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Spatiotemporal Pattern Identification and Driving Mechanism of Urban Shrinkage in the Yellow River Basin from 2000 to 2020

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Abstract: The regional differences in the Yellow River Basin have increased, and the aggravation of this unbalanced state has seriously restricted the high-quality development of the Yellow River Basin during the accelerated urbanisation that has taken place in recent years. In this regard, heterogeneity in the trends of evolution and the causes of population shrinkage in different regions of the Yellow River Basin can be adopted as targeted countermeasures. The present study uses data from the fifth, sixth, and seventh national censuses and takes the administrative units of different levels in the Yellow River Basin as the object, considering 72 prefecture-level cities within the autonomous prefectures and 595 county-level administrative units in nine provinces (autonomous regions). The population shrinkage coefficient, night light index, bivariate spatial autocorrelation, geographic detectors, and other methods were used, with the final objective of exploring the spatial–temporal distribution pattern and impact mechanism of urban shrinkage from 2000 to 2020. The results of the study show the following: (1) The shrinkage patterns in 2000–2010 (T1) and 2010–2020 (T2) were quite different. From T1 to T2, the shrinkage situation worsened, with the number of districts experiencing population shrinkage increasing from 175 to 373 and the number of districts experiencing continuous night light and shrinkage districts increasing from 146 to 163. (2) The phenomenon of urban shrinkage is spatially scale dependent, with the shrinkage of prefecture-level cities and county-level cities being characterised by both spatial differentiation and spatial nesting relationships. (3) There is a certain inconsistency in the representation of the shrinkage patterns of the nighttime lighting and population data. The nighttime lighting dimension can reflect the structural shrinkage characteristics of the city more accurately and sensitively, and the representation of population loss is lagging. (4) The main impact factors and the intensity of urban shrinkage are the aggravated aging level, the declining level of industrial greening and intensification under market-driven economic structure adjustments, and the decreased natural growth rate in the population structure and public service facilities.

Keywords: shrinking cities; urban shrinkage; nighttime light; spatiotemporal pattern; Yellow River Basin

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1. Introduction

1.1. Motivation and Literature Review

The "shrinking city" concept originated from population loss studies carried out in the mid-20th century. In 1988, Häußermann proposed the concept of a "shrinking city" in their empirical research conducted in Germany [1], with the term "shrinking city" officially entering the academic field. Before that, some studies used terms such as "decline", "decay", "deurbanization", and "urban crisis" [2]. The life cycle theory is the main theory that is used to interpret urban shrinkage. Most scholars, such as Robert A., believe that urban shrinkage is a temporary and reversible phenomenon [3]. Until the 21st century, Ohio's population loss and housing vacancies as well as the housing foreclosure crisis in the United States prompted it to become an international research hotspot [4], and institutions such as the Shrinkage Cities Network (ACIRN) were later established.

However, there is still no unified standard for shrinking cities in the research [5]. Among the existing definitions, the International Shrinking Cities Research Network (SCIRN) defines a shrinking city as a city with at least 10,000 residents and in which most areas have experienced population loss for more than two years and is experiencing dense urban areas with a structural crisis characterised by economic transformation [6]. The international research on urban shrinkage mainly focuses on four aspects: spatial patterns, quantitative measurements, motivation mechanisms, and policy responses. At the spatial pattern level, shrinking cities are usually characterised by perforated and broken urban landscapes. They are mainly divided into two categories: one is perforated shrinkage, which is typical of European cities [7]; the other is doughnut-shaped shrinkage [8]. The old industrial cities in the north-eastern United States are the most common examples of doughnut-shaped shrinkage [9], with a significant portion of the inner-city population moving out to the suburbs, the expansion of urban fringes, and serious hollowing out in the interior, forming a ring-like shrinkage pattern. The quantitative measurement level cites quantitative measurement methods such as socioeconomic measurement [10], geospatial statistics measurement and geographical landscape measurement [11]. Measurement methods and quantitative models of analysis for shrinking cities are also research hotspots at this stage [12]. At the motive mechanism level, the motives of urban shrinkage in the existing literature can be summarised and roughly divided into three categories: economic structure adjustment [13], social structure change [14], and urban spatial mismatch [15]. At the same time, emerging words such as neoliberalism, landscape, and ecology have appeared, indicating that some scholars have begun to interpret urban shrinkage from the perspective of neoliberalism, believing that urban shrinkage is a spatial representation of capital surplus and labour surplus [16]. Research on shrinking cities is no longer limited to the urban level. Instead, it develops at different scales, such as within communities and buildings. At the policy response level, Sousa and Pinho divide the strategies for coping with shrinkage into two categories: "Reaction" and "Adaptation" [17]. "Reaction" refers to a series of strategies and measures that attempt to reverse shrinkage and restore growth; an "adaptive strategy" is a series of strategies and measures that regards shrinkage as an unavoidable consequence and optimises the possible shrinkage results.

Since shrinking cities first appeared in developed regions such as Europe and North America, relatively speaking, research on shrinking cities in China gradually began after 2010, and the theoretical research and the practical application of that research are still in their infancy. The research progress in China mainly includes the following aspects: (1) defining the concept of shrinking cities; (2) case studies and experiential references of shrinking cities found in international research as well as comparative studies on shrinking cities in China and abroad; (3) case studies on the characteristics of planning responses to shrinking cities; and (4) the identification of shrinking cities and the application of quantitative research methods. At the conceptual definition level, different measurement methods are adopted. Some use a single population index for measurement. Some scholars have processed two types of lighting data and have identified shrinking cities according to the pixels. At the same time, the shrinkage intensity index and the shrinkage ratio have been used to characterise the patterns of shrinking cities in China [18], using more accurate night light data collected over three consecutive years to characterise shrinking cities. Some scholars have used POI and natural road networks to divide the natural boundaries of the Yellow River Basin and have pointed out the mismatch between Landsat population data and VIIRS night data [19]; some scholars use the changes in the ratios of different types of population data to characterise and classify continuously shrinking cities, frequently shrinking cities, continuously and frequently shrinking cities [20]; some use comprehensive socioeconomic indicators as well as changes in the comprehensive index of development to represent the degree of urban shrinkage [21]. At the level of local case studies in China, Zhang Jingxiang et al. summarised the generative logic of urban shrinkage in China [22]. Finally, the article attempts to propose several key strategies for Chinese cities to cope with shrinkage. At the level of identification and quantitative research, scholars have analysed spatial scales such as the national urban scale [19], small town scale [23], district and county scale, town and street scales [24], and shrinkage patterns; watershed scales, such as the Yellow River Basin [25], Beijing–Tianjin–Hebei and Yangtze River Delta [26], and Pearl River Delta [27]; and administrative area scales, such as the three eastern provinces [28] and Heilongjiang Province [29], analysing urban shrinkage patterns. Due to the convenience of data acquisition, most urban shrinkage is represented by data at the district and county scale [30]. Research from the perspective of geography mostly identifies urban shrinkage using different measurement methods on different spatial and temporal scales and uses quantitative or qualitative methods to analyse its influencing factors and to make suggestions. Some scholars have used the national 1% sample census data to study the urban shrinkage in different periods over a five-year span and have classified the data according to the degree of time and space shrinkage, conducting detailed analyses of the spatial autocorrelation [31]. In China, the emergence of shrinking cities has challenged the traditional growth-oriented urban planning concept. Overall, China's urban shrinkage can be seen as a mismatch between the market-driven resource flow allocation and the government's growthist model, resulting in unsuitable urban development and negative growth. The academic community should objectively face up to the phenomena of urban population reduction and economic slowdown and increase the research and attention on shrinking cities.

