UNCOVERING SPATIAL SYNERGY OF THE MEGACITY REGION: A FLOW PERSPECTIVE

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ABSTRACT:

The Pearl River Delta (the PRD) is a strategic region for China's development. Since the Reform and Opening up of China in 1983, the PRD has been growing from several isolated cities to one megacity region. Uncovering spatial characteristics is essential for the megacity region synergy, regional planning, and governance. Massive mobile phone location data contains hidden information of complex spatial networks. From the flow perspective, this study thereafter constructs a large-scale mobility network using long-period mobile phone location data. The Louvain method is adopted to detect spatial communities, which reveals the spatial cooperation within the detected area. The disparity filter is used to extract the backbone network, which unravels the geographical connection among these areas. An experiment in the PRD was conducted to investigate the spatial synergy in the PRD. The results suggest that the PRD is with a significant trend of spatial synergy; the backbone of mobility network demonstrates that Guangzhou and Shenzhen are the spatial cores; the East-West differences do exist, the closer to the central urban areas, the higher the degrees of spatial integration. These results will benefit the synergic spatial planning and governance of the PRD.

1. INTRODUCTION

With the advancement of globalization and urbanization, more and more cities appear and spatially grow, especially in the developing countries of Asia and Africa (Hall, 2009). As more people migrate from rural to urban areas, the boundaries of cities extend, contact, and merge. Multiple cities are connected and form one megacity region, such as the Greater London, the Greater Tokyo, and the Pearl River Delta (the PRD) in China (Mookherjee, 2020). The megacity region is a special form of regional organization with three dimensions, i.e., shape, function, and governance (Cowell, 2010). The functional polycentricity of the megacity region is sourced from the initial spatial layout of city networks (Hanssens et al., 2014). Cities in the polycentric urban area have great impacts on regional connection, interaction, and cooperation (Taylor et al., 2008). Around cities are attracted by the polycentric urban area for the spatial synergy. Therefore, cross-city travels increase to overcome the administrative divisions and form inconsistent anthropological boundaries (Ratti et al., 2010; Yin et al., 2017).

The Pearl River Delta is a world-class megacity region with the highest degree of openness and the strongest economic vitality in China. In February 2019, the State Council of China issued the "Outline Development Plan for the Guangdong- Hong Kong-Macao Greater Bay Area", pointing out that The Greater Bay Area aims to establish a mutually beneficial relationship in regional cooperation, promote coordinated economic development, and develop a vibrant and internationally competitive bay area. However, the hinterland of the city clusters in the PRD is mainly affected by administrative divisions which greatly limits the spatial coordination and development of this megacity region (Feng and Wang, 2022). Therefore, exploring the spatial structure and cross-boundary cooperation of cities in the PRD is of vital importance to understanding how the PRD has developed and evolved. It provides useful insight into future short-term decision-making and long-term spatial planning of the PRD.

Previous studies of the megacity region focus on the spatial, social, and ecological issues. From the spatial perspective, most of them rely on spatial analysis of complex spatial networks to depict micro-and macro-urban features, for instance, investigating the firm producer service linkages and city connectivity in the megacity region (Yeh et al., 2015), detecting spatial communities to identify the spatial structure of Chinese megalopolis (Tao et al., 2019), etc. For example, He et al. (2021) used the wavelet transform to fuse Night-time Light data (NTL), Point-of-Interests data and Tencent Migration data. The final image is segmented by multiresolution segmentation to delineate the urban agglomeration boundary. Taking the Yangtze River Delta as an example, Li and Wu (2008) discussed the top-down state-mandated process and the bottom-up process initiated by local governments and revealed the spatial synergy of internal and external driving forces. These studies reveal the connection and interaction among cities in the megacity region, therefore deepening our understanding of spatial interactions and cooperation.

