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The Effect of Urban Form on Urban Shrinkage—A Study of 293 Chinese Cities Using Geodetector

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Abstract: Chinese cities are experiencing urban shrinkage due to demographic, environmental, economic, and political changes. However, urban form is another reason for urban shrinkage. This study first identified the shrinking of 293 cities in China based on the values of the change in brightness extracted from multi-year nighttime light data. Next, the characteristics of construction land morphology from 2019 were analyzed using landscape pattern analysis. Finally, the impact of urban form on urban shrinkage was explored using Geodetector. The results show that: (1) In total, 293 cities experienced different degrees of shrinkage. Regions with severe shrinkage were concentrated in the underdeveloped provinces, and autonomous central and western regions of China; moreover, (2) All factors of urban form significantly affected urban shrinkage. The largest q-values were found in patch density (0.144) and urban area (0.133), indicating that the degree of construction land fragmentation and urban area scale affected urban shrinkage the most; and (3) The interaction effects of pairwise factors were mutually or nonlinearly enhanced. The influence of urban form and socio-economic factors was stronger than that of socio-economic factors alone. This shows that the coupling of urban form and socio-economic factors strengthens the impact of urban form on urban shrinkage.

Keywords: urban shrinkage; urban form; landscape pattern analysis; Geodetector; China

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1. Introduction

Urbanization is an important sign of a country's socio-economic development [1]. Although a fairly new subject in the field of urbanization [2–4], urban shrinkage has become widespread and poses huge social, economic, and environmental risks [5–7], threatening the United Nations Sustainable Development Goals.

The term urban shrinkage was first proposed by German scholars to refer to cities suffering from population and economic loss due to deindustrialization [8]. Coping with urban shrinkage is an unresolved issue for urban policymakers and scholars. The main problem lies in defining urban shrinkage. A population-based definition is the first and most distinctive one [9]. In particular, periods are commonly used to judge population loss. The amount of population left at the end of a certain period is compared to the amount at its beginning [10–12]. However, this method only compares population loss in two years' time, which is highly accidental and cannot reflect a long-term trend [13]. Therefore, scholars decided to define urban shrinkage as the negative annual population change rate in cities and towns over a period of time [14,15]. Nonetheless, a single population index cannot reflect the degree of social and economic development in urban areas. The current means to determine urban shrinkage is based on an administrative region, such as a city or a town, which cannot fully describe the distribution of local urban shrinkage, i.e., shrinkage within a city. With the development of big data, nighttime light data are used to identify shrinking cities [13,16]. This proved useful not only in testing real economic growth, but also in measuring economic activities such as agglomeration, urbanization, population mobility, and energy consumption [17–20]. Likewise, this makes up for the shortcomings of the time difference in existing demographic data and the limitations of the administrative division. Therefore, nighttime light data are ideal for detecting urban shrinkage, particularly local shrinkage.

Another problem is understanding why shrinkage occurs. Existing studies proposed demographic, environmental, economic, and political changes as the main drivers of urban shrinkage [2,21,22]. Although the four types of change narrow down the choice of potential drivers, they ignore the role of urban form in urban shrinkage. Urban form refers to the spatial distribution of a city and its internal components [23]. It combines various factors that affect the city and sustainable development [24–27]. For example, studies have found that urban form is associated with economic and population growth [28,29]. In particular, an irregular and degraded urban form limits economic growth. This is why population and economic losses are the main manifestations of urban shrinkage. Therefore, the influence of urban form on urban shrinkage should receive more attention. However, few scholars have touched upon this subject. Meng et al. [30] explored the correlation between urban shrinkage and urban compactness in old industrial cities, such as Siping. The drawback of this study was a limited selection of urban form factors and research objects, which failed to reveal the association between urban form and urban shrinkage.

China's tremendous economic growth since the Chinese economic reform in 1978 has led to rapid urbanization [31], which is constantly shaping and changing the urban form [32]. However, local shrinkage was discovered in the 2010s and was characterized by population loss, economic recession, and unemployment [33]. According to the big data of Baidu, China's Internet search engine, it was found that about half of the physical cities (1506) in China showed some degree of shrinkage during 2016–2018 [34]. Due to this, one could ask whether urban form affects urban shrinkage, how much it affects it, how should the urban form of shrinking cities be planned in the future, etc. Therefore, this study aims to identify urban shrinkage in 293 cities using characteristics of construction land morphology and nighttime light data observed over a longer time span. This study compensates for the limitation of a single population index observed in a shorter time span, and improves the accuracy of identifying urban shrinkage. Furthermore, it crosses the administrative boundaries of cities, which enables it to identify urban shrinkage within physical cities. This study also uses landscape analysis and Geodetector to analyze the development pattern of construction land, and explore the influence of urban form on urban shrinkage and the interaction between urban form factors and socio-economic factors. In the study, the degree of urban shrinkage is the dependent variable, while urban form and socio-economic factors are independent variables.

Urban shrinkage is spreading in China, but the mainstream research on urban shrinkage is based on the context of developed Western countries, and its findings and experiences have significant limitations for developing countries. This study, therefore, explores the identification of urban shrinkage in China and the role of urban form in urban shrinkage, which not only provides a localized exploration of the phenomenon of urban shrinkage and its mechanisms in China, but also provides a Chinese perspective on urban shrinkage studies in Western academia, enriches the paradigm of urban shrinkage studies in developing countries, and provides similar case studies for other developing countries that are undergoing rapid urbanization.

2. How Urban form Affects Urban Shrinkage in China

In the Chinese context, it was found that urban form mainly affects the development level of urban production and the living and ecological space through fragmentation, compactness, urban size, and urban sprawl. In the context of rapid urbanization, the non-agriculturalization of a large amount of low-cost agricultural land around cities paved the way for rapid industrial expansion and urbanization [35,36]. However, the inefficient and disorderly urban expansion deteriorated urban form, resulting in a fragmented and less compacted urban periphery, low-density and dispersed urban expansion, the internal congestion effect, and environmental issues [37]. This method of development squeezes the space so that urban production activities and facilities cannot thrive, which is, on one hand, reflected in the intertwining of industrial and arable land in the periphery, which is not conducive to improving industrial productivity. On the other, the disorderly distribution of industrial parks reduces the agglomeration effect and input–output benefits, and increases transportation, time, and coordination costs [38]. At the same time, the internal congestion effect affects labor productivity [39,40]. The adverse effects on the living space are reflected in, on one hand, low density, urban sprawl with long intra-city distances, and irregular urban form. These increase the cost of intra-city public services, and the money and time required for infrastructure construction and commuting [28]. They also decrease the availability of urban infrastructure [41], and the level of accessibility and spatial homogeneity of public services within cities [42,43]. On the other, city size and density affect labor income [44,45]. All of the aforementioned issues reduce urban residents' satisfaction with the city and increase population loss. In addition, the ecological quality of cities is affected by poor urban form [46–48]. When cities are too small, the dense population challenges the city's ecological resources. The fragmented spatial layout of the city undermines the integrity of the environment as well [41]. Finally, inefficient and disorderly urban expansion increases land consumption per capita, which hurts sustainable urban development.

