Identifying City Shrinkage in Population and City Activity in the Middle Reaches of the Yangtze River, China

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Abstract: In the context of globalization, cities have undergone a polarization of growth and shrinkage. Urban shrinkage is typically measured by a decrease in population. However, city activity is usually ignored. Accordingly, this study measured city shrinkage in the middle reaches of the Yangtze River based on whether city activities and population shrank from 2000 to 2010. This study drew on the Cobb-Douglas production function using multiple big data [such as nighttime light (NTL) data, patent data, and land transaction data] to calculate a city activity index to examine city activity. The geographically weighted regression (GWR) model was applied to explore the influencing factors of city shrinkage. Results showed the following: (1) in the area of study, 14.87% of cities experienced population loss, considering the city activities, an increase in the latter accounted for 57.36% in depopulation cities; (2) urban shrinkage spatial pattern presented the feature of "overall growth, local shrinkage"; (3) in the urban shrinkage regression model, urban spatial expansion and the increase in secondary industry population were factors that aggravated urban shrinkage. The main influencing factors of city shrinkage in the regions are different and need to be studied in-depth and meticulously in combination with the local development situation. This study plays a vital role in characterizing city activities and identifying urban shrinkage while providing a reference for urban planning and policy setting. **DOI: 10.1061/(ASCE)UP.1943-5444.0000593**. *© 2020 American Society of Civil Engineers*.

Author keywords: Shrinking cities; Big data; City activities; Urban agglomeration; China.

Introduction

Globalization has led to a rapid flow of economic factors and a continuous spread of economic activities (Smith 2010). In the process of globalization, cities have undergone polarized growths and shrinkages (Danko and Hanink 2018; Galster 2019; Khavarian-Garmsir et al. 2018; Lee et al. 2018; Reis et al. 2016). The migration of capital and industry along with a subsequent decline in employment, impoverishment of the population, disintegration of communities, and other changes in the economic structure contribute to the emergence of urban shrinkage. Urban shrinkage is the new challenge of urban development and planning. Urban shrinkage has been proven to be a very diverse and complex phenomenon. Some scholars described city shrinkage as population loss (Hollander 2009), a sudden increase in unemployment, an increase in abandoned houses (Rhodes and Russo 2013), a decline in the quality of community life, recession and social instability, or low levels of innovation and intellectual engagement (Martinez-Fernandez et al. 2012b). Population loss is regarded as the core indicator of urban shrinkage (Long et al. 2015). Existing multiple criteria describe how population shrinkage could be defined as city shrinkage (Delken 2008; Schilling and Logan 2008; Wu and Long 2015).

City shrinkage is not an isolated phenomenon, but a growing global concern (Zhang et al. 2019). In different local contexts, the causes and characteristics of urban shrinkage also vary (Grossmann et al. 2013). The shrinkage of the American rust belt and Europe's old industrial cities is characterized by marked population loss and economic decline (Pallagst et al. 2017; Schwarz et al. 2018; Shetty and Reid 2014). Other countries such as China have seen the shrinkage of resource-exhausted cities (e.g., the industrial base in northeast China), the short-term shrinkage of industrial transformation and upgrading cities (e.g., some cities in the Pearl River Delta and Yangtze River Delta), and the shrinkage areas around big cities (e.g., Beijing, the capital of China). One-third of China's cities are experiencing population shrinkage (Long and Wu 2016) alongside rapid urban expansions and growing urban economic vitality (Du and Li 2017, 2018). The same paradox in the country's urban economy and population also occurred in some of Germany's cities (Bartholomae et al. 2017). These two different local situations illustrate key information: the uncoupling of economic wealth and population growth (Wiechmann and Pallagst 2012), that is, economic growth was insignificantly affected by population shrinkage in some cities (Jin and Management 2018). Population loss is the only indicator by which to identify urban shrinkage in the existing studies while potentially ignoring certain socioeconomic issues (Beauregard 2009). Few studies have sought to reveal the relationship between the changes in population and socioeconomics among cities (Monsson 2014).

City activity is a necessary factor of a "successful" urban space (Jin et al. 2017). City activity is described as the interaction

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between people and cities, that is, the activity of production and lifestyle in the city. Lefebvre's theory of urban space production focuses on urban activities and their frequency as a way of understanding the essence of urban space (Ruddick 1987). Urban activity should be regarded as the important socioeconomic indicator of identifying urban shrinkage. Additionally, some scholars have undertaken shrinkage type identification research according to the intensity and durativity of population loss (Alves et al. 2016; Martinez-Fernandez et al. 2016; Turok and Mykhnenko 2007), whereas attention to the prediction of possible shrinkage in cities has been limited. Extensive studies on urban shrinkage have typically been conducted at administrative city level, whereas studies using big data to identify shrinking cities on urban patches at a small scale are scant.

In this study, we first collected and processed data on a built-up urban area, population, NTL, land transaction, and patent of 341 cities from 2000 to 2010. We calculated the values of city activities by using the Cobb-Douglas production function. We then identified urban types (including urban shrinkage) based on whether city activities and population shrank or grew. GWR was chosen to identify the relationships between urban shrinkage size and influencing variables and address spatial heterogeneity. Finally, we analyzed the spatial distribution characteristics and the quantitative structure of different types, which are the influencing factors affecting urban shrinkage. This study aims to address the following issues: (1) How does city shrinkage identification results differ when considering the city activity? (2) What type of spatial distribution patterns do city shrinkage present in the middle reaches of the Yangtze River in China from 2000 to 2010? (3) Which factors affect the size of a shrinking city, and does the degree of impact occur as spatial nonstationary? The findings will contribute to the literature on quantifying urban models and provide a reference for urban development and planning policy setting.

This paper is structured as follows. The following two sections discuss the study area and the necessary dataset used in the study, respectively. The next section describes the adopted methodology. The analysis results are described in the penultimate section. The final section provides discussion and concluding remarks on this study.

Study Area

In China, administrative regions are broken down and subdivided into province–city–county–town. Cities include municipalities directly led by the nation, subprovincial cities, other provincial cities, prefecture-level cities, and county-level cities. Within the Chinese administrative division system, a prefectural-level city (di ji shi) ranks below a provincial-level unit but above county-level units [see (Chen 2016) for a comprehensive review of the Chinese planning and administrative system]. A prefectural-level city usually comprises core urban districts and their surrounding region, which includes districts, county-level cities, counties, towns, and/or other subdivisions (Liu and Wang 2016). In addition, counties and some large-scale towns are also viewed as "cities" from the perspective of the city as a functional entity (Long and Wu 2016). Notably, this study defines cities according to the extent of their built-up area rather than by their administrative or jurisdictional boundaries. The current study area comprises the cities in the middle reaches of the Yangtze River in central China (Fig. 1). This agglomeration includes four provincial cities, 55 prefecture-level cities, and 282 county-level cities, as such providing a rich sample with which to study the growth, shrinkage, and other types of cities. Urban development patterns that emerged between 1995–2005 and 2005–2015 vary due to different policies with different purposes (He et al. 2017a). The current study takes 2000–2010 as its research period to compare the cities' different patterns of development.

Data and Processing

With the rapid development of ICT technology, substantial data-driven urban computing and analytics have become essential in tackling fundamental issues. This study uses data pertaining to built-up areas and emerging geographic datasets in 2000–2010. The latter includes China's Population Grid Data, nighttime light data, land transaction data, and patent data. Fig. 2 shows the samples of data processing.