Mobile phone location data is produced by the mobile communication companies. It contains regular location updating

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records which are triggered by moving from one base station to another. It is with the characteristics of wide coverage, high penetration, and low collection cost. It can provide massive individuals' spatio-temporal location information (Tu et al., 2020). With these advantages, mobile phone location data has been widely used in human mobility and urban planning studies, including revealing the heterogeneity of individual travels (Cao et al., 2021), estimating dynamic population (Yang et al., 2016), predicting travel demand (Colak et al., 2015), population evacuation (Yin et al., 2020), epidemic diffusion (Romanillos et al., 2021), identification of urban functions (Ratti et al., 2006; Tu et al., 2017), assessment of areas' connectivity (Galpern et al., 2018), and delineation of megalopolis boundaries (He et al., 2021). For example, Hui et al. (2020) investigated the regional cooperation and spatial connection in the megacity region using Tencent Location Big Data, railway service and census data. They analyzed the centrality of human movements, traffic flow and railway network with spatial network analysis. Their results demonstrate strong spatial and transport connections harness regional cooperation and boost viable development of the Greater Bay Area. These studies demonstrate the potential of demonstrating mobility flow and uncovering spatial cooperation of multiple cities in the megacity region.

Focusing on the PRD, this study presents a big geodata-driven approach to quantitatively recognize the spatial synergy of the megacity region. Massive mobile phone location data are processed to construct the high-resolution spatial network. The Louvain method is adopted to detect spatial communities, which reveals the spatial cooperation within the detected area. The disparity filter is used to extract the backbone network, which unravels the connection among these areas. An experiment in the PRD was conducted to investigate the spatial synergy in the PRD. These results will benefit the synergic spatial planning and governance of the PRD.

2. STUDY AREA AND DATASETS

2.1 Study area

The study was conducted in the Pearl River Delta, containing nine cities, namely Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, and Zhaoqing, as Figure 1 shows. The PRD is a complex urbanized area with high-density population, intensive economic activities, and increasing technological innovation, becoming a powerful growth pole in China. However, the PRD is still developing and has the problem of insufficient integration, which is inconsistent with future spatial planning. Therefore, we selected it as the study area for better understanding the PRD's regional integration situation and spatial planning strategies.

2.2 Data

Mobile phone location data is provided by one mobile communication company. It contains the 1-hour interval location record of millions of phone users in the study area, covering the period from July 2017 to June 2019. Each month, the location records in the first week were provided. 168 days of mobile phone location data can be accessed. The raw mobile phone location data were first sorted by the timestamp and clipped into time-sequential positioning records. Then we transferred the tower-level locations of mobile phones into grid-level locations by dividing the study area into 500-m grids. Therefore, each record consists of the origin cell id, the destination cell id, and the mobile population count from the origin to the destination. In total, 240 million records were stored. All places in the PRD are covered. An average of 1.42 million data were obtained every day. Therefore, these data facilitate the big data-driven region study. Using these useful data, a high-resolution mobility network is generated by aggregating the mobile phone location records. The node is the center of the grid. The edge is the link from one node to another. The weight of each edge is the total travel volume. Finally, the travels from one grid cell to another are summed for future analysis. It should be noted that only the aggregated flow can be accessed. Any personal information is not provided to protect private privacy.

Moreover, the county-level administrative boundary is used to demonstrate the spatial cooperation by comparing with the detected communities.

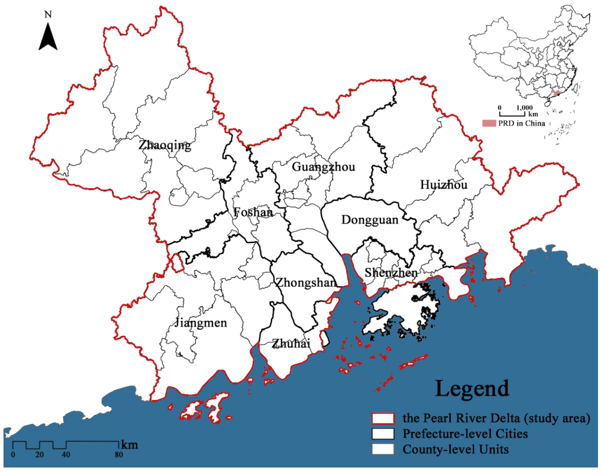

Figure 1. The layout of the Pearl River Delta.