Therefore, the influence of urban form on urban shrinkage can mainly be observed through the change of the external shape of construction land, which is caused by urban expansion. The change of the urban form affects the level of internal urban functions, the sustainable development of urban production, and living and ecological spaces, and ultimately influences urban shrinkage. The mechanism of the influence is summarized in Figure 1.

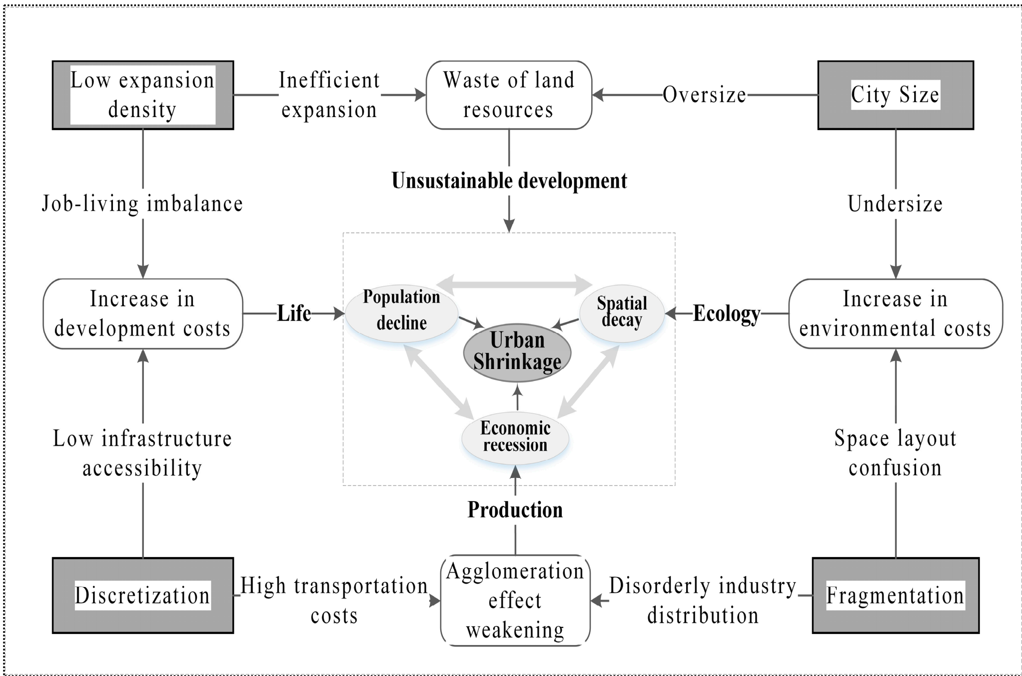

Figure 1. The theoretical mechanism behind the influence of urban form on urban shrinkage.

Based on the mechanism, this study quantitatively analyzed the influence of urban form on urban shrinkage through four dimensions, i.e., fragmentation, compactness, urban scale, and urban sprawl.

3. Methods and Data

3.1. General Framework

The period included in the study is 2013–2019. According to existing research, the constraining effect of the construction land control policy emerged after 2013 [49]. Not only did cities show prominent traces of rapid expansion before 2013, but they were also affected by planning regulations after 2013, reflecting the stage characteristics of urban development (expansion and regulation) and the appearance of urban shrinkage during subsequent slow development, which has greater research value. Due to the outbreak of Covid-19 in 2020, economic activities were affected in some regions, so this study selected the change trend of nighttime light during 2013–2019 to identify urban shrinkage. The nighttime light data are used not only to test real economic growth, but also to measure agglomeration, urbanization, population migration, etc.

Due to the inaccessibility of socio-economic data for some cities, this study analyzed 293 prefectural cities out of 333 prefectural administrative units in mainland China. By processing the nighttime light data, this study obtained multi-year nighttime light trends and their slope K values of construction land patches in 293 cities. Then, it judged the shrinkage of construction land patches based on positive and negative K values. Finally, the study calculated the proportion of shrinking construction land patches to the total construction land patches within cities to obtain the degree of urban shrinkage.

Urban form and socio-economic factors were selected as independent variables (some of the urban form data were obtained from the results of landscape pattern analysis in the FRAGSTATS software), while the urban shrinkage degree was selected as the dependent variable to carry out factor detection and interaction detection in Geodetector [50]. Lastly, the study investigated the influence of urban form on urban shrinkage, and the influence of socio-economic factors combined with urban form factors on urban shrinkage.

The research framework is shown in Figure 2. Some of the methods covered in the framework are described in detail in the following subsections.

