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Estimating the effects of “community opening” policy on alleviating traffic congestion in large Chinese cities by integrating ant colony optimization and complex network analyses

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ABSTRACT

According to an urban planning directive issued by the Chinese Central Government in early 2016, the Community Opening Policy will be put on the agenda to ameliorate transportation networks, which has aroused much attention regarding the coming changes in traffic, especially in road network structures. Nevertheless, few studies were concerned with the direct and indirect impacts of opening gated communities. This study aims to analyze the impact of opening gated communities on road structure by integrating ant colony optimization (ACO) and complex graph theory and to investigate its influence on resident commuting efficiency and the traffic flow centroid. First, with a traffic road network based on OpenStreetMap (OSM), alteration in the connectivity between two road nodes and the resident overall commuting time and distance are computed using an ACO algorithm. Second, using complex graph theory, the attraction index of every road is calculated, and the congestion area before and after the opening policy is obtained. The research areas include Beijing, Shanghai, Guangzhou, and Shenzhen, which are first-tier Chinese cities. The results demonstrate that opening gated communities will increase the connectivity and accessibility of the current road network by 9.43–29.80%, generating a decrease of 2.57–4.50% in resident commuting time for short-distance travel. Furthermore, with the decline in traffic stream in the urban trunk roads, the number of potentially congested junctions will decrease, resulting in an alteration in the spatial position and coverage area of the urban congestion areas. This study carried out quantitative research into the effect of opening gated communities, providing a reference for urban planners and government.

1. Introduction

The Chinese Central Government issued an urban planning guideline, which is known as the Community Opening (CO) policy, in early 2016. The guideline indicated that newly established communities will no longer be closed, and old gated residential communities must be opened to the public road system (Xinhua News Agency, 2016). Heated debate has arisen in society regarding whether this directive will have a positive impact on city development. The policy better utilizes the urban land; therefore, the majority of comments and opinions suggest that CO will improve the road network structure, thus alleviating the case of urban traffic congestion (Daily, 2016; Kai, 2016). Nevertheless, few studies evaluate the impacts of opening communities on traffic issues, such as residents' commuting and traffic congestion, at a large scale quantitatively, which hinder the comprehensive evaluation of this guideline.

The urban road network is a type of spatial network, which requires both topological information about the graph and spatial information about the nodes (Barthélemy, 2011). Previous studies have proposed a number of indicators to evaluate the robustness of road networks, including heterogeneity, connectivity, accessibility, and interconnectivity (Liu & Yu, 2012; Patarasuk, 2013; Xie & Levinson, 2007). In addition, many studies have focused on exploring the road network structure of Chinese cities, where road networks were abstracted as a directed graph in graph theory. Qian et al. (2012) established a directed graph model of the road network in Lanzhou, where the connectivity reliability of the road network in the valley city was studied based on complex graph theory (Qian et al., 2012); Liu and Yu (2012) quantitatively evaluated the connectivity and accessibility of the road network in the Wuhan Metropolitan Area (Liu & Yu, 2012). However, because of the

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complexity of the urban functional structures and the large data volume, building and comparing the road network models of Chinese megacities are considerably difficult.

Several studies have demonstrated that as the Chinese urbanization process continues to accelerate, the urban traffic congestion issue will be increasingly severe (Guo, Liu, & Yu, 2011; Kong, Yang, & Yang, 2015; Zhang et al., 2011). The problem of urban traffic congestion causes inconvenience and concern to commuting residents (Wang et al., 2016), causes severe air contamination (Cao et al., 2016), affects where activities are located or relocated to, and impacts the choice of travel modes (Levinson & Falcocchio, 2011). Furthermore, cities around the world have introduced a number of policies to alleviate this universal problem. Local governments in London, Singapore, and Stockholm have started to impose congestion charges (Harks et al., 2015), while the development of public transportation has also had certain effects in easing traffic congestion (Currie & Sarvi, 2010; Le & Tu, 2016). Fields et al. (2009) noted that by providing additional road capacity, the increasingly severe traffic congestion in the US can be alleviated (Fields et al., 2009). However, Litman (2013) argued that the benefits that roadway expansion can bring are overestimated, and policymakers should choose different traffic congestion mitigation strategies considering the situation (Litman, 2013). As the opening of the residential areas makes it possible for roads in the gated zone to connect to the urban road network, it is important to consider the way and extent the opening will alleviate the urban traffic problem.

This study is particularly concerned with the implementation of the CO policy and its positive impact on the traffic congestion problem in Chinese megacities. The following work was conducted. (1) The alteration in the road network structure, especially the robustness and connectivity, is obtained. (2) The influence of enforcing the CO policy on resident travel efficiency is calculated under different spatial scales. (3) By comparing the range and spatial position of the potential traffic congestion points and area in a city before and after the implementation of the CO policy, we can evaluate the easing degree of the traffic congestion in different cities.

2. Research design

The mitigation of urban traffic congestion after the implementation of the CO policy is quantitatively explored. The study is divided into the following three steps. (1) On the basis of the OSM road network data, the urban road network model is established, and the road network connectivity changes after the implementation of the CO policy are examined. (2) The real travel speed of each road is obtained from GPS floating car data (FCD), and the resident commuting distance and time were calculated using the ant colony algorithm (ACO). (3) By adopting PageRank centrality and a clustering algorithm, the urban potential traffic congestion points and congestion areas are obtained, and the spatial position and scope change of the congestion areas are analyzed. The flow chart of this study is shown in Fig. 1.

2.1. Urban road network model construction

The road network data acquired from OSM are abstracted to a weighted directed graph (Corcoran, Mooney, & Bertolotto, 2013; Hasenfratz et al., 2015). A weighted directed graph $G \equiv (V, E, W)$ consists of a set of vertexes V, their connecting edges E, and the weight of edges W. In this study, the starting, ending, and intersection points of the road are regarded as vertexes V; the roads connecting these vertexes are deemed as edges E. The spatial network represents a true geographical entity; thus, the weight of each edge W is given the geographical length or the transit time of the road, and its direction is derived from the actual road direction. To store data more efficiently, the adjacency list is chosen to represent the graphs' structure. Here, adjacency list is an array of unordered lists used to represent a graph, where each list describes the set of neighbors of a vertex in the given graph. By using the adjacency list, the weighted directed graph of each city in the study area can be stored and invoked with high efficiency.

Furthermore, attribute information contained in the OSM road data can determine whether a certain road is within a community. More specifically, based on the OSM official document, roads under the category “residential” are located within a residential zone. Besides, as “living street” roads are also situated within a certain community, we regard them inner-community roads as well. All other types of roads are treated as outer-community roads.

The alteration in network connectivity can directly reflect the improvement in road network structure after the implementation of the CO policy. Although the average clustering coefficient (ACC) was initially proposed as an indicator to determine whether a graph is small-world (Watts & Strogatz, 1998), it is widely adopted to evaluate the robustness and well-connectivity of a certain network (Barthélemy, 2011; Ponton, Wei, & Sun, 2013), including road networks (Duan & Lu, 2014; Jiang, 2007; Porta, Crucitti, & Latora, 2006). Specifically, the ACC is calculated from the local clustering coefficient (LCC) (Prokhorenkova, 2015; Watts & Strogatz, 1998). The LCC of a vertex is defined as the ratio of the number of actually connected adjacent vertexes to the theoretical maximum connections. Let edge e_{ij} connect vertex v_i with vertex v_j; then, the neighbor N_i for a node v_i is defined as follows:

$$N_i = \{v_j : e_{ij} \in E \bigvee e_{ji} \in E\} \tag{1}$$

Defining k_i as the number of N_i, the LCC of vertex v_i is given as follows:

$$LCC(v_i) = \frac{|e_{jk} : v_j, v_k \in N_i, e_{jk} \in E|}{k_i(k_i - 1)} \tag{2}$$

By calculating the average LCC of all vertexes, which is also known as the ACC, the connectivity degree of the network is expressed as follows:

$$\mathrm{ACC} = \frac{1}{n}\sum_{i=1}^{n} LCC(v_i) \tag{3}$$

Therefore, the improvement in the overall connectivity in the urban road network is obtained by comparing the network ACC before and after the implementation of the CO policy.

In this section, we transform the real geographical road network into a virtual weighted directed graph, and two urban road network models are constructed: models with roads within the residential community and models without them. In addition, the improvement in road network connectivity during the CO progress is calculated.

