

Detecting and Evaluating Urban Agglomerations in Mainland China From the Perspective of Spatial Interactions

Tao Jia ¹, Binbin Wang ¹, and Xin Li ²

Abstract—It has been a long-standing topic to detect the formation of urban agglomerations; however, current studies remain constrained by the definition of criterion or the usage of remote sensing technique, ignoring the impact of spatial interactions. This study aims to develop a methodological framework to detect and evaluate urban agglomerations by fusing human activities and their spatial interactions. To verify our methods, experiments were conducted in Mainland China, where nighttime light imageries and human movement data were used. 1) Urban boundaries of all cities were extracted from nighttime light imageries using the Lorenz curve and the watershed method; 2) they were combined with human movement data to construct the spatial interaction network, and urban agglomerations were then derived using the network community detection method; 3) the development levels of urban agglomerations were evaluated quantitatively according to the National Thirteenth Five-Year Plan (NTPF). Experimental results suggest that a total of 17 urban agglomerations were derived, and compared with those planned in the NTPF, they can be classified into four categories with different levels of development. Our methods can enrich studies on detection of urban agglomerations, while experimental results can provide decision-making support for regional management and development of planning policies.

Index Terms—Human movement, nighttime light imagery, spatial interactions, urban agglomeration.

I. INTRODUCTION

THE urban agglomeration is composed of a set of cities clustering together with dense connections in terms of people, information, or goods [1], and it plays an important role on accelerating urbanization and boosting global economic development. It is regarded as a highly developed spatial organization of integrated cities and is probably the result of the growing cooperation and competition among cities [2]. There are many definitions in the literature, and the earliest concept may be related to the “Garden city” model, where a central city is integrated with many nearby garden cities [3]. Central-place

theory, proposed by Christaller [4], gave a systematical definition of the spatial organization and hierarchical structure of the urban agglomeration [5]. Then, a new term “megalopolis” was clearly articulated by Gottmann [6], who was considered as the primary contributor to the theory of urban agglomeration [7]. This concept has been also coined as other terms, such as conurbation [8], global city region [9], highly integrated groups of cities [10], [11], or concentrated region of population and economy [12]. These definitions agree that an urban agglomeration should have one or few cores connected with many peripheral cities socioeconomically, but it remains an open question to define it in a consistent and quantitative way. Information about urban agglomerations can reflect the spatial concentration of economic activities in cities, which may be useful to the development of policies on urban master plans, transportation networks, financial systems, and market systems for the participated cities. Additionally, urban agglomerations are considered to take significant roles on participating in the global cooperation and competition, forming strong united economic community, and addressing the challenges of globalization. Hence, it has been a long-standing topic and is of significant importance to detect the formation of urban agglomerations.

However, there lack effective methods to detect or delineate the urban agglomeration, because its boundary is blurring and its development is dynamic [13]. Conventional methods can be roughly classified into two categories: Criteria-based definition and remote sensing-based detection. The first strand of methods intends to define the urban agglomeration by imposing different criteria of population density, commuting pattern, industrialization, or transportation [9], [14], [15], [16], [17]. For instance, Ning [17] suggested six criteria to detect urban agglomerations in China, including two core cities with many peripheral towns, a total population over 10 million, a high level of urbanization, a convenient transportation network, and historical coherence of common identity. The other strand of methods tends to use remote sensing imageries to detect the spatial extent of the urban agglomeration in the aspect of land uses [18], [19], [20], [21]. For instance, Liu et al. [20] used the optimal threshold function to segment urban agglomerations and further compared the accuracy using three different nighttime light imageries. Actually, the formation of urban agglomerations is not only related to human activities, but can be much more affected by the human interactions between cities. Specifically, He et al. [21]

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argued that the accuracy of detecting urban agglomerations can be improved by fusing nighttime light imagery with point of interest data. However, human interaction patterns are not fully utilized and integrated in these previous studies.

Recent advancements on information and communications technology have enabled the availability of massive human movement data. These data contain connections across space, and thus they can be used to build spatial interaction networks. Community detection methods have been applied to various types of network to delineate geographical space into coherent communities [22], [23], [24], [25], and each community can be considered as a spatial cluster composed of a set of densely connected nodes. For instance, a consistent organization of communities can be obtained via a direct application of the spectral-based detection method on a large-scale telecommunication network of the U.K. [22], whereas the state borders of the US resemble very well with the boundaries of communities extracted from banknote-tracking network using a stochastic Monte–Carlo method [23]. Additionally, human movements within a city can be used to delineate the urban space, e.g., a Weibo check-in spatial network was used to derive urban clusters at different spatial scales [24] and a spatial interaction network from taxicab trajectories was adopted to obtain a hierarchical organization of urban clusters with statistical significance [25]. These methods can provide a consistent way to detect urban clusters by using human interaction patterns, but they are rarely used to examine urban agglomerations.

