated by dark areas, while the light-colored area gradually increased in the K-value maps of the edge and infilling expansions, and even many white areas (k > 0, means no population shrinkage occurred) appeared. As the shade of color represents the shrinkage intensity, the darker the color, the greater the shrinkage intensity. This meant that many cities that expanded in the outlying type experienced a relatively significant population loss, while land that expanded in the marginal and infilling type within the city had little or no population shrinkage. In addition, the distribution trend of the population shrinkage intensity in the outlying expansion land was roughly consistent with China's "Hu Huanyong Line". The K-value on the eastern side of the Hu Line was small, which meant that the intensity of population shrinkage was small. The K-value on the western side of Hu Line was higher, which

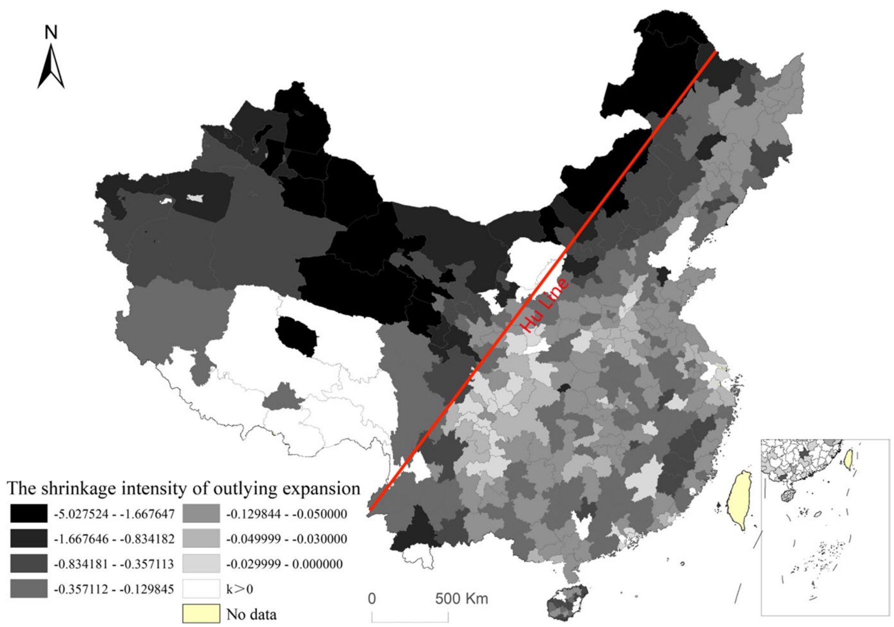

Fig. 9 Spatial distribution of K-values for outlying expansion

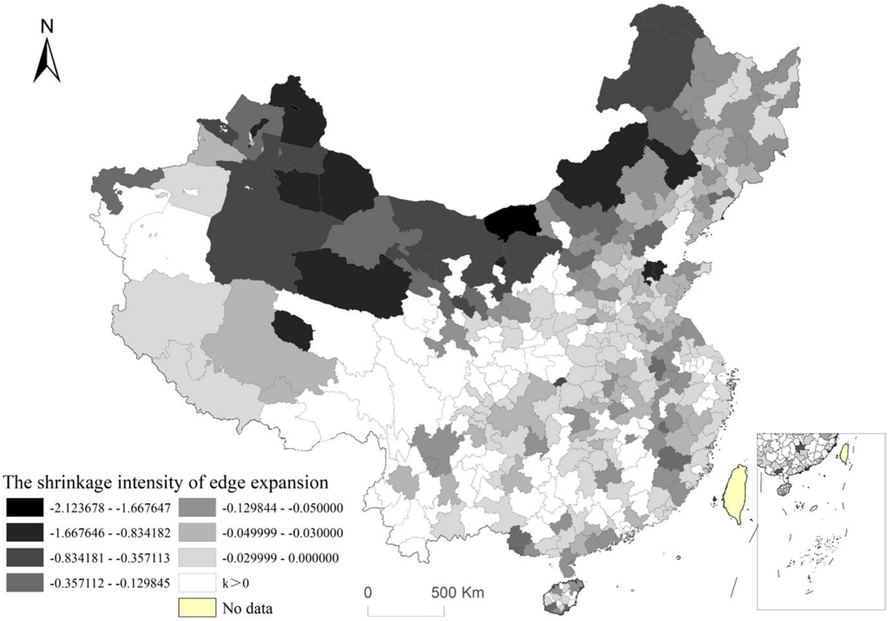

Fig. 10 Spatial distribution of K-values for edge-expansion

