# Methodological Framework for Understanding Urban People Flow from a Complex Network Perspective

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**Abstract:** Cities are connected by their functions and so are the spaces within cities. With the emergence of multisource data containing abundant urban residents' mobile information and the introduction of complex network methods to urban space research, a large amount of research has focused on exploring spatial structures from spatial interaction networks. Previous studies have limitations of lacking an understanding of the urban spatial structure from a systematic perspective and have not addressed the application value of research results from the perspective of urban planning. To address this research gaps, this paper proposed an analytical framework for a multiscale urban spatial characteristics analysis that is sufficiently intuitive for understanding both the spatial structure and organization relationship from a complex network perspective based on urban resident mobility data. This framework includes the full cycle workflow from data preprocessing, the construction of people flow network, method choice, and application. Unlike other works that focus on the community identified, this analytical framework considered the spatial characteristic within the communities and the relationship between communities and then compared the research results and planned urban structure. The goal of this research was to propose an analytical framework that can be applied for the identification of urban spatial structure, division of spatial management units, assessment of the implementation effects of spatial planning, and the configuration and optimization of auxiliary public service facilities. Two weeks of mobile phone signaling data that cover the Wuhu city center area were used in the empirical analysis. The results showed that (1) there is significant spatial heterogeneity between the compactness and intensity of the people flow network, (2) the community that was identified from the people flow network is more dispersed and microscopic in space compared with the communities from master plan; and finally, (3) at the community scale, there are fewer communities in the urban north area than in other areas and the interaction between communities in the urban north area is much looser and weaker in intensity. These findings may help in understanding the organizational relationship of urban groups from a systematic perspective and provide useful information to the division of planning groups and show the effects of assessment planning implementation to the planer. **DOI:** 10.1061/(ASCE)UP.1943-5444.0000689. 

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## Introduction

Cities are connected due to their functions and so are the spaces within cities. Therefore, a city is regarded as a complex system composed of nodes, networks, places, and flows, wherein the interaction between system subjects is realized by *flow* so the transmission mode and intensity affect the evolution of the system directly (Batty 2007; Healey 2006). Different from the physical city structure, the city structure represented by people flow shows more complex connection patterns and function allocation (Bettencourt 2013). As the main subject of the urban complex system, people's activities promote interaction between different urban spaces and affect the flow of various elements such as materials, information, and funds, contributing to the formation of a complex network with spaces being the nodes and elements' flow being the connections (Castells 2011; West 2017). The differentiation of the function of flow on spatial nodes leads to reconstruction of urban spatial physical form and social functions (Gao et al. 2017; Hodson et al. 2012; Liu et al. 2015b). The reconstruction of urban space function brings about changes of people flow distribution and structure in the city, which in turn affects the flow of other elements, reacting on the nodes and connections of the network and finally promoting the continuous evolution of the urban complex system (Batty 2008). Therefore, the flow of people is the driving force for the continuous evolution of the complex urban system, and the spatial distribution of people flow is the comprehensive spatial expression of the relations among various elements in the complex urban system. The spatial distribution and structure of people flow have long been a

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core of research topics in urban geography. Although there is a large body of literature in this field, to the best of the authors' knowledge, studies on exploring the spatial distribution and structure of people flow in the intracity from the complex network perspective are quite rare.

Early studies mainly used census data and high-spatial-resolution remote image data (Amaral et al. 2006; Lu et al. 2006) (such as Google Earth, DMSP/OLS, and the like) and employed the spatial interpolation method (Liu et al. 2008), population density model, and multivariate data fusion model (Wu et al. 2005) to identify the spatial distribution and make qualitative analysis of the structure of people in cities. However, constrained by data acquisition technology, traditional research had a significant shortcoming. First, the spatial resolution of data was too low to obtain a detailed study of the population distribution characteristics of more microcosmic space inside the city. Second, these data lacked information about population mobility, so it was difficult to support the research on urban population mobility and the relationship between people mobility and space.

In recent years, with the development of information and communication technology (ICT), we have embraced an era of big data. Moreover, it is now more convenient to obtain high-spatial- and -temporal-resolution individual activity data on a large scale. Many sources of novel data have emerged and have been applied to research on the characteristics of the spatial structure of an urban population on a microscale. A large number of scholars, with the help of floating vehicle location data (Liu et al. 2015a; Xia et al. 2018; Yue et al. 2012), smart traffic card data (Gong et al. 2017; Maeda et al. 2019), social media footprints (Chen et al. 2019; Qin et al. 2019; Sagl et al. 2012; Zhen et al. 2017), and the network and flow theory, have studied spatial distribution characteristics of urban populations and have obtained rich research results. As one of the popular novel data sources, mobile phone data are featured by high quality, good continuity, large coverage, huge sample size, wide distribution, and high spatiotemporal resolution (Jiang et al. 2013; Steenbruggen et al. 2015; Wang et al. 2018; Luo and Zhen 2019). In light of these comprehensive advantages, mobile phone signaling data are thus more suitable for research on urban space from the people flow perspective. Many scholars have focused on using mobile signaling data and the network theory to analyze spatiotemporal distribution characteristics of an urban population and have built a spatial interaction network based on people flow and then applied the network community detection method to extract urban subregion partitioning and hierarchical structure for uncovering the polycentric structure from a spatial interaction perspective (de Montis et al. 2013; Liu et al. 2015a). Although these studies have attached more importance to spatiotemporal distribution of people flow and the urban spatial structure analysis from the spatial interaction perspective, they tend to treat communities extracting from the spatial interaction network as an independent spatial component and ignore the connection between them. This shortcoming may lead to an insufficient understanding of the structural relationship of urban communities from a systematic perspective. Moreover, little attention has been paid to how the urban structure detected by new big data sources might be similar to or different from what is planned by planning authorities (e.g., city master plan). How the results can be used in practical urban planning has rarely been studied. To a certain extent, this shortcoming may weaken the application value of research results in the evaluation of the implementation effect of urban spatial planning and the adjustment and optimization of urban public facilities.

In the case study, a two-week mobile signaling data set of China's Wuhu City was utilized to construct the spatially embedded network. The community detection method was used to identify the spatial structure and further analyze the interaction characteristics between the communities based on the movement of urban people. Several indicators adopted from network and graph theories were calculated to quantify the people flow intensity and spatial interaction characteristics in the city. Kernel density estimate analysis was employed to analyze the spatial distribution characteristics of people flow intensity and spatial interaction in the city. The structure planning scheme from *Wuhu City Master Plan (2012–2030)* was used as a reference to compare with the results of the study.

This paper is organized as follows: section "Related Work" reviews relevant studies that use mobile data to probe into urban population distribution and urban structure; section "Analytical Approach" presents the proposed methodological framework and describes analytical methods in detail; section "Study Area and Data" describes the study area and data used in the analysis; section "Results and Analysis" outlines the results of the case study; and finally, section "Discussion and Conclusion" summarizes the study and discusses its implications for research in the future.

## Related Work

While a rich body of urban research has used mobile positioning data that contain people flow information, this study focuses on the application of mobile phone data in urban population distribution and structure research. To highlight the contribution of this study, the related works are subdivided into two parts: (1) visualizing spatial population distribution based on mobile data; and (2) identifying the urban structure from the people flow perspective.

### *Visualizing Urban Population Distribution Based on Mobile Phone Data*

Cities are the most densely populated areas, and the flow of an urban population is influenced by the physical spatial form and social function (Batty 2018). Thus, the spatial distribution of an urban population is closely related to urban land-use and spatial structure. Therefore, grasping the spatial distribution of an urban population in a timely and accurate way is key to resolving different problems in a city. A wide range of studies based on various data have been conducted on the spatial distribution of an urban population. Mobile phone data are unprecedentedly characterized by large coverage of a population and geographic area; high spatiotemporal resolution; a sufficiently long period of data collection; detailed and abundant location and motional information conveyed; and so on. These attributes have attracted scholars to applying them to research on urban population distribution and structure that provides insight into urban space and systems.