To sum up, the existing research mainly focuses on the shrinkage of general areas over a short period, and we found that the existing research still has some deficiencies in terms of the indicator selection, time scale, evaluation dimensions, and research scale. In the existing research, the following issues exist: (1) There is a lack of comprehensive evaluations of shrinking cities in different dimensions: most studies only start from the dimension of population [25–27] and lack a multi-faceted analysis of the effects of shrinking cities, such as on economic development, land development, shrinking areas, etc., but propose support policies regardless of these issues. The application of NPP-VIIRS night lighting data in urban studies has focused on exploring the spatial distribution of the population and the spread of certain diseases or on dynamically monitoring urban sprawl. There are fewer studies that focus on urban shrinkage at this point, and the related research needs to be strengthened. (2) There is insufficient research on the mechanisms of impact and planning responses to specific areas of study: different regions have different shrinkage characteristics and mechanisms. Existing studies exploring mesoscopic scales such as watersheds have mostly studied coastal regions such as the Pearl River Delta [27], lacking specific shrinkage mechanisms for the Yellow River Basin, which is densely populated with resource-based cities.

1.2. Objective and Expected Contribution

Based on the problem of unbalanced spatial development caused by urban shrinkage in the Yellow River Basin and problems with urban development, to fill these research gaps, this paper uses data from the fifth, sixth, and seventh censuses and nighttime lighting data to analyse the urban shrinkage pattern of the Yellow River Basin during the 20-year period from 2000 to 2020, the characteristics of this period of evolution, and the shrinkage mechanism of its influencing factors in order to (1) provide an analysis path and research framework for multi-dimensional spatiotemporal identification shrinkage based on long-term resident populations; (2) analyse the spatiotemporal pattern of shrinking cities in the Yellow River Basin; (3) determine the spatial inconsistency behind different data sources and analyse their internal relationships in depth, laying the foundation for the realisation of multi-source data identification and shrinkage in the future; and (4) optimise the urban spatial structure of the river basin, providing a basis and putting forward suggestions for the high-quality development of the Yellow River Basin.

2. Research Methodology

2.1. Study Area

The Yellow River Basin is located between 32° N~42° N and 96° E~119° E and has a total length of 5464 km and a drainage area of 795,000 km$^{2.}$ The basin has complex and diverse landform types and significant differences in terms of climate and environment. It is an important agricultural area, industrial belt, and ecological security barrier in China. In comprehensive cross-provincial research, the boundaries of the Yellow River Basin are not divided. This study takes into account the integrity of the county-level administrative units and the correlation between regional social and economic development to characterise the Yellow River Basin study area. The whole district contains 72 prefecture-level cities and autonomous prefectures and 595 county-level administrative units in 9 provinces (autonomous regions): Shanxi, Shaanxi, Henan, Shandong, Gansu, Sichuan, Qinghai, Ningxia, and Inner Mongolia. The streams of the Yellow River are defined by the town of Hekou and Ketuo County (Figure 1). As of 2020, the total land area of the Yellow River Basin is 2.0336 million square kilometres, accounting for 21.39% of the national land area of China; the permanent population is 210 million, accounting for 15.14% of the country; and the population density is 92.17 people/km^2, which is 58.19 less people than the national population density /km2. The total population and population density in the Yellow River Basin show an increasing trend, but the population density and population growth rate are lower than the national average, and the total population accounts for 15% of the national total. The regional GDP is CNY 25.4 trillion, accounting for 10.71% of the national total. The percent ratio of the three industrial structures is 8.19:56.42:35.39, and the urbanisation rate is 46.70%. The urbanisation and industrialisation of the whole region are currently in a period of accelerated development, and the contradiction between urban development and spatial imbalance is becoming more and more serious. At the same time, the depletion of non-renewable resources such as coal during this period of rapid industrialisation has led to the economic decline of some of the cities that are dependent on these resources. The Yellow River Basin is therefore an area of high research value, as it is an area in which shrinking cities have become typical, which is why it was chosen as the study area.

With the acceleration of urbanisation and the rapid development of industry and tertiary industry in recent years, the spatial gaps in the levels of social and economic growth have continued to expand [32]; population flow has continued to accelerate; and the population has rapidly gathered in economically developed prefecture-level cities, resulting in regional gaps in the Yellow River Basin, which has seriously restricted high-quality socioeconomic development. It is imperative to identify the urban shrinkage pattern and to analyse the shrinkage mechanism in the Yellow River Basin.

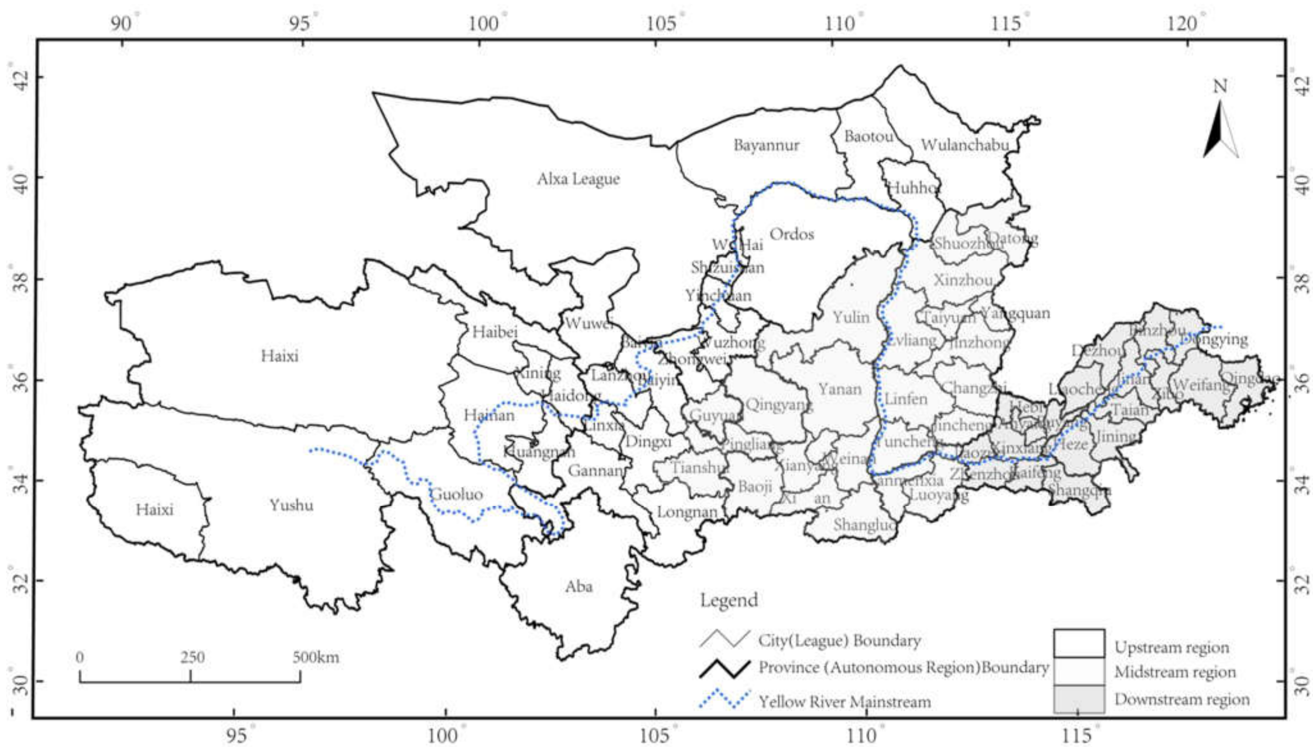


Figure 1. The scope of administrative divisions and the upstream, midstream, and downstream region of the Yellow River Basin. Note: This map has the approval number of GS (2016) No. 2556 and was downloaded from the 1:1 million national basic geographic database of the National Geographic Information Resource Catalog Service System.

