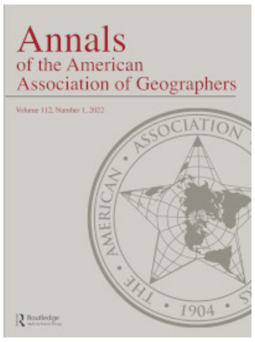

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Evolution of Urban Spatial Clusters in China: A Graph-Based Method Using Nighttime Light Data

Congxiao Wang,[*] Bailang Yu,[†] Zuoqi Chen,[‡] Yan Liu,[§] Wei Song,[#] Xia Li,[¶] Chengshu Yang,[¶] Christopher Small,[£] Song Shu,[¢] and Jianping Wu[¶]

[*]*Key Laboratory of Geographic Information Science (Ministry of Education) and School of Geographic Sciences, East China Normal University, and School of Earth and Environmental Sciences, The University of Queensland*

[†]*Key Laboratory of Geographic Information Science (Ministry of Education), School of Geographic Sciences, and Research Center for China Administrative Division, East China Normal University*

[‡]*Key Laboratory of Spatial Data Mining and Information Sharing of Ministry of Education, National & Local Joint Engineering Research Center of Satellite Geospatial Information Technology, and the Academy of Digital China, Fuzhou University*

[§]*School of Earth and Environmental Sciences, The University of Queensland*

[#]*Department of Geography and Geosciences, University of Louisville*

[¶]*Key Laboratory of Geographic Information Science (Ministry of Education), and School of Geographic Sciences, East China Normal University*

[£]*Lamont-Doherty Earth Observatory, Columbia University*

[¢]*Department of Geography and Planning, Appalachian State University*

An urban spatial cluster (USC) describes one or more geographic agglomerations and the linkages among cities. USCs are conventionally delineated based on predefined administrative boundaries of cities, without considering the dynamic and evolving nature of the spatial extent of USCs. This study uses Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS) nighttime light (NTL) satellite images to quantitatively detect and characterize the evolution of USCs. We propose a dynamic minimum spanning tree (DMST) and a subgraph partitioning method to identify the evolving USCs over time, which considers both the spatial proximity of urban built-up areas and their affiliations with USCs at the previous snapshot. China is selected as a case study for its rapid urbanization process and the cluster-based economic development strategy. Four DMSTs are generated for China using the urban built-up areas extracted from DMSP/OLS NTL satellite images collected in 2000, 2004, 2008, and 2012. Each DMST is partitioned into various subtrees and the urban built-up areas connected by the same subtree are identified as a potential USC. By inspecting the evolution of USCs over time, three different types of USCs are obtained, including newly emerging, single-core, and multicore clusters. Using the rank-size distribution, we find that large-sized USCs have greater development than medium- and small-sized USCs. A clear directionality and heterogeneity are observed in the expansions of the ten largest USCs. Our study provides further insight for the understanding of urban system and its spatial structures, and assists policymakers in their planning practices at national and regional scales. *Key Words: dynamic minimum spanning tree, nighttime light data, urban dynamics, urban spatial clusters.*

As a global phenomenon, urbanization leads to the physical expansion of urban areas, rapid population growth, and the increasing coalescence of cities (Bettencourt and West 2010; American Association for the Advancement of Science [AAAS] 2016; X. Li et al. 2017). An urban cluster is formed as a result of the rapid urbanization of multiple large cities that are in close proximity (Hall and Pain 2006; Lang and Knox 2009; F. Wu 2016). Urban clusters play important roles in facilitating the regional economy through the well-connected infrastructures and the resource reallocation between large and small cities. The definition of urban cluster has evolved over the past century (Geddes 1915; Fawcett 1932; Gottmann 1957; B. Yu et al. 2014; Fang and Yu 2017; Peng et al. 2020), but has not yet reached a consensus among scholars. Various terms have been used to denote a vast metropolitan area, including conurbation (Geddes 1915; Fawcett 1932), megalopolis (Gottmann 1957), urban agglomeration (Fang and Yu 2017), and urban spatial cluster (USC; B. Yu et al. 2014). Despite the variations

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in terminology, the existence of an extensive and multicity urban agglomeration has been well recognized (Scott 2001; Taubenböck et al. 2014; Harrison and Hoyler 2015). We adopt the terminology of USC in this study given its emphasis on the geographic linkage between urban areas and their spatial structures (B. Yu et al. 2014).

The previous relevant studies use socioeconomic indicators as the key measures of USCs (Gottmann 1957; Hagler 2009; Q. Zhang et al. 2012; Yao et al. 2016). For instance, Hagler (2009) identified the megaregions in the United States using five county-level factors: population density, population growth rate, employment growth rate, population density change, and whether a county is part of a Core Based Statistical Area (CBSA). These studies rely heavily on census data that are collected based on geographic units defined for administrative purposes. The spatial extents of these administrative units are changing over time. The differences in definition of USC and the change in the spatial extent of the administrative unit often lead to biases and obscurity when examining the spatiotemporal evolution of urban areas, as well as when comparing urban development in different countries and regions (Rozenfeld et al. 2008; Small et al. 2011). On the other hand, previous studies on the dynamic flow of urban phenomena, such as goods, services, materials, people, money, and information, are typically based on the fixed spatial extent of USCs (De Goei et al. 2010; Y. Li and Phelps 2017). The fact that the spatial extent of USCs is dynamic and evolving over time is often overlooked. Thus, a nonsubjective delineation of the USCs and their evolution over time without the intervention of administrative division is crucial for understanding the real spatial extent and pattern of USCs.

Spatial proximity is an essential feature of the USCs. Different statistical methods (based on socioeconomic factors) have been used to determine the spatial proximity among cities that belong to the same USC (Portnov and Wellar 2004; Portnov 2006). Spatial interaction methods, such as gravity models (Huff and Lutz 1995; Liang 2009; Peng et al. 2020) and Voronoi diagrams (Mu and Wang 2006) are used to detect the USCs. In Europe, a megacity region is usually defined in terms of contiguous functional urban regions (Hall and Pain 2006). Hence, geographic proximity can serve as a proxy variable for identifying localities that are likely to belong to a USC.

Nighttime light (NTL) images have been proven useful in providing spatiotemporal representations of various human activities on the Earth's surface, such as urban expansion (Small, Pozzi, and Elvidge 2005; T. Ma et al. 2012; Zhou et al. 2018), population density (Elvidge et al. 1997; Sutton et al. 2001; Doll and Pachauri 2010), socioeconomic indicators (Doll, Muller, and Morley 2006; Forbes 2013; Yang et al. 2019), electric power consumption (Elvidge et al. 1997; Shi et al. 2014; Shi et al. 2018), and CO_2 emissions (Doll, Muller, and Elvidge 2000; Shi et al. 2016). Recent studies also demonstrate that Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS) NTL data can be highly effective in facilitating the spatiotemporal analysis of urban expansion in USCs (T. Ma et al. 2012; Taubenböck et al. 2014; Q. Zhang and Su 2016; Lu et al. 2018). The long-term evolution of USCs, however, has not been examined from the perspective of USC's spatial structure at a very short time interval (e.g., four years in this study). B. Yu et al. (2014) proposed an object-based method for detecting and characterizing USCs using DMSP/OLS NTL data, which identifies the spatial pattern of USCs by simultaneously considering spatial proximity between urban patches. This object-based method is highly sensitive to the emergence of new urban patches, which complicates the use of this method for exploring the evolution of USCs over time. Florida, Gulden, and Mellander (2008) produced a consistent set of megaregions for the globe by thresholding the pixel values of DMSP/OLS NTL data. Peng et al. (2020) also used DMSP/OLS NTL time-series images to identify the boundaries of USCs in China from 2000 to 2012 by thresholding the NTL images to obtain urban areas. Their results are largely influenced by the selection of optimal threshold values, however.

This study presents a quantitative time-series view of the USCs in a nonsubjective way. We expanded the minimum spanning tree (MST) to the dynamic minimum spanning tree (DMST) to analyze the spatiotemporal evolution of USCs. Each discrete urban built-up area derived from DMSP/OLS NTL images is represented as an urban object. The DMST was used to represent the spatial proximity relationship between urban objects over time. A partitioning method was developed based on the Gestalt theory (Zahn 1971) to split the DMST into various subtrees. The urban objects connected by the same subtree form a potential USC. The dynamics of the USC over time were then detected through examining the affiliation of its urban objects with the USCs identified at the previous snapshot. The DMST and the partitioning method can overcome the instability of a single MST in several time-series situations to identify the spatiotemporal dynamics of the USCs without the intervention of administrative divisions. We selected China as a case study for its rapid urbanization process and cluster-based economic development strategy (Bai, Chen, and Shi 2012; Wang et al. 2015). The dynamic identification of USCs can allow policymakers to develop relevant policies according to the actual development of USCs. The driving forces to the evolution of USCs in China, as well as the implications, can also help urban researchers to rethink the mechanism behind the evolving USCs in urban systems.

Study Area and Data Sets

Study Area

China has experienced rapid urbanization since 1979 and the adoption of its opening-up policy (Chan 1992; Gaughan et al. 2016). Following a series of market reforms since 1979, local governments became responsible for the direct implementation of policies regarding local economies, leading to intercity competition and uncoordinated regional development (F. Wu 2016; Jia et al. 2020). The central government aims to maintain its leadership since the 1994 fiscal reform in regional development, and encourages provincial and local governments to formulate metropolitan strategies that focus on regional collaboration to restrict intercity competition and promote economic development (Vogel et al. 2010; Ye 2014). The national development strategies, such as the National New-type Urbanization Plan (2014–2020) and the Two-horizontal Three-vertical Urbanization Initiative, are implemented to develop the USCs as key carriers for regional economic development (National Development and Reform Commission 2014; Preen 2018). Our study area covers mainland China, Hong Kong, and Macao, but excludes Taiwan due to the nature of its island state.

