Landscape Ecol
https://doi.org/10.1007/s10980-019-00956-y

RESEARCH ARTICLE

Spatiotemporal evolution of urban agglomerations in China during 2000–2012: a nighttime light approach

Jian Peng · Haoxi Lin · Yunqian Chen · Thomas Blaschke · Lingwei Luo · Zihan Xu · Yi'na Hu · Mingyue Zhao · Jiansheng Wu

Received: 5 January 2019 / Accepted: 8 December 2019

Abstract
Context Urban agglomeration is an advanced spatial organization of cities, usually caused by urbanization processes when cities develop to a certain level - typically associated with higher population density and a certain density of built environment. However, compared with various studies focusing on specific cities, urban agglomerations are still understudied, especially for the quantitative identification of spatiotemporal evolution of urban agglomerations.
Objectives This study aims to identify the boundary of urban agglomerations in China from 2000 to 2012, and to explore the temporal evolution and spatial difference of urban agglomerations.
Methods Firstly, the core zone of urban agglomerations was identified using an appropriate threshold of the digital number (DN) of nighttime light. Secondly, the mean patch area and gravity model were used to determine the affected zone of urban agglomerations. Thirdly, spatiotemporal contrast was conducted focusing on the 23 main urban agglomerations in China.
Results By 2012, the most highly developed Yangtze River Delta and Pearl River Delta urban agglomerations met the standard of world level, with the Beijing–Tianjin–Hebei urban agglomeration for regional level, as well as 11 urban agglomerations for sub-regional level. Regional differences in urban agglomerations between southern and northern China, or between coastal and inland China remained stable over the study period of 2000–2012. Compared with the western urban agglomerations, the outward expansion of eastern urban agglomerations decelerated. From 2000 to 2012, the overall development mode of urban agglomerations shifted from the core-expansion to the peripheral-development, together with slower expansion of urban agglomerations after 2006.
Conclusions Nighttime light data are effective in exploring the spatiotemporal evolution of urban agglomerations.

J. Peng (✉) · Y. Chen · L. Luo · Z. Xu · Y. Hu · M. Zhao
Laboratory for Earth Surface Processes, Ministry of Education, College of Urban and Environmental Sciences, Peking University, Beijing 100871, China
e-mail: jianpeng@urban.pku.edu.cn

H. Lin
Guangzhou Institute of Geography, Guangzhou 510070, China

T. Blaschke
Department of Geoinformatics—Z_GIS, University of Salzburg, Schillerstrasse 30, 5020 Salzburg, Austria

J. Wu
Key Laboratory for Environmental and Urban Sciences, School of Urban Planning and Design, Shenzhen Graduate School, Peking University, Shenzhen 518055, China

Keywords Urban agglomeration · Nighttime light data · Gravity model · Spatiotemporal evolution · China

Introduction

As a significant trend of human development, urbanization has become the most prominent feature of social development since the twentieth century (Li et al. 2010; Qiu et al. 2017). Meanwhile, with the continuous development of central cities and their surrounding cities, the frequent interaction and integration among cities gradually led to the formation of urban agglomerations. From the perspective of external radiation effects, with the increase of urbanization rate, central cities in the urban agglomeration imposed stronger impact on the surrounding areas. From the perspective of internal development, the internal interaction within the urban agglomeration deepened and the boundaries of urban agglomeration constantly changed (Zhang et al. 2013; Zeng et al. 2016; Fang and Yu 2017). It can be seen that with the continuous development of society, the temporal and spatial changes inside and outside the urban agglomeration are increasingly complicated. Exploring the temporal and spatial dynamics of urban agglomerations can help to reveal the functional orientation and development direction of urban agglomerations, which is of great significance for the sustainable development of the region (He et al. 2019).

Although there is a lack of generally accepted and clear definition of urban agglomeration, there is high degree of consistency when describing its crucial characteristics. Urban agglomeration is acknowledged as the aggregation of relatively independent urban communities and the sum of intercity relationships (Gottmann 1957; Baigent 2004). In terms of structural characteristics, in general, one or two central cities exist within the urban agglomeration regardless of its scale. On this basis, central cities and the influenced surrounding area consist a combination of cities, and there will be full of integrality and close connections (Lin 2000; Robinson 2002; Yan et al. 2016). From the operational characteristics, the urban agglomeration is generally centered on the central cities, with industry radiation and linkage as the link, the industrial chain as the channel, and logistics, capital flow, technology flow as well as people flow as operational content (Fang and Yu 2017). All the characteristics reflect the heterogeneity of spatial and temporal patterns of urban agglomerations and the complexity of dynamic changes, which make it more difficult to accurately identify the dynamics of urban agglomerations.

In recent years, studies on urban agglomerations have shown a diversified trend, but the research limitations are also clear. For example, urban agglomeration research is highly restricted by urbanization datasets. Conventionally, to determine the boundary of urban agglomeration, various statistical data have been used, including gross domestic product (GDP), population, industrialization rate, etc. (Elvidge et al. 1997). However, these researches were accompanied by inherent disadvantages due to changing statistical standards, alternating statistical techniques and uncontrollable statistical errors (Zhou et al. 2011; Kuang et al. 2016). In contrast, owing to the advantages in providing timely and spatially explicit information, remote sensing data have been widely applied in detection of urban expansion (Fenta et al. 2017; Garouani et al. 2017; Liu et al. 2018). As a kind of remote sensing data, nighttime light (NTL) data are widely used in spatialization of socioeconomic indicators, urban expansion monitoring, environmental assessment, energy consumption estimation, and poverty evaluation (Elvidge et al. 2001; Tilottama et al. 2009; Yu et al. 2015). They are typical signals of economic and social activities because various human activities exist in the nighttime in the modern society. There are significant correlations between NTL intensity and a variety of urban development indicators, including GDP, population density, land use intensity, urbanization rate, etc. (Ma et al. 2012; Bennett and Smith 2017; Rybnikova and Portnov 2017). Therefore, NTL data is suitable for large-scale dynamic monitoring of urbanization, and it has gradually been accepted in monitoring urban development (Huang et al. 2014; Ma et al. 2014; Yu et al. 2014; Fu et al. 2017).

Despite the fact that NTL data have been used widely in measuring urban development (Cai et al. 2017; Hu et al. 2017; Zou et al. 2017), there are still few studies focusing on urban agglomeration, especially on quantitative identification of the spatiotemporal evolution of urban agglomeration (Li et al. 2013). The key to accurately identify urban agglomeration with the aid of NTL data, is how to determine an appropriate threshold of DN value. Previous studies have proposed various methods for defining urbanized areas using NTL data, including empirical threshold, Thematic Mapper (TM) satellite image comparison, and statistical data comparison methods. As a result, the range of DN values used to distinguish between urban and non-urban patches was summarized (Cao et al. 2009; Yu et al. 2014; Dou et al. 2017). Moreover, considering the comparability among different urban agglomerations, the fixed DN value was more accepted.