Therefore, this study contributes a methodological framework to detect urban agglomerations from the perspective of spatial interactions and to evaluate their development levels via a quantitative comparison with the National Thirteenth Five-Year Plan (NTPF, 2016–2020). The novelty of our method is to extract urban agglomerations by fusing nighttime light imagery and human movement data, which set the major difference from the previous studies. Specifically, the Lorenz curve is integrated with the watershed method to extract the boundaries of individual cities from nighttime light imagery in an automatic way, and the Infomap method is employed to detect urban agglomerations using the spatial interaction network from human movement data in a consistent way. In addition, this study proposes a method to evaluate the development levels of urban agglomerations, where spatial similarities are determined quantitatively between the detected urban agglomerations and those proposed in the NTPF. Experiments were conducted in Mainland China. Urban boundaries of individual cities were extracted to build the spatial interaction network, a set of urban agglomerations were detected from the network using our methods, and their development levels were evaluated. The results are valuable for understanding the spatial organization and development levels of urban agglomerations, and they can also provide decision-making support for regional management and development of planning policies.

II. METHODS

This section presents an overview of the methodological framework (Fig. 1). First, we illustrate methods to extract urban

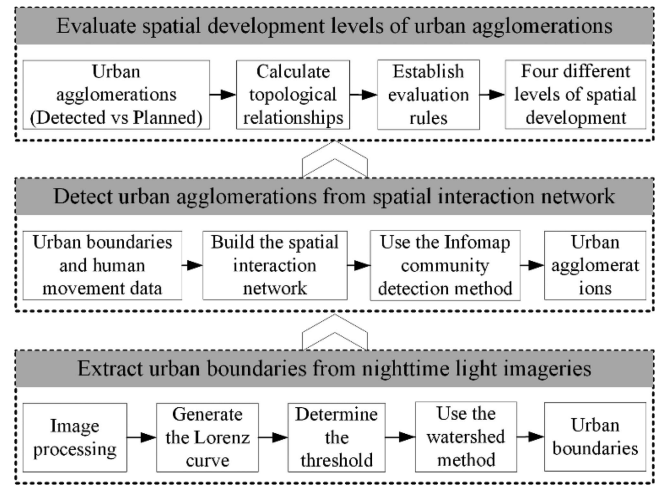


Fig. 1. Methodological framework of our study.

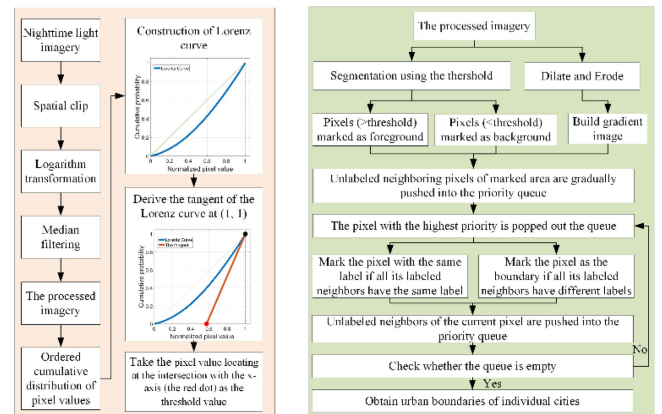


Fig. 2. Method to extract urban boundaries by combining the Lorenz curve and the watershed technique.

boundaries from nighttime light imagery. Second, we demonstrate community detection method to obtain urban agglomerations from the spatial interaction network. Third, we show how to evaluate the development levels of urban agglomerations.

A. Extracting Urban Boundaries From Nighttime Light Imageries

As shown in Fig. 2, this method consists of two major steps that proceed successively to extract urban boundaries of individual cities: 1) Determination of nighttime light imagery threshold automatically using the technique of the Lorenz curve; and 2) extraction of urban boundaries using the threshold-based watershed method.

The first step is to determine the threshold value automatically from nighttime light imagery, which will be directly used in the watershed method. Pixel values of nighttime light imagery are unevenly distributed in geographical space. On the one hand, cities with different development levels may display different light intensities; on the other hand, within one city, a majority of the pixels have low values located in suburb or rural area,

whereas very few of them have high values located in urban area. Thus, the original nighttime light imagery is first preprocessed to improve the reliability of threshold determination, which includes spatial clipping to obtain small-scale images and logarithmic transformation to make the statistical results much more effective. Then, a nonparametric method based on the derivative of the Lorenz curve is applied to each small-scale image to calculate the corresponding threshold value automatically [26]. The Lorenz curve is actually the cumulative probability distribution of normalized pixel values, and the threshold is determined as the pixel value that locates at the intersection of the tangent of the Lorenz curve at (1, 1) and the x -axis; for instance, the red dot shown in Fig. 2.

The second step is to extract urban boundaries of individual cities using the threshold-based watershed method [27]. 1) Morphological operations in terms of dilation and erosion are first applied to produce image with high contrast. 2) This image is then used to generate gradient image, on which the flooding process is operated. 3) To avoid the problem of oversegmentation, pixels are marked with two different labels according to the threshold value: Pixels with values greater than the threshold value constitute urban areas, which are contracted toward city center and labeled as urban cores; pixels with values less than the threshold value denote rural areas, which are contracted toward the edge of city and labeled as urban outskirts. 4) Neighboring pixels of marked areas are gradually pushed into a priority queue, and the gradient value of each pixel is taken as its priority level. 5) The pixel with the highest priority is popped out the queue. As for the current pixel, if all its labeled neighbors have the same label, then it is marked with the same label; otherwise, it is labeled as the urban boundary. As for the unlabeled neighbors, they are inserted into the queue if they are not yet in the queue. 6) The flooding process is terminated if the queue is empty; otherwise, it continues to perform step 5).