Data

The Version 4 DMSP/OLS NTL time-series images from 2000 to 2012 were obtained from the Earth Observation Group of the Colorado School of Mines Web site (see https://eogdata.mines.edu/dmsp/downloadV4composites.html, accessed February 2020). These images were captured by different DMSP satellites (F14, F15, F16, and F18) on an annual basis. Each image is a composite of the NTL detected by a satellite over the entire year. The digital number (DN) value of each pixel can vary from 0 to 63, and represents the observed mean NTL intensity on Earth's surface (Elvidge et al. 1997; Imhoff et al. 1997; Sutton et al. 2001). The NTL images collected in different years have low continuity and comparability due to the lack of on-orbit radiance calibration (Small, Pozzi, and Elvidge 2005; Z. Liu et al. 2012; Shi et al. 2018), which makes it impossible to compare directly the multiyear NTL images. Previous studies have attempted to reduce the discrepancies between multiyear images (Elvidge et al. 2014; Shi et al. 2016). Among these, the invariant region method is commonly used to calibrate multiyear DMSP/OLS data (Wei et al. 2014). We calibrated the multiyear DMSP/OLS images from 2000 to 2012 using Sicily, Italy, as an invariant region following the method proposed by Elvidge et al. (2014). Figure 1A shows the processed NTL image of China in 2012.

We used the urban built-up area data generated by Z. Chen et al. (2019) from DMSP/OLS NTL time-series data and Moderate Resolution Imaging Spectroradiometer (MODIS) data using a region-growing support vector machine classifier and a bidirectional Markov random field model. The urban built-up data has a spatial resolution of 30 arc-seconds (approximately 1 km). Figure 1B shows the urban built-up areas in China from 2000 to 2012 with an interval of four years. The Chinese administrative boundary was obtained from the National Geomatics Center of China (see http://bzdt.ch.mnr.gov.cn/, accessed January 2020) and was used to extract the urban built-up area and the DMSP/OLS NTL time-series images in China. The core cities identified in Zhen, Wang, and Wei (2015) were used as a seed to identify the USCs. All the spatial data were projected to the Albers conical equal area projection.

Method

The methodological framework (Figure 2) consists of two main components. The first is USC identification. The urban built-up areas extracted from NTL data comprise a series of urban patches. Each urban patch consists of spatially connected urban

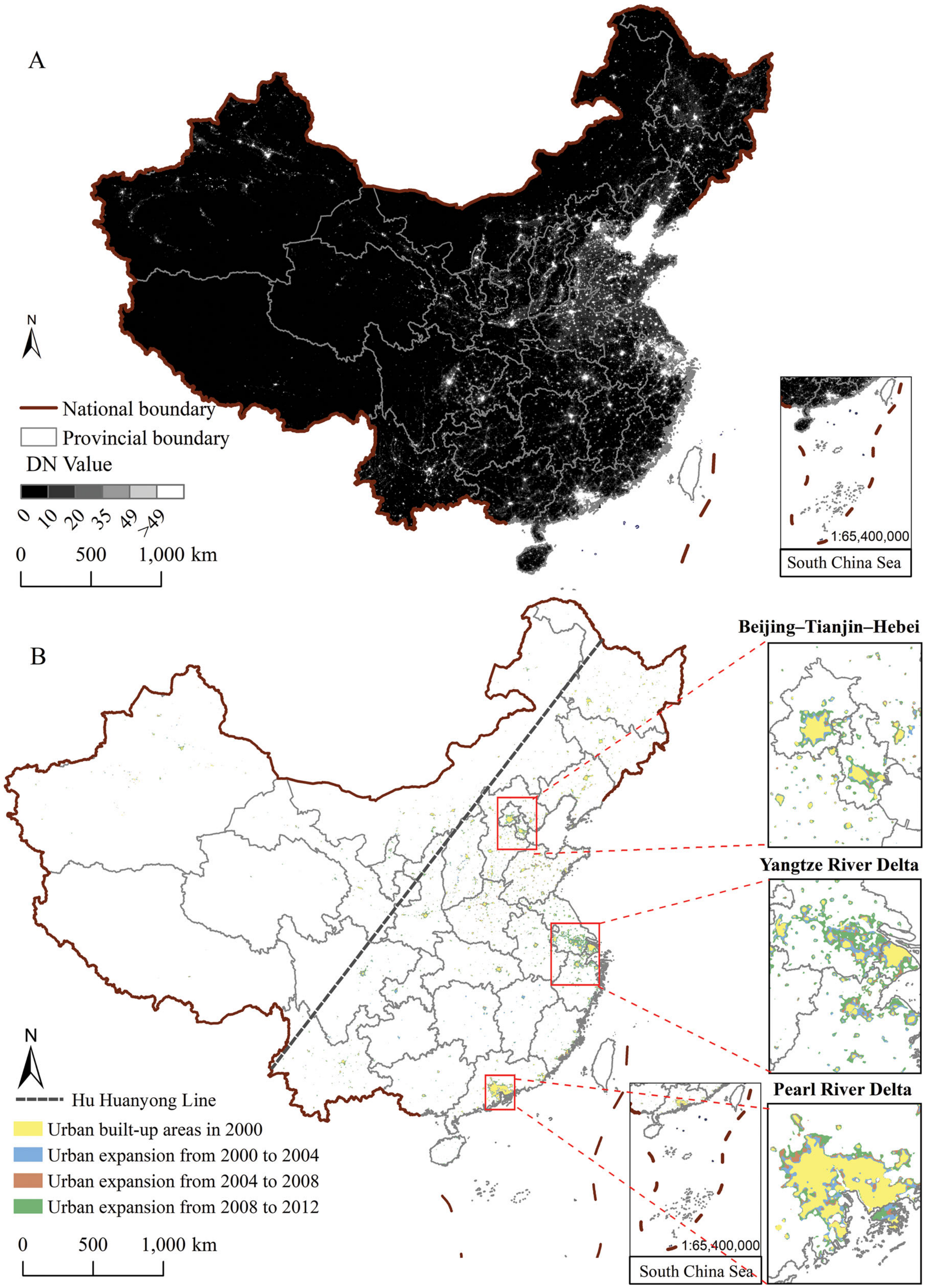


Figure 1. Input data: (A) Nighttime light image of China in 2012; (B) urban expansion in China derived from the DMSP/OLS nighttime light and MODIS data in 2000, 2004, 2008, and 2012. *Note:* DMSP/OLS = Defense Meteorological Satellite Program/Operational Linescan System; MODIS = Moderate Resolution Imaging Spectroradiometer; DN = digital number.

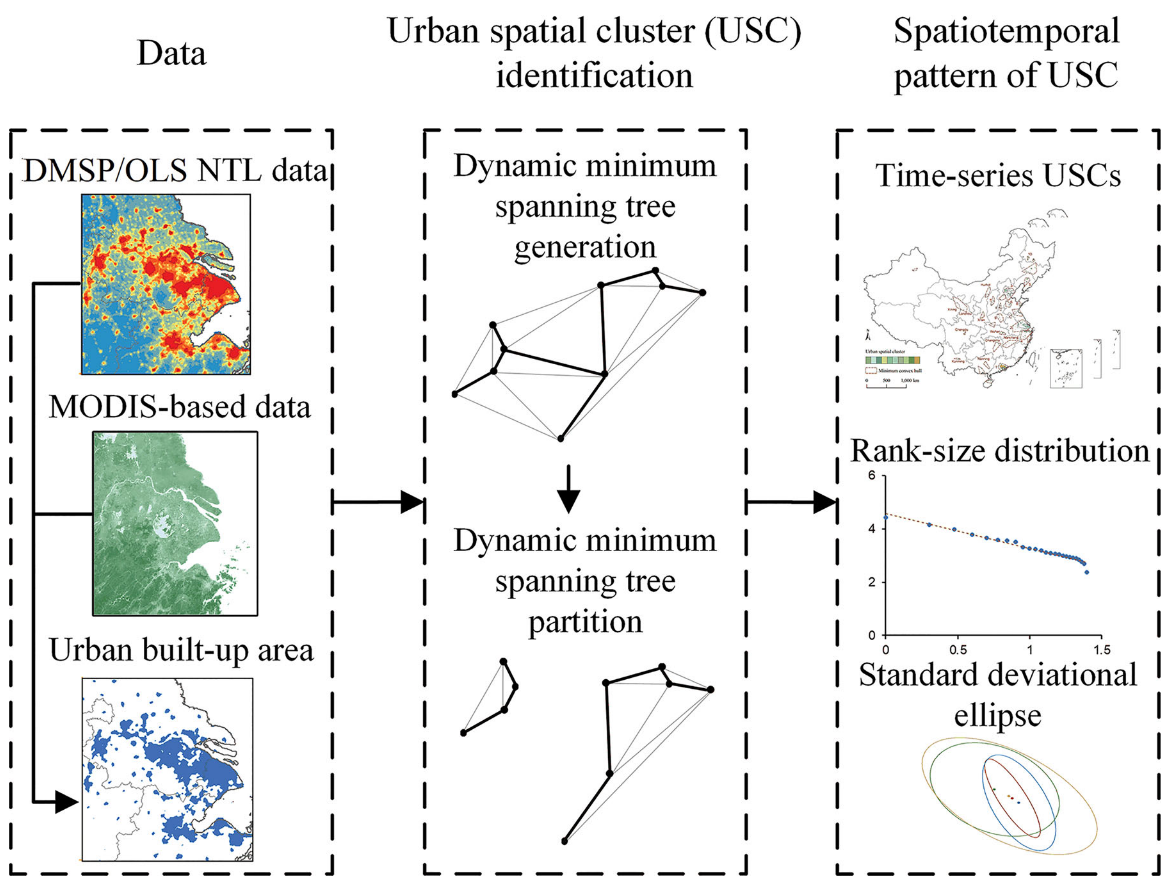


Figure 2. Methodological framework for examining the evolution of urban spatial clusters from DMSP/OLS nighttime light (NTL) images. *Note:* DMSP/OLS = Defense Meteorological Satellite Program/Operational Linescan System; MODIS = Moderate Resolution Imaging Spectroradiometer.

pixels and was identified as an urban object. An MST was built based on the urban objects in each year and was then expanded to a DMST. A partitioning method was applied to divide the DMST into USCs based on the spatial proximity between urban objects and their affiliations with USCs at the previous snapshot. The second component was spatiotemporal pattern analysis. The spatial and temporal patterns of USCs were analyzed using the rank-size distribution and the standard deviational ellipse (SDE) methods.