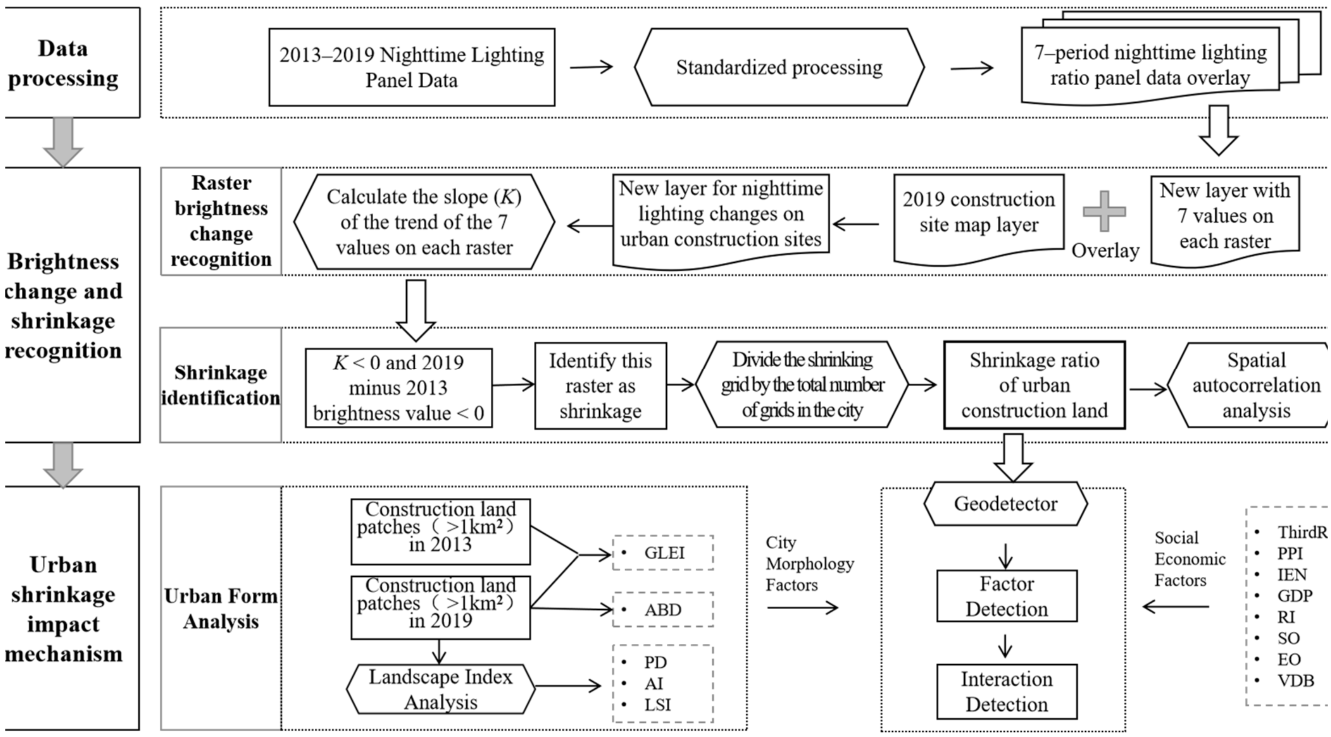

Figure 2. Research framework diagram.

3.1.1. Identification of Urban Shrinkage

This study determined whether the patch shrunk during 2013–2019 based on the positive and negative *K* values of the change in brightness calculated using nighttime light data. It also judged construction land shrinkage in 293 cities based on the proportion of shrinking patches to the total patches in each city.

There are several steps in identifying urban shrinkage. (1) In the ArcGIS software, the nighttime light data from 2013 to 2019 were preprocessed, corrected, and overlaid. There were seven values on each raster, each representing the brightness of light in a year. (2) The study then overlaid this new layer on construction land patch layers from 2019 to obtain the nighttime light changes of urban construction land. To eliminate possible interference of random factors over the years, this study transformed the brightness values of the raster into degrees by calculating the proportion of brightness of each raster to the sum of the brightness of all raster data. (3) The slope (*K*) of the brightness change in the raster was obtained by calculating the trend of the seven degrees in each raster. This information was then used to analyze whether a raster was shrinking. In other words, when the brightness of a raster decreased (*K* was less than 0) during 2013–2019 and the brightness at the end of the period minus the first period was also less than 0, the nighttime light of the raster weakened, socio-economic activities decreased, and the population declined. Therefore, the raster was said to be shrinking. (4) The percentage of urban shrinkage of each city was obtained based on the ratio of shrinkage rasters to the total number of rasters within the city. Thus, the study was able to identify the degree of urban shrinkage.

3.1.2. Spatial Autocorrelation

Spatial autocorrelation is used to analyze whether the degree of urban shrinkage is spatially agglomerative. The global autocorrelation index is used to reflect the similarity between attribute values of neighboring regional units. Its formula is [51]

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

where N is the observed value; $(x_i - \mu)$ and $(x_j - \mu)$ are the differences between the observed value of the i-th and j-th patches and the mean value of all patches, respectively; and $S_0 = \sum_i^n \sum_j^n W_{ij}$, W_{ij} is the spatial weight: if patches i and j are adjacent, then $W_{ij} = 1$; otherwise, $W_{ij} = 0$. If I is positive, the observations are spatially positively correlated; if I is negative, the observations are spatially negatively correlated.

The local spatial autocorrelation index is used to reflect the specific geographical distribution of agglomeration. Its formula is [52]

$$L_i = \frac{(x_i - \overline{x})}{m_2} \cdot \sum_{j=1}^{n} W_{ij}(x_j - \overline{x}) \quad (2)$$

where x_i is the attribute value of the spatial unit i, W is the spatial weight matrix, and W_{ij} represents the degree of influence between spatial units i and j. A positive L_i means that the spatial unit has similar attribute values (high-value aggregation or low-value aggregation) to the neighboring units, while a negative L_i means that the spatial unit does not have similar attribute values to the neighboring units.

3.1.3. Landscape Pattern Analysis

The landscape index can synthesize landscape pattern information, reflecting its structural composition and spatial configuration characteristics [53]. Landscape pattern analysis captures the morphological characteristics and spatial heterogeneity of urban forms. Based on the data of construction land patches (>1 km^2) of 293 cities in 2019, this study selected three landscape indexes—the landscape shape index (LSI), patch density (PD), and aggregation index (AI)—to analyze urban forms in FRAGSTATS.

3.1.4. Geodetector

Geodetector is a spatial statistical method based on the principle of spatially stratified heterogeneity. It quantitatively analyzes the influence of explanatory factors on detection targets and measures the interaction between variables [54]. Although Geodetector consists of four modules, this study included only factor and interaction detection. On one hand, factor detection is used to analyze the influence of different driving factors on the degree of urban shrinkage. The formula is

$$q = 1 - \frac{1}{n\sigma^2} \sum_{h=1}^{L} n_h \sigma^2{}_h \tag{3}$$

where q represents the influence of a driver on the degree of urban shrinkage; n, σ^2 are sample size and variance, respectively; and n_h, $\sigma^2{}_h$ are sample size and variance of the h (h = 1, 2, . . . , and L) stratum, respectively. The value of q is in the range [0,1]. Larger values indicate a stronger influence.

On the other, interaction detection is used to identify whether the two drivers act independently of the outcome variable or interact, and thus increase or decrease the influence of the dependent variable Y [50]. The expressions are shown in Table 1 (where P is the influencing factor).

Table 1. The expressions and meaning of interaction detection.