B. Detecting Urban Agglomerations From the Spatial Interaction Network

As shown in Fig. 3, this method involves three steps to detect urban agglomerations from the spatial interaction network: 1) Construction of the spatial interaction network using human movement data and urban boundaries; 2) detection of urban agglomerations from the network using the Infomap method [28]; and 3) refinement of the detected urban agglomerations using the criteria-based definition.

The first step is to build the spatial interaction network, where urban boundaries are taken as network nodes and human movements represent connections between two network nodes. Human movement is one of the most important sources that drive the spatial spread of population, goods, and information, and thus it can be used to represent various types of connections between two locations. Besides, the intensity of the spatial connection can be approximated by the total amount of people to and from two locations. However, to reflect the extent of spatial interactions between two urban boundaries, these intensities are spatially aggregated at the level of urban boundaries.

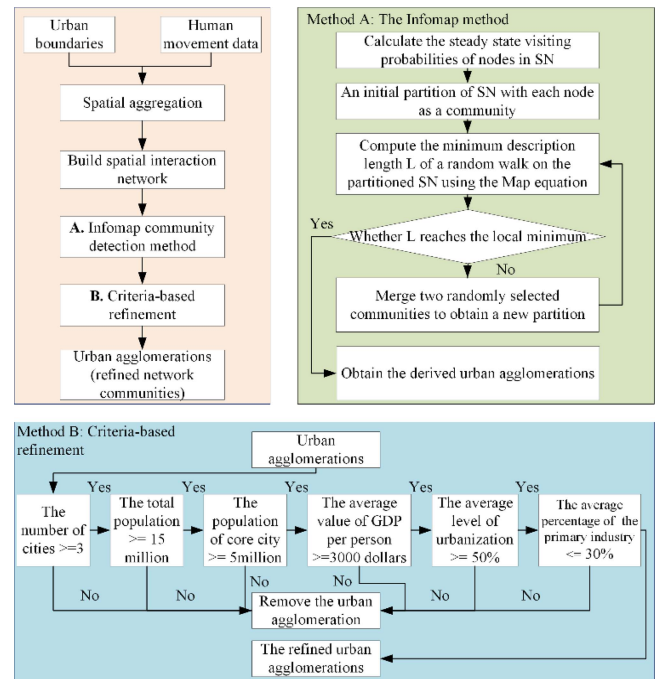


Fig. 3. Method to derive urban agglomerations by using the Infomap technique and the socioeconomic criteria.

The second step is to detect urban agglomerations from the spatial interaction network using the Infomap method. It attempts to reveal the community structure by minimizing the description length of the movements of a random walker on a network [28]. The detected community or urban agglomeration is composed of a set of intensely connected cities, where human movements can flow quickly and easily. 1) It calculates the visiting probability of each node in steady state using the power method. 2) It obtains the first partition of the network by taking each node as a community, and it computes the minimum description length L of a random walk on the partitioned network using (1). In this equation, m is the number of communities, n is the number of nodes, n_α is the number of nodes in community α , p_i is the visiting probability of node i in steady state, q_α is the probability of exiting from community α as shown in (2), θ is the damping factor denoting the probability that a random walk will continue and is set as 0.85, and w_i^{out} is the fraction of the sum of weights of the outgoing edges of node i to the sum of weights of all its edges. 3) It merges any two communities to obtain a new partition as long as the value of L gives the largest decrease. 4) It repeats the above step 3) until no mergence can further decrease the value of L , and an optimal partition is eventually derived, where each community corresponds to a single urban agglomeration.

The third step is to refine the detected urban agglomerations according to the following six criteria [2]: 1) The number of cities should be equal to or larger than 3. 2) The total population should be equal to or larger than 15 million. 3) The population of the core city should be equal to or larger than 5 million. 4) The average value of gross domestic product (GDP) per person should be equal to or greater than 3,000 dollars. 5) The average

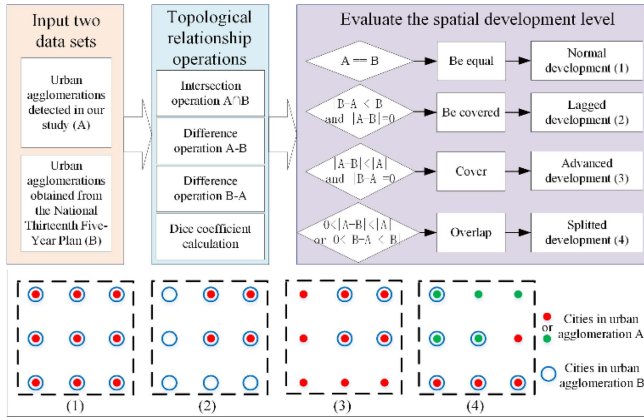


Fig. 4. Method to evaluate the spatial development levels of urban agglomerations.

level of urbanization should be equal to or greater than 50%. 6) The average percentage of the production value of the primary sector should be equal to or less than 30%. Urban agglomerations that cannot satisfy the above six criteria are removed, because they cannot play significant roles on industrialization and urbanization.