2.2. Data Sources

Three types of data were collected: census data, night light data, and socioeconomic statistics. The population data are based on data from the fifth, sixth, and seventh censuses and are published on the official websites of the National Bureau of Statistics and local municipal governments. Statistical analysis was carried out according to the latest administrative divisions in 2021. The nighttime light data refer to the global 500-m resolution "NPP-VIIRS-like" nighttime light dataset based on the auto-encoder-based cross-sensor (DMSP-OLS and NPP-VIIRS) nighttime light data correction scheme released by the National Earth System Science Data Center (2000–2020) (the data come from the National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn), which uses the DMSP-OLS nighttime light data from 2013 as input data. To verify the output data, the NPP-VIIRS yearly composite NPP-VIIRS NTL data from the same years are used. After iterative training, the DMSP-OLS nighttime light data from 2000 to 2012 are, in turn, input into the trained model to obtain the NPP-VIIRS-like NTL data for the respective years. The dataset has the same parameter attributes as the NPP-VIIRS night light data. By selecting random pixels and cities around the world and selecting typical countries from each continent as the verification areas, the data accuracy meets the research requirements. Socioeconomic statistics were obtained from the China Statistical Yearbook (National Bureau of Statistics of China).

2.3. Research Methods

2.3.1. Population Shrinkage Index (PI)

The degree of shrinkage in different cities was calculated and classified based on the population shrinkage coefficient. Based on the ten-year period between Chinese population censuses, the study divided the research time into two stages: T1 and T2, where T1 was the period of 2000–2010 and T2 was the period of 2010–2020. At the same time, we defined the annual average shrinkage rate of the permanent resident population in each city during each period using the PI (population shrinkage index). The PI value was introduced to represent the population shrinkage coefficient. The calculation formula for PI is as follows:

$$\mathrm{PI} = \frac{(\mathrm{pt2} - \mathrm{pt1})}{\mathrm{pt1}} * 0.1;\ \mathrm{t1}, \mathrm{t2} \in [2000{,}2010{,}2020] \quad (1)$$

where PI is the population index, and pt1 and pt2 represent the populations cited in the national censuses carried out in t1 and t2, respectively. When t1/t2 is 2000, pt1/t2 are data from the fifth national census; when t1/t2 is 2010, pt1/t2 are data from the sixth national census; when t1/t2 is 2020, pt1/t2 are data from the seventh national census.

2.3.2. Night Light Shrinkage Index (NI)

(1) Calculating the rate of change of nighttime light mean value R(t)m

The regional statistics tool in ArcGIS was used to quantify the average slope of NTL changes in each city and district and to calculate the mean value of the nighttime lighting change rate from 2000 to 2020, year by year, defining R(t)m as the nighttime lighting change rate from year t–1 to t–2 for city m.

(2) Assigning values to S(t)(m)

According to the definition of a shrinking city [21,33,34], three years is the shortest study period for which a shrinking city can be identified. To quantify the spatial and temporal characteristics of shrinking cities, cities that shrank in size were identified for the entire study period from 2000 to 2020 and for every three years from 2000 to 2020. A value was assigned to each study area based on the calculation of the annual rate of change in nighttime lighting, R, for each year, where S(t)(m) was assigned a value of 1 when R(t)m was less than 0.

$$\mathrm{S(t)(m)} = \begin{cases} 1 & \mathrm{R(t)(m)} < 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

(3) Calculation of the nighttime light shrinkage index (NI)

For further refinement, shrinkage was classified into three categories according to its frequency: constant shrinkage, frequent shrinkage, and frequent continuous shrinkage. The frequency of shrinkage was assessed for each city for three consecutive natural years (by identifying continuous shrinkage) and for the entire study period (by identifying frequent shrinkage) based on equations to determine whether the city was a constantly contracting city. Slope changes for the nighttime light in each city during a specific period can be calculated using the NI (nighttime light index) [21].

$$\mathrm{NI} = \begin{cases} 1 & \mathrm{S(t)(m)} = 1 \qquad \mathrm{S(t+1)(m)} = 1\mathrm{S(t+2)(m)} = 1 \\ 1 & \sum_1^x \mathrm{S(t)(m)} > x/3 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where t is the number of serial years in the study period, and x is the number of years in the entire study period. When the calculation period is the entire study period from 2000 to 2020, x = 20; when the calculation period is 2000–2003, x = 3. When NI = 1, it is determined that city m is a contracting city.

2.3.3. Bivariate Spatial Autocorrelation

Combining population and nighttime light, the bivariate local spatial autocorrelation was used to analyse the spatial agglomeration distribution pattern under the dual effects of population and nighttime light. The geographic element described by the spatial autocorrelation of a single element has only one variable, while the spatial autocorrelation based on two variables has high applicability and effectiveness in describing the spatial association and dependency characteristics of two geographic elements. To investigate the spatial correlation properties of the two, bivariate global spatial autocorrelation (also known as bivariate Moran's I) can be used. The outcome represents the overall spatial distribution correlation between the independent variable in region I and the dependent variable in region j and can be calculated as follows [35]:

$$\text{Moran's } I_{i,k,l} = \frac{(X_{i,k}-\overline{X_k})}{\delta_k}\sum_{j=1}^{n} w_{ij}\frac{(x_j-\bar{x})}{\delta_l} \quad (4)$$

where $X_{I,k}$ *and* $X_{j,l}$ represent the value of attribute k of spatial unit i and the value of attribute l of spatial unit j, respectively; $\overline{X_k}$ *and* $\overline{X}_l$ represent the mean values of k and l; w_{ij} represents the spatial connectivity matrix between spatial units i and j; δ_k *and* δ_l represent the variance of k and l, respectively; and n is the number of spatial units [35].

2.3.4. OLS Regression Model

The causes of urban shrinkage can be divided into internal and external pull forces. An internal push force means that urban industries, public services, and population composition cannot meet the development demands of the current population and promotes the outward migration of the urban population; an external pull force refers to growth-oriented cities that rely on competition. The advantages of this pull force attract the rapid inflow of production factors such as population in peripheral cities and towns, resulting in population loss in peripheral cities and towns. Based on this, according to the regional social and economic development status and data availability, the population shrinkage coefficient for the prefecture-level cities was used as the dependent variable, and an OLS regression model was constructed through the consideration of three aspects, public service level, industrial structure, and population structure, and had a total of 10 indicators. The influencing factors of urban shrinkage in the Yellow River Basin were identified quantitatively, and the index structure of the influencing factors is shown in the Table 1.

Table 1. Urban shrinkage evaluation index system.

