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Identification and Measurement of Shrinking Cities Based on Integrated Time-Series Nighttime Light Data: An Example of the Yangtze River Economic Belt

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Abstract: Urban shrinkage has gradually become an issue of world-concerning social matter. As urbanization progresses, some Chinese cities are experiencing population loss and economic decline. Our study attempts to correct and integrate DMSP/OLS and NPP/VIIRS data to complete the identification and measurement of shrinking cities in China's Yangtze River Economic Belt (YREB). We identified 36 shrinking cities and 644 shrinking counties on the municipal and county scales. Based on this approach, we established the average urban shrinkage intensity index and the urban shrinkage frequency index, attempting to find out the causes of shrinking cities for different shrinkage characteristics, city types and shrinkage frequencies. The results show that (1) the shrinking cities are mainly concentrated in the Yangtze River Delta city cluster, the midstream city cluster and the Chengdu–Chongqing economic circle. (2) Most shrinking cities have a moderate frequency of shrinking, dominated by low–low clusters. Resource-based, heavy industrial, small and medium-sized cities are more inclined to shrink. (3) The single economic structure, the difficulty of industrial transformation and the lack of linkage among county-level cities are possible reasons for the urban shrinkage in the YREB. Exploring the causes of urban shrinkage from a more micro perspective will be an inevitable task for sustainable development in YREB and even in China.

Keywords: shrinking cities; nighttime lights (NTL); urban shrinkage intensity; urban shrinkage frequency; the YREB

Citation: Tan, Z.; Xiang, S.; Wang, J.; Chen, S. Identification and Measurement of Shrinking Cities Based on Integrated Time-Series Nighttime Light Data: An Example of the Yangtze River Economic Belt. *Remote Sens.* **2023**, *15*, 3797. https://doi.org/10.3390/rs15153797

Academic Editors: Dino Ienco, Hossein Shafizadeh-Moghadam, Tingting Xu and Jay Gao

Received: 14 June 2023
Revised: 15 July 2023
Accepted: 24 July 2023
Published: 30 July 2023

1. Introduction

Urban shrinkage has gradually become a prominent issue of worldwide sustainable development in recent years [1–4]. The concept of urban shrinkage was first proposed by Häußermann and Siebel, scholars from Germany [5]. It is a phenomenon of continued loss of population and productive urban vitality. More than 25% of the world's main cities have become shrinking cities decades ago [6]. The early studies on urban shrinkage mainly focused on older industrial cities in advanced countries such as the UK and Germany [7]. Suburbanization, climate change, deindustrialization and aging populations are all the reasons for urban shrinkage around the world [8,9]. For example, the shrinkage of the "Rust Belt" in the U.S. is mainly due to suburbanization, while in Detroit and Pittsburgh it is due to the decline of local manufacturing [10]. A single industrial structure may be responsible for the shrinkage of some cities in Germany and Australia, while the pressures of an ageing population may have resulted in the shrinkage of Japan [8,11]. Currently, scholars have gradually expanded the study of urban shrinkage from large scale cities to small and medium ones. Small towns and rural areas in Germany, the United States and France are all at risk of urban shrinkage [12–14]. Small towns with poor infrastructure are more vulnerable to the siphoning effect of metropolitan areas than large cities [15,16]. Despite the relatively rapid urbanization, 180 cities in China have experienced urban shrinkage between 2000 and 2010 [17]. The Northeast region, the Yangtze River Delta, the Pearl River Delta and the Yellow River Basin are the major concentrations of shrinking cities [18,19]. The Yangtze River Economic Belt (YREB) spans China's central, east and west regions, whose economy and resource endowment are highly strategy-oriented for the national development. Currently, Chinese scholars have mainly used population data to measure urban shrinkage of the upstream individual cities [20], the midstream Wuhan urban area [21] and the downstream Yangtze River Delta urban agglomeration [22]. Resource depletion in industrialized cities, population outflow from developed regions and urban migration due to administrative planning are all the main causes of urban shrinkage [23]. Moreover, shifts in national strategic planning and social transformation will also lead to it [24]. The discussion of existing urban shrinkage research mainly covers influencing factors, identification and measurement methods and spatial and temporal analyses. The causes of urban shrinkage can be summarized as mainly natural, economic, demographic and institutional reasons. Among them, severe changes in natural conditions, such as environmental pollution, geological disasters and climate change, will cause cities to become uninhabitable, resulting in shrinking functional areas [2,25,26]. Moreover, excessive economic structural differences, including the declining traditional industries and de-industrialization, will lead to hollowing out of industries and population displacement [27]. Furthermore, demographic changes caused by aging populations and declining birth rates will reduce labor force, which is incapable and inefficient to support urban development [28]. In addition, institutional drivers such as national political transition [29], rental configuration policies [30], fiscal and taxation policies [31] and reform of the household registration system [32] are also influential causes of urban shrinkage. Identifying and measuring shrinking cities, grasping the current situation and exploring the mechanisms are of great significance for the government as well as urban planners to formulate rational development plans.

There is no academic consensus on the connotation of urban shrinkage, but most scholars have initially limited their understanding to population decline [33,34]. For example, Hoekveld (2012) [35] defines a shrinking city as the one in which the total regional population has been declining for at least five consecutive years; Yang (2021) [36] and others use three years as the threshold for identifying urban shrinkage. The current definition with high academic acceptance comes from the SCIRN. It explains that urban areas with a population of more than 10,000, experiencing a structural economic crisis and losing population for more than two years are defined as shrinking cities [37,38]. Nowadays, urban shrinkage is not just a reduction in population density but a multidimensional and all-encompassing phenomenon of urban decay, and the definitions associated with urban shrinkage are also gradually changing.

Scholars in the early years mainly used population loss as the main indicator to identify and measure shrinking cities [9,34,39]. They mainly measured the degree of urban shrinkage through the rate of population loss, population density, changes in employment, etc., or selected a specific threshold value to identify shrinking cities [40–42]. As research has evolved, the understanding of urban shrinkage is no longer limited to the reduction of population density but is a common manifestation of social phenomena such as population loss and economic recession [43]. Nowadays, the research has shifted from traditional approaches to emerging ones, with multi-dimensional indicator system substituting one single indicator. From the multiple perspective of demographic, economic and spatial aspects, scholars have realized the identification measurement of shrinking cities [44–46]. For example, they began to incorporate factors such as unemployment rate, household purchasing power and GDP into the multidimensional system [47]. However, it is rather difficult to construct a comprehensive indicator system with universal applicability, which also fails to explain well its dynamic trend over time. In addition, the problem of mismatch between macro statistical data and the physical boundaries of cities has also emerged due to the continuously changing administrative planning boundaries in China. To solve these problems, some scholars have tried to redefine urban systems and entities, while others have tried actively from the perspective of emerging data, such as remote sensing image [48].

The application of remote sensing image data in urban shrinkage mainly focuses on population distribution, land use, environment and climate and night lighting. Among them, the global land cover map [49] (2017 FROM-GLC10) and LandScan high-resolution global population dataset [50] are commonly used in urban shrinkage research, which mainly alleviate the problem of mismatch between traditional macro statistical data and the boundary of urban entities. In order to carry out more detailed research work from the perspective of environment and climate, scholars have used MODIS products to calculate the intensity of urban heat island on the surface [51] or measure the urban morphology indicators of shrinking cities through high-resolution vegetation image data to complete the classification of shrinking cities [52]. In addition, the combination of remote sensing tools with big data, AI and other intelligent technologies is also an important direction of urban contraction exploration, such as through the Internet Location Based Services (LBS) [53] and 3S technology application [54], in order to realize the contraction of the city real-time monitoring, the estimation of the housing vacancy rate and other purposes. Considering the economic and social expressions reflected in nighttime lighting and the availability of data, we think that the adaptability of nighttime lighting data to our study is relatively high.