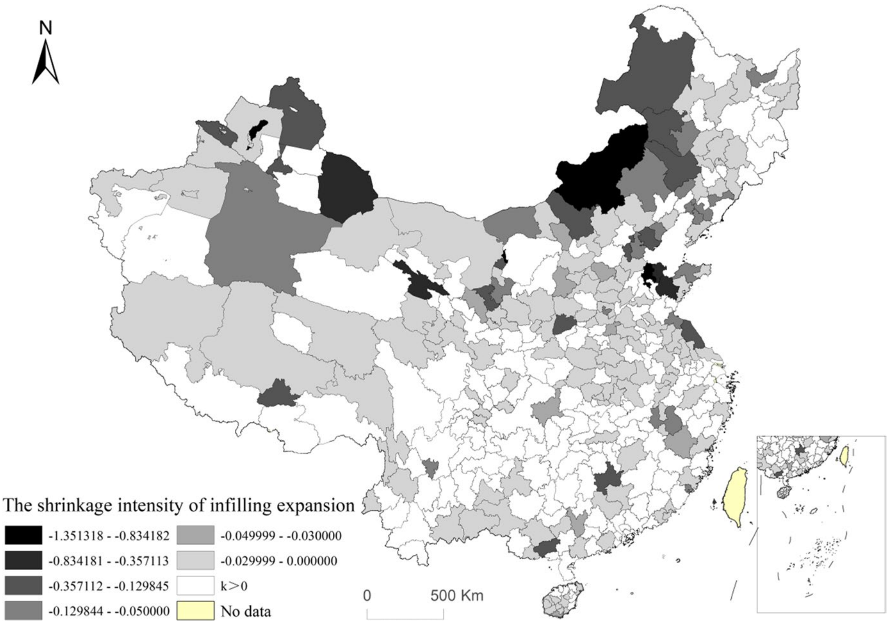

Fig. 11 Spatial distribution of K-values for infilling expansion

meant the intensity of population shrinkage was more serious(Only for the shrinkage region, not considering $k > 0$ region). The intensity of population shrinkage in marginal and infilling expansion land increased roughly from south to north, and finally reached a strong shrinkage in Inner Mongolia Province and northern Xinjiang Province, indicating that relatively serious population loss also occurred under marginal and infilling expansion in these areas.

Overall, compared to the marginal and infilling expansion modes, the population shrinkage intensity in the outlying expansion mode was relatively more serious, and the shrinkage intensity decreases in the order of marginal and infilling. The intensity of population shrinkage on the infilling expansion land was the smallest, and the population on this type of expansion land did not decrease in many cities. The population shrinkage intensity of the three types of expansion was spatially weaker in the south and stronger in the north and increased from south to north.