Due to the diverse spatial resolution of mobile phone data, the research scale of urban population distribution also takes on diversified characteristics. Many of these studies adopt the kernel density estimation (KDE) method to visualize the spatial distribution of urban population and investigate the variations of spatiotemporal characteristics. For example, Deville et al. (2014) used data sets of more than one billion mobile phone call records from Portugal and France and gave an explicit estimation of the spatiotemporal population density at national scales, further demonstrating how maps of human population change can be produced over multiple timescales. Gao (2015) explored human mobility patterns and intraurban communication dynamics with large-scale, detailed mobile phone call records in a city based on the spatiotemporal analytical framework composed of spatiotemporal visualization, space–time KDEs and spatio-autocorrelation analysis. Von Landesberger et al. (2016) presented a flow visualization method called mobility graphs to make up for the limitations of traditional approaches for investigating the complex variation of movements over a long time period. Yang et al. (2016) pointed out that few studies were focused on human spatial convergence and divergence patterns and their evolutions over time characteristics. To remedy this deficiency, they obtained a mobile phone location data set from Shenzhen, China, and identified eight distinct patterns. Afterward, they discussed the spatial distribution of these patterns in the context of urban function regions. Yet, these studies focused more on the visualized spatial distribution of an urban population, while less attention was paid to the spatial heterogeneity of urban population distribution and the spatial heterogeneity of flow intensity from the perspective of overall and spatial interaction.

### *Identifying Urban Structure from the Spatial Interaction Perspective*

A complex network is both a theory and a method to analyze the interaction between subjects in complex systems (Batty and Marshall 2012; Ducruet and Beauguitte 2014). It abstracts the main unit of the complex system as nodes and the complex interaction between the units as edges, thereby abstracting the entire system as a network. The research object of the complex network is the whole system rather than the part. It understands the nature of the whole system from different levels by studying the characteristics of the nodes, structure, and relationships of the network. It is widely accepted that the city is a complex system formed by the interaction of different elements (Batty 2005). Complex network theory has been widely used in regional and urban science, such as city network, urban road network (Ozuduru et al. 2020), and public transportation network (Ding et al. 2015), which have promoted an in-depth understanding of the urban spatial structure from different scales. With the continuous development of perception technology, we can capture the flow of microscale elements to gain insight into the spatial interaction network. The complex network provides a theoretical perspective on how the individual activity forms the urban spatial structures as well as a set of analytical tools to analyze those interactions and spatial structures as networks of nodes (actors) and activity.

A large number of empirical studies have applied the community detection method to identify the urban structure based on mobile data. Some scholars have capitalized on the indicators of urban resident mobile patterns suchas daily route distance, daily communication distance, and raids of gyration (ROG) to aggregate and visualize them in geographical space and reveal the structure of a city on the macroscale. For instance, Sevtsuk and Ratti (2010) examined the daily routine of urban mobility from aggregate mobile phone data that covered Rome, Italy, by using the volume of call activity in mobile network cells as the unit of spatial analysis. Louail et al. (2014) measured the average distance between individuals and how it evolved during the day; this was called an urban dilatation index, with mobile phone data used to indicate the structural characteristics of the city and 31 Spanish metropolitan areas involved to highlight different types of urban structures. Lee et al. (2018) explored the potential of using mobile phone data to characterize and compare urban activity and mobility patterns from daily and hourly mobile phone records across 10 cities in Korea. They identified urban activity at subcenters and hot spots by using the criteria of density, time persistence, and compactness.

Community is the basic structural attribute of a network, and the community detection method has been utilized extensively to identify network groups that are composed of nodes with internal connections tighter than external connections in the network. In studies of urban structure, the concept of community has been used to present spatial groups composed of spatial units with compact interaction based on a complex interactive network that relies on people activity between different spaces. Constructing an interactive spatial network based on individual movement by virtue of mobile phone data is a universal method to analyze urban space. For example, Gao et al. (2013) used a one-week mobile phone data set of a city in China to explore and interpret patterns embedded in the network of phone–call interaction and the network of phone–user movements and discovered the clustering structure of spatial interaction communities. Guo et al. (2018) developed a new method that partitioned the network to detect spatial communities by optimizing the chosen measure with a new spatial Tabu optimization method. They applied the method using a data set of mobile communication detail record (CDR) in Shanghai and discovered 11 urban communities. Then, they overlaid the results onto boundaries of 18 administrative districts of Shanghai that showed large consistency with the administrative boundaries, particularly in the suburbs.

With the rise of various data sources of urban resident movement and the integration of complex network and flow theories with spatial networks, the studies of spatial networks have gone deep into microcosmic spaces in a city. The spatial community formed based on the spatial interactive network is closer to the spatial structure mentioned in the urban space in that it transcends the physical space and pays more attention to the functional space. Despite the rich and growing body of literature along these lines, most studies only focus on identifying urban communities but lack analysis of the spatial characteristic difference within the communities and interactive relationship between the communities. As such, they are limited in providing insights into planning scenarios in practice. For instance, the optimization and adjustment of planning communities need to consider the interactions among different communities from a systematic perspective. The allocation and optimization of public facilities within different groups also need to consider different spatial interaction characteristics from both internal and external perspectives. To address these shortcomings, a framework including mobile data processing, network construction, and specific analysis and application is needed to realize the analysis of urban spatial structure from a systematic and connective perspective.

## Analytical Approach

A city is a complex system composed of various elements interacting with each other. The essence of this interaction is the corresponding relationship between urban space and function, and its visual presentation at the macrolevel is the characteristic of the concentration and diffusion of people in the urban space (Jiang et al. 2012; Rodríguez et al. 2020). People is the most core and active subject in the urban space. People flow between different spaces builds spatial interactions and at the same time promotes the interrelation, gathering, and diffusion of other elements in the space (Xi et al. 2016). Gradually, urban functional spaces are formed, which promotes urban form and structure development and reshaping (Xu et al. 2019). Thus, this paper took the change of urban people flow as the object of observation based on the theories of flow space, complex network, and spatial interaction. We proposed conceptualization of urban people flow, aiming to study the structural characteristics of the spatial interaction network based on microscopic people flow and to understand the macroscale urban spatial structure. On the one hand, the flow of people promotes the flow of various elements such as information, transportation, and economy and promotes the aggregation of elements in the urban space, which makes the spatial functional attributes different. On the other hand, the heterogeneity of the distribution of urban space elements interacts with the flow of people by changing the attractiveness of urban space nodes, thereby changing the flow and structure of urban people, and changes in the flow structure will further change the flow of urban population. Therefore, from the perspective of people flow, the interaction mechanism of urban spatial elements can be understood as a dynamic closed-loop process of cyclic causality and mutual feedback between people, space, facilities, services, information, and other elements established by the flow of people as the media.

Accordingly, we propose an analytical framework based on mobile signalling data for urban people flow. The framework is composed of three stages (Fig. 1). In the first stage, a method of mobile phone user trajectory preprocessing is proposed, including data cleaning, aggregating to cell unit, and then the building of a spatially embedded network for model intracity spatial interaction. In the second stage, the basic properties of mobility network analysis used the descriptive analysis method and then analyzed the spatial interaction compactness and strength to visualize the result. Finally, the community structure of the spatial interaction network was analyzed using the community detection method to identify the structural relationships between space communities to compare the results and for planning purposes.