The nighttime lighting technology has been maturely used in the exploration of urban shrinkage research. The remotely sensed nighttime light (NTL) data accurately records the trajectory of human production and life, reflecting the integrated demographic, economic and spatial changes of cities. These advantages has attracted many scholars to employ it [55]. Since Croft first used DMSP/OLS data to extract urban built-up areas in 1978 [56], scholars in China and the rest of the world have used NTL data for more in-depth studies on impervious layers, urban sprawl, urbanization processes, and simulated urban residential CO_2 emissions [57–60]. Moreover, NTL data have been gradually applied to the study of urban shrinkage and began to change from the separate DMSP/OLS or NPP/VIIRS dataset to the integration of nighttime lighting dataset application. Existing studies have focused on identifying and measuring shrinking cities through nighttime light brightness selection, shrinkage index calculation and city scale index construction [59] and have also focused on exploring the spatial and temporal patterns of shrinking cities [36], as well as predicting the future trend of urban shrinkage [61]. However, the biggest difficulty in using this method to measure urban shrinkage lies in the light data correction and the integration of DMSP/OLS and NPP/VIIRS data. Current methods mainly include the function fitting method [62], the combination of function modeling and Gaussian filtering [63] and geographically weighted regression modeling [64], among which the more widely used integration method is the function fitting method.

In summary, most of the current studies identified and measured shrinking cities at the global or national scale, while there are fewer ones that applied nighttime lighting data to identify urban shrinkage in important urban agglomerations. The YREB, as a leading urban agglomeration in China, is a representative city cluster of great research significance in China. However, the current studies have mainly used macro statistics such as population and economy at the prefecture level. And they also have failed to explore and summarize the shrinkage patterns and types of different regions from a comprehensive perspective. In addition, there are still several limitations in examining and analyzing the pattern of regional urban shrinkage, spatial distribution patterns and long-term evolution issues, as well as its formation mechanisms.

To break the limitations of the single evaluation dimension of population, this study develops a DMSP/OLS and NPP/VIIRS integrated time series data to identify shrinking cities in China's YREB from the perspective of time and space spans. In order to exclude other disturbances caused by economic development, this study attempts to extract shrinkage pixels and identify shrinkage frequencies for further measurement of shrinkage cities. The advantages of this method are as follows: (1) the period range of NTL data is expanded, which is more conducive to analyzing the evolution of urban shrinkage in YREB. (2) It not only overcomes the problems of inconsistent macro statistical caliber and data omission in some administrative regions but also quantitatively identifies the urban shrinkage in YREB from multiple scales such as municipal and county levels. (3) By forming multiple sets of indicator data for measuring urban shrinkage, we effectively reduce the uncertainty caused by measurement errors and deepen the analysis of urban shrinkage patterns, spatial distribution and causes of formation in YREB. Meanwhile, the difficulties of this paper mainly include accurately identifying shrinking cities in the YREB, guaranteeing the robustness of the NTL integration data and exploring the intrinsic reasons for the formation of shrinking cities.

The structure of this study is arranged as follows. Section 2 mainly shows the data sources, data processing and methods for identifying and measuring shrinking cities. Section 3 contains the analysis of the spatial distribution of shrinking cities at the municipal and county level, spatial auto-correlation analysis, analysis of different shrinkage types, city types, shrinkage frequency and accuracy and performance analysis of integrated NTL time series data. Section 4 includes the accuracy and performance analysis of integrated NTL time series data, the limitations and future directions of this research. Section 5 mainly shows research conclusions and policy recommendations for urban shrinkage in YREB. The idea framework of the article is illustrated as follows (Figure 1):

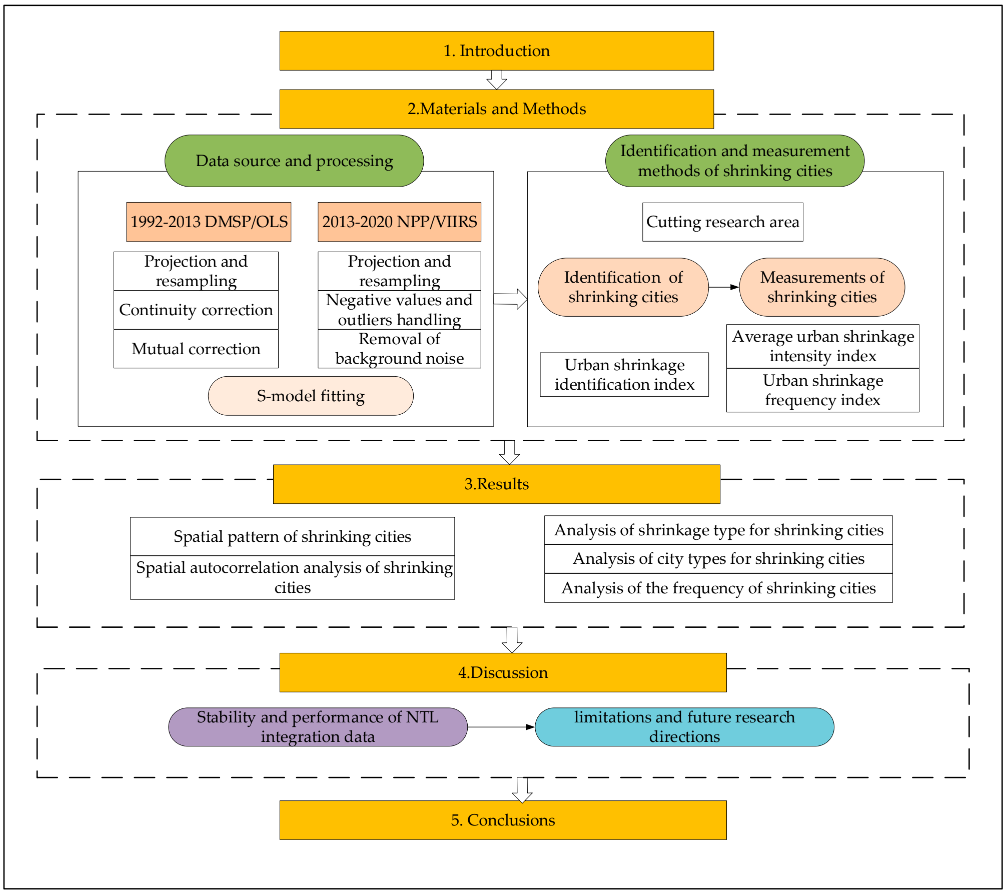

Figure 1. Idea framework.

2. Materials and Methods

2.1. Data Source and Processing

The DMSP/OLS NTL data were obtained from the 4th edition of DMSP/OLS data provided by the National Oceanic and Atmospheric Administration of the U.S. (Version 4 DMSP-OLS Nighttime Lights Time Series), and the NPP/VIIRS data were obtained from the 2nd edition of annual data (Annual VNL V2), provided by Colorado public research universities in the U.S. We resampled the data after mask cropping the Chinese regional NTL data. To avoid the effect of image grid deformation and to ensure the same spatial resolution of both data sets, the projection coordinates were set to Lambert, and the resolution was uniformly set to 1 km^2. The sources of the remaining data are all shown in Table 1. For the basic processing of DMSP/OLS and NPP/VIIRS NTL data, we followed Wu et al., Cao et al. and Zhao et al. [63,65,66]. For the integration of the two datasets, we mainly referred to Wu et al. and Ma et al. [67,68].

Table 1. Description of the data used to identify and measure shrinking cities.