1. Built-up urban area data (Chinese Academy of Sciences 2010b). Urban built-up areas were extracted from the National Land Use/Cover Database (NLUD-C). The verified NLUD-C

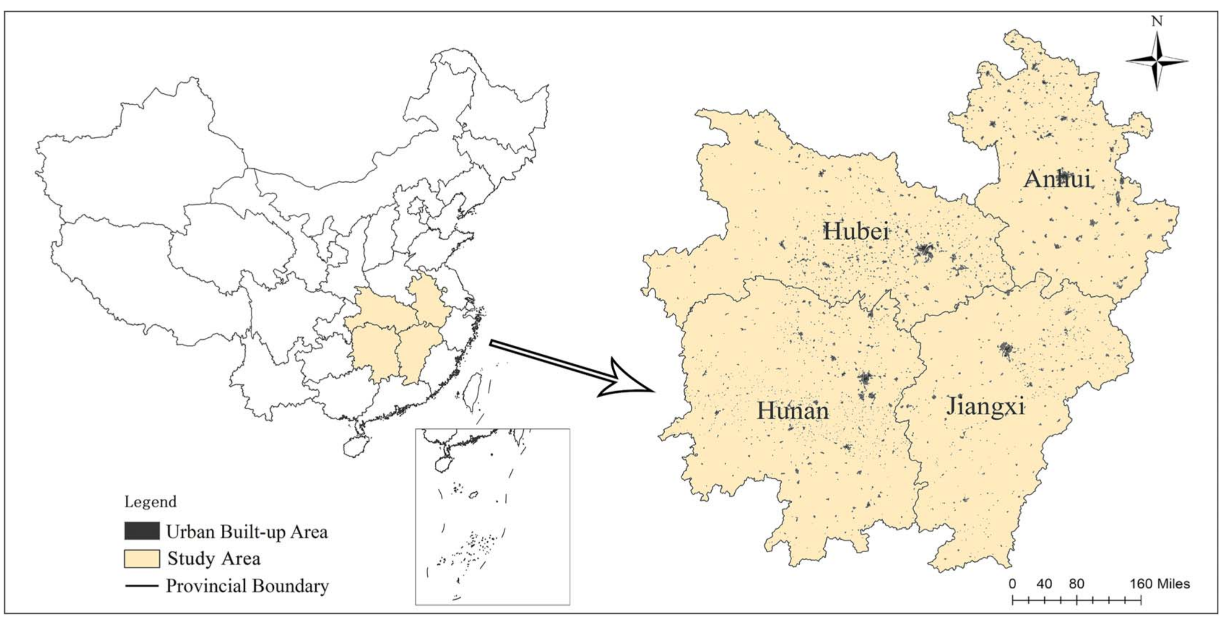

Fig. 1. Cities in the middle reaches of the Yangtze River in 2010.

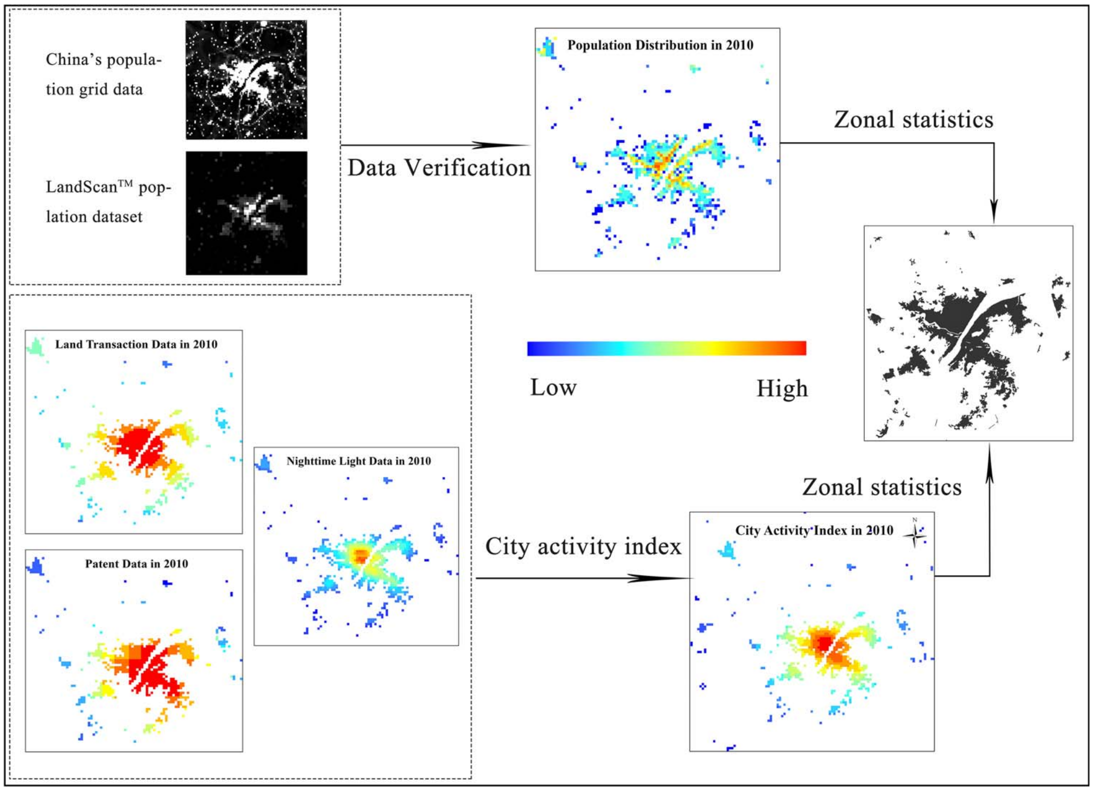

Fig. 2. Data processing samples.

classification accuracy is over 90% (Tan et al. 2014). Built-up areas with an area of less than 3 km^2 were generally considered rural residential areas (Yang et al. 2015), which were not within the scope of the study area and were thus removed.

2. Population distribution data (Chinese Academy of Sciences 2000, 2010a). LandScan High Resolution Global Population Dataset (Dobson et al. 2000) estimates population distributions at a 30×30 arc-second (<1 km) resolution. China's population grid data (CAS) have been generated using a multifactor weight distribution method that comprehensively considers land use type, residential density, and other factors.

   Within the study area, the authors aggregated LandScan and China's population grid data to the county level, using China's census data (National Bureau of Statistics 2001, 2011) as a basis for testing. Spearman correlation coefficient assesses how well the relationship between two variables can be described by using a monotonic function and is appropriate for continuous and discrete variables, including ordinal variables. It was used to test the correlation between LandScan, China's population grid data, and China's census data. In the test, if the correlation was significant, LandScan, and China's population grid data could be considered reliable. From the results of the Spearman correlation coefficient test (Fig. 3), the correlation between China's population grid data and the census data was slightly higher than the correlation between LandScan and the census data. Therefore, the authors used China's population grid data in 2000 and 2010 to describe population agglomeration and diffusion features. Evidently, the outliers of China's population grid data were truncated.
3. NTL data are used to represent the capital and population activities (National Centers for Environmental Information 2014). One study detected urban centers and their spatial structure with NTL remote sensing, which is represented as a continuous mathematical surface of human activity (Chen et al. 2017b). One study aimed to investigate the potential of NTL data in modeling GDP through a case of China and reveals that NTL data can be a powerful tool for modeling socioeconomic indicators (Shi et al. 2014). Previous research confirmed that the calibrated NTL products that act as a single indicator are effective in reflecting the spatial variations of capital, population activity intensity, and density. We obtained the global radiance calibrated NTL products from the National Geophysical Data Center at the National Oceanic and Atmospheric Administration. The resolution of NTL data is 30 arc seconds. Referring to the previous paper (Chen et al. 2017a), we processed the NTL data.
4. Land transaction data. Land market transaction data were used to reflect the intensity of land trading activity. Land transaction types include land mortgages, land transfer, and land leases. Assuming that all costs and benefits (including nonmonetary forms) are fully internalized within a land market, using different types of land transactions was deemed reasonable as indicators of different types of city activities.
5. Patent data were used to characterize the level of urban innovation activity. Innovation and knowledge economies are local development engines and nodes in globally networked agglomerations (Martinez-Fernandez et al. 2012a). Patent data were drawn from the website (China State Intellectual Property Office 2000, 2010), whereby locating the source of the inventors' registered patents and then visualizing these addresses on the map were possible. A spatial aggregation analysis was conducted for land transaction data and patent data in 2000 and 2010 using the Kernel Density toolbox in ESRI ArcGIS [a geographic information system (GIS) software; for more introduction about the function of ArcGIS, refer to https://desktop.arcgis.com/en/]. A high-density value increases the vibrant tendency of the land transaction activities or patent applications.