2.2. Resident commuting efficiency computation

GPS FCD are introduced in the study to obtain the speed of each road. To match the FCD records with the urban road network quickly and accurately, we generate the service range of each urban road using the watershed algorithm. By projecting into the watershed layer and judging the road service area in which it lies, each FCD record is matched with its corresponding urban road, by a map-matching algorithm based on geometry (Greenfeld, 2002; Zheng, 2015). Then, on the basis of the OSM data description and the Code for Design of Urban Road Engineering (2016 version), the urban road is classified into four levels from high to low, namely the expressway, arterial road, secondary trunk road, and branch way. The speed information contained in the matched FCD is used to calculate the average speed of each road class and further generalize all roads in the study area. Therefore, the passage of time t_i on road i is given by the following equation:

$$t_i = \frac{d_i}{v_k} \tag{4}$$

where d_i is the actual length of road i, k indicates the class to which road

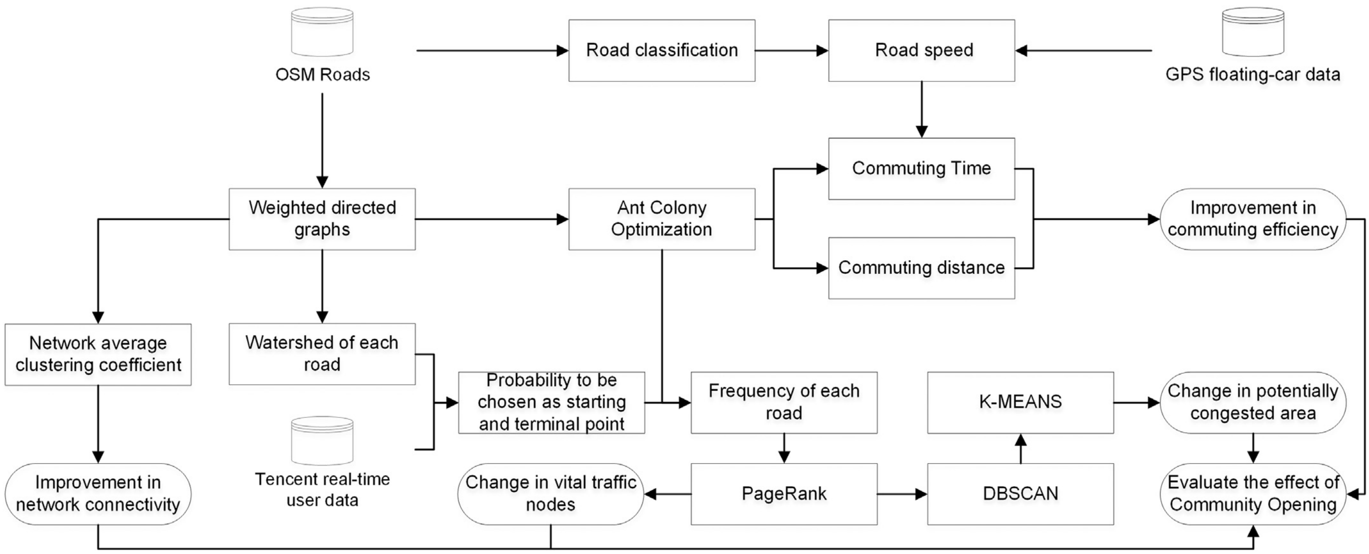

Fig. 1. Flowchart of analyzing the impact of opening gated communities on road structure by ant colony optimization and complex graph theory.

i belongs, and v_k represents the average traveling speed corresponding to road level k.

In this section, the travel time and distance of two nodes in the weighted directed graph are calculated, and their alterations are compared before and after the implementation of the CO policy. As one of the approximate optimization algorithms, ACO can solve the issues of huge computation at high efficiency while ensuring certain accuracy (Blum, 2005; Neto & Filho, 2013). The road network in the study area is highly complex; therefore, the efficiency of the algorithm will directly affect the ability to obtain reliable results. Furthermore, in comparison with traditional algorithms, ACO can fit the dynamic change in the weighted directed graph (Kponyo, Kuang, & Li, 2012), which can greatly reduce the number of commuter efficiency calculations. For these reasons, ACO is chosen as the algorithm for calculating the inhabitant commuting efficiency.

More specifically, ACO is a heuristic algorithm for calculating the optimal path in a connected graph, of which the core is the introduction of pheromones, which are enhanced or weakened through the simulation of the ant foraging process. The algorithm assumes that a few ants start from the starting point and select the walking path based on the pheromone concentration until all possible paths are selected or the end is reached. During the iterative process, the pheromone concentration in the optimal path of each ant will be enhanced and that in the remaining paths will be attenuated. Assuming that ant k is at the i-th vertex, the probability ${p_{ij}}^k$ that it reaches the adjacent node j is given as follows (Maboudi et al., 2017; Stützle, 2006):

$$p_{ij}^k = \frac{(\tau_{ij}^{\alpha})(\eta_{ij}^{\beta})}{\sum_{j \in Allowed_j} (\tau_{ij}^{\alpha})(\eta_{ij}^{\beta})} \tag{5}$$

where τ_{ij} indicates the pheromone concentration on the edge connecting vertexes i and j; η_{ij} is the visibility between vertexes i and j, which is set as the weight (length or transit time) of edge e_{ij} in this study; and α and β are the pre-set weight constants. The pheromone concentration on the edge where an ant has walked will be attenuated according to the following equation:

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) \tag{6}$$

This equation implies that the pheromone concentration τ_{ij} will be attenuated by the ratio of ρ, where the value of parameter ρ is in the range of 0 to 1. After all ants have completed their respective paths, the pheromone concentration on the specific edges will be enhanced as follows:

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \sum_{k=1} \Delta\tau_{ij}^k \tag{7}$$

where $\Delta\tau_{ij}^k = \begin{cases} \frac{Q}{L_k} & \text{if ant } k \text{ uses curve } ij \text{ in its tour} \\ 0 & \text{otherwise} \end{cases}$, L_k is the sum of the weights of the path traveled by ant k, and Q represents the weight parameter.

In this study, along with setting the road weights as length or passage of time, the shortest path between any two points in the graph before and after the implementation of the CO policy is calculated to obtain the commuting distance and time improvement.

2.3. Potentially congested area acquisition

The degree of importance of each road node in the overall transport network is measured by calculating its PageRank value, which was initially proposed to rank websites in their search engine results (Brin & Page, 2012) and subsequently widely used in centrality measures for various types of networks (Gleich, 2014; Mukai, 2013). One of the ways to calculate the PageRank of a vertex is as follows:

$$\boldsymbol{C}_p(v_i) = \alpha \sum_{j=1}^{n} \boldsymbol{A}_{j,i} \frac{\boldsymbol{C}_p(v_j)}{d_j^{out}} + \beta \tag{8}$$

where $\boldsymbol{C}_p(v_i)$ and $\boldsymbol{C}_p(v_j)$ represent the PageRank value of vertexes v_i and v_j, respectively; $\boldsymbol{A}$ is the adjacency matrix that stores the structure of the graph; d_j^{out} represents the output degree of vertex v_j; n is the number of neighboring vertexes of v_i; and α and β are fixed parameters. However, the PageRank algorithm considers only the original structure of the network but not the actual road traffic flow. Hence, to be as consistent as possible with the real situation, the ideology of the TrustRank algorithm (Akoglu, Tong, & Koutra, 2015; Gyöngyi, Garcia-Molina, & Pedersen, 2004) is used to calculate the traffic pressure of each vertex in the transportation network in advance, which acts as an input parameter to calculate the PageRank centrality instead of the out-degree d_j^{out}.

The traffic pressure of each vertex is calculated from the real-time Tencent user density (RTUD) data. This study was conducted on a relatively large time and space scale; therefore, it is assumed that the probability of using a vehicle for commuting is exactly equal for all the citizens; that is, the probability that each road will be selected as a starting point or an end point in a commuter path is equal to the proportion of the active crowd in the road service area to the total active crowds in the city. Therefore, the proportion of RTUD in the road service area is taken as the probability of the road being selected, where the starting and end points of the commuter path are randomly selected, and the shortest path connecting the two vertexes is further calculated by ACO. The number of shortest paths passing through the vertex is deemed as the traffic pressure of each vertex.