When exploring the characteristics of urban agglomerations, it is important to measure the extent of the linkages between the regions and the delineation of the boundary. At present, the use of gravity model and its derived models to identify or measure spatial development of urban agglomerations is becoming more and more abundant in China (Chen and Huang 2018). It is believed that a central city has a relatively large gravitational pull on a certain area, which can be regarded as affected zone of urban agglomeration related to the central city (Reilly 1931). However, this kind of identification lacks an in-depth understanding of the essential characteristics of urban agglomerations. It can only identify the potential hinterland of the urban agglomerations and the maximum expansion of the urban agglomerations, rather than the developmental extent of the urban agglomerations. Mean Patch Area (MPA) can characterize the degree of fragmentation of the landscape and quantify the fragmentation change of urban agglomeration under different gravitational intensities. By focusing on the inflection point, it is possible to obtain a region that has developed into a group with integrity. Within this region, the urban agglomeration is mature and can truly reflect the development of the urban agglomeration, which helps to scientifically and effectively identify the temporal and spatial changes of the urban agglomeration.

The outline of China's Eleventh Five-Year Plan clearly stated the development mode and needs of urban agglomerations, which emphasized the core of the urban agglomeration, i.e. the role of large cities and mega-cities as central cities of urban agglomerations. In response to the policy, from 2000 to 2010, China's urbanization rate was fast, i.e. national urbanization rate increasing from 40% to over 50%. During this period, many urban agglomerations have evolved from scratch, or from immature to mature. Thus, focusing on Chinese mainland, the spatial and temporal characteristics of urban agglomerations in China from 2000 to 2012 is analyzed. The objectives of this study are: (1) to identify the range of urban agglomerations in China during 2000–2012; and (2) to compare the temporal evolution and regional differences of urban agglomerations.

Materials and methods

Data sources

The Defense Meteorological Satellite Program (DMSP) Operational Line-scan System (OLS) has a strong optical amplification capability to detect light of low intensity. As a result, small-scale residential areas can also be distinguished accurately from the dark rural background. At present, four types of nighttime light data are released, including average visible lights, stable lights, cloud-free coverages, and average lights X Pct. The data of stable lights are most commonly used, which is the result of removing the brief flicker and excluding the background noise. Thus, stable lights product was selected as the data source to characterize urbanization.

It's noteworthy that currently available global NTL data from 1992 to 2012 were captured by six different satellites. Due to different orbital parameters, technical equipment, and atmospheric refraction among the different satellites, the measured NTL brightness could differ significantly even if the observation target had not changed. As a result, consistency of the raw data could not be guaranteed. Therefore, data preprocessing was required to minimize the noise and discrepancies of the dataset. In this study, the systematic correction method proposed by Liu et al. (2012) was used to calibrate the images of different years with different satellites, so as to promote the continuity and comparability of the NTL data throughout the study period. The preprocessing included three main steps: inter-calibration, intra-annual composition, and inter-annual series correction. After data preprocessing, pixels with unstable intra-annual DN values were removed, and inter-annual discrepancy of DN values was highly minimized. The DN values of different years and different satellites became comparable.

Research framework

Taking nighttime light images as data source to identify the range of cities, the framework of identifying urban agglomerations was developed (Fig. 1). Firstly, DMSP-OLS images were preprocessed using inter-calibration, intra-annual composition and inter-annual series correction, and nighttime light images with comparable DN values were obtained from 1992 to 2012. Secondly, the threshold of DN value was set and the largest patch or the largest two patches were selected as the core zone of urban agglomeration. Thirdly, mutation point detection based on MPA index was developed to select the optimal threshold of

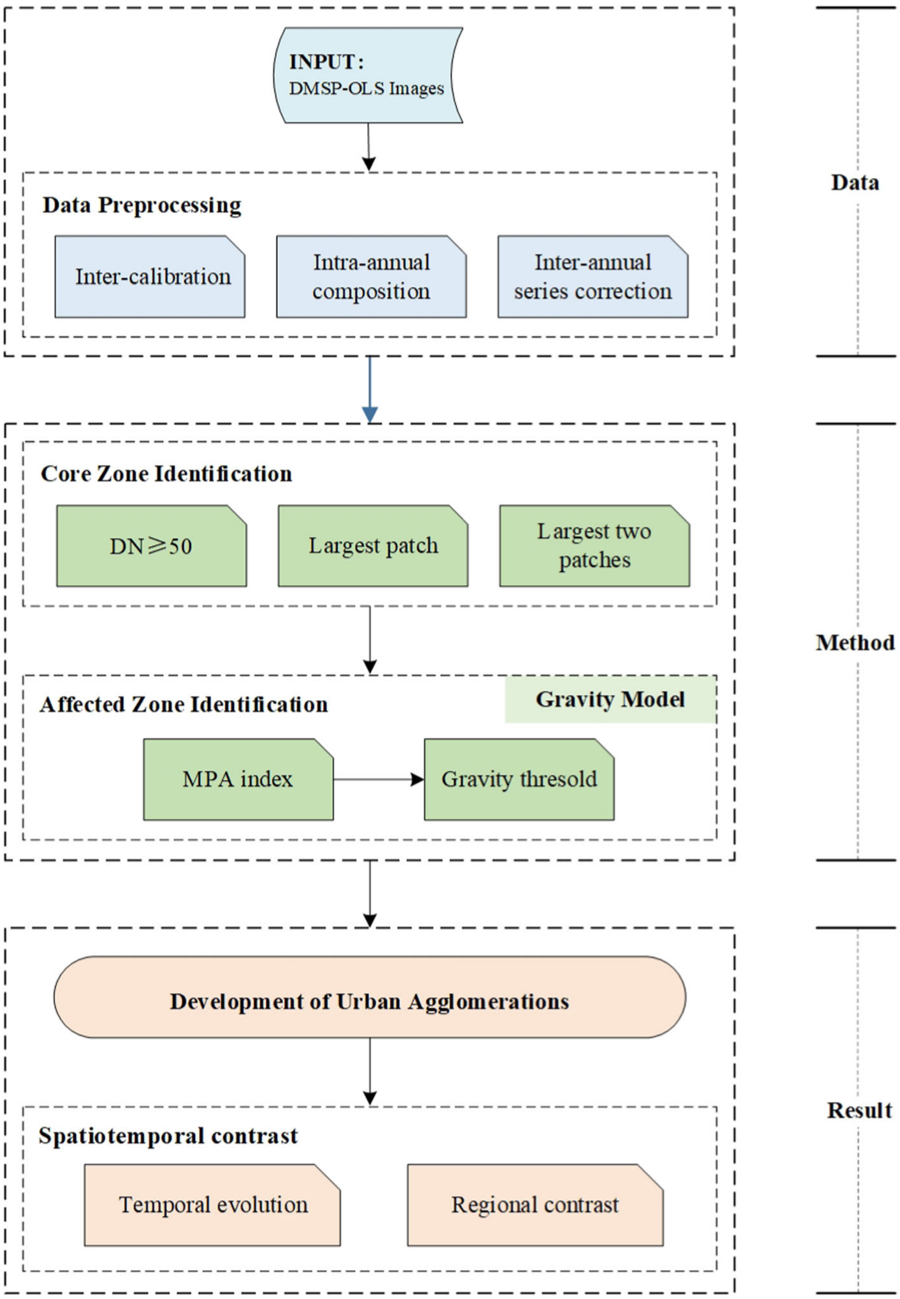

Fig. 1 Research framework for urban agglomeration identification and spatiotemporal evolution evaluation

gravitational force in the gravity model. The area with the gravitational force higher than the optimal threshold was identified as the affected zone of urban agglomeration. Urban agglomeration is composed of core zone and affected zone. Finally, comparison among the development of urban agglomerations was conducted in terms of temporal evolution and regional contrast.