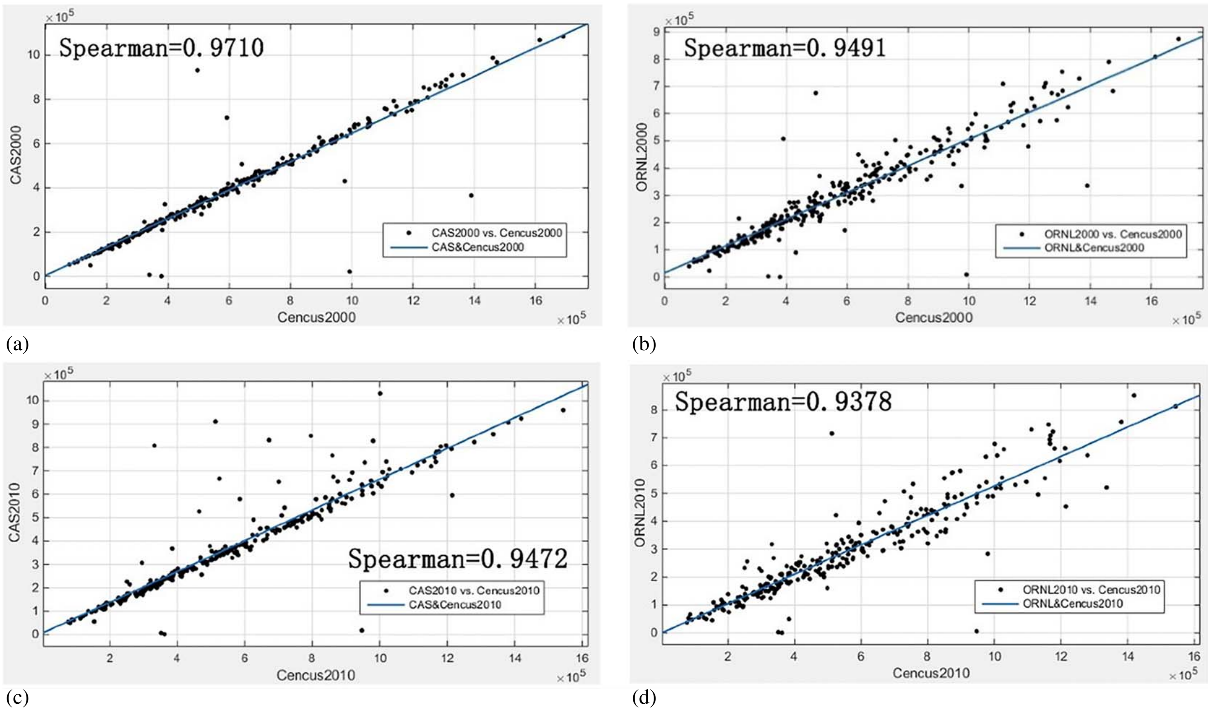

Fig. 3. Scatter diagram for the LandScan and China's population grid data: (a) the correlation between China's population grid data and China's census data in 2000; (b) the correlation between LandScan and China's census data in 2000; (c) the correlation between China's population grid data and China's census data in 2010; and (d) the correlation between LandScan and China's census data in 2010.

Methods

The study follows the logical research framework on urban shrinkage consisting of data input urban shrinkage identification, pattern study, underlying driving forces, and planning and policy setting suggestions (Fig. 4). Specifically, the authors drew on the Cobb-Douglas production function using multisource big data in calculating a city activity index to examine aspects of the state of city activity. With the zonal statistics tool in ArcGIS, a mean statistic is calculated for each built-up area patch based on values from city activity or population grid data. Then, the study measures urban shrinkage based on the changes in population and city activity from 2000 to 2010. Ultimately, the GWRs for urban shrinkage were established to explore the shrinkage-influencing mechanism.

City Activity Index

This study constructed a city activity index to characterize the intensity of urban activities. Capital, labor, land, technology, and information were considered the elements of productivity. Thus, the authors calculated our city activity index by inputting the above factors into production functions. The authors referenced the idea of the Cobb-Douglas production function, which is a mathematical economic model used to calculate the production value of industries or enterprises. The parameters in the function are related to the economic significance of the variables, and the variables' values can be linearized by taking logarithms. The Cobb-Douglas production function can also be introduced into the calculation of urban space production. The intensity of city activities was evaluated using Eq. (1), denoting that city activities tend to be vibrant, with several people living there and with high capital and land and innovation activities aggregating there.

$$A = \text{POP\_CAP}^{\alpha} * \text{LAND}^{\beta} * \text{INNO}^{\mu} \tag{1}$$

The authors then performed a logarithmic function conversion for Eq. (1) to obtain Eq. (2), in which every data item was standardized. In addition, if a certain item is zero, it will not cause the city activity index to be zero in Eq. (2).

$$\text{Act} = \lg A = \alpha \lg(\text{POP\_CAP}) + \beta \lg(\text{LAND}) + \mu \lg(\text{INNO}) \tag{2}$$

where Act = the city activity index; POP_CAP = capital and population activities; LAND = land trading activities and INNO innovation activities; α, β, μ = the respective elastic coefficients of NTL, land transaction, and innovation. Under the condition of constant returns on scale, $\alpha + \beta + \mu = 1$. The α, β, μ values can be weighted values correspondingly assigned to the nighttime light data, land transaction data, and innovation, indicating the relative importance of each item in the urban space production process. The authors referred to several relevant studies (Tang et al. 2005) and assigned α, β, μ to denote 0.5, 0.25, and 0.25, respectively.

Identification of City Shrinkage

The city activity change refers to changes in innovation, capital, and land transaction activities. Therefore, urban growth during a specific period of $[t_0, t_1]$ was expressed using the following equations:

$$\Delta \text{Pop}_i = \overline{\text{Pop}_{i\_t1}} - \overline{\text{Pop}_{i\_t0}} \tag{3}$$

$$\Delta \text{Act}_i = \overline{\text{Act}_{i\_t1}} - \overline{\text{Act}_{i\_t0}} \tag{4}$$

The shapes and boundaries of the built-up area were kept consistent with built-up area in 2010. Here, ΔPop_i = the population change in the i-th built-up area from t_0 to t_1; $\overline{\text{Pop}_{i\_t1}}$ = the population mean in the i-th built-up area of t_1; $\overline{\text{Pop}_{i\_t0}}$ = the population mean in the i-th built-up area of t_0; ΔAct_i = city activity index change in the i-th built-up area from t_0 to t_1; $\overline{\text{Act}_{i\_t1}}$ = the city

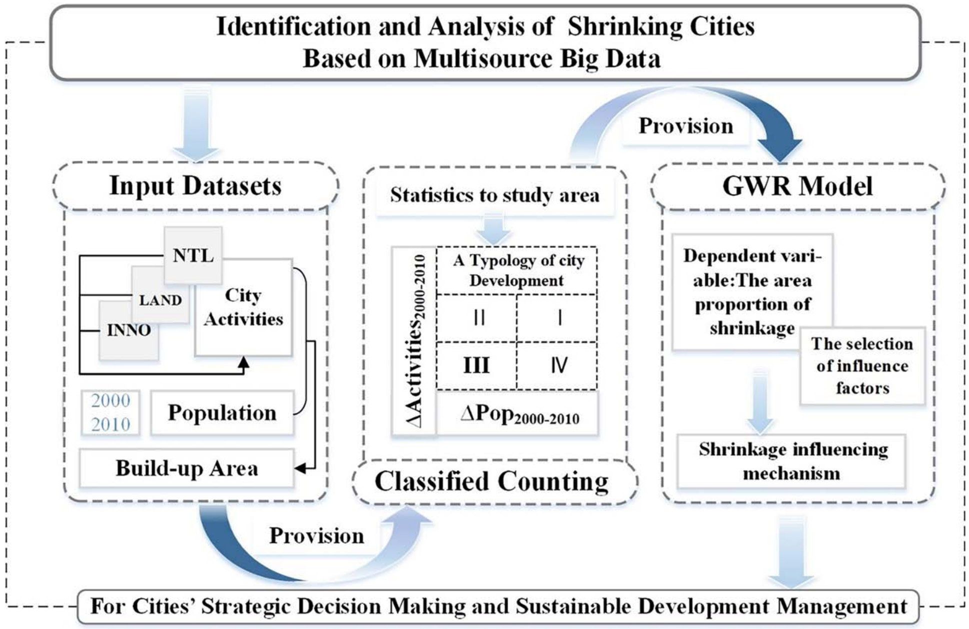

Fig. 4. Research methods.

activity index mean in the i-th built-up area of t_1; $\overline{\mathrm{Act}_{i\_t0}}$ = the city activity index mean in the i-th built-up area of t_0.

For a given built-up area, the relationships between $\Delta\mathrm{Pop}_i$ and $\Delta\mathrm{Act}_i$ were measured using the four quadrants corresponding to four possible types of urban growth (Fig. 5): increase–increase (I), increase–decrease (II), decrease–decrease (III), and decrease–increase (IV). These four combinations were estimated based on the zero values of population and city activities. If both the population and the degree of city activity index change were more than zero, the area was categorized as type I (growing); if both the population and city activities scored less than zero, the area was categorized as type III (shrinking). By contrast, if one is more than zero and the other is less than zero, then, the area was categorized as type II or IV.

