# Identifying Shrinking Cities with NPP-VIIRS Nightlight Data in China

Zhidian Jiang[1]; Weixin Zhai[2]; Xiangfeng Meng[3]; and Ying Long[4]

**Abstract:** Although there has been a rapid urbanization in China since the 1980s, the simultaneous urban shrinkage phenomenon has existed for a long time. The study of shrinking cities is particularly important for China as the current urban development has changed from physical expansion to built-up area improvement. After redefining what constitutes a city (what we term a *natural city*), we compared the adjusted nightlight intensity of National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) data between 2013 and 2016 to accurately identify shrinking cities throughout China. The results indicate that there are 2,862 redefined natural cities in China and that the total area reaches 53,275 $km^2$, about 0.5% of the national territory. Based on this, we identified 798 shrinking cities with a total area of 13,839 $km^2$. After analyzing the relative position of shrinking cities and internal shrinking pixels in the geometric space, the morphological characteristics of shrinking cities were systematically classified into six patterns. The majority of shrinking cities belong to scatter shrinkage, central shrinkage, and local shrinkage; only 5% are complete shrinkage; the rest are unilateral shrinkage and peripheral shrinkage. In addition, six shrinkage causes were quantitatively classified and summarized by referring to multiple-source urban data and municipal yearbooks. To enrich the methodological system for urban shrinkage, the research provides a reminder of the need to consider the other side of urbanization (i.e., dissolution of social networks) and proposes appropriate strategies and policies to address shrinkage issues. **DOI: 10.1061/(ASCE)UP.1943-5444.0000598.** *© 2020 American Society of Civil Engineers.*

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## Introduction

*Shrinking city* is not a new concept in the study of urban science (Pallagst et al. 2013). The study of shrinking cities began with Häußermann and Siebel's (1988) work on population loss and economic decline in Germany. Recently, there have been an increasing number of studies on shrinking cities in Western developed countries (Haase et al. 2014). It is generally believed that population loss is an important basis to quantify the shrinking of urban (town) areas, but the specific criteria are not uniform. Howe et al. (1998) discussed the development of four cities in Ohio using census data. Shrinking Cities International Research Network (SCIRN) identified cities with population loss lasting for more than two years as shrinking cities (Wiechmann 2008; Pallagst et al. 2013). Oswalt and Rieniets (2006) argued that shrinking cities are cities with a decline of at least 10% of the total population or more than 1% of the annual average population loss rate. Schilling and Logan (2008) defined shrinking cities as cities with 25% or more persistent population loss, and increasing housing vacancy and abandonment rates over the past 40 years. Martinez-Fernandez et al. (2012) acknowledged that urban areas experiencing structural crises such as economic recession, population loss, employment decline, and social problems are shrinking cities. Bartholomae et al. (2017) applied population data and urban gross value added (GVA) data (1996–2012) to identify shrinking cities in Germany. Wiechmann and Pallagst (2012) used population data (1960–2010) to present urban shrinkage and provided a critical overview of the development paths and local strategies of four shrinking cities: Schwedt and Dresden in eastern Germany; Youngstown and Pittsburgh in the United States. Martinez-Fernandez et al. (2016) employed population data (1960–2010) to identify shrinking cities in Australia, Japan, Germany, the UK, France and the United States, and put forward corresponding strategies to cope with shrinking cities from a policy perspective. Buhnik (2012) investigated the factors behind urban decline within a metropolitan area considered as shrinking in Japan—the Osaka Metropolitan Area—based on the 2000 and 2005 national censuses, as well as time series data provided by the Portal Site of Official Statistics of Japan.

Although urban shrinkage is not a new phenomenon (Martinez-Fernandez et al. 2012), there are limited relevant studies on the progress of quick industrialization in countries. During the last several decades, China experienced a dramatic urbanization process (Deng et al. 2010; Kuang et al. 2016). As the global economy entered a new normal, the phenomenon of partial shrinkage accompanying rapid urbanization has gradually drawn widespread attention. However, the shrinking cities (cities and towns) and the relevant research are still in the preliminary stage of exploration. Referring to the methodology of international urban shrinkage research and practice, a growing number of scholars have begun to focus on the problems and contributing factors of shrinking cities in China employing quantitative approaches. Urban shrinkage, as a complex urban process, evolved multiple dimensional manifestations and incentives. Consequently, various studies were conducted that focused on the formations, distribution patterns,

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and social influences on both regional and nationwide scales in different time periods (Olsen 2013; Long and Wu 2016). He et al. (2017) aimed to enhance the understanding of shrinking cities in China and shed light on the policy-making of economic development for other resource-based cities in developing countries. Long and Wu (2016) found that 19,882 of 39,007 townships were losing their population from 2000 to 2010, and the total area was 3.2 million $km^2$, which covered almost one-third of the territory area of China. Li and Mykhnenko (2018) built a morphologic taxonomy of China's shrinking cities that used Chinese political-administrative population data (1990–2010). Nighttime remote sensing data have been widely applied to study urban issues, including calculating urban growth (Wei et al. 2014), analyzing landscape patterns (Yu et al. 2014) and dynamics (Zhang and Seto 2011; Ju et al. 2017), mapping urban areas (Bagan et al. 2019; Wu et al. 2018b), and ghost cities (Lu et al. 2018). In addition, a few scholars tried to exploit nighttime images for research on shrinking cities in China. Du and Li (2017) used population data, gross domestic product (GDP), and the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) to identify potential shrinking or significantly shrinking, finding that from 2009 to 2014, the number of shrinking towns in Dongguan accounted for 7.87%. Liu et al. (2018) identified and quantified the urban shrinkage from different dimensions and scales in northeast China during the transformation period, referring to population statistics (2010–2014) and DMSP-OLS nightlight data (2010–2013).

Most of the existing studies examined this problem based on administrative cities and identified China's shrinking cities with the support of the traditional urban population and local economic data. However, such research omitted the fact that real urban areas are not equivalent to administrative cities (Long 2016; Li et al. 2018), especially in the case of several urbanization areas caused by the independent development of multiple urbanization areas within the administrative city. In order to comprehensively describe the causes of shrinking cities from the aspects of society, economy, space and environment, the inherent structure of spatial entities should be confirmed, thus providing an alternative way of revisiting complex city systems to describe the natural development process of cities (Long et al. 2018). In addition, compared with ordinary demographic data and statistical yearbooks, urban nighttime light remote-sensing images are more objective and instant for reflecting human activities and habitation, which has been confirmed by many scholars (Shi et al. 2014; Wei et al. 2014). It is well recognized that remote sensing images, as a type of large-scale and objective data, have been widely applied to urban science for a certain period of time, as important reference parameters of social economy (Wu et al. 2018a), monitoring of urban environments (Shu et al. 2011), and judgment of urban expansion trends (Lee and Cao 2016).

How can the characteristics of shrinking cities be quantitatively identified and described? What kinds of shrinkage patterns are there in China? This is the focus of this paper. In this research, we redefined the natural city as a benchmark, overcoming the shortcomings of previous research into shrinking cities, as an effective and convenient way to precisely describe the latest distributional characteristics. Based on natural cities, we utilized stable nighttime light data to identify the shrinking cities in China. The patterns of shrinking cities are determined by the spatial relations of shrinking regions within cities. Further, the reasons for urban shrinking are classified by quantitative processing of big data. This paper presents a comprehensive and systematic analysis of China's shrinking cities from the aspects of natural city definition, shrinking city identification, morphological classification, and causes of shrinkage. It provides a new analysis path and research framework for the study of urban shrinkage in China.