Identifying core zone and affected zone of urban agglomerations

Although NTL data can be used to distinguish urban and non-urban areas, there is still no widely accepted optimal threshold of DN value. In general, the threshold of DN value determined in different methods fluctuated around the value of 50 (Milesi et al. 2003; Cao et al. 2009; Dou et al. 2017). Therefore, considering that the uniform DN value can help to effectively compare the temporal and spatial variation of different urban agglomerations, the DN value of 50 was set as the threshold. That was to say, the area with DN value no less than 50 would be identified as core urban areas. In addition, two situations were considered when identifying the core zone of urban agglomeration. Firstly, the core zone should be the largest patch within an urban agglomeration, and there should be an obvious and continuous decreasing trend of DN value from the inside out (i.e., a radiation effect). Secondly, when it is dual-core urban agglomeration, such as Beijing–Tianjin–Hebei urban agglomeration, the largest two patches should be chosen as the core zone. After obtaining the core zone, the gravity model was applied to identify the spatial boundary of urban agglomerations (Batty 1978; Schneider 2010). Then, the index of MPA was introduced to quantitatively characterize the fragmentation of a specific urban agglomeration under different threshold of gravitational force (Pôças et al. 2011). The inflection point of MPA was identified, and thus the corresponding threshold of gravitational force was selected to extract the affected zone of urban agglomeration.

More specifically, within the core zone of urban agglomeration, the NTL center was identified based on DN values, which was weighted by the sum of the DN values around it (1×1 km^2 grids). The gravity model was used to calculate the gravitational force between the core zone of urban agglomeration and its surrounding grids (Ferrari et al. 2011), which was as follows:

$$F_{ik} = \frac{Z_i \times Z_k}{D_{ik}^2} \quad (1)$$

In Eq. (1), F_{ik} is the gravitational force between core zone i and its surrounding grid k; Z_i is the sum of DN value in core zone i; Z_k is the DN value of surrounding grid k; and D_{ik} is the distance between core zone i and grid k. The constant value of 2 is a commonly used friction coefficient.

The MPA index is commonly used in landscape ecology to measure the degree of landscape fragmentation. It is generally considered that a landscape with smaller MPA is more fragmented than that with larger MPA. MPA is calculated as follows:

$$C_i = \frac{A_i}{N_i} \quad (2)$$

In Eq. (2), C_i is the index of MPA; A_i is the total area of patch type i; and N_i is the number of patches with the same type i. The lower is the value of C_i, the higher is the degree of patch fragmentation (Wu et al. 2002).

In this study, the index of MPA was used to quantify the varying development pattern of an urban agglomeration under different threshold of gravitational forces. As the gravitational force threshold increases from 0, the MPA changes accordingly. Theoretically, when the gravitational force threshold is 0, the development area of an urban agglomeration would be the entire area. In this case, the entire surrounding area would be included within urban agglomeration, and both MPA and the area of urban agglomeration reach the maximum. As gravitational force threshold increases, the area with lower DN value is excluded from the development range, the entire urban agglomeration would begin to break piece-by-piece from the periphery with decreasing MPA. If the gravitational force threshold further increases, the area with a large distance from the core zone cannot form a “high gravitational force” with the core zone even if its DN value is high, and the MPA would begin to increase because the urban agglomeration is more and more contracting as a whole. At last, When the gravitational force threshold is the largest, i.e. reaching infinity, the urban agglomeration is reduced to the core zone of the urban agglomeration, and the MPA is equal to the area of the core zone.

During the variation of MPA index with changing gravitational force threshold, the inflection point, i.e. the point with a trend flipping of MPA was identified to select the optimal threshold for extracting the affected zone of urban agglomerations.

By 2012, there were three mature urban agglomerations in China, i.e. the Beijing–Tianjin–Hebei, Yangtze River Delta, and Pearl River Delta urban agglomerations (Song 2010). Thus, these three most highly developed urban agglomerations in China were set as examples to select the threshold of gravitational force. As shown in Fig. 2, during gradual increasing of the gravitational force threshold, the MPA reaches the minimum when the gravitational force value is about 1,000,000. Thus, areas with the gravitational force higher than this threshold were all identified as the affected zone of urban agglomerations in this study. These area had following characteristics: (1) These areas were strongly attracted by the core zone of urban agglomerations. (2) These areas and core zone had an integration trend. (3) The area extraction was dominated by the DN value and distance. These features were highly consistent with the definition of urban agglomeration.

Spatiotemporal contrast of urban agglomerations

In order to better understand the spatiotemporal pattern of urban agglomerations, spatial contrast was conducted from 2000 to 2012. As a process that urban development must undergo, urban agglomeration refers to an advanced stage (Taubenböck et al. 2013), with various examples in developed countries, such as the Atlantic coast of the United States, the Great Lakes of North America, the Pacific coast of Japan, the metropolitan area of London, and the urban agglomeration of northwestern Europe. In temporal comparison, according to the development area of urban agglomerations, which is the area sum of core zone and affected zone of urban agglomerations, urban agglomerations in China can be divided into 5 development levels, i.e. world level urban agglomerations ($\geq$ 100,000 km^2), regional level urban agglomerations (50,000–100,000 km^2), sub-regional level