3. METHODS

3.1 The analytic framework

The proposed analytic approach consists of three steps, as Figure 2 displays. In the first step, the mobile phone location data is cleaned, filtered, and aggregated. A human mobility network covering the PRD is constructed for further analysis. The descriptive statistics is done to reveal the basic characteristics of human travels and the hidden spatial cooperation among cities. Secondly, spatial community detection is by the Louvain algorithm to find spatial areas with high spatial connections. The disparity filter method is conducted to identify the mobility network backbone, which shows how multiple cities cooperate to produce world-class products. Finally, the results are analyzed to reveal the spatial synergy among the cities in the PRD.

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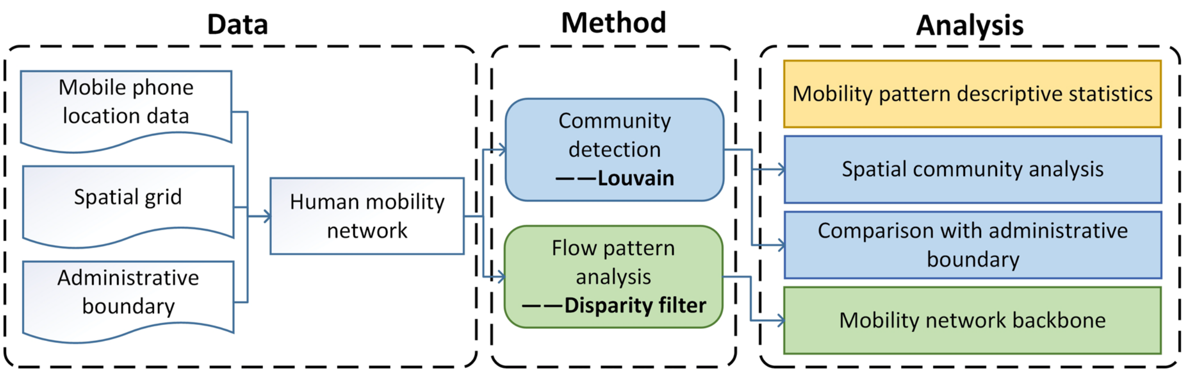

Figure 2. The research framework.

3.2 Spatial community Detection

The goal of community detection is to divide the large-scale network into several connected parts by considering the connections. Generally, the units in the same community are stronger the internal relations than external relations. Community detection methods are categorized into two types: agglomerative methods and divisive methods. For the agglomerative methods, edges are added one by one to a network which only contains nodes. Stronger edges are firstly added (Kumar et al., 2018). While the divisive methods remove edges one by one to produce multiple subnetworks (Cafieri et al., 2011).

This study utilizes the Louvain algorithm (Newman, 2004; Newman, 2006) to detect hidden spatial communities in the large-scale mobility network in the PRD. Clustering is foundation of community detection Louvain algorithms. The reasons for selecting Louvain are twofold: the method itself is well-accepted in both industry and academia, and it weighs the weight and direction of edges (flows) to detect communities. The Louvain algorithm is one of the fastest modularity-based algorithms that suit large networks. Given a network, the Louvain algorithm clusters network nodes into multiple groups by maximizing the modularity, as Eq 1,2,3:

$$Q = \frac{1}{2m}\sum_{i,j}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta(c_i, c_j) \tag{1}$$

$$k_i = \sum_{j} A_{ij} \tag{2}$$

$$m = \frac{1}{2}\sum_{ij} A_{ij} \tag{3}$$

where i, j = the clustered index
c_i = the community to which node i has been assigned
A_{ij} = whether there is an edge between nodes i and j (A_{ij} = 1) or not (A_{ij} = 0)
k_i = the degree of node i
m = the total number of edges in the network
$\delta(c_i, c_j)$ = whether nodes i and j belong to the same community.

Higher values of the modularity function in Eq 1 are supposed to indicate a better community structure. Given a network of n nodes, the idea of modularity-based community detection therefore is to try to find values of c_1, ..., c_n that maximize Eq 1. These values of c_1, ..., c_n are considered to represent the optimal community structure for the given network.