Expressions	Meaning
If P(X1 ∩ X2) < min(P(X1), P(X2))	It suggests that nonlinearity weakens after the interaction between factors X1 and X2.
If min(P(X1), P(X2)) < P(X1 ∩ X2) < max(P(X1), P(X2))	It means that the monoclinic line is weakened after the interaction of X1 and X2.
If P(X1 ∩ X2) > max(P(X1), P(X2)) and P(X1 ∩ X2) < P(X1) + P(X2)	It shows that X1 and X2 enhance each other after interaction.
If P(X1 ∩ X2) > P(X1) + P(X2)	It shows that nonlinearity is strengthened after the interaction of X1 and X2.
If P(X1 ∩ X2) = P(X1) + P(X1)	It shows that X1 and X2 are independent of each other.

3.2. Indicator Selection and Data Sources

The formula and abbreviation of each indicator are shown in Table 2. Based on indicators commonly used in research to evaluate urban form, this study selected PD, AI, LSI, urban area (ABD), and the landscape expansion index (LEI) to measure the development level of urban form through four dimensions: fragmentation, compactness, urban scale, and urban sprawl. PD, AI, and LSI were obtained from urban land patch data from 2019 using FRAGSTATS. PD and AI indicators explain fragmentation in terms of landscape density and agglomeration. In other words, the higher the PD, the higher the fragmentation of urban land, and the smaller the AI, the more scattered the distribution of urban land patches. Next, the LSI indicator explains urban form in terms of shape, meaning that the smaller the LSI, the more compact the patch. The ABD explains urban form based on a city scale. Based on the LEI index proposed by Liu et al. [55], the general landscape expansion index (GLEI) explains the compactness of construction land patches in the city. This index was obtained by weighting urban construction land patches by area in 2013 and 2019. When it comes to socio-economic indicators, GDP was selected to measure the level of urban development. Furthermore, the VDB indicator was selected to measure the influence of the local financial environment on socio-economic development and population mobility. IEN, PPI, and ThirdR were selected to measure the influence of industrial structure on local employment and population absorption capacity. Finally, RI, SO, and EO were selected to measure the level of urban livelihood and the influence of inter-city differences in the level of science and technology education on local population mobility, respectively.

Table 2. Index selection.

	Abbreviations	Measurement Dimensions	Indicators	Calculation Formula/Unit
Urban form indexes	PD	Fragmentation	Patch density	$\mathrm{PD} = \frac{\mathrm{NP}}{\mathrm{A}}$ NP is the number of patches. A is the total area of the landscape or patch.
	AI	Compactness	Aggregation Index	$AI = \frac{g_{ii}}{maxg_{ii}} \times 100$ $maxg_{ii}$ is the number of edges of similar neighboring rasters when patch type i reaches maximum aggregation.
	LSI		Landscape Shape Index	$LSI = \frac{\sum_{k=1}^{m} e_{ik}}{4\sqrt{A}}$ m is the number of patch types. A is the total area of the landscape (m^2); e_{ik} is the total length of adjacent edges. between patches of type i and k (m)
	GLEI	Urban sprawl	Landscape Expansion Index	$GLEI = \frac{A_o}{A_o + A_v} \times 100$ A_o is the area of intersection between the buffer zone of the new patch and the original patch. A_v is the area of intersection of the buffer zone of the new patch with other areas, except the original patch.
	ABD	City Size	Urban area	Square kilometers
Socio-economic indexes	GDP	Level of urban development	Gross Regional Product	Billion
	PPI	Industry Structure	The proportion of employees in the primary industry	%
	ThirdR		Value added of tertiary industry as a proportion of GDP	%
	IEN	Industry Development Level	Number of industrial enterprises above the scale	individual
	RI	People's livelihood level	Real estate investment situation—residential investment	Ten thousand Yuan
	SO	Science and education level	Science and technology expenditures	Ten thousand Yuan
	EO		Education Expenses	Ten thousand Yuan
	VDB	Local financial level	Balance of various deposits in RMB	Ten thousand Yuan

In this study, the nighttime light data (NPP-VIIRS) from 2013 to 2019 were obtained from the National Geographic Data Center of the National Atmospheric and Oceanic Administration (NGA) (downloaded from https://eogdata.mines.edu/products/vnl/ (accessed on 12 March 2020)). Urban land patch data from 2019 were extracted from the National Land-Use/Cover Database of China (NLUD-C, produced by CAS (city, country) (Beijing, China) with a spatial resolution of 30 m, based on Landsat TM imagery and the

China–Pakistan Earth Resources Satellite image data). The socioeconomic statistics of each city (such as the proportion of employees in the primary industry, the proportion of added value in the tertiary industry to GDP, and gross regional product) were obtained from the China Statistical Yearbook, the China Regional Economic Statistical Yearbook, and the statistical yearbook of each province, city, and autonomous region (some of the socio-economic data of Beijing were not publicly available, so the previous year's data were used in this study).

4. Results and Analysis

4.1. Spatial Distribution of Urban Shrinkage

The degree of urban shrinkage of 293 cities was divided via ArcGIS using the natural breakpoint method to obtain four classes of shrinkage (Figure 3). In this study, the classes were defined from small to large: potential shrinkage (0.001–6.338), slight shrinkage (6.339–9.971), moderate shrinkage (9.972–17.189), and severe shrinkage (17.190–43.264). Although the degree of shrinkage in the eastern region was generally small (only cities with potential shrinkage accounted for the most significant proportion), a considerable number of cities in the other three regions showed slight to severe shrinkage. Cities with moderate and severe shrinkage between 2013 and 2019 were concentrated in China's northern, northeastern, and southwestern regions.

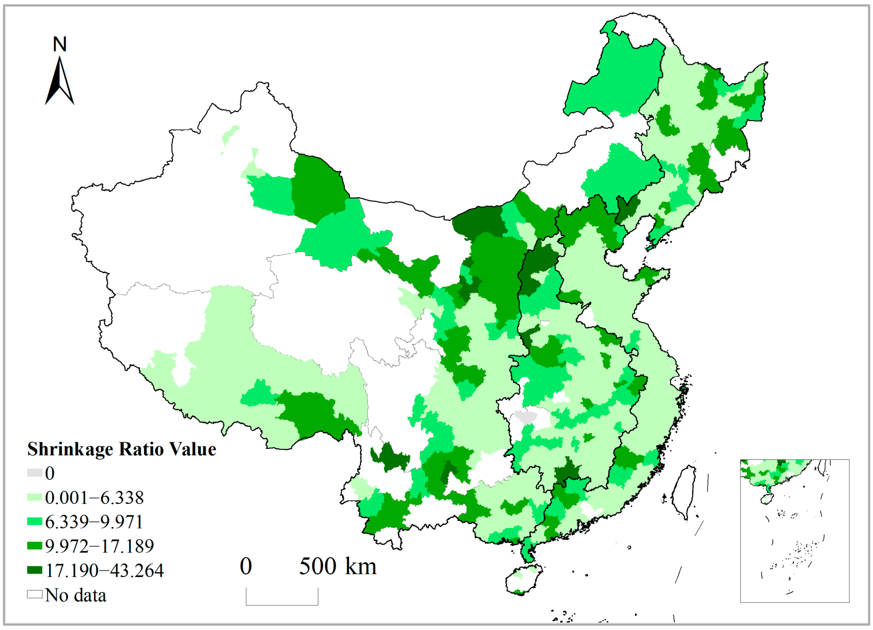

Figure 3. Spatial distribution of the degree of urban shrinkage.