Data	Data Description	Time Range/Resolution	Source
DMSP/OLS	annual DMSP/OLS nighttime steady light data	1992–2013 1 km^2	NOAA/NGDC https://www.ngdc.noaa.gov/eog/dmsp/download V4composites.html (accessed on 1 July 2022)
NPP/VIIRS	annual NPP/VIIRS nighttime light data	2013–2020 500 m^2	https://payneinstitute.mines.edu/eog/nighttime-lights (accessed on 1 July 2022)
RCNL	Global radiance calibrated night lighting products	2006	NOAA/NGDC https://www.ngdc.noaa.gov/eog/dmsp/download_radcal.html (accessed on 1 July 2022)
Population	National population data	1992–2019	National Bureau of Statistics of the People's Republic of China http://data.stats.gov.cn/index.htm (accessed on 23 January 2023)
GDP	National GDP data	1992–2019	National Bureau of Statistics of the People's Republic of China http://data.stats.gov.cn/index.htm (accessed on 23 January 2023)
Boundaries	Shapefile of Counties and Cities in China and the YREB	2021	China National Geographic Information Center National Geomatics Center of China http://sgic.geodata.gov.cn (accessed on 23 January 2023)
Electricity consumption	Electricity Consumption in Municipal Cities of YREB	1995–2020	National Bureau of Statistics of the People's Republic of China http://data.stats.gov.cn/index.htm (accessed on 23 January 2023)
Land area for urban construction	Land area for urban construction in the YREB	2003–2020	City Statistical Yearbook of China (accessed on 23 January 2023)

2.1.1. DMSP/OLS NTL Data Processing

Because the DMSP/OLS data have the problems of no calibration and over-saturation of image elements, we apply continuity correction and mutual correction on it. First, to improve its continuity and stability, we use the 2006 global radiometric calibration nighttime light (RCNL) data as the baseline image [65] and the Hegang city as the invariant area to perform continuity correction of the 1992–2013 light data. The continuity correction model is shown in Equation (1):

$$\mathrm{DN}' = \mathrm{a}\cdot\mathrm{DN}^{\mathrm{b}} \tag{1}$$

where DN′ represents the light value from the calibrated year, and DN is the light value from the base year.

Second, to fully utilize the light information between different sensors in the same year, we obtain the average value of light DN in the same year by Equation (2):

$$\mathrm{DN}''_{(\mathrm{n,i})}\begin{cases} 0, \mathrm{DN}^{\alpha}_{(\mathrm{n,i})} = 0 \text{ or } \mathrm{DN}^{\beta}_{(\mathrm{n,i})} = 0 \\ \frac{\mathrm{DN}^{\alpha}_{(\mathrm{n,i})}+\mathrm{DN}^{\beta}_{(\mathrm{n,i})}}{2}\mathrm{DN}^{\alpha}_{(\mathrm{n,i})} \neq 0 \text{ and } \mathrm{DN}^{\beta}_{(\mathrm{n,i})} \neq 0 \end{cases} \tag{2}$$

where $DN''_{(n,i)}$ is the DN value of the ith pixel value from the n-th year after correction; $DN^{\alpha}_{(n,i)}$ and $DN^{\beta}_{(n,i)}$ are those before correction for sensor α and sensor β.

2.1.2. NPP/VIIRS NTL Data Processing

We corrected the NPP/VIIRS data by referring to Zhao et al. [63]: (1) Background noise removal: the regions with 2013 DMSP/OLS lighting thresholds greater than 0 were used as masks to remove the background noise of NPP/VIIRS data. (2) Negative value processing: we replaced the negative DN values less than 0 with 0. (3) Outlier processing: the nationwide lighting thresholds cannot exceed the maximum in the most developed regions of China, such as Beijing, Shanghai, Guangzhou and Shenzhen. Thus, we first cropped out the lighting images of these cities and extracted the highest lighting thresholds. Secondly, we used these lighting thresholds to replace those NTL outliers. Finally, if the lighting DN value still exceeded 400 after processing, we assigned it a value of 400. The maximum threshold values for Beijing, Shanghai, Guangzhou and Shenzhen are shown in Table 2.

Table 2. The maximum thresholds for Beijing, Shanghai, Guangzhou, Shenzhen.

Year	Beijing and Shanghai	Guangzhou and Shenzhen
2013	**192.779**	174.89
2014	209.976	**296.256**
2015	**443.53**	340.514
2016	**769.782**	260.427
2017	238.213	**269.902**
2018	243.683	**337.364**
2019	**2083.39**	341.573
2020	**373.565**	293.881

2.1.3. Data Fitting and Integration Processing

To mitigate the variance caused by the large variation of the NPP/VIIRS data, we took the logarithm of it [68]. As shown in Figure 2c, the NPP/VIIRS data in 2013 showed an obvious "S" relationship with the DMSP/OLS data, so we finally chose the "S" model (3) to fit the two types of lighting data. The fitting formula is shown in Equation (3):

$$DN_{DMSP} = a\left(\frac{1}{1 + e^{-b(DN_{NPP} - c)}}\right) \tag{3}$$

The results show that the R2 of NTL in 2013 is 0.8488, which indicate that the simulated data is credible. Hence, we applied the relationship between the both lighting data to fit that from 2014 to 2020. Ultimately, to make the NTL data more accurately reflect China's economic development and demographic changes, we corrected the NTL data based on economic and demographic data. The calculation formulas are shown in Equations (4) and (5):

$$\beta = \frac{\sqrt{(GDP_n/GDP_1) \times (POP_n/POP_1)}}{\sqrt{TDN_n/TDN_1}} \tag{4}$$

$$DN'_{(n,i)} = \beta \times DN_{(n,i)} \tag{5}$$

where GDPn, POPn and TDNn represent the GDP, population and total nighttime light value of China in the n-th year; GDP1, POP1 and TDN1 represent the GDP, population and total nighttime light value of China in the first year. The NTL data processing is as follows (Figure 2).

