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RESEARCH ARTICLE

Characterizing the urban spatial structure using taxi trip big data and implications for urban planning

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Abstract Urban spatial structure is an important feature for assessing the effects of urban planning. Quantifying an urban spatial structure cannot only help in identifying the problems with current planning but also provide a basic reference for future adjustments. Evaluation of spatial structure is a difficult task for planners and researchers and this has been usually carried out by comparing different land use structures. However, these methods cannot efficiently reflect the influence of human activities. With the wide application of big data, analyzing data on human travel behavior has increasingly been carried out to reveal the relationship between urban spatial structure and urban planning. In this study, we constructed a human-activity space network using the taxi trip big data. Clustering at different scales revealed the hierarchy and redundancy of the spatial structure for assessing the appropriateness and shortcomings of urban planning. This method was applied to a case study based on one-month taxi trip data of Dongguan City. Existing urban spatial structures at different scales were retrieved and utilized to assess the effectiveness of the master plan designed for 2000 to 2015 and 2008 to 2020, which can help identify the limitations and improvements in the spatial structure designed in these two versions of the master plan. We also evaluated the potential effect of the master plan designed for 2016 to 2035 by providing a reference for reconstructing and optimizing future urban spatial structure. The analysis demonstrated that the taxi trip data are important big data on social spatial perception, and taxi data should be used for evaluating spatial structures in future urban planning.

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1 Introduction

Urban planning has been generally used by governments for various purposes, such as meeting development goals and designing land use patterns and spatial structures. Urban plans are commonly designed for a certain period, such as every 20 years. With rapid urbanization, urban lands are expected to significantly expand to meet the needs of growing population and economic development during the planning period. The actual pattern of urban spatial structures may not be as per the planned layout, which becomes increasingly obvious over time. Assessing the implementation of the plan can be important to examine this difference and ensure efficiency in urban planning. However, urban planning in regions with rapid urbanization is frequently modified, thus, evaluating the implementation should be carried out at every planning phase.

Qualitative methods have been applied for evaluating the implementation of plans in the proposed policy-plan/program-implementation-process (PPIP) model (Alexander and Faludi, 1989; Innes and Booher, 1999). It has been indicated that, ignoring the uncertain influences, a higher consistency between the implemented and designed plans is associated with more efficient plan implementation (Wildavsky, 1973). As computer technology has rapidly developed, quantitative methods, such as comparing the difference between presented and planned layouts, integrating quantitative methods, and PPIP principle, have been widely applied for evaluating the implementation of the plans (Talen, 1996; Laurian et al., 2004; Brody et al., 2006; Han et al., 2009). Studies have shown that determining the layout of spatial structures is important for urban planning. Unreasonable spatial structures are considered to impede sustainable urban development.

Therefore, evaluating spatial structure designs has been generally considered as a key for assessing their implementation. Such evaluation cannot only highlight issues with urban development, but also indicate the direction for future space restructuring. Real spatial structure patterns are influenced by different factors, such as social conditions, economic development, and eco-environment. Some researchers have considered that the identification and perception of urban regional structures can help in dividing units with similar functions and physical appearances into functional zones (Gordon and Richardson, 1996). This is one of the basic guiding theories of spatial structure design in urban planning. Many theoretical models (e.g., concentric circles, fan-shape (wedge-shape) model, and multi-core model (Parr, 2004)) have been introduced to perceive urban regional structures. However, due to the development of modern cities, urban regional structures have become a complex of natural and human elements. This has made it difficult to characterize spatial structures under the influence of human activities using a single standardized model, which has significantly complicated the study of regional structure evaluation.

Researchers have proposed that the visual form of urban structures can be evaluated using land-use spatial structures with remote sensing methods (Li and Yeh, 2000; Wang et al., 2001; Liu et al., 2003). Multi-source remote sensing can provide urban observation images at different granularities and can accurately identify various regional structures under human-computer interaction mode (Voorde et al., 2011; Heiden et al., 2012), providing an excellent means for perceiving the urban environment. However, urban regional structures represented in this way are only static physical modes and illustrating the intrinsic relationship between human activity and regional structure remains difficult. Additionally, it is difficult to reveal the manner in which existing urban regional structures spatially interact.

Studies have indicated that real conditions of urban spatial structures can be more accurately identified through the character analysis of human activities (Liu et al., 2015). As early as the 1960s, some researchers proposed using complex flows to analyze urban spatial structures (Berry, 1968; Castells and Cardoso, 2005). Due to the limitations of technology at that time, small sample size surveys were frequently used, however, these were unable to examine the sophisticated structure of human-land relationships. The development and extensive use of global satellite navigation and positioning technology have made it possible to observe the spatial track of human activities. An increasing number of devices are now equipped with positioning functions, thus, enabling the tracking of spatial movements of individuals (Yuan et al. 2012; Hasan et al. 2013; Shi et al. 2015). Mobile phone, smart card, and taxi trajectory data have been widely used to explore human mobility and urban spatial structure (Yuan et al., 2012; Liu et al., 2012; Gong et al., 2017; Zhou et al., 2018; Li et al., 2020a and 2020b). Among these data sources, taxis are mass transit carriers operating in urban spaces. Taxi trips big data can fully record the spatial characteristics of human activities, and thus, are an extremely important means of analyzing the spatial relationship between human activities and land. These data can efficiently reflect the spatial characteristics of human activities in urban areas, for a realistic representation of the urban spatial structure. The usage of these data enables associating land use types, assessing spatial structures, and designing urban development plans from the perspective of human activities for optimizing urban community management (Veloso et al., 2011; Rahmani et al., 2015; Gao et al., 2013; Wang et al., 2013; Kang et al., 2013).