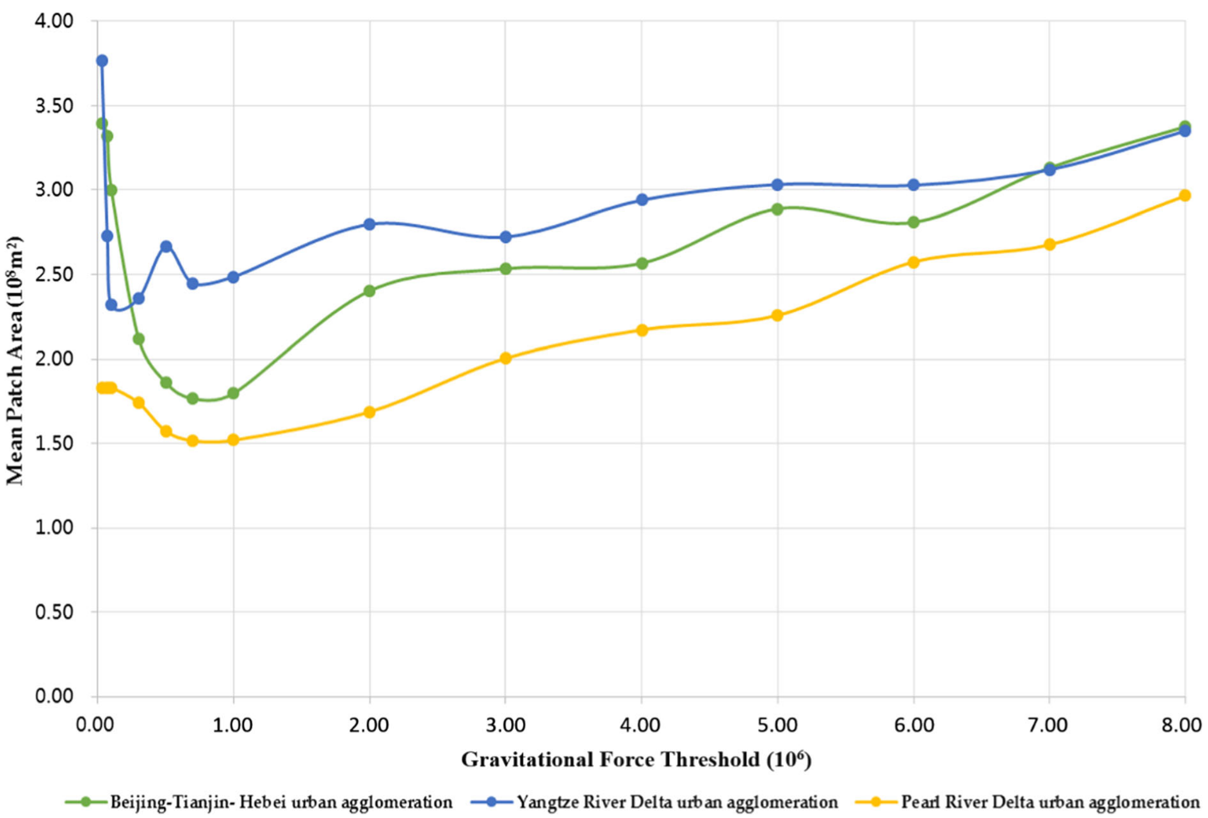

Fig. 2 Relationship between MPA and gravitational force threshold in top three Chinese urban agglomerations

urban agglomerations (10,000–50,000 km^2), local level urban agglomerations (5000–10,000 km^2), and potential level urban agglomerations (< 5000 km^2). The development levels of urban agglomerations in year 2000, 2006 and 2012 were identified and compared together with the change of development area.

In view of spatial contrast, three kinds of geographical zoning schemes in China were considered: (1) the northern and southern China, dividing by Qinling Mountains–Huaihe River; (2) the eastern and western China, dividing by the Heihe–Tengchong line; and (3) the coastal and inland China, depending on whether it is close to the coastline. Under these zoning schemes, the total area, average area as well as area ratio of urban agglomerations in different regions were calculated and compared, respectively. The comparison revealed regional difference of urban agglomerations in China.

Results

Development area of urban agglomerations

Based on the development area quantified through nighttime light gravity, the development of urban agglomerations can be measured. There were 14 urban agglomerations in 2012 that met or exceeded the standard of sub-regional level: Yangtze River Delta, Pearl River Delta, Beijing–Tianjin–Hebei, Shandong Peninsula, Central Plain, Chengdu–Chongqing, Eastern of Liaoning Peninsula, Harbin–Dalian–Changchun, Central Shaanxi Plain, Western Strait, Yangtze River and Huai River, Central Shanxi, Wuhan, and Changsha–Zhuzhou–Xiangtan. The best-developed Yangtze River Delta urban agglomeration had reached the development area of 150,000 km^2.

From the spatial perspective, urban agglomerations in coastal areas have developed rapidly. The Beijing–Tianjin–Hebei urban agglomeration and the Shandong Peninsula urban agglomeration gradually integrated, while northern Hebei Province failed to become a part of Beijing–Tianjin–Hebei urban agglomeration. The Pearl River Delta urban agglomeration expanded significantly and posed great impact on its surrounding areas. In details, it merged with the Western Strait urban agglomeration and extended westwards to Guangxi Province. Other urban agglomerations along China's east coast such as the Shandong Peninsula urban agglomeration and Western Strait urban agglomeration became well developed. In contrast, the inland urban agglomerations experienced slower development, although the Chengdu–Chongqing, Central Plain, Central Shaanxi Plain and Wuhan urban agglomerations developed relatively better than other inland urban agglomerations. However, the Lanzhou–Baiyin–Xining, Central Guizhou, and Jiuquan–Jiayuguan–Yumen urban agglomerations didn't even meet the standard of local level urban agglomeration (Table 1, Fig. 3).

Temporal evolution of urban agglomerations

During 2000–2012, the number of sub-regional level and local level urban agglomerations increased substantially, especially for sub-regional level. The Yangtze River Delta urban agglomeration had developed from sub-regional level to world level, and had developed into the only one world level urban agglomeration in China in 2006 (Figs. 4, 5). The top three urban agglomerations, i.e. the Yangtze River Delta urban agglomeration, the Pearl River Delta urban agglomeration, and the Beijing–Tianjin–Hebei urban agglomeration, had all reached the regional level of urban agglomeration since 2006 (Figs. 4, 5).

Typically, the development area of the most highly developed Yangtze River Delta and Pearl River Delta urban agglomerations exceeded 150,700 km^2 and 103,600 km^2 respectively, indicating that both met the standard of world level urban agglomeration in 2012. Meanwhile, from 2000 to 2012, the development area in the most developed Yangtze River Delta, Pearl River Delta, Beijing–Tianjin–Hebei and Shandong Peninsula urban agglomerations increased by 109,100 km^2, 54,500 km^2, 46,700 km^2, and 36,400 km^2 respectively. Although the expansion of the other urban agglomerations was relatively small, the development area also at least doubled in 12 years, except Wuhan urban agglomeration. In addition, it could be noticed that a majority of urban agglomerations expanded rapidly during 2000–2006, with slower expansion during 2006–2012.

Comparing the urban agglomerations' development area in 2000, 2006 and 2012, it could be found that the urban agglomerations in China showed a continuous growth in the study period, but the polarization was more and more serious. Since 2000,

Table 1 Development area of urban agglomerations in China during 2000–2012

Urban agglomeration	Development area (10^4 km^2)		
	2000	2006	2012
Yangtze River Delta (YRD)	4.16	11.67	15.07
Pearl River Delta (PRD)	4.91	7.14	10.36
Beijing–Tianjin–Hebei (BTH)	3.49	6.71	8.16
Shandong Peninsula (SP)	1.09	3.78	4.73
Central Plain (CP)	0.74	2.74	3.36
Chengdu–Chongqing (CC)	0.65	1.92	2.78
Eastern of Liaoning Peninsula (ELP)	0.94	1.49	2.52
Harbin–Dalian–Changchun (HDC)	0.87	1.63	2.47
Central Shaanxi Plain (CSP)	0.63	1.35	1.95
Western Strait (WS)	0.59	1.27	1.73
Yangtze River and Huai River (YRHR)	0.19	0.58	1.46
Central Shanxi (CS)	0.46	0.82	1.20
Wuhan (WH)	0.62	1.16	1.05
Changsha–Zhuzhou–Xiangtan (CZX)	0.23	0.69	1.05
Central Yunnan (CY)	0.29	0.52	0.75
North Slope of Tianshan Mountain (NSTM)	0.22	0.36	0.72
Yinchuan Plain (YP)	0.12	0.34	0.66
Hohhot–Baotou–Erdos (HBE)	0.15	0.28	0.59
Poyang Lake (PL)	0.26	0.38	0.58
Nanning–Beihai–Qinzhou–Fangchenggang (NBQF)	0.15	0.33	0.53
Lanzhou–Baiyin–Xining (LBX)	0.13	0.22	0.43
Central Guizhou (CG)	0.09	0.28	0.37
Jiuquan–Jiayuguan–Yumen (JJY)	0.01	0.06	0.06

the development of the top three urban agglomerations (YRD, PRD, and BTH) had been far superior to the other urban agglomerations. Comparing the top three urban agglomerations, the growth rate of the PRD urban agglomeration was relatively stable. In both study periods of 2000–2006 and 2006–2012, the growth rate was similar, i.e. 45.42% and 45.10%. However, for YRD and BTH urban agglomerations, both grew rapidly between 2000 and 2006, increasing by 180.53% and 92.26% respectively. During 2006–2012, their growth became slow significantly with the growth rate of 29.13% and 21.61% respectively. Moreover, it could also be concluded that, during the study period, the larger the core zone area and the better the development of the urban agglomeration in the beginning, the greater the extent of its expansion. The development area of small urban agglomerations such as CY, NSTM, YP, HBE, PL, NBQF, LBX, CG, and JJY increased slowly with low economic development, and their gap to the top three urban agglomerations was growing (Fig. 4).