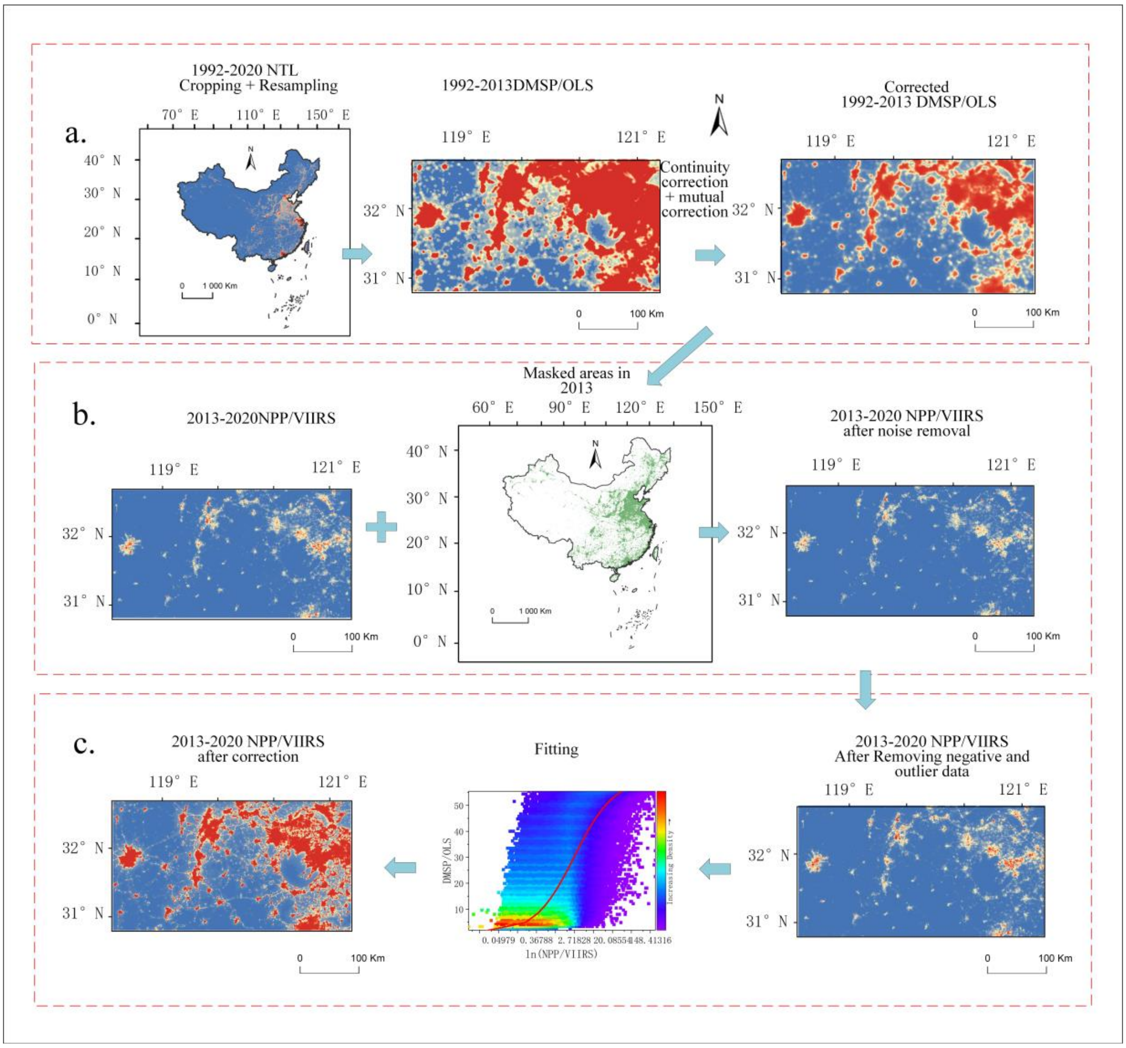

Figure 2. Data processing framework: (**a**) calibration of DMSP/OLS data; (**b**) correction of NPP/VIIRS data; (**c**) integration of long time series NTL data.

2.2. Methodology

2.2.1. Identifying Shrinking Cities

(1) The urban shrinkage identification index

As mentioned above, NTL data can overcome various shortcomings of macro data of population or economic statistics. To further identify and analyze the spatial distribution characteristics of shrinking cities, we use Arcgis 10.4 to identify shrinking cities by the TDN values.

Since SCIRN identifies urban areas with a total population of more than 10,000 and population loss lasting for more than 2 years as shrinking cities [38,69], and we set the identification threshold of shrinking cities as 3 years, where 1996, 1999, 2002, 2005, 2008, 2011, 2014 and 2017 are the base years. The formula for the urban shrinkage identification index is as follows:

$$\mathrm{shrink1}_{i,t} = -\ln\left(\frac{\mathrm{TDN}_{i,t}}{\mathrm{TDN}_{i,t-3}}\right) \tag{6}$$

where $\mathrm{shrink1}_{i,t}$ is the urban shrinkage identification index of the ith city in the tth year; $\mathrm{TDN}_{i,t}$ is the total nighttime light value of the ith city in the tth year; $\mathrm{TDN}_{i,t-3}$ is the total nighttime light value of the ith city in the base year. If $\mathrm{shrink1}_{i,t} > 0$, the city is identified as a shrinking city; otherwise it is a non-shrinking city.

2.2.2. Measuring Urban Shrinkage

(1) The average urban shrinkage intensity index

Since the shrinkage and growth phenomena both exist in Chinese cities, we refer to Yang [36] to exclude the effect of economic growth and nighttime light growth. First, we identified pixels with a 15% decrease in DN value during one year as shrinking pixels. Second, these shrinking pixel points were extracted separately. Finally, we calculated the average intensity index of urban shrinkage with the following equation:

$$\mathrm{Shrink1}_{t+1} = \frac{\sum\left(\mathrm{DN}_{(i,t)}(n) - \mathrm{DN}_{(i,t+1)}(n)\right)}{S_t} \tag{7}$$

where $\mathrm{DN}_{(i,t)}(n)$ is the DN value of the ith pixel in the tth year from the n-th region; $\mathrm{DN}_{(i,t+1)}(n)$ is the DN value of the ith pixel in the t + 1st year from the n-th region; and St is the total shrinkage pixels in the region in the tth year.

(2) Urban shrinkage frequency index

Oswalt and Rienitz [69] identified the cities with an annual population loss rate greater than 1% as shrinking cities. To further analyze the shrinkage frequency of cities in YREB, we identified cities with a 1% decrease in TDN value in two adjacent years as ones with the tendency to shrink. If the growth rate of the TDN value of the city was less than -0.01, the shrinkage frequency of the city was 1; otherwise, it was 0. Finally, we added up the shrinkage frequencies of all years to obtain the city shrinkage frequency index. The calculation process is as follows:

$$\triangle \mathrm{TDN}_{i,t+1} = \frac{\mathrm{TDN}_{i,t+1} - \mathrm{TDN}_{i,t}}{\mathrm{TDN}_{i,t}} \tag{8}$$

$$P_{i,t+1} = \begin{cases} 1, \triangle \mathrm{TDN}_{i,t+1} < -0.01 \\ 0, \text{otherwise} \end{cases} \tag{9}$$

$$\mathrm{Shrink}_{2it} = \sum\nolimits_0^n P_{i,t+1} \tag{10}$$

where $\mathrm{TDN}_{i,t}$ is the total nighttime light value of the ith city in the tth year; $\mathrm{TDN}_{i,t+1}$ is the total nighttime light value of the ith city in the t + 1st year; $P_{i,t+1}$ is the shrinkage frequency of the ith city in the tth year; Shrink_{2it} is the summed urban shrinkage frequency index of the ith city in the tth year.

3. Results

3.1. Spatial Pattern of Shrinking Cities

We calculated the urban shrinkage identification index for 130 cities and 1069 counties in the YREB and finally identified 36 shrinking cities and 644 shrinking counties. As shown in Table 3, the shrinking cities and the shrinking counties account for 27.69% and 60.24% of the total sample, respectively. At the municipal level (Figure 3), there are 12 shrinking municipal cities upstream of YERB, which are mainly concentrated in the Chengdu–Chongqing economic circle, the central Yunnan city cluster and the surrounding cities. It is because of the siphoning effect of the central cities, which are primed for development opportunities, attracting the inflow of resources and talents from neighboring cities, such as Ya'an, Leshan, Mianyang, Neijiang and Dazhou. Meanwhile, the resource outflow is more serious in some deep inland areas with humid climate and low openness to the outside world, such as Zhaotong, Lijiang and Chuxiong Yi Autonomous Prefecture [70]. There are 11 shrinking cities in the midstream of YREB, mostly concentrated in the Wuhan city circle and its surrounding cities. Compared with other city clusters, the midstream cities have weaker development linkage, transportation conditions and infrastructure conditions. The Wuhan city cluster is the most densely populated area in Hubei province in terms of industries and production factors, meeting the working population's expectations of high wages and social value, which leads to the surrounding population inflow. There are nine downstream shrinking cities, mainly concentrated in certain areas of the Yangtze River Delta. In the context of the integrated regional development strategy, the economic factors flow more freely among the cities in the Yangtze River Delta. And massive urban populations flock to larger cities and provincial capital metropolitan areas with better economic development. For example, Hefei, the main central city of Anhui Province, has produced this obvious "siphon effect" on Huainan, Huabei and Chuzhou. Some cities in southern Zhejiang and western Jiangsu have also experienced urban shrinkage as a result of lacking regional competitiveness and agglomeration advantages. The resources and population of these areas mainly flowed into the more developed areas such as Hangzhou and Nanjing.

Table 3. Shrinkage of municipal and county-level cities in the YREB.