The vertexes with higher PageRank values within a traffic network are considered to sustain higher traffic flow and are spots more prone to trigger traffic congestion. These spots will cause impacts on the traffic in the surrounding area; therefore, the aggregation of high-value vertexes stands for regions where traffic congestion is very likely to be generated. In this study, the easily congested areas are uncovered by sites with the highest PageRank values. We divide this clustering process into two steps: (a) the density-based spatial clustering of applications with noise (DBSCAN) algorithm is first introduced to locate relatively isolated vertexes that are unlikely to co-effect with other vertexes and are excluded from further analysis. (b) The K-MEANS algorithm is adopted to cluster the remaining nodes, thereby identifying easily congested areas.

DBSCAN is a density-based clustering algorithm, which depicts the tightness of the sample distribution by using a set of neighborhood characterization parameters ($\varepsilon, MinVertex$) (Ester, Kriegel, & Xu, 1996). This algorithm can divide the samples into "core objects," "non-core objects," and "noise samples," which avails the identification of the relative spatial position of each traffic node. The K-MEANS algorithm minimizes the squared error of the divided cluster $\mathscr{C} = \{C_1, C_2, \cdots, C_k\}$ for the given sample set $D = \{x_1, x_2, \cdots, x_m\}$:

$$E = \sum_{i=1}^{k} \sum_{\boldsymbol{x} \in C_i} \|\boldsymbol{x} - \boldsymbol{\mu}_i\|_2^2 \tag{9}$$

where $\boldsymbol{\mu}_i = \frac{1}{|C_i|} \sum_{\boldsymbol{x} \in C_i} \boldsymbol{x}$ denotes the mean vector of cluster i. To quantitatively evaluate the clustering results, we introduce the Silhouette index (Rousseeuw, 1987), which measures both the degree of cohesion within a class and the degree of dispersion between classes (De Amorim & Hennig, 2015); thus the most appropriate cluster number can be determined (Lletí et al., 2004). When the average silhouette value of the data objects in all categories is the largest, the cluster number is optimal.

First, the DBSCAN algorithm is adopted to cluster the input data, retaining the "core objects" and "non-core objects," while eliminating the "noise samples." Then, the K-MEANS algorithm is used to divide the remaining points by geographical location. We repeated a number of clustering experiments and finally chose the one with the largest Silhouette index as the final result. Finally, the standard deviation ellipse is calculated for each category to determine the convergence of the traffic congestion area.

Thus, the traffic congestion areas are obtained before and after the opening of communities, and the variation in their location and scope is further analyzed.

3. Study area and data description

Beijing, Shanghai, Guangzhou, and Shenzhen, four cities in China, were selected as the study area (Fig. 2). With a total administrative area of approximately 31,900 km^2 and > 65 million residents, these cities are regarded as first-tier Chinese cities. According to the China City Statistical Yearbook of 2016, their Gross Domestic Product (GDP) ranks the highest among all Chinese cities, with a total amount of more than $1 trillion. Because of the large urban size, complex road networks, and great many communities, they are ideal places to study the impact of the CO policy.

The administrative boundary data were acquired from the Database of Global Administrative Areas (http://www.gadm.org/), from which the administrative boundaries of the cities were extracted. Because of the excessive size of the administrative areas of Beijing and Shanghai, the urban areas within the Beijing 5th-ring road and Shanghai outer ring road were selected as the research areas; these boundaries are also commonly considered in previous studies (Liu, 2016; Liu et al., 2015).

The main dataset is the road data in the study area, which was produced by OSM (http://www.openstreetmap.org) (Fig. 3A–D). OSM is an open-source map site designed to provide free and easy-access digital map data (Haklay, 2010), which are highly accurate for the study area (Zhang et al., 2015a, 2015b, Zhao et al., 2015). In addition to the positioning information, including the latitude and longitude of the roads themselves, the road data in the OSM also contain attribute information such as the type of the road, which can be used to classify the road in accordance with the type description.

Additionally, the hourly density maps of social network users on Tencent, which is referred to as RTUD in this study, were used to obtain the citywide crowd distribution. Because of its large user base, the RTUD data can represent human activities (Chen et al., 2017). The RTUD data were obtained in 2016, and for each city, the average RTUD value of three periods, 8:00–9:00, 15:00–16:00, and 22:00–23:00 during weekdays (Fig. 4), was calculated to cover the population activity throughout the day. After coordinate correction, data cleaning, and interpolation, the RTUD data were converted into data images with geographic coordination of WGS1984 and spatial resolution of 25 m (Fig. 3E–H) (Yao et al., 2017).

To obtain the real road speeds and visits, the GPS FCD in Guangzhou and Shenzhen (Fig. 5) were adopted, which were acquired in May 2012 from the transport commission of the two cities. The actual road traffic conditions can be speculated based on FCD, which contain running information of vehicles that steer on the road. After removing abnormal records, to reflect the road conditions in the course of the resident commuting period, we selected FCD that were obtained from 7:00 a.m. to 22:00 p.m. on the working days during the data acquisition date; the values were then matched with their corresponding roads.

4. Results

4.1. Impact on urban commuting efficiency

By calculating the average of the local clustering coefficients of all vertexes in different research cities, the ACC was obtained at two different stages, as shown in Table 1.

As presented in the table, although the network average clustering coefficients of all cities were significantly improved after implementation, there were differences in the promotion ratio, among which Guangzhou reached the most significant improvement of 29.80%, followed by promotion ratios of 18.69% and 16.15% in Shenzhen and Beijing, respectively, while the road connectivity enhancement in Shanghai was limited. As a whole, all the final network average clustering coefficients were > 0.50, indicating that roads are highly clustered in sub-networks as part of the whole road network, which are connected directly and efficiently (Zhang et al., 2015a, 2015b). Open access to the roads within the residential areas will cause significantly increased connectivity and accessibility of the road network in first-tier Chinese cities, especially in Guangzhou, Shenzhen, and Beijing.

In addition to exploring the impact on the road itself, the policy impact on the commuting efficiency of the residents is also considered. In the built city road network, the shortest distance and the shortest commuting time were calculated from the randomly selected starting and end points by the ant colony algorithm. To consider both the representativeness and computational efficiency of the data, the selected path for calculations accounts for 1% of the total possible paths of the city (approximately 1000,000). Tables 2 and 3 list the commuting improvement degree at a distance of 5000 m, and Fig. 6 shows the commuting amelioration extent at a distance of 1000 m. The results in both graphs indicate that the commuting distance and time are reduced at different travel distances. With the increase in travel distance, the improvement degree of commuting efficiency gradually decreases, which indicates a reduction in the impact of CO policy. It is noteworthy that

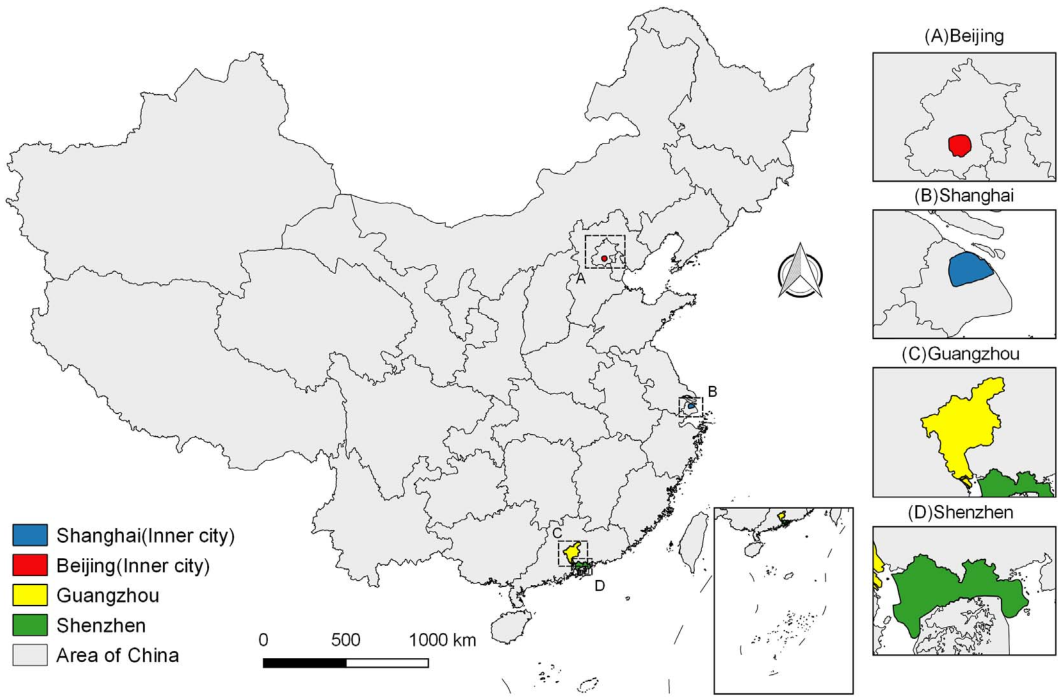

Fig. 2. Case study area: (A) Beijing (inner city), (B) Shanghai (inner city), (C) Guangzhou, and (D) Shenzhen.