Many studies have focused on this aspect of spatial structure evaluation (Yu, 2014; Niu et al., 2017). For example, Norton (2008) used content analysis methodology to evaluate urban master plans. Alterman and Hill (1978) and Tian and Shen (2011) assessed urban planning by analyzing the differences between land use status and planning. Long et al. (2012) evaluated the temporal and spatial heterogeneities in the urban master plans of Beijing City using logistic regression and geographic information system methods. However, these evaluation methods mainly focused on material spaces and overlooked the requirement for human activities (Xi and Zhen, 2017). The availability of big data recently has created opportunities for characterizing human activities and carrying out new urban spatial structure research (Lim et al., 2018; Zhou et al., 2018). Many recent studies have examined "space of flows" and associated human travel behavior with urban structure (Liu et al., 2015; Wang et al., 2020; Wei et al., 2020). Liu et al. (2015) applied a community detection method to uncover sub-regional structures based on the taxi data. Wei et al. (2020) employed taxi data to measure urban polycentricity from a multiscale perspective. Wang et al. (2020) used taxi trip data to delineate functional urban regions and further assessed polycentric urban system. However, most studies have focused on high-density metropolitan areas, such as Shanghai, the central city of China with a highly developed economy, and the characteristics of urban spatial structures differ across cities based on the context. Unlike previous studies, our research contributes to the existing knowledge by evaluating the case of an international manufacturing city without county (district) administrations in China. In this study, we used the big data of GPS-enabled taxis to quantify human-land relationships in Dongguan City, known as the "world's factory." We selected taxi trips that reflected the monthly travels of the residents and used network analysis to explore the urban community structure for urban management.

2 Data and methodology

2.1 Study area

Dongguan City is an international manufacturing metropolis located in the Pearl River Delta, China (Fig. 1). Over the last three decades, Dongguan, considered as the “world’s factory”, has transformed from a traditional agriculture county to a modern manufacturing city (Li et al., 2013). As one of the five prefecture-level cities without county (district) administrations in China, Dongguan City has a total of 28 townships. This unique administrative mode implies that the townships have greater economic autonomy in the urbanization process. Due to rapid urbanization, a typical multi-center spatial structure has been formed. However, this development pattern has resulted in many eco-environmental problems, such as the deterioration of water quality. To address these problems, the expansion of urban land was strictly carried out away from the sensitive lands for ecological preservation, i.e., the red line of ecological security. Recently, the Chinese government has prepared a national development strategy to build the Guangdong–Hong Kong–Macao Greater Bay Area into a world-class urban agglomeration area. Thus, upgrading reliable spatial structures and improving development quality have become major issues to address.

2.2 Taxi trip data and data preparation

We obtained approximately 1 billion GPS records from April 25 to May 25, 2015 from over 7200 taxis for this study. These trips recorded time, latitude, longitude, speed, mileage, and vacancy or occupancy every 15 s. In case of the absence of a passenger in the taxi, its state was marked as 1. Otherwise, the taxi was considered to be occupied and its state was marked as 0. An example of the taxi trip data are shown in Table1. Duplicate records, outliers with speeds over 120 km/h, and those with mileages over 100 km (this distance exceeds the maximum travel distance inside Dongguan City) were removed. Ultimately, 1815857 and 1428647 valid records for workdays and non-workdays were obtained, respectively. Origin-destination data identifying the original location and destination of each trip record were produced by analyzing the status of the taxis. Each trip was expressed as a directed vector graph with the original $\mathrm{O}\left((x_0,y_0),t_0\right)$ and destination $\mathrm{D}\left((x_d,y_d),t_d\right)$ statuses, including the information of time t and location (x, y). The travel mileages of valid records were statistically analyzed and results showed that on workdays, the median travel mileage was 3.7 km and quartile travel mileages were 0.1 (0%), 2.1 (25%), 6.4 (75%), and 100 km (100%). On non-workdays (including the May Day holiday), the median travel mileage was 3.8 km and quartile ride mileages were 0.1 (0%), 2.2 (25%), 6.4 (75%), and 100 km (100%).

Short-ride ($\mathrm{T_S}$) and long-ride ($\mathrm{T_L}$) mileage trips were defined as those below and above the median ride mileage of the workdays, respectively. Due to different travel modes on workdays, the peak hours of both long and short rides were found to be 9:00, 14:00, and 21:00. The number of long trips was more than short trips during the day, while the opposite was observed in the evening. On non-workdays, the peak hours of long and short trips were 9:00 and 19:00–21:00 h, respectively. In the evening, short trips were dominant, and the peak hour at 14:00 h observed on workdays was not significant.