$$\begin{aligned}
 L(P) &= \left(\sum_{\alpha=1}^m q_{\alpha} \right) \log \left(\sum_{\alpha=1}^m q_{\alpha} \right) \\
 &\quad - 2 \sum_{\alpha=1}^m q_{\alpha} \log(q_{\alpha}) - \sum_{i=1}^n p_i \log(p_i) \\
 &\quad + \sum_{\alpha=1}^m \left(q_{\alpha} + \sum_{i=1}^{n_{\alpha}} p_i \right) \log \left(q_{\alpha} + \sum_{i=1}^{n_{\alpha}} p_i \right) \quad (1) \\
 q_{\alpha} &= \theta \sum_{i=1}^{n_{\alpha}} p_i w_i^{out} + (1 - \theta) \frac{n - n_{\alpha}}{n - 1} \sum_{i=1}^{n_{\alpha}} p_i. \quad (2)
 \end{aligned}$$

C. Evaluating the Spatial Development Levels of Urban Agglomerations

As shown in Fig. 4, we present the procedure to evaluate the spatial development levels of urban agglomerations. First, two sets of urban agglomerations are obtained, namely, those detected using our method (A) and those planned in the NTFP (B). Second, the topological relationships between the two sets are determined using the operations of spatial intersection and difference. Third, the dice coefficient s is calculated for measuring the spatial similarity of two urban agglomerations using (3), where $|\cdot|$ denotes the cardinality of a set. Specifically, it tells how much the spatial development of an urban agglomeration is deviated from the planned one.

$$s = \frac{2 * |A \cap B|}{|A| + |B|}. \quad (3)$$

Last, four different types of spatial development levels of urban agglomerations can be determined quantitatively using the following rules. The normal development is decided if two

urban agglomerations contain similar cities and a high value of dice coefficient can be observed. The lagged development is determined if cities in A are completely covered by cities in B, indicating that it is not developed as planned. The advanced development is obtained if cities in B are fully covered by cities in A, suggesting that the level of its urban development is much higher than planned. Finally, the splitted development is determined if only a few common cities can be identified between two urban agglomerations, implying that the planned one is not formed but instead one or more new urban agglomerations are developed.

III. EXPERIMENT AND RESULTS

A. Study Area and Datasets

Experiments were conducted in Mainland China, owing to the rapid development of urban agglomerations and the consequent environmental problems in recent years. Actually, most urban agglomerations in the developed countries, such as the United States, have faced very few environmental or ecological issues. However, urban agglomerations in the developing countries, such as China, are in emerging and rapid growing stages with tremendous challenges from the growing population, environmental degradation, and natural resources depletion. Besides, urban agglomerations in Mainland China have concentrated the majority of economic activities, and they have been regarded as the primary carriers for China's new urbanization development strategy. In this sense, it is plausible and valuable to choose Mainland China as the study area.

In this study, nighttime light imageries and human movement data were obtained for our study area. Specifically, all prefecture-level cities were included, where Hong Kong, Macau, and Taiwan were excluded from our analysis owing to the unavailability of relevant data. Movements among these cities can reflect well the spatial interactions in Mainland China. As shown in Fig. 5(a), these cities have different intensities of average nighttime lights, and they tend to be clustered together to form potential urban agglomerations.

The VIIRS nighttime light data were used to extract boundaries of individual cities, because they have been widely used as proxies of human activities. With the spatial resolution of 15 arc second, we downloaded it freely from the official site¹ in 2020, belonging to the version 2 time series of annual average radiance composites. The data had been preprocessed to remove sunlit, moonlit, cloudy pixels, and outliers with high and low radiance values [29]. As shown in Fig. 5(b), we can see that nighttime lights are unevenly distributed in space with large variations in different regions, indicating concentrations of human activities.

The human movement dataset was used to provide spatial interactions between individual cities, which is provided by the Baidu Company and can be freely downloaded from the official site.² It covers 12 days ranging from 2021-05-12 to 2021-05-23 and includes a total of 67 161 human movements. Each record of human movement contains the information of origin city,