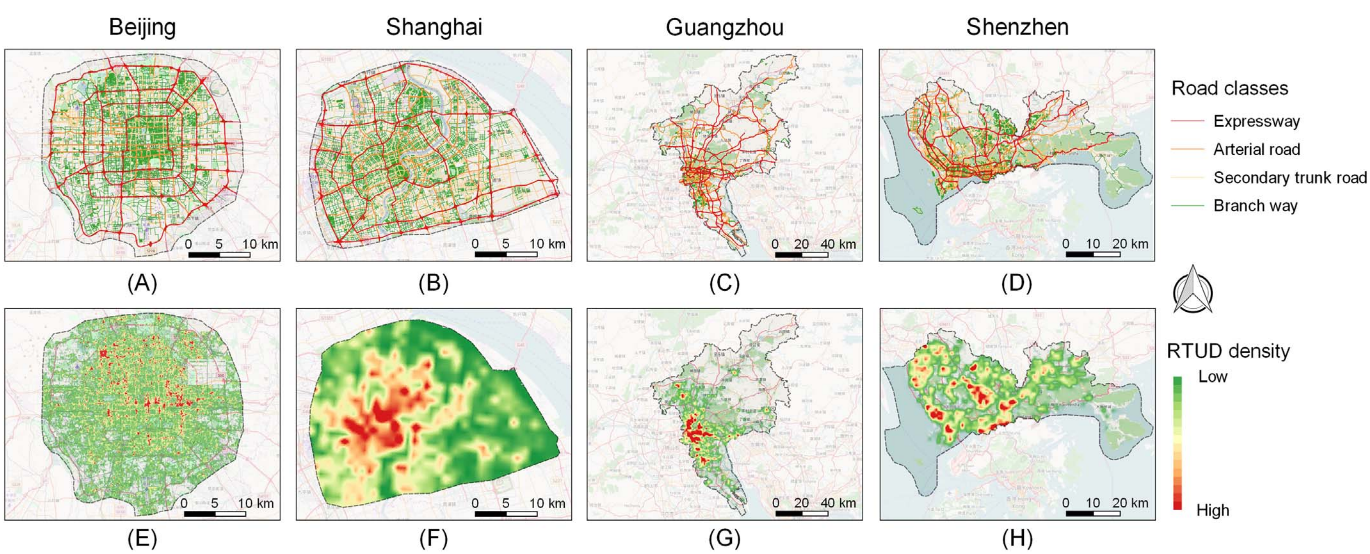

Fig. 3. Road network data obtained from OSM (A–D) and RTUD data (E–H) in the study areas.

the improvement degree of commuter distance is more remarkable than that of commuting time, which is mainly due to the lower average vehicle speed within residential areas.

The improvement in each city was compared, and depending on the results, the four cities were divided into the following two groups: Guangzhou and Shanghai, where both the commuting distance and commuting time were improved significantly, and Beijing and Shenzhen, where the effect was relatively insignificant. Although the connectivity and accessibility of road networks in Beijing and Shenzhen were significantly increased, the commuter efficiency exhibited limited improvement for various reasons.

Because of the influence of historical context and planned activities, the urban structure of Beijing is largely influenced by its concentric ring roads, which follows the concentric zone theory to a certain extent (Tian, Wu, & Yang, 2010). Hence, the main frame of the road network in the city consists of concentric ring roads and the link roads connecting them, which split the urban area into relatively regular land parcels. Instead of traversing the residential areas, the side roads that connect the main roads are utilized more frequently around the residential areas.

As a special economic zone of Chinese reform and opening and having a relatively small city area (of only 1996 km^2, compared with 16,410, 6340, and 7343 km^2 for Beijing, Shanghai, and Guangzhou, respectively), Shenzhen established a stringent land management policy (Qian et al., 2015), resulting in relatively smaller average residential land areas. Unlike Shanghai and Guangzhou, where strategic roads sometimes appear within "Big Mac" residential communities, inner-community roads in Shenzhen tend not to connect with several trunk roads.

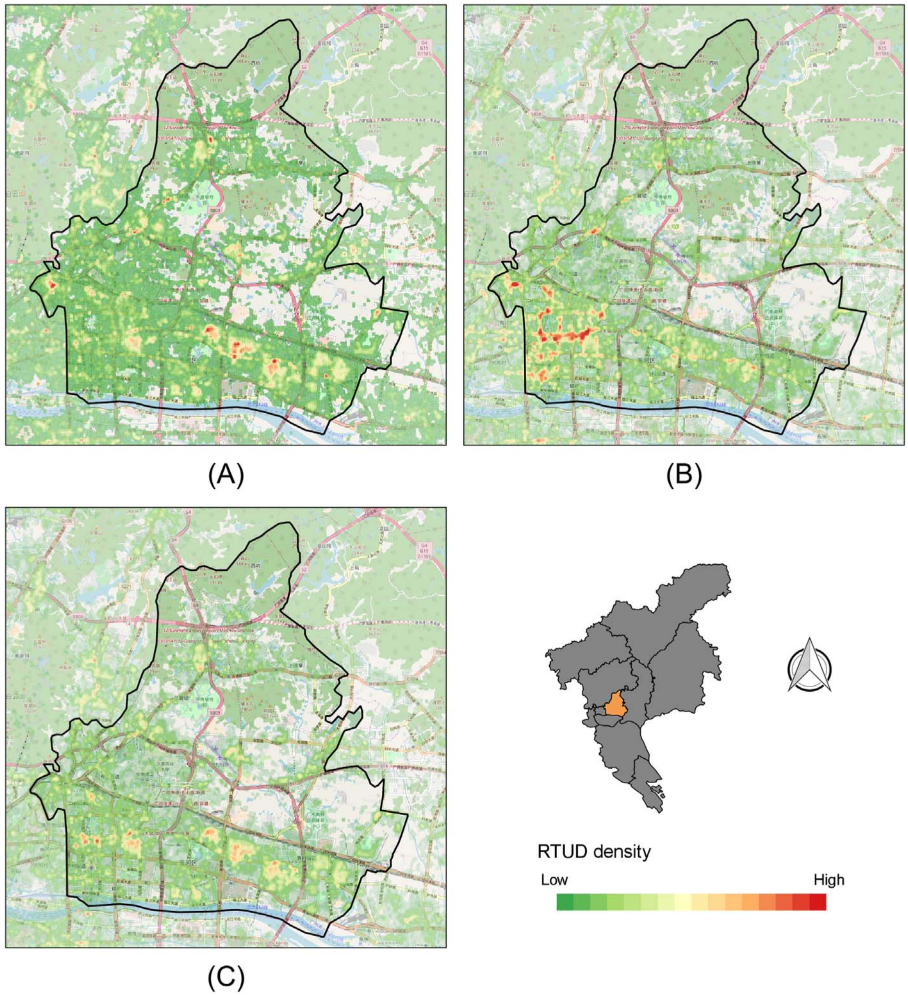

Fig. 4. Distribution of RTUD over three different time periods: (A) 8:00–9:00, (B) 15:00–16:00, and (C) 22:00–23:00 in Tianhe district, Guangzhou.

4.2. Impact on traffic flow

The Big Data Report of City Travel Radius released by the Tencent location service in early 2017 claimed that the average travel radius of residents in the study area is approximately 7.8 km (https://heat.qq.com/). Because of the huge user base and data volume, the report reflected the true travel behavior of urban residents in China's first tie cities. According to this report, approximately 45% of the residents travel < 5 km on a working day, while > 90% travel < 20 km. Moreover, the result we obtained in the previous part illustrated that

Table 1
ACC of the study area.