Identification of USCs

Generating a DMST to Represent Proximal Relations between Urban Objects. A recursive connected-region labeling algorithm (H. Liu and Jezek 2004; B. Yu et al. 2014) was employed to mark out the urban objects based on the spatial 4-connectivity of the foreground urban pixels extracted from NTL data. Data preprocessing, including a filling operation, a closing operation, and small spurious objects exclusion, were applied to the urban objects to smooth their boundaries and reduce the data noise. The MST in graph theory (AssunÇão et al. 2006; B. Yu et al. 2014; Caruso, Hilal, and Thomas 2017; B. Wu et al. 2018) is a spanning tree with a minimum weight among all possible spanning trees (see more details on the explanation of graph theory and MST in the Supplemental Material). In this study, the MST was built for all urban objects in each year to represent the spatial proximity of all urban objects in an entire region. As illustrated in Figure 3A, each node in the MST is an urban object; each edge links one urban object with its nearest urban object and the weight of the edge refers to the minimum distance between the boundaries of the two nearest urban objects. The MST is represented by:

$$\mathrm{MST} = \{N, E, W\} \tag{1}$$

where N represents a set of urban objects, E represents the edges that connect urban objects, and W represents the weights of the edges.

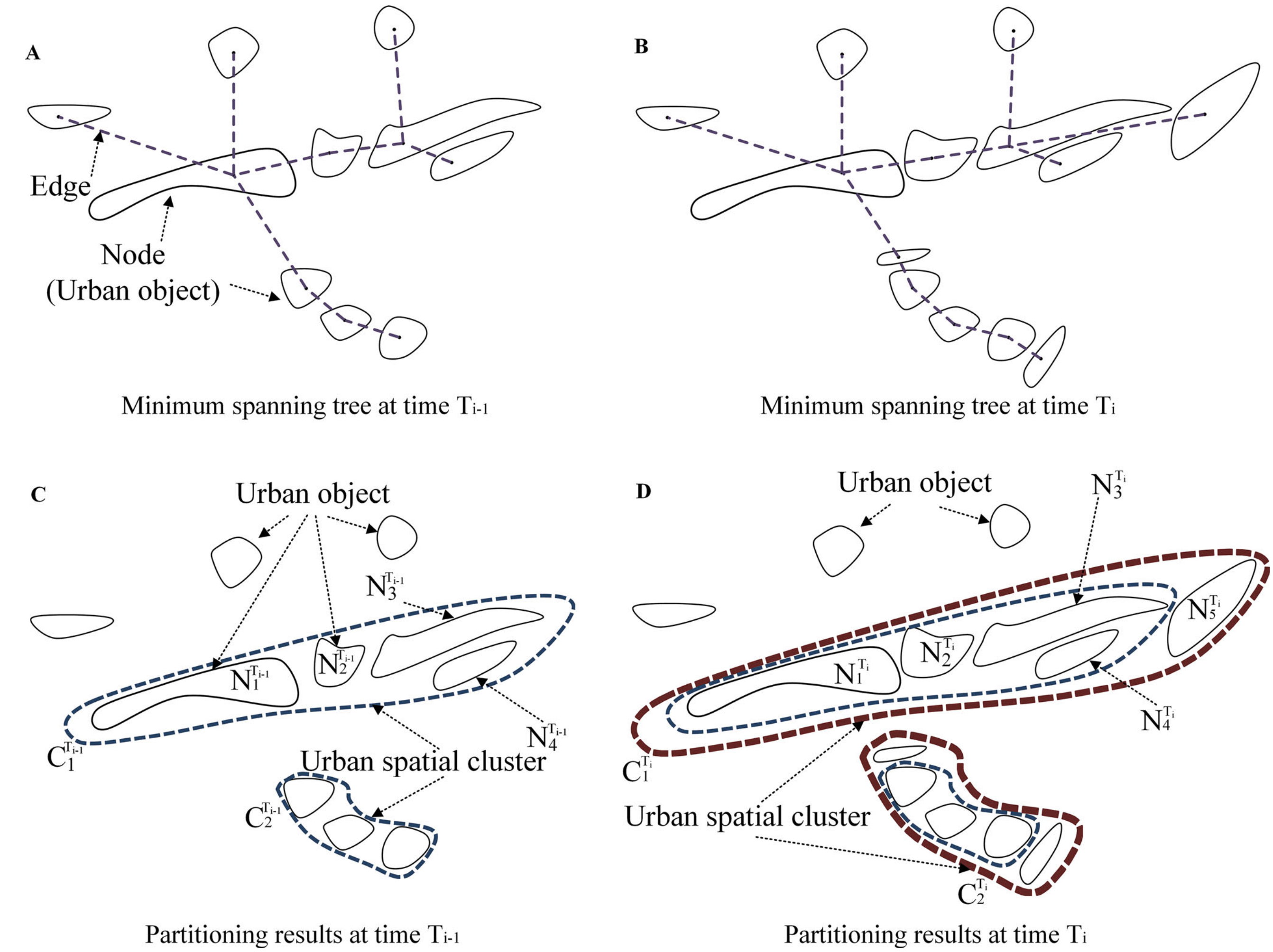


Figure 3. Minimum spanning tree at (A) time T_{i-1} and (B) time T_i. Partitioning results at (C) time T_{i-1} and (D) time T_i.

We first generated four MSTs from 2000 to 2012 at four-year intervals (from T_1 to T_4). Although the MSTs can reflect the spatial relations between urban objects in each snapshot, they cannot record the variations of urban objects' relationships over time. Moreover, the emergence of new urban objects over time can also change the local structure of the MST. Hence, to overcome this problem, we expanded the basic MST to the DMST by an additional set (C) with a timestamp. C was defined as a set of identified USCs (C_1, C_2, … , C_r) consisting of urban objects (the identification of USCs is discussed in the next section). By expanding the MST to the DMST, we could track the relationship variations of urban objects over time. The DMST at time T_i consists of the basic MST with nodes (N^{T_i}), edges (E^{T_i}), and weight (W^{T_i}), as well as the identified USCs ($C^{T_{i-1}}$) at time T_{i-1}. Figure 3B is an example of the basic MST at time T_i.

The DMST at time T_i is represented by:

$$\mathrm{DMST}^{T_i} = \{N^{T_i},\ E^{T_i},\ W^{T_i},\ C^{T_{i-1}}\} \tag{2}$$

where N^{T_i} is a set of nodes ($N_1^{T_i}$, $N_2^{T_i}$, … , $N_j^{T_i}$) at time T_i, which can be described as:

$$N^{T_i} = \{N_1^{T_i},\ N_2^{T_i},\ \ldots,\ N_j^{T_i}\} \tag{3}$$

E^{T_i} is the edges ($E_{1,2}^{T_i}$, $E_{2,3}^{T_i}$, … , $E_{j-1,j}^{T_i}$) that connect urban objects at time T_i:

$$E^{T_i} = \{E_{1,2}^{T_i},\ E_{2,3}^{T_i},\ \ldots,\ E_{j-1,j}^{T_i}\} \tag{4}$$

W^{T_i} is the weights ($W_{1,2}^{T_i}$, $W_{2,3}^{T_i}$, … , $W_{j-1,j}^{T_i}$) of the edges at time T_i. The set W^{T_i} has the form of:

$$W^{T_i} = \{W_{1,2}^{T_i},\ W_{2,3}^{T_i},\ \ldots,\ W_{j-1,j}^{T_i}\} \tag{5}$$

$C^{T_{i-1}}$ represents the identified USCs ($C_1^{T_{i-1}}$, $C_2^{T_{i-1}}$, … , $C_q^{T_{i-1}}$) consisting of urban objects at time T_{i-1} (the identification of USCs is discussed in the next section). For the DMST in the first time T_1, C^{T_0} is an empty set. The set $C^{T_{i-1}}$ has the form of:

$$C^{T_{i-1}} = \{C_1^{T_{i-1}}, C_2^{T_{i-1}}, \dots, C_q^{T_{i-1}}\} \quad (6)$$

Identifying USCs by Partitioning the DMST. USCs were identified by partitioning the DMST into different subtrees following Gestalt theory. Based on the MST, Zahn (1971) developed a partitioning method for detecting Gestalt clusters that are compatible with a human's visual perception of the two-dimensional point sets. B. Yu et al. (2014) adopted a similar strategy as in Zahn (1971) to partition the MST and confirmed that this method is suitable for generating USCs in China. Following the method by B. Yu et al. (2014), the urban objects connected by the same subtree represent a potential USC. An edge was cut off from the DMST when the weight is larger than a given threshold. Three types of indicators were defined to cut off the edge ($E_{m,n}^{T_i}$), namely, the distance ($W_{m,n}^{T_i}$) between the boundaries of two urban objects ($N_m^{T_i}$ and $N_n^{T_i}$), the average distances ($\overline{W}_m^{T_i}$ and $\overline{W}_n^{T_i}$) of its nearby edges for each urban object ($N_m^{T_i}$ and $N_n^{T_i}$) in the edge $E_{m,n}^{T_i}$, and the standard deviations ($STD_m^{T_i}$ and $STD_n^{T_i}$) of the distances of its nearby edges for each urban object ($N_m^{T_i}$ and $N_n^{T_i}$) in $E_{m,n}^{T_i}$ (see more details on the indicators for partitioning the DMST and the uncertainty and sensitivity analysis of the thresholds for indicators in the Supplemental Material). After partitioning the DMST at time T_1, the urban objects connected by the same subtree were considered as one USC. Previous studies show that a USC usually consists of more than one core city together with peripheral areas connecting to the core cities (Kabisch and Haase 2011; Yao et al. 2016). Following these studies, we used the locations of the core cities proposed by Zhen, Wang, and Wei (2015) in China and excluded those USCs whose urban built-up areas do not encompass more than one of these core cities. Next, we excluded the small spurious USCs with fewer than five urban objects.

