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Potential Change of Spatial Accessibility to Health Services With the Opening of Private Streets in Shenzhen, China

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ABSTRACT The spatial accessibility to urban health services is a key issue for urban environment and public health studies, especially among developing countries with explosive population growth and limited urban land space. Chinese cities have experienced rapid growth and obtained remarkable economic achievements in the last three decades, while this also brings out numerous urban planning problems, e.g., spatial access disparities to urban services. For this, the Chinese government worked out a new policy, community opening policy, for the improvement of urban accessibility through opening the private intra-community streets and increasing the spatial density of public street network. Although this policy has not been implemented yet, this paper aims at predicting the extent to which the community opening policy increases the spatial accessibility to health services at different places. This paper simulates the new system of street network and compares the results of the spatial accessibility of health services within the current and potential (planned) network systems. More specifically, the Delaunay triangulation skeleton model is constructed from geographic information system building footprints data for generating intra-community street segments; then, with adding these private streets to the existing inter-community street network, the two-step floating catchment area method based on the network path distance is employed to assess spatial accessibility to health services under both the current and potential urban contexts of Shenzhen, China. The results show that the impacts of the community opening policy on spatial accessibility of health services have spatial variations, and the most positively and negatively affected places are gathered together in the center area of the city.

INDEX TERMS Spatial accessibility, public health, two-step floating catchment area, network analysis, Shenzhen.

I. INTRODUCTION

Spatial accessibility to urban health services is an important issue in fields such as urban planning [1], public health [2], spatial epidemiology [3], and health geography [4]. Urban region can be considered as a compact space crowded with populations, while it only has a health facility or a set of health facilities located at discrete locations [5], [6]. Poor accessibility to health facilities could lead to aggravation of health problems because treatment cannot be promptly given, especially for disease conditions that have a short incubation period. Actually, no matter the developed countries or the developing countries, either the wealthy or the poor cannot avoid such a proposition——equality and convenience of spatial access to health services, which is deeply relevant to their development and sustainability.

The Economic Intelligence Unit [7] suggests that the population of China's top twenty emerging cities (e.g., Shenzhen) will grow by twenty-seven percent over the next decades. This explosive population growth could bring out significant sustainability problems in compact city space with limited resources. In this regard, a series of strategies/policies have been recently proposed by Chinese government to prompt the current infrastructures and transportation systems to work more effectively. As one of the most discussed strategies in this year, community opening policy aims at opening gated communities for the purpose of optimizing the whole street network layout [8]. It is believed that opening the private intra-community streets will help to increase the spatial density of public street network and further improve residents' travel environment and urban landscape [9]. However, most of the previous studies are conducted from the perspective of jurisprudence, and empirical studies are quite few. Thus, this paper proposes to use data-driven methods to accurately assess potential impact of such a policy on the spatial accessibility of health services.

Accessibility implies the capacity of an individual to participate in activities, which is based on two elements including "supply" (facilities that provide health services) and "demand" (people who access healthcare services) [10]–[12]. The spatial interactions between supply and demand leads to the complex disparities in access to health services. For example, in China, as in many other developing countries, the health facilities are usually gathered together within few central areas, and some real estate developers also attempt to get the health facilities as an advertisement to publicize its new housing project in the proximity. Thus, the inequalities in the accessibility of health services are mainly caused by the lack of territoriality, sustainability, and coordination of planning. In this regard, assessing the accessibility in planned health care systems is essential for China's emerging cities, though it involves many complex factors such as service providers, population's socioeconomic properties, and transportation networks (e.g., street network).

Various studies have been conducted on the topic of accessibility, in order to highlight the impacts of various factors on opportunities to reach particular destinations. In a wide range of fields (e.g., employment and health services), many advanced models and methods have also been developed to calculate the accessibility indicators since the late nineties, when geo-referenced data acquiring and geographic information system (GIS) techniques begin to boom. GIS can facilitate the basic spatial-join operations in accessibility measures such as counting the number of providers within census tract boundaries and searching all of the providers near to a demand point according to their geometric distances (e.g., Euclidean distance and travel distance) [13]–[16]. Although previous research shares the same objective, i.e., identifying poorly served areas for healthcare, they usually employ different measures or approaches [17]. For example, Guagliardo [3] concluded four commonly used measures of accessibility to health services including provider-to-population ratios, distance to nearest provider, average distance to a set of providers, and gravitational models of provider influence. Recently, some scholars also classified accessibility measures into five groups: the distance to closest service, the number of services within a certain distance or travel time, the mean distance to all services, the mean distance to a certain number of closest services, and the gravity model [18]. The first four measures are easy to use and implement. The gravity model is inspired by Newton's law of gravitation, and it assumes that the spatial accessibility to a service diminishes with distance and that the associated travel impedance increases [5]. However, the gravity model only considers the impact of supply on spatial accessibility, while the access of health services is actually constrained by the complex interactions (containing spatial and non-spatial aspects) between population and services.