City	Before CO	After CO	Improvement
Beijing	0.437	0.507	16.15%
Shanghai	0.481	0.526	9.43%
Guangzhou	0.398	0.516	29.80%
Shenzhen	0.455	0.539	18.69%

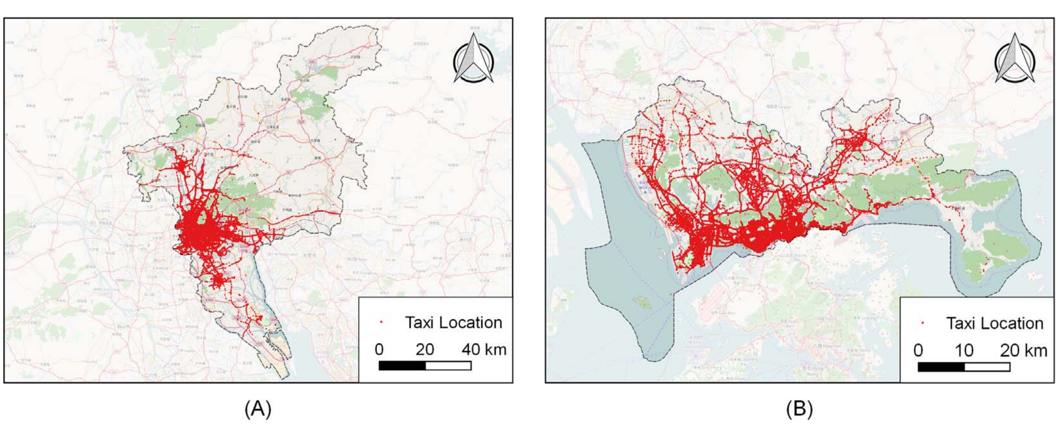

Fig. 5. Spatial distribution of GPS FCD in (A) Guangzhou and (B) Shenzhen.

Table 2
Decrement in commuting distance after CO policy per 5000 m.

Direct distance (m)	0–5000	5000–10,000	10,000–15,000	15,000–20,000
Beijing	2.58%	1.54%	1.31%	1.14%
Shanghai	4.29%	2.27%	1.77%	1.51%
Guangzhou	4.50%	2.02%	1.08%	0.73%
Shenzhen	2.57%	1.31%	0.80%	0.61%

Table 3
Decrement in commuting time after CO policy per 5000 m.

Direct distance (m)	0–5000	5000–10,000	10,000–15,000	15,000–20,000
Beijing	1.51%	0.80%	0.60%	0.48%
Shanghai	2.95%	1.46%	1.05%	0.83%
Guangzhou	3.11%	1.47%	0.86%	0.60%
Shenzhen	1.74%	0.89%	0.65%	0.53%

the impact of the policy is limited to short-distance commuting. To consider the vast majority of commuting needs, this study limits the straight-line distance between commuting start and end points to 20 km, which implies that only the node pair within 20 km is considered.

Here, the road visits before and after the implementation of the CO policy obtained by the ant colony algorithm were demonstrated. Figs. 7 and 8 show the number of road visits in each study area and compare the effects before and after policy's implementation. To present the result evidently, roads with < 10,000 visits were ignored, and the remaining roads were classified for display.

As shown in Figs. 7 and 8, roads with the highest visits are mainly located in the central city areas, such as Qianmen Street in Beijing, Huaihai Road in Shanghai, Guangzhou Avenue in Guangzhou, and the Nanping Expressway in Shenzhen. Furthermore, high-visit roads are also found for highways that connect downtown and an urban edge, for instance, the Guangyuan Expressway in Guangzhou and Fulong Road in Shenzhen. Obviously, after the implementation of the CO policy, the number of most visited roads gradually declined in each study area, and the corresponding traffic pressure was alleviated; additionally, relatively fewer visits rose significantly, easing the overall traffic pressure.

Compared with the actual road traffic flow (e.g., real-time traffic status service provided by the Baidu map) and related research (Kong et al., 2015), the road visits based on RTUD data sampling has considerable credibility. The experiment shows that with the visit diminution in high-visit roads and the increment in low-visit roads, the urban traffic flow will be dispersed to different roads, which will alleviate the traffic congestion situation in downtown areas.

4.3. Impact on traffic congestion area

PageRank can be used to measure the centrality degree of a vertex in the network (Koschützki et al., 2005). The adjacency matrix that conserves the network structure is required as an input parameter for calculating PageRank values (Zhao, Zhao, & Cui, 2017). However, in many practical cases, the network structure alone cannot comprehensively measure the importance of a given node in the network and may introduce more noise. Here, the distribution of the points with higher PageRank values calculated using the adjacency matrix (Fig. 9A) and node visits (Fig. 9B) is demonstrated before the implementation of the CO policy in Beijing. Given that PageRank values would be high at relatively isolated network locations (Gleich, 2014), the results obtained using the adjacency matrix were not in accordance with realistic results (Fig. 9A). In contrast, calculating PageRank values using node visits can reflect the actual traffic flow and the possibility of congestion to a certain extent (Fig. 9B).

Figs. 10 and 11 show the relatively higher PageRank vertexes of each study area, where higher values are displayed in deeper color with larger dots, and the statuses before and after implementation are compared. Because PageRank measures the vertex centrality, in a road network that considers account traffic flows, traffic congestion is more likely produced at vertexes with high PageRank values. It is worth noting that the calculated PageRank value cannot be compared between cities because of differences in road numbers and road network topologies in each city.

From Figs. 10 and 11, the potential traffic jam spots can be divided into the following three categories: (a) compared with high risk, the possibility of causing traffic congestion is alleviated or even removed after implementation (high-low spots), (b) the risk is not affected by the opening of residential areas (stable spots), and (c) compared with low risk, the possibility is enhanced after implementation (low-high spots). Apparently, high-low spots represent the positive effects on urban traffic pressure caused by the policy, considering the Mingguang Bridge in Beijing, the Central Military Road overpass in Shanghai, the Tongxin Road exit of the inner ring road in Guangzhou, and the Wuhe Interchange in Shenzhen as typical examples. For stable spots, the opening of the residential area is not associated with their congestion risk. The emergence of low-high spots, where special attention should be paid, indicates that the traffic flow redistribution after the implementation of the CO policy generates potentially new traffic congestion spots in the urban road network. Representative spots are the junction connecting Zhushikou East Street and East Gate Road in Beijing, the East Long Avenue overpass in Shanghai, and the Futian Interchange in Shenzhen.

The number of high-low spots was much higher than those of stable spots and low-high spots in each city, indicating that by dispersing the traffic flow of main city roads, the policy reduced the number of high-risk congestion spots, thus easing traffic pressure on urban roads. Moreover, the spatial position of the risk points also changed, indicating that traffic congestion may occur in entirely different urban regions. It is worth noting that the policy implementation will cause distinct effects in different cities. Better implementation effects are found in Beijing and Shanghai compared to Guangzhou and Shenzhen. This part of the experiment explores the influence of the CO policy on the potential congestion spots in the city, forecasts the congestion

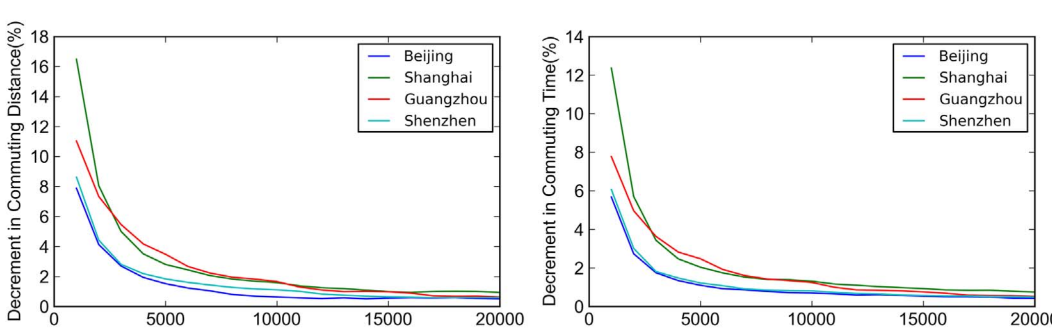

Fig. 6. Improvement in commuting efficiency after CO policy.