Fig. 1 Location of the study area and boundaries of Dongguan.

2.3 Community detection method for recognizing geographical spatial structure

Trips with similar destinations (e.g., business or medical centers) form a specific geographical space structure. The GPS track of a trip is a directed graph, and the GPS tracks of all trips constitute a network (Rinzivillo, 2012), similar to a road, flight, or railway network. They have various features common with complex networks, such as being “small-world” or “scale-free” (Guimerà et al., 2005; Zhong et al., 2014). Complex networks can be divided into node clusters, such that any two nodes in the same cluster are closer than those in two different clusters. This topological feature is defined as a community structure, with each node cluster constituting a community (Newman, 2004). The cluster analysis of tracks in the network can determine urban spatial structures at different scales. In this study, we used grid-based analysis for community detection as it can be used to easily divide the study area into cells (Wei et al., 2020). The smaller the grid, the more accurate the taxi

Table 1 Example of the taxi data

ID	time	longitude	latitude	speed	mileage	state
16088205A9B6	2015-04-25 00:00:00	114021566	22971816	40	264697	1
16088205AC48	2014-04-25 00:00:00	114021750	23107033	50	150107	0
...	...	...	...			
16088205AE58	2014-04-25 00:00:00	114070366	23025783	80	348720	1

starting and ending points can be expressed, and the more precisely the urban spatial structure can be characterized. However, the presence of too many grids significantly increases the computational complexity. Hence, a 500 m grid was adopted as the spatial scale. We divided the study area into 18480 discrete minimum travel units with a grid size of 500 m × 500 m. Each minimum travel unit (G_i) was treated as a node (V_i) of the trip network. If the point of a taxi ride fell in the grid of e was G_i. In the network space, G_i corresponded to node V_i and the trip from V_i to V_j formed the edge E_{ij}. If there were n trips from V_i to V_j, then the weight of E_{ij} was n. All trips formed a weighted network N. It was assumed that T was the trip collection of all taxis in the network N and T_i was the trip collection of all taxis with a ride distance below i km. N_i was the network corresponding to T_i and N_{all} was the network of all rides of all taxis. Then, the network formed by the taxi trips was defined as a community network. The detailed process of constructing a community network is shown in Fig. 2.

Many methods can be used to detect the structure of a community network (De Montis et al., 2007; Ratti et al., 2010), such as Girvan–Newman (Girvan and Newman, 2002), Kernighan-Lin, greedy (Newman, 2004), simulated annealing (Guimerà and Nunes Amaral, 2005), tabu search (Arenas et al., 2008) and SCAN algorithms (Xu et al., 2007). Among them, the Infomap algorithm (Rosvall and Bergstrom, 2007) has been applied to a weighted directional network with stability and a fast operation time (Rosvall and Bergstrom, 2007; Lancichinetti and Fortunato, 2009; Fortunato, 2010). Its basic principles are as follows:

Assuming that the community division (M) of a given network divides n network nodes into m communities, then, the average description length of each step of an infinite random walk on the network is expressed as:

$$L(M) = q \times H\ (Q) + \sum_{i=1}^{m} p^i \times H(P^i). \qquad (1)$$

The right side of the equation consists of two terms: the first one indicates the entropy of movement between different communities, where q is the probability of random walk switching between different communities and H (Q) is the entropy of the community names; the second term indicates the entropy of movements within the communities, where p^i is the faction of within-community movements in community i and H (P^i) is the entropy of within-community movements, including the exit code for community i. More details on the estimations of these two terms are provided by Rosvall and Bergstrom (2007). The goal of network community detection is to find the division that minimizes the average description length L (M) as the optimal community division of all possible community divisions. The optimal division was achieved using the greedy algorithm in which, at the beginning, each node is assigned to an independent community. The two communities causing the most decrease in the average description