Regional contrast of urban agglomerations

As shown in Fig. 6, from 2000 to 2012, in terms of total area of all urban agglomerations, the ratio between southern and northern China remained at 2.10 (core zone) and 1.30 (entire zone) respectively. In contrast, the ratio between coastal and inland China remained at 3.00 (core zone) and 2.40 (entire zone) respectively. This indicated that the spatial difference of urban agglomerations between southern and northern China, and between coastal and inland China remained stable without obvious enlargement during 2000–2012. In view of average area of all urban agglomerations, the ratio between southern and northern China was around 2.30 (core zone) and 1.45 (entire zone) during 2000–2012. However, the ratio of coastal/inland urban agglomerations exceeded

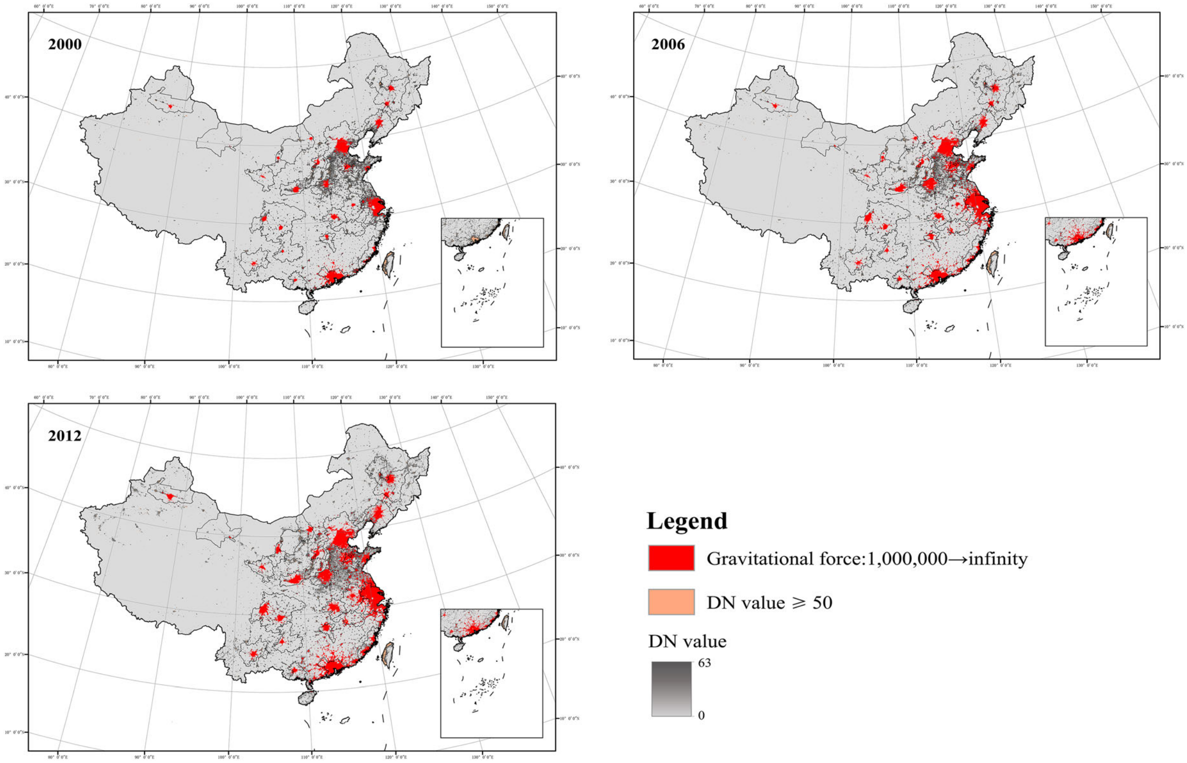

Fig. 3 Spatiotemporal development of urban agglomerations in China during 2000–2012

8 (core zone) and 6 (entire zone), indicating the huge gap in average area of urban agglomerations between coastal and inland China.

In contrast, in terms of core zone, the total area ratio of eastern/western urban agglomerations increased from 19.28 to 24.63 during 2000–2012. Considering the entire zone of urban agglomerations, this ratio dropped from 32.07 to 24.43, which indicated that compared with the western urban agglomerations, the outward expansion of eastern urban agglomerations decelerated but the construction intensity of urban areas accelerated (Fig. 6).

Discussion

Development mode of urban agglomerations

To better understand the development mode of urban agglomerations, the relationship between the areas of core zone and entire zone were further explored. The results showed the area proportion of core zone gradually decreased while affected zone expanded continuously during 2000–2012 (Fig. 7), which indicated that development mode of urban agglomerations in China might have been transforming from core-expansion to peripheral-development. Specifically, the data points of the YRD and BTH urban agglomerations were always located above the fitted line, indicating both were characterized as peripheral-development type. In contrast, the data point of PRD urban agglomeration were all located below the fitted line during 2000–2012, characterizing the PRD urban agglomeration as core-expansion type correspondingly.

By exploring the difference of urban development mode, it is helpful to understand the relationship between the areas of core zone and entire zone of urban agglomerations. The YRD regional planning, which has been approved by the National Development and Reform Commission of China, clearly stated that the YRD region should coordinate the spatial development and form a “one-core and nine-belt” spatial pattern with Shanghai City as the core and the rivers around as the development belts. This policy helped the rapid development of the surrounding areas