Increase–increase (I): an increasing population and city activity growth indicated significant growing city areas. Increase–decrease (II): an increase in population and a decrease in city activities indicated that some cities had special geopolitical relationships with metropolises and developed with high dependence. Decrease–decrease (III): the counterpart to the growing cities is shrinking areas characterized by a decrease in both population and city activities. Decrease–increase (IV): a decrease in population and an increase in city activities indicated that some problems, such as an inadequate drive for economic development and dilemmas in industrial conversion, have emerged in some cities.

Geographically Weighted Regression

An influencing mechanism exists behind the differentiation of urban regional development. Based on existing studies, the factors affecting urban shrinkage can be summarized on the society/population (Couch et al. 2005; Hoekveld 2012; Lin et al. 2017), resource/land (He et al. 2017b), and economy/industry (Grossmann et al. 2013; Martinez-Fernandez et al. 2012a). GWR is a spatial varying-coefficient regression model employed to analyze the explanatory ability of variables in local areas. GWR has been extensively used in economics, geography, and other fields. Therefore, fitting the urban shrinkage regression models using GWR is appropriate. The expression is

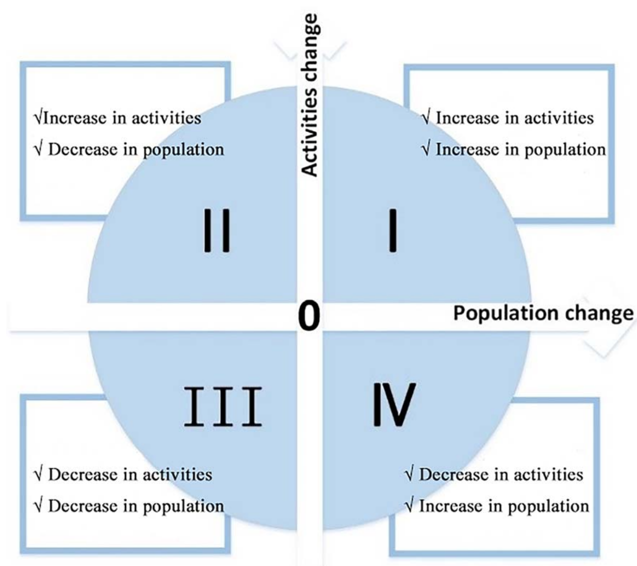

Fig. 5. A typology of growing and shrinking cities.

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_{j=1}^{k} \beta_j(\mu_i, \nu_i)\chi_{ij} + \varepsilon_i \quad (5)$$

where y_i = the size of the built-up of the i-th city; (μ_i, ν_i) = the spatial geographic location coordinate of the i-th city; $\beta_j(\mu_i, \nu_i)$ = j-th regression parameter at the i-th sample point; χ_{ij} = the influencing factor; ε_i = the random error term; and β_0 = a constant.

In terms of independent variables, this study focuses on the selection of explanatory variables from the demographic, land use, and industrial economic dimensions. The proportion of the population aged 15–64 and the number of immigrants and married people reflect the population structure characteristics. The area of urban expansion and the number of houses purchased and rented houses reflect land/housing characteristics.

The employment rate as well as the number of employed people in secondary and tertiary industry reflect employment/industry characteristics. These data are from the two censuses of 2000 and 2010.

The exploratory regression tool in ArcGIS was used to determine the best combinations of the input candidate explanatory variables. This tool uses ordinary least squares (OLS) and Global Moran's I spatial autocorrelation (Global Moran's I can be described as a measure of spatial autocorrelation based on feature locations and attribute values using the Global Moran's I statistic) in conducting collinearity diagnosis and significance test. Through inputting the above candidate explanatory variables and setting default values for parameters, the output table contained the models that best explain the dependent variable. Explanatory variables related to the urban shrinkage GWR model were the urban expansion area, secondary industry population, and the number of rented houses and immigration. The area proportions of urban shrinkage were used to represent the model dependent variable. To visually demonstrate the difference in the influence degree of the model's independent variables, this study sets the extended parameters (such as coefficient raster workspace) in the GWR model analysis tool of ArcGIS software to realize the rasterized visual effect of model coefficients. The rasterization of the coefficients of the GWR model reflects the heterogeneity of effects on the dependent variables in different city regions.

Results and Analysis

Spatial Distribution Characteristics of Different Types

The urban shrinking and growing patterns in the middle reaches of the Yangtze River in 2000–2010 are known as "overall growth, local shrinkage" features (Fig. 6). Type I can be observed as dominant. Combined with data statistics, rapid population growth was accompanied by positive changes in city activities in the provincial capital cities (Wuhan, Changsha, Nanchang, and Hefei) and at the prefecture-level city jurisdiction. A key phenomenon is that types II and I city areas have high spatial proximity. The possible reason for this scenario is that growing cities attract the population of the surrounding city area while simultaneously having a radiation effect on the growth of social and economic activities. Urban growth may be productive or parasitic, and the predictability of urban growth creates a surplus for a larger urban area (Balchin et al. 2000). The development of type II city areas depends on the surplus created by the significantly growing cities, meaning that the type II city areas can be regarded as dependent growing city areas.

Urban shrinkage (type III) can be observed in some cities in the northern Anhui province, such as Huaibei, Huainan, and Suzhou. In Bozhou the population is shrinking while city activities are also declining. Shrinkage is concentrated in partial urban areas and county cities that are often overlooked. When a large range of shrinkage occurs, type IV city areas are also clustered. Type III areas can be seen to be mostly distributed around type IV, which indicates that the development momentum of the type IV city area is somewhat weak and very likely to face the risk of shrinkage. Therefore, type IV can be regarded as areas "at risk of shrinking." Within the study area, the "at risk of shrinking" type proved to be concentrated in some resource-based and industrialized cities regions such as Huaibei, which was going through a phase of industrial restructuring, causing underemployment of surplus labor, aggravation in the social burden, restrictions in economic development, and the triggering of a series of issues. Given the circumstances, a phenomenon could occur in which the population did not decrease but the urban activity declined. A few shrinking urban areas, such as Huaibei and Huainan, are coal resource-based cities that have exhausted their resources and experienced a seriously delayed development of substitute industries, consequently causing a development crisis and gradual shrinkage of the city.

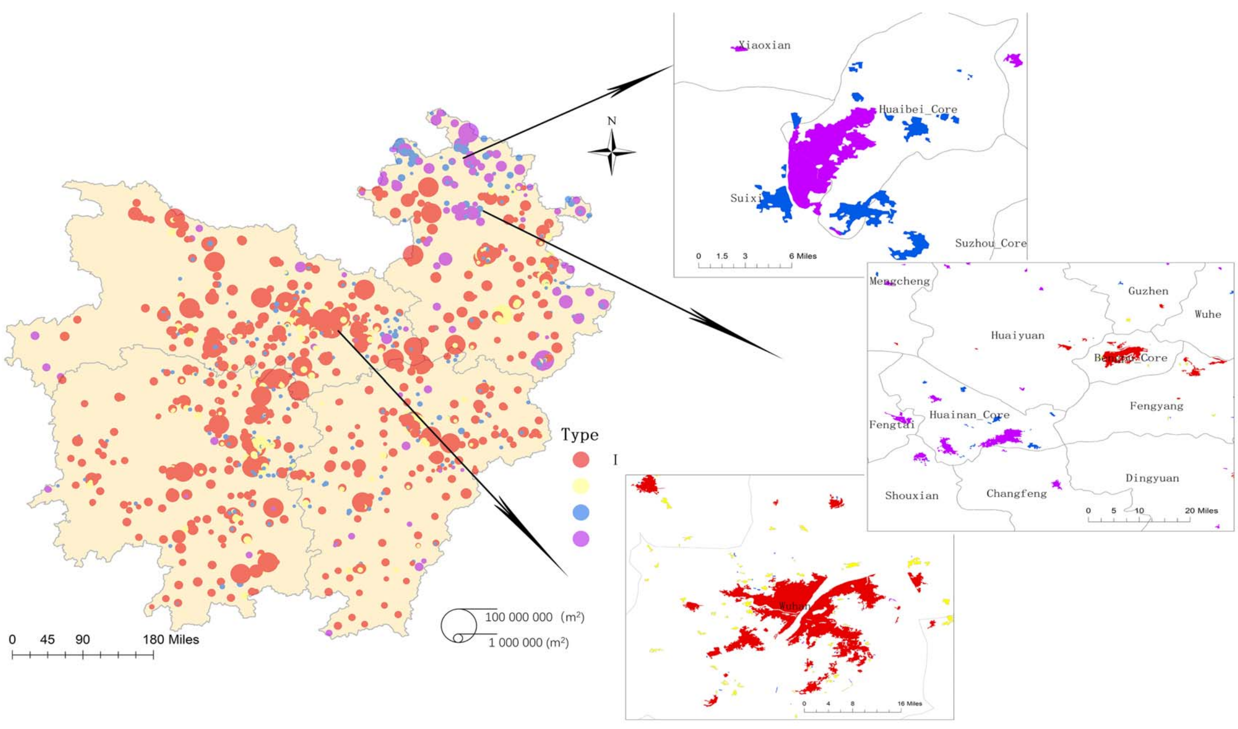

Fig. 6. Spatial pattern of city shrinkage and growth.