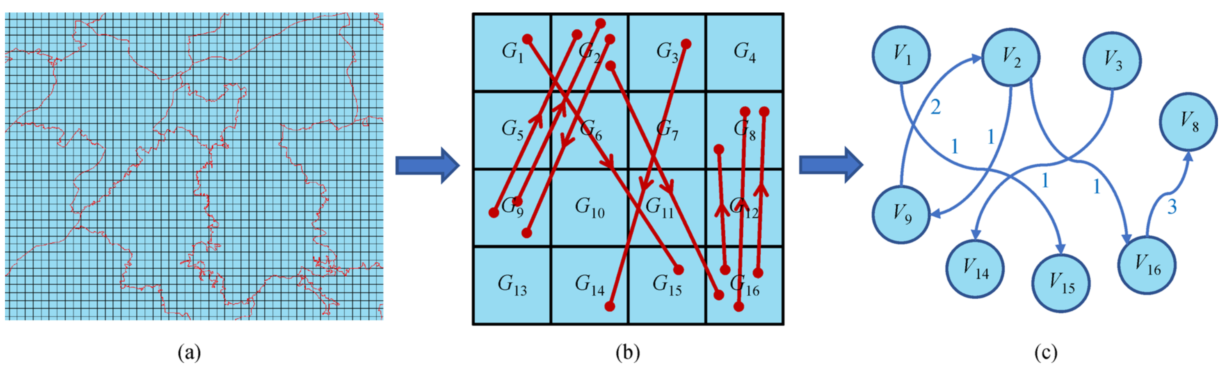


Fig. 2 Process of constructing discrete minimum travel units with a grid size of 500 m × 500 m from the taxi trips. (a) Grids distributed in the study area. (b) Rides $\overrightarrow{O\left((x_o,y_o),t_o\right)D\left((x_d,y_d),t_d\right)}$ connecting the grids G_i and G_j. (c) Trips from node V_i to V_j. All trips formed a complex, directed, and weighted community network.

length L (M) were merged and this process was iterated until all communities were merged into one community.

3 Results

The Infomap package of R software (Csardi and Nepusz, 2006) was used to cluster the constructed community network to reveal the underlying urban structure. The networks of community cluster structures were labeled from N_1–N_{all}, corresponding to various taxi ride distances (i.e., 1, 3, 5, 7, and 9 km), and all rides are shown in the supplementary figure. This indicates that the community structures gradually merged with the increase in the taxi ride distance. However, starting from N_5, the structure began to stabilize, indicating that a taxi ride distance of 5 km was the equilibrium point in the central city area. Considering all taxi rides (N_{all}), 16 stable community structures were formed throughout the city, which is similar to the multi-center feature of Dongguan City. It indicates that almost every township has its own sophisticated living and working accommodations. People do not need to travel across different townships to resolve working and living requirements.

3.1 Spatial structure of short-ride and long-ride networks

The constructed network presented typical spatial patterns characterized by the difference in the taxi ride distance. Short trips (T_S) were mainly distributed in the Hongfu Commercial District, First International-One Mall Commercial District, Dongcheng Center Commercial District, Huanan Mall Commercial District, and Dongguan City Bus Terminal (Fig. 3(a)). Of these, rides in Hongfu Commercial District had the highest density in the central city area, while those in the township district were mainly distributed in the central area of the township. Long trips (T_L) were mainly distributed in the transportation hubs, such as the Dongguan City Bus Terminal, Dongguan Nancheng Bus Station, Dongguandong Bus Station, Humen Railway Station, Dongguandong Railway Station, and Dongguan Railway Station (Fig. 3(b)). These results indicated that short trips were mainly made for commuting, leisure, and entertainment, while long trips indicated the