	Shrinking Counties	Growing Counties	Shrinking Municipalities	Growing Municipalities
Number	644	425	36	94
Percentage	60.2432%	39.7568%	27.6923%	72.3077%

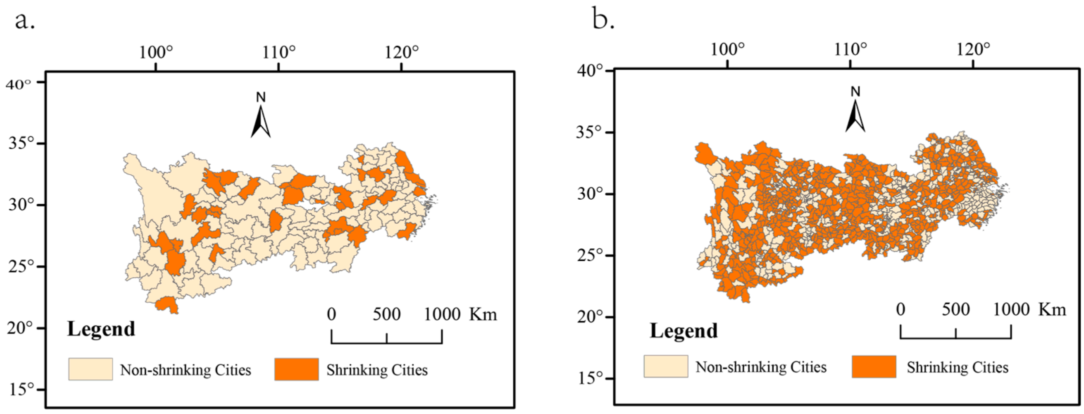

Figure 3. (**a**) Spatial distribution pattern of municipal shrinking cities in the YREB; (**b**) spatial distribution pattern of county-level shrinking cities in the YREB.

At the county level, more than half of the cities show urban shrinkage. It is noted that many non-shrinking ones at the municipal level also show a gradual reduction in night-time lighting. The overall trend of urban shrinkage in YREB shows a further expansion from municipal cities to county-level cities, with these shrinking counties mainly situated around central cities and major urban agglomerations. Because of the homogeneous industrial structure and small economic volume, this agglomeration shrinkage and contiguous shrinkage are also more inclined to appear in county-level cities. Furthermore, the shrinkage also exists within cities such as Chongqing, Chengdu, Wuhan and Zhejiang. It is mainly because these cities are more remote from the central area and not enough to receive the radiation effect of the central city.

3.2. Spatial Autocorrelation Analysis of Shrinking Cities

We calculated Moran's I values of the average urban shrinkage intensity index for municipal and county-level cities in the YREB from 1993 to 2020 (Tables 4 and 5). The results pass the significance test at the 0.01 level for almost all years. This suggests a positive correlation between shrinking cities in the YREB, showing high–high grouping and low–low hugging in space. Moreover, the spatial autocorrelation of county-level cities is weaker than that of municipal cities. To further clarify the spatial autocorrelation of shrinking cities, we plotted the LISA distribution of municipal and county-level cities in YREB in 2000, 2010 and 2020. Finally, we identified the spatial clustering patterns of four categories: high–high clusters, high–low clusters, low–high clusters and low–low clusters. As seen in Figure 4, the high–high clusters were mainly distributed in the Yangtze River Delta at the beginning, gradually shifted to Yunnan and cities around Chongqing in the middle stage and concentrated in the upper regions such as Jiangsu and Anhui provinces in the later stage. This trend is further spread in county-level cities. We find that these shrinking cities are mostly resource-based cities and old industry-based cities with inconvenient transportation and low openness level, such as Xuzhou and Zhenjiang in Jiangsu, Qujing and Pu'er in Yunnan. The low–low clusters were distributed around the Chengdu–Chongqing economic circle in the early stage, concentrated around the Wuhan economic circle in the middle stage and showed a small distribution in the upstream, midstream and lower reaches in the later stage. Compared with their neighboring cities, these cities have a low degree of shrinkage, and the overall development trend is relatively stable. The low–high clusters mainly centered in Suzhou, Anhui, Jiangxi and a few other county-level cities with strong economic strength. Although these cities have not shrunk much, they have caused the surrounding cities to shrink significantly, showing a pattern of "internal growth and peripheral shrinkage" in general. The high–low cluster shows a high degree of urban shrinkage while its neighboring cities show a low degree of shrinkage, manifested by urban decentralization and a serious outflow of resources and population. As a representative of this cluster, Xiaogan and the surrounding districts are mainly affected by the siphoning effect of Wuhan. A few eastern districts, such as Ganzi Tibetan Autonomous Prefecture and Aba Tibetan and Qiang Autonomous Prefecture in Sichuan Province, are particularly affected by the complex geographic structure and harsh environment. As a result, the supply of local public services such as education and healthcare cannot meet the needs of residents, ultimately leading to serious regional population loss.

Table 4. Results of Moran's I Index for Municipal Cities in the YREB.

Year	Z	I	Year	Z	I
1993	6.034	0.339 ***	2007	9.138	0.518 ***
1994	13.332	0.764 ***	2008	4.928	0.270 ***
1995	3.294	0.179 ***	2009	13.907	0.775 ***
1996	9.745	0.519 ***	2010	6.075	0.332 ***
1997	4.807	0.265 ***	2011	11.646	0.651 ***
1998	6.465	0.362 ***	2012	8.455	0.480 ***
1999	9.447	0.535 ***	2013	13.054	0.740 ***
2000	4.741	0.264 ***	2014	8.486	0.482 ***
2001	8.875	0.504 ***	2015	6.374	0.358 ***
2002	10.110	0.573 ***	2016	9.726	0.552 ***
2003	7.505	0.406 ***	2017	−0.268	−0.023
2004	11.447	0.645 ***	2018	7.513	0.422 ***
2005	6.263	0.344 ***	2019	11.040	0.630 ***
2006	6.520	0.368 ***	2020	6.469	0.363 ***

Note: *, ** and *** indicate that the variables provide significance at 10%, 5% and 1%.

Table 5. Results of Moran's I Index for County-level Cities in the YREB.

Year	Z	I	Year	Z	I
1993	−3.105	−0.046 ***	2007	3.937	0.056 ***
1994	−1.760	−0.026 *	2008	2.675	0.038 ***
1995	−0.751	−0.011	2009	−2.601	−0.039 ***
1996	4.316	0.061 ***	2010	6.014	0.087 ***
1997	−1.012	−0.016	2011	0.396	0.005
1998	2.234	0.030 **	2012	−3.739	−0.055 ***
1999	1.047	0.014	2013	1.911	0.027 **
2000	0.493	0.006	2014	−1.594	−0.024
2001	−3.167	−0.047 ***	2015	3.163	0.046 ***
2002	3.834	0.054 ***	2016	−3.137	−0.046 ***
2003	−6.061	−0.089 ***	2017	−2.147	−0.031 **
2004	0.946	0.013 **	2018	1.837	0.025 **
2005	1.942	0.029 *	2019	−1.575	−0.024
2006	4.204	0.060 ***	2020	0.210	0.004

Note: *, ** and *** indicate that the variables provide significance at 10%, 5% and 1%.

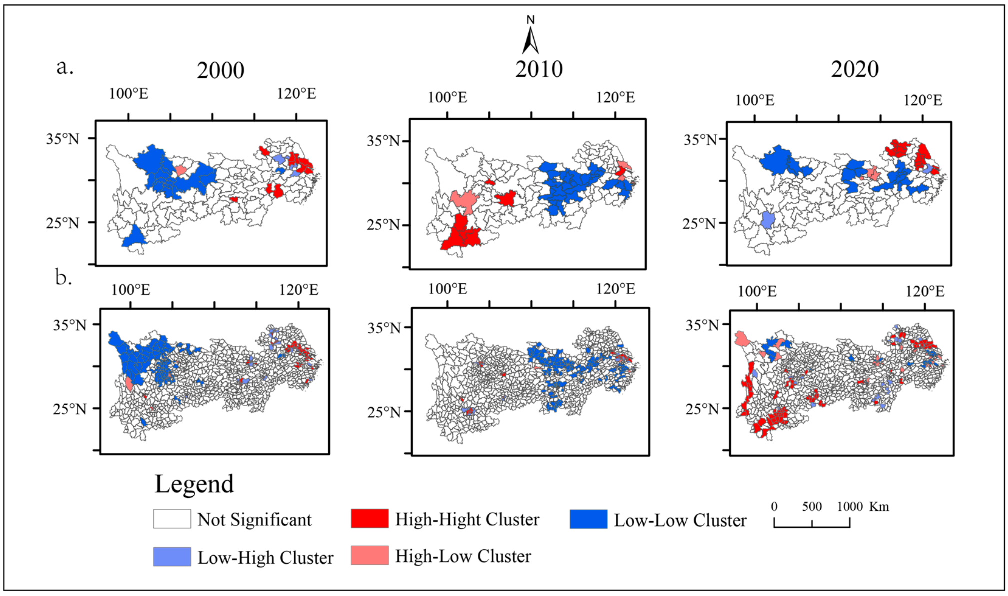

Figure 4. (**a**) LISA distribution of municipal cities in the YREB in 2000, 2010 and 2020; (**b**) LISA distribution of county-level cities in the YREB in 2000, 2010 and 2020.