Analysis of Urban Types Structure

This section analyzes the quantitative structure of different urban types at the provincial and provincial capital levels to explore the relationships of different types and urban development laws. Fig. 7 shows the proportion of increasing city activities in cities with population loss on the regional dimension; 14.87% of urban areas experienced population loss in the study area. Considering city activities, the urban areas with increasing city activities accounted for 57.36% in depopulation cities (56.18% in Hunan, 70.42% in Hubei, 52.95% in Anhui, 60.27% in Jiangxi), indicating the uncoupling of population and city activities to some extent. Differences in the proportion values among various cities within Anhui province obviously exist. The proportion values of various cities within Hubei province are more aggregated, concentrated in 0.8.

The proportions of the four types (I, II, III, IV) in the four provincial capitals and four provinces respectively show the difference in urban and regional development models (Fig. 8). At the provincial city level, Wuhan can be seen to have a growth-led development model, whereby type I accounts for 95%, and types III and IV account for almost zero. The development structure of Changsha and Hefei is similar, where types I and II are dominant and types III and IV have a very small proportion. The provinces of Hunan, Hubei, and Jiangxi are growth-led development models with the type I making up the proportions of 83%, 85%, and 75%, respectively. Meanwhile, type II accounts for above 10% in the provinces of Hunan, Hubei, and Jiangxi. Anhui province presents the shrinkage and growth coexisting development model, whereby type I accounts for 54%, and types III and IV account for nearly 38% with a clear shrinkage phenomenon. From the above, the authors found that few cities of a single type exist. That is, the development status of different regions in one particular city is not the same, which can help us understand why some growing cities experience partial shrinkage. The spatial cooperativity between growing (I) and dependent growing (II) city regions is high, as is the spatial cooperativity between shrinking (III) city regions and those at risk of shrinking (IV).

Analyzing the Influencing Factors Affecting Urban Size of Shrinkage Type

From the analysis of urban-type structure, the authors found two or more possible existing types within cities, which can provide a certain city or city area sample to explore shrinkage-influencing mechanism. This study takes the area proportions of urban shrinkage as the dependent variable and urban expansion area and secondary industry population as the independent variables to construct the GWR model. The adjusted R^2 of urban shrinkage GWR model is 0.7826. Therefore, the model has a good fit for performance. Fig. 9 shows the regression coefficients visualization. In general, with the exception of the northern cities of Anhui province, the expansion area's impact on the size of shrinking city regions is negative. In the northern cities of Anhui province, shrinkage is dominant while the regression coefficient of the urban expansion area is positive, indicating that the size of the shrinking city region expanded with the increase in the urban expansion area. The impact of the number of rented houses in the shrinkage GWR model shows spatial heterogeneity.

The regression coefficients of some cities on the edge of the urban agglomeration such as Enshi, Hengyang, Fuyang, Yingtan are negative, signifying that the urban shrinkage region size is shrinking alongside an increase in rented houses. A large spatial differentiation exists in terms of the influence of the secondary industry population on the size of shrinking city regions. The industrial city belt from the western province of Hubei to the eastern province of Anhui was negatively affected by the secondary industry population. However, in some shrinking regions such as Bengbu, Huaibei, and Suzhou, the size of urban shrinkage is positively correlated with secondary industry population, indicating that the increase in secondary industry population may aggravate shrinkage. The degree of impact of immigration on the size of shrinking city regions was found to be negative and weaker than other explanatory variables. That is, if the aim is to change the status of shrinkage in a city, increasing immigration does not have a significant effect.

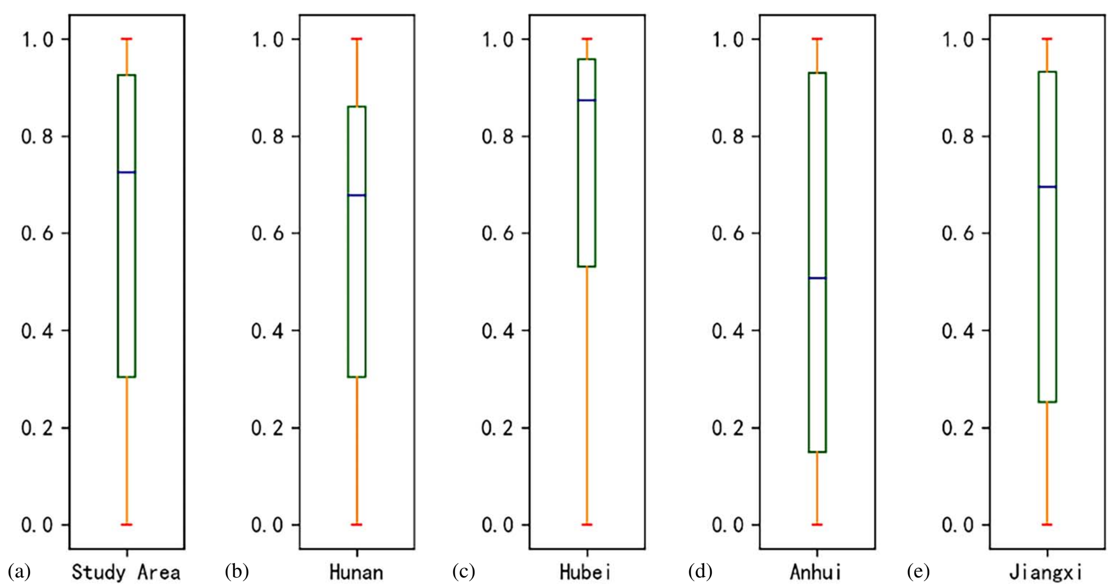

Fig. 7. Proportions of type II (decrease in population and increase in city activities) and population loss: (a) proportions of type II (decrease in population and increase in city activities) and population loss in study area; (b) proportions of type II (decrease in population and increase in city activities) and population loss in Hunan province; (c) proportions of type II (decrease in population and increase in city activities) and population loss in Hubei province; (d) proportions of type II (decrease in population and increase in city activities) and population loss in Anhui province; and (e) proportions of type II (decrease in population and increase in city activities) and population loss in Jiangxi province.

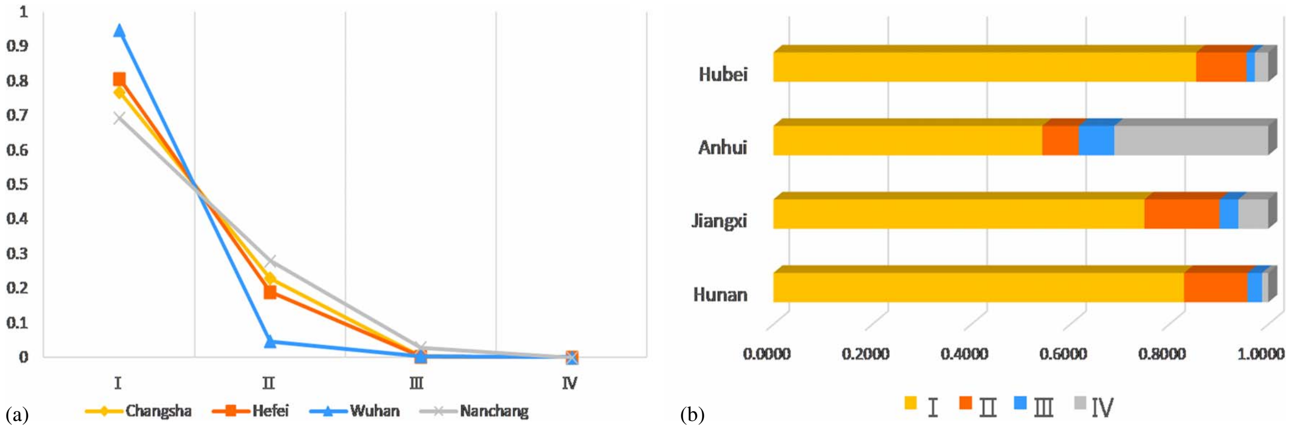

Fig. 8. Proportions of the four types (I, II, III, IV) in the four provincial capitals (left) and in four provinces (right); (a) proportions of the four types (I, II, III, IV) in the four provincial capitals; and (b) proportions of the four types (I, II, III, IV) in four provinces.