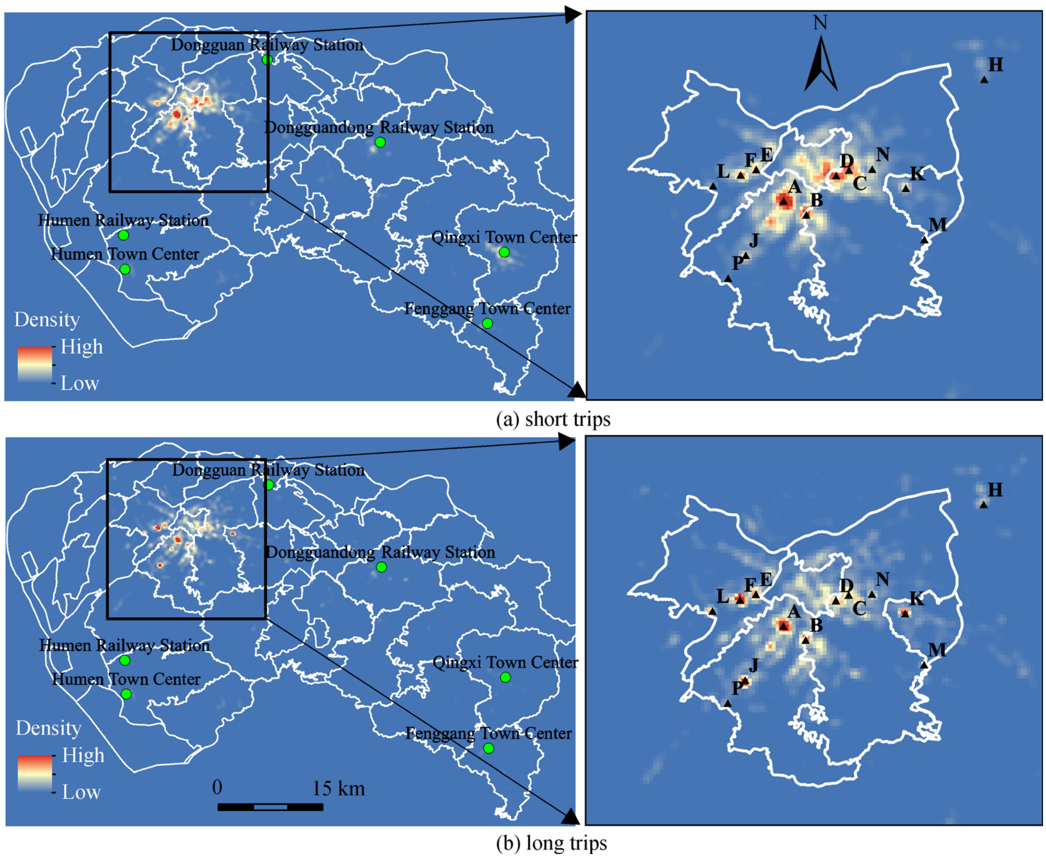
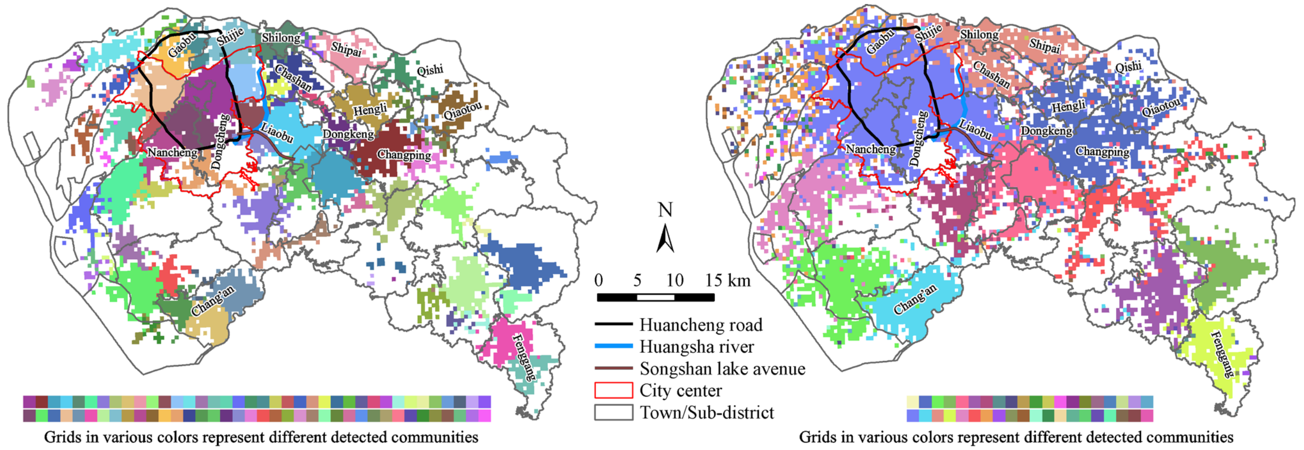


Fig. 3 Spatial distributions of all pick-up and drop-off points.
A: Hongfu Commercial District B: First International-One Mall Commercial District, C: Dongcheng Wanda Plaza, D: Dongcheng Center Commercial District, E: Huanan Mall Commercial District, F: Dongguan City Bus Terminal, G: Humen Railway Station, H: Dongguan Railway Station, I: Dongguandong Railway Station, J: Dongguan Nancheng Bus Station, K: Dongguandong Bus Station, L: Dongguan People’s Hospital, M: Dongguan TCM Hospital, N: Dongguan Maternity and Child Healthcare Hospital.

Table 2 Attributes of short-ride and long-ride networks

	Trip number	Nodes	Edges	Average edge weight	Proportion of edges with a weight equal or less than 3
Short	910,203	6798	97,211	8.691	18.7%
Long	905,654	8742	334,228	2.641	85.5%



(a) Detected communities with N_s

(b) Detected communities with N_l

Fig. 4 Communities detected with N_s and N_l, respectively.

need for transfers during long-distance travel.

Complex networks were constructed for T_S and T_L, labeled as N_s and N_L, respectively. The statistical attributes are listed in Table 2. In N_L, rides with $\leqslant 3$ repeats accounted for 85.5%. In contrast, in N_S, rides with > 3 repeats accounted for more than 80%. This indicates long trips were more random than short trips, as short trips generally shared destinations and had greater regularity.

Structures of T_S and T_L communities were further determined. The distribution structure of Ns (Fig. 4(a)) was found to be highly consistent with the township administrative boundaries, indicating that short trip activities were compartmentalized in the townships. In some townships, two or more communities were present. For example, Nancheng District was divided into two communities with Huancheng Road as the boundary; Dongcheng District showed a similar division. Liaobu Township was divided into three communities by the Huangsha River and Songshan Lake Avenue. This indicated that the rivers and roads in the townships exerted a certain compartmentalizing effect on the travel of people.

The structure of N_L (Fig. 5(b)) reflected the regional integration of townships where the city center district was closely connected with Liaobu, Gaobu, and Shijie townships. Shilong, Shipai, and Chashan townships were closely connected, similar to Qishi, Hengli, Dongken, Changping, and Qiaotou townships. Even when short trips were not taken into account, long-distance trips within these regions were also found to be very common. In addition, trips between Chang'an and Fenggang townships and Shenzhen City were found to be very common.