¹[Online]. Available: <https://eogdata.mines.edu/products/vnl/>

²[Online]. Available: <https://qianxi.baidu.com/>

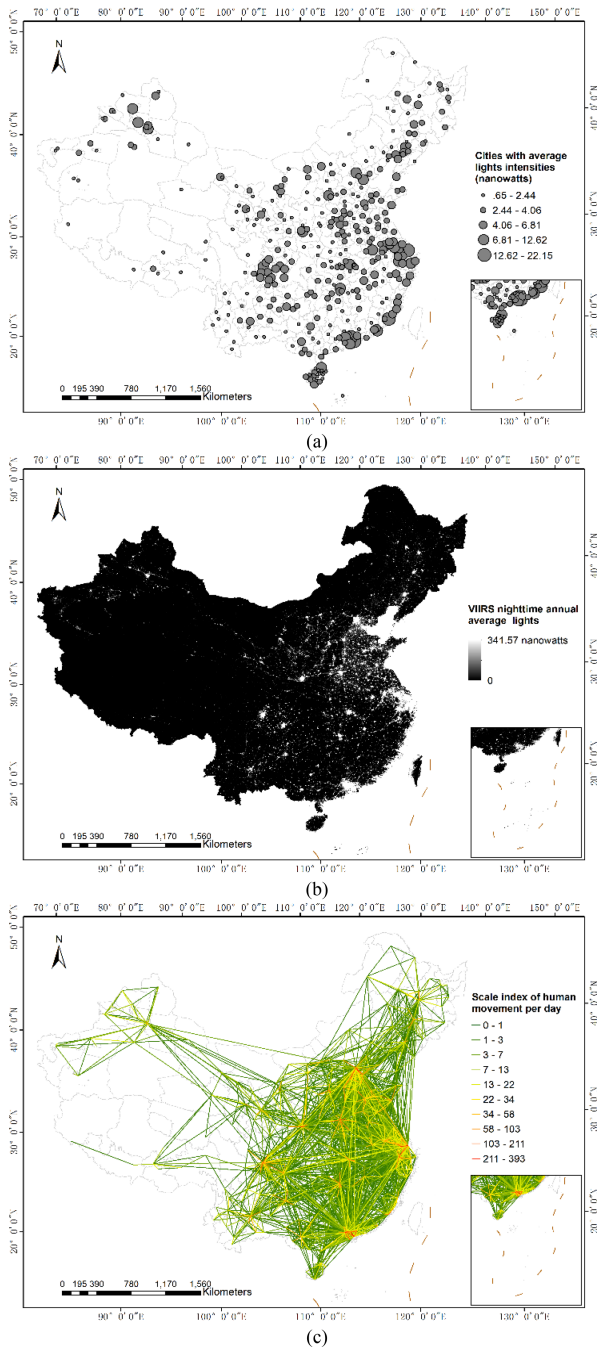


Fig. 5. Data used in our experiment. (a) All prefecture-level cities. (b) VIIRS nighttime light data. (c) Human movement data.

destination city, and human movement scale index. Human movement scale index is used as a proxy of the normalized amount of human movements, such that different cities can be compared over time. As shown in Fig. 5(c), we can see that near-cities are much more connected with each other than distant cities, which agrees well with the first law of geography.

B. Urban Boundaries Extracted From Nighttime Lights

By applying our method to the VIIRS nighttime light data, we obtained the urban boundaries of individual cities. As shown

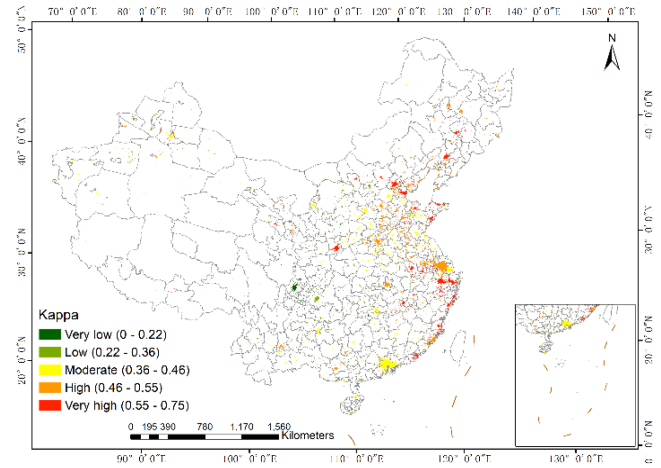


Fig. 6. Urban boundaries with different kappa values extracted from nighttime light data.

in Fig. 6, urban boundaries of different cities are visualized with different colors, and two facts can be clearly observed. First, there is a huge variation of the urban extent, which can be mathematically approximated by a power law distribution (e.g., $y = 332.21 \times x^{-2.07}$, $p = 0.05$). This finding coincides with many phenomena in nature and human society [30], implying that most cities are likely to have small sizes while very few of them may have extremely large sizes. Second, it is difficult to distinguish the urban boundaries of most cities in the Southeast region, because they have been partially integrated together owing to the high level of urbanization. For instance, cities in the Pearl–River–Delta region or the Yangtze–River–Delta region have been merged together to form a large urban boundary, respectively.

To evaluate the reliability of urban boundaries, we conducted accuracy analysis via comparisons with the built-up area from the national land-use/land-cover product [31]. The results suggest that urban boundaries of all cities have the overall accuracy of 0.97 and the kappa value of 0.51, which is relatively high and suggests the reliability of urban boundaries as a whole in Mainland China. Additionally, to understand how the accuracy varies in space, we evaluated the accuracy of individual urban boundaries. The results show that urban boundaries tend to have high values of the overall accuracy irrespective of cities; for instance, around 90% of cities have the values of the overall accuracy greater than 0.85. However, as shown in Fig. 6, the kappa value varies largely in cities, and particularly, boundaries of eastern cities tend to be much more accurate than those of western cities. For instance, boundaries of Beijing and Xiamen have the kappa values as high as 0.70 and 0.68, while boundaries of Chongqing and Chengdu have low kappa values of 0.36 and 0.43.