Discussion

Urban shrinkage has been a major issue that cannot be ignored in China in the future. This study first identifies construction land patches within Chinese cities that experienced population shrinkage between 2000 and 2015, and then uses the ratio of shrinkage patches to the total built-up land patches within cities to identify the city-scale shrinkage conditions. The results of this part indicate that 80% of the 366 cities in China are shrinking, with the most severe shrinkage concentrated in northeastern China, a result that is consistent with some existing studies (Ma et al., 2020a, b; Yang et al., 2021). The less-severe relatively shrinkage is found in the less economically developed regions of northern and central China, a finding that is consistent with the results of county-level city shrinkage identified by Zhou et al. (2021) using nighttime light (NTL) data and Gong et al. (2022) using data from three censuses. What is different is that this study also identifies some city shrinkage phenomena that have not been found in existing mainstream studies. Among them, we find that some cities in coastal areas of China have already seen severe urban shrinkage, which is consistent with the findings of Zhang and Pei (2022) and Jiang et al. (2020). Zhang et al. divided 1995–2015 into four research periods by using urban population data and found that from 1995 to 2015, cities in coastal areas of China that had not experienced population shrinkage eventually experienced urban shrinkage, among which Shandong Province and Jiangsu Province showed outstanding performance. Jiang et al. used NPP-VIIRS data to find that severe population loss occurred in the southern coastal urban agglomeration. These results suggest that longer time series studies and more refined spatial data can identify more precise urban shrinkage, and of greater concern is that urban shrinkage in China is spreading over time, even in economically developed regions.

It is worth noting that the figure of 80% in the results of this paper does not mean that 80% of cities in China are facing severe urban shrinkage, but that some areas within the 80% of cities are already facing population loss due to lack of vitality and industrial shrinkage. This conclusion is consistent with the research results of Chinese scholar Li et al. (2015) on the urban shrinkage of the Pearl River Delta in

China. Li investigated the urban shrinkage of the Pearl River Delta (PRD) at the scale of towns and streets within cities and found that a total of 50 towns and streets in the core area of the PRD region experienced population shrinkage from 2000 to 2010, accounting for 36.49% of the urban shrinkage of the PRD. This means that although the PRD region absorbs a large number of people every year due to its good economic development, some areas within the city also suffer from population loss. The results of this study indicate that a considerable number of Chinese cities appear a regional development gap in inner cities and the population movement resulting from this disparity will profoundly affect the local development potential, and the government departments concerned should pay attention to this and formulate a reasonable regional development plan to promote the synergistic development of intra-city regions.

Population shrinkage is accompanied by the continuous expansion of urban space in China. Therefore, this article investigates the relationship between the density of urban expansion and the intensity of urban shrinkage and finds that population shrinkage still exists in regions where urban space is expanding. The result confirms the urban shrinkage paradox that population loss and spatial expansion coexist in a significant number of Chinese cities, as found by Yang et al. (2015). This study further proves the inverse correlation between urban expansion density and population shrinkage intensity by quantitative methods and finds that inefficient expansion patterns will bring more serious population loss, which strengthens the theoretical basis for the correlation between urban expansion and population shrinkage. And provides ideas for further research on the relationship between the two in the future. At the same time, it deepens the practical significance of urban shrinkage research, which is conducive to the subsequent adjustment and formulation of urban planning.

With the acceleration of urban development, the impact of the urban space expansion efficiency on the intensity of urban population shrinkage will continue to deepen. Aiming at this phenomenon, this study makes the following suggestions: (1) China's future urban planning should adjust the top-level design centered on "growth" and the mainstream idea of "development towards the outside city". It should actively explore applicable planning strategies for cities experiencing shrinkage, adhere to the planning concept of "reduction" and "refinement", and promote the economical, intensive and sustainable use of urban land stock; (2) Governments of the cities experiencing shrinkage should adhere to the people-oriented and ecological-oriented concepts, switch from economic growth to humanistic care, optimize citizen services, enhance citizens' sense of happiness and gain, and reduce quantity without reducing quality; and (3) The urban space expansion should improve the efficiency of the urban space use and the compactness of urban form development, scientifically coordinate the misallocation of resources between urban expansion and population shrinkage, in order to improve the quality of cities, achieve efficient urban expansion and slow down population shrinkage, and respond to the "shrinking cities should lose weight and strengthen their bodies" emphasized in the "Key Tasks of New Urbanization Construction and Urban–Rural Integration Development in 2020" by the National Development and Reform Commission.