### Constructing a Spatial Interaction Network Based on Mobile Phone Data

Reprocessing of the mobile signaling data relating to user trips was composed of three steps. First, the coverage of each cell tower was generated by creating Thiessen polygons, whose boundaries define the area that is closest to each point relative to all other points, for cell towers (Chen et al. 2016). Each Thiessen polygon covered an area that was closest to its associated cell tower compared to other cell towers. Second, the generated Thiessen polygons were overlapped with the predetermined spatial grid unit (SGU) for constructing a trip chain. Given that the boundaries of the Thiessen polygons were not consistent with those of the SGUs, Eq. (1) was used to estimate trips of SGUs (Deville et al. 2014):

$$\mathrm{POP}_{sgu_i} = \sum_{V_n} \alpha_{V_n} A_{(sgu_i \cap V_n)} \tag{1}$$

where $sgu_i = i$th SGU; $V_n$ = Thiessen polygons that overlapped with the $i$th SGU; and $\alpha_{V_n}$ = percentage of the intersection area of a Thiessen polygon $V_n$ and $sgu_i$ taking up the total area of $V_n$. Third, based on formula (1), traffic flows between any two SGUs are considered to be the sum of proportional trips among cell towers within the two SGUs. The number of trips from any given $sgu_i$ to $sgu_j$ is calculated as follows:

$$\mathrm{Trip}_{sgu_{i,j}} = \sum_{V_m}\sum_{V_n} \mathrm{Trip}_{m,n}\alpha_{V_m}\alpha_{V_n}A_{(sgu_i \cap V_m)}A_{(sgu_j \cap V_n)} \tag{2}$$

where $V_m$ and $V_n$ = Thiessen polygons overlapped with $sgu_i$ and $sgu_j$, respectively; and $\alpha$ = percentage of the intersection area of a Thiessen polygon and SGU taking up the total area of the Thiessen polygon.

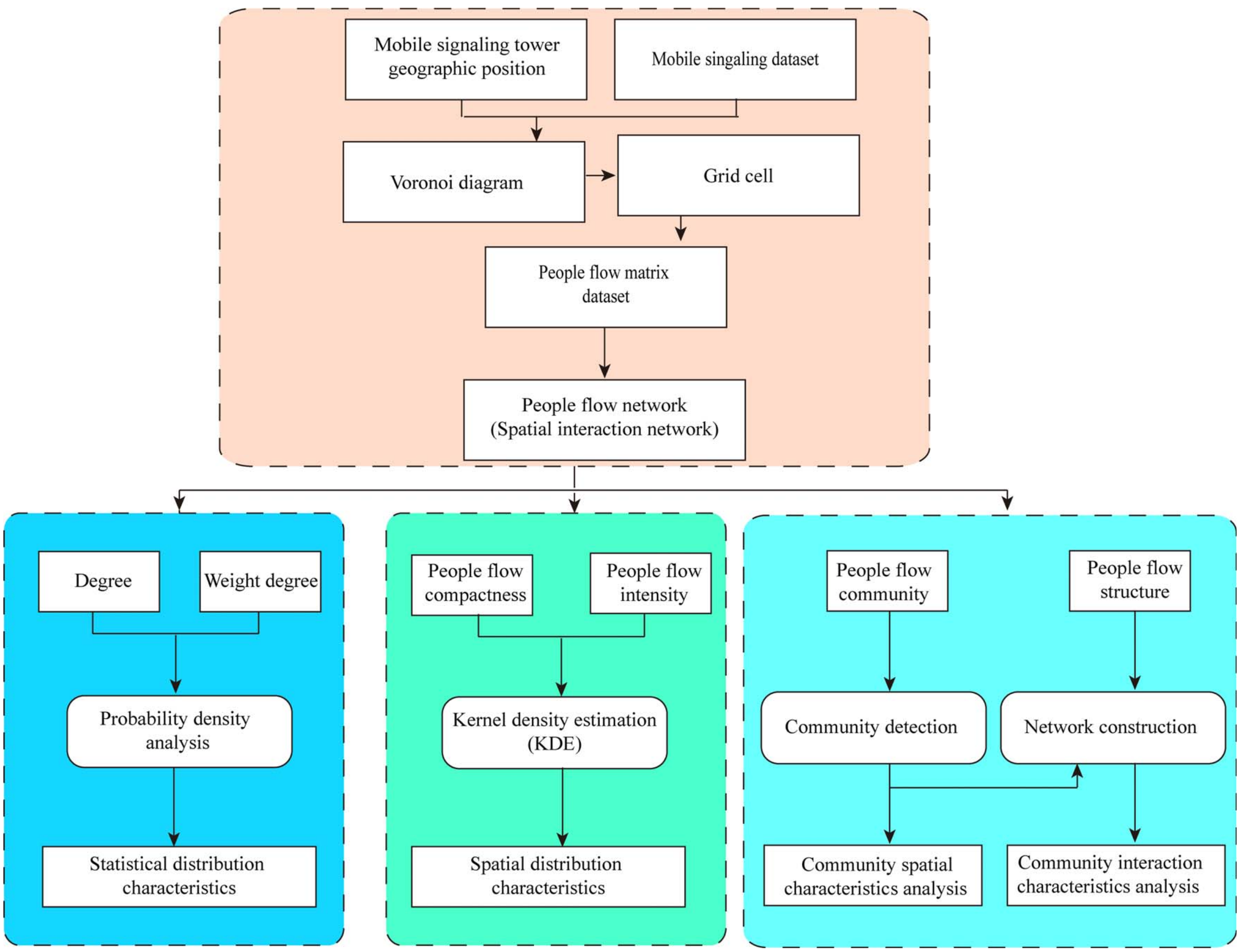


**Fig. 1.** Methodological framework.

Similarly, the number of trips within an SGU can be calculated by adding up the trips among cell towers within the SGU [Eq. (3)]:

$$\mathrm{Trip}_{sgu_i} = \sum_{V_m} \sum_{V_n(m<>n)} \mathrm{Trip}_{m,n} \alpha_{V_m} \alpha_{V_n} A_{(sgu_i \cap V_m)} A_{(sgu_i \cap V_n)} \quad (3)$$

where $V_m$ and $V_n$ = Thiessen polygons overlapped with $sgu_i$; and $\alpha$ = percentage of the intersection area of a Thiessen polygon and SGU taking up the total area of the Thiessen polygon.

The network was constructed by igraph 0.8.3, a package of Python, based on the spatial interaction matrix database. In this network, each node in the network (graph) denoted an urban spatial grid, each edge denoted travel between any two grids, and the weight of an edge denoted the volume of travel, which was the number of trips made.

### Measuring the Compactness and Intensity of People Flow

Node location analysis is the primary step of complex network research and the basis of further study on the network structure. The indicators measuring the importance of a node in networks include degree, betweenness, and closeness centrality. Degree is used to describe the numbers of other nodes that connect to that node in the network. If the degree indicator is calculated with the weight of network edges, it presents the frequency of connections between nodes. In this paper, the degree and weighted degree were used to measure the connection compactness and intensity of spatial grid units in the spatial interaction network and were defined, respectively, as how many connections between spatial units and the sum travel volume between them. Finally, the KDE method, which is a nonparametric way to estimate the probability density function of a random variable, was used to project the indicator value back onto geographical space. The indicators can be calculated by Eqs. (4) and (5) as follows:

$$k_i = \sum_{j=1}^{N} a_{ji} \quad (4)$$

$$S_i = \sum_{j=1}^{N} w_{ij} \quad (5)$$

where $k_i$ = numbers of nodes connected with the $i$th node; $S_i$ = sum volume of trips between the $i$th node and others; $a_{ji}$ = number of connections between the $i$th node and the $j$th node; $w_{ji}$ = trip volume between the $i$th node and the $j$th node; and $N$ = set of nodes connecting with the $i$th node.

### Identifying the Structure of Urban Space Based on the Spatial Interaction Network

Graph communities were extracted through the community detection method and were considered the structure of the city. Furthermore, a graph was rebuilt based on the extracted communities by accounting for people flow among these communities. A multiscale investigation was then carried out to explore the urban structure distribution and compare the identified structure with the planned structure. Then, at the community scale, the relationship among communities was extracted based on people flow. Then, the urban structure distribution and relationship at the multiscale level were investigated and compared with the planned structure.