C. Urban Agglomerations Detected From the Spatial Interaction Network

By applying our method to the spatial interaction network, we obtained a total of 17 urban agglomerations in Mainland

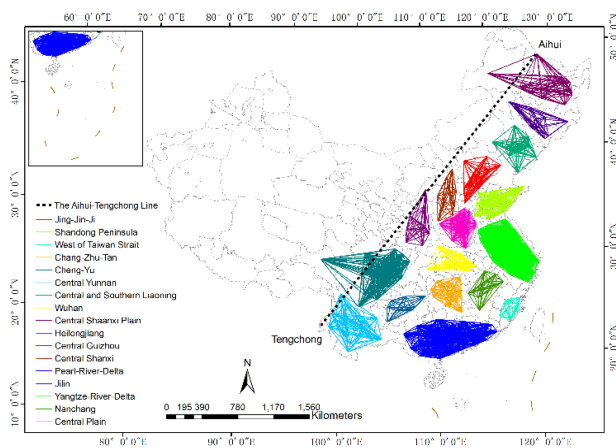


Fig. 7. Urban agglomerations with different colors derived from the spatial interaction network.

China, which corresponds to a relatively high modularity value of 0.63. As shown in Fig. 7, the spatial distribution of urban agglomerations is displayed, and their spatial extents as well as the intense connections can be clearly observed. Our findings are roughly consistent with those planned in the NTFP, although slight differences can be found. First, the number of urban agglomerations (17) is slightly less than that (19) planned in the NTFP, which indicates that most urban agglomerations in Mainland China have developed as expected. Second, it is obvious that all urban agglomerations are located in the southeastern division of the Aihui–Tengchong Line. This finding implies the uneven distribution of urban agglomerations during the implementation of the NTFP [2].

Specifically, we have a look at the top urban agglomerations with the largest number of cities. The top three are the Yangtze–River–Delta urban agglomeration, the Pearl–River–Delta urban agglomeration, and the Cheng–Yu urban agglomeration, which are also the top three with the largest population of 235.38 million, 176.41 million, and 121.65 million, respectively. These urban agglomerations agree well with those planned in the NTFP, although urban agglomerations of both the Yangtze–River–Delta and the Pearl–River–Delta have much more cities than those planned by the government, indicating the rapid urban development in these regions. However, the last three with the smallest number of cities are the West of Taiwan Strait urban agglomeration, the Central Guizhou urban agglomeration, and the Jilin urban agglomeration, which are partially consistent with those planned in the NTFP. For instance, the West of Taiwan Strait urban agglomeration has less cities than planned, suggesting the slow urban development in this region. Additionally, the Central Guizhou urban agglomeration has experienced rapid urban development, although it remains in the early stage.

D. Evaluation of the Spatial Development Levels of Urban Agglomerations

A quantitative comparison of our urban agglomerations with those planned in the NTFP was conducted using our method, which intends to evaluate their spatial development levels. As

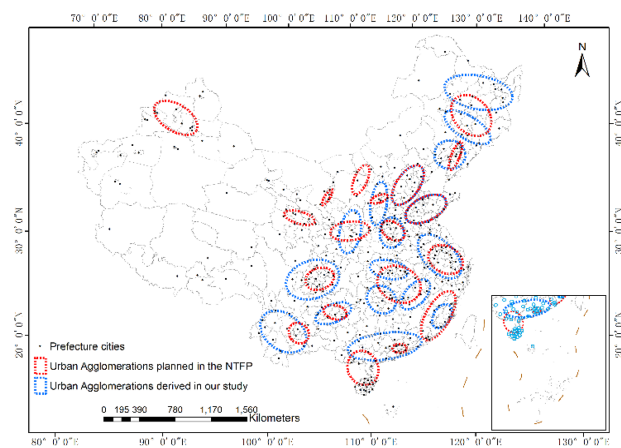


Fig. 8. Comparison of our agglomerations with those planned in the NTFP.

shown in Fig. 8, the results suggest that all urban agglomerations can be classified into four categories according to their development levels, including eight urban agglomerations with the splitted development, one urban agglomeration with the lagged development, six urban agglomerations with the advanced development, and two urban agglomerations with the normal development.

As shown in Table I, we listed the spatial development levels of all urban agglomerations. It is reported that the Pearl–River–Delta urban agglomeration has experienced the most rapid growth among those with the advanced development. Additionally, both the Jing–Jin–Ji urban agglomeration and the Shandong Peninsula urban agglomeration belong to the normal development, indicating that their urban development is in line with what was expected in the plan. However, the West of Taiwan Strait urban agglomeration has not developed very well and belongs to the lagged development, which has a smaller size than that expected in the plan. Importantly, most urban agglomerations have experienced the splitted development. For instance, the Haerbin–Changchun urban agglomeration is not appeared as expected in plan, but two urban agglomerations of Heilongjiang and Jilin has emerged unexpectedly, indicating a relatively slow urban development in the Northeastern region. Another similar example is the urban agglomeration in the middle reaches of the Yangtze River, which was planned in the NTFP but is actually replaced by three independent urban agglomerations of Wuhan, Chang–Zhu–Tan, and Nanchang. Lastly, four urban agglomerations planned in the NTFP, including the Tianshan Mountains northern slopes urban agglomeration, the urban agglomeration centered around the Ningxia section of the Yellow River, the Lanzhou–Xining urban agglomeration, and the Hohhot–Baotou–Ordos–Yulin urban agglomeration, are not detected in our study. These urban agglomerations are all located in the western region, further indicating the uneven urban development in Mainland China.