Guideline Layer	Index Layer	Index Meaning
Public service compactness	Level of natural growth	Natural population growth rate
	Ageing level	Proportion of people over 60 years old
Industry compactness	Level of industrialisation	The added value of the secondary and tertiary industries/GDP
	Scale of service industry development	The added value of the tertiary industry/the sum of the added value of the secondary and tertiary industries
	Industrial greening	Total industrial SO_2, NO_x, smoke, and dust emissions/industrial added value
	Level of industrial intensification	Industrial output above designated size/gross regional product
Public service compactness	Level of public finance	Per capita fiscal revenue
	Fixed asset level	Fixed asset investment per capita
	Educational development level	Per million students
	Medical development level	Number of medical beds for 100 people

2.3.5. Geodetector

The geodetector was used to measure the magnitude of the effect of the factors identified in the OLS regression model on the strength of urban shrinkage in the Yellow River Basin to determine the dominant influences on urban shrinkage in the Yellow River Basin at a regional scale. The geodetector works by calculating the ratio of the total variance of an indicator over different sub-regions to the total variance of that indicator over the whole study area:

$$P_{D,H} = 1 - \frac{1}{n\delta_H^2} \sum_{i=1}^{m} n_{D,i}\ \delta_{H_{D,J}}^2 \quad (5)$$

In the formula, D is the influencing factor of urban shrinkage; H is the urban shrinkage difference index; $P_{D,H}$ is the explanatory power of D to H; n and δ^2 are the number of shrinking towns and the variance in the shrinkage difference index; m is the factor influencing the number of classifications; $n_{D,i}$ is the number of D index samples in class i; and the range of values for $P_{D,H}$ is (0, 1), and the higher the value, the more strongly this component influences urban shrinkage [28].

3. Results

3.1. The Evolution of the Spatiotemporal Pattern of Urban Shrinkage in the Population Dimension

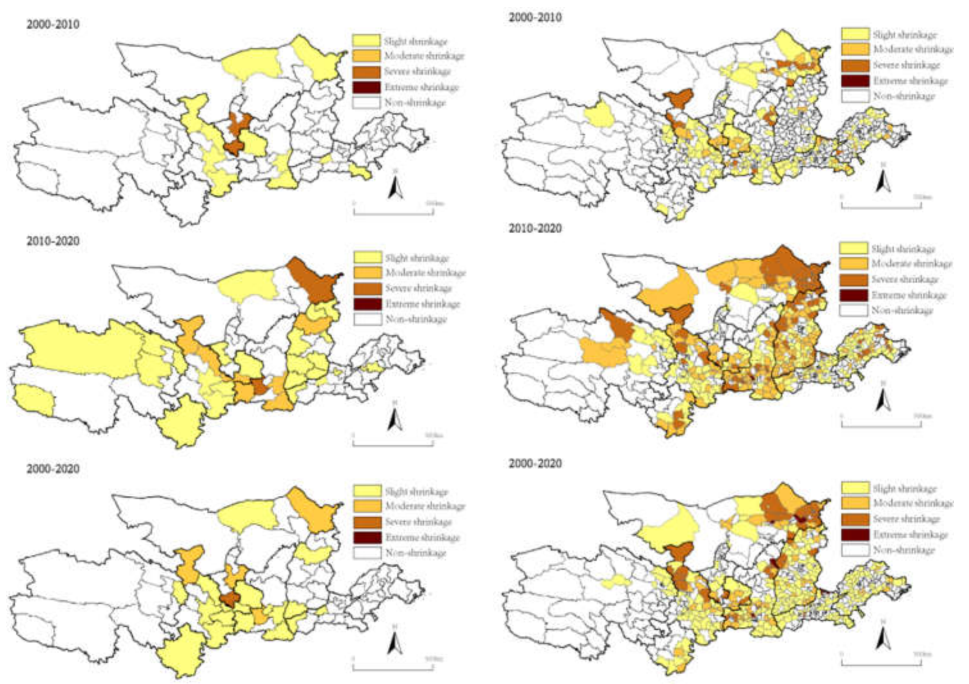
Referring to the classification criteria of the shrinkage intensity [21,33,34], the population shrinkage coefficient is classified into the five following levels (Table 2, Figure 2): non-shrinkage (PI > 0), mild shrinkage (0 > PI > −1%), moderate shrinkage (−1% > PI > −2%), high shrinkage (−2% > PI > −5%), and severe shrinkage (−5% > PI).

Table 2. Shrinkage numbers during different time spans in Yellow River Basin under the population dimension.

Scale	T	Non-Shrinkage (PI > 0)	Shrinkage				
			Total (PI < 0)	Slight Shrinkage (0 > PI > −1%)	Moderate Shrinkage (−1% > PI > −2%)	Severe Shrinkage (−2% > PI > −5%)	Extreme Shrinkage (−5% > PI)
City scale	T1	58	14	12	0	2	0
	2000–2010	81%	19%	17%	0%	1%	0%
	T2	39	33	23	8	2	0
	2010–2020	56%	44%	32%	11%	1%	0%
	2000–2020	50	22	17	4	1	0
		70%	30%	24%	5%	1%	0%
District scale	T1	420	175	130	30	15	0
	2000–2010	71%	29%	22%	5%	3%	0%
	T2	222	373	166	134	71	2
	2010–2020	37%	63%	28%	23%	12%	0.3%
	2000–2020	277	318	223	58	31	6
		47%	53%	37%	10%	5%	1%

At the city level, the extent of the shrinkage mainly shows the phenomena of upstream diffusion and midstream transfer. Compared to the T1 period, the scope of the city shrinkage expanded significantly in the T2 period. In terms of the depth of the shrinkage, the severe shrinkage in the middle areas became moderate and high shrinkage in the downstream areas; a large number of cities in the upper, central, and eastern regions shifted from mild shrinkage to moderate shrinkage; and the degree of shrinkage has intensified.

At the district and county level, the representation of the population shrinkage is broader than at the prefecture and city levels, and the depth of the shrinkage is intensified. As for the extent of the shrinkage, the scope of the shrinkage was significantly expanded. Regarding the depth of the shrinkage, the degree of the shrinkage was intensified significantly. This is reflected in the increase in the shrinkage coefficient: the proportion of the mild, moderate, and high shrinkage districts has increased significantly; the threshold range of the shrinkage coefficient is larger compared to in T1, and there are districts experiencing severe shrinkage during T2, with PI < −5%. In terms of space, the shrinkage areas around the Yellow River shrinkage and in the counties as a whole show a substantial expansion trend from the upper middle areas of the region to the upstream and downstream areas. Among them, the urban agglomeration represented by the bend located along the Yellow River, the urban agglomeration in the Guanzhong Plain, the urban agglomeration of Lanzhou–Xining, and the Shandong Peninsula urban agglomeration show a more obvious continuous shrinkage trend.



(**a**) (**b**)

Figure 2. Shrinking patterns during different time spans in Yellow River Basin under the population dimension: (**a**) shrinkage patterns at city scale; (**b**) shrinkage patterns at district scale.

