Measuring Urban Shrinkage

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Most of the shrinking cities experience an unbalanced de-urbanization across different urban areas in cities. However, traditional ways of measuring urban shrinkage are focused on tracking population loss at the city level and are unable to capture the spatially heterogeneous shrinking patterns inside a city. Consequently, the spatial mechanism and patterns of urban shrinkage inside a city remain less understood, which is unhelpful for developing accommodation strategies for shrinkage. The smart city initiatives and practices have provided a rich pool of geospatial big data resources and technologies to tackle the complexity of urban systems. Given this context, we propose a new measure for the delineation of shrinking areas within cities by introducing a new concept of functional urban shrinkage, which aims to capture the mismatch between urban built-up areas and the areas where significantly intensive human activities take place. Taking advantage of a data fusion approach to integrating multi-source geospatial big data and survey data, a general analytical framework is developed to construct functional shrinkage measures. Combining geospatial big data with urban land-use functions obtained from land surveys and Points-Of-Interests data, the framework further enables the comparison between cities from dimensions characterized by indices of spatial and urban functional characteristics and the landscape fragmentation; thus, it has the capacity to facilitate an in-depth investigation of fundamental causes and internal mechanisms of urban shrinkage.

Keywords: functional urban shrinkage ; urban built-up area ; human activity area ; geospatial big data

1. Introduction

The “urban shrinkage”, first put forward by [1] as an alternative paradigm of urbanization that is completely different from the traditional “urban growth”, has become an important topic in urban studies. Research on this phenomenon has been carried out in Germany [2], the United States [3], and other countries. Urban shrinkage took place in China more than two decades ago and has had profound economic, social, and environmental impacts [4]. With the Chinese economy slowing down in recent years, it has received much attention from both researchers and policymakers [5][6]. Several studies found that more than 20% of Chinese cities have experienced or been experiencing shrinkage [7][8]. As China has entered the new era of spatial planning [9], the traditional paradigm of growth-oriented planning is being replaced by a new paradigm that reinforces the coordination between various spatial systems and plans, posing new opportunities as well as challenges for the understanding of urban shrinkage.

A new planning model known as “smart shrinkage” was proposed to address the challenges caused by urban shrinkage [10][11]. This model emphasizes accommodating shrinkage, diversifying the economy, and prioritizing adaptive strategies and policies that can attract and preserve investments, given the local context that may vary across places within a city. Before tailoring the shrinkage-mitigating strategies to local conditions, we must recognize the shrinking areas that are of great interest. Most existing measurements to identify urban shrinkage are at the city level and are unable to capture the local shrinking patterns inside a large city that are often spatially heterogeneous. Furthermore, these measurements mainly take a single indicator or a combination of several ones to identify shrinking cities based on the longitudinal changes of indicators, which inevitably neglects the functional relationship between shrinkage-related factors, e.g., the human activities and built environment. More importantly, the mismatch between the relevant factors may unveil causes for urban shrinkage.

As geospatial big data proliferated in recent years, unprecedented opportunities surface to supplement reliable but costly survey data for urban studies with high spatiotemporal resolution data collected cost-efficiently, such as volunteered location-based big data and remotely sensed data. Various sources of data collected by all types of sensors and a number of newly developed models and tools have been utilized to gain new insights into optimizing the efficiency of city operations and services and into connecting citizens with their urban environments under the umbrella of the Smart City concept [12][13][14]. Applying smart city technologies to the investigation in the context of city shrinkage instead of growth becomes a promising approach to facilitating the study and management of urban shrinkage.

This paper aims to close the gaps in existing measurements of urban shrinkage discussed above by proposing a new concept, namely functional urban shrinkage, to guide the development of better measures for the delineation of local shrinking areas within cities. Taking advantage of a data fusion approach to integrate multi-source geospatial big data and survey data, a general analytical framework is developed to construct the functional shrinkage measure, which aims to capture the spatial mismatch between urban built-up areas and the areas where significantly intensive human activities take place, dubbed as the functional shrinkage area. Specifically, Landsat-8 remote sensing images were used for extracting urban built-up areas by supervised neural network classifications and Geographic Information System (GIS) tools, while cellular signaling data from China Unicom Inc. was used to detect human activity areas by spatial clustering methods. Once the functional shrinkage areas for a city are delineated, the framework further examines the spatial distributions, morphological features, and urban land-use compositions of these areas, and it enables the comparison of functional urban shrinkage patterns between cities from these dimensions by combining geospatial big data with urban land-use functions obtained from land survey data and Points-Of-Interests (POI) data. Therefore, the framework for functional urban shrinkage has the capacity to facilitate an in-depth investigation of the fundamental causes and internal mechanisms of urban shrinkage. With a case study of the Beijing-Tianjin-Hebei megaregion (BTH) using data from various sources collected for the year of 2018, we demonstrate the validity of this approach and its potential generalizability for other spatial contexts in facilitating timely and better-informed planning decision support.

2. Geospatial Big Data for Urban Shrinkage Research

Our understanding of urban shrinkage is highly dependent on the availability of data. Previous research mainly utilized traditional data, such as population census and land surveys, due to their availability and reliability. However, collecting these data is often time-consuming and costly. Consequently, they have been limited to either small-scale or temporally sparse data samples. The proliferation of geospatial big data in recent years provides unprecedented opportunities to study both human and environmental dimensions of urban dynamics in shrinking cities [19][20][21].