It can be inferred from our evaluation analysis that the formation of urban agglomerations in Mainland China can be affected by a variety of socioeconomic factors and government policies. Urbanization, industrialization, globalization, and

TABLE I
SPATIAL DEVELOPMENT LEVELS OF ALL URBAN AGGLOMERATIONS

Our urban agglomerations	Urban agglomerations in the NTFP	Dice coefficient	Category
Jing-Jin-Ji	Jing-Jin-Ji	1.0	Normal development
Shandong Peninsula	Shandong Peninsula	1.0	Normal development
Central Plain	Central Plain	0.75	Splitted development
Central Shaanxi Plain	Central Shaanxi Plain	0.64	Splitted development
	Hu-Bao-E-Yu	0.13	Splitted development
Jilin	Haerbin-Changchun	0.57	Splitted development
Heilongjiang	Haerbin-Changchun	0.42	Splitted development
Central Shanxi	Central Shaanxi Plain	0.18	Splitted development
	Central Plain	0.08	Splitted development
	Central Shanxi	0.62	Splitted development
Nanchang	West of Taiwan Strait	0.07	Splitted development
	The middle reaches of the Yangtze River	0.48	Splitted development
Wuhan	The middle reaches of the Yangtze River	0.55	Splitted development
Chang-Zhu-Tan	The middle reaches of the Yangtze River	0.36	Splitted development
Pearl-River-Delta	Pearl-River-Delta	0.41	Advanced development
Yangtze-River-Delta	Yangtze-River-Delta	0.78	Advanced development
Cheng-Yu	Cheng-Yu	0.80	Advanced development
Central Yunnan	Central Yunnan	0.50	Advanced development
Central and Southern Liaoning	Central and Southern Liaoning	0.72	Advanced development
Central Guizhou	Central Guizhou	0.80	Advanced development
West of Taiwan Strait	West of Taiwan Strait	0.69	Lagged development

culture are the four major factors driving the formation and growth of urban agglomerations. Urban agglomerations with the advanced development or the normal development should be guided by relevant policies on industrialization and globalization to participate in global competition and become world-class urban agglomerations; for instance, the rapid development of the Pearl–River–Delta urban agglomeration has been facilitated by the implementation of the development strategy of the Guangdong–HongKong–Macao Greater Bay Area in 2019. Urban agglomerations with the splitted development should be guided by the policies related to urbanization, industrialization, and culture, and they will form national-level urban agglomerations. For instance, urban agglomerations not detected but located in the western region should take advantage of the national strategic policies of “the Western Development” and “the Belt and Road”; and the middle reaches of the Yangtze River urban agglomeration are splitted into three independent urban agglomerations, which can be mainly explained by the fierce competition from similar industries and the diversity of

cultures. Specifically, the Wuhan urban agglomeration is mainly influenced by the Chu Culture, the Chang–Zhu–Tan urban agglomeration is dominated by the Hunan–Xiangjiang Culture, and the Nanchang urban agglomeration is mostly affected by the Gan Culture. In this respect, culture related policies should be also recommended and implemented to boost the development of urban agglomerations.

IV. DISCUSSIONS

First, this study provided a methodological framework to detect urban agglomerations and evaluate their spatial development levels in a quantitative way. The novelty of our methods can be manifested in the following aspects. 1) We proposed a method to extract urban boundaries from nighttime light data, which integrates the Lorenz curve technique and the watershed method. The Lorenz curve is used to automatically determine the threshold that will be directly used in the watershed method, which is rarely reported in the previous studies. 2) We employed the network community detection method to derive urban agglomerations, which not only utilizes the human interactions in space but also considers the conventional criteria-based definition. 3) We developed a quantitative method to evaluate the spatial development levels of urban agglomerations, and they are classified into four categories according to the urban development levels.

Second, it is necessary to discuss the fundamental concept of the urban agglomeration, which remains ambiguous and hinders its detection in an effective way. This study argues that urban agglomerations can be effectively detected by fusing nighttime light data and human movement data. It is in line with the very characteristics of urban agglomerations: concentration and integration, widely reported in many previous studies [13]. Nighttime light data can reflect the concentration of human activities in space, which can be used to extract urban boundaries. Human movement data can reflect the intense human interactions in space, which can be used to connect different cities via the exchange of resource, goods, or information. Nonetheless, it requires further studies to examine our urban agglomerations, e.g., they may be compared with the urban agglomerations derived from the mobile phone data as the proxy of spatial interactions.

Third, it is necessary to evaluate the robustness of our urban agglomerations. Specifically, the human movement data are demarcated into 10 folds. Then, we randomly select nine folds to build the spatial interaction network, which is fed into the same Infomap method to detect urban agglomerations. The above procedure is repeated 10 times, and we obtained 10 sets of urban agglomerations. Thereafter, for each set of urban agglomerations, we compare them with our results by calculating the value of ARI (Adjusted Rand Index) [33], which is used for measuring the similarity between two partitions of the data and is adjusted for chance partitioning of data elements. The experimental results suggest that our urban agglomerations are highly consistent with those derived in our experiments with an average value of ARI as high as 0.99.