## Study Area and Data Sources

### City System in China

The administrative city system in China is spatially defined as administrative city boundaries for management and statistics, which is different from the metropolitan statistical areas in the United States and Australia and the functional urban areas in European Union countries (Long 2016; Zhou 2006; Jin et al. 2017). According to the classification criteria of China's cities in Fig. 1, the administrative city system can be divided into 664 cities proper and another 1,461 counties. The cities proper can be further divided to include four municipalities directly led by the nation (MDs), 294 prefecture-level cites (PLCs), and 363 county-level cities (CLCs). Twenty-three urban agglomerations (UAs) are formed in places where cities are relatively concentrated (Fang and Yu 2017). The traditional city system divides cities with relatively large urban scales, dense population, and high socioeconomic status across the country and the provinces, however, it cannot effectively cover all the real urban central areas. As of August 2018, the total built-up area was 61,739 $km^2$, accounting for 7.8% of the whole area of the 664 administrative cities. In addition to these urban areas, there are still built-up regions of 13,745 $km^2$ in other 1,461 counties. In other words, China's city system has obvious insufficiency, that is, administrative cities include untapped suburban and rural areas and do not cover all urban regions with built-up areas. In this research, the city is redefined as real, spatially closely connected urban central regions; where the built environment and infrastructure conditions are intact; or where cities form boundaries in the process of natural development. Therefore, the redefined city (i.e., the natural city) covers all urban centers in China. This method of division makes it easier to express the state of development within a single city, and does not ignore the imbalance in the development of multiple natural cities within the same administrative city.

### Data Sources

With the development of science and technology, big data is constantly being applied by researchers to different fields for analysis and research (Fan et al. 2014). A diverse open data platform provides a research foundation for our work and is summarized in Table 1. Nightlight data provide significant support to describe human social and economic activities objectively and quantitatively. The National Polar-orbiting Partnership Visible Infrared Imaging Radiometer (NPP-VIIRS) stable nightlight data are among the most useful sources for delineating the changes of urban areas (Shi et al. 2014). With a resolution of 430 m from 2013 to 2016, it is practical and operational to adopt a novel technique for normalizing time series NPP-VIIRS nightlight data and identifying China's shrinking cities detection threshold by the pseudo invariant features (PIF) method. In general, the demographic data cannot accurately and effectively distinguish between transient population and permanent population, and the time series of the statistical caliber is not continuous. Therefore, the population data in 2013 and 2016 are from ORNL's LandScan, which are tailored to match the data conditions and geographical nature of each individual country and region (a community standard for global population distribution data). With an approximately 1 km spatial resolution, it represents an ambient population distribution averaged over 24 h (Dobson et al. 2013). Points of interests (POIs) are the accurate locations of important infrastructure and other urban hotspots, so they are usually regarded as useful and self-defined components in urban management systems (Liu and Long 2016). In addition, POIs are a proper proxy variable

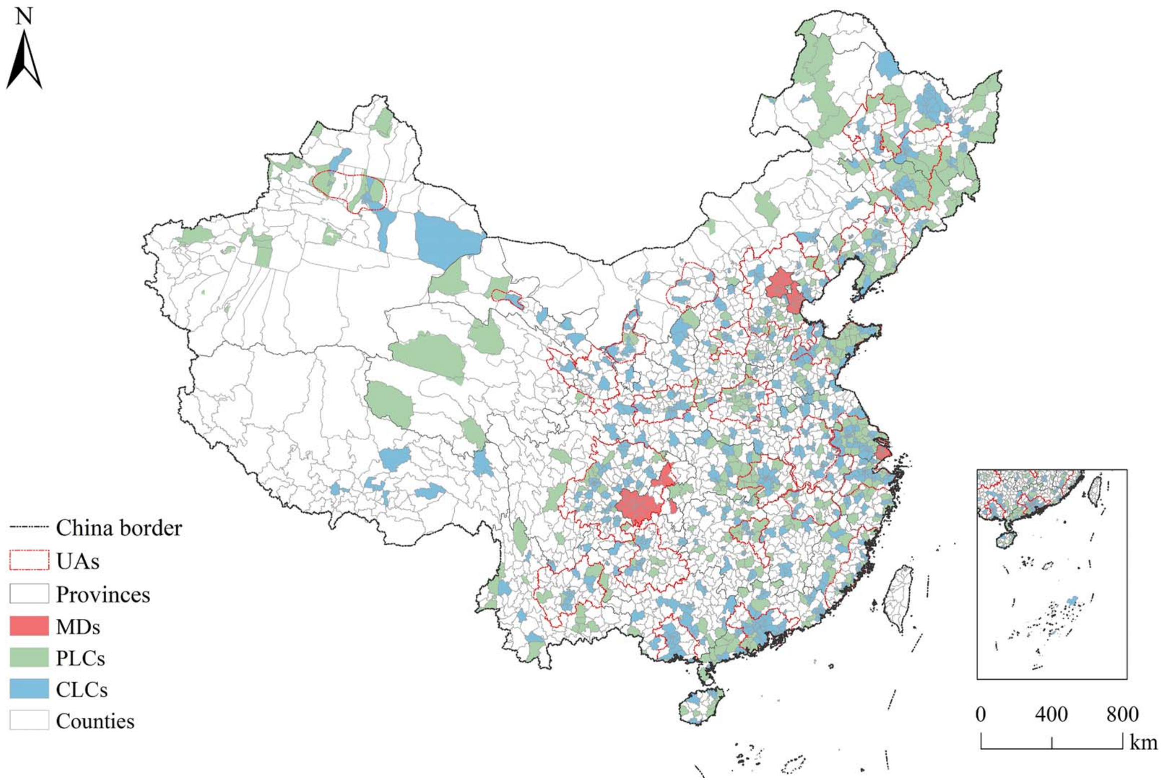


**Fig. 1.** Administrative city system of China.

**Table 1.** Basic information and main applications of multisourced urban data

| Types of data | Sources[a] | Periods | Resolution | Application |
|---|---|---|---|---|
| Nightlight | NPP-VIIRS | 2013/2016 | 430 m | Identifying shrinking cities |
| Population | LandScan | 2013/2016 | 1 km | As reference to nightlight data |
| Point of interests | Baidu LBS | 2016 | 5 points/ $km^2$ | Redefining natural cities |
| Road networks | Baidu API | 2016 | 600 $m/km^2$ | Modifying urban boundaries |
| Municipal yearbooks | Official statistics | 2013 | / | Assisting in judging the shrinking reasons |
| Other data[b] | Official platforms | 2016 | / | Correcting the division adjustment |

[a]Data sources: NPP-VIIRS data in http://www.ngdc.noaa.gov/eog/viirs/download_dnb_composites.html; LandScan data in http://landscan.ornl.gov/landscan-datasets; POIs and road networks data in http://developer.baidu.com/map/index.html; China's administrative boundary in http://www.webmap.cn/commres.do?method=dataDownload; and Administration regionalization of China reference in http://xzqh.mca.gov.cns/map.
[b]Including wilderness, reservations (Ma and Long 2020), city center boundaries for nightlight correction, China and provincial boundaries for determining spatial location, etc.

for capturing active human activities and residential development (Chi et al. 2015). The increase and extension of the road network density drives the development of surrounding cities (Meng et al. 2018). A total of 44,913,302 POIs and 12,583,733 road network data in 2016 (the national-level densities are 5 POIs/$km^2$ and 600 $m/km^2$, respectively) are rendered to redefine boundaries of natural city regions and blocks inside cities to distinguish between the administrative cities, based on Baidu location-based services (LBS) and application programming interface (API).

Accessing multisourced urban data through open data platforms ensures that the spatial scale and geographic location of research, redefinition of natural cities, identification of shrinking cities, and classification of shrinkage patterns can be determined successively. The National Bureau of Statistics and the Ministry of Civil Affairs online data, municipal yearbooks, and another basic geography information are used to confirm China's administrative boundaries at all levels and to adjust the latest administrative divisions.

## Methods

In this research, we quantitatively identified and described the characteristics of urban shrinkage in China from 2013 to 2016 and analyzed its specific causes. The different patterns of shrinkage were also categorized, and the summarizing reasons are proposed at the end. First, we collected POIs and road data from the study area to redefine the natural city and rename it. Second, based on the natural city, the NPP-VIIRS data were adjusted by the PIF method utilized to identify the shrinking cities, and the LandScan data was used to compare the results. Third, the shrinkage patterns were determined by the relative position between the shrinking city and the internal shrinking pixels. Finally, we also used nightlight intensity, population density, POIs density, statistical yearbook data, geographic location, urban area and renaming rules to determine the possible underlying causes of shrinkage for each shrinking city (Fig. 2).