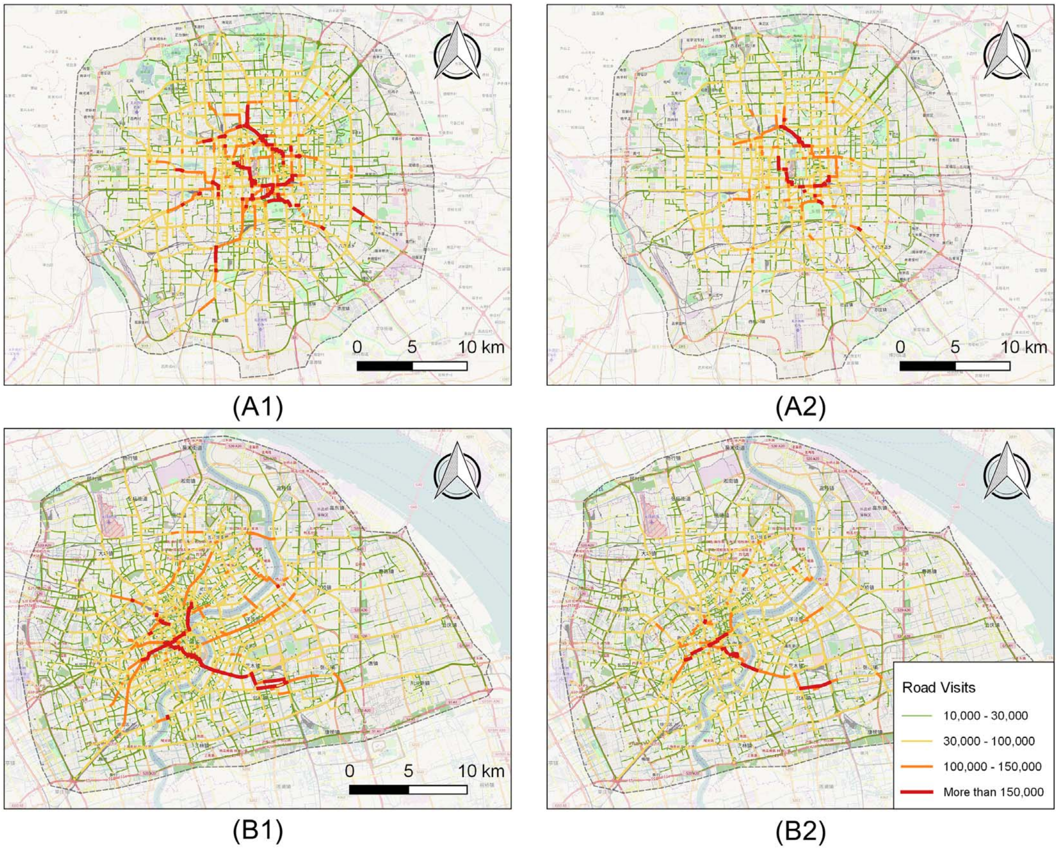

Fig. 7. Road visits of (A1) Beijing before CO policy, (A2) Beijing after CO policy, (B1) Shanghai before CO policy, and (B2) Shanghai after CO policy.

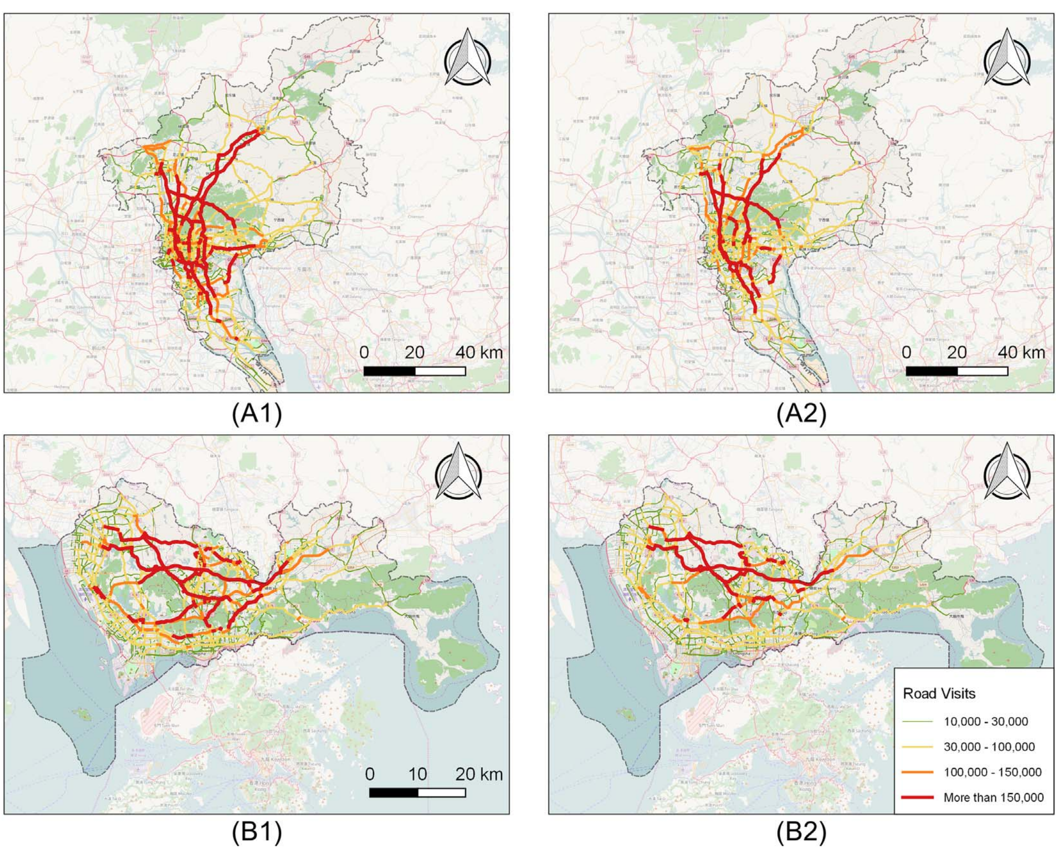

Fig. 8. Road visits of (A1) Guangzhou before CO policy, (A2) Guangzhou after CO policy, (B1) Shenzhen before CO policy, and (B2) Shenzhen after CO policy.

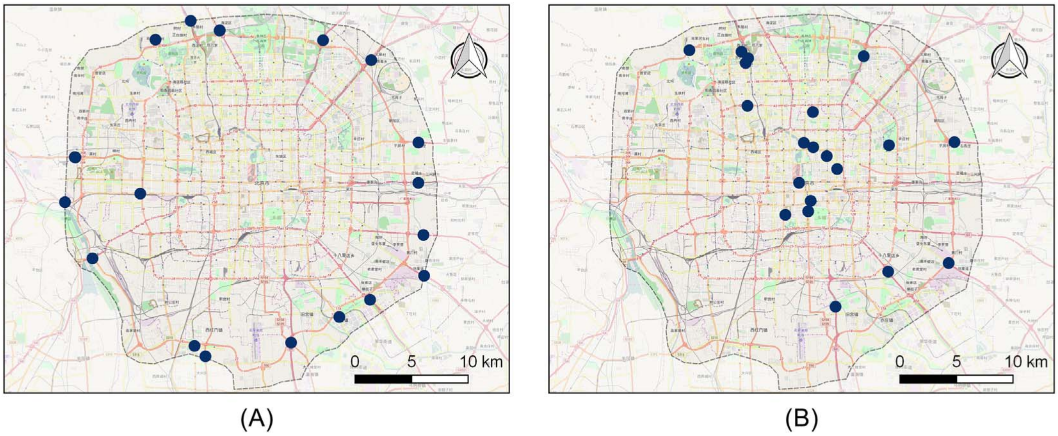

Fig. 9. High PageRank vertexes before CO policy calculated using (A) the adjacency matrix and (B) node visits. PageRank values exceeding a certain bound are considered and displayed with the same size and color.