Louvain algorithm is divided into two stages. In the first stage, it partially optimizes the modularity by searching for some small communities. In the second stage, it combines the nodes of the same community into a supernode and creates a new subnetwork for the following clustering. These two stages are repeated until the maximum modularity Q_{max} is achieved. Once the maximum modularity is obtained, the algorithm stops and reports the found communities. If *the* Q_{max} is near to 1, it indicates that the detected network communities with a strong internal connection. If *the* Q_{max} is near 0 (or close to 0), the detected network is similar to a random network (Varsha and Patil, 2000).

This study detects spatial communities hidden in large-scale mobility networks in PRD. The spatial community with high internal interaction will be reported. We compare them with the administrative boundaries to understand the cooperation of different areas.

3.3 Flow pattern analysis

From the flow perspective, the movement from one place to another is used as the real relational data to reflect the interaction between cities, prompting the study of regional spatial structure to shift from the internal characteristics of the city to the external relationship among cities. The focus has changed from the urban form, core-periphery, and hierarchical system to the structure, function and connection of the urban network (Yao et al., 2017).

The fundamental characteristic of flow data like mobile phone position data is their heavy-tailed distribution. It has a sharp vertically rising “head” followed by a long “tail”, which make study dramatically exacerbated if zero values had not been removed beforehand (Tao et al., 2020). Data with this characteristic is difficult to capture the main patterns in the large-scale network. Therefore, a graph filtering method that considers local properties of nodes, such as the weights over all edges linked to specific nodes is needed to reveal the network backbone. This study uses the disparity filter to capture the main travels in the PRD. The disparity filter methods consider local heterogeneity and local correlation to extract the main edges while retaining most of the nodes and weights and reducing the number of networks edges (Serrano et al., 2009; Truica et al., 2018).

The disparity filter uses the NULL model to define significant edges, where the NULL hypothesis states that the normalized weights that correspond to the connections of a certain node of degree k are produced by a random assignment from a uniform distribution. To visualize this process, in the NULL model, the normalized weights of a certain node with degree k is generated like this: $k-1$ points are randomly assigned between the interval 0 and 1. The interval is then divided into k subintervals. The length of the subinterval represents the normalized weights p_{ij} of each link in the null model. The probability density function for one of these variables taking a particular value x is, as Eq 4:

$$\rho(x)\,dx = (k-1)(1-x)^{k-2}\,dx \tag{4}$$

where k= the degree of the node

The disparity filter proceeds by identifying strong and weak links for each node. The discrimination is assessed by calculating the normalized weight p_{ij} and the probability α_{ij} which is compatible with the NULL hypothesis for each edge. All the links with $\alpha_{ij} < \alpha$ reject the NULL hypothesis. The statistically relevant edges will be those whose weights satisfy the Eq 5.

$$\alpha_{ij} = 1 - (k-1)\int_0^{P_{ij}} (1-\mathrm{x})^{k-2}\,\mathrm{dx} < \alpha \tag{5}$$

where k= the degree of the node
p_{ij} = the normalized weight
α = the significance level

The superiority of this disparity filter method can significantly reduce the number of edges of a large-scale network while keeping a large fraction of important nodes and edges. The study uses this method to extract the main backbone network of mobile phone position data, thereby revealing the interaction among different nodes, and analyzing the important role played by core cities in the PRD.

4. EXPERIMENT AND RESULTS ANALYSIS

4.1 Descriptive statistics of mobility pattern

Descriptive statistics is conducted to understand the mobility patterns in the PRD. Figure 3 shows the spatial distribution of travel volume and average travel distance. For the travel volume, Figure 3a shows that the mobility flows are concentrated in two areas: the Guangzhou-Foshan area and the Shenzhen area. There are also some local travel centers, such as the Zhuhai-Zhongshan area and Dongguan. For the remained areas, most of them are with travel less than 40 thousand per square km. By summarizing the travels cross county boundary, the results demonstrate the inter-county trips account for 65.5% of total travels. When looking at the city boundary, the results suggest that inter-city trips account for 39.5% of total travels. These results suggest the hidden high connection and cooperation among main cities like Guangzhou and Shenzhen in the PRD.