3.2. The Evolution of the Spatiotemporal Pattern of Urban Shrinkage in the Night Light Dimension

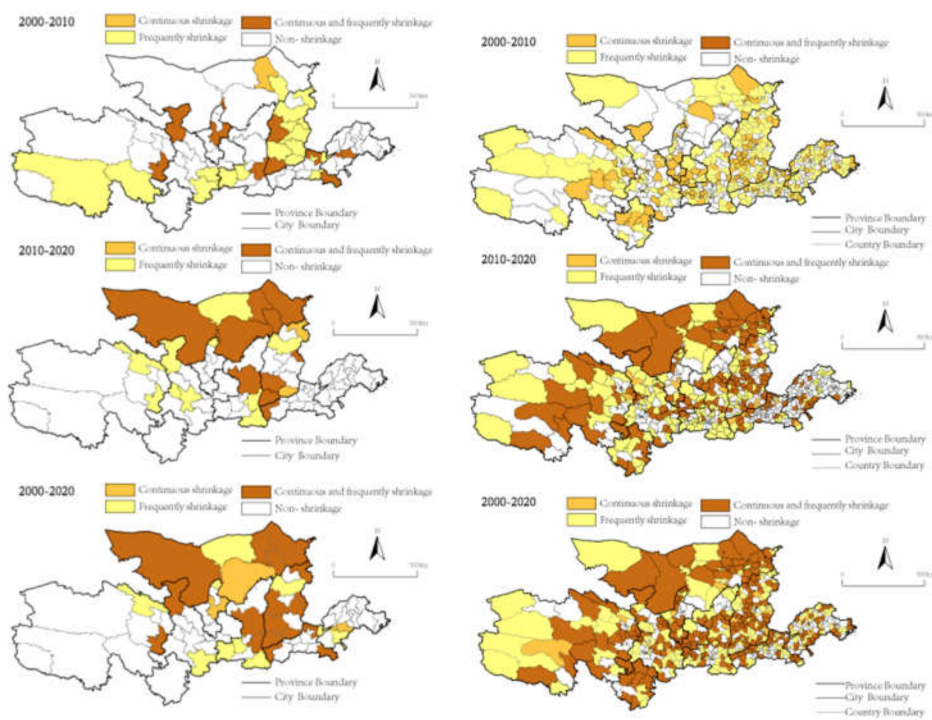
Population loss and economic recession are two of the most commonly used indicators to identify shrinking cities. [36] Studies have shown that the brightness of the light in an area is positively correlated with the level of local economic development. In addition, data can also estimate the area illuminated by lights in a city at night by using light spots [37]. Therefore, the "triple attribute" of nighttime light data makes it possible to incorporate urban population, land, and economic factors into urban-scale measurements at the same time. Based on the characteristics of long-term time-series NL data and the related research, we define shrinking cities as continuously shrinking cities: cities experiencing a continuous loss of brightness (i.e., annual TDN reductions for three consecutive years), or frequently shrinking cities (i.e., cities that have been shrinking for at least one-third of a selected study period). In line with previous research, continued shrinkage for no less than 3 years will represent the time standard for cities to be classified as experiencing continuous shrinkage [37] (Table 3, Figure 3). Firstly, we calculated the nighttime light change values for each study area, year on year; secondly, we screened cities and time periods where the nighttime light change values were negative [33] (i.e., nighttime light shrinkage); thirdly, based on previous studies, we used a continuous shrinkage of no less than three years as the time criterion [21,33,34] for a continuously shrinking city. As the frequency of shrinkage was variable with the length of the study period, we used more than one-third of the study period as the criterion.

Table 3. Shrinkage numbers during different time spans in Yellow River Basin under the night light dimension.

Type	T	Shrinking Cities	Shrinking Districts
Frequent shrinkage	T1 (2000–2010)	33	391
	T2 (2010–2020)	23	329
	2000–2020	31	446
Continuous shrinkage	T1 (2000–2010)	12	160
	T2 (2010–2020)	14	177
	Both T1and T2	23	59
Continuous and Frequent shrinkage	T1 (2000–2010)	11	146
	T2 (2010–2020)	12	163
	2000–2020	14	257

According to the rate of change analysis of nighttime lighting at the local municipality level, 31 localities in the Yellow River Basin show frequent nighttime lighting shrinkage from 2000 to 2020, accounting for 43% of all localities. The frequently contracting municipalities expand from the middle reaches of the basin to the eastern part of the upper reaches of the Yellow River, while the eastern upper reaches show a more obvious phenomenon of continuous shrinkage clustering. In general, most of the cities in Inner Mongolia in the eastern part of the upper reaches of the Yellow River show a shrinkage trend, while the overall shrinkage trend in the middle reaches of the Yellow River, such as in northern Shaanxi and western Shanxi, increases and spreads to the east.

In 2000–2020, 446 districts, accounting for 75% of all districts, experienced frequent nighttime light shrinkage. The number of shrinking cities doubled in T2, showing a face-to-face distribution in the upper and middle reaches. In general, the Yellow River Basin shows overall shrinkage at the district and county levels that extends from the upper and middle reaches to the eastern part of the lower reaches.



(**a**) (**b**)

Figure 3. Shrinkage patterns during different time spans in Yellow River Basin under the night light dimension: (**a**) shrinkage patterns at the city scale; (**b**) shrinkage patterns at the district scale.

3.3. The Spatial Agglomeration Pattern of Urban Shrinkage in the Yellow River Basin

3.3.1. Global Spatial Correlation

Comparing the global autocorrelation indices of population shrinkage at three scales, the results show that there is spatial heterogeneity in the regional population shrinkage at both the prefecture and city and district and county scales. Among them, the overall Moran's I index of the population at the county level from 2000 to 2020 was 0.3946, which showed more significant heterogeneity compared with the overall Moran's I index of 0.095 at the prefecture-level scale. Compared to the score of 0.27 for T1, it shows a stronger spatial correlation. Therefore, using macro-positioning at the municipal level, it is possible to locate the counties experiencing shrinking and clustering and the overall spatiotemporal pattern of the counties in a more targeted and precise manner.

3.3.2. Local Spatial Correlation

At the city level, the local Moran's I index generally reflects the fact that the city of Wuzhong in the upper central part of the basin has experienced a shrinkage depression, while Guyuan, Qingyang, Pingliang, and their surroundings all show a more pronounced shrinkage association, with the population of Shaanxi Province being concentrated from the periphery to Xi'an. In T2 (2010–2020), Xi'an shows HL-type characteristics, and it can be assumed that Xi'an has become a major migration area for the surrounding cities, thus causing the population growth in Xi'an to increase while the surrounding population shrinks.

By analysing the local Moran's I index at the district and county levels, it is found that the Moran value is higher and more spatially correlated than the local Moran's index values at the prefecture and city levels, revealing more obvious spatial agglomeration characteristics, with the number of HH-type areas increasing from 49 to 62 and the number of LL-type areas increasing from 14 to 37 from T1 to T2, with increased spatial imbalance. Overall, this reflects a more general trend of urban population concentration towards central cities, as shown by the nine HL-type districts observed from 2010 to 2020, such as Qingyang County, Xifeng District in Qingyang City; Chang'an District in Xi'an City; Yaozhou District in Tongchuan City; and Yanhu District in Yuncheng City. Chang'an District in Xi'an City changes from being an LH-type city in T1 to an HL-type city in T2, showing a transformation of the Chang'an District from a population depression area to an area in which the peripheral population is concentrated. A total of six LH-type districts can be observed from 2010 to 2020, such as Zhouzhi County in Xi'an, Anyang County in Anyang City, Jun County in Hebi City, and Dongxiang Autonomous County in the Linxia Hui Autonomous Prefecture, all of which show obvious characteristics in a shrinking local population and an increasing peripheral population, which requires special attention in later studies. The areas along the eastern part of the upper reaches of the basin, such as Ulanqab and Baotou, show an overall spatial correlation of population shrinkage.