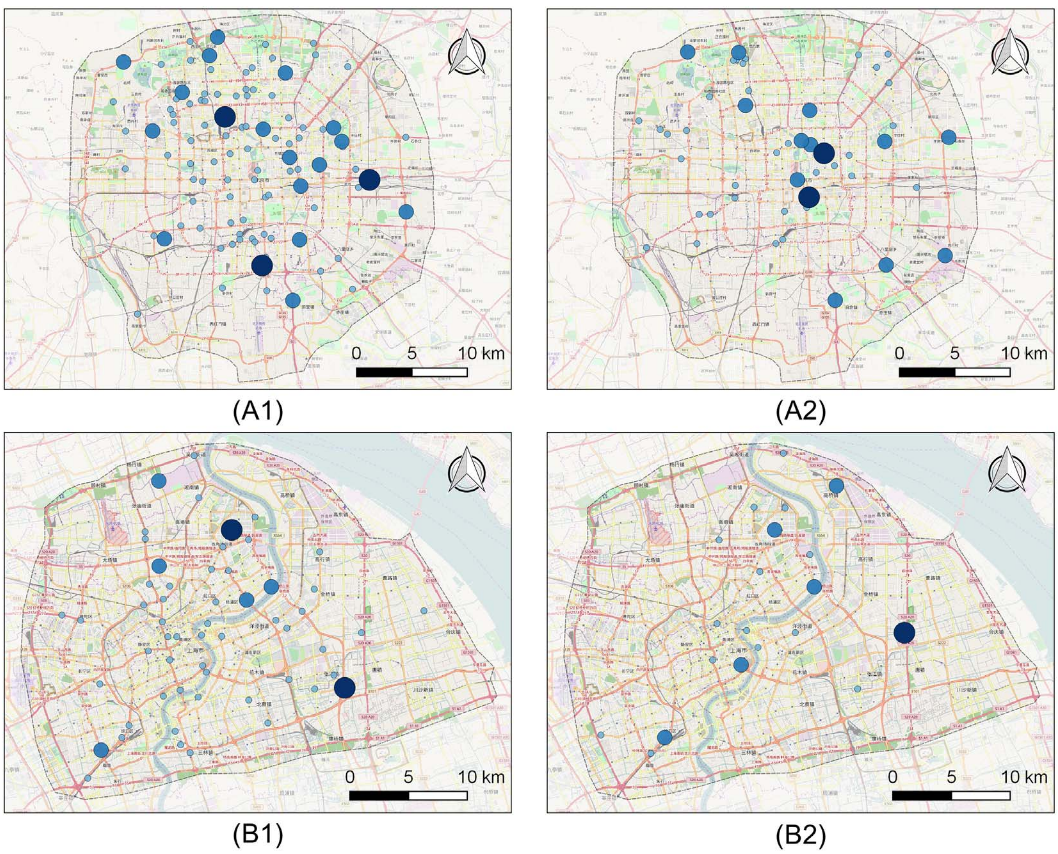

Fig. 10. High PageRank vertexes of (A1) Beijing before CO policy, (A2) Beijing after CO policy, (B1) Shanghai before CO policy, and (B2) Shanghai after CO policy.

situation of first-tier Chinese cities after full policy implementation, and provides a strong reference for the government and urban planners.

Each potential traffic jam spot has a certain range of radiation; therefore, the aggregation of single points will lead to the emergence of regional traffic congestion areas, where heavy traffic pressure is sustained. Apart from generating heavy traffic jams, these areas are more likely to become the transportation hub and center of the city. By adopting a clustering algorithm, the traffic congestion area during the opening process of each city was obtained, as shown in Figs. 12 and 13.

The number and extent of traffic congestion areas in each study area were reduced to a certain extent after implementing the CO policy in the district. Particularly, in areas around the Capital Museum and Dahongmen, the traffic conditions of Beijing improved significantly, where existing traffic congestion areas were reduced inordinately or even disappeared. Furthermore, the changes in Shanghai were also notable, and the congestion areas in the Hongkou and Yangpu Districts showed alleviation in all existing congestions. However, the emerging traffic congestion area in the Huangpu District deserves special attention. The impact of the CO policy on the traffic congestion areas of Guangzhou and Shenzhen is limited; although the coverage area of the congested area was significantly reduced, the congestion locations hardly changed.

5. Discussion and conclusions

In this section, we first discuss the adopted traffic flow model. This

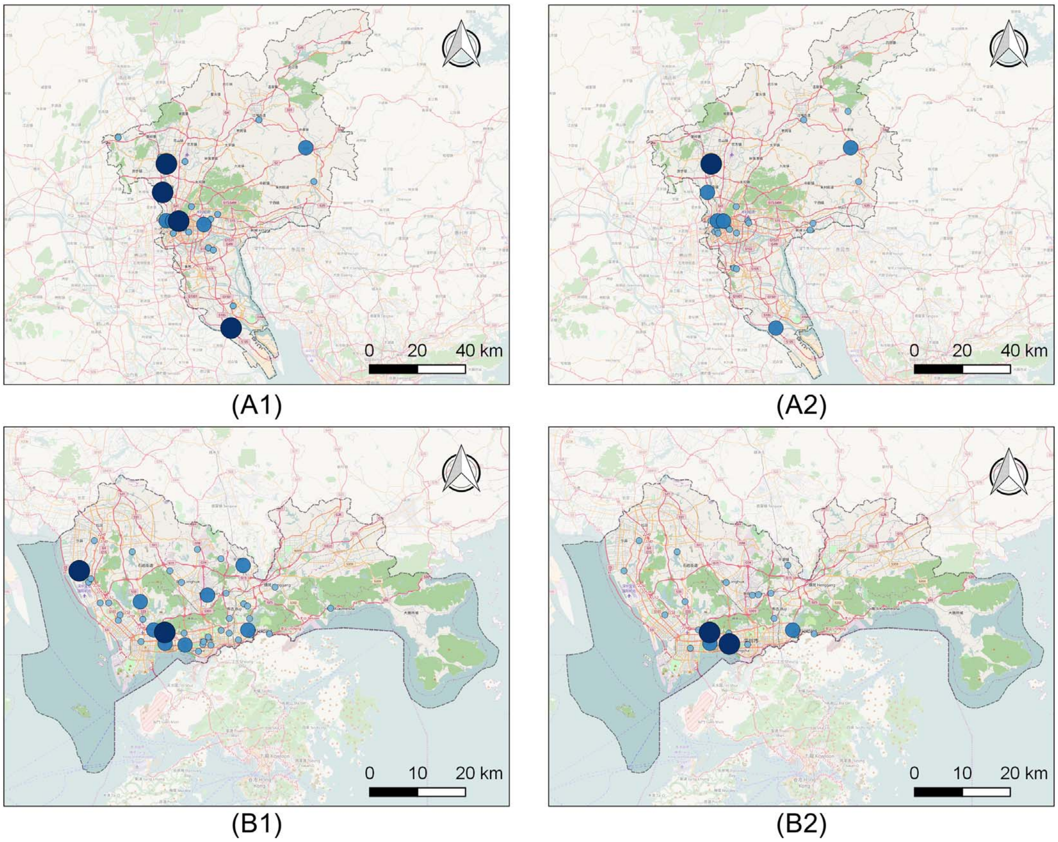

Fig. 11. High PageRank vertexes of (A1) Guangzhou before CO policy, (A2) Guangzhou after CO policy, (B1) Shenzhen before CO policy, and (B2) Shenzhen after CO policy.