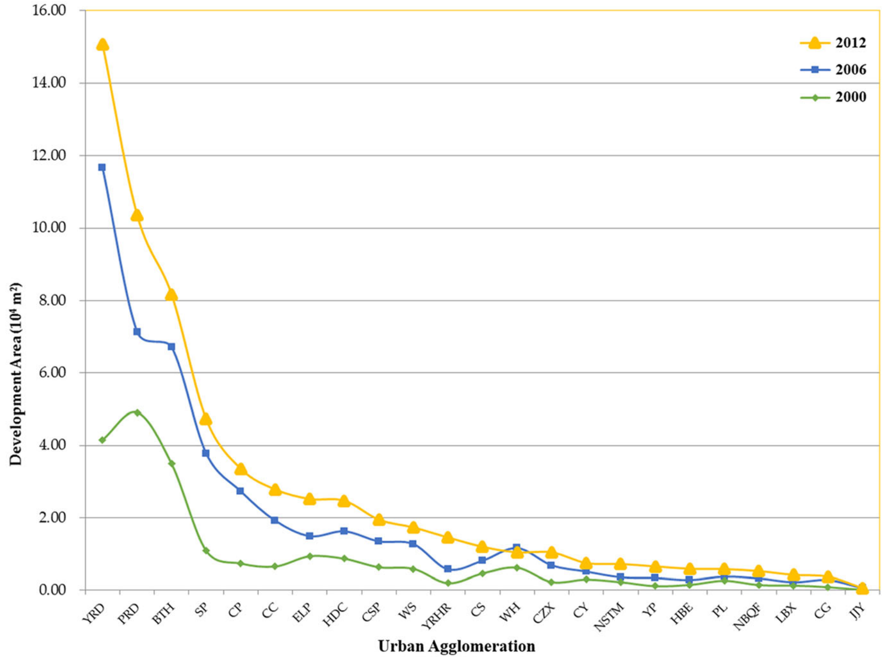

Fig. 4 Change of the development area of urban agglomerations in China during 2000–2012

of YRD urban agglomeration. The development of the BTH urban agglomeration mainly highlighted the dual core role of Beijing City and Tianjin City, opening up the traffic channels between the two cities and thus promoting the efficient development of the surrounding areas. The PRD urban agglomeration has been evolving to be multi-city dominant region. It took multiple levels of central cities and clustered industrial clusters as nodes, and different types and sizes of urban areas and industrial areas gathered to nodes to form a network-based and open spatial development pattern. Thus, the PRD urban agglomeration presented the status of multi-core driven development. It should be also emphasized that the YRD, PRD and BTH urban agglomerations have large scale, rapid development, clear development mode and strong typicality. Therefore, the top three urban agglomerations are mainly compared, thus highlighting the main evolutionary trend of urban agglomerations in China. Other urban agglomerations have short development time, small scale, and unrepresentative development mode, which needs further studies.

Limitations and future research directions

In this study, the mutation point detection method was proposed using the MPA index, NTL data and gravity model, which successfully identified the range of urban agglomerations, i.e. core zone and affected zone. Conventionally, the boundary identification of urban agglomerations is usually based on various social-economic indicators such as gross domestic product, population density etc., which are not easy to be quantified and mapped in a large area. In contrast, this study has provided a rapid and accurate NTL data based approach to identifying urban agglomeration boundaries, which divides the core zone and affected zone of urban agglomerations.

Although DMSP/OLS data have demonstrated high temporal continuity and spatial coverage in characterizing urbanization with various case studies at both global and regional scales, there are still some limitations in this study. Firstly, the intrinsic limitations in DMSP-OLS data such as coarse resolution, saturation effect and blooming effect would bring uncertainty to the results. The availability of superior Visible Infrared Imaging Radiometer Suite (VIIRS) data since 2012 may provide an alternative solution. Secondly, there are uncertainties in determining the optimal threshold of DN value which was used to extract the core zone of urban agglomerations. To ensure the spatiotemporal comparability, the uniform threshold of DN value was set. However, further verification of the specific DN value of 50 is still

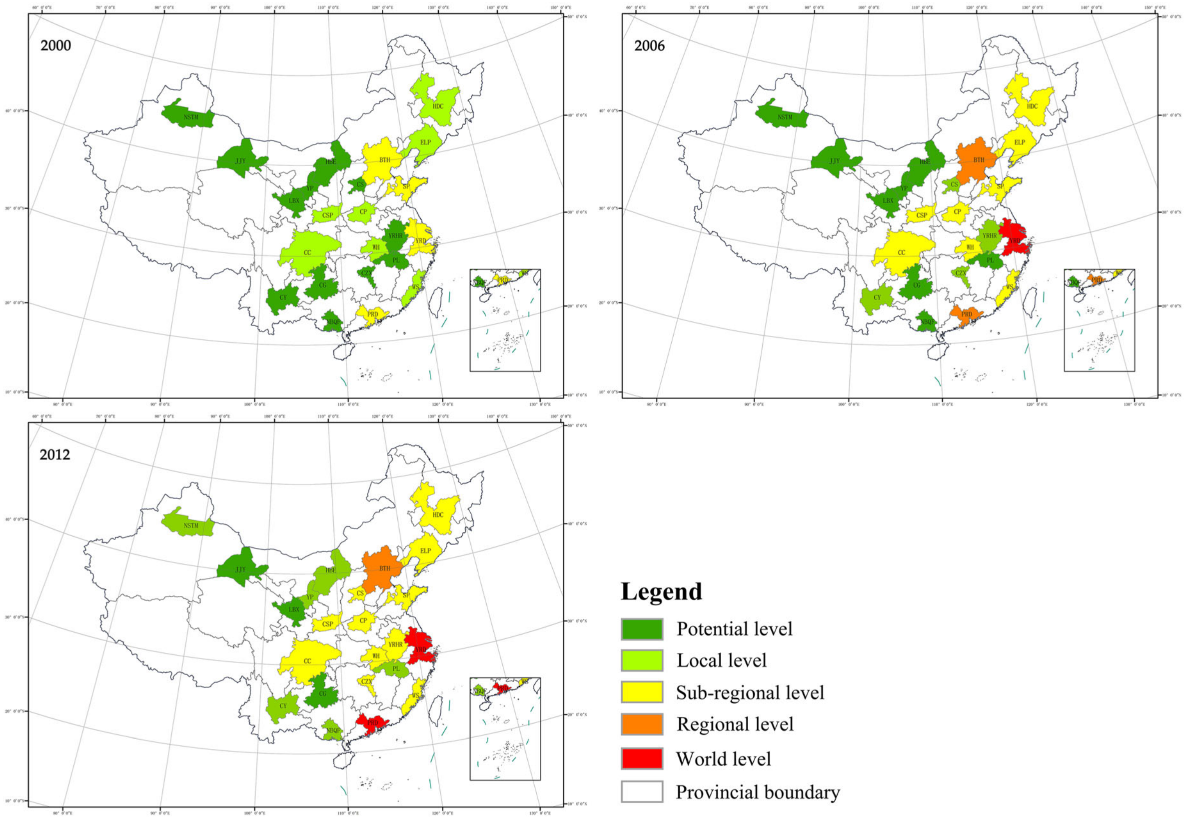

Fig. 5 Spatial patterns of development level of urban agglomerations in China during 2000–2012

needed, together with uncertainty contrast in different regions. In view of this concern, exploring and understanding the relationship between the brightness of NTL and urbanization would be helpful. Lastly, the Euclidean distance used in the gravity model could also be improved through commuting time based on different transportation models, since it is not spatial distance but transportation time that highly affects the gravitational force between two regions.