3.3.3. Space–Time Bivariate Spatial Autocorrelation

A spatiotemporal bivariate local spatial autocorrelation analysis was carried out using GeoDa software to analyse the spatial clustering patterns of shrinkage at the district and county levels at different times and to further analyse the spatial correlation characteristics of the variables under the dual factors of population and nighttime lighting (Figure 4, Table 4). The results show that L-H clustering indicates a decrease in the population but an increase in the nighttime light index, indicating an increase in the socio-spatial index along with population loss in the contracting counties. The LL-type agglomeration indicates lower population variables and less nighttime light in the surrounding area, indicating that the degree of shrinkage may intensify further, while in T1, the LL-type agglomeration in the lower reaches is coupled with a large shift in the shrinkage space to the lower reaches of T1 to T2, which is observed in both the values of population and nighttime light. The H-L-type agglomeration, which indicates population growth but nighttime light shrinkage, is mainly distributed in Inner Mongolia Erdos and Alashan League, Ningxia Zhongwei, and Shaanxi Qingyang in T2, and this area may experience a specific shrinkage trend in the future.

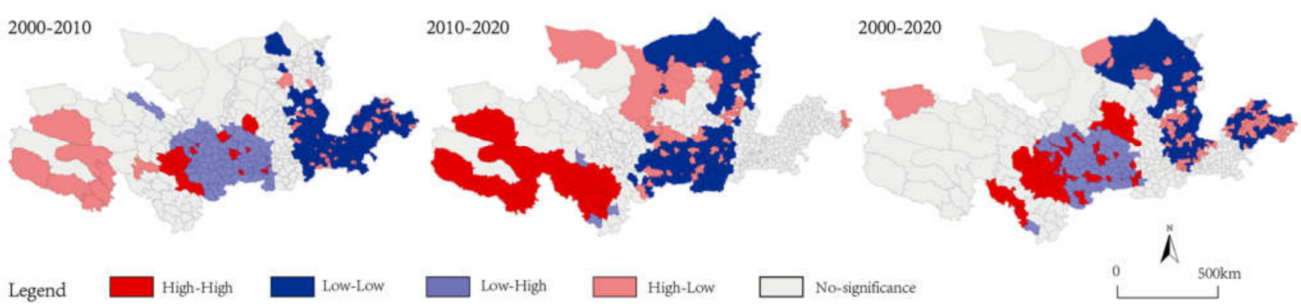


Figure 4. Local space–time bivariate spatial autocorrelation from 2000 to 2020.

Table 4. Bivariate shrinkage pattern recognition.

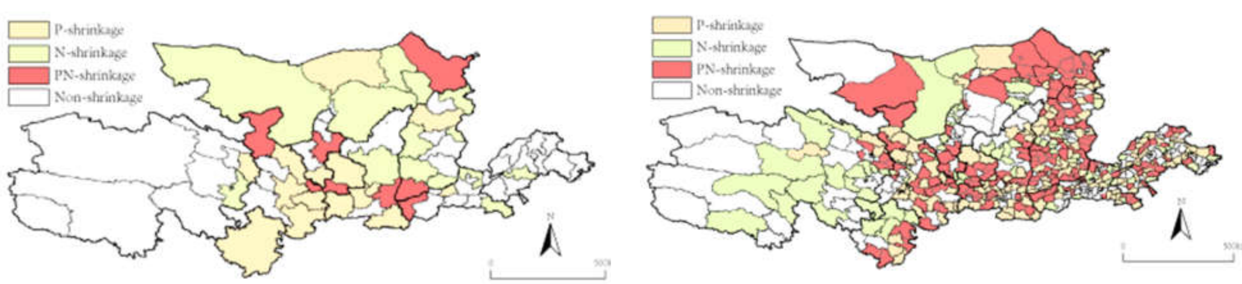
Scale	NI	PI < 0	PI > 0
City scale	1	7	16
	0	15	36
District scale	1	171	51
	0	48	155

3.4. Comprehensive Identification of Shrinking Cities in the Yellow River Basin

In order to avoid the limitations of a single evaluation dimension and a single spatial scale, this paper combines population and DMSP/OLS and VRIIIS nighttime lighting data to construct urban shrinkage characterisation criteria to more accurately identify shrinking cities. NI = 1 indicates the frequent and continuous shrinkage of nighttime lighting from 2000 to 2020, and PI < 0 indicates population shrinkage (Table 4 and Figure 5).

At the city level, there are seven cities experiencing bivariate shrinking, accounting for 9% of all local cities. The cities of Wulanchabu, Wuwei, and Wuzhong in the upper reaches of the basin and the cities of Pingliang, Yuncheng, and Weinan in the middle reaches of the basin contract in both dimensions, while the northern part shows shrinkage in the nighttime light dimension and no population shrinkage, and the southern part of the basin shows population shrinkage and no shrinkage in the nighttime light dimension. This suggests that the northern part is more likely to experience a structural imbalance with little change in the population, while the southern part is more likely to experience a more pronounced population loss at the municipal level.

At the district and county level, the shrinkage is more widely distributed than at the municipal level. There are 171 counties experiencing bivariate shrinkage in the Yellow River Basin, accounting for 29% of all counties. While the eastern, middle, and lower reaches of the Yellow River Basin show widespread and patchy shrinkage in both dimensions, the western and northern reaches of the Yellow River Basin show shrinkage in the nighttime light dimension and no population shrinkage, while the middle and lower reaches of the Yellow River Basin show shrinkage in the nighttime light dimension and no population shrinkage.



(**a**) (**b**)

Figure 5. Spatial distribution map showing bivariate shrinkage recognition: (**a**) shrinkage patterns at the city scale; (**b**) shrinkage patterns at the district scale.

3.5. The Influencing Factors and Mechanisms of Urban Shrinking

Based on the theoretical analysis of the causes of population shrinkage, this paper divides the different causes of population shrinkage according to quantitative methods. First, combined with the existing research, after data cleaning, we analysed the data of 33 shrinking cities and conducted an OLS regression analysis with the rate of population change of shrinking cities from 2000 to 2020 as the dependent variable and 10 influencing factors indicators in 2020 as the independent variables (Table 5), and further combined the correlation between each influencing factor, and population shrinkage was determined; on this basis, a cluster analysis was used to divide the different causes of population shrinkage. This study uses the K-means classification method to discretise the detected factors and applies the geographic detector model to analyse the impact mechanism of the spatial gaps of urban shrinkage (Figure 6).

Table 5. OLS regression results of factors influencing urban shrinkage in the Yellow River Basin.

Influencing Factors	City Shrinkage	VIF
Constant	−0.141	
Level of natural growth	0.081 *	1.714
Ageing level	−1.993 ***	3.195
Level of industrialisation	0.307	3.170
Scale of service industry development	−0.005*	5.571
Industrial greening	−0.093 ***	1.381
Level of industrial intensification	−0.038 ***	1.911
Level of public finance	0.077	3.895
Fixed asset level	0.031	1.882
Educational development level	0.234	2.853
Medical development level	−0.030 *	1.932
R^2	0.543	
F	2.021	

Note: *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Multicollinearity for this regression analysis has been checked using the variance inflation factor (VIF). All variables have variance inflation factors less than 10, which indicates that the issue of multicollinearity is acceptable and the model is well constructed.