Network anatomy is important to characterize because structure affects function and vice versa. The community detection method was used to divide up several groups with internal interaction significantly stronger than external interaction. There are a large number of algorithms for network community detection; the Newman module degree algorithm (Newman 2006), which, due to its excellent efficiency and effect, is able to find hierarchical community structure and quantitatively assess the results, is widely used in various networks (Barthélemy 2011; Newman and Girvan 2004). In this paper, therefore, the module degree algorithm was chosen to identify the spatial network structure. The algorithm is defined as follows:

$$Q = \frac{1}{2m} \sum_{i,j} \left[ A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \quad (6)$$

where $Q$ = module degree, and the value range is [0,1]. The larger the value, the more stable the community partition results. $A_{ij}$ = weight of edges between the $i$th node and the $j$th node and represents the volume of trips between nodes in this paper; $k_i$ = sum weight of edges that connect to the $i$th node; $m$ = sum of weight of all the edges; and $c_i$ = code number of communities that include the $i$th node. The steps of the process are as follows:

- Step 1: Take every node of the network as an independent community.
- Step 2: Assign each $i$th node and try in proper sequence to allocate it to the community that includes its neighbor nodes. Calculate the module variation delta $Q$ with the change. If the biggest delta $Q$ is more than 0, allocate this node to the community that includes the neighbor nodes of this node. Otherwise, the nodes remain unchanged.
- Step 3: Repeat Step 2 until the communities that all nodes belong to do not change anymore.
- Step 4: Evaluate the result of community division based on the value of $Q$.

## Study Area and Data

### Study Area

The city of Wuhu (hereafter referred to as Wuhu) was selected for studying the aforementioned research objectives. Wuhu is located in China's Anhui Province and covers an area of 5,767 $km^2$. According to the *Chinese City Developments Statistic Yearbook 2015*, the built-up area of Wuhu totals 165 $km^2$, ranking Wuhu 61st in size among Chinese cities (out of 663 cities) (MOHURD 2015). Typically, studies on Chinese cities focus on metropolitan cities such as Beijing, Shanghai, and Shenzhen, but Wuhu may be a better representation of Chinese cities where the built-up areas and population sizes are much smaller. In addition, Wuhu, like many other Chinese cities, is undergoing a rapid urbanization and development process. In this process of development, the problems that emerge, such as conflict in urban planned strategy and rapid development, are universal. Understanding the spatial organization structure of the city from the perspective of residents' daily activities may be beneficial for allocating urban spatial resources reasonably and effectively and easing the *imbalance* problem. This research focuses on the downtown area of Wuhu (Fig. 1). The study area consists of spatial grid units (500 × 500 m) with an average size of 0.25 $km^2$. According to the *Wuhu City Master Plan (2012–2030)*, this area will be divided into three communities from north to south: the northern industrial community, the Jiangnan business center community, and the scientific and educational industrial community (Fig. 2).

### Data Description

The data sources consist of mobile signaling data, POI data, and the master plan scheme. (1) The mobile phone data were collected from December 1to 15, 2017 by a major cellular operator in Wuhu. There are 1,264 cell towers in the study area. The data set contains the positions of 0.8 million mobile phone users, approximately 25% of the city's total population. In the data set, positions of mobile phone users were recorded at 10-min intervals. For privacy reasons, information about mobile phone users was not disclosed in the data set. Instead, the number of mobile phone users that have moved from one cell tower to another during the 10-min interval was recorded. (2) The POI data were collected from Baidu, the largest Chinese search engine. POI data are a type of point data describing spatial and attribute information related to geographic entities and are widely used in research on urban space as a proxy to land use. The data include information of latitude and longitude coordinates, names, and categories. (3) *Wuhu City Master Plan (2012–2030)*, which introduces in detail the planning for spatial structure and development objectives of the downtown areas, is collected from the website where Wuhu Urban Planning Bureau shared the document.

## Results and Analysis

### Basic Statistical Properties of the People Flow Network

With the grid cell people flow aggregated based on mobile signaling data, people flow was abstracted as a weighted spatial interaction network where grids served as nodes, flow as edges, and times of flow as edge weights. Since the data used in this paper was the average amount of flow on an hourly scale, and the difference between the outflow and inflow of grids was extremely subtle; it was therefore decided that a weighted undirected network would be constructed. With the amount of flow between grids regarded as the network path flow, a statistical analysis of changes in indexes was performed such as the number of nodes, the number of paths, the network density, the average flow, and the flow proportion on different flow thresholds. Through the estimation of the loss of subnetwork features on different thresholds, a subnetwork on the appropriate threshold was determined as the network object for further analysis.

The result of statistics on the basic characteristics of the network based on different flow thresholds (Table 1) shows that the larger the flow threshold, the lower the number of network nodes, node flow, and network density. However, the average flow goes another way around, suggesting that people flow connection of medium-high intensity in urban space concentrates between a small numbers of spaces. When the flow threshold is greater than or equal to 5 person-time, i.e., the amount of flow between grids goes below 5 person-time in 1 h, the flow proportion of the subnetwork is