In terms of travel distance, Figure 3b displays the spatial distribution of average travel distance. It can be seen the centers of Guangzhou-Foshan and Zhuhai are with many short-distance travels. While the centers of Shenzhen-Dongguan are with medium-distance travels. For the remained areas, the farther their distance to these centers, the longer the average travel distance. These results indicate spatial heterogeneity of human mobility in the PRD.

Figure 4 further displays the average travel distance in county-level administrative districts. It can be seen that the average county-level travel distance is within the range from 4 to 11.2 km. On the average, people in Foshan and Dongguan travel shorter, no more than 6.8 km per trip. The core districts of the central cities in the PRD are with longer travel, such as Yuexiu District and Tianhe District in Guangzhou, Yantian District, Nanshan District, and Futian District in Shenzhen. While the Luohu district in Shenzhen is with an average travel distance of 9.117 km per trip. That is due to the fact that there are many ports to Hongkong. People from Hongkong enter the PRD from these land ports and go to other cities. Therefore, many long-distance travels will be generated therefore it will enlarge the average travel distance. The distance in the core areas of non-central cities in the PRD is below the average value, such as Huicheng District in Huizhou, Duanzhou District in Zhaoqing, etc. They suggest short daily travels of residents in the two cities.

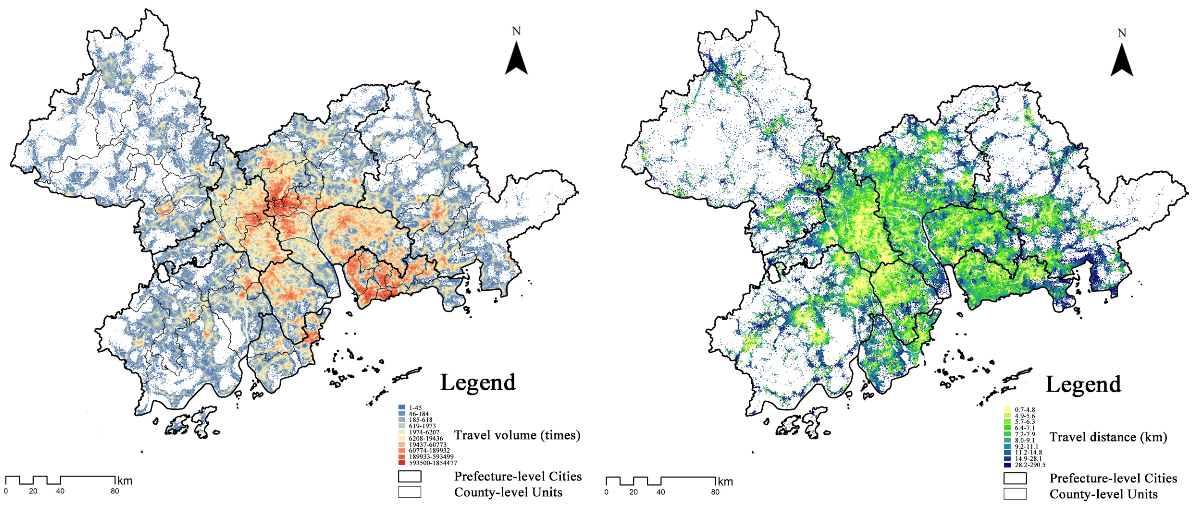

Figure 3. The travel volume and average travel distance (km) in the PRD

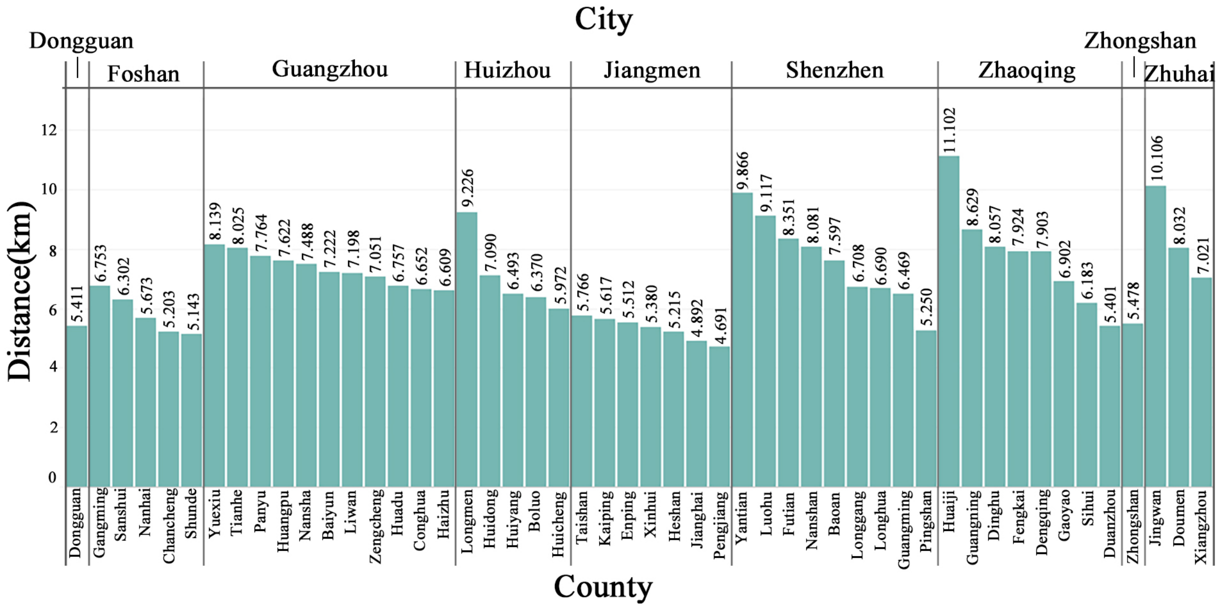

Figure 4. The spatial distribution of counts and distances of population flows at the 500-*m* grid level in the PRD.

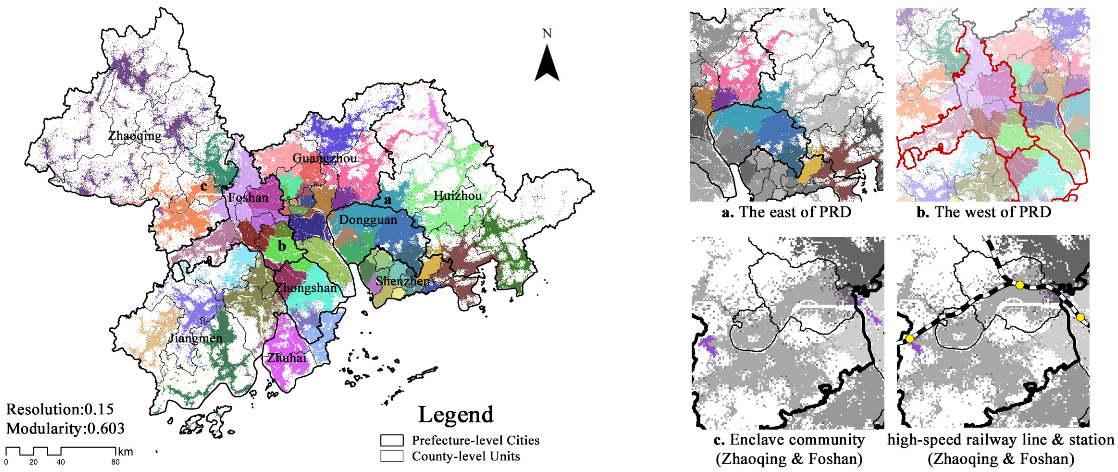

Figure 5. Detected communities in the PRD.