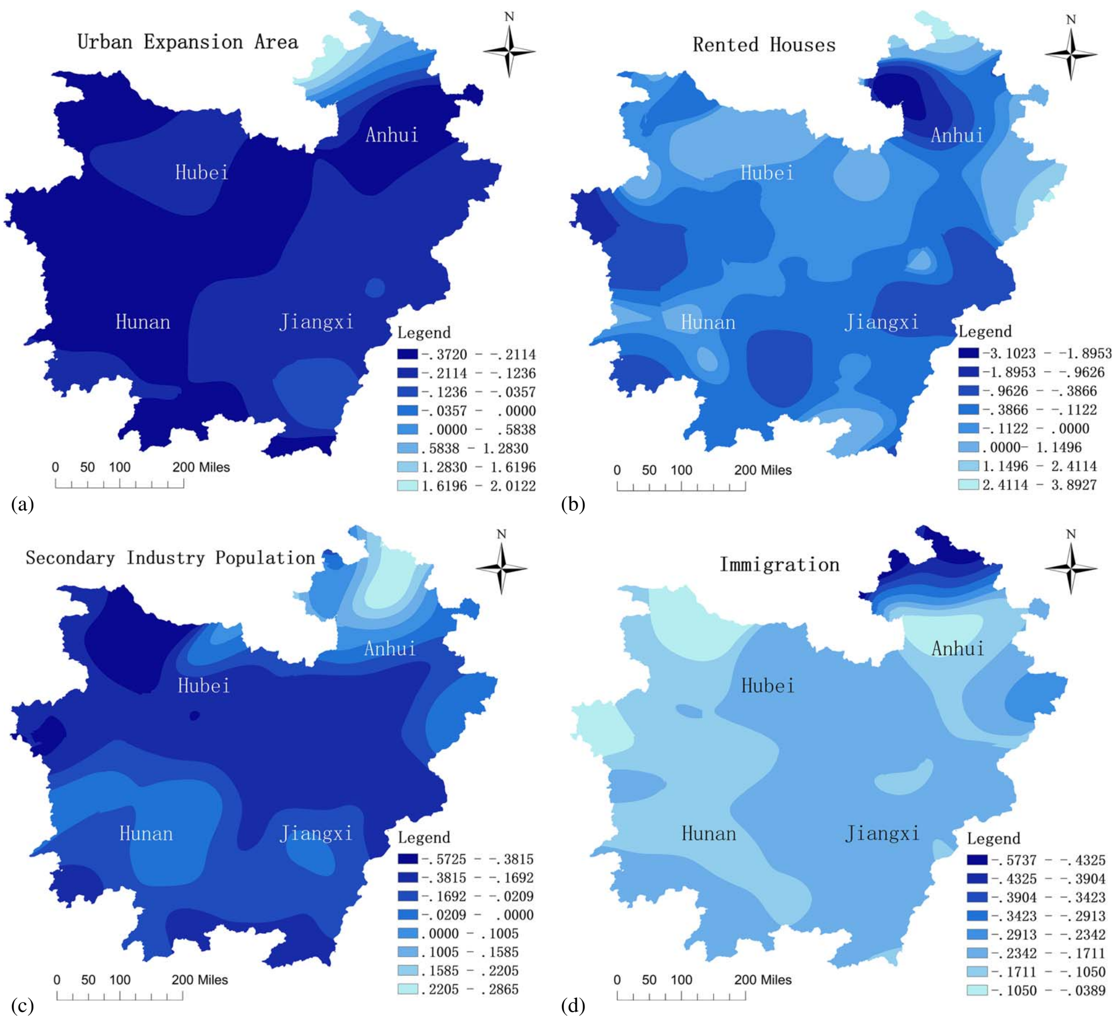

Fig. 9. Spatial distribution of the regression coefficients of explanatory variables in the city shrinkage model: (a) spatial distribution of the regression coefficients of urban expansion area in the city shrinkage model; (b) spatial distribution of the regression coefficients of rented houses in the city shrinkage model; (c) spatial distribution of the regression coefficients of secondary industry population in the city shrinkage model; and (d) spatial distribution of the regression coefficients of immigration in the city shrinkage model.

Conclusion and Discussion

This study identified city shrinkage based on population loss and the changes in city activities. It then discussed the factors affecting city shrinkage from 2000 to 2010 in the middle reaches of the Yangtze River in China. In the area of study, city shrinkage identification results differed when considering city activity. Approximately 14.87% of cities experienced population loss. Considering city activities, an increase in the latter accounted for 57.36% in depopulation cities. Urban shrinkage spatial pattern presented the feature of "overall growth, local shrinkage." Shrinkage was concentrated in urban partial areas and county cities. Moreover, few cities were found to be of a single type, with different types of development coexisting in most of the cities studied. Furthermore, these types have a certain regularity in spatial distribution and structure. That is, the spatial proximity and cooperativity between growing and dependent growing type were found to be high, as well as that between the shrinking and "at risk of shrinking" types. The unbalanced development exists within cities.

City shrinkage is a consequence of multifactor interactions. In the middle reaches of the Yangtze River in China from 2000 to 2010, the number of rented houses has the most significant impact on urban shrinkage, followed by urban expansion. In shrinking urban areas, urban spatial expansion and the increase in secondary industrial population are factors that do not drive urban growth but aggravate urban shrinkage. Deindustrialization (Liu and Yang 2017), out-migration (Chen et al. 2016; Du et al. 2019; Zhang 2015), urban sprawl, and real estate (Grossmann et al. 2013; Lin et al. 2017) have been proven to have an effect on urban shrinkage in existing studies. Out-migration is considered the main cause of local city shrinkage in China, which is caused by unbalanced regional economic development and different urbanization levels (Wu and Long 2015). The urban area has expanded at a remarkable speed in China (He et al. 2019), and the negative effects on urban development have slowly emerged. Many cities in China are facing the challenge of transformation (Ren 2014). How to effectively supply land scale to match urban activities and population is a problem that requires solutions in the process of urban transformation. In addition, industrial transformation is an important part of urban transformation. According to Kuznets' rule, the labor force flows smoothly between industrial sectors when the industrial structure is optimized and upgraded. Industrial-based cities (e.g., Huaibei, Huainan, and Suzhou in the northern of Anhui province) should make the transition from traditional industry to advanced manufacturing processes, modernized service industries, and diversified industry structure; they should also scale up employment to promote city growth (Du and Li 2018). In the case of China alone, the main influencing factors of city shrinkage in different regions are different, and the influence degree has prominent spatial heterogeneity. The impact mechanism of shrinking cities is a proposition that needs to be studied in-depth and meticulously in combination with the local development situation.

In this study, the urban typology category divided through this study can be well couched within certain urban developmental patterns. Shrinking and "at risk of shrinking" regions were actually in areas that had experienced deindustrialization or resource depletion in the study. We considered the city activities in identifying city shrinkage research based on the belief that city vitality could exist even if the city is experiencing population loss. Certain issues relating to cities' demographic structure (according to sex, age, and different educational attainment), scientific and technological levels, resources endowment, and so on, somewhat decide the intensity and density of city activity. We emphasize that increasing or refining the indicators of city activities is also possible, so that these indicators can be applied to specific types of cities (tourism-based cities, resource-based cities, industrial cities, etc.).

Traditional statistical data support the urban research from the perspective of administration but ignore the characteristics within cities. The spatial scale of evaluating urban development is important. We explored the methods of big data aggregation to focus on regional changes within cities on a small scale, which contributed to the urban community shrinkage identification and the exploration of how to energize the urban community. Although some estimation errors may occur, the datasets from the same source successfully reflected the changing trends of population and city activities over a prolonged time series (Liu and Wang 2016). A few limitations were encountered in the current study. For example, given the restrictions in the available data, we only studied cities in the middle reaches of the Yangtze River from 2000 to 2010 but did not expand this to the present day.

City shrinkage in European and American countries mainly occurred in the context of development stability and economic stagnation. China remains the biggest developing country in the world; the shrinkage of some cities in China reflects the negative effect brought by excessive growth, which is alarming for other countries and regions of urban development. Moreover, China has a vast territory. The types of city shrinkage are complex and diverse. The impact mechanisms are different from those in Western countries, which provide rich and diversified cases for international urban shrinkage research to understand better and deal with the shrinkage.