### *Redefining Natural Cities*

Within an administrative city, there may be several urban areas that develop independently, but there is no absolute dependency between them. In order to precisely describe the development of natural cities, we redefine China's city system. The process of redefining cities is described using Song et al.'s (2018) method

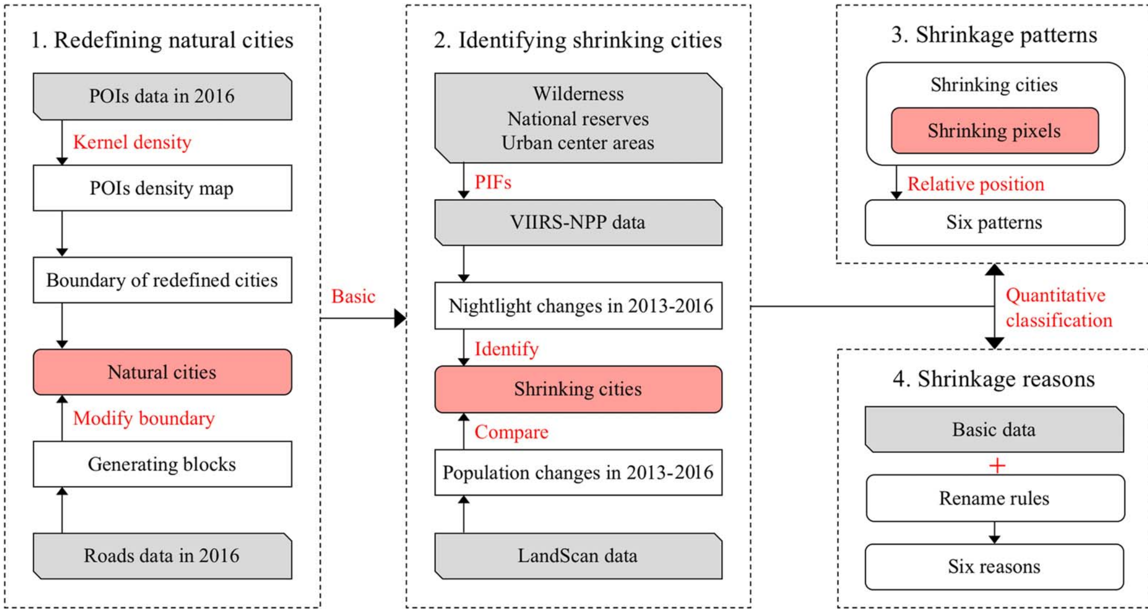


**Fig. 2.** Analytical framework (shrinkage patterns).

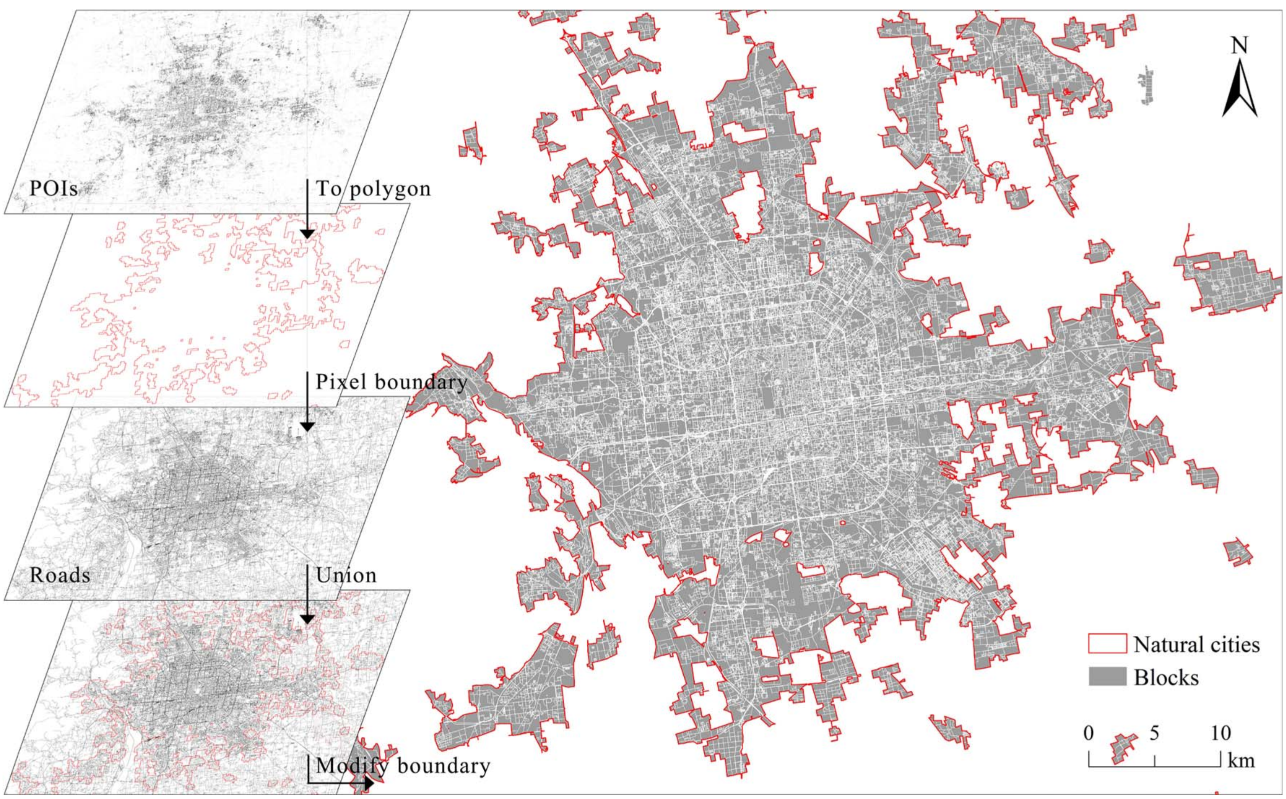


**Fig. 3.** Processing of determining natural cities.

of determining the boundary of urban central regions that generates a natural city by using the cumulative distribution function (CDF) of POIs density. The first step is to calculate POI density and generate a POI density map with kernel density functions with the spatial resolution of 500 m (search radius 1 km). Then, the boundary of the central urban regions is defined where the local POI density exceeds 50 points/km$^2$. Third, the redefined city area is at least 2 km$^2$, which presents the urban central regions of administrative cities. Fourth, based on the ArcGIS 10.5 software platform, the method of overlay analysis is used to further modify the urban boundary by using road network data. If the intersecting area is larger than 50%, it is defined as an urban interior block area. Otherwise, it is defined as a nonurban block area in the natural city. Fig. 3 shows the spatial distributions of POIs, preliminary boundary, road networks, and ultimate natural urban boundary in Beijing.

In order to better distinguish redefined natural cities, they can be renamed according to the original administrative division city by formulating a set of renaming rules:

- Natural cities in MDs or PLCs follow Rule a. Within district-level administrative units, the natural city with the largest area is renamed XXmain-city, with XX being the administrative city name (the main urban area, e.g., Beijing main-city); other natural cities are renamed XXcityXXdistrict 1, 2, 3…, with the second XX being the name of the original district (e.g., Beijing city Haidian district) and the number being the city's ranking by area.
- Natural cities in a CLC or county follow Rule b. In county administrative units, the natural city with the largest area is renamed XXmain-city (in CLC) or XXmain-county (in county) with XX being the current administrative name; other natural cities are renamed XXvice-city (in CLC) or XXvice-county (in county) 1, 2, 3… sorting by the city area.

If the PLC is not divided into districts (a city without districts), the renaming rules shall be implemented with regard to Rule b; special administrative units, such as autonomous-prefecture or autonomous-banner, also reference Rule b.