Many smart city-related studies [22][23] have demonstrated that geospatial big data enabled by sensors ubiquitously embedded in various mobile devices and by location-based services provided by various telecom operators and Internet companies at a low cost can effectively capture the dynamics of human activities covering large-scale urban areas. Compared to traditional data, such data record various human activities with a very fine spatiotemporal resolution, making feasible the dynamic monitoring, detection, and evaluation of the human dimensions of urban shrinkage. For example, a project called “London Dashboard” established at University College London provides the dynamic tracking and visualization of 12 kinds of data including jobs and economy, transport, environment, and so on, which can be accessed by every citizen [24]. Sulis et al. [25] use the Twitter data and smart card data as proxies of human activities and mobility flows to extract the most vibrant areas.

On the other hand, remote sensing platforms, as a well-known geospatial big data source, can provide diversified information on urban morphology. Various data products with different spatial and temporal resolutions have proved very useful in research with different purposes and needs. For example, MODIS 500-m data has been used for global urban mapping studies [26], and a series of Landsat data have been widely used in urban environment studies, such as urban growth monitoring [27], urban change detection [28], and land-use and land-cover classification [29]. In particular, such data have been employed to delineate built-up areas [30], which can be used as a key element to identify and assess urban shrinkage [31]. Compared to traditional land surveys, remote sensing data are automatically collected and much more cost-efficient due to its good geographic coverage and the high spatiotemporal resolutions, making it the best candidate for large-scale monitoring, detection, and evaluation of the physical/environmental dimensions of urban shrinkage.

Fusing geospatial big data from multiple sources including location-based services and remote sensing platforms allows for an integrated data approach, supplemented with traditional survey data, to the study of both human and physical/environmental dimensions of urban shrinkage. Moreover, the superior spatiotemporal resolution and geographic coverage of the big data approach empower the large-scale and dynamic monitoring, detection, and evaluation of urban shrinkage patterns and processes. As there have been few studies focusing on such an integrated data approach to urban shrinkage study, this paper aims to fill this gap.

3. Measurement of Urban Shrinkage

The measurement of urban shrinkage in the literature mainly takes two approaches. First, the univariate approach refers to a way to measure urban shrinkage by the change of individual indicators, such as population or economy or land-use, to characterize one of many aspects of urban shrinkage. Among these indicators, some research only focused on the widely used population change [32][33], while other studies use several indicators, such as the change of economic development level [34] and the physical change of the built environment [35] to investigate shrinkage from different aspects separately. Rieniets et al. [36] found that as the entire city was growing, population decline occurred in some local areas of the city reflecting a pattern of spatially unequal development. Du and Li [34] applied the Neo-Marxist urban theory to systematically investigate how the capital flow can cause urban shrinkage measured by the population decline.

Secondly, the multivariate approach takes a way to examine urban shrinkage by a combination of multiple indicators as a single index. The most widely used index is the population density which considers both the number of residents and the built-up area on which they dwell. Employing this index, Zheng et al. [37] identified "ghost cities" from an angle of the discrepancy between lit areas and built-up areas, which reflects the house vacancy ratio in those cities and represents an aspect of urban shrinkage. Chi et al. [38] identified more than 50 shrinking cities using estimated areas of vacant housing that were derived from combining the resident population estimated by location-based data of user activities acquired from Baidu Maps and housing-related urban services extracted from POI data. Jin et al. [39] combined indicators such as intersection density, POI point density, LBS based human activity records and other variables to construct a rather comprehensive index to evaluate urban vitality in order to identify the "ghost cities" in China.

Both the above approaches take either a single aspect or several ones to examine urban shrinkage as changes of indicators between snapshots in time. Being a rather static way of measurement, they both ignore the interactions between the dynamic changes in those aspects, e.g., the human activities and built environment, which may lead to the functional mismatch between them and thus become a cause for urban shrinkage. As early as the 20th century, American researchers began to pay attention to the relationship between land use and population loss at the neighborhood scale [40] [41]. Some researchers [10][42] further investigated the relationship between different land-use types, urban morphology, and depopulation. Yang et al. [43] compared population changes and the land expansion of cities in 2000 and 2010 and identified a paradox of population loss and land development existing in a large number of cities. At the intra-city level, Long and Wu [5] found that the coexistence of the rapid land development in general and the urban shrinkage in some local areas was quite common in China.

Although studies discussed above touch upon the relationship between different aspects of urban shrinkage, a formal definition of the functional relationship between those aspects, such as population and land-use, with respect to the extent to which they are mutually adaptive or mismatched in relation to urban shrinkage, remains missing. Hence, the associated measure for this functional shrinkage is lacking. Furthermore, most existing research took measurements at the city or provincial level, which missed out the spatially heterogeneous distribution of urban shrinkage at finer resolutions, such as intra-city or street block levels, and thus lacks the capacity to study the functional mismatch between different aspects of urban shrinkage at smaller geographies. To fill the two gaps, this study takes a multi-source data fusion approach to measure the functional urban shrinkage (formally defined in Section 3.2) by leveraging both conventional survey data and geospatial big data. The new measurement is applied to BTH as a case study to demonstrate its validity.

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