In order to take into account both the supply and demand of a service, another method referred to as two-step floating catchment area (2SFCA) method is developed [12], [19], [20]. Such method firstly constructs a spatial buffer (or catchment) using a certain bandwidth around each health service centroid and searches all the census tracts fallen within the catchment to compute the provider-to-population ratio of services; then it constructs catchments around census tract centroids to sum up the provider-to-population ratios of the enclosed services. In this way, the result is treated as the spatial accessibility index which is able to address the supply-demand issue. 2SFCA method shows a wide application prospect in health geography area, and thus many improved models have also been developed recently [21]–[23], e.g., improved 2SFCA method based on gravity model [20], [24], [25] and 3SFCA method based on competition scheme [26].

For all these methods there are three common factors: service capacity, population demand, and geographic impedance [27]. Previous research mainly focuses on the first two factors and their interactions, and few pay enough attention to the effects of geographic impedance on spatial accessibility to health services. It is believed that geographic impedance is capable of influencing accessibility in terms of street network layout [22], [28]. Therefore, this paper aims at assessing the potential spatial accessibility of health services under the community opening policy decision which is expected to change the street network layout in China's cities in the near future.

In sum, our paper includes the following contributions:

(1) The problem of assessing the impact of the community opening policy on the accessibility of health services is introduced;

(2) A new framework is developed using Delaunay triangulation model. Compared to the traditional 2SFCA methods, our method improves the accessibility measure by taking into account the potential change of geographic impedance.

(3) Our results identify the poorly served areas for healthcare under the context of the community opening policy, and those could have potential value in the processes

of urban planning, policy decision, and public health management.

The remainder of this paper is organized as follows. Section 2 introduces the study region and the methods, including the Delaunay triangulation skeleton mode used for generating intra-community streets and the 2SFCA method used for assessing the spatial accessibility to health services. Section 3 presents the experiment results and discussion. Section 4 concludes this paper with an outlook.

II. FRAMEWORK

As described in Section 1, there are three main factors which should be taken into account in our application: the health services, the population, and the computation of 2SFCA measures based on network shortest-path distance. The data of health services and population has been stored in official databases or web open access data sources. Since our study aims at calculating the accessibility measures under a potential urban landscape which is formed by the community opening policy, a pre-computation step should be conducted in order to simulate the planned street network. In this way, it is possible to assess the potential change of accessibility to health services after sharing the private intra-community streets with the public in the study region. In sum, there are two main steps in the implementation of 2SFCA method in our context as follows.

First, simulate the potential street network under the context of community opening policy for calculating the network shortest-path distance between supply and demand. This step needs to generate the private intra-community street segments from GIS building footprint data (i.e., GIS polygon data) and then add these private streets to the public inter-community street network to form the simulated network. In China's GIS topographic database, the intra-community streets are usually not stored explicitly as the way that the inter-community streets are stored. In addition, the field surveying operations are costly. In this regard, additional data sources (e.g., remote sensing image data or GIS building footprint data) should be used in our research to automatically generate the intra-community streets. The main reason that we choose building footprint data instead of remote sensing image data for this task lies in the following two aspects: (1) since the intra-community streets in the study region are narrow, covered by the trees (please see Figure 1), it is hard to extract these private streets from remote sensing data; (2) the intra-community streets are sandwiched between rows of buildings in reality, and thus we can generate intra-community street segments from the building footprint data which has already been stored in GIS topographic database. More specifically, computational geometry techniques (e.g., Delaunay triangulation skeleton model) and graph models are used here to construct the potential street network (please see Section 3.2).

Second, calculate the 2SFCA accessibility measures of health services in the two networks–pre and post the planning, in order to identify those areas with poorer or better accessibility after opening communities. Based on the data of health services and population, 2SFCA accessibility measures are calculated using the network distances, which are considered in two network systems, i.e., the current network without private streets and the simulated network with private streets. By comparing the results, the impact of the community opening policy on accessibility to health services can be evaluated quantitatively. Furthermore, it can provide policy decision makers with accurate information by mapping accessibility measure values in city space.