The provinces with more significant degrees of shrinkage were concentrated in the underdeveloped provinces and autonomous central and western regions (Figure 4). Among them, the Ningxia Hui Autonomous Region had the most significant degree of shrinkage (15.8), followed by the Inner Mongolia Autonomous Region (10.9), Yunnan Province (10.7), Guizhou Province (9.9), Shanxi Province (9.8), and Gansu Province (9.2). It can be observed that four of the top five provinces with the highest degree of shrinkage belonged to the western region of China. The five provinces (municipalities directly under the central government) with the most minor shrinkage belonged to the eastern region, including the municipalities of Shanghai (2.802), Tianjin (2.160), and Beijing (0.864). Overall, all provinces showed varying degrees of shrinkage, with the most severe shrinkage (Ningxia, 15.8) being about 17 times greater than the least severe one (municipality directly under the central government—Beijing, 0.9).

The spatial autocorrelation analysis of the shrinkage of each city resulted in Moran's I value of 0.1928 and Z value of 9.4334, which passed the significance test at the 0.01 level. This indicates a significant positive correlation in the spatial distribution of urban shrinkage in China. The results of the analysis of local spatial autocorrelation (Figure 5) indicate that the spatial distribution of shrinkage shows clustering characteristics, with low–low clustering in the eastern coastal region and high–high clustering in the northern and southwestern regions.

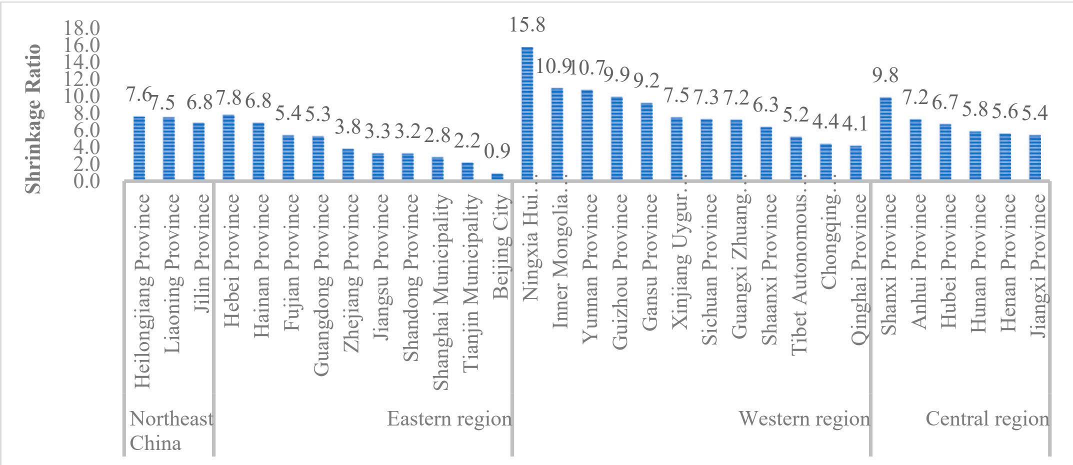

Figure 4. The average degree of urban shrinkage in provinces.

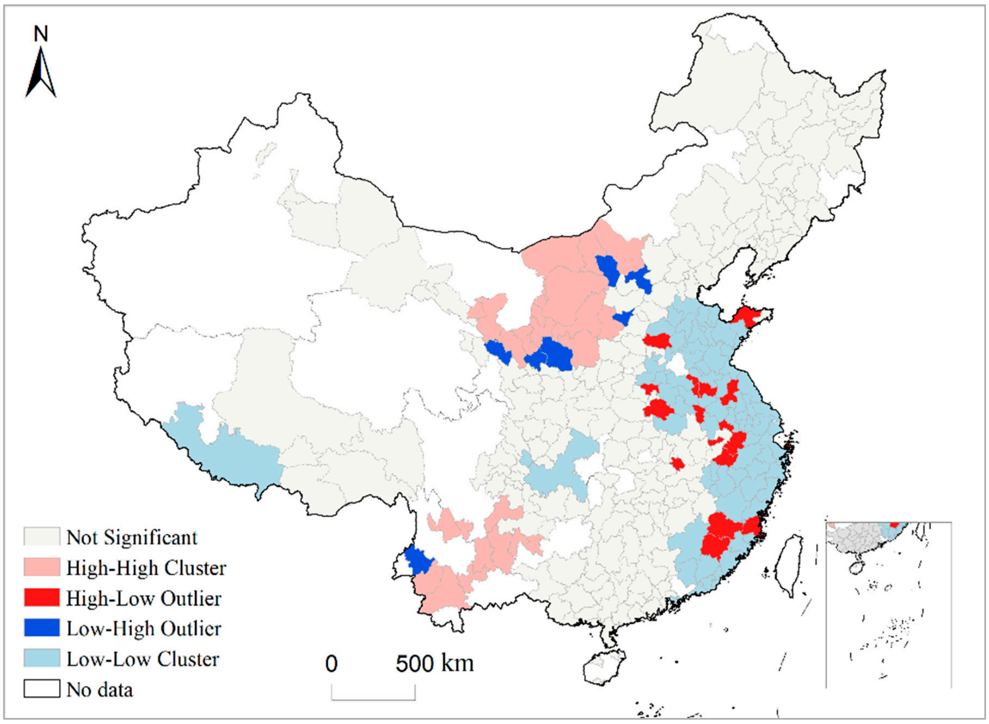

Figure 5. Local clustering of urban shrinkage.