3.2 Spatial structure of all-ride network

The spatial structure of the network constructed from all taxi rides was also obtained (Fig. 5), which showed that grids with taxi rides were mostly located outside the ecological control line with a size of 970 km^2, accounting for 80% of the entire community (1222 km^2). Continuous and adjacent spaces formed a single community, complying with the principle of distance attenuation. Some isolated units formed "enclaves," differentiated by the long trips. Guangcheng, Nancheng, Dongcheng, and Wanjiang townships and the north-western parts of Liaobu Township were clustered into one community, indicating that most facilities were available in the central city, thus, concentrating the range of residents' activities. Changping, Donmgken, Hengli, Shijie, Shilong, and Chashan townships formed groups, while the rest were divided according to the administrative divisions of the townships. These indicated that in Dongguan City, human activities and administrative boundaries were in good agreement, which further highlighted the multi-center pattern of the city and relative independence of the townships.

4 Discussion

4.1 Communities in Dongguan

According to the "Urban Master Plan of Dongguan City for the period from 2000 to 2015" (Fig. 6(a)), the spatial distribution and development of future townships should

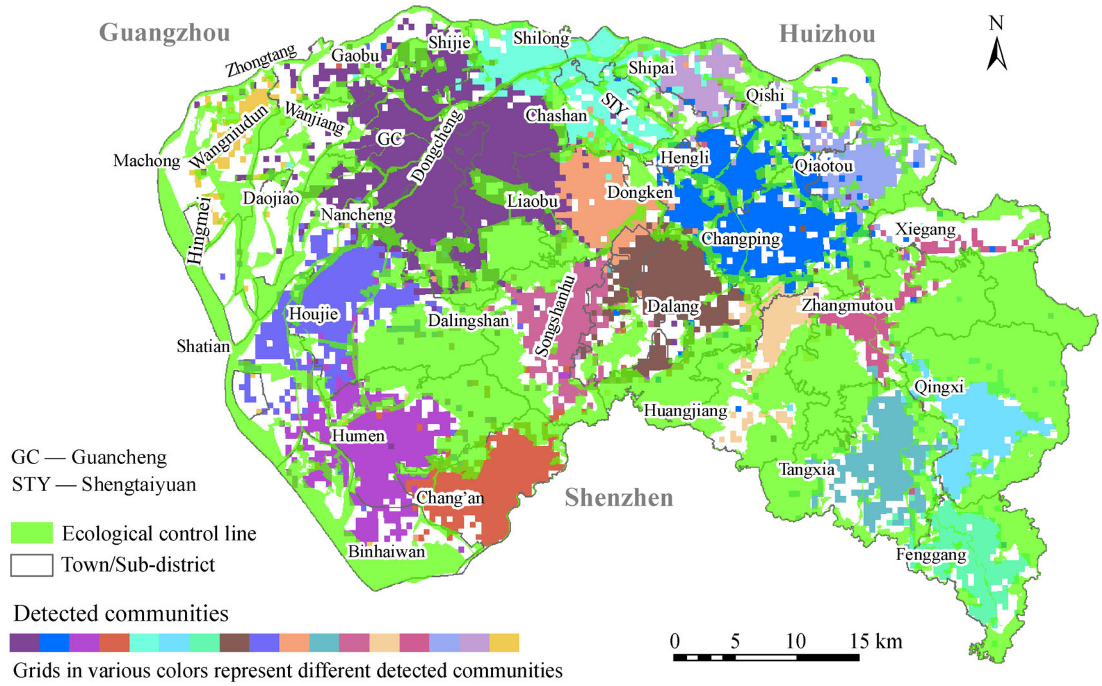


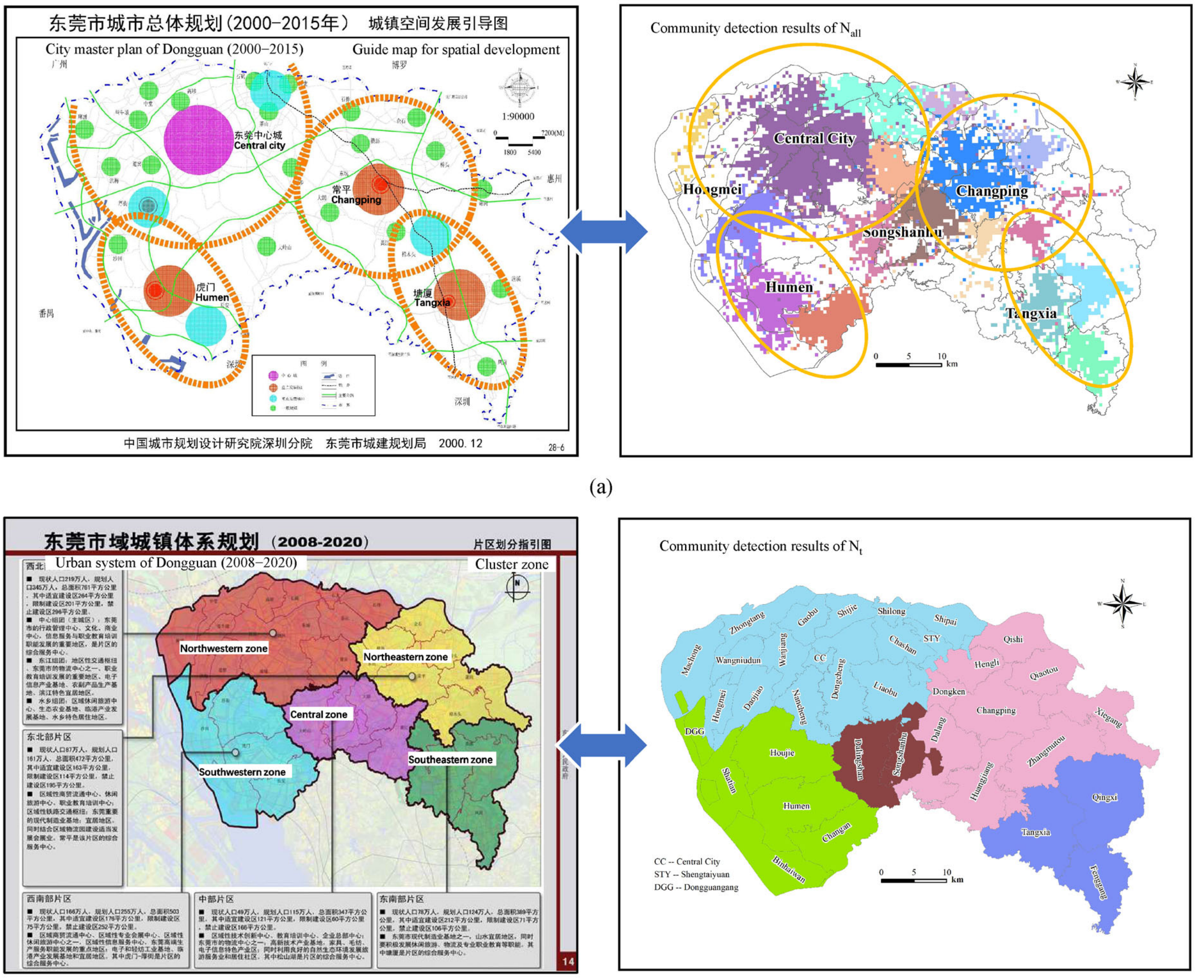
Fig. 5 Communities detected with N_{all}.

essentially adhere to the city and township layout and that “the city districts of Dongguan City should connect the east and west wings horizontally.” The east wing is the Guangzhou–Shenzhen Railway township belt centered at Changping Township, and the west wing is the high-density township belt centered at Humen Township along the Guangzhou–Shenzhen Expressway and 107 State Highway. Based on the detected community structure, while the center of Changping Township was developed as per the original plan, the rapid development of Houjie and Chang’an townships deviated from the human-centered pattern of the original plan. Additionally, the development of Qingxi and Fenggang townships that are close to Shenzhen City was also sufficiently fast, but the old version of the urban master plan underestimated the spatial influence of Shenzhen City on Dongguan City.