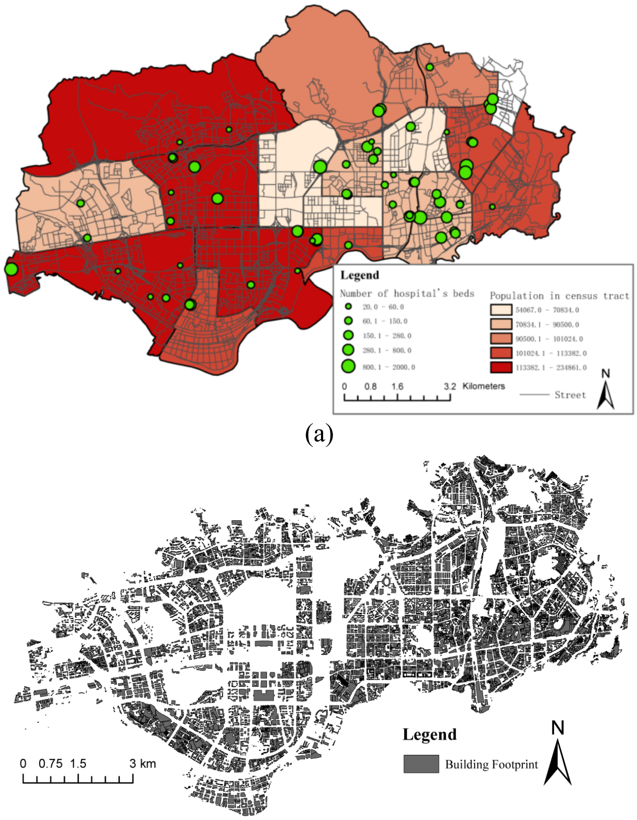
FIGURE 1. An illustration of private intra-community streets existing between buildings but hidden beneath lush trees using Google Earth image.

III. DATA AND METHODS

A. DATA

The study city is Shenzhen, which is one of the most developed cities in China due to the adoption of the policy of reform and opening up. This study focuses on the central areas of Shenzhen, Futian and Luohu districts, which are the first special economic zone in China (Figure 2) [29]. The reason that we choose these areas is in the last decades the special economic zone has usually been chosen by the Chinese government for the testing of new policies. Therefore, the community opening policy will probably be implemented first in Futian and Luohu districts. In addition, the land use of these areas is much intensive and there is not much available space for constructing new road infrastructures. In this regard, in order to optimize the current street network systems in the study region, sharing the private streets with the public could be a promising solution. Therefore, we collected relevant data from the official sources of Shenzhen for assessing the potential impacts of the community opening policy on accessibility.

Our application requires three types of data including the health services, the population, and the GIS topographic datasets. More specifically, the data of health services in our case study contains 65 hospital points with a total of 20326 beds (Figure 2a). Hospital points and their property were provided by the Urban Planning



(a)

(b)

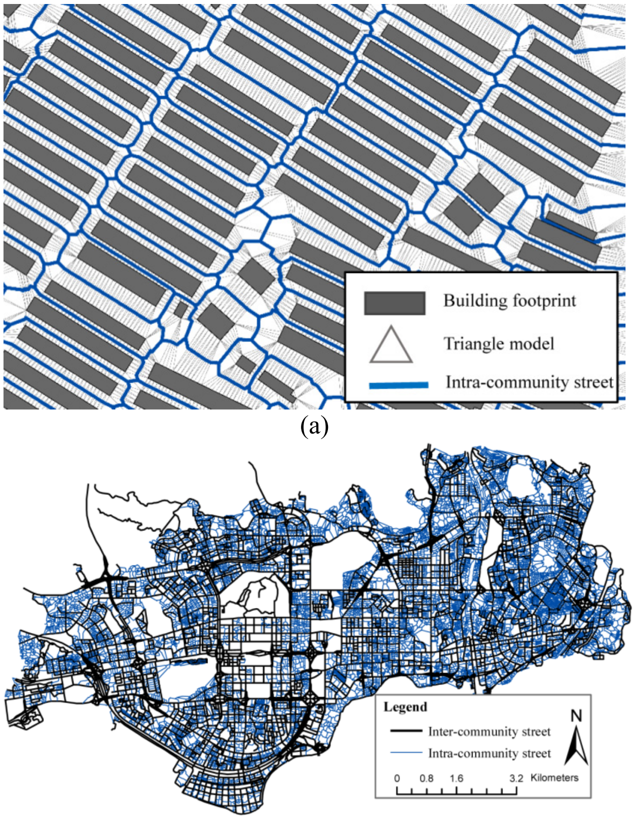
FIGURE 2. Data sets in Shenzhen: hospital locations and census tracts (a), and building footprints (b).