3.3. Analysis of Shrinkage Type for Shrinking Cities

To further discuss the internal characteristics and the causes of shrinking cities, we classified the 130 municipal cities in the YREB into six types: dichotomous shrinkage, sporadic shrinkage, region-wide shrinkage, encircling shrinkage, central shrinkage and segmented shrinkage (e.g., Figure 5). There are 36 dichotomous shrinking cities in YREB, accounting for 27.69%. This is mainly because of the imbalance of regional economic development caused by favorable policies and resource advantages. The representative cities are Anqing, Anshun, Xiaogan, Ya'an, etc. Meanwhile, we identified 23 sporadic shrinking cities, accounting for 17.69%, which mainly showed that some shrinkage areas were sporadically distributed within municipal cities. It is mostly found in some central cities such as Chengdu, Chongqing, Hefei, Changsha and in minority autonomous areas such as Ganzi Tibetan Autonomous Region and Dali Bai Autonomous Region. The former is mainly due to several larger industrial and manufacturing development centers within the cities, while the latter is mainly tourism-based, far from the economic center cities. Furthermore, 22 cities in the YREB are shrinking in a region-wide manner, accounting for

16.92%. These cities are mainly in the form of co-shrinkage of internal cities, represented by Chizhou, Chuzhou, Huaibei, Huainan and Xuancheng. These cities are mostly at the edge of central cities and important urban clusters, with poor consumption and employment absorption capacity. In addition, the pressure of aging and the lagging transformation of the industrial structure are also possible reasons for their shrinkage [71]. The encircling shrinkage is manifested by the shrinkage of peripheral cities and the growth of central cities. In addition, 11 cities, including Yichang, Hengyang, Guang'an and Lishui, show this shrinkage phenomenon. The agglomeration effect of the central city, where infrastructure, education and medical resources are well equipped, will continue to attract population inflows. The representative cities of central shrinkage are Wuhan, Guiyang, Suzhou, Jiaxing, etc., which are mostly provincial capitals or economically developed central cities and have begun to drive the development of neighboring cities by sending resources and population to the periphery. Segmented shrinkage is specifically dominated by 15 cities such as Zunyi, Huanggang, Yiyang and Suqian, where the shrinkage is sectionalized. It is mainly owing to the differences in development levels between different counties within the cities, with a clear discontinuity in the economic and social development. Moreover, special geographical conditions can also lead to this type of shrinkage. For example, because Zunyi, Guizhou Province, is located on the slope of the transition from the Yunnan-Guizhou Plateau to the Hunan hills and the Sichuan Basin, its undulating topography and complex geomorphology directly affects the regional resource allocation. The details of the shrinking city types can be found in Table 6.

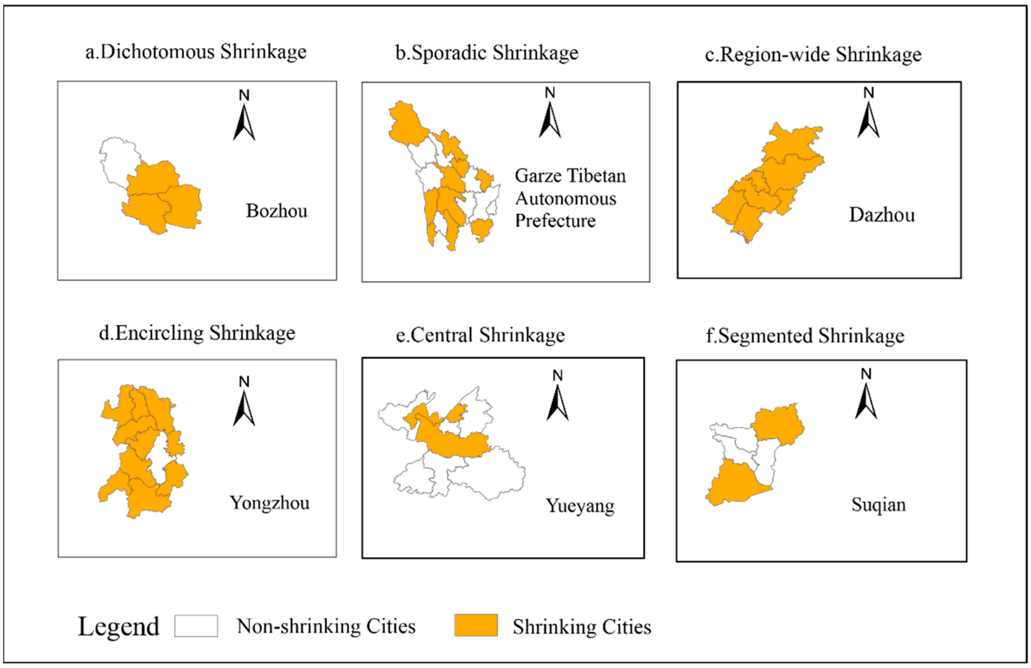

Figure 5. Six types of shrinking cities in the YREB. (**a**) Dichotomous shrinkage; (**b**) Sporadic shrinkage; (**c**) Region-wide shrinkage; (**d**) Encircling shrinkage; (**e**) Central shrinkage; (**f**) Segmented shrinkage.

Table 6. Number and proportion of shrinking city types in the YREB.

Shrinkage Type	Dichotomous Shrinkage	Sporadic Shrinkage	Region-Wide Shrinkage	Encircling Shrinkage	Growing Cities	Central Shrinkage	Segmented Shrinkage
Number	36	23	22	11	6	12	20
proportion	27.69%	17.69%	16.92%	8.46%	4.62%	9.23%	15.39%

3.4. Analysis of City Types for Urban Shrinking

The YREB is the treasure of resources and industrial bases in China. The study found that more than half of the cities are resource-based cities and old industry-based ones. Among them, 15 prefecture-level cities are recognized both as resource-based and old industry-based ones. The statistical results show (Table 7) that among the resource-based cities in YREB, shrinking prefecture-level cities and shrinking counties account for 52.78% and 33.68%, respectively. Furthermore, 19 resource-based cities, including Tongling, Huaiibei, Chongqing, Nanchong, Pu'er and Qujing, have experienced urban shrinkage. Highly resource-dependent cities have more homogeneous industrial structures and employment opportunities than non-resource-based cities. Once local resources are depleted, the pillar industries of resource-based cities will be extremely vulnerable to external impacts, which directly leads to various development problems such as industrial decline and population exodus. In addition, there are many heavy chemical industries densely distributed along the YREB basin, including the industrial bases of iron and steel and light textiles centered in Wuhan, the industrial bases of electricity and iron and steel centered in Yichang and Chongqing, the mining base centered in Wujiang Hydropower Station in Guizhou and the iron and steel industrial base centered in Panzhihua. There are currently 35 municipalities classified as old industrial bases. Among them, shrinking cities and shrinking counties account for 64.71% and 32.71%, respectively. This is mainly driven by the loss of traditional industrial advantages in old industrial bases and the backward development of urban agriculture and services. The difficulty in technological innovation and industrial transformation has directly led to vicious population movements [72]. In general, resource-based cities distribute more in upstream and downstream areas, while old industry-based cities are located in midstream areas more. The low level of industrial chain extension and industrial diversification is another key reason for cities shrinkage in YREB. Therefore, the transformation of resource-based cities and old industry-based cities is an essential way to promote the sustainable development of the YREB [72].

Table 7. Number and proportion of different city types of shrinking cities in the YREB.