### Identifying Shrinking Cities

The preprocessing of the nightlight data before identifying shrinking cities used the PIF method (Wei et al. 2014) to calibrate NPP-VIIRS data for 2013 and 2016. Due to seasonal climate changes and weather-driven differences in human routine, remote-sensing images from May to September were not effective in northern and southwestern China. The annual average nightlight intensity value was obtained by selecting NPP-VIIRS raster data for 7 months (January to April and October to December). In order to make the nightlight data in 2013 and 2016 comparable, we determine the brightest areas and the performed dark area to carry out correction on the grid map. The downtown area or commercial concentration regions are regarded as the brightest areas to determine the maximum intensity values of the nightlight. The intersection of the national protected area and the nature reserve was used as a dark area to determine the minimum intensity values of the nightlight. The city center areas, national reserves, and wilderness were combined as PIFs for the smoothing correction in 2013 and 2016. Then, the corrected nightlight data achieve continuous floating values after a mask of China's border.

On the basis of redefined natural cities, we identified the shrinking cities by corrected NPP-VIIRS data during the three-year period 2013–2016. The average value of raster data or vector data within each natural city was stored in the polygon, and the ratio of changes between the initial year and the cutoff year of nightlight was identified in the shrinking cities. Referring to previous research standards for identifying shrinking cities (Zhou et al. 2019) and considering the urban development phenomenon of natural fluctuation the study utilized 10% of the original year average nightlight intensity changes as the threshold to divide shrinking and nonshrinking cities. We defined the average nightlight intensity changes of NPP-VIIRS data in 2013 and 2016 as less than −10% [(nightlight intensity (2016–2013)/2013) × 100%] in a natural city as a shrinking city, and ratio >−10% as a nonshrinking city. With the same threshold value (−10%), we also used population data in 2013 and 2016 to compare the results of different data sources and potential connections between them.

### Categorizing Patterns of the Identified Shrinking Cities

Previous studies used empirical judgments or classified urban contraction types by identifying spatially presented patterns of concentrated areas of idle land and population loss over a small scale (Li and Mykhnenko 2018; Li et al. 2018). As far as we know, there is no quantitative method to judge the shrinkage patterns of a large number of cities at the same time. Based on identifying the shrinking cities in China, we purposed the spatial analysis of multivariate urban datasets to divide the shrinkage patterns into categories. At the city level, we identified shrinking cities if the change of nightlight data in 2013 and 2016 was lower than −10%. At the pixel level (430 m × 430 m resolution on raster images), a shrinking pixel was identified with a nightlight intensity variation of less than −10% inside the shrinking city, and then the shrinkage pattern of the shrinking city was determined by judging the spatial distribution characteristics of aggregation and dispersion of the shrinking pixels.

Fig. 4 is the flow chart of the division of shrinkage patterns. It can be seen from the figure that we divided the shrinkage patterns

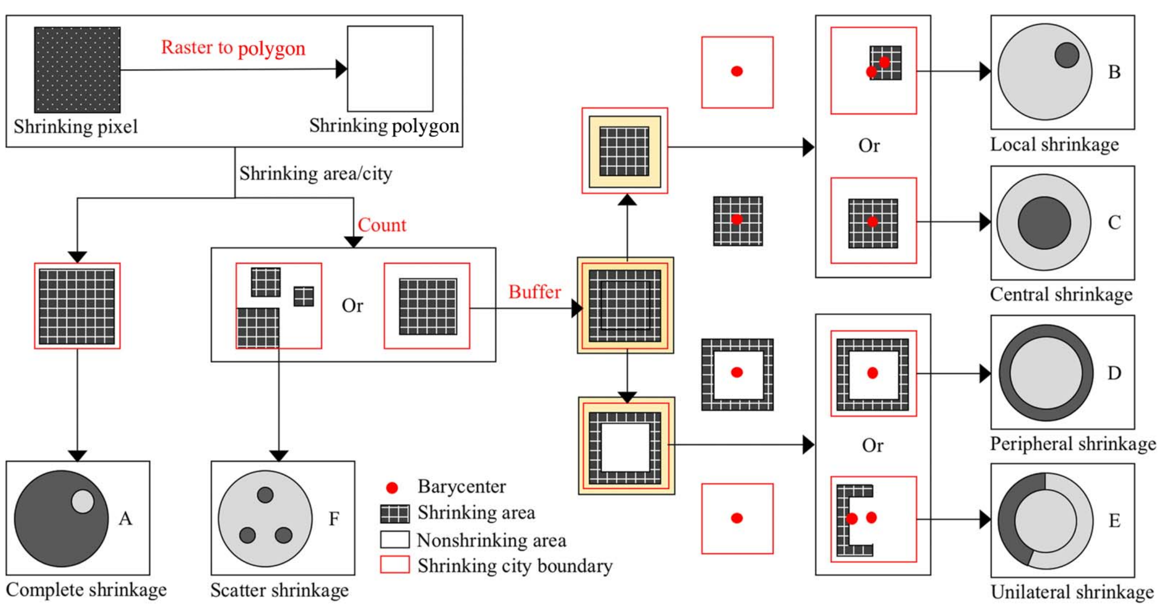


**Fig. 4.** Classification process of shrinkage patterns.

into six categories. Before classification, the grids of shrinking pixels were converted into polygon storage changes of nightlight intensity values with fusing raster images. This helped to carry out the quantitative classification of subsequent shrinkage patterns. First, if the proportion of the shrinking region to the shrinkage city was more than 80%, that can be judged as pattern A, complete shrinkage. If the shrinking city has more than two shrinking regions (there are more than two polygons), it is defined as pattern F, scatter shrinkage. Other than these two, the remaining shrinking polygons generated buffers of one-quarter radius distance (the average distance) from the geometric center of gravity of the city to the boundary. It was then determined whether there was an intersecting region between the buffer and the urban area. If the buffer area was still inside the shrinking city (no intersection), it was either pattern B or C, local shrinkage or central shrinkage. On the contrary, if the buffer area surpassed the boundaries of shrinking city (intersection), it was either pattern D or E, peripheral shrinkage or unilateral shrinkage. This means that patterns B and C exist in the urban center, patterns D and E exist in the urban fringe. Further, we distinguish the shrinkage patterns B from C, and D from E, by calculating the relative distance between the barycenters of the shrinking region and the shrinking city. If the distance is less than a quarter of the radius, the shrinking city belongs to pattern C or D, otherwise pattern B or E. Owing to the limitations on pixel number and resolution, for smaller shrinking cities there are fewer pixels in the city interior; therefore, the shrinkage pattern cannot be accurately determined by quantitative spatial relations. We also manually calibrated and corrected the results in accordance with the municipal yearbooks.

### *Quantitatively Identifying Reasons Behind Shrinking*

The reasons for urban shrinkage are complex and diverse, and include economic factors, social factors, ecological environmental factors, and national policy orientation. Moreover, there may be interaction effects and mutual causalities among various factors (Hartt 2018). Owing to the limitations of data acquisition, based on census data, economic data, and urban built-up area, previous research has divided the causes for the shrinking of Chinese cities into four categories classified as resource depletion, traditional industrial cities, population migration and adjustment of administrative division (Long et al. 2015), or into three categories classified as incontrollable expansion, depopulation, and regional drainage (Jiang et al. 2016). Considering the reason for urban shrinkage is intricate, the results for each shrinking city usually stem from several different contributing factors.

Using multisourced data, we present six possible reasons for each shrinking city by quantitative statistics: economic status, population trends, social infrastructure, municipal yearbooks, geographical location, and natural city area. In view of simplifying the threshold analysis process, a 10% threshold has commonly been selected in previous studies to determine that a factor is a possible cause of urban shrinkage (Oswalt and Rieniets 2006; Zhou et al. 2019). Using basic data and renaming rules (Fig. 5) to analyze the shrinking city with a larger area of shrinkage, five reasons for urban shrinkage are identified. The shrinking cities named XXmain-city or XXmain-county are successively selected to determine reason I, economic recession, where the nightlight intensity in 2016 is less than 10% of the average. Next, where the population density in 2016 is less than 10% of the average, that is considered reason II, population drain. Similarly, where the population density in 2016 is less than 10% of the average POI density (2016), this is expected to be caused by the inadequate social service facilities, as reason III. In addition, if a shrinking city that is among the 130 old industrial-based cities (including 95 PLCs, and 25 municipal districts) affected by the "National old industrial base adjustment and transformation plan" promulgated in 2013, its shrinkage is judged to be caused by reason IV, industrial decline (rust-belt cities). Likewise, if a shrinking city is among the 262 resource-based cities (including 126 PLCs, 62 CLCs, 58 counties, and 16 municipal districts) affected by the "Notice on sustainable development planning of national resource-based cities" released in 2013, the leading cause of shrinkage is considered to be reason V, resource exhaustion.