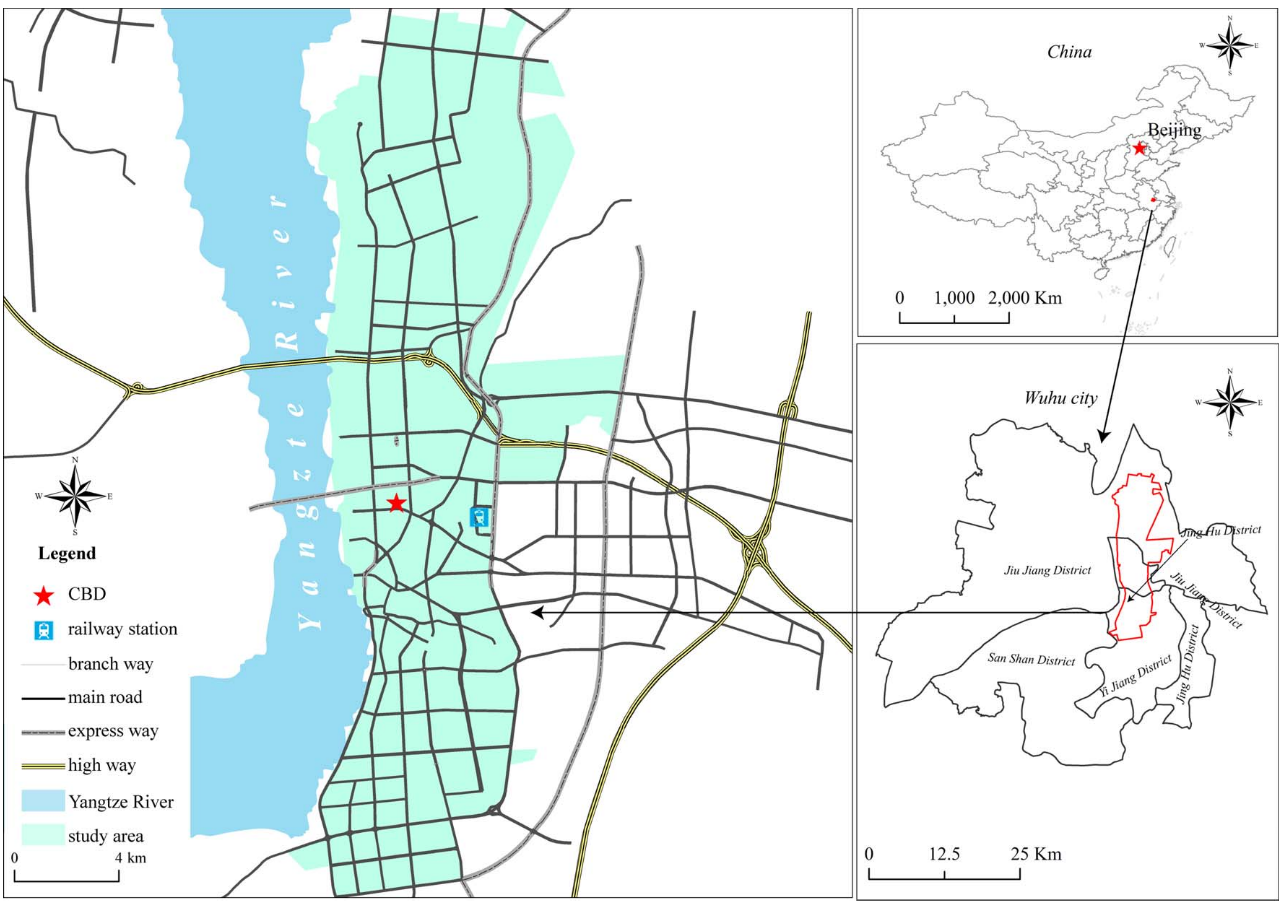


**Fig. 2.** Study area.

**Table 1.** Characteristics of the people flow network in different volumes of flow

| Flow threshold (persons/h) | Number of nodes | Number of paths | Network density | Average flow (persons/h) | Flow proportion (%) |
|---|---|---|---|---|---|
| ≥1 | 837 | 65,558 | 0.09 | 0.67 | 100 |
| ≥5 | 352 | 1,691 | 0.01 | 20.87 | 80.63 |
| ≥10 | 287 | 1,001 | 0.01 | 30.41 | 69.55 |
| ≥20 | 187 | 477 | 0.01 | 48.47 | 52.83 |

80%, the number of nodes drops to 352 person time, and the average flow between space is about 21 person-time/h. This indicates that the network retained on this flow threshold could still depict the people flow characteristics in most areas of Wuhu, China. Finally, this network was chosen as the object for further analysis. A further step was made in extracting the indicators of network degree and weighting degree to draw a statistical histogram, and the results are shown in Fig. 2: there are significant differences in both the connection compactness and intensity between space units. As shown in Fig. 3, nearly 60% of the grids have connection with the other six grids, while the number of grids shows a significant downtrend along with an increase of flow strength. It is speculated that this has something to do with the belt-shaped space along the Yangtze River in central Wuhu. On the other hand, it might be attributed to the population density and the pace of urban life in the city.

### Analysis of Spatial Distribution Characteristics of People Flow

As seen from the previous analysis, the statistical distribution of the people flow degree and strength within the city shows a significant difference. To identify the spatial heterogeneity of interaction

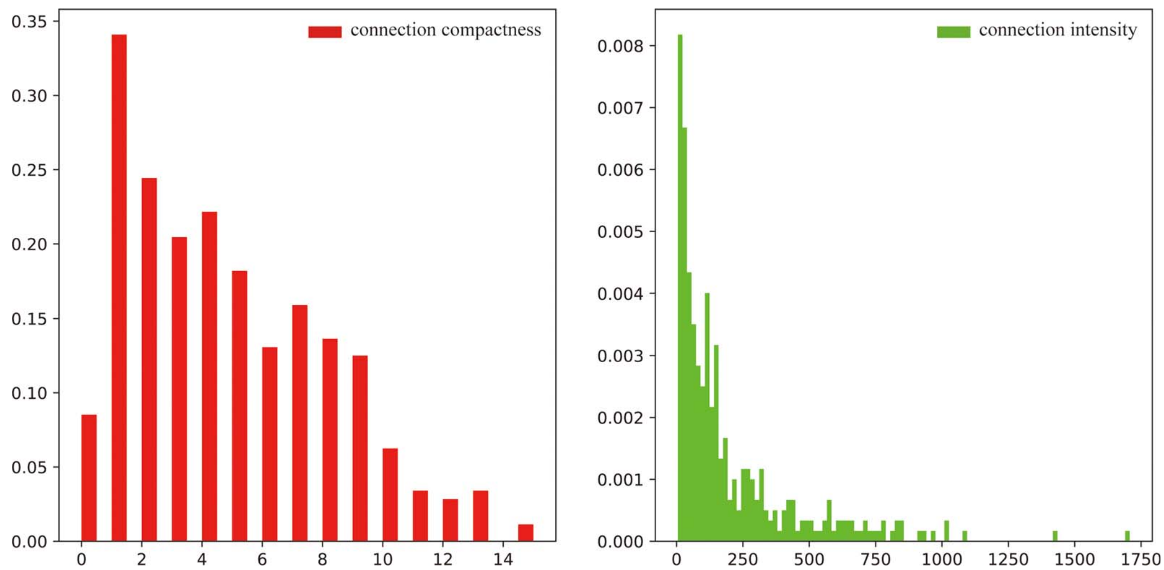


**Fig. 3.** People flow network degree and strength histograms.

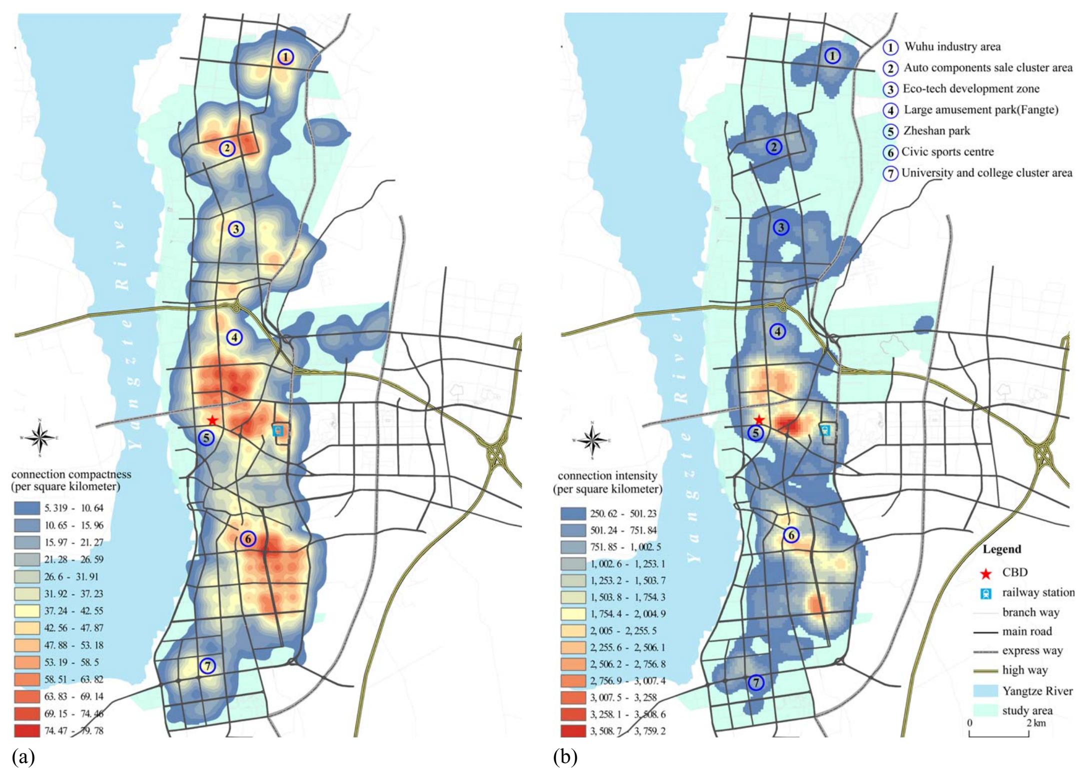


**Fig. 4.** Spatial characteristics of the people flow network: (a) connection compactness distribution; and (b) connection intensity distribution.

connection compactness and intensity between spaces based on people mobility network, first, the values of the degree and weighted degree of network nodes were assigned to the grid center; second, to project the indicator value back onto geographical space, the KDE method was applied to estimate the degree and weighted degree values around the nodes; finally, the characteristics of people flow connection compactness and intensity were converted from points into a continuous surface, contributing to further analysis of spatial distribution characteristics.