4.2. Spatial Distribution of Urban Form

This study explored the influence of urban form on urban shrinkage, and the influence of combined urban form and socio-economic factors on urban shrinkage. Firstly, the study conducted spatial pattern analysis of AI, PD, and LSI indexes based on construction land patches in 2019. The results are shown in Figure 6. The AI and PD indexes showed obvious north-to-south differences in the eastern region, with the Qinling Mountains and the Huaihe River as the boundary. The AI index was higher and the PD was lower north of the boundary, indicating that the aggregation of construction land in northern China was higher, the degree of connectivity was more remarkable, and the degree of fragmentation was lower. However, south of the boundary, the situation was the opposite because the LSI index was higher. In other words, the construction land patches in this region were more scattered. Furthermore, GLEI had higher agglomeration values in the coastal areas north of the Beijing–Tianjin–Hebei and Yangtze River Delta urban agglomerations, and lower values in the rest of the region. However, GLEI values were generally low in the 293 cities, which indicated that urban expansion from 2013 to 2019 was dominated by inefficient expansion. In addition, the GLEI values showed a decreasing feature from coastal to inland. The ABD index showed no noticeable agglomeration effect in spatial distribution, except in the Tibetan, northern Heilongjiang regions, and parts of the Central Plains, where it was lower.

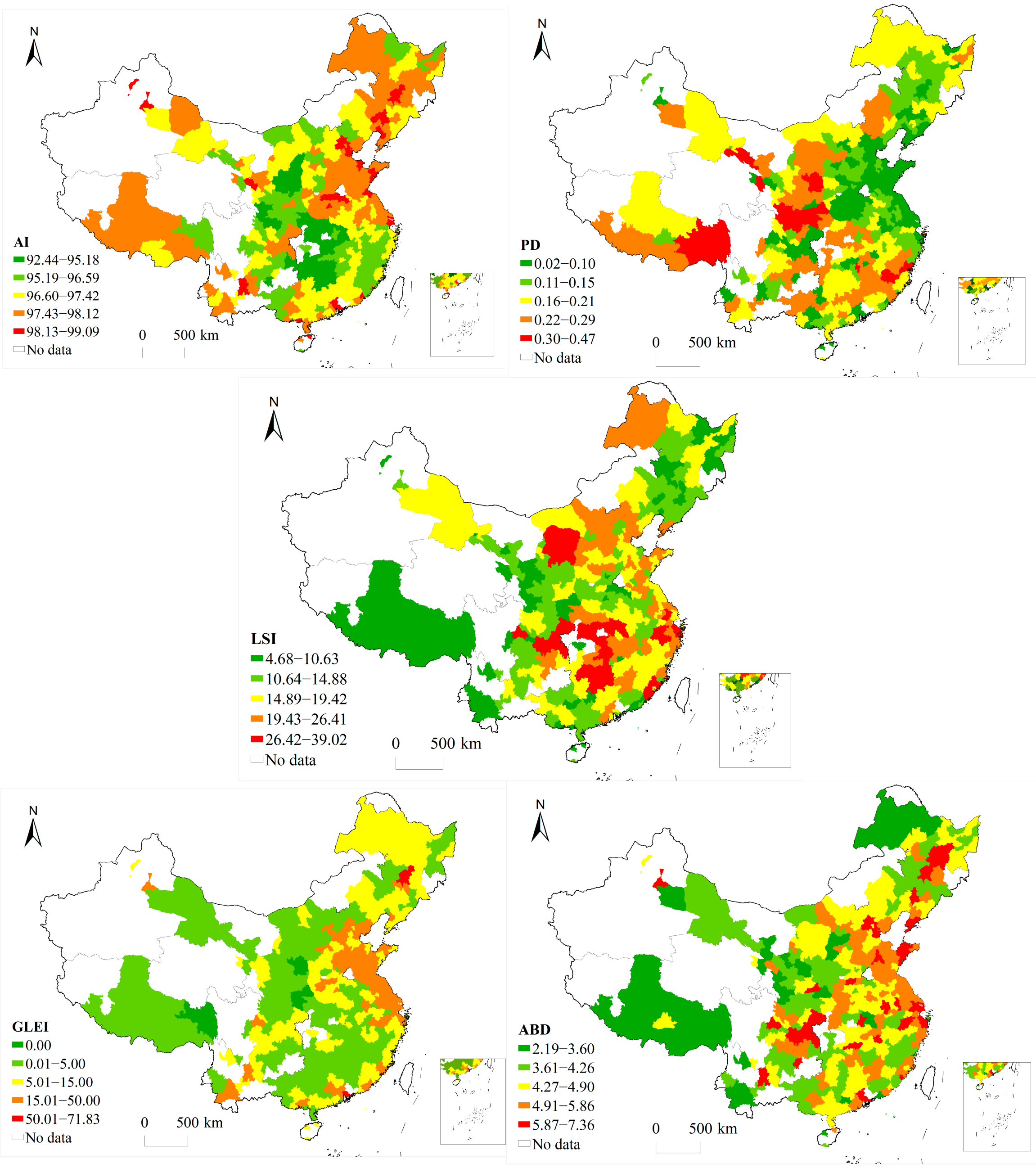

Figure 6. Distribution of values of 5 urban morphological indicators.

4.3. The Effect of Urban Form on Urban Shrinkage

The results in Table 3 were obtained using factor detection in Geodetector. It can be seen that all the detected factors passed the significance test. Firstly, the two urban form factors that had the most decisive influence on urban shrinkage were PD (0.144) and ABD (0.133). The q-values of GLEI, LSI, and AI were below 0.1, so their influence was relatively weak. Moreover, the two socio-economic factors with the most substantial influence were IEN (0.198) and RI (0.170). EO, GDP, and VDB had a medium influence, while the remaining factors had the weakest influence.

Table 3. Results of detecting driving factors.

		Drive Factor	q-Value	q-Value Sorting
City Form Factors	PD	Plaque Density	0.144 **	1
	ABD	Urban Area	0.133 **	2
	GLEI	General Landscape Expansion Index	0.092 **	3
	LSI	Landscape Shape Index	0.082 **	4
	AI	Aggregation Index	0.075 **	5
Social Economy Factor	IEN	Number of industrial enterprises above the scale (pcs)	0.198 **	1
	RI	Real estate investment situation—residential investment (million yuan)	0.170 **	2
	EO	Education expenditure (million yuan)	0.150 **	3
	GDP	Gross regional product (billion yuan)	0.147 **	4
	VDB	Balance of various deposits in RMB (RMB million)	0.142 **	5
	PPI	The proportion of employees in the primary industry (%)	0.115 **	6
	SO	Science and technology expenditure (million yuan)	0.109 **	7
	ThirdR	Added value of tertiary industry as a proportion of GDP (%)	0.087 **	8

Note: ** denotes significance of 0.01 or less.