After obtaining the USCs at time T_1, we partitioned the DMST at time T_2, time T_3, and time T_4. We first determined whether the edges are consistent or not using the same three types of indicators at time T_1 in the Supplemental Material. Second, we detected the dynamics of the USC over time through examining the affiliation of its urban objects with the USCs identified at the previous snapshot. Because the partitioning method proposed by B. Yu et al. (2014) is sensitive to the emergence of new urban objects when used over an extended period, we proposed a partitioning method for the DMST to overcome this problem. Our partitioning method was based on the principle that once an urban object becomes part of a USC, it is unlikely to be separated from the USC in later years. For urban object N_j at time T_i ($N_j^{T_i}$), we analyzed the status of N_j at time T_{i-1} ($N_j^{T_{i-1}}$). If $N_j^{T_{i-1}}$ belongs to the USC $C_p^{T_{i-1}}$, $N_j^{T_i}$ was considered as a part of the USC $C_p^{T_i}$. Meanwhile, the edges connecting the urban objects in the USC $C_p^{T_i}$ were reset to be consistent at time T_i. For instance, Figure 3C shows the identified USCs at time T_{i-1} ($C_1^{T_{i-1}}$ and $C_2^{T_{i-1}}$). The USC C_1 at time T_{i-1} ($C_1^{T_{i-1}}$) contains four urban objects ($N_1^{T_{i-1}}$, $N_2^{T_{i-1}}$, $N_3^{T_{i-1}}$, $N_4^{T_{i-1}}$). At the next time T_i (Figure 3D), the urban objects ($N_1^{T_i}$, $N_2^{T_i}$, $N_3^{T_i}$, $N_4^{T_i}$) are belonging to the USC $C_1^{T_i}$. Finally, we excluded those USCs if their urban built-up areas do not encompass more than one core city, as well as the small spurious USCs with fewer than five urban objects except the USCs that have been identified at the previous snapshot, using the same method at time T_1. The minimum convex hull (MCH) polygon was used to delineate the relatively regular shape of each USC (B. Yu et al. 2014).

Spatiotemporal Analysis of USCs

The rank-size distribution method was employed to evaluate the rank-size relationship of USCs in China. The size of each USC was measured with the total urban built-up area within that USC. After a logarithmic transformation, the rank-size relationship can be presented as a linear function shown as (Guerin-Pace 1995; Fragkias and Seto 2009; Small et al. 2011; Small et al. 2018):

$$\lg P_i = \lg P_1 - q\lg R_i \quad (7)$$

where P_i is the urban built-up area of a USC that ranks in the ith position among all USCs, with P_1 being the largest USC, P_2 the second largest USC, and so on. R_i is the rank of the ith USC, and q is the slope. The distribution of q indicates the degree to which the relationship may conform to a scaling law between the size and number of USCs (Fragkias and Seto 2009; Shi et al. 2018). When q equals 1, it indicates that the size of the top-ranked USC is twice as large as that of the second-ranked USC, three times as large as that of the third-ranked USC, and so on (Zipf 1949; Fragkias and Seto 2009; Jiang and Jia 2011; Small and Sousa 2016). A rank-size distribution with a slope less than one indicates that the study area is dominated by a large number of small-sized USCs, whereas a distribution with a slope greater than one indicates that the study area is dominated by a small number of large-sized USCs (Fragkias and Seto 2009; Shi et al. 2018).

The SDE is an effective tool for measuring the spatial dispersion of a set of geographical events (Lefever 1926; Shi et al. 2018; Xu et al. 2018). An SDE was generated for each USC and used to indicate the direction of each USC's spatial expansion. Based on the boundaries and the NTL pixel values of urban objects within each USC, four parameters were calculated for each SDE—the ellipse center, the azimuth, and the standard deviations along the long and short axes (see more details in the Supplemental Material). The ellipse center is the centroid of all urban objects within a USC, weighted by the NTL pixel value. The long axis, short axis, and azimuth represent the dispersion and directional trends of the USC (Lefever 1926; Shi et al. 2018; Xu et al. 2018). The ratio of the long to short axis reflects the degree of clustering or dispersion of the USCs. A large ratio with a value greater than one indicates that the USC has an apparent directional expansion. A ratio equal to one, however, indicates no directional characteristic in the USCs (Xu et al. 2018).

Results

USCs in China from 2000 to 2012

An MST was constructed for 2000, 2004, 2008, and 2012, respectively (Figure 4). These MSTs have more edges in eastern and southern China than in northwestern China. By expanding the basic MSTs to the DMSTs and partitioning the DMSTs, we can see that the subtree at the Yangtze River Delta (YRD) region (Figure 1B) consists of ninety-five consistent edges and ninety-six urban objects in 2012 (Figure 4D).

The number and size of USCs in China changed substantially from 2000 to 2012 (Figure 5). In total, we detected twenty, thirty-three, thirty-one, and thirty-one USCs in 2000, 2004, 2008, and 2012, respectively (Figure 5). Three types of USC evolution, namely, the single-core cluster (Figure 6A), the newly emerging cluster (Figure 6B), and the multicore cluster (Figure 6C), are identified in this study. Overall, the development of large-sized USCs is more prominent than the small and medium-sized USCs (Figure 7). The slope (q) of the rank-size distribution decreased from 1.16 in 2000 to 1.08 in 2004 and increased to 1.21 in 2012. The SDEs of the ten typical USCs are illustrated in Figure 8. The ellipse center of the YRD (Figure 8A) moved northwest by 5.80 km from 2008 to 2012. The ellipse center of the Pearl River Delta (PRD; Figure 8E) shifted northwest by 2.80 km from 2000 to 2012. The ratio of the long to short axis reduced from 1.62 in 2000 to 1.55 in 2012, indicating that the expansion of the PRD is relatively stable with a slight decreased directional tendency.

Discussion

An Innovative Approach to Identifying and Monitoring the Evolving USCs

Previous studies have demonstrated that NTL images have the potential of identifying USCs through visual interpretation or by applying an object-based algorithm or a threshold method to the images (Lo 2002; Florida, Gulden, and Mellander 2008; B. Yu et al. 2014). Few studies, however, focus on the spatial evolution of USCs over time. In this study, we developed a graph-based method to detect and characterize the spatiotemporal patterns of USCs using the DMSP/OLS NTL satellite images. Compared with the USCs detected by Peng et al. (2020), who also used the DMSP/OLS NTL data from 2000 to 2012, the approach in this study not only reflects the spatiotemporal development of the USCs, but also the spatial structures of the USCs.

Our method is more robust and effective for understanding the evolving USCs than the approach developed by B. Yu et al. (2014) and is not influenced by the emergence of new urban objects from a time-series perspective. As a comparison, we applied the method developed by B. Yu et al. (2014) to identify the USCs in China at four snapshots T_1 (2000), T_2 (2004), T_3 (2008), and T_4 (2012). A comparison of the identification of the Liaodong Peninsula (LDP) cluster based on the method proposed by B. Yu et al. (2014) and our method can be seen in the Supplemental Material.

Furthermore, our method is also more suitable for identifying USCs than that using the administrative