In summary, this paper contributes to the existing international literature in three ways. First, the urbanization process varies significantly across the world, with countries in Europe and North America having completed industrialization and urbanization, countries in Southeast Asia and Africa (e.g., India) being in the process of rapid industrialization and urbanization, and China, with its remarkable rate of urbanization, being in a period of transitional development. Therefore, although urban shrinkage is widely occurring worldwide, the phenomenon and the formation mechanisms behind it are not uniform across countries and regions (e.g., the dynamic changes of population decline and land expansion that China experienced in the past and the paradoxical phenomenon of economic development and population decline that it is experiencing now). however, for countries and regions with a background of continuous land expansion and population shrinkage, the correlation between the two has been little discussed in the literature. Therefore, this study explores the association between urban expansion and population contraction in China. will enrich the research paradigm of urban shrinkage phenomenon in the world. Provide a differentiated paradigm and perspective on urban shrinkage for countries in different urbanization processes. To provide theoretical and practical references for urban development research in developing countries and regions. It will help governments and policy makers in the relevant countries to improve urban expansion patterns and promote urban development in a sustainable manner. Second, the refined spatial scale and long time series research methods will help other countries in the world to enrich empirical studies based on more accurate identification results of urban shrinkage. Third, while early urban shrinkage researchers believed that urban shrinkage was accompanied by economic recession, this study demonstrates that urban shrinkage was found in most cities in China where both economies grew, showing that economic growth and urban shrinkage can coexist, enriching the scope of urban shrinkage research and providing a theoretical basis for research on urban shrinkage in other developing countries around the world.

Conclusions

In this study, the population shrinkage identification and classification of 366 prefecture-level cities in China from 2000 to 2015 were conducted from the inside of the city. The long-term analysis avoided the contingency of the traditional two-phase study, and the 1 km patch containing the population data was used as the basic research unit. This approach compensated for the insufficiency of previous studies based on administrative units, and the study conducted an exploratory analysis of the correlation between patterns of urban spatial expansion and intensity of population shrinkage. The main conclusions are as follows:

(1) Between 2000 and 2015, 80% of China's 366 cities experienced various degrees of shrinkage, of which medium and low shrinkage accounted for 64%. Urban shrinkage has become a common phenomenon. Through spatial autocorrelation

analysis, it was found that high-high agglomeration appeared in the northeast and the Beijing-Tianjin-Hebei regions and low-low agglomeration appeared the southwest region.

(2) By analyzing the landscape pattern, it was found that of the 291 cities where urban shrinkage had occurred in China, 99% of the cities experienced weak shrinkage, and only 1% experienced moderate shrinkage. Overall, the shrinkage intensity of Chinese cities was relatively weak. In addition, according to the shrinkage type analysis, cities in northern China were mainly experiencing shrinkage in the center, and the cities in the south had an alternate distribution pattern with marginal and center shrinkage. The type of urban shrinkage may be related to the speed of local economic development. Excessive economic development and unreasonable urban spatial expansion may lead to a marginal shrinkage of the urban population.

(3) Based on the identification of the expansion pattern of China's new construction land from 2000 to 2015, the correlation between the expansion pattern and the intensity of shrinkage was analyzed. It was determined that the expansion compactness of China's construction land is inversely proportional to the intensity of population shrinkage. The lower the compactness, the greater the population shrinkage. During the study period, China was dominated by outlying expansion(71%, Table 4), and its population shrinkage was also the most significant.

Although this study had conducted a more precise identification of urban shrinkage and explored the correlation characteristics between spatial expansion and population shrinkage, the research on the correlation between the efficiency of spatial expansion and the intensity of population shrinkage could be improved. To better adapt to the future trend of urban shrinkage, and put forward scientific and reasonable countermeasures, it is necessary to continue in-depth research on this topic.

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Data Availability Data available upon request.

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