4.2 Spatial community detection results

By setting the resolution to 0.15, 70 communities with the modularity of 0.627 are obtained. The spatial distribution of detected communities is shown in Figure 5. To show the communities clearly, we fill them with different colors. The black lines outline the county-level administrative boundary. The hollow areas are unclassified, most of which are nature reserves, hills, or water areas. It suggests these are the following findings: first, the central cities in the PRD, such as Guangzhou, Shenzhen, and Dongguan have experienced spatial growth. Some found communities expanded eastward to Huizhou. For example, Place a in the eastern PRD shows stronger cohesion and cross the administrative boundary between Dongguan, Shenzhen and Huizhou. Second, the intra-city boundary in the west PRD is closely aligned with the administrative boundary. Place b indicates that intra-city connections are much stronger than inter-city connections, such as those of Guang zhou-Foshan, Foshan-Jiangmen, and Jiangmen-Zhongshan. Third, some areas have enclave communities because of the high frequency travels among them. Place c is an enclave community in the middle Zhaoqing-Foshan, where are several high-speed railway stations, including the Zhaoqing West Station, the Zhaoqing East Station, and the Foshan Sanshui West Station. The detected community is distributed along the Nanning-Guangzhou High-speed Railway and Guiyang-Guangzhou High-speed Railway. These results suggest the transport infrastructure plays an important role in the spatial synergy of multiple cities as it upgrades the travels people in the megacity region.

The results also demonstrate that the regional integration is with the east-west difference in the PRD. The east PRD relies on the attractiveness of Guangzhou and Shenzhen. The surrounding Dongguan and Huizhou therefore are with high-frequency and long-distance travels; cities in the west, such as Zhaoqing and Jiangmen, are far from these central cities, are affected by a small centripetal force thus showing a low regional integration. The results are closely related to the geographical location of the Pearl River Delta. Cities near the estuary of the Pearl River have better economic and social development due to convenient traffic conditions, and therefore a higher degree of regional integration. As for cities far away from the estuary of the Pearl River, the degree of regional integration is relatively low.

4.3 Network backbone in the PRD

The backbone network extraction is further performed to reveal the mobility pattern and interaction among communities. The significance level α controls the remained nodes and edges in the final network. By reducing the statistical confidence α, more restrictive nodes and edges can be obtained. For example, when α is set as $4*10^{-3}$, the number of edges is reduced to the minimum and the number of nodes remains unchanged; when α is set to $1*10^{-4}$, the number of nodes and edge weights converge the minimum value. After trying many values, we set α to $4*10^{-3}$ to extract the backbone network in the PRD.

Figure 6 displays the final network backbone in the PRD. It can be seen that the network backbone mainly takes Foshan-Guangzhou-Dongguan-Shenzhen as the core skeleton. Generally, it shows a hierarchical spatial structure. Guangzhou has a close internal connection between the Baiyun District, Panyu District, Tianhe District, and Huangpu District, and closely connects to Foshan, which is with a low-density backbone subnetwork. The central Shenzhen, including the Nanshan District, Nanshan District, Futian District, Luohu District, and Longhua District also contains a high-volume backbone subnetwork, simultaneously radiating northward to the cities of Dongguan and Huizhou with a low-volume backbone network. This result is consistent with the development status of the PRD. Guangzhou and Foshan have always advocated the Guangzhou - Foshan metropolis area, while Shenzhen has also proposed the Shenzhen-Dongguan -Huizhou metropolis area. Therefore, the backbone network structure can well reflect the connectivity and the status quo of these metropolis areas. From the results extracted from the backbone network, the current cross-city connections are low-density connections, and the development of the metropolis circles needs to be further strengthened.

It can be also seen that there are differences in the spatial synergy of the PRD. The final network backbone are with two centers: Guangzhou and Shenzhen. The degree of spatial synergy is higher in the regions closer to the central cities (including Guangzhou and Shenzhen) due to the differences in population, industry, economy, and technology innovation.

4.4 Comparison with city boundary

To further reveal the spatial interaction among cities, we carry out the city-level spatial community detection. By setting the resolution to 5.0, 7 communities are obtained with the modularity of 0.675. As shown in figure 7, we obtain the result reflecting communities accurately. It indicates that the core cities expand to their neighboring cities, which is mainly caused by massive cross-city population flows, such as the Zhuhai-Zhongshan community, the Guangzhou-Foshan community, and the Shenzhen-Dongguan community. It can also be observed that the PRD cities have different degrees of integration. Generally, Foshan and Guangzhou are merged into one big city. Shenzhen also expands to the north and includes the south Dongguan. These results further verify the spatial synergy of multiple cities in the PRD.