Currently, most urban planning and policies in China are indeed growth-oriented, ignoring the specialization of the urban transformation period and the coordination among urban development elements. Shrinking cities of different types and in different developmental stages and local contexts face various challenges. When shrinkage happens, changes occur in population structure, in the socioeconomic environment, in land use and residential location choices, urban planning paradigm shift, and policy adjustments in response to these changes. The planning paradigms, planning systems, planning strategies, and planning cultures of shrinking cities require in-depth discussions (Pallagst 2010). Some scholars have studied housing demolition and explored land use policies for smart declines such as developing open space networks in shrinking cities (Frazier and Bagchi-Sen 2015), and urban greenery in local neighborhoods (Schetke and Haase 2008). The Chinese government, which has proposed certain policies, such as "small and fine-skilled" and "strictly increase the increment, revitalize the stock" for small- and medium-sized cities, no longer blindly expands the area and uses public resources to guide the population to the central city. We will examine the different types and drivers, impacts of, countermeasures to, and shrinkage against global and local backgrounds in our future research. We intend to present case studies, which feature typical shrinking cities identified in this paper, such as resource-based cities. We will review the development history and planning policies in these cities and analyze the noticeable problems resulting in shrinkage and general and place-based countermeasures for city shrinkage. Findings could drive the shift from understanding to the governance of urban shrinkage.

Data Availability Statement

Some or all data, models, or code used during the study were provided by a third party. Patent data were drawn from the website of the China State Intellectual Property Office. Census data were provided by the website of the National Bureau of Statistics. Built-up urban area data and China's population grid data can be downloaded from the Resource and Environment Data Cloud Platform. The authors obtained the nighttime light data from the National Geophysical Data Center at the National Oceanic and Atmospheric Administration (NOAA/NGDC). And the data used during the study are cited in the reference section.

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References

Alves, D., A. P. Barreira, M. H. Guimaraes, and T. Panagopoulos. 2016. "Historical trajectories of currently shrinking Portuguese cities: A typology of urban shrinkage." *Cities* 52: 20–29. https://doi.org/10.1016/j.cities.2015.11.008.

Balchin, P. N., D. Isaac, and J. Chen. 2000. *Urban economics: A global perspective*. Basingstoke, UK: Palgrave.

Bartholomae, F., C. W. Nam, and A. Schoenberg. 2017. "Urban shrinkage and resurgence in Germany." *Urban Stud.* 54 (12): 2701–2718. https://doi.org/10.1177/0042098016657780.

Beauregard, R. A. 2009. "Urban population loss in historical perspective: United States, 1820–2000." *Environ. Plann. A* 41 (3): 514–528. https://doi.org/10.1068/a40139a.

Chen, C., Z. D. Luo, and H. M. He. 2016. "The progress of the research on the shrinkage of small towns: Mechanism and countermeasures." *Mod. Urban Res.* 2: 23–28.

Chen, F. 2016. "Li Yu, Chinese city and regional planning systems." *Environ. Plann. B* 43 (2): 436–437. https://doi.org/10.1177/0265813515604983.

Chen, Y. M., X. P. Liu, and X. Li. 2017a. "Analyzing parcel-level relationships between urban land expansion and activity changes by integrating Landsat and nighttime light data." *Remote Sens.* 9 (2): 164. https://doi.org/10.3390/rs9020164.

Chen, Z. Q., B. L. Yu, W. Song, H. X. Liu, Q. S. Wu, K. F. Shi, and J. P. Wu. 2017b. "A new approach for detecting urban centers and their spatial structure with nighttime light remote sensing." *IEEE Trans. Geosci. Remote Sens.* 55 (11): 6305–6319. https://doi.org/10.1109/TGRS.2017.2725917.

China State Intellectual Property Office. 2000. "Patent search and analysis." Accessed March 31, 2011. http://patdata.cnipa.gov.cn/.

China State Intellectual Property Office. 2010. "Patent search and analysis." Accessed March 31, 2011. http://patdata.cnipa.gov.cn/.

Chinese Academy of Sciences. 2000. "China's population grid data." Accessed December 11, 2017. http://www.resdc.cn.

Chinese Academy of Sciences. 2010a. "China's population grid data." Accessed December 11, 2017. http://www.resdc.cn.

Chinese Academy of Sciences. 2010b. "China's land use status data." Accessed December 12, 2017. http://www.resdc.cn.

Couch, C., J. Karecha, H. Nuissl, and D. Rink. 2005. "Decline and sprawl: An evolving type of urban development—Observed in Liverpool and Leipzig." *Eur. Plann. Stud.* 13 (1): 117–136. https://doi.org/10.1080/0965431042000312433.

Danko, J. J., and D. M. Hanink. 2018. "Beyond the obvious: A comparison of some demographic changes across selected shrinking and growing cities in the United States from 1990 to 2010." *Popul. Space Place* 24 (6): e2136. https://doi.org/10.1002/psp.2136.

Delken, E. 2008. "Happiness in shrinking cities in Germany—A research note." *J. Happiness Stud.* 9 (2): 213–218. https://doi.org/10.1007/s10902-007-9046-5.

Dobson, J. E., E. A. Bright, P. R. Coleman, R. C. Durfee, and B. A. Worley. 2000. "Landscan: A global population database for estimating populations at risk." *Photogramm. Eng. Remote Sens.* 66 (7): 849–857.

Du, Z., and X. Li. 2017. "Growth or shrinkage: New phenomena of regional development in the rapidly-urbanising Pearl River Delta." *Acta Geogr. Sin.* 72 (10): 1800–1811. https://doi.org/10.11821/dlxb201710006.

Du, Z. W., and X. Li. 2018. "Characteristic and mechanism of urban growth and shrinkage from demographic change perspective: A case study of dongguan." *Sci. Geogr. Sin.* 38 (11): 1837–1846. https://doi.org/10.13249/j.cnki.sgs.2018.11.011.

Du, Z. W., H. O. Zhang, Y. Y. Ye, L. X. Jin, and C. J. Wang. 2019. "Spatiotemporal evolution and influences of urban population shrinkage in Guangdong since 2000." *Trop. Geogr.* 39 (1): 20–28. https://doi.org/10.13284/j.cnki.rddl.003105.

Frazier, A. E., and S. Bagchi-Sen. 2015. "Developing open space networks in shrinking cities." *Appl. Geogr.* 59: 1–9. https://doi.org/10.1016/j.apgeog.2015.02.010.

Galster, G. 2019. "Why shrinking cities are not mirror images of growing cities: A research agenda of six testable propositions." *Urban Affairs Rev.* 55 (1): 355–372. https://doi.org/10.1177/1078087417720543.

Grossmann, K., M. Bontje, A. Haase, and V. Mykhnenko. 2013. "Shrinking cities: Notes for the further research agenda." *Cities* 35: 221–225. https://doi.org/10.1016/j.cities.2013.07.007.

He, Q. S., Y. Song, Y. L. Liu, and C. H. Yin. 2017a. "Diffusion or coalescence? Urban growth pattern and change in 363 Chinese cities from 1995 to 2015." *Sustainable Cities Soc.* 35: 729–739. https://doi.org/10.1016/j.scs.2017.08.033.

He, Q. S., C. Zeng, P. Xie, S. K. Tan, and J. Y. Wu. 2019. "Comparison of urban growth patterns and changes between three urban agglomerations in China and three metropolises in the USA from 1995 to 2015." *Sustainable Cities Soc.* 50: 101649. https://doi.org/10.1016/j.scs.2019.101649.

He, S. Y., J. Lee, T. Zhou, and D. Wu. 2017b. "Shrinking cities and resource-based economy: The economic restructuring in China's mining cities." *Cities* 60: 75–83. https://doi.org/10.1016/j.cities.2016.07.009.

Hoekveld, J. J. 2012. "Time-space relations and the differences between shrinking regions." *Built Environ.* 38 (2): 179–195. https://doi.org/10.2148/benv.38.2.179.

Hollander, J. B. 2009. "Polluted and dangerous: America's worst abandoned properties and what can be done about them." *J. Am. Plann. Assoc.* 75 (4): 498–499. https://doi.org/10.1080/01944360903169675.

Jin, L., and S. O. Management. 2018. "Research on the inter-influences between hidden shrinkage of urban population and economic growth——A case study of Maoming in Guangdong Province." *J. Harbin Inst. Technol.* 20 (1): 133–140.

Jin, X. B., Y. Long, W. Sun, Y. Y. Lu, X. H. Yang, and J. X. Tang. 2017. "Evaluating cities' vitality and identifying ghost cities in China with emerging geographical data." *Cities* 63: 98–109. https://doi.org/10.1016/j.cities.2017.01.002.