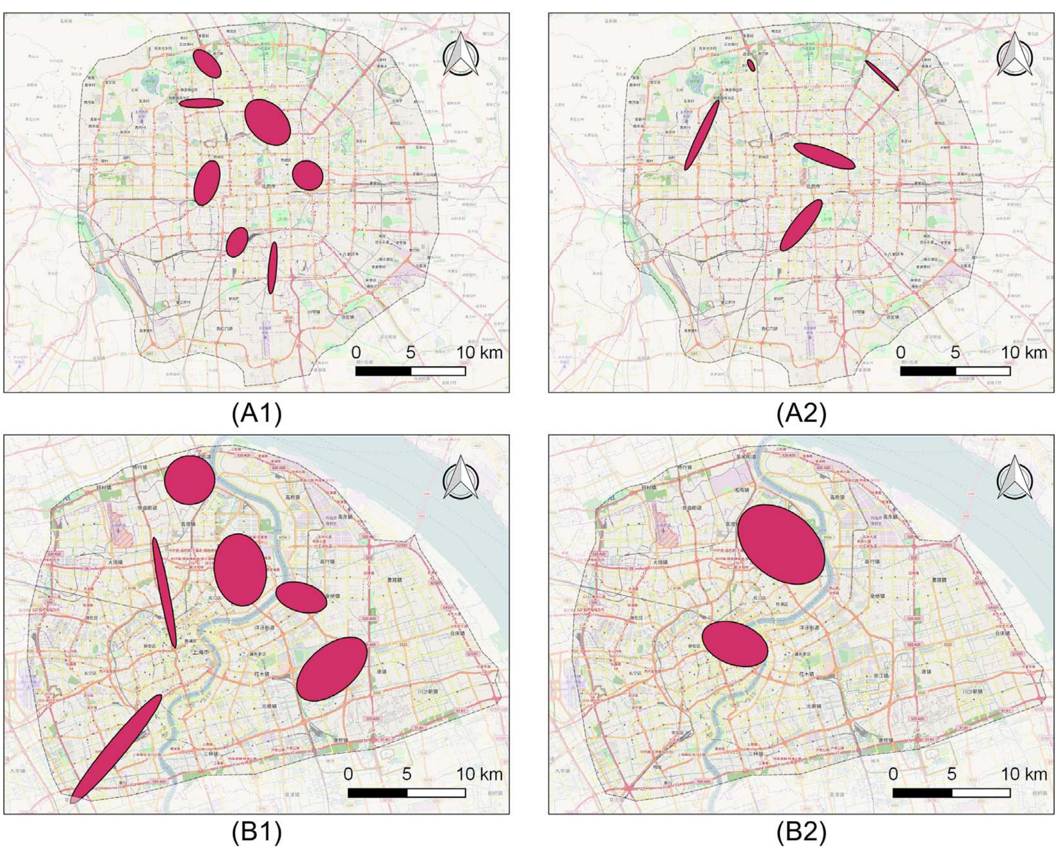

Fig. 12. Traffic congestion area of (A1) Beijing before CO policy, (A2) Beijing after CO policy, (B1) Shanghai before CO policy, and (B2) Shanghai after CO policy.

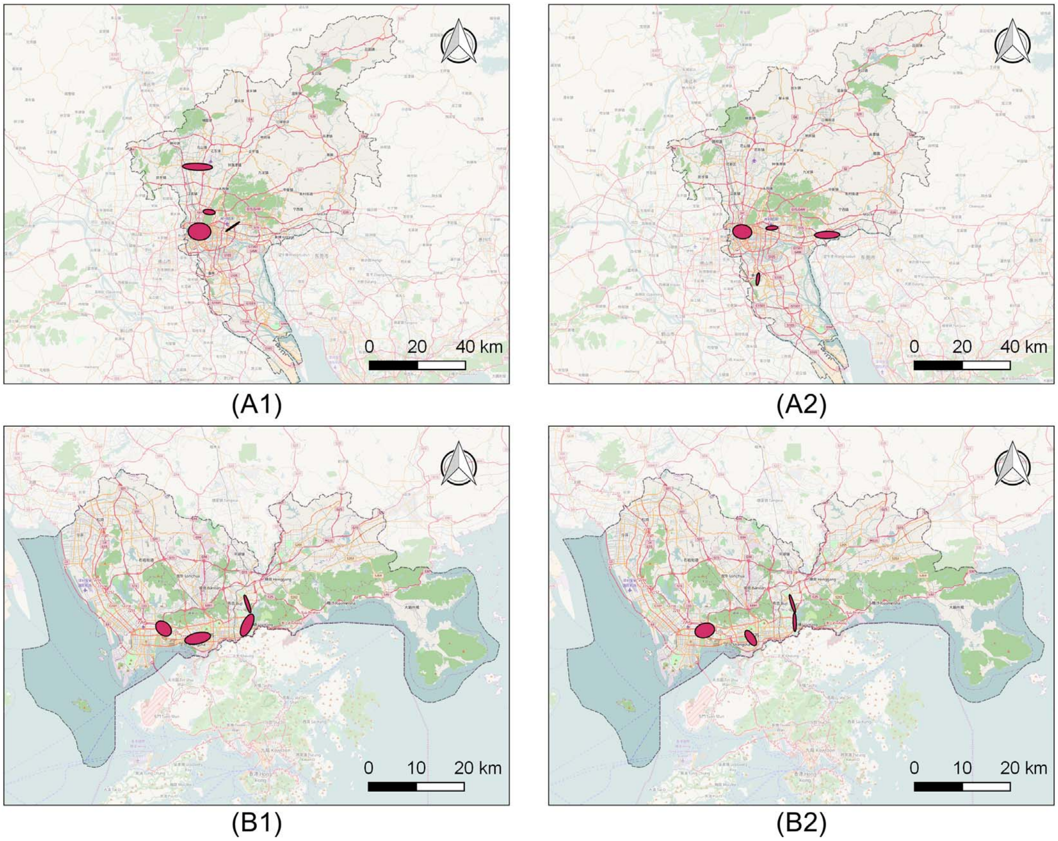

Fig. 13. Traffic congestion area of (A1) Guangzhou before CO policy, (A2) Guangzhou after CO policy, (B1) Shenzhen before CO policy, and (B2) Shenzhen after CO policy.

study conducted a preliminary simulation of urban traffic flow, which was mainly based on the hypothesis of the correlation between traffic flow and human activity. However, urban traffic is a very complex interaction system with many variables that need to be considered. In the future, coupling multi-agent system modeling and ant colony algorithms to simulate urban traffic is worth studying, where various variables could be considered to obtain more detailed and accurate urban traffic flow simulations under different policy environments.

Another noteworthy issue is the Braess's paradox (BP), which is a counterintuitive phenomenon that in a "selfish routing" traffic network, removal of certain edges can improve the performance of the network's equilibrium flow (Murchland, 1970). As BP frequently occurs in large-sized networks (Valiant & Roughgarden, 2010), BP will unquestionably be found in the road network involved in this study, which may affect the traffic improvement of opening residential communities to some extent. Nevertheless, it should be mentioned that the detection of BP is a computationally intractable problem (Park, 2011; Roughgarden, 2001), especially in large urban road networks (Bagloee et al., 2014). The previous BP detection study was performed on a small scale using the heuristic approach (Bagloee et al., 2014). Because of the large network structure, it is extremely difficult for us to simulate the BP problem under real conditions.

Despite some of the abovementioned disadvantages, the proposed research framework is the first to quantitatively explore the impact of the CO policy on traffic roads and residents' commuting at a large scale. This study not only measures the overall effect and understands the best possible outcome of opening gated community but also assists government officials and urban planners in predicting the possible alterations in traffic flow, traffic congestion points and areas, and even urban land use. However, several realistic issues should be noticed in the execution of the directive. For example, because of the different locations and surrounding environments, opening different communities will generate distinct impacts on urban traffic systems. How and in what order the community will be opened is a complex optimization problem. This study proposed a research model to evaluate the impact of opening communities, and on the basis of this model, the process of opening community could be optimized, which is also our forthcoming work.

This study analyzed the influence of the CO policy on road network structures, urban resident commuting efficiency, and the alteration in traffic congestion centers using the ant colony algorithm and complex graph theory. The experiments were carried out in four major Chinese cities, namely Beijing, Shanghai, Guangzhou, and Shenzhen, and the mitigation effect of the policy on traffic congestion in each city was analyzed. The results demonstrated that the CO policy significantly improved the connectivity of the road network and generated positive impacts on the short-distance commuting of the vast majority of residents. For the residents who travel within 5 km on weekdays, which accounts for approximately 45% of the total travel, the commuting time decreased by 3.11%, 2.95%, 1.74%, and 1.51% in Guangzhou, Shanghai, Shenzhen, and Beijing, respectively.

Furthermore, as considerable amounts of roads are added to the urban road network, the traffic flow will be more dispersed after the implementation of the CO policy, alleviating local traffic congestion in city center areas. Moreover, it is worth noting that the degree of mitigation varies from city to city, and its impact on traffic congestion in Beijing and Shanghai is more obvious, while limited effects are found in Guangzhou and Shenzhen. In general, the CO policy has a certain positive effect on easing the traffic pressure in first-tier Chinese cities. Nevertheless, given that the traffic congestion problem in large cities is both long-standing and highly complex, remitting or even resolving the issue fundamentally requires a meticulous study of the actual situation of each city and the introduction of targeted policies.

In short, this study will enable the prediction of possible changes to urban space before the full implementation of the CO policy, providing references for policy makers and urban planners.

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