The results show that the driving force of a single factor was generally low. In fact, PD and ABD factors indicate that the degree of construction land fragmentation and the size of urban areas strongly correlated with economic and demographic changes in cities. The large city scale and fragmentation imply inefficient land use, which hinders the efficient flow of population, information, etc., and is not conducive to the multiplier effect in relation to the urban infrastructure layout. These issues also lead to higher urban development costs, inhibiting economic and population loss, and most likely causing urban shrinkage. It can be said that these results answer the first question posed at the beginning of this study. In truth, poor urban form (fragmentation, dispersion, low-density urban expansion, etc.) exacerbates urban shrinkage.

Among the socio-economic factors, IEN and RI had the first- and second-highest influence, indicating that the development level of industries in cities and the state of local real estate development had a relatively significant impact on urban shrinkage. Large industrial enterprises can affect the quality of the local living environment through pollution, causing population migration. In addition, a large number of industries with high energy consumption and industrial parks with low production efficiency can hinder the transformation of the local industrial structure and inhibit rapid economic development. Furthermore, higher residential investment in real estate was generally related to the demand for city housing and market expectations. However, in some cities, the industrial development status hardly raised the local employment rate and wages (such as in resource-based cities in the northeast). The developers' blind optimism for the real estate industry led to the development of significant real estate projects around the city, causing a drop in population density in the main city. The newly built area was then reduced to a ghost town lacking vitality.

5. Discussion

5.1. The Effect of Urban Form and Socio-Economic Factors on Urban Shrinkage

Most studies have proposed countermeasures based on socio-economic factors to control urban shrinkage. In the face of China's changing economy, there is tremendous pressure on economic and administrative resources available to the government and society. As a result, there is an urgency to improve the effectiveness of shrinkage management in other ways. Based on the above results, this study found that urban form has an incredible influence on managing urban shrinkage. Naturally, one can ask whether its coupling with socio-economic factors can further explain the causes of urban shrinkage. Therefore, this study explored the influence of urban form and socio-economic factors on urban shrinkage using interaction detection in Geodetector. The results are shown in Figure 7. The influence of the pairwise interaction of 13 factors was found to be greater than that of a single factor, indicating that multiple factors drive urban shrinkage.

	PD	LSI	AI	ABD	GLEI	ThirdR	PPI	RI	IEN	EO	GDP	VDB	SO
PD	0.144												
LSI	0.277	0.082											
AI	0.228	0.196	0.075										
ABD	0.320	0.303	0.289	0.133									
GLEI	0.246	0.259	0.202	0.195*	0.092								
ThirdR	0.364	0.244	0.343	0.279	0.287	0.087							
PPI	0.365	0.295	0.312	0.272	0.303	0.333	0.115						
RI	0.338	0.295	0.294	0.302*	0.280	0.296	0.293	0.170					
IEN	0.348	0.341	0.289	0.269*	0.272*	0.367	0.314	0.264*	0.198				
EO	0.346	0.294	0.262	0.254*	0.244	0.239	0.211*	0.250*	0.247*	0.150			
GDP	0.355	0.342	0.276	0.236*	0.273	0.276	0.270	0.261*	0.271*	0.226*	0.147		
VDB	0.312	0.300	0.267	0.249*	0.252	0.299	0.255*	0.252*	0.252*	0.222*	0.190*	0.142	
SO	0.289	0.294	0.215	0.218*	0.223	0.266	0.273	0.268*	0.240*	0.188*	0.231*	0.232*	0.109

Figure 7. The results of interaction detection. Note: (1) From blue to red, the effect of interaction goes from small to large. The darker the blue, the smaller the effect, and the darker the red, the greater the effect; (2) Band * is mutual enhancement, while the rest are nonlinear enhancement.

There were 25 pairs of mutually reinforcing interactions, which mainly occurred between socio-economic factors. The rest of the interactions, however, showed non-linear reinforcement. Nonetheless, the interaction between urban form and socio-economic factors had a significantly higher influence on urban shrinkage compared to the influence of socio-economic factors alone. The distribution of several high-value interactions was concentrated where urban form and socio-economic factors interacted the most (the green box in Figure 7).

PD interacted with socio-economic factors the most. Moreover, the influence of the interaction between PD and IEN, EO, GDP, PPI, and ThirdR reached about 0.35. However, the interaction between LSI, AI, ABD, GLEI, and socio-economic factors decreased successively. While interacting with socio-economic and other factors, the influence of a single urban form factor increased from about 0.1 to about 0.25–0.35. The significant increase in the driving force of urban form factors combined with socio-economic factors answers the second question posed in this study: urban form does strengthen its influence on urban shrinkage when combined with socio-economic factors.

Under the interaction, the influence of PD increased from 0.144 to 0.228–0.365, AI increased from 0.075 to 0.202–0.343, and LSI increased from 0.082 to 0.196–0.342. The fragmentation and dispersion of urban land, characterized by the three indexes, indicate that various subjects of economic activities in social production are spatially independent and do not actively collaborate. Therefore, fragmented construction land, when intertwined with industrial structure and public services, leads to the sporadic distribution of industrial parks and a weakened industrial cluster effect, increased investment costs, uneven distribution of public resources such as medical and educational resources, and increased spatial inequity in public services. This, in turn, leads to a low level of local industrial development, unemployment, and low quality of public services, causing population and economic losses.

When ABD interacted with other factors, the influence increased from 0.133 to 0.195–0.302. ABD interacted with ThirdR, PPI, and RI the most. This shows that a larger city size does not necessarily imply better urban development. Under the influence of local industrial development and real estate marketing, housing prices, transportation, and living costs become higher, limiting the sustainable growth of the urban population. This confirms the research results of Jing Liang et al.: city size and labor productivity in prefectural cities develop a significant inverted U-shaped relationship, with city size having both positive and negative effects on labor productivity.

Moreover, the influence of GLEI increased from 0.092 to 0.223–0.303. GLEI also interacted significantly with ThirdR, PPI, and RI. This implies that urban shrinkage has been exacerbated by urban sprawl, the slow transformation of industrial structures, inefficient industrial layout, a low level of industrial development, and an even lower quality of people's livelihood brought about by unrestricted residential development in the last decade.