The reasons for a shrinking city with small-scale or unsound data cannot be determined through these treatments. These shrinking cities have a low elasticity development and self-repair ability, and are mainly supported by the development of the surrounding large cities. In this research, we named this dependency on the growth

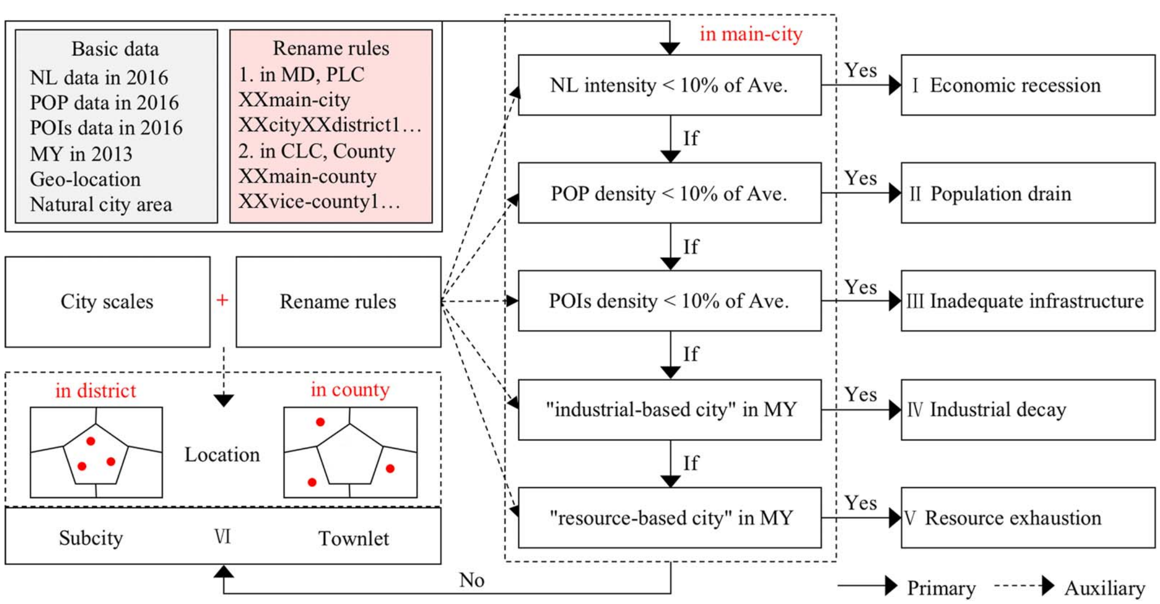


**Fig. 5.** Classification process to identify the reasons for shrinking cities. Note: NL = NPP-VIIRS nightlight data; POP = LandScan population data; POIs = points of interests; MY = municipal yearbooks; and Ave. = average value.

of the XXmain-city or XXmain-county as reason VI (Fig. 5). For the shrinking cities that are renamed as XXcityXXdistrict or XXvice-city, the reason for their shrinkage is defined as Subcity. For those renamed as a XXvice-county, the reason is defined as a Townlet.

## Results

### Redefined Cities Interpreted from POIs and Roads in 2016

Based on the POI and roads data in 2016, we finally redefined 2,862 natural cities in China, as shown in Fig. 6. These natural cities contain China's prefecture-level and county-level administrative cities, covering an area of 53,275 $km^2$, accounting for about 0.5% of the national territory. Among these natural cities, 149 are in the MDs, 885 in the PLCs, 646 in the CLCs, and 1,182 in the county. Compared with the current official cities, the number of natural cities is obviously larger, and there is more than one natural city in some administrative cities. The higher the city administrative levels, the more natural cities that are identified. The cities with the largest number of natural cities are Shanghai (47), Beijing (42), and Chongqing (35). Natural cities are unevenly distributed between the eastern and western parts of China. Larger natural cities are mainly concentrated in the eastern coastal areas, while natural cities in western regions are relatively small, which is the opposite of the traditional administrative city areas.

We have further focused on the three urban agglomerations of Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Pearl River Delta, which are considered to be the most urbanized regions in China (Fig. 6). There are 189, 377, and 145 natural cities with areas of 4,542, 9,981, and 6,326 $km^2$, respectively. One of the largest natural cities is 3,283 $km^2$, located in the Pearl River Delta, stretching over Guangzhou, Zhongshan, Foshan, and other cities. The second largest natural city, with an area of 2,127 $km^2$, is located within the administrative scope of Shanghai; the third is situated in the administrative area of Beijing, with an area of 1,961 $km^2$. The spatial distribution of the Beijing-Tianjin-Hebei urban agglomeration indicates that the two core cities (Beijing and Tianjin) have promoted the development of surrounding cities that are identified as independent natural cities. The Yangtze River Delta and the Pearl River Delta urban agglomerations display a clustered multipolar development, resulting in a large natural city across several administrative cities.

Fig. 7(a) reveals a gradient variation where the number of natural cities decreases with an increase in area. The area of 2,209 natural cities is between 2 and 10 $km^2$, accounting for 77.2% of all natural cities. There are 585 natural cities (20.4% of all) in the 10–100 $km^2$ interval, 62 natural cities (2.2% of all) in the 100–1,000 $km^2$ interval, and 6 natural cities (0.2% of all) with an area of over 1,000 $km^2$. The study verified the reliability and effectiveness of the number of natural cities, referring to Zipf's law (Jiang and Jia 2011; Wu et al. 2018b). The results depict a significant power function relationship between the number of natural cities and the natural city area. The coefficient of determination ($R^2$) is 0.98 [Fig. 7(b)]. In urban areas in the range of less than 100 $km^2$ in particular, natural city areas and number are a better match.

### Identified Shrinking Cities by 2013–2016 NPP-VIIRS Data

Using NPP-VIIRS data from 2013 to 2016, the 798 shrinking cities with a total area 13,839 $km^2$ were identified from 2,862 natural cities. About 28.4% of natural cities have indicated the shrinking phenomenon, including 23 shrinking cities in MDs, 221 in PLCs, 175 in CLCs, and 379 in the county. Fig. 8 shows the spatial distribution of three levels of shrinking ratio in China. Shrinking cities have a centralized distribution in the Yangtze River Delta, the Pearl River Delta, the Liaodong Peninsula, the Chengyu Agglomeration,