3.5.1. Market-Driven Economic Restructuring

Industry greening, the level of industrial intensification, and the scale of service industry development are negatively correlated with the town shrinkage variability index, indicating that there is a problem of one pole of industry being dominant in shrinking towns due to more polluting industries, a relative lack of service industry development, and a low degree of industrial structure correlation. Due to ecological destruction, resource depletion, and industrial transformation, resource-based cities are facing a serious resource crisis, and changes in domestic demand and supply have led to the decline of traditionally leading industries, the weak growth of production factors, the reduced import of production factors, and the decline of regional competitiveness, resulting in a structural crisis. The towns experiencing shrinkage in the Yellow River Basin are resource-oriented in their industrial development, with fragmented enterprise layouts and relatively small agglomeration sizes. Resource-based cities adopt the development mode of "combining mining and city, enterprise running society" and build residential areas for workers near production areas, so that the employment and livelihoods of residents are highly dependent on industrial production. As a result, the development of the commercial service industry is relatively sluggish. With the depletion of resources, the number of jobs provided by industrial enterprises is decreasing, while the commercial service industry is developing slowly and cannot grow into a succession industry, making it difficult for industrial areas and the residential areas where workers live to achieve economic transformation and causing them to gradually degenerate into poor urban areas, forcing residents, especially young and strong labourers, to lose their jobs. Since 2014, the path of "stabilising growth and adjusting structure" has been taken, emphasising industrial intensification. However, over the past two decades, the Yellow River Basin has become the target of the government's "supply-side" structural reform due to the over-development of polluting industries such as iron and steel as well as chemicals and cement, which have accumulated a large number of products and have saturated external market demand. The 41 resource-based cities account for 57% of the total number of cities in this area, and the changes in the breadth and depth of the shrinkage of resource-based cities from 2000 to 2020 are more obvious. The shrinkage of resource-based cities occupies a larger proportion of the urban shrinkage phenomenon, and resource-based contracting cities should also receive more attention.

3.5.2. Demographic Changes

The natural growth rate in the Yellow River Basin is positively correlated with the PI (population shrinkage index), and the proportion of the elderly population is negatively correlated with the PI (population shrinkage index). China's demographic structure is facing the arrival of the Lewis inflection point, and the consequent decline in the birth rate, rising labour costs, and decreased population ageing are leading to the gradual disappearance of the demographic dividend. The regression results show that the elderly proportion of the population has the most serious impact on the shrinkage factor. Urban shrinkage is highlighted by the massive loss of young and middle-aged labourers, leading to the continued "ageing" of the urban population structure and increased social burdens; the ageing population structure also has a low fertility rate, which indirectly leads to a lack of "dynamism", thus weakening the attractiveness of these shrinking towns for young people. Young and middle-aged labourers "flee" these cities through further education or work, while older people are forced to stay and accumulate a large labour force, leading to a "labour shortage" of the young and middle-aged labourers required for urban economic development. Commercial development is losing its appeal, as it does not correspond to the consumer preferences of modern youth.

3.5.3. Level of Development of Public Service Facilities

The population shrinkage index is positively correlated with the level of government finance and fixed asset investment and passes the significance test, indicating that the lack of per capita finance and fixed asset investment will accelerate the population loss in shrinking towns. On the one hand, a decline in government finance and fixed asset investment leads to a decline in employment, urban public services, and infrastructure as well as a shortage of educational and medical resources, indirectly exacerbating population loss and increasing the amount of unused space as well as the structural shrinkage of the city.

Using a geographic detector and using the elderly proportion of the population, the level of industrial greening, the scale of service development, and per capita fixed asset investment as independent variables, we compared and analysed the strength of the influencing factors mentioned above on the urban population shrinkage index in the Yellow River Basin. The results were as follows: aging level (0.09) > per capita fiscal income (0.05) > industrialisation level (0.04) > per capita fixed asset investment (0.03) > number of medical beds (0.02); therefore, the aging level, per capita fiscal income, and industrialisation level in the Yellow River Basin are determinants of the spatial differentiation of shrinking cities. The level of public services has little impact on the level of urban shrinkage in comparison. With the dominance of demographic and market-driven economic restructuring, public services such as education and healthcare are adjusted and lead to transformations in the regional urban spatial structure, resulting in the "Matthew Effect", which ultimately leads to accelerated urban shrinkage.

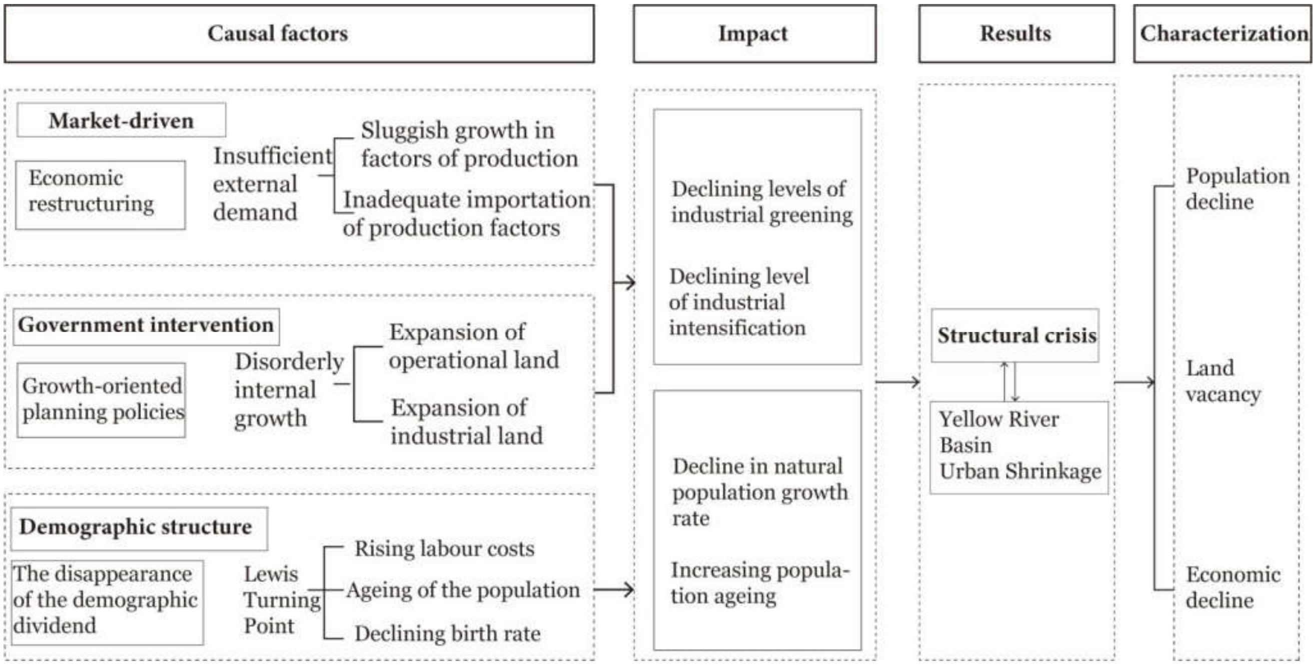


Figure 6. Urban shrinkage mechanism in the Yellow River Basin.