5.2. Suggestions for Urban Shrinkage Control

Urban form is closely related to sustainable urban development. Studying the relationship between urban form and national economy, social development, and the environment is conducive to promoting sustainable urban form and guiding for urban planning. This study explored the correlation between urban form and the level of urban development from the perspective of urban shrinkage. It concluded that fragmentation and dispersion of urban form, oversized or undersized cities, and urban sprawl affect the internal function of cities by squeezing the space required for urban production, living, and ecosystems, thus aggravating urban shrinkage. Therefore, this paper puts forward the following suggestions for urban planning:

(1) The government should improve urban compactness prudently. As one of the important indicators of urban form, compactness is often associated with shorter travel distances, mixed land use, and a higher density of urban structures [56]. Increasing urban compactness can reduce urban sprawl and inefficient land use, and enhance the environment's vitality. Some scholars believe that improving compactness can control urban shrinkage [57,58]. However, for some rapidly developing cities in China, improving compactness may lead to crowded spaces, environmental degradation, and reduced ecological function, negatively impacting health and increasing costs [59]. On the premise that the environment does not deteriorate and based on the development status of cities, urban compactness should be linked to ecological strengthening and integrated into future devel-

opment planning of sustainable urban spaces, together with other urban form optimization strategies, to create a healthier environment.

(2) The way fragmented land is used should be changed. Some studies have proven that the energy efficiency of shrinking cities is often low, resulting in serious environmental issues [60]. To sustainably develop shrinking cities, the way fragmented land in the city is used should be changed. For example, a smaller non-productive space can be reused for ecological and cultural purposes to improve the green space network and ecosystem [61], promote energy conservation, and make the city more sustainable.

(3) Lastly, the government should revitalize 'lost spaces' of different forms to increase the popularity and vitality of local areas in the city. Since there are regional differences between shrinking cities, it is possible to revitalize 'lost spaces'. Based on the needs of residents in areas surrounding 'lost spaces', the missing functions should be supplemented by combining functions of the surrounding spaces. Through regional design and urban form planning, an organic and continuous spatial interface can be formed, and a new, integrated, and complementary spatial order can be established to promote the popularity and vitality of inner-city areas.

Urban shrinkage originated in western developed countries and has formed a relatively clear research lineage. However, with the development of geospatial big data, research on urban shrinkage in the world has gradually become more refined in its methods, from using demographic data to using geospatial big data such as nighttime light data. With the emergence of urban shrinkage in developing countries in Asia and Africa, national urban shrinkage studies are exploring the diversification of the causes behind urban shrinkage and the adaptation of countermeasures to local conditions in terms of content. Therefore, this study is, first of all, an inheritance of international urban shrinkage research. At the same time, it enriches the research samples from developing countries' urban shrinkage, which can support the study of urban shrinkage differences between different developing countries. Finally, it provides a new perspective on the mechanism of urban shrinkage and brings the importance of spatial form into the sight of international scholars and urban planning experts.

The more refined identification results of urban shrinkage in China derived from this study will provide the leadership of Chinese provinces and prefectures with a realistic basis for future urban development and planning, and transform the growth-focused urban development philosophy in order to achieve a fit between urban planning and urban reality, to avoid the dilemma of decoupling planning from reality.

6. Conclusions

This study used nighttime light data from 2013–2019 to identify urban shrinkage and landscape pattern analysis, in order to analyze the morphological characteristics of construction land in China. The degree of urban shrinkage was included as the dependent variable, while urban form and socio-economic factors were the independent variables. By entering the variables in Geodetector, the study explored the influence of urban form and socio-economic factors on urban shrinkage and conducted interaction analysis. The following conclusions were drawn:

(1) The cities showed varying degrees of shrinkage, with a more significant proportion of shrinkage in the more underdeveloped cities in the central and western regions. A generally higher proportion of shrinkage was observed in the northeast and central regions, while a relatively lower degree was found in the eastern region. Both western and eastern regions largely differ in the degree of shrinkage. Based on autocorrelation analysis, the spatial distribution of urban shrinkage in China has significant clustering characteristics, with low–low clustering in the eastern coastal region and high–high clustering in northern and southwestern regions.

(2) Using factor detection in Geodetector, it was concluded that urban form factors indeed affect urban shrinkage. This result also proves that poor urban form exacerbates urban shrinkage. However, the influence of a single factor on urban shrinkage was small,

indicating that a combination of factors causes urban shrinkage. The largest q-values were found in patch density (PD, 0.144) and urban area (ABD, 0.133), indicating that urban land fragmentation and urban area size have a relatively great influence on urban shrinkage.

(3) Furthermore, interaction detection shows that the effects of the interaction between two factors were mutually or non-linearly enhanced. Consequently, the influence of a single urban form factor increased from about 0.1 to about 0.25–0.35 while interacting with other factors. The influence of the interaction between urban form and socio-economic factors was more substantial than that of the interaction between socio-economic factors. In particular, the interaction of PD with other factors was the most significant. This result indicates that urban form development conditions, such as the degree of urban land fragmentation, urban scale, and urban expansion efficiency and pattern, would strengthen the influence of urban form on urban shrinkage when coupled with socio-economic factors.

The innovation of this study is that, in terms of research methodology, it uses multi-year Chinese nighttime light data to calculate the change trends of urban spatial economic activities in order to identify the shrinkage of Chinese cities and analyze their spatial characteristics, to achieve a long time series of shrinkage dynamic research in the time dimension, and to break the administrative district boundaries in the spatial dimension, so that the research has more refined spatial details and responds to subtler local characteristics within the city, making the study of urban shrinkage more scientific. In terms of research content, we explore the mechanism of urban form effect on urban shrinkage and the impact of the interaction between urban form factors and socio-economic factors on urban shrinkage, and quantify the differences in the impact of different urban form factors on urban shrinkage. It provides new perspectives for urban shrinkage response strategies and sustainable urban spatial form optimization, and more precise theoretical support for urban planning and policy formulation.

As urban shrinkage has received more attention from scholars, the research on it needs to be leveraged with more accurate geospatial big data, and more scientific shrinkage identification and classification methods, so as to go deeper into the inner city and explore more microscopic details of inner city shrinkage, in order to help government departments better cope with urban local shrinkage.

However, there are some limitations to this study. Due to data unavailability, the selection of urban form factors is not comprehensive enough. There is room for further research on how urban form affects urban shrinkage, and room to explore patterns of spatial morphology that are conducive to the sustainable development of shrinking cities.

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