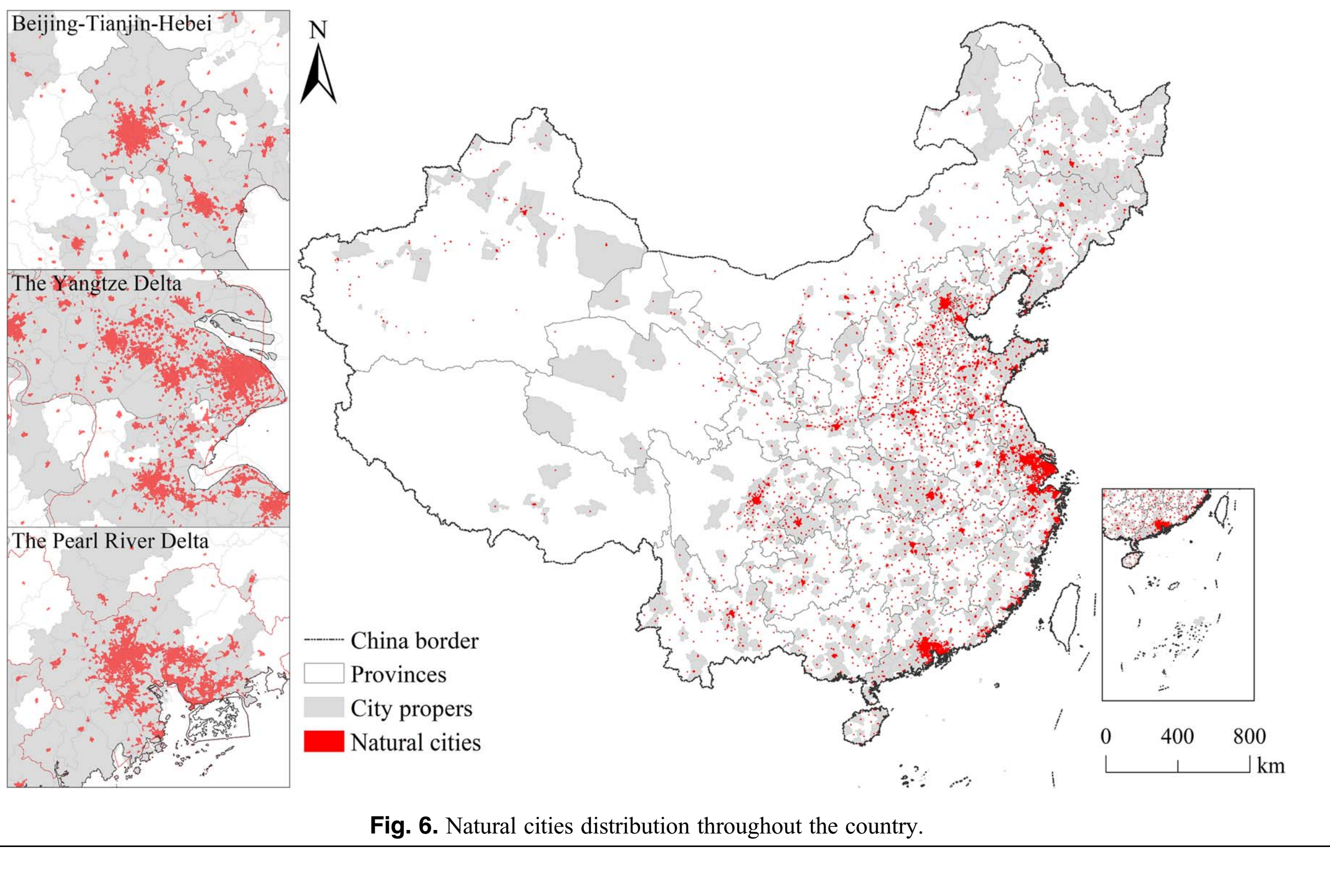


**Fig. 6.** Natural cities distribution throughout the country.

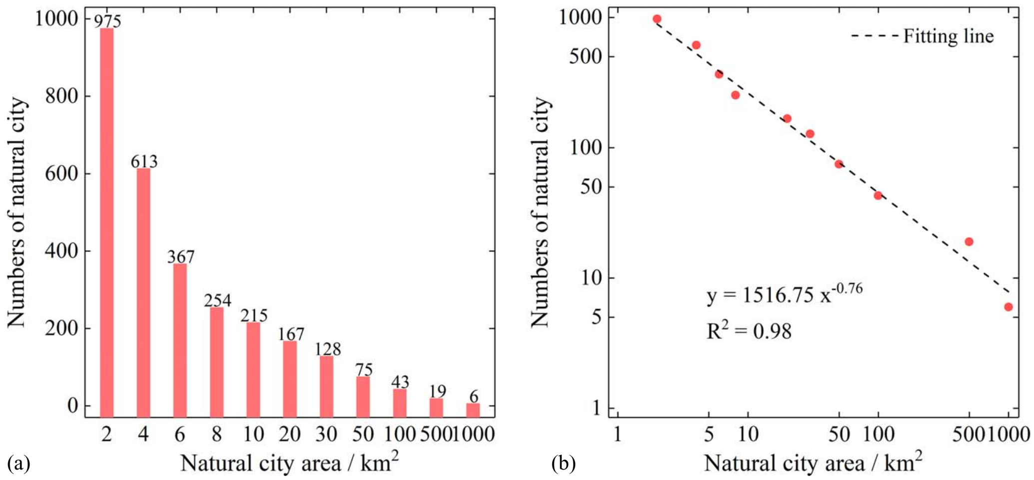


**Fig. 7.** (a) Relationship between natural city areas and the numbers of natural cities; and (b) linear regression between the natural city areas and the numbers of natural cities.

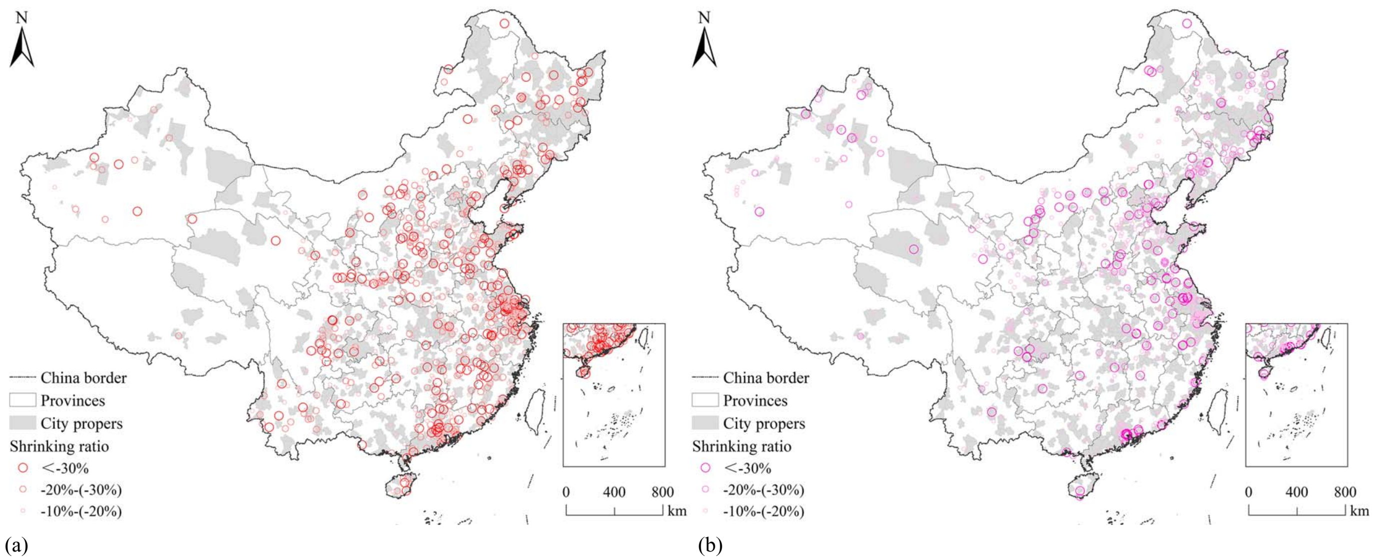


**Fig. 8.** (a) Shrinking cities with the shrinking ratio in nightlight data; and (b) shrinking cities with the shrinking ratio in population data. Note: Shrinking ratio = (nightlight intensity or population density (2016–2013)/2013) × 100%.

and the Guanzhong Agglomeration. Within the urban agglomerations, there are 481 shrinking cities with a total area of 9,125 km$^2$; and in the three urban agglomerations of Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Pearl River Delta, there are 32, 135, and 49 natural cities with an area of 482, 2,378, and 1,406 km$^2$, respectively. At the same time, with a ratio of the same period of population data (2013–2016), the spatial distribution characteristics of the shrinking cities are consistent with the NPP-VIIRS data.

Fig. 9 indicates that the number of shrinking cities was higher when we applied NPP-VIIRS nightlight data identification rather than employing LandScan population data. Through the 2013–2016 nightlight data, 798 shrinking cities were identified, of which 356 shrinking cities showed mild shrinkage with a shrinkage ratio between −10% and −20%; 253 shrinking cities showed moderate shrinkage with a shrinkage ratio between −20% and −30%; 189 shrinking cities showed severe shrinkage with a shrinkage ratio below −30%; and 2,064 nonshrinking cities (shrinkage ratio >−10%). Using population data from 2013 to 2016, 381 shrinking cities were found, of which 194 were between −10% and −20%, 107 were between −20% and −30%, 79 were below −30%, and 2,482 were nonshrinking cities. Through regression and correlation analysis between different sources in nightlight and population data, it was also found that all natural cities or shrinking cities do not show a significant correlation. In other words, the impact of population data on the shrinking cities identified by nightlight data is of dual character.