Conclusion

In this study of spatiotemporal evolution of China's urban agglomerations, NTL data of DMSP/OLS were used instead of data from statistical yearbooks, using the threshold of DN value and MPA index to extract the core zone and affected zone of urban agglomerations respectively. The results showed that by 2012, 14 urban agglomerations met or exceeded the standard of sub-regional level, and the most highly developed Yangtze River Delta and Pearl River Delta urban agglomerations met the standard of world level, together with the Beijing–Tianjin–Hebei urban agglomeration for regional level. During 2000–2012, regional differences in urban agglomerations between southern and northern China, and between coastal and inland China remained stable. However, compared with the western urban agglomerations, the outward expansion of eastern urban agglomerations decelerated, with the accelerated construction intensity of their core zone. During 2000–2012, the overall development mode of urban agglomerations in China has experienced the shift from the core-expansion to the peripheral-development, although the expansion of urban agglomerations became slower after 2006. In spite of the limitations brought by coarse resolution, saturation effect and blooming effect, NTL data are effective in exploring the spatial pattern and temporal change of urban agglomerations. The boundary identification of urban agglomerations including the core zone and affected zone, is of great significance for

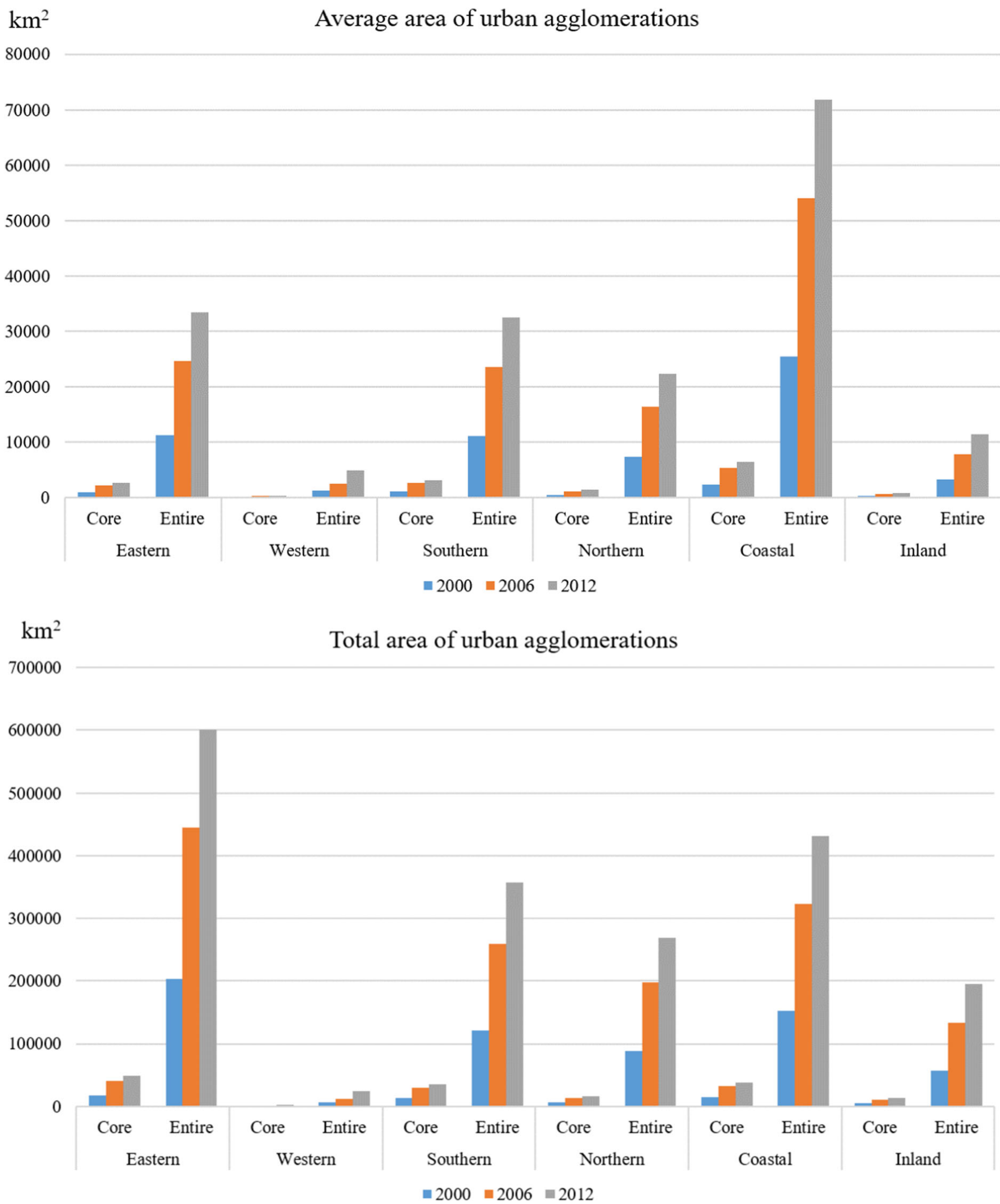

Fig. 6 Regional contrast of total area and average area of urban agglomerations in China during 2000–2012

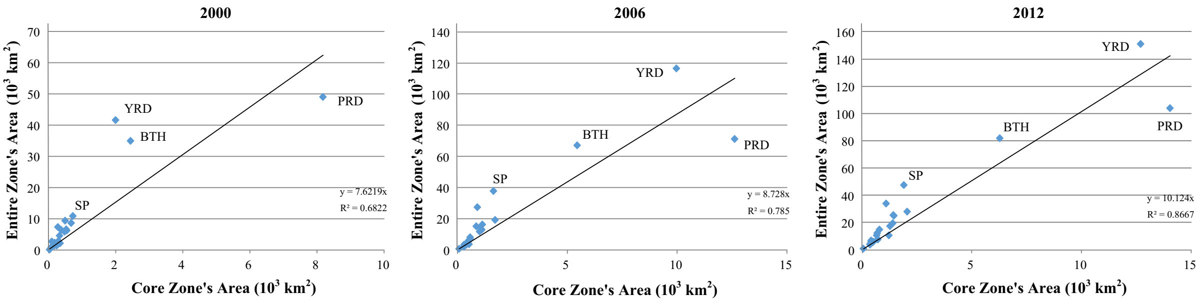

Fig. 7 Area correlation between core zone and entire zone of China's urban agglomerations in 2000, 2006, and 2012

process-based monitoring, assessing, and governing China's urbanization.

Acknowledgements This research was financially supported by the National Natural Science Foundation of China (Grant No. 41322004).

References

Baigent E (2004) Patrick Geddes, Lewis Mumford and Jean Gottmann: divisions over 'Megalopolis'. Prog Hum Geogr 28(6):687–700

Batty M (1978) Reilly's challenge: new laws of retail gravitation which define systems of central places. Environ Plan C 10(2):185–219

Bennett M, Smith L (2017) Advances in using multitemporal night-time lights satellite imagery to detect, estimate, and monitor socioeconomic dynamics. Remote Sens Environ 192:176–197

Cai JX, Huang B, Song YM (2017) Using multi-source geospatial big data to identify the structure of polycentric cities. Remote Sens Environ 202:210–221

Cao X, Chen J, Imura H, Higashi O (2009) A SVM–based method to extract urban areas from DMSP-OLS and SPOT VGT data. Remote Sens Environ 113(10):2205–2209

Chen Y, Huang L (2018) A scaling approach to evaluating the distance exponent of the urban gravity model. Chaos Solitons Fractals 109:303–313

Dou YY, Liu ZF, He CY, Yue HB (2017) Urban land extraction using VIIRS nighttime light data: an evaluation of three popular methods. Remote Sens 9(2):175

Elvidge CD, Baugh KE, Kihn EA, Kroehl HW, Davis ER, Davis CW (1997) Relation between satellite observed visible near infrared emissions, population, economic activity and electric power consumption. Int J Remote Sens 18(6):1373–1379