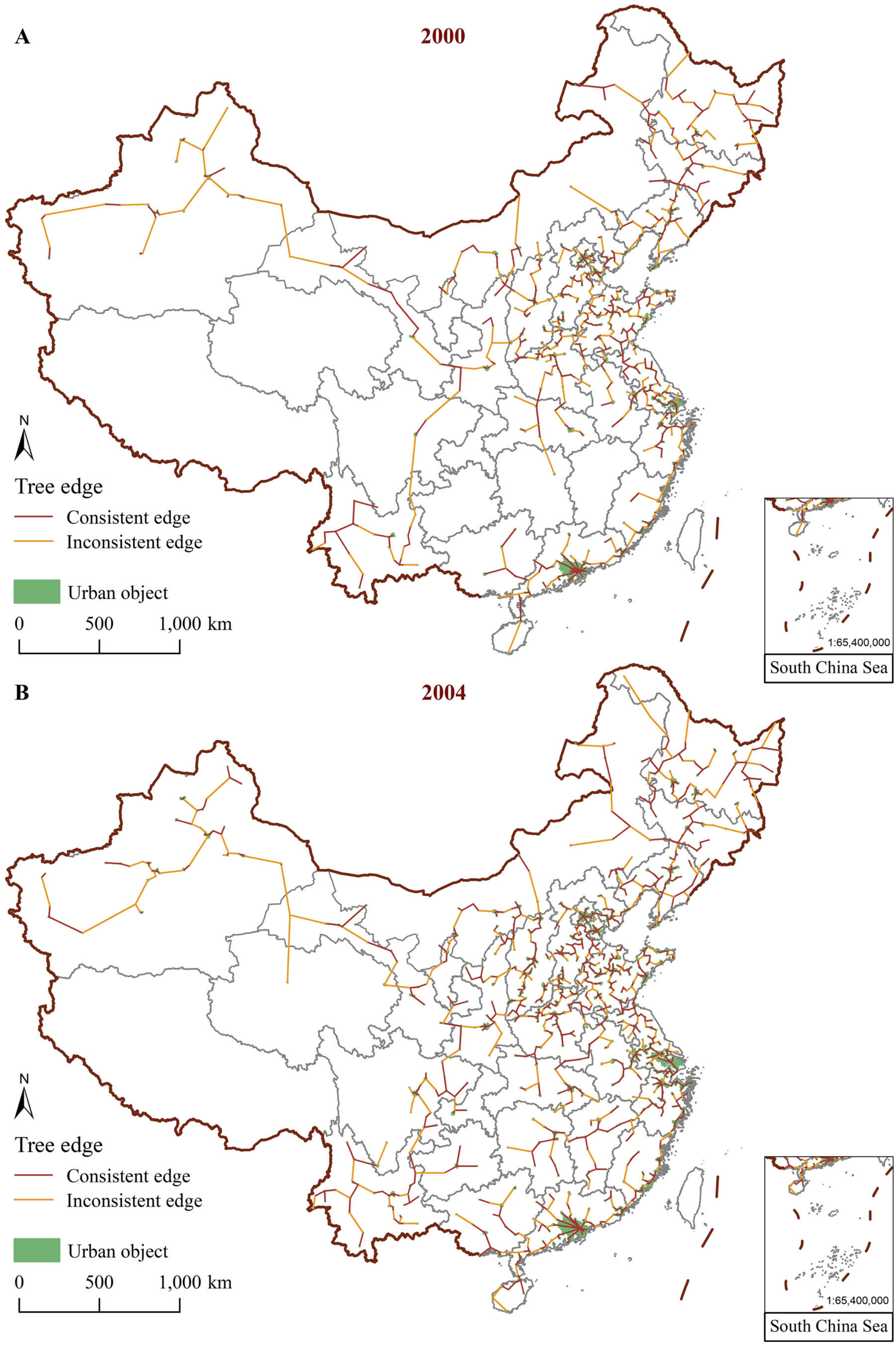
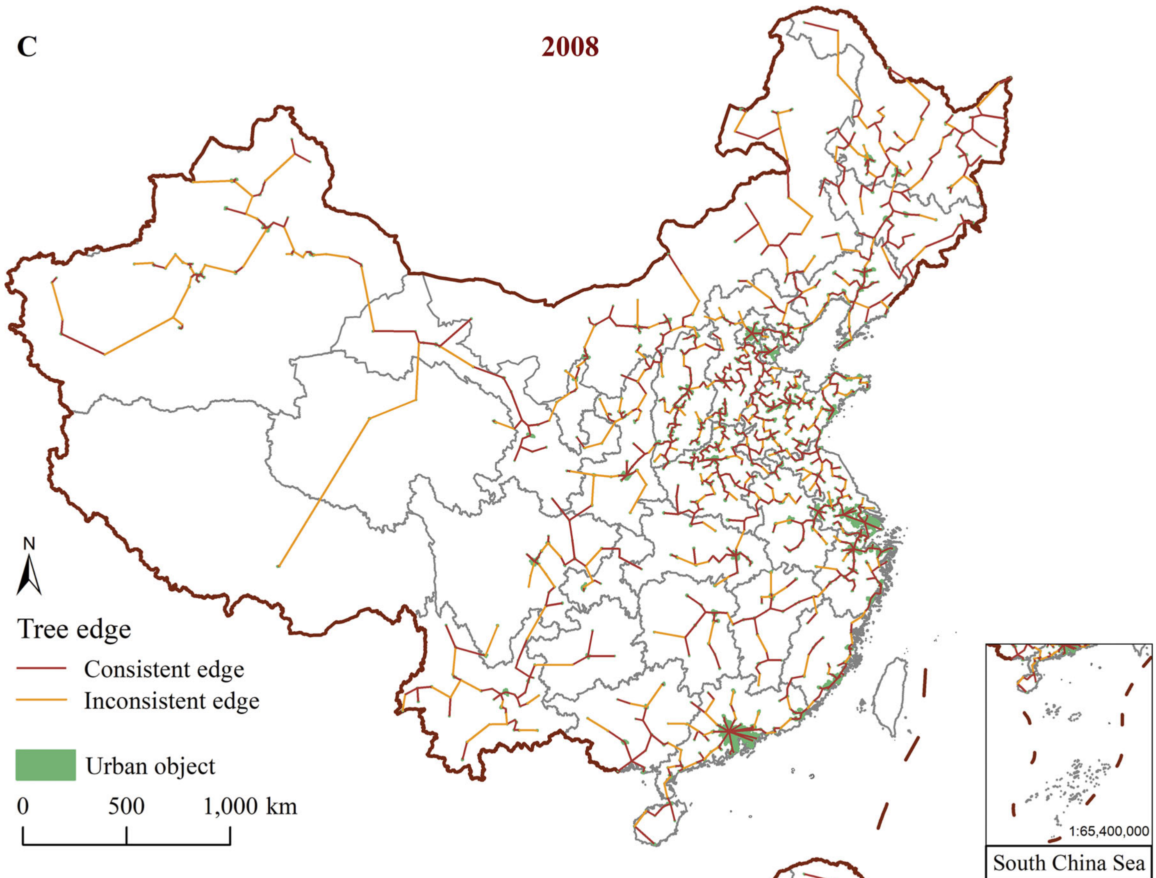


Figure 4. The generated and partitioned dynamic minimum spanning trees: (A) 2000, (B) 2004, (C) 2008, and (D) 2012.



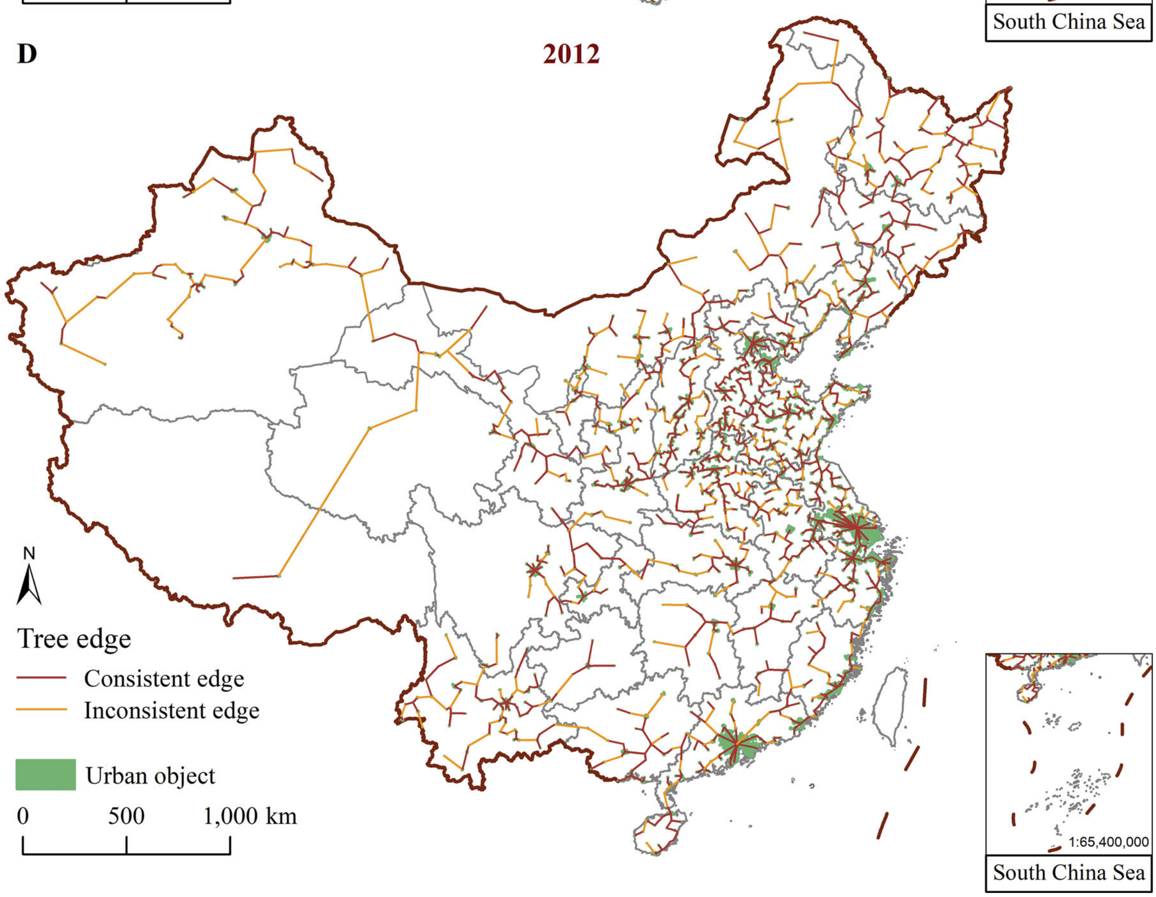


Figure 4. Continued.