The analysis results (Fig. 4) showed that both people flow connection compactness and intensity in the central district feature striking spatial heterogeneity and that the high spatial coupling of connection compactness and intensity runs a bit low, indicating a hierarchy in the space of people flow. Overall, the hot spots of people flow in the central city were characterized by pointlike group distribution, and the spatial distribution was relatively consistent with the three clusters drawn up in *Wuhu City Master Plan (2012–2030)* (Fig. 5). To beef up the distinctiveness of the identification results of hot spot space, Baidu Place API was used with the coordinates of hot spots as input to search out POI information within 500 m of the coordinate points. The results suggested that hot spots for people flow from north to south are Wuhu Industrial Zone, Wuhu Auto Parts City, Jiujiang Economic and Technological Development Zone, Wuhu CBD surrounding Zheshan Park, Wuhu Railway Station, Wuhu Fangte Paradise (a large theme park), large residential community clusters near the Olympic Sports Center in the south of the city, as well as university clusters such as Anhui Normal University, Wuhu Vocational and Technical College, and Lugang New District.

The spatial characteristics of people flow intensity are similar to those of connection compactness. However, the high-intensity space diminishes significantly and takes on a typical double-center structure. Specifically, the high-intensity spaces are the areas around Zheshan Park, the urban railway station, as well as the large residential areas near the Olympic Sports Center (a civic sports center) in the south of the city. The spatial distribution of these areas matches with the central area in Jiangnan (the south of the lower reaches of the Yangtze River) and the scientific and

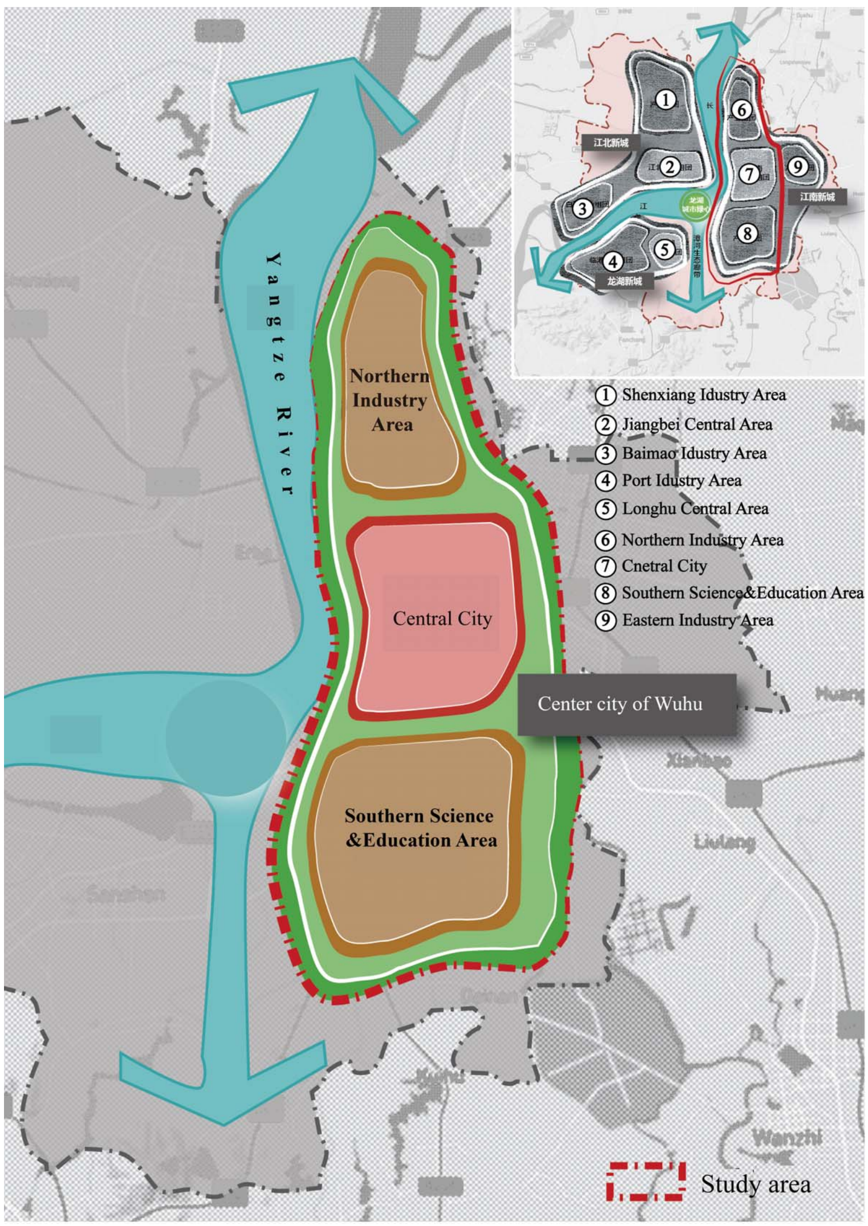


**Fig. 5.** Schematic diagram of the Wuhu center city planning structure. (Base map courtesy of Wuhu Municipal People's Government.)

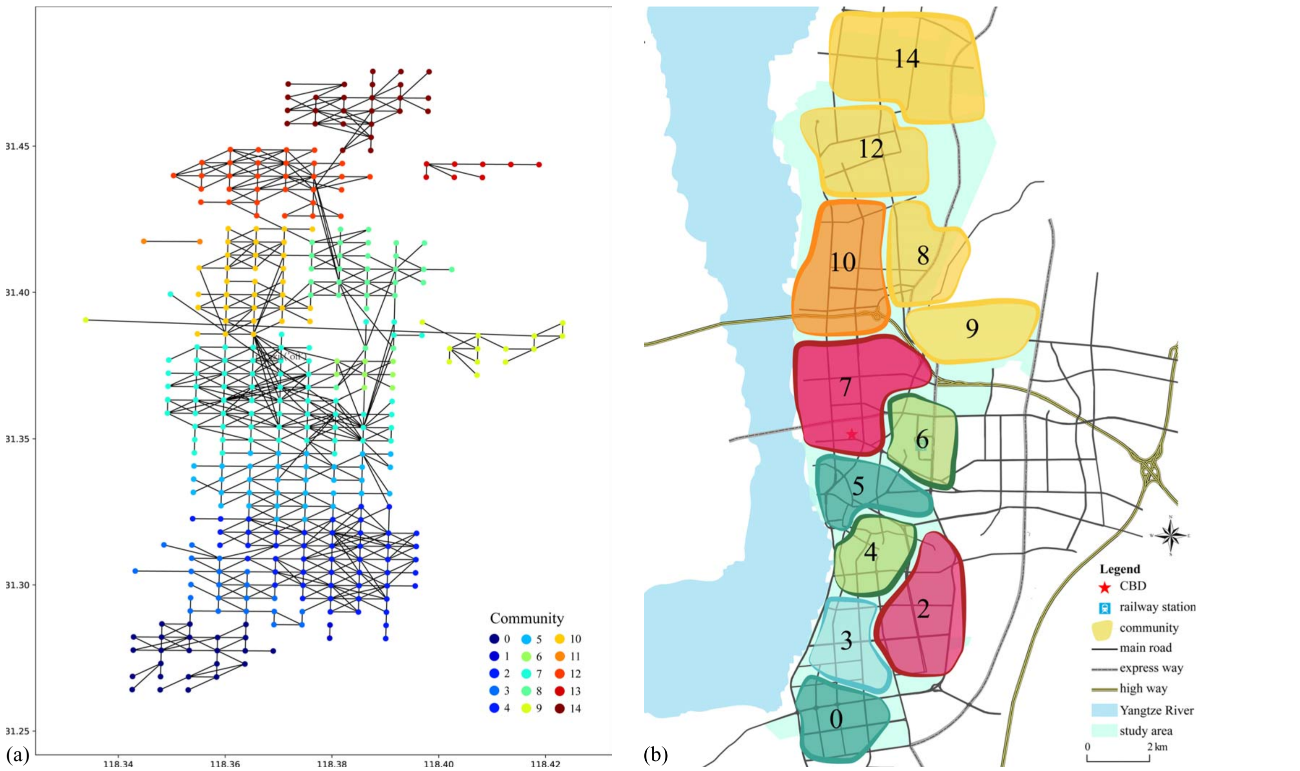


**Fig. 6.** People-flow network communities and spatial distribution: (a) community-detected result; and (b) community boundary spatial distribution.

educational industrial area in the south of the city in the functional structure diagram of *Wuhu City Master Plan (2012–2030)*. Hence, among the three areas in central Wuhu, the central area and the southern scientific and educational industrial area are the areas where daily activities of urban residents concentrate the most. In light of the spatial characteristics of people flow connection compactness and intensity, the planning and construction of area spatial development in Wuhu's urban areas in Jiangnan have achieved remarkable results. Besides, the central area and the southern scientific and educational industrial area have seen an intense concentration of people, indicating to a certain extent that the infrastructure facilities and services in the groups are relatively sophisticated.