A shrinking city is not determined by one single factor, but the result of a combination of various factors. For example, although the population of natural cities on the eastern coast of China has increased, the urban environment has not been optimized over time, and the infrastructure has not been improved simultaneously, thus the urban function improvement has not matched the corresponding population increase. These are also the products of China's disorderly extensive urbanization, in which urban social-economic development is inversely proportional to the population (Du and Li 2017), resulting in excessive development, wasting of resources or insufficient development, and poor quality of daily life. Similar to Jiang et al.'s (2016) conclusion, the urban built-up areas have increased by 113%, while the total population of urban districts has only increased by 55%; thus, the urban expansion rate is twice the rate of population growth. Incremental development has led to the uncontrolled expansion of urban construction land in China; that is, the artificial disorderly expansion has intensified the shrinkage phenomenon.

The process of identifying shrinking cities in nightlight data (economic development) and population are not synchronized, which also confirms the theory/hypothesis of the three stages of increasing population, economy, and quality of space (Long 2019): the partial population is lost, but the economy and urban areas are still developing and expanding continuously; then, a large number of people are lost, resulting in labor shortages and declining vitality, which, in turn, causes an economic downturn; living space is gradually decayed by the combined impact of population and economic decline. They interact as both cause and effect. In general, when the city shrinks to the third stage (later stage of development in shrinking cities), population, economy, and urban space are destroyed at the same time.

### *Shrinkage Patterns Classification*

In order to identify the internal dilapidated space of the shrinking cities, we determined the shrinking area of the spatial distribution and the shrinking ratios at the pixel level, which helped us to quantitatively define shrinkage patterns. The natural city method we have defined in the Chinese context allowed us to analyze the basic geographic morphology attributes of shrinking cities, including the layout and patterns of shrinkage within each urban area. Fig. 10 depicts the distribution of the six shrinkage patterns across

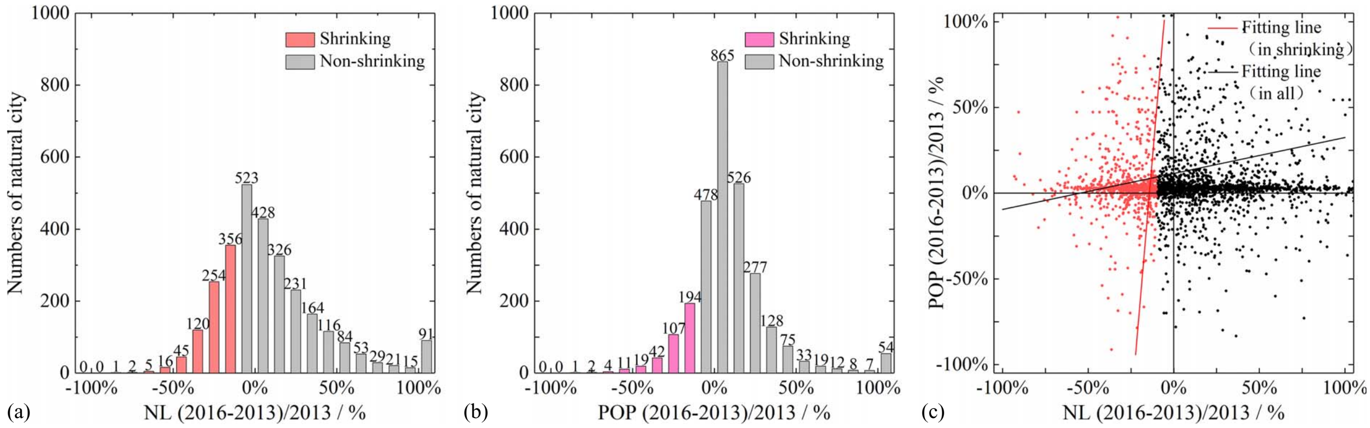


**Fig. 9.** (a) Relationship between the shrinkage ratio and the numbers of the shrinking cities in NL; (b) relationship between the shrinkage ratio and the number of shrinking cities in POP; and (c) linear fitting between nightlight and population data. Note: NL = NPP-VIIRS nightlight data; and POP = LandScan population data.

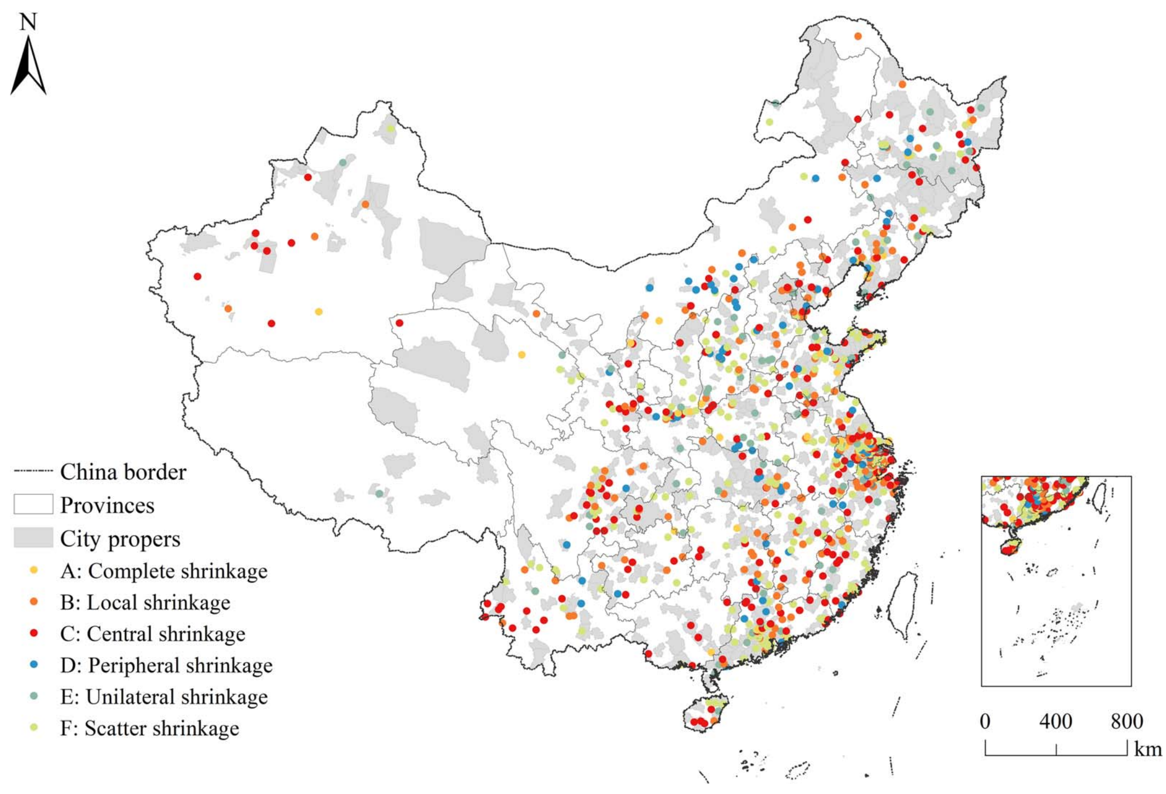


**Fig. 10.** Distribution of shrinkage pattern in China.

**Table 2.** The patterns of shrinkage in shrinking cities

| | Renamed shrinking cities (only in XXmain-city) | | |
|---|---|---|---|
| Shrinkage patterns | Mild shrinking | General shrinking | Severe shrinking |
| Complete shrinkage (32, 4%)[a] | Liuyang | Qingtongxi, Xingping | Liaoyang, Yongji |
| Local shrinkage (173, 21.6%) | Chibi, Zhangshu, Xinghua, Anshan, Huaihua, Jiaozhou, Xichang | Gaizhou, Bazhong, Changning, Hegang, Shaowu, Shenzhou | Nanping, Kaili, Maoming, Langzhong, Huixi'an |
| Central shrinkage (158, 19.8%) | Zaoyang, Lianzhou, Laizhou, Guigang, Jinggangshan, Nanyang, Taicang, Taizhou, Tianshui, Rugao, Laibin | Wuzhishan, Yantai, Ala'er, Kaiyuan, Xianyang, Suifenhe, Baishan, Huizhou | Fengzhen, Beizhen, Hongjiang, Lingbao, Muling |
| Peripheral shrinkage (76, 9.5%) | Chenzhou, Yingkou, Hejian, Huolinguole, Qian'an, Xi'an, E'zhou, Qitaihe, Changzhou | Yingde, Ji'an, Suihua, Shouguang | Bayannao'er, Siping |
| Unilateral shrinkage (122, 15.3%) | Lechang, Longyan, Sanhe, Fushun, Huazhou | Yong'an, Hailin, La'sa, Wuchang | Yichun, Manzhouli, Jixi |
| Scatter shrinkage (237, 29.7%) | Zixing, Fuqing, Guixi, Weinan, Zhucheng, Aletai, Chuzhou, Haimen, Jieyang, Nanjing, Huadian, Dangyang | Zhongshan, Luoding, Lushui, Daqing, Shangrao, Yangjiang, Shuangyashan, Hezhou, Panzhihua, | Shaoshan, Fengcheng, Zhaoqing, Dongguan, Huangshan |