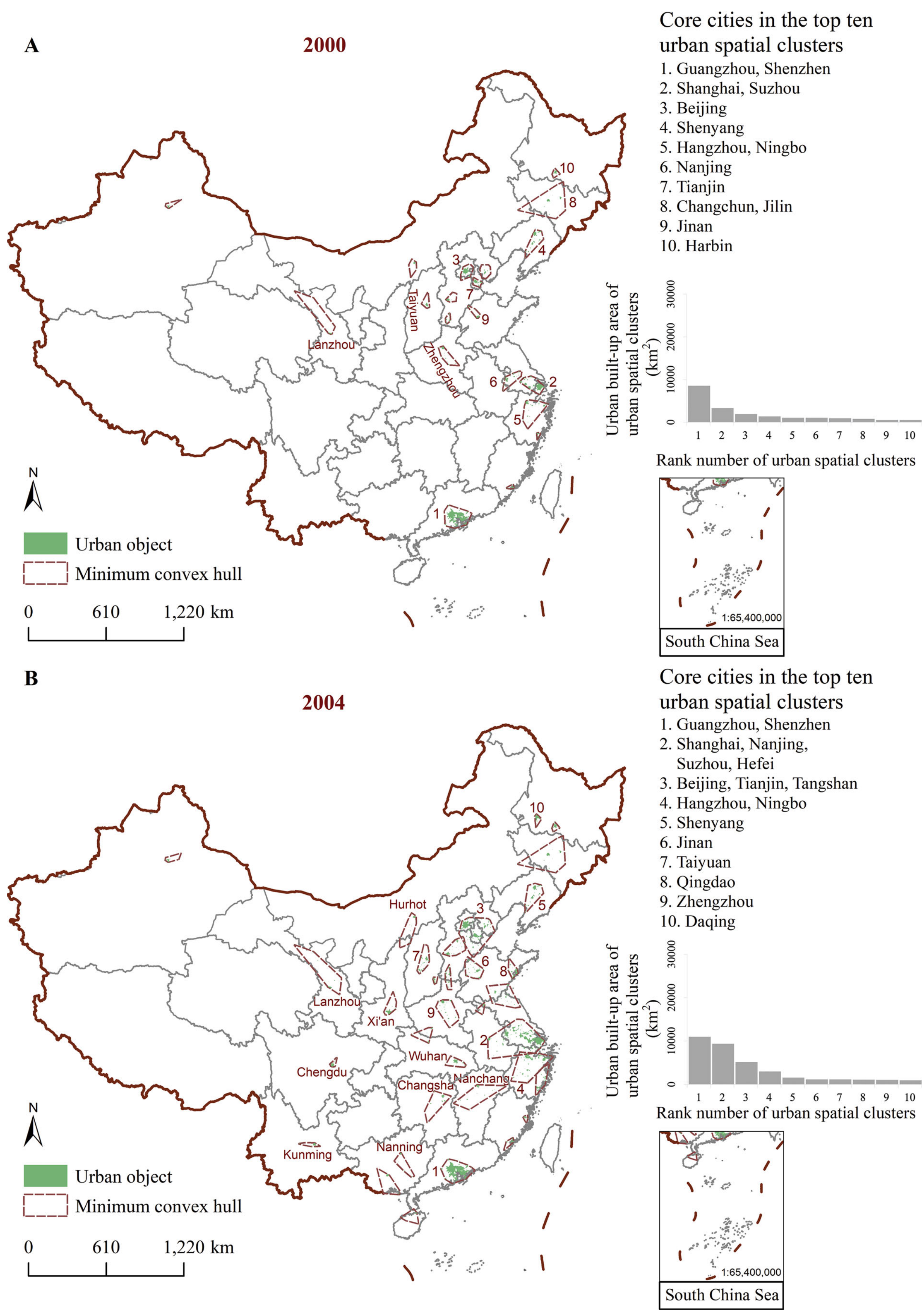


Figure 5. Urban spatial clusters, their minimum convex hulls, sizes, and core cities: (A) 2000, (B) 2004, (C) 2008, and (D) 2012. Names and abbreviations of the top ten urban spatial clusters in 2012: 1. Yangtze River Delta (YRD); 2. Beijing-Tianjin-Hebei (BTH); 3. Pearl River Delta (PRD); 4. Central Plain (CPL); 5. Taiyuan Basin (TYB); 6. Eastern Fujian (EFJ); 7. Liaodong Peninsula (LDP); 8. Lianyungang (LYG); 9. Harbin-Changchun-Jilin (HCJ); 10. Guanzhong Plain (GZP).

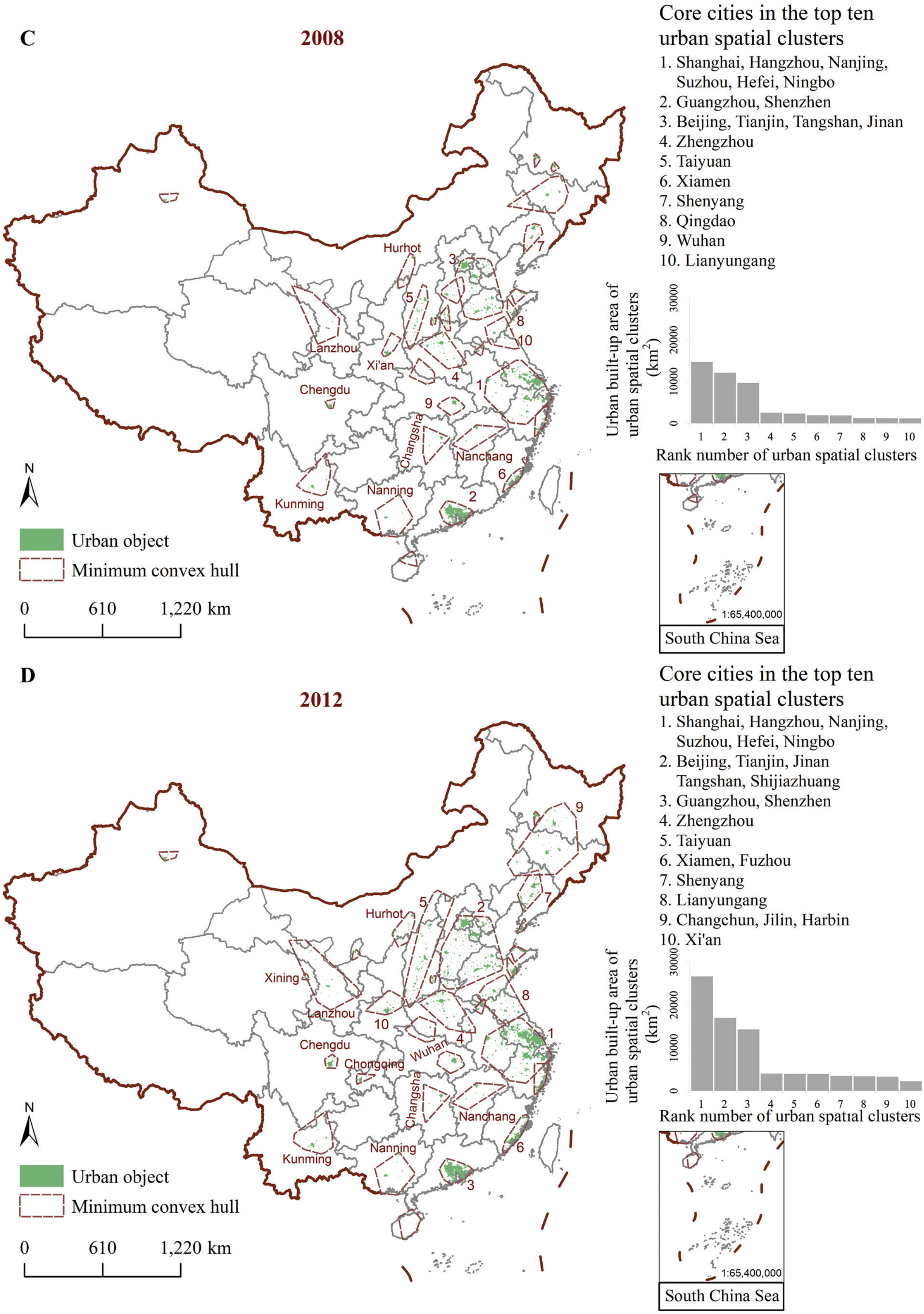


Figure 5. Continued.

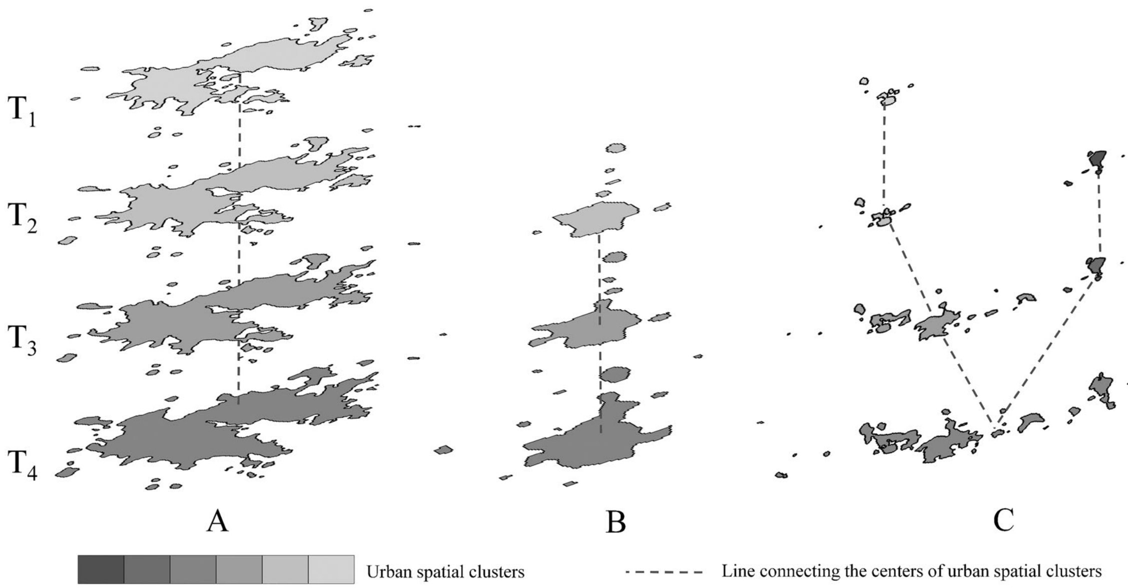


Figure 6. Simplified illustration of three evolution types of urban spatial cluster (USC): (A) single-core cluster, (B) newly emerging cluster, and (C) multicore cluster at time T_1, time T_2, time T_3, and time T_4. The single-core cluster is expanded around the existing USC over the twelve-year period from 2000 to 2012. The newly emerging cluster is the USC that emerged over the twelve-year period from 2000 to 2012. The multicore cluster is formed after the coalescence of multiple adjacent USCs that existed in earlier years. Each USC is represented by polygons in a different gray color.

boundaries, due to the following features of our method. First, our method does not need specific socioeconomic and demographic data, which are typically derived based on the city's predefined boundary (e.g., its administrative boundary). The quality of these data across cities is inconsistent (Niedomysl et al. 2017; S. Ma and Long 2020), and explanations and interpretations of data could provide inconsistent outcomes (Rozenfeld et al. 2008). Second, our approach can be used to determine the location and time of the emergence of a USC, and to show how multiple USCs can emerge into one integrated USC. Understanding these processes in a timely manner is critical for cross-city management and coordination; such an understanding is difficult to obtain based on the administrative boundaries. For instance, the middle reaches of the Yangtze River agglomeration (MYRA) proposed by the central government in 2015 was meant to promote central China's economic development, covering three megacity groups, including Wuhan, Nanchang, and Changsha, and their corresponding metropolitan areas (China State Council 2015). We identified MYRA as three newly emerging USCs, namely the Wuhan USC, the Nanchang USC, and the Changsha USC, during the twelve-year period (Figure 5) and confirmed that these had not reached an entire USC.

Driving Forces for the USC Evolutions

In China, USCs have undergone a significant transformation since 1979 due to the combined effects of policies, demographic, macro- and micro-economic conditions, globalization, industrialization, and geographical characteristics (Lin 2001; Ye 2014; F. Wu 2016; G. Li, Sun, and Fang 2018).