4. Discussion

Shrinking cities face various constraints to urban development, including population loss, economic downturn, and spatial idleness, and as a result, compact cities, smart shrinkage, and the intensive and efficient use of land are gaining attention in many fields [38–40]. However, most of the existing studies on shrinking cities focus on the identification of specific regions in a single dimension within a short period of time, and the shrinkage patterns and mechanisms of specific regions such as the Yellow River Basin have not been fully explored. Compared to the existing research, the contributions of this paper mainly include three aspects: First, the two dimensions of population and night light were used to measure the shrinkage patterns of the Yellow River Basin over two time periods covering a total time span of 20 years. From the empirical results and the combination of the two dimensions, the shrinkage pattern can be revealed more comprehensively, with regional shrinkage showing periodic characteristics on a long-term scale. This reveals a future trend of increased shrinkage in the upper bend of the Yellow River and in the cities in the Shandong Peninsula. Second, the quantitative identification of urban shrinkage in the Yellow River Basin from multiple scales, such as at the prefecture and county levels, is beneficial to reduce the scale dependence of geographical phenomena. The prefecture-level quantification results are a comprehensive reflection of the county-level results, which support the findings of other scholars and establish a theoretical basis for later studies on the multidimensional scale of urban shrinkage. Third, the impact mechanism of urban shrinkage in the Yellow River Basin was analysed by combining quantitative and qualitative methods. With regard to the quantitative results, in contrast to the results of similar studies, this paper also demonstrates that the level of population ageing and the level of industrialisation play a significant role in the degree of urban shrinkage, but the impact of the degree of spatial agglomeration on the degree of shrinkage is not fully demonstrated in this paper [28].

In light of the research findings, this paper proposes the following policy recommendations to address the existing problems: First, the driving force of economic growth should be shifted, and industrial transformation and upgrading should be promoted. We should gradually change the scale expansion model of growth by relying on traditional factor inputs such as land, labour, and capital and pay more attention to and rely on the contributions of new factors such as human capital, scientific and technological innovation, and cultural institutions to economic development to change the economic growth model and to improve the quality of economic development. For resource-based cities in particular, there are a variety of ways to promote industrial transformation and upgrading. By improving natural resource and carbon emission management systems, resource-based cities will be forced to change from forced to active management, strengthen the management of pollutant emissions, improve the utilisation rate of solid waste, and promote the establishment of an industrial system with "low energy consumption, low material consumption and low emissions". At the same time, resource-based cities should strengthen the interaction between secondary and tertiary industries during the transformation process, vigorously develop service-oriented manufacturing, promote new models such as customised services and supply chain management, and encourage the integrated development of manufacturing and service industries in order to gradually change the development pattern of a single industrial structure and the dominance of one industry and to form a modern industrial system with diversified support. As the trend of urban shrinkage in the upper bend of the Yellow River and the Shandong Peninsula intensifies, a large amount of unused land is likely to emerge in the future. How to achieve sustainable development through the rational exploitation of resources in these cities, such as the development of renewable energy sources like solar energy and the promotion of carbon neutrality, is a topic we need to focus on in the future. Secondly, the fertility policy should be re-examined and adjusted, and local governments should take targeted measures to curb the continued population outflow from the region. In addition to the "citizenship" of migrant workers, implementing a policy focusing on people–land welfare through the creation of urbanisation policies that co-ordinate the welfare of people and places, the adjustment of indicators such as per capita construction land and per capita welfare of public expenditure to be in line with population migration, and the implementation of policies that correspond to the welfare of people and places will allow those cities that are already experiencing a decreasing trend to face the reality and adopt a proactive shrinkage strategy. Thirdly, a smart shrinkage strategy should be implemented at the urban planning level. According to the organic city theory proposed by Saarinen in 1930, cities, like organisms, have a life cycle of growth, prosperity, and decline, so it is necessary to build a flexible and contractible planning spatial structure. It is necessary to construct a resilient city, to shrink smartly, and to achieve sustainable development.

5. Conclusions

The aim of this study was to explore the urban shrinkage pattern in the Yellow River Basin and the shrinkage mechanisms of different shrinkage types. Firstly, the population shrinkage coefficient was established to analyse the intensity of urban shrinkage in the Yellow River Basin during two periods according to the population census dimension, and the night light index was established to analyse the frequency of shrinkage during the two time periods according to the 20-year continuous night light dimension. Then, the spatial association and dependence characteristics under the dual effects of population and night light were analysed through bivariate local spatial autocorrelation. Based on the data of the two dimensions, the distribution patterns and intensity patterns of shrinking cities and districts were characterised, respectively, and a framework for the analysis of shrinking cities with different dimensions and different scales of a long time series was established. Finally, OLS regressions were used to analyse the influencing factors of different shrinkage types and to generalise the influencing mechanisms. The following main conclusions can be drawn: (1) The scope and extent of shrinkage in the Yellow River Basin from 2010 to 2020 intensified compared to that observed from 2000 to 2010. Among the 595 districts in 72 prefecture-level cities (leagues) in nine provinces in the Yellow River Basin, 175 districts contracted in T1 and 373 contracted in T2, accounting for 62.7% of all the districts in the Yellow River Basin, which is twice the proportion of T1. This indicates that the situation of shrinking cities has become more critical, which is similar to the result identified by Meng and Long [41]. (2) The phenomenon of urban shrinkage is spatially scale dependent, and in this regard, our findings are consistent with LIU [20] that the quantitative identification of municipal-scale spaces is not representative of all the county-scale spaces it includes. The shrinkage of prefecture-level cities and county-level cities are being characterised by both spatial differentiation and spatial nesting relationships. (3) Based on the spatial bivariate autocorrelation analysis, the shrinkage patterns observed in the nighttime light and population data are somewhat inconsistent. Comparing the nighttime lights dimension with the population dimension of the Yellow River Basin shrinkage characteristics, the nighttime light dimension can reflect the structural shrinkage characteristics of a city more accurately and sensitively, while population loss lags. Possible reasons for this result is the fact that night lighting data can provide a direct reflection of actual human activity [42] and has better continuity and accuracy than census data, while census data has a 10-year time span and is counted in administrative divisions, which may produce unscientific statistical results in the face of administrative division adjustments. It has also been mentioned that there is a certain saturation and spillover effect of night lighting [20]. Thus, combining multiple data to identify shrinkage can compensate for identification inaccuracies caused by different data characteristics. (4) The factors influencing urban shrinkage and the intensity of their effects are, in order, the greening and intensification of industry under market-driven economic restructuring, the reduced natural growth rate and increased ageing in the population structure, and the lack of public service facilities.

There are still several shortcomings in this paper that require subsequent in-depth study: First, in terms of the research data and methodology, urban shrinkage is characterised by phases and unevenness, so the urban shrinkage in the Yellow River Basin has complex characteristics and causes, which are especially prominent when studying resource-based cities in a widely distributed region. The causes of shrinkage in China's metropolitan areas and urban agglomerations are beginning to emerge. Due to the limitation of data collection, this paper is only based on an analysis of population and nighttime lighting data. In the future, we can build multi-source datasets from industry, transportation, and ecology data to explore the urban shrinkage mechanism in more depth using machine learning methods, such as the random forest method. Secondly, in terms of research content, urban shrinkage in the Yellow River Basin has not only brought about a reorganisation of material space but also a reconfiguration of social networks. In the future, the correlation between urban shrinkage and social networks [43] in the Yellow River Basin should be explored from a socioeconomic perspective. Thirdly, in terms of the research framework, there is a lack of continuity and comparability in the nighttime light data, and shrinkage is only identified at the macro- and mesolevels at the municipal and county scales, while research at the microlevel is still lacking. As such, how can a comprehensive identification method that uses nighttime light data and population data be built and how can the scope of a "city" be defined based on functional territory? Further investigation is needed to obtain large-scale, high-accuracy urban data for shrinkage analysis and predictive simulations [44].

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