Note: The city names listed in the table are the redefined natural city names instead of the administrative city names. Shrinking cities are ranked by shrinkage ratio from large to small.
[a]The number of shrinking cities and their proportions in matching reason.



China, and Table 2 lists the renamed corresponding identified shrinking cities in XXmain-city.

There are 32 shrinking cities for pattern A, complete shrinkage. These are facing a comprehensive dilapidated situation, and most of these cities are located in small and medium areas. There are 173 shrinking cities in pattern B, local shrinkage. This formation is usually accompanied by the completion of major events and projects and the relocation of large industrial factories. There are 158 shrinking cities for pattern C, central shrinkage; they rapidly expand to the periphery, and the old downtown is not energetic, and its attraction is declining. Some 76 shrinking cities are in pattern D, peripheral shrinkage. In these shrinking cities, the residents of the surrounding area move into the center, or the resources around the city are limited. There are 122 shrinking cities in pattern E, unilateral shrinkage. Owing to natural obstruction or limited development, these cities expand in the opposite direction. A total of 237 shrinking cities are in pattern F, scatter shrinkage. This means that an unbalanced urban development leads to a reduction in more than one commercial point, or the overall migration of settlements to other places due to demolition.

### *Shrinking Reasons Summarization*

We also classified China's shrinking into six categories according to the shrinkage reasons: economic recession, inadequate service, population drain, industrial decay, resource exhaustion, and subcity and townlet. The number of shrinking cities caused by the mentioned reasons are 293, 275, 228, 121, 85, and 154, respectively. There are four possible reasons for about 6% of shrinking cities, and there are at least two reasons for 40% of shrinking cities. Since urban shrinkage is usually not caused by a single reason, in some cases, a shrinking city corresponds to multiple reasons (Hartt 2018; Khavarian-Garmsir et al. 2019).

From the analysis results previously presented, the proportion of shrinking cities under the influence of economic development is the largest, which stems from China's rapid development stage and the tendency of policies to gradually enlarge the imbalance of regional development (Long et al. 2015). The rapid development of a few large cities has attracted an influx of people from many small cities, and the large outflow of small and medium-sized cities has led to insufficient economic development and a decline of labor absorption, which has driven further shrinkage of the city (García-Ayllon 2016; Xie et al. 2018). With the development of the society and the economy, the improvement of people's living standards and changes in values have led to a city's livability increasingly replacing simple economic growth as a core component of urban competitiveness (Schwarz and Hoornbeek 2012). The livability of the city is mainly reflected in the improvement of its infrastructure and social services. Therefore, social services have a certain impact on China's urban contraction. Although the number of shrinking cities caused by the industrial recession and resource depletion is relatively small, according to existing research (Du et al. 2018; Zhao et al. 2017), its shrinking amplitude is relatively large, so it is a typical Chinese shrinking city. The outflow of the population is usually the ontological mark of the reduction of the total urban population and urban shrinkage.

## Conclusions and Discussions

In this paper, we have studied the shrinking cities in China by redefining natural cities, identifying shrinking cities, classifying the patterns of shrinking cities, and trying to summarize the causes of shrinkage. The study provides an approach to identifying shrinking cities in a globally applicable model, based on NPP-VIIRS nightlight data in a period of three years. In detail, we used POIs and road network data and redefined 2,862 natural cities in China. Compared with administrative cities, using natural cities for identifying shrinking cities in China is more in line with Zipf's law. Furthermore, we identified 798 shrinking cities by nightlight data, and categorized them into mild, general, and severe shrinkage levels. Among them, 189 severe shrinking cities should be the focus of future urban planning. Further, China's urban agglomerations are the regions with the highest levels of urbanization. They cover about 65% of the number and 75% of the area of all natural cities. Urban agglomerations are also the areas with a highest degree of urban shrinkage, covering about 60% of numbers and 67% of the area of all shrinking cities. While reasonably meeting the requirements of urban area construction, more attention must be paid to the mismatch between expansion planning and urban shrinkage. There are spatial differences in the shrinkage patterns, which also correspond to different stages of development. When the city had begun to shrink, the dilapidated space appeared in a local area of the city, or the expansion outside the city led to insufficient vitality in the old city center, or people flowed into the city center causing urban peripheral shrinkage. Next, with some declined conventional business, the city shrunk simultaneously in multiple places. Finally, the city lost its ability to self-regulate and led to overall shrinkage. In addition to economic and social factors, especially in China, many cities rely on natural resources for development and are guided by national policy orientation. By judging the types of shrinkage patterns and summing up the shrinking reasons, an effective planning strategy to guide smart shrinking development can be proposed.

In contrast to previous studies based on traditional statistical data to define shrinking cities at the administrative city level, we utilized the natural city as a benchmark, which is more compatible with the inherent structure of spatial entities, thus providing an alternative way of widely and precisely depicting the latest distributional characteristics of shrinking cities. The redefined natural city exceeded the limitations of the independent development of multiple urbanization areas within the administrative city and will help to explain the evolution of each natural city. We then identified the shrinking cities based on the natural cities through the transformation of the nightlight data for the period 2013–2016, visualizing the shrinkage ratio at both city and pixel levels. The urban nightlight data has been verified as an efficient and time-sensitive data type for urban studies. It allows for accurate capturing of shrinking cities to guide future cities to carry out smart shrinkage, flexible planning, response strategies, and development direction. Furthermore, previous studies have paid more attention to the number and distribution of shrinking cities and did not delve into the internal morphology in each shrinking city. This study identified the areas of shrinkage within the city through quantitative methods and classified the shrinkage patterns. The results can effectively track the shrinking characteristics and differences of human activity space inside the city, thus conducting the city's renewal and recovery, and structural adjustment.

In addition, there are several deficiencies in the work that need to be improved. Due to the limited resolution and time-effectiveness of the nightlight data products, a few grid values can represent the nightlight intensity in a small natural city, and the identified shrinking cities can only be considered as the typology of temporary shrinkage; compared with the results of the LandScan data at the same time, the distribution of shrinking cities is commonly consistent, but the divergence in resolution affecting the number and proportion are significantly less than the NPP-VIIRS data. Despite problems such as data parsing and asynchrony, our exploration of redefining natural cities, identifying shrinking cities, and categorizing shrinkage patterns indicates the potential to act as a new reference for urban shrinkage research. As data products are updated and refined, we will extend the study period to more accurately define shrinking cities.

With the dynamic process of development, a city's socioeconomic and population changes, infrastructure construction, and related policies are out of sync to a certain extent. In brief, the urban shrinkage phenomenon not only caused the decline and reorganization of the physical space, but also led to the collapse and reconstruction of the social network, which should attract the attention of policymakers and urban planners. While comprehending the impact of urban shrinkage on material space, we should also focus on the social space problem behind it, explore the mechanism of urban shrinkage and its planning response strategy, and achieve urban sustainable development.

## Data Availability Statement

The data produced by this research are available online at Beijing City Lab (www.beijingcitylab.com).

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