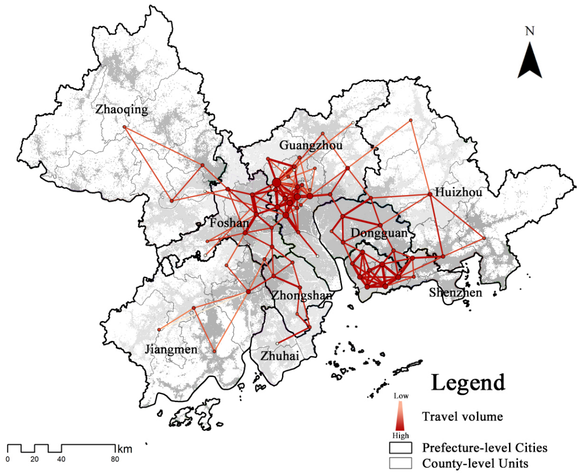

Figure 6. The backbone network in the PRD (α=$4*10^{-3}$).

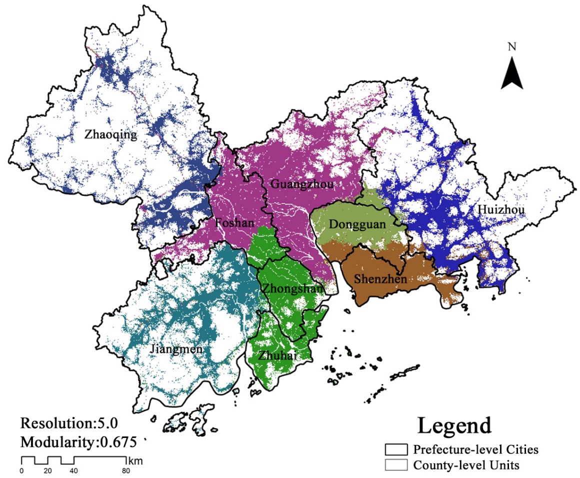

Figure 7. Comparison between detected communities and city boundary.

5. CONCLUSION

Since the Open and Reforming of China in 1983, the PRD is growing from several isolated cities to one megacity region. From the flow perspective to uncover spatial synergy is essential for regional planning, and governance. Massive mobile phone location data contains hidden information of complex spatial networks thus they benefit the understanding of complex spatial networks. This study constructs a large-scale mobility network using long-period mobile phone location data. The Louvain method detecting spatial communities is used to reveal the spatial cooperation within the detected area. The disparity filter extracting the backbone network is used to unravel the connection among these areas. An experiment in the PRD was conducted. The results suggest that the PRD is with a significant trend of spatial synergy. The backbone of mobility network demonstrates that Guangzhou and Shenzhen are the spatial cores promoting the cooperation with surrounding cities. However, some developing cities such as Zhaoqing and Jiangmen still need to strengthen interconnection. Sufficient and close integration mainly occurs around the core cities which located in the east of the Pearl River Delta. It reflects that large-scale mobility occurs more frequently in the east than in the west. Thus, the entire PRD presents an integration status of "strong east and weak west".

This study contributes to the study of megacity regions in the following points. Firstly, we conceptualize regional spatial synergy through the network perspective. Secondly, community detection and flow analysis methods have shown their merits and importance in multi-scale spatial analysis. Third, compared with traditional travel surveys, mobile phone location data enables us to conduct a finer-grained beyond the city/county boundary network analysis.

As an emerging megacity region, the PRD has the favorable industrial, social, and environmental synergy policies. These merits have gradually eliminated the constraints of administrative boundaries and further promoted inter-city mobility. In the future, the PRD should catch the advantages of each city. This way, it will fully leverage the vast hinterland to promote circulation and complementarity. Further, it will gradually improve the coordination and integration within the world-class megacity region.

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