Urban development policies at the national or regional government levels are important driving forces for the formation of USCs (Jonas 2012; Fang, Li, and Wang 2016; F. Wu 2016; W. Yu and Zhou 2018), especially for the early stage of a USC (Kuang et al. 2014). Because the central government emphasizes improving the leading function of large cities and developing the medium- and small-sized cities in the Tenth Five-Year Plan (2001–2005; W. Yu and Zhou 2018), most newly emerging USCs are all formed during this period (Figure 5). At the regional government level, the PRD is a typical example, under the jurisdiction of one provincial government (Guangdong). The government-led regional policies in the PRD can be more effective than in other areas, leading to a good synergy among cities within the PRD and a rapid urban expansion in the early stages of its development (Xu and Yeh 2005; Ye 2014). Our results show that the PRD was the most stable USC from 2000 to 2012 in China (Figure 5 and Figure 8E).

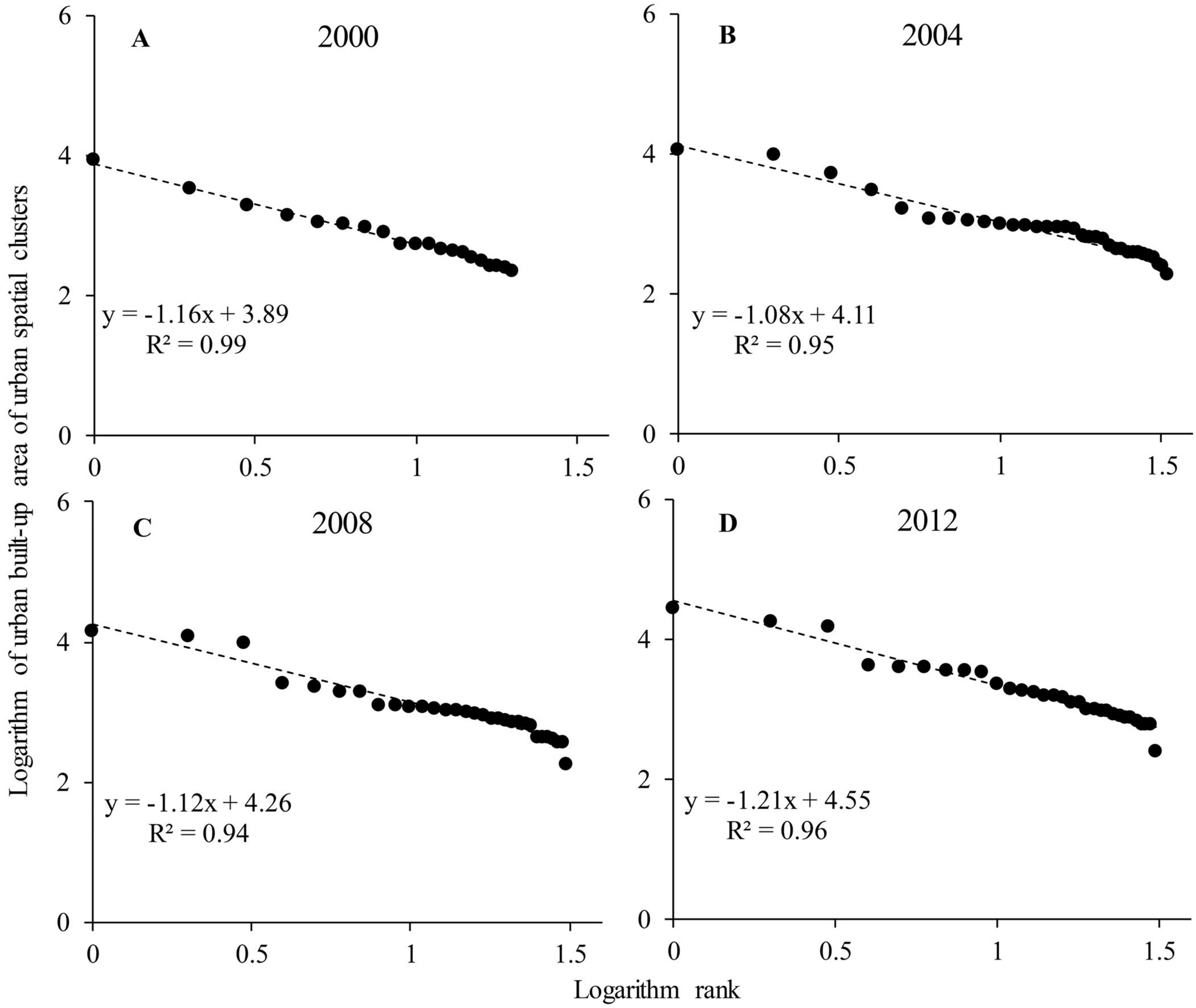


Figure 7. The rank-size distribution of urban spatial clusters in China.

Economic incentives, such as urban industrial relocation and transformation and foreign direct investment, also play an important role in driving the USC development process (Seto and Kaufmann 2003; Fragkias and Seto 2009; Ye 2014; F. Wu 2016). For instance, in 2005, Shougang Group, a giant iron and steel company in China, began to relocate its factory and more than 60,000 employees from Beijing (the core city of the Beijing-Tianjin-Hebei [BTH] cluster) to Tangshan. This relocation resulted in strong connectivity between the two cities and the development of BTH from 2004 to 2008 (Figure 5). Similarly, in 2008, Guangzhou, the core city of the PRD, began to move more than 300 plants to Foshan, which resulted in a slight shift of the ellipse center of the PRD to the northwest from 2008 to 2012 (Figure 8E). In addition to industrial relocation, industrial transformation can also have an impact on the development of USCs. For instance, Harbin and Changchun are two core cities of the Harbin-Changchun-Jilin (HCJ) cluster (Figure 5). Each city has a different dominant urban function. Harbin has experienced the industrial transformation from heavy industry to tertiary industry, whereas Changchun is dominated by secondary industry. After connecting these two cities vas economic connections, the HCJ became an integrated USC in 2012 (Figure 5 and Figure 8D).

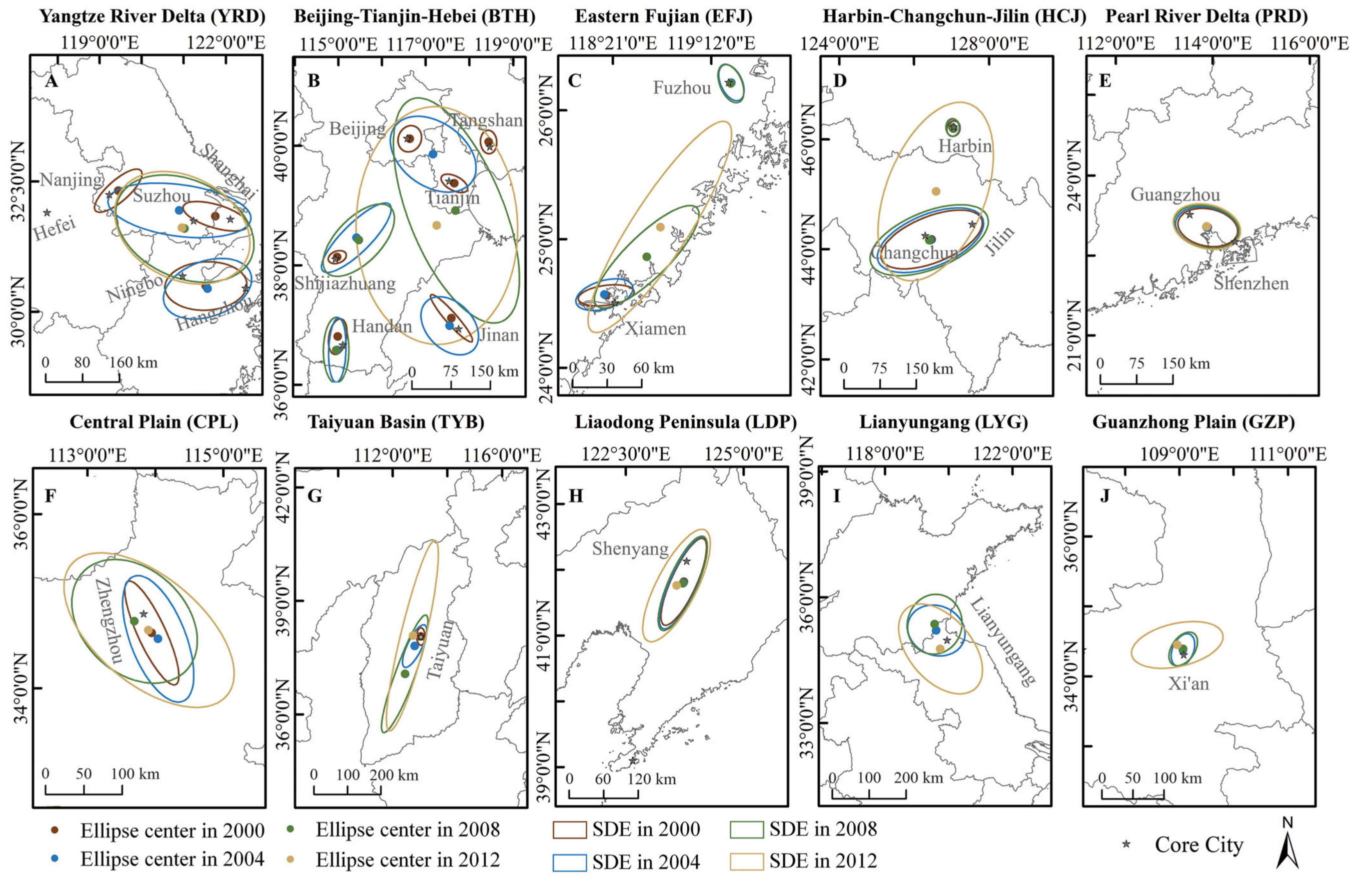


Figure 8. The standard deviational ellipses (SDEs) for ten typical urban spatial clusters from 2000 to 2012. Multicore clusters: (A) Yangtze River Delta (YRD), (B) Beijing-Tianjin-Hebei (BTH), (C) Eastern Fujian (EFJ), and (D) Harbin-Changchun-Jilin (HCJ). Single-core clusters: (E) Pearl River Delta (PRD), (F) Central Plain (CPL), (G) Taiyuan Basin (TYB), and (H) Liaodong Peninsula (LDP). Newly emerging clusters: (I) Lianyungang (LYG), and (J) Guanzhong Plain (GZP).