To address the issues with the urban master plan, the “Urban System Planning of Dongguan for the Period from 2008 to 2020” proposed the concept that townships (streets) with similar functions form the development zones. The results of community discovery analysis agreed with the spatial structure planning of this urban master plan (Fig. 6(b)), with the townships (streets) essentially clustered as planned, central zone centered at Songshan Lake, south-west zone centered at Humen, north-east zone centered at Changping, and south-east zone centered at Tangxia. However, the expansion of Songshan Lake in 2015 did not meet the expectations and has not yet covered Dalang and Huangjiang areas, which needs to be improved.

4.2 Implications for urban planning

The results of this study can provide valuable insights for urban planning implications for such an international manufacturing city with special administrative divisions. Urban development over time has gradually exposed the limitations in the above two mentioned versions of the urban master plan. To improve the layout of the urban spatial structure, a comprehensive zone-based “one center, four clusters, and six zones” development layout was proposed in the “Dongguan City Urban Master Plan for the period from 2016 to 2035” to form a coordinated development pattern with central, south-west, north-west, north-east, and south-east clusters, establishing a three-level “city center–cluster center (strategic node)–township center” and finally a “three-core, six-pole, and multi-pivot” urban central system. A comparison with community discovery results of N_{all} (Fig. 7) indicated sufficiently close connection between the central zone and Songshan Lake, with the radiation effect of the central city center not being fully utilized. In the future, the connection between the city center and Songshan Lake needs to be further strengthened to enhance the driving effect of the central city zone, thereby forming a central aggregating effect. The centers of Changping and Tangxia clusters have been already formed, while Shuixiang and Xincheng clusters need to be strengthened, with three strategic nodes (i.e., Dongguan Port, Eco-park, and Yinping Cooperation and Innovation Zone) needing improvement. Binhaiwan New District, as a



(b)

Fig. 6 Comparison of urban planning and community detection results: (a) Master plan for 2000 to 2015 and community detection results of N_{all}; (b) Urban planning system for 2008 to 2020 and community detection results of N_t.

core area for the interaction of Dongguan with the Guangdong–Hong Kong–Macao Greater Bay Area, is a key future development region and N_{all} community discovery results were not able to include Binhaiwan New District, which is partially because the new district is still under planning and in its initial construction stage. The development of Binhaiwan New District needs to be strengthened, which is also in line with the formulated plan and development policy.