Fourth, it is necessary to interpret and analyze our urban agglomerations through a comparison with those reported in the literature. In this study, a total of 17 urban agglomerations were

detected, and they are slightly different from those reported in the previous studies, where 14, 22, 11, and 20 urban agglomerations were identified in [34], [35], [13], and [2], respectively. Obviously, our results are relatively close to those (19 urban agglomerations) reported in the NTFP, but it is difficult to determine which one is better owing to the ambiguity of the definition. Specifically, a few common urban agglomerations can be identified in both our study and the previous studies [2], [13], [34], [35], including the urban agglomerations of the Pearl–River–Delta, the Yangtze–River–Delta, the Jing–Jin–Ji, the Shandong Peninsula, the Cheng–Yu, the West of Taiwan Strait, the Central and Southern Liaoning, the Central Plain, and the middle reaches of the Yangtze River. Most of these common urban agglomerations belong to the advanced development or the normal development, suggesting that they are relatively stable and those with the splitted development need further studies.

Fifth, it remains unclear about the mechanism governing the formation of the urban agglomeration. It is argued that urban agglomerations can be formed if a country is at the advanced stage of industrialization and urbanization, where an ensemble of cities are integrated together through a natural progress with their roles gradually changing from competition to assimilation [32]. Actually, this process can be affected by both the top-down based national macro-strategic policies and the bottom-up based regional cooperation. However, in Mainland China, the development of urban agglomerations can be much more affected by the national strategy, such as the NTFP, than the bottom-up based regional cooperation. In this respect, time series of human movement data and nighttime light data can be used in future studies to derive urban agglomerations in different years. Combined with the strategic policy, the expansion and densification of urban agglomerations can be investigated for a better understanding of its formation and solving the issue of “urban agglomerations diseases.”

Sixth, it is interesting to discuss the spatial dependence and potential spatial spillover effect in the formation of urban agglomerations. As for the spatial dependence, we find that cities within urban agglomerations have spatial positive correlations in terms of socioeconomic indicators. Specifically, urban population, GDP, and urbanization are clustered in some urban agglomerations with the average values of Moran’s index of 0.30, 0.50, and 0.45, respectively, at the significance level of 0.05. This finding provides potential evidence for the formation of urban agglomerations that an ensemble of cities are clustered together with gradual assimilation of some socioeconomic indicators, but further study is needed to understand how the spatial dependence changes with time in the formation of urban agglomerations. Meanwhile, the formation of urban agglomerations can be also accompanied by the spatial spillover effect [36], which may reveal how the change of one socioeconomic indicator affects the other indicators in spatially nearby cities. However, in our study, no spatial spillover effect can be significantly observed for different socioeconomic indicators in the urban agglomerations. In this respect, it points out our future study to investigate the spatial spillover effect and the dynamic influences using a time series of urban agglomerations derived in many years.

Seventh, it is necessary to discuss the potential limitations of our method. On the one hand, compared with the remote sensing-based detection, we only used the nighttime light imageries, and further study is needed to fuse remote sensing data from multiple sources to improve the accuracy of urban boundaries. On the other hand, compared with the criteria-based definition, the values of different criteria were set in a relatively arbitrary way; for instance, the population criterion was set as 5 million according to a previous study in 2017 [2], but the urban population in many cities have increased in recent years. To examine the changes of criteria on our results, the values of socioeconomic criteria were refined by considering the changes of population, GDP, and urbanization. Specifically, the value of population criterion was corrected by multiplying it with the ratio of urban population in 2020 to that in 2017, and we corrected the values of GDP criterion and urbanization criterion using the same way. Our experimental results suggest that only two urban agglomerations (Central Yunnan and Heilongjiang) would be removed if the corrected values of socioeconomic criteria were used. Nonetheless, further study is required to select the optimal criteria and specify the appropriate values to improve the robustness of urban agglomerations.

V. CONCLUSION

In this study, we developed a methodological framework to detect and evaluate urban agglomerations from the perspective of spatial interactions. The methodological framework is composed of three parts. First, it combines the Lorenz curve and the watershed method to extract urban boundaries of individual cities from nighttime light data, which represents the spatial units of the concentration of human activities. Second, it adopts the Infomap method and the criteria-based definition to detect urban agglomerations from the spatial interaction network, where urban boundaries are taken as network nodes and human movements are used as network edges. Third, it evaluates the spatial development levels of urban agglomerations by quantifying them into four categories according to their spatial similarities with those planned in the NTFP. This methodological framework provides a convenient and novel way to detect and evaluate countrywide urban agglomerations with freely available data.

Experiments were conducted in Mainland, China, considering the rapid growth of urbanization and urban development in recent years. Generally, a total of 17 urban agglomerations can be identified, which are very close to those (19) planned in the NTFP. Additionally, urban agglomerations are unevenly distributed in space, where all of them are located in the southeastern division of the Aihui–Tengchong Line. Compared with these planned in the NTFP, urban agglomerations have been classified into four categories with different levels of urban development, where those with the splitted development need further studies considering the inconsistencies in the literature. Actually, the formation of urban agglomerations can be affected by both the government-defined development policies and many socioeconomic factors in terms of urbanization, industrialization, globalization, and culture. In this sense, to enhance the further development of urban agglomerations, relevant policies

should be proposed and implemented to improve the open economic system, enhance the ability of scientific and technological innovation, form the cultural competitiveness with distinctive characteristics, and raise the level of participation in international competition and cooperation.

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