### *Analysis of Spatial Community Structure Characteristics*

The difference in the spatial distribution characteristics of urban people flow on the macroscale is the embodiment of impacts on people flow incurred by differences in physical forms of microunit space, allocation of public infrastructure and land use. The community detection and network reconstruction method was applied to the spatial interaction network for analyzing the structural characteristics of the network that revealed such a difference from the perspective of actual movement to get a deep understanding of the spatial structure and the organizational relationship of the city.

In this paper, Newman modularity, a network community detection method, was adopted to divide the spatial structure organizations of the central district of Wuhu and then to reconstruct the interaction network among different communities based on the urban residents' movement between communities. As a result, identification of the urban spatial structure based on actual people flow was accomplished. The results of the community detection method showed that the research area is actually divided into 15 different communities according to the characteristics of people flow, and at that time, the evaluation value of the network community detection results was 0.79. As described in the "Analytical Approach" section, the closer this value gets to 1, the better the partition results. In this case, the divided result maintains good stability and could fully reflect the structure of people flow. Fig. 6 shows a visual depiction of the community detection method.

In light of the fact that different communities are in different spatial locations and different built environments, their characteristics of people flow also vary significantly. By extracting the number of nodes, the number of sides, the network density, and the total and average network flow of the communities, analysis of the characteristics of different communities were made from different aspects such as the size of communities, the degree and strength of internal people flow, and the POI attributes within. The number of nodes included in the communities and the average people flow were characterized, respectively, as the size of communities and the strength of people flow. Table 2 shows the analysis result: the top three communities are Community 7 located in the CBD of Wuhu downtown, Community 6 near the railway station and Shenshan Park, and Community 2 dominated by large communities such as Nanrui New Town. In terms of people flow strength, the Olympic Center and Community 4 near Senhai City Garden, a large residential community, show the highest strength, followed by Community 7 and Community 2. The total people flow carried by the three communities of high people flow strength is close to half of the total number of people in the research area, suggesting that these three communities are the most important people flow concentration areas in central Wuhu. To carry out preliminary exploration for the differences in the functional structure of land use in the high people flow strength communities, web crawlers were employed to extract POI data in communities, and the main POI types were used to characterize the nature of land use. Community 4 includes the old densely located residential communities in the south of Qingyi River, where the living facilities are relatively sophisticated, and it

**Table 2.** Characteristics of communities based on the flow network of people

| No. | Number of nodes | Number of sides | Density | Average flow (persons/h) | Total flow (persons/h) | Landmarks of communities |
|---|---|---|---|---|---|---|
| 0 | 28 | 89 | 0.12 | 19.05 | 1,695.51 | New area of Lugang, Wuhu Vocational and Technical College |
| 1 | 2 | 2 | 1.00 | 12.99 | 25.99 | — |
| 2 | 47 | 268 | 0.12 | 25.55 | 6,848.40 | Hospitals, Yi Jiang Jiayuan[a] |
| 3 | 36 | 128 | 0.10 | 18.86 | 2,414.23 | Ru Lin xiyuan,[a] No. 12 Middle School |
| 4 | 34 | 139 | 0.12 | 31.27 | 4,347.05 | Civic Sports Center, City Garden[a] |
| 5 | 37 | 117 | 0.09 | 15.70 | 1,836.34 | Jinghu Park, Jiuliangtan Park |
| 6 | 44 | 148 | 0.08 | 24.32 | 3,599.93 | Wuhu Railway Station, Shenshan Park |
| 7 | 63 | 340 | 0.09 | 28.26 | 9,608.53 | Xinglong Shopping Mall, Zhenshan Park, Babaiban Shopping Mall |
| 8 | 39 | 128 | 0.09 | 12.91 | 1,652.01 | Feng Huang Bei,[a] High-Speed Rail Station |
| 9 | 14 | 31 | 0.17 | 11.71 | 363.01 | Textile market |
| 10 | 49 | 173 | 0.07 | 15.31 | 2,648.24 | Chery Automobile |
| 11 | 2 | 1 | 0.50 | 5.17 | 5.17 | — |
| 12 | 36 | 179 | 0.14 | 12.28 | 2,198.83 | Heshan Huayuan[a] |
| 13 | 8 | 14 | 0.25 | 9.34 | 130.72 | — |
| 14 | 27 | 102 | 0.15 | 14.31 | 1,459.33 | Chery BoBO City[a] |

[a]Large residential community.

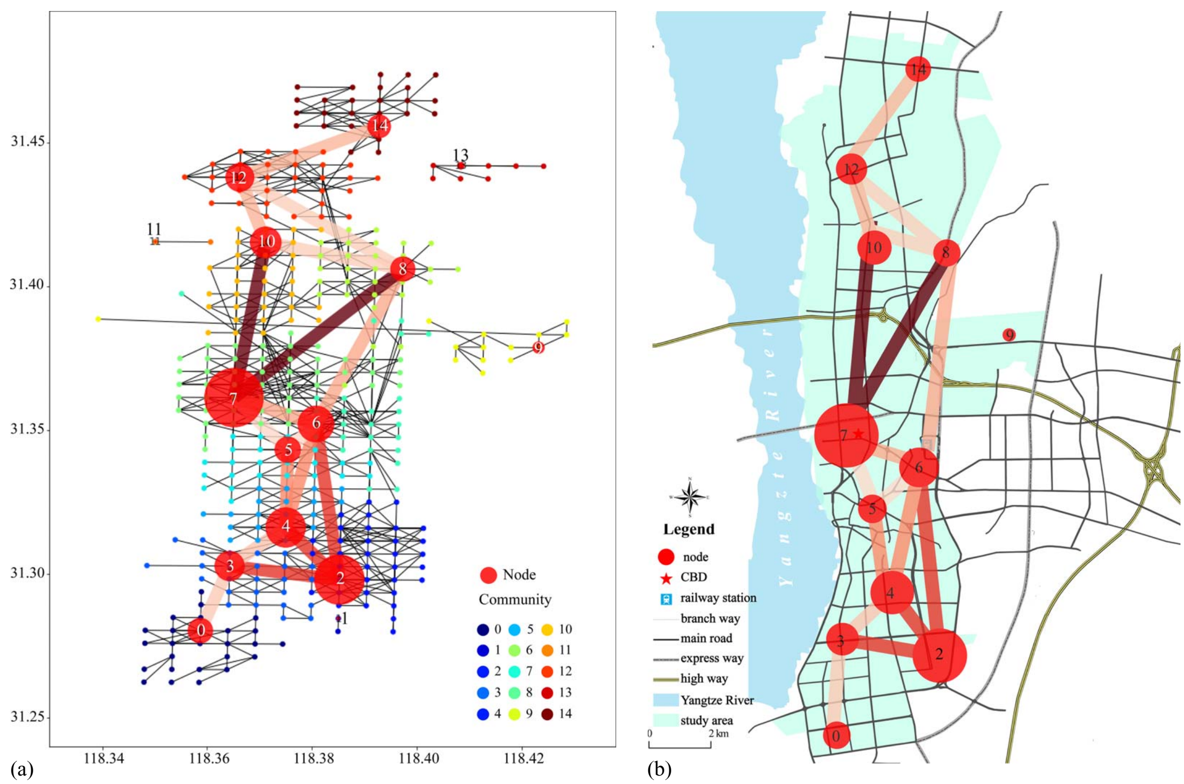


**Fig. 7.** People-flow network structure and spatial distribution: (a) community network; and (b) network structure spatial distribution.

stands adjacent to large public service facilities such as the Olympic Sports Park and the Golden Eagle Shopping Center. Community 7, composed mainly of large shopping centers, large communities, and green theme parks, is also close to Wuhu Railway Station and the bus station and is hence an important commercial and transportation hub in the city. Community 2 is dominated by large residential communities such as Yijiang Jiayuan and Nanrui New Town newly built that boast excellent public facilities such as schools, hospitals, and parks.