5 Conclusions

Spatial structure is one of the core elements of urban planning. A rational spatial structure follows historical development principles, and can play an efficient role in guiding urban development. The GPS-acquired taxi ride data can effectively reflect the spatial characteristics of human activities and provide valuable information for the design of urban spatial structure. In this study, we adopted the community detection method to analyze the characteristics of the network to perceive urban spatial structures at different scales. This analysis provides the basis for evaluating the effectiveness of spatial structure design in urban planning as well as for recommending improvements for future plans.

The network formed by the taxi trip data showed significant spatial clustering characteristics. Clustering at different scales revealed the hierarchy and redundancy of spatial structure features. When the travel distance was small, the urban space was observed to form several clusters. As the distance between clusters increased, small clusters continuously merged and, ultimately, the entire city was considered as a community. When the distance between the clusters was approximately 5 km, the clustering result was in agreement with the administrative boundaries of the townships, indicating that the study area has a significant multi-center spatial structure feature.

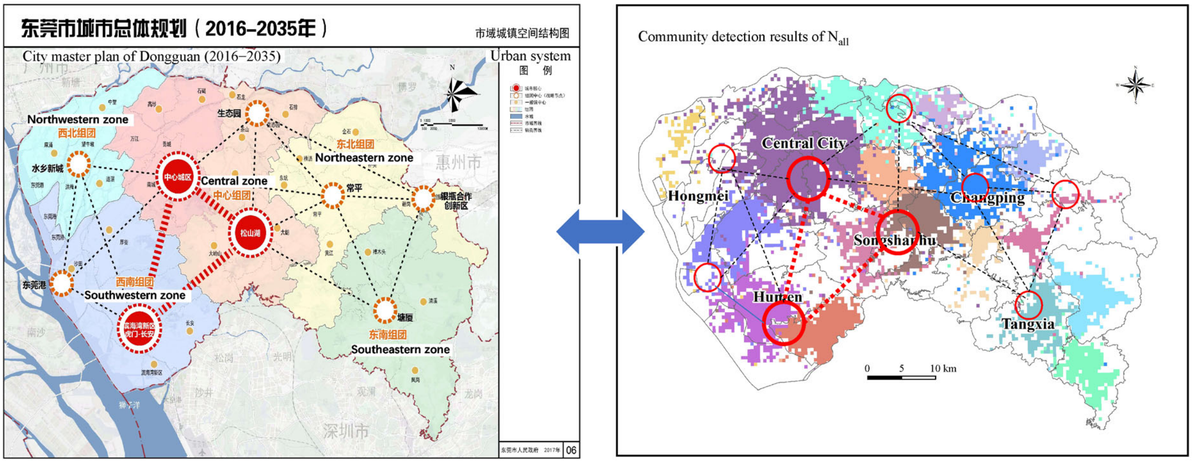


Fig. 7 City master planning for 2016 to 2035 and community detection results of N_{all}.

Evaluation using community detection results indicated that the urban master plan for 2000 to 2015 underestimated the driving effect in Shenzhen City and did not consider Songshan Lake High-Tech R&D Center as a planning focus, thus, exhibiting some limitations in the urban spatial structure design. The urban development master plan for 2008 to 2020 has made some revisions, with the spatial structure being more in line with that revealed by the taxi trip data, but the driving role of Songshan Lake High-Tech R&D Center still needs further strengthening. In the new version of the urban master plan for 2016 to 2035 emphasizing the "one center and four group" strategy, the shortcomings in the spatial structure were accurately revealed by the taxi trip big data of 2015, which confirmed the feasibility and accuracy of using this data in an urban spatial structure study.

Spatial trajectory data are important social-perception big data and record the spatial behavior characteristics of individuals. The introduction of this data into urban planning can help to identify problems that are overlooked or cannot be revealed using traditional remote sensing surveys or sampling analysis. This study demonstrated that the taxi-trip big data provide a new perspective for analyzing urban spatial structures for such an international manufacturing city with special administrative divisions. It is foreseeable that integrating social spatial perception big data (e.g., taxi trips, bus card uses, mobile phone positioning, shopping, and Weibo) into urban planning is the future development direction.

Despite the merits of this study, two limitations remain to be discussed. First, this study focused on characterizing the urban spatial structure from the travel patterns on weekdays but neglected the travel trips on non-workdays. Although the travel patterns on weekdays are more typical, which effectively reflect the spatial structure of the city, recent research in Shanghai showed a significant difference between traveling behaviors on weekdays and weekends (Liu et al., 2015; Wang et al., 2020; Wei et al., 2020). These differences can be compared and added to comprehensively characterize the urban spatial structure in future studies. Second, the population and industrial structures affect the urban spatial structure in such an international manufacturing city. These issues that were not considered in this study, however, should be further analyzed in the future.

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