Khavarian-Garmsir, A. R., A. Pourahmad, H. Hataminejad, and R. Farhoudi. 2018. "A comparative assessment of economic and physical inequality between shrinking and growing cities: A case study of Khuzestan province, Iran." *Int. J. Urban Sci.* 22 (1): 104–122. https://doi.org/10.1080/12265934.2017.1358653.

Lee, J., G. Newman, and Y. Park. 2018. "A comparison of vacancy dynamics between growing and shrinking cities using the land transformation model." *Sustainability* 10 (5): 1–17.

Lin, X. B., J. W. Yang, X. C. Zhang, and H. Chao. 2017. "Measuring shrinking cities and influential factors in urban China: Perspective of population and economy." *Hum. Geogr.* 32 (1): 82–89.

Liu, C. Y., and P. F. Yang. 2017. "A comparative study on the motivation mechanism and performance characteristics of Chinese and foreign shrinking cities." *Mod. Urban Res.* 3: 64–71. https://doi.org/10.3969/j.issn.1009-6000.2017.03.010.

Liu, X. J., and M. S. Wang. 2016. "How polycentric is urban China and why? A case study of 318 cities." *Landscape Urban Plann.* 151: 10–20. https://doi.org/10.1016/j.landurbplan.2016.03.007.

Long, Y., W. U. Kang, and J. Wang. 2015. "China's shrinking cities and its research framework." *Mod. Urban Res.* 9: 14–19. https://doi.org/10.3969/j.issn.1009-6000.2015.09.002.

Long, Y., and K. Wu. 2016. "Shrinking cities in a rapidly urbanizing China." *Environ. Plann. A* 48 (2): 220–222. https://doi.org/10.1177/0308518X15621631.

Martinez-Fernandez, C., I. Audirac, S. Fol, and E. Cunningham-Sabot. 2012a. "Shrinking cities: Urban challenges of globalization." *Int. J. Urban Reg. Res.* 36 (2): 213–225. https://doi.org/10.1111/j.1468-2427.2011.01092.x.

Martinez-Fernandez, C., T. Weyman, S. Fol, I. Audirac, E. Cunningham-Sabot, T. Wiechmann, and H. Yahagi. 2016. "Shrinking

cities in Australia, Japan, Europe and the USA: From a global process to local policy responses." *Prog. Plann.* 105: 1–48. https://doi.org/10.1016/j.progress.2014.10.001.
Martinez-Fernandez, C., C. T. Wu, L. K. Schatz, N. Taira, and J. G. Vargas-Hernandez. 2012b. "The shrinking mining city: Urban dynamics and contested territory." *Int. J. Urban Reg. Res.* 36 (2): 245–260. https://doi.org/10.1111/j.1468-2427.2011.01094.x.
Monsson, C. K. 2014. "Keys to the city: How economics, institutions, social interaction, and politics shape development." *Eur. Plann. Stud.* 22 (5): 1106–1108. https://doi.org/10.1080/09654313.2013.872386.
National Bureau of Statistics. 2001. "The Fifth National Population Census." Accessed March 28, 2001. http://www.stats.gov.cn/tjsj/pcsj/rkpc/5rp/index.htm.
National Bureau of Statistics. 2011. "The Sixth National Population Census." Accessed April 28, 2011. http://www.stats.gov.cn/tjsj/pcsj/rkpc/6rp/indexch.htm.
National Centers for Environmental Information. 2014. "Global Radiance Calibrated Nighttime Lights." Accessed February 20, 2014. https://ngdc.noaa.gov/eog/dmsp/download_radcal.html.
Pallagst, K. 2010. "Viewpoint: The planning research agenda: Shrinking cities—A challenge for planning cultures." *Town Plann. Rev.* 81 (5): 1–6. https://doi.org/10.3828/tpr.2010.22.
Pallagst, K., R. Fleschurz, and F. Trapp. 2017. "Greening the shrinking city—policies and planning approaches in the USA with the example of Flint, Michigan." *Landscape Res.* 42 (7): 716–727. https://doi.org/10.1080/01426397.2017.1372398.
Reis, J. P., E. A. Silva, and P. Pinho. 2016. "Spatial metrics to study urban patterns in growing and shrinking cities." *Urban Geogr.* 37 (2): 246–271. https://doi.org/10.1080/02723638.2015.1096118.
Ren, C. H. 2014. "The research on the industrial heritage tourism development in the transformation of resource-exhausted cities." In *Sustainable development of industry and economy, Pts 1 and 2*, edited by Q. Xu, H. Li, and Q. Li, 69–71. Stafa-Zurich, Switzerland: Trans Tech Publications.
Rhodes, J., and J. Russo. 2013. "Shrinking 'smart'?: Urban redevelopment and shrinkage in Youngstown, Ohio." *Urban Geogr.* 34 (3): 305–326. https://doi.org/10.1080/02723638.2013.778672.
Ruddick, S. 1987. "The social production of urban space." *Econ. Geogr.* 63 (2): 198–199. https://doi.org/10.2307/144160.
Schetke, S., and D. Haase. 2008. "Multi-criteria assessment of socio-environmental aspects in shrinking cities. Experiences from eastern Germany." *Environ. Impact Assess. Rev.* 28 (7): 483–503. https://doi.org/10.1016/j.eiar.2007.09.004.
Schilling, J., and J. Logan. 2008. "Greening the rust belt a green infrastructure model for right sizing America's shrinking cities." *J. Am. Plann. Assoc.* 74 (4): 451–466. https://doi.org/10.1080/01944360802354956.
Schwarz, K., A. Berland, and D. L. Herrmann. 2018. "Green, but not just? Rethinking environmental justice indicators in shrinking cities." *Sustainable Cities Soc.* 41: 816–821. https://doi.org/10.1016/j.scs.2018.06.026.
Shetty, S., and N. Reid. 2014. "Dealing with decline in old industrial cities in Europe and the United States: Problems and policies." *Built Environ.* 40 (4): 458–474. https://doi.org/10.2148/benv.40.4.458.
Shi, K. F., B. L. Yu, Y. X. Huang, Y. J. Hu, B. Yin, Z. Q. Chen, L. J. Chen, and J. P. Wu. 2014. "Evaluating the ability of NPP-VIIRS nighttime light data to estimate the gross domestic product and the electric power consumption of China at multiple scales: A comparison with DMSP-OLS data." *Remote Sens.* 6 (2): 1705–1724. https://doi.org/10.3390/rs6021705.
Smith, N. 2010. *Uneven development: nature, capital, and the production of space*. Athens, GA: Univ. of Georgia Press.
Tan, R. H., Y. L. Liu, Y. F. Liu, Q. S. He, L. C. Ming, and S. H. Tang. 2014. "Urban growth and its determinants across the wuhan urban agglomeration, central ChinaUrban growth and its determinants across the wuhan urban agglomeration, central china." *Habitat Int.* 44: 268–281. https://doi.org/10.1016/j.habitatint.2014.07.005.
Tang, X., Y. Mu, and Y. Ma. 2005. "A further study of cost function under Cobb-Douglas production function." *Chin. J. Manage. Sci.* 13 (4): 1–6.
Turok, I., and V. Mykhnenko. 2007. "The trajectories of European cities, 1960–2005." *Cities* 24 (3): 165–182. https://doi.org/10.1016/j.cities.2007.01.007.
Wiechmann, T., and K. M. Pallagst. 2012. "Urban shrinkage in Germany and the USA: A comparison of transformation patterns and local strategies." *Int. J. Urban Reg. Res.* 36 (2): 261–280. https://doi.org/10.1111/j.1468-2427.2011.01095.x.
Wu, K., and Y. Long. 2015. "Urban shrinkage in the Beijing-Tianjin-Hebei region and Yangtze River Delta: Pattern, trajectory and factors." *Mod. Urban Res.* 12 (9): 26–35.
Yang, R., Y. Liu, H. Long, and C. Chen. 2015. "Spatial-temporal characteristics of rural residential land use change and spatial directivity identification based on grid in the Bohai Rim in China." *Geog. Res.* 34 (6): 1077–1087.
Zhang, L. 2015. "Increasing cities and shrinking regions: Migration in China's urbanization: Cases from Sichuan Province and Xinyang City in Henan Province." *Urban Dev. Stud.* 22 (9): 74–80. https://doi.org/10.3969/j.issn.1006-3862.2015.09.011.
Zhang, Y. J., Y. Fu, X. S. Kong, and F. Zhang. 2019. "Prefecture-level city shrinkage on the regional dimension in China: Spatiotemporal change and internal relations." *Sustainable Cities Soc.* 47: 101490. https://doi.org/10.1016/j.scs.2019.101490.