City Category	Description	Shrinking Cities	Proportion	Shrinking Counties	Proportion
Resource-based Cities		19	52.78%	97	33.68%
Old industrial base cities		22	64.71%	88	32.71%
Large-Scale Cities	Cities with an urban non-farm population of 500,000 or more	18	81.82%	119	47.98%
Medium-Scale cities	Cities with an urban non-farm population of 200,000–500,000	31	64.58%	292	77.66%
Small-scale cities	Cities with an urban non-farm population of 200,000 or less	13	86.67%	52	50.49%

Furthermore, we classify these cities in the YREB into large-scale cities, medium-scale cities, and small-scale cities according to the non-farm population in urban areas. From the municipal city level, the shrinking cities account for 81.82%, 64.58% and 86.67% of the large, medium and small-scale cities, while the shrinking counties account for 47.98%, 77.66% and 50.49%. The results indicate that the number of shrinking small and medium-sized cities has far exceeded that of large-scale cities. Economies of scale are more difficult to achieve in small and medium-sized cities, which have lower administrative levels and weaker industrial advantages, regional advantages and access to resources [73], leading to a greater possibility of shrinkage. In terms of the level of urban function, the smaller the city is, the worse the transportation conditions are, and the higher the likelihood of urban shrinkage is [18].

3.5. Analysis of the Frequency of Shrinking Cities

To study the distribution pattern of urban shrinkage in YREB in the temporal dimension, we classified them into three categories based on the frequency of urban shrinkage from 1993 to 2020 using the Natural Breaks method. Cities with 1–6 shrinking frequency, 7–9 shrinking frequency and 10–15 shrinking frequency are defined as mild, moderate and frequent. As shown in Figure 6 and Table 8, a total of 62 county-level cities are mild, accounting for 9.63%, mainly located in the downstream area of YREB; 109 frequent shrinking cities, accounting for 16.93%, are mainly located in the upstream and midstream area, scattering in the Chengdu–Chongqing economic circle, the Wuhan urban agglomeration and ethnic minority autonomous prefectures. Medium-sized cities account for 73.44% of all shrinking cities, showing a contiguous clustering of upper, middle and lower reaches. Overall, more than half of county-level cities are moderately shrinking, with frequent ones mainly concentrated in upstream and midstream areas, and mild ones mainly distributed in downstream areas. It implies that urban shrinkage is not permanent and irreversible, and that the government can alleviate population loss and the urban shrinkage phenomenon by improving urban infrastructure conditions and competitiveness [70].

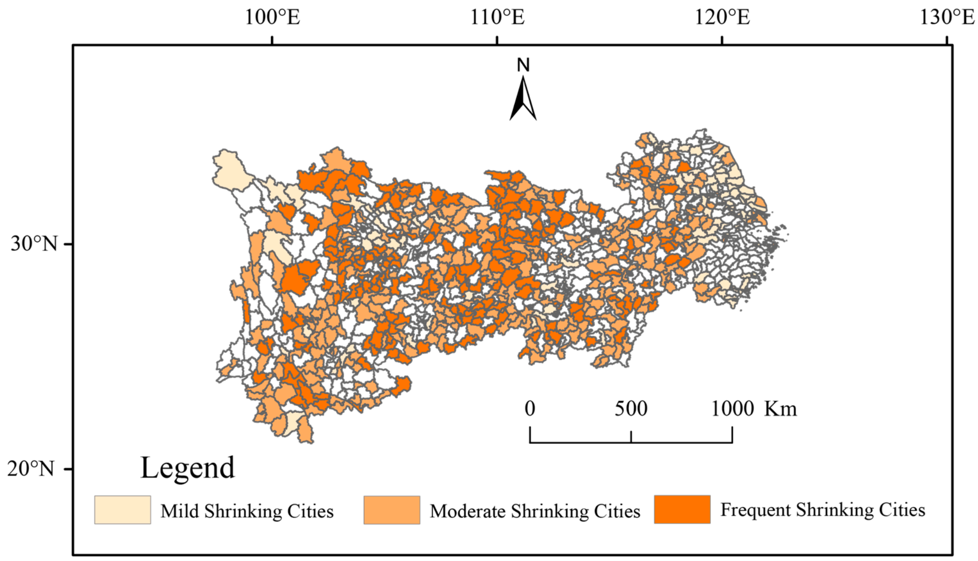

Figure 6. Spatial distribution of urban shrinkage frequency in the YREB.

Table 8. Frequency of urban shrinkage in the YREB.

Shrinkage Frequency	Mild Shrinkage	Moderate Shrinkage	Frequent Shrinkage
Number	62	473	109
proportion	9.63%	73.44%	16.93%

4. Discussion

4.1. Stability and Performance of NTL Integrated Data

To ensure the robustness of the integrated data, we mainly take the Chinese total nighttime light value data (TDN) as the standard. First, we performed the continuity correction and mutual correction of DMSP/OLS data. Second, we removed the background noise and corrected outliers of the NPP/VIIRS data. Finally, we chose the "S" model to fit the two types of lighting data. Demonstrated as in Figure 7a, it suggests that the issue of discontinuous TDN values of NTL has been solved. Considering the influence of economy and population on the national NTL, we crop out the YREB to linearly fit the national TDN and the YREB (shown in Figure 7b), and their R2 are 0.9695 and 0.8546. It implies that the TDN values of YREB and the whole country are robust.

Furthermore, to guarantee the precision and feasibility of integrated NTL data, the study fits the TDN value of YREB with electricity consumption and urban construction land area. The results are displayed in Figure 7c,d. It shows a strong positive relationship between the corresponding socio-economic parameters in 1995–2020 and TDN values of the integrated NTL. Moreover, the R2 are 0.91402 and 0.9843, implying the positive linear relationship between integrated NTL with human activities and socio-economic conditions.