Elvidge CD, Imhoff ML, Baugh KE, Hobson VR, Nelson I, Safran J, Dietz JB, Tuttle BT (2001) Night-time lights of the world: 1994–1995. ISPRS-J. Photogramm Remote Sens 56(2):81–99

Fang C, Yu D (2017) Urban agglomeration: an evolving concept of an emerging phenomenon. Landsc Urban Plan 162:126–136

Fenta AA, Yasuda H, Haregeweyn N, Belay AS, Hadush Z, Gebremedhin MA, Mekonnen G (2017) The dynamics of urban expansion and land use/land cover changes using remote sensing and spatial metrics: the case of Mekelle City of northern Ethiopia. Int J Remote Sens 38(14):4107–4129

Ferrari C, Parola F, Gattorna E (2011) Measuring the quality of port hinterland accessibility: the Ligurian case. Trans Policy 18(2):382–391

Fu H, Shao Z, Peng F, Cheng Q (2017) The dynamic analysis between urban nighttime economy and urbanization using the DMSP/OLS nighttime light data in China from 1992 to 2012. Remote Sens 9(5):416

Garouani AE, Mulla DJ, Garouani SE, Knight J (2017) Analysis of urban growth and sprawl from remote sensing data: case of Fez, Morocco. Int J Sustain Built Environ (Netherlands) 6(1):S2212609016300668

Gottmann J (1957) Megalopolis or the urbanization of the northeastern seaboard. Econ Geogr 33(3):189–200

He Y, Zhou G, Tang C, Fan S, Guo X (2019) The spatial organization pattern of urban-rural integration in urban agglomerations in China: an agglomeration-diffusion analysis of the population and firms. Habitat Int 87:54–65

Hu YN, Peng J, Liu YX, Du YY, Li HL, Wu JS (2017) Mapping development pattern in Beijing–Tianjin–Hebei urban agglomeration using DMSP/OLS nighttime light data. Remote Sens 9(7):760–773

Huang QX, Yang X, Gao B, Yang Y, Zhao YY (2014) Application of DMSP/OLS nighttime light images: a meta-analysis and a systematic literature review. Remote Sens 6(8):6844–6866

Kuang WH, Liu JY, Dong JW, Chi WF, Zhang C (2016) The rapid and massive urban and industrial land expansions in china between 1990 and 2010: a CLUD-based analysis of their trajectories, patterns, and drivers. Landsc Urban Plan 145:21–33

Li T, Li W, Qian Z (2010) Variations in ecosystem service value in response to land use changes in Shenzhen. Ecol Econ 69(7):1427–1435.

Li JX, Li C, Zhu FG, Song CH, Wu JG (2013) Spatiotemporal pattern of urbanization in Shanghai, China between 1989 and 2005. Landsc Ecol 28(8):1545–1565

Lin GCS (2000) The growth and structural change of Chinese cities: a contextual and geographic analysis. Cities 19(5):299–316

Liu ZF, He CY, Zhang QF, Huang QX, Yang Y (2012) Extracting the dynamics of urban expansion in China using DMSP-OLS nighttime light data from 1992 to 2008. Landsc Urban Plan 106(1):62–72

Liu Y, Wei S, Deng X (2018) Understanding the spatiotemporal variation of urban land expansion in oasis cities by integrating remote sensing and multi-dimensional DPSIR-based indicators. Ecol Indic 96:23–37

Ma L, Wu JS, Li WF, Peng J, Liu H (2014) Evaluating saturation correction methods for DMSP/OLS nighttime light data: a case study from China's cities. Remote Sens 6(10):9853–9872

Ma T, Zhou CH, Pei T, Haynie S, Fan JF (2012) Quantitative estimation of urbanization dynamics using time series of DMSP/OLS nighttime light data: a comparative case study from China's cities. Remote Sens Environ 124:99–107

Milesi C, Elvidge CD, Nemani RR, Running SW (2003) Assessing the impact of urban land development on net primary productivity in the southeastern United States. Remote Sens Environ 86(3):401–410

Pôças I, Cunha M, Pereira LS (2011) Remote sensing based indicators of changes in a mountain rural landscape of Northeast Portugal. Appl Geogr 31(3):871–880

Qiu GY, Zou Z, Li X, Li H, Guo Q, Yan C, Tan S (2017) Experimental studies on the effects of green space and evapotranspiration on urban heat island in a subtropical megacity in China. Habitat Int 68:30–42

Reilly WJ (1931) The law of retail gravitation. The Knickerbocker Press, New York

Robinson J (2002) Global and world cities: a view from off the map. Int J Urban Reg Res 26(3):531–554

Rybnikova NA, Portnov BA (2017) Remote identification of research and educational activities using spectral properties of nighttime light. ISPRS-J Photogramm Remote Sens 128:212–222

Schneider M (2010) Gravity models and trip distribution theory. Pap Reg Sci 5(1):51–56

Song JD (2010) Agglomeration economies of china's three major urban agglomerations, 1994–2008. Int Area Stud Rev 13(4):25–58

Taubenböck H, Klotz M, Wurm M, Schmieder J, Wagner B, Wooster M, Esch T, Dech S (2013) Delineation of central business districts in mega city regions using remotely sensed data. Remote Sens Environ 136:386–401

Tilottama G, Sharolyn A, Rebecca LP, Sutton PC, Elvidge CD (2009) Estimation of Mexico's informal economy and remittances using nighttime lights data. Remote Sens 1:418–444

Wu JG, Shen WJ, Sun WZ, Tueller PT (2002) Empirical pattern of the effects of changing scale on landscape metrics. Landsc Ecol 17(8):761–782

Yan Z, Zheng H, Yang Z, Li Y, Liu G, Su M, Yin X (2016) Urban energy flow processes in the Beijing–Tianjin–Hebei (Jing-Jin-Ji) urban agglomeration: combining multi-regional input–output tables with ecological network analysis. J Clean Prod 114:243–256

Yu BL, Shi KF, Hu YJ, Huang C, Chen ZQ, Wu JP (2015) Poverty evaluation using NPP-VIIRS nighttime light composite data at the county level in China. IEEE J Sel Top Appl Earth Observ Remote Sens 8(3):1217–1229

Yu BL, Shu S, Liu HX, Song W, Wu JP, Wang L, Chen ZQ (2014) Object-based spatial cluster analysis of urban landscape pattern using nighttime light satellite images: a case study of China. Int J Geogr Inf Sci 28(11):2328–2355

Zeng C, Zhang A, Xu S (2016) Urbanization and administrative restructuring: a case study on the Wuhan urban agglomeration. Habitat Int 55:46–57

Zhang ZH, Su SL, Xiao R, Jiang DW, Wu JP (2013) Identifying determinants of urban growth from a multi-scale perspective: a case study of the urban agglomeration around Hangzhou Bay, China. Appl Geogr 45:193–202

Zhou WQ, Huang GL, Pickett STA, Cadenasso ML (2011) 90 years of forest cover change in an urbanizing watershed: spatial and temporal dynamics. Landsc Ecol 26(5):645–659

Zou YH, Peng HQ, Liu G, Yang KD, Xie YH, Weng QH (2017) Monitoring urban clusters expansion in the middle reaches of the Yangtze River, China, using time-series nighttime light images. Remote Sens 9(10):1007–1026