Furthermore, the transportation infrastructure can also drive the expansion of a USC (X. Li et al. 2016; Long, Zheng, and Song 2018; Yue et al. 2019; H. Zhang et al. 2019). For instance, Hefei originally had a weak connection with the cities in the YRD and did not fully receive the contributions from the spillover effects of Shanghai or Nanjing (two core cities in the YRD; J. Chen et al. 2020). The construction of the first high-speed railway from Hefei to Nanjing was started in 2005 and completed in 2008. The spatial redistribution of economic activities and population was improved with the benefit of the high-speed railway (X. Li et al. 2016; Shao, Tian, and Yang 2017). According to our results, the ellipse center of the YRD moved toward Anhui Province (Hefei as the capital city) from 2008 to 2012 (Figure 8A). These results are in agreement with the YRD Regional Plan and the results from Lu et al. (2018) and Yao et al. (2016).

Policy Implications for China

The evolution of USCs should be considered to formulate the industrial transformation policies for the heavy-industry-led USCs. Like other USCs led by heavy industry development, such as the Detroit-Warren-Dearborn metropolitan region in the United States, the developments of those USCs including HCJ and LDP in China are also affected by the industrial transformation in recent years. Under the policy of industrial transformation in northeast China (China State Council 2007; P. Zhang 2008), the HCJ consisted of two separate USCs from 2000 to 2008 and became an integrated USC in 2012. The LDP cluster, however, became the seventh-largest USC in 2012 from the fourth-largest USC in 2000 (Figures 5A and 5D). This indicates that the national industrial transformation policy had a different impact on the development of HCJ and LDP clusters. Our results show that the HCJ is a multicore cluster, whereas the LDP is a single-core cluster. In the future, the spatial structures and types of USCs, along with economic strength and natural environment, should be deeply analyzed to help policymakers formulate a more effective regional plan.

Regional coordination should be considered to formulate the USC policies, as we found the spatial heterogeneity of USCs in China, which echoes its population distribution pattern as illustrated by the Hu Huanyong Line (Hu 1935). The Hu Huanyong Line (Figure 1B) divides mainland China into two parts: The eastern part accounts for approximately 36 percent of China's land area and contains 96 percent of its population, whereas the western part contains only 4 percent of China's population but accounts for approximately 64 percent of its land area. Regional development plans, such as the China Western Development Plan in 2000 (China State Council 2000) and the Rise of Central China Plan in 2006 (China State Council 2006), had impacts on the development of medium- and small-sized USCs, as the slope (q) of the rank-size distribution decreased from 1.16 in 2000 to 1.08 in 2004 (Figure 7A). The rapid development of medium- and small-sized USCs from 2000 to 2004 was mostly observed in western and central China. The large USCs developed faster than the small and medium-sized USCs from 2004 to 2012, however (Figure 7), indicating that these plans might not be sufficient to support the sustainable development of USCs in western and central China.

Implications for Urban Research

This study presents a novel USC detection approach and applies it successfully to identify the dynamic evolution of USCs in China. It contributes to urban research in multiple dimensions. First, this research demonstrates the value of using nontraditional data sources (e.g., remote sensing) and "data mining" capabilities to dynamically identify function- and association-based USCs and structures, which can uncover spatial regimes or other forms of spatial heterogeneity in the urban system. This method uses information extracted from the NTL remote sensing data as the input, which is easier to obtain as compared to other approaches that need data to measure urban spatial interactions, such as population, information, and material flows (Dewar and Epstein 2007; Nelson and Rae 2016). In addition, this method can also help to identify the functional linkages or development association between cities that might not always be easily detectable by other methods. As such, it can help researchers in countries or regions where data pertaining to functional linkages are not readily available.

Furthermore, the spatial extents of the detected USCs are not constrained by any administrative boundary, which helps us better understand the spatial evolution of USCs. Previous research has documented the existence of the USCs in many countries, such as the megaregions in the United States (Hagler 2009), the megacity regions in Europe (Hall and Pain 2006), and the urban agglomerations in China (Fang and Yu 2017). These USCs were regionally specific due to the lack of global definition and comparable data (Florida, Gulden, and Mellander 2008). Owing to the long time-series and global coverage of NTL data, our approach contributes to addressing the ongoing challenges of data heterogeneity in other regions as well as varying administrative units, which have long hampered comparative studies.

Conclusion

This article presents a graph-based method using a DMST algorithm and a partitioning approach to detect the evolution of USCs. We used DMSP/OLS NTL time-series images and urban built-up data extracted from the DMSP/OLS NTL images as input data. The emergence of new urban objects over time might influence the identification of USCs when dividing the MSTs into subtrees. Therefore, we expanded the MST to the DMST and improved the partitioning method by taking into account the spatial proximity between urban objects and their affiliations with USCs at the previous snapshot. We also employed the rank-size distribution approach and SDE analysis to assess the spatiotemporal patterns of USCs and their spatial directional expansions over time. Our methods allow researchers to explore and visualize USCs in other regions and provide an empirical framework for further inquiry into the identification of USCs.

We included all cities in China (except those in Taiwan) to detect the evolution of USCs over the twelve-year period from 2000 to 2012. In total, twenty, thirty-three, thirty-one, and thirty-one USCs were detected in 2000, 2004, 2008, and 2012, respectively. The USCs in the eastern coastal or southern regions appear to develop faster than those in the western region. The USCs can be classified into three types: the newly emerging cluster, the single-core cluster, and the multicore cluster. The large-sized USCs have greater development than medium- and small-sized USCs over the twelve-year period from 2000 to 2012. The top ten USCs exhibit a directional expansion pattern at the regional scale. The development policies at national and regional government levels, economic incentives, and transportation infrastructures have collectively played important roles in shaping and governing the development of China's USCs. The policy implications from industrial transformation and regional coordination can provide feedback to central or local governments to help them justify the development levels of USCs, and can also assist policymakers in conducting national and regional planning practices. The identified USCs also offer valuable insight for urban researchers to rethink the dynamic nature of the spatial structure of USCs in urban system.

Supplemental Material

Supplemental data for this article can be accessed online at http://dx.doi.org/10.1080/24694452.2021.1914538. The supplemental material consists of five sections. Section A is an explanation of graph theory and MST. Section B provides the indicators for partitioning the DMST based on Gestalt theory. Section C includes the uncertainty and sensitivity analysis of the thresholds for indicators. The calculation of SDE is shown in Section D. Section E gives the comparison of the identification of the LDP cluster based on the method proposed by B. Yu et al. (2014) and our method.

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ORCID

Bailang Yu http://orcid.org/0000-0001-5628-0003
Yan Liu http://orcid.org/0000-0002-1612-779X
Xia Li http://orcid.org/0000-0003-3050-8529

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CONGXIAO WANG is a PhD Candidate in Geographic Information Systems at the Key Laboratory of Geographic Information Science (Ministry of Education), School of Geographic Sciences, East China Normal University, Shanghai 200241, China. E-mail: cxwang1992@126.com. Her research interests include nighttime light remote sensing and its application in urban research.

BAILANG YU is Professor of Geography at the Key Laboratory of Geographic Information Science (Ministry of Education), School of Geographic Sciences, East China Normal University, Shanghai 200241, China and also at the Research Center for China Administrative Division, East China Normal University, Shanghai 200241, China. E-mail: blyu@geo.ecnu.edu.cn. His research interests include urban remote sensing, nighttime light remote sensing, LiDAR, and object-based methods.

ZUOQI CHEN is an Assistant Research Fellow of Geography at the Key Laboratory of Spatial Data Mining and Information Sharing of Ministry of Education, and the Academy of Digital China, Fuzhou University, Fuzhou 350002, China. E-mail: zqchen@fzu.edu.cn. His research interests include urban remote sensing, nighttime light remote sensing, and the development of geographic information systems.

YAN LIU is Professor in Geographical Information Science at the School of Earth and Environmental Sciences, The University of Queensland, Brisbane, Australia. E-mail: yan.liu@uq.edu.au. Her research interests include urban modeling and geo-simulation, spatial data analytics, and spatially integrated social studies.

WEI SONG is Professor of Geography in the Department of Geography and Geosciences, University of Louisville, Louisville, KY 40292. E-mail: wei.song@louisville.edu. His research interests include urban geography, location and transportation analysis, quantitative methods, and applications of geographic information systems.

XIA LI is Professor of Geography at the Key Laboratory of Geographic Information Science (Ministry of Education), School of Geographic Sciences, East China Normal University, Shanghai 200241, China. E-mail: lixia@geo.ecnu.edu.cn. His research interests include cellular automata, land use modeling, global land use simulation, and spatial optimization.

CHENGSHU YANG is a PhD Candidate in Geographic Information System at the Key Laboratory of Geographic Information Science (Ministry of Education), School of Geographic Sciences, East China Normal University, Shanghai 200241, China. E-mail: yjack90824@gmail.com. His research interests include nighttime light remote sensing and its application in urban research.

CHRISTOPHER SMALL is Lamont Research Professor of Marine Geology and Geophysics at the Lamont-Doherty Earth Observatory, Columbia University, Palisades, NY 10964.

E-mail: small@ldeo.columbia.edu. His research interests include geophysics, land surface processes, remote sensing, and population and environment.

SONG SHU is an Assistant Professor of Geography in the Department of Geography and Planning, Appalachian State University, Boone, NC 28608. E-mail: shus@appstate.edu. His research interests include remote sensing applications applied to Arctic snow, lake hydrology, water resources, cryospheric processes, and global climate change.

JIANPING WU is Professor of Geography at the Key Laboratory of Geographic Information Science (Ministry of Education), School of Geographic Sciences, East China Normal University, Shanghai 200241, China. E-mail: jpwu@geo.ecnu.edu.cn. His research interests include remote sensing and geographic information systems.