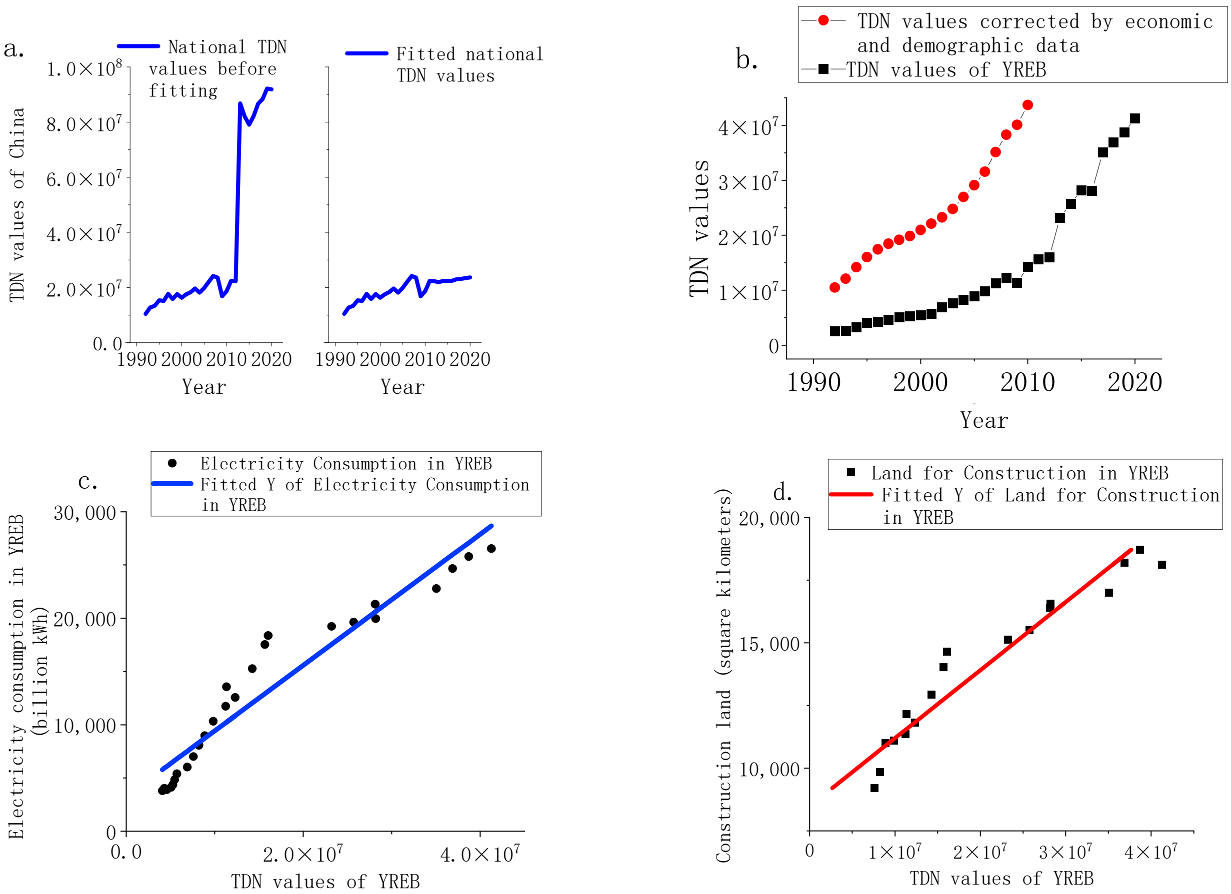

Figure 7. Process of original and corrected integrated NTL data; (**a**) comparison of national TDN values before and after fitting; (**b**) national as well as YREB's TDN values; (**c**) fitting of YREB's TDN values with electricity consumption; (**d**) fitting of YREB's TDN values with construction land.

4.2. Limitations and Future Research Directions

In this paper, we recognize the shrinking cities and analyze the type and spatial layout of them using NTL data. Furthermore, we have extended our research statistics on urban shrinking NTL to county-level cities, overcoming the defects of frequent political district adjustment and different calibers of permanent residence and household registration. It further complements and enriches the research methodology for the identification or measurement of urban shrinkage, providing a reference for urban sustainable development in China. However, there are still some limitations. Although it is applicable to use NTL as the indicator of urban shrinkage, the NTL is influenced by many factors, such as automotive energy conservation and emission reduction and urban night lighting control. This study only utilizes economic and demographic data for NTL data correction but fails to integrate it with multiple data sources better. For example, we did not make sufficient use of multi-source data sets on land use, transportation, ecology and other data that may be relevant to urban shrinkage. In addition, due to the limitations of the NTL source data, the study failed to identify urban shrinkage while ensuring higher resolution, and the treatment of NTL desaturation was relatively simple.

There are many aspects of urban shrinkage in China worthy to be explored. For example, the identification and measurement of urban shrinkage can be further investigated by identifying the built-up areas utilizing the Landsat4-5 TM satellite digital product remote sensing data [74]. Although we have attempted to analyze the reason for urban shrinkage in YREB through city types and scale, there is room for further research as the reason and mechanism of urban shrinkage is complex. With the rise of the Internet and big data, the combination of urban shrinkage and transport logistics is also one of the future research directions for urban shrinkage [21,75].

5. Conclusions

This paper attempts to correct and integrate DMSP/OLS and NPP/VIIRS data to complete the identification and measurement of shrinking cities in the YREB and extend the identification scale to county-level cities. Under the premise of ensuring the stability of the integrated NTL data, we examine and analyze the pattern of urban shrinkage, the spatial distribution pattern of shrinking cities and the long-term evolution process of shrinking cities. We find that (1) there is a prominent phenomenon of "group development and sporadic development" in YREB, with obvious regional and agglomeration characteristics, which shows a trend of gradual expansion to county-level cities. (2) According to the shrinkage characteristics, we divide the shrinking cities into six types: dichotomous shrinkage, sporadic shrinkage, region-wide shrinkage, encircling shrinkage, central shrinkage and segmented shrinkage. The dichotomous, sporadic and region-wide cities account for more than half of the ones. Considering the shrinking frequency, the cities in YREB are divided into mild, moderate and frequent shrinkage. Our research shows that the mild shrinking cities are scattered in upstream areas, while the frequent shrinking cities are mainly in upstream and midstream areas. (3) Along the YREB, there are old industry-based cities with many heavy chemical industries and resource-based cities with a strong dependence on natural resources. The shrinkage of these cities is even more pronounced since they suffer from a homogeneous industrial structure and difficulties in transformation. (4) Due to the lack of inter-regional development linkages, county-level cities and smaller regions are more susceptible to a vicious cycle of economic decline and population loss. In addition, shrinking cities of the same type accumulate more easily in spatial distribution.

The cities in YREB shrink in various types for different reasons. Many city-level and county-level cities in the YREB have shrunk already or shown a trend of shrinkage. Given the complexity and specificity of China's current urban shrinkage situation, we propose the following policy suggestions.

First, within the context of national strategies and policies, the local government should enhance the communication with other ones to strengthen the inter-regional linkage. (1) The local government should positively promote effective resources flow across different regions, breaking down the municipal administrative divisions and market barriers. (2) The local government is supposed to plan the transportation infrastructure rationally, taking full advantage of the opening of regional transportation facilities to encourage the extension of transportation network facilities in county and small-scale cities to rural areas. (3) The local government should promote industrial cross-border cooperation and realize the resource transfer from the central city to the surrounding areas by industrial transfer, bringing radiation and promotion effects to the surrounding counties [10]. (4) It is important for the local government to introduce advanced talents through various methods, such as financial and tax subsidies and transfer payments. Crucially, governments should avoid the malicious plundering of resources and talents between regions when strengthening the inter-regional linkage.

Second, the local government should transform the rigid planning model to enhance the resilience of urban development and the ability to withstand external risks, which includes (1) promoting the industrial structure transformation of old industry-based cities and resource-based ones in YREB and positively introducing emerging industries such as new energy, new materials and modern biology; (2) introducing the foreign investment to facilitate the start-up of small and medium-sized enterprises [76]; (3) seeking the reasonable positioning of these urban clusters, economic zones and other regions, based on the resource endowment and location conditions. For upstream cities, the government should fully utilize its industrial advantage in automobile, electronic information, equipment manufacturing and so on, promoting the deep integration of its advanced manufacturing and serving industries. For midstream cities, the government should promote the upgrade of the traditional manufacturing industry to green and smart manufacturing. Furthermore, relying on the cultural tourism advantage of Wuhan, Changsha and Nanchang, the government could strengthen the capability of technological innovation driving and cultural and commercial branding in midstream cities. For downstream cities, the government should attract the concentration of advanced elements and promote the development of high-tech industries while taking advantage of their geographical location and economic advantages.

Third, the policymakers should focus more on the essence of urban shrinkage on the premise of following the cyclical law of urban shrinkage and realize the change from the "growthism" to "smart shrinkage" development concepts [36,77]. Moreover, instead of exaggerating the severity and harm of urban shrinkage, the government should attach importance to the essential causes such as resource misallocation, disordered production structure and the decline of traditional industries. For frequently shrinking cities and high intensity shrinking ones, the government should fundamentally adjust the regional planning or streamline the urban layout to boost the new industrialization and new urbanization process of YREB. Meanwhile, in order to enhance overall competitiveness, the government could guide the radiation and extension of high-quality public resources to surrounding counties.

Author Contributions: Conceptualization, resources, supervision, project administration, funding acquisition, writing—review and editing, Z.T.; methodology, software, validation, formal analysis, investigation, writing—original draft preparation, visualization, data curation, writing—review and editing, S.X.; data curation, writing—review and editing, J.W.; writing—review and editing, S.C. All authors have read and agreed to the published version of the manuscript.

Funding: The authors declare that fund support was received from the Fundamental Research Funds for the Central Universities of Chongqing University (2022CDJSKPT30, 2022CDJSKJC26).

Data Availability Statement: The sources of all the data have been included in this paper.

Acknowledgments: The authors are immensely grateful to the editor and reviewers for their valuable comments on our manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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