To discuss further the structural relations of urban people flow distribution, network reconstruction was carried out based on analysis given in section "Analysis of Spatial Community Structure Characteristics" of basic characteristics of communities to construct a community network and analyze its structural characteristics. Fig. 7 shows the community network structure identified from mobile phone data. In the figure, the radius of nodes represents the degree of the community network, i.e., the amount of connection with other communities, and the color of line represents the strength of people flow, with deeper color indicating stronger connection between two nodes. The results are shown in Fig. 6: there are notable differences in the spatial connection between different communities in the urban areas, and a distinct spatial structure of *one center, one subcenter, two axes, and multiple points* has already taken shape. The *center* is Community 7 in the downtown, the *subcenter* is Community 2 in the newly developed urban district in the south of the city, and the *two axes* are the south and north connection axes that intersect at Community 7. As for the overall structure, Community 7 is the city's most significant spatial intersection node and takes the role as the north–south interactive hub in the city. In terms of connection strength, Community 10 and Community 8 in the north of the Yangtze River Bridge, as well as Community 7 in the inner city, show the highest connection strength, followed by Community 2 in the south of the city and the adjacent Communities 3, 4, and 6. With regard to the medium-level areas, people flow in the industrial areas in the north of the Yangtze River Bridge is relatively loose. In the meantime, a secondary people flow network pivoting on Community 8 has already emerged. On the other hand, the scientific and educational industrial area in the southern part of the city shows fairly close internal interaction, leading to the formation of a secondary people flow network pivoting on Community 2 that involves newly constructed large residential areas.

In summary, it can be inferred from the analysis of people flow that the three major functional areas in the central district of Wuhu display distinct distribution characteristics and that Wuhu has an obvious spatial layout of *one center, one subcenter, two axes, and multiple points.* In the spatial structural relationship, CBD, located in the heart of the city, is the most important node. Besides, as the intersection of the south–north development axis of the city, it plays a pivotal role in connecting the industrial area in the north of city and the scientific and educational industrial area in the south. On the inside of different areas, the industrial area in the north of the city is overshadowed by the areas in the central city and the southern city both in terms of people flow compactness and strength. It may be related to the functional positioning of the northern area. On the other hand, it might be that the supporting facilities for daily life in the northern area need to be improved. The area in the southern city has become the city's subcenter, and the internal people flow degree and strength are evenly distributed, suggesting that the daily living infrastructure in the area is complete and the spatial distribution is reasonable.

## Discussion and Conclusion

The study of urban space structure is one of the key research fields of urban space. Traditional studies have focused mostly on recognizing and expressing the distribution characteristics of elements from the perspective of static isolated space.With continuous intensification of urbanization and rapid development of information technology, the flow speed of various elements in a city continues to accelerate, leading to more frequent interaction among urban spaces. Urban space has become a space of high-speed flow, wherein the flow of urban residents is a direct reflection of spatial interaction. Therefore, investigating spatial distribution and organization of people flow as a proxy of urban space interaction is conducive to investigation into it are conducive to an in-depth understanding of the urban spatial structure. Numerous studies that focus on the urban space structure with the help of traffic card data, taxi trip data, and social media check-in data but fewer resort to mobile phone data. However, compared with the other movement data, mobile phone data boast unique and comprehensive advantages that are described in the "Introduction" section. In view of this, we propose an analytical framework composed of the processing of mobile signaling data, construction of a spatial network, and analysis of the characteristics of the network by combining the methods of network analysis and spatial analysis to analyze urban space from the perspective of urban residents' movement. The analytical framework is applicable to not only the analysis of people flow but also the analysis of other flow elements such as transportation, information, and logistics, and it can help to deepen the understanding of urban spatial mobility from the perspective of actual flow of elements.

In this study, we have selected a medium-sized city as a case study rather than a metropolitan city because metropolitan cities have been investigated in many previous studies. Because most of the cities in China and other developing countries, as is the case with the one examined in this case study, are undergoing rapid urbanization and have a low level of information infrastructure and planning technology, as a result, they are faced with problems such as unbalanced economic development both in planning and the status quo, as well as an inefficient use of space resources. In this analytical framework, therefore, we have proposed a comparative analysis of the current urban spatial structure identified from the spatial interaction network and the planning content extracted from the planned scheme. Although it is not a quantitative comparison, the result is potentially beneficial for understanding the current urban space and has provided support to evaluation of planning implementation and further planning revision.

There are several limitations associated with the proposed framework that should be addressed in future studies. First, the spatiotemporal characteristics of the urban spatial structure are not involved in the analytical framework. Second, the spatial network was constructed based only on the urban residential physical movement at a single-scale spatial grid unit. Hence, future studies can combine traffic flow, information flow, logistics, and other elements and build a multiple-layered spatial interaction network based on multiple spatial units as a traffic area zone (TAZ) or a residential community to extensively explore the real characteristics of flow and timely spatial mapping of various elements in urban complex systems. With one step further, this data can be combined with the city's land use and transportation network structure and then be used along with the network embedding and machine learning method to explore the influence factors and mechanism of spatial flow intensity to improve the analytical framework of urban space characteristics.

In the empirical study we conducted, results show a high level of spatial variability in people flow intensity and spatial interaction tightness, and the relationships between the spatial structures at the microscale are identified. The spatial community identified from the spatial interaction network established by the flow of people is more refined than the planning scheme. The network can further describe the structure of and the level of association between spatial communities. These findings can provide a reference for the delineation of the urban space management unit in Wuhu City and the evaluation of the effect of the implementation of the urban spatial planning plan. To optimize Wuhu's spatial structure, the construction of public infrastructure in the northern area should be strengthened to compensate for the existing restrictions led by single industrial function area, and the functional connection between the north and the center and the south should be strengthened through the adjustment of land use. According to the results of the current division, the space group identified by the urban people flow network can be used as the smallest urban planning unit, and facilities can be configured and optimized according to the flow characteristics of the unit. By providing facilities and services from the actual spatial scope of urban residents' activities, the efficiency of facility utilization may be improved.In the study, POI was used to make the qualitative descriptive analysis of the land use and functions within the communities. The result shows differences between communities, which reflect the actual utilization degree and spatial difference of urban space resources and facilities by residents from a micro perspective. These results are conducive to breaking the original planning concept based on static residents' space resource allocation and public facilities supply, and rationalizing it on a reasonable basis. As such, the actual needs of residents can be considered for adjusting and allocating spatial resources. The land-use functions and public resources within the groups can also be adjusted accordingly. Also, the results of the interaction analysis for different groups offer insight into the spatial structural relationship of the city and provide a clear direction and targeted guidance for the revision of the urban planning scheme. Finally, the empirical research, on the one hand, strengthened the recognition of urban and spatial organization from the perspective of spatial interaction theory and complex networks; on the other hand, it verified the applicability of the method framework constructed in this article.

## Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request, including the street network data and POI.

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