Land and Resources Commission of Shenzhen Municipality (UPLRCSM). In addition, the data of population contains 18 census tract polygons with a total of 2068958 inhabitants (Figure 2a). Census tract polygons were provided by the UPLRCSM, and the demographic data was collected from the website of the Shenzhen Bureau of Statistics [30]. This website provides the most recent census data of 2010. Finally, the GIS topographic data contains 6338 inter-community street segments and 14164 building footprints (Figure 2b), which were also provided by the UPLRCSM. The inter-community street segments were generated by splitting the original network at the street intersections. Based on the building polygons, computational geometry techniques were used to generate the intra-community street central lines (please see Section 3.2).

B. METHODS

1) DELAUNAY TRIANGULATION MODEL FOR GENERATING INTRA-COMMUNITY STREET SEGMENTS

As shown in Section 2, the first step of our method is to generate intra-community street segments from building footprint data. Within a private community, intra-community street central lines are usually along the middle of neighboring building polygons. Thus, this process can be divided into two sub-processes: extracting the gap space between neighboring buildings and generating the skeleton lines of gap space. Therefore, we propose to use Delaunay triangulation model for these purposes. Delaunay triangulation is a well-known model in computational geometry domain for identifying and analyzing the proximity relations between geometric objects [31]–[33]. It is the dual graph of Voronoi diagram, which can assure no input point is located within the circum-circle of any Delaunay triangle. Delaunay triangulation has also been extensively used in the skeletonization of a GIS polygon because of its merits such as avoiding sliver triangles and maximizing the minimum angle [31]. Thus, our method uses this model for generating intra-community streets as shown in the following four procedures (Algorithm I).



(a)

(b)

FIGURE 3. Generating intra-community streets from building footprints data using Delaunay triangulation skeleton model: the Delaunay triangulation skeleton model (a) and the simulated street network in Shenzhen (b).

(1) First, construct a Delaunay triangular network (see grey lines in Figure 3) for the boundary points of building footprints (Step 1).

(2) Second, remove the triangles the three vertices of which are located on the same building footprint's boundary, and keep the other ones the vertices of which are located on at least two building footprints' boundaries (Steps 3-9).

(3) Third, connect the midpoints of the sides of the remaining triangles to form skeleton lines of the gap space (see blue lines in Figure 3). In this way, each community will have a skeleton network, which corresponds to the network of private intra-community streets (Steps 10-12).

Algorithm 1 Delaunay Triangulation Based Skeletons

```
Inputs:
  {$b$}: the set of building footprints
  {$e$}: the set of inter-community street segments
Outputs:
  the network $N$ consisting of the inter-community streets {$e$} and the skeleton lines {$e'$} between neighboring buildings
Steps:
  (1)  D←Triangulation({$b$}) // construct the Delaunay triangular from the buildings using the incremental algorithm
  (2)  $T \leftarrow \Phi$ // Initialize the triangle set $T$
  (3)  for each triangle $t$ in D do
  (4)        if all the three vertices of $t$ are located on the same buildings then
  (5)        continue
  (6)        else
  (7)        insert $t$ into $T$
  (8)     end if
  (9)  end for
  (10) for each triangle $t$ in $T$ do
  (11)      $e'$ ←Line(midpoint($e_1$), midpoint($e_2$)) // connect the midpoints of the edges $e_1$ and $e_2$ of $t$ that are not on the buildings
  (12) end for
  (13) return $N$ ←{$e$, $e'$}
```

(4) Finally, add the skeleton lines generated from Step (3) to the surrounding inter-community street lines and construct their topological relations in order to form a complete network structure (Step 13).

Based on the procedures above, the potential street network after opening private communities can be simulated, which is the basis of calculating accessibility measures to health services in the planned urban environment. As presented Figure 3b, the generated street network contains 45138 segments. In this way, it is possible to assess the potential effects of the community opening policy on increasing accessibility. Although the spatial density of street network increases with the implementing of this policy, the potential change of accessibility to health services can vary across the space because it must consider the supply-demand issue.

2) TWO-STEP FLOATING CATCHMENT AREA METHOD FOR CALCULATING ACCESSIBILITY TO HEALTH SERVICES

The 2SFCA method improves the classic gravity model by considering both aspects of supply and demand [12], [19]. Since this method was first proposed by Radke and Mu [12], it has been widely used to estimate spatial accessibility to health services in an urban environment. The calculating of 2SFCA measures involves two main steps as following.

(1) First, construct a buffer area (catchment) with a threshold distance (d) for each health service j, searching all census tract centroids (demand locations) within such catchment and calculating the supply-to-demand ratio R_j using the following equation (Steps 1-21 in Algorithm II ***2SFCA***).

$$R_j = \frac{S_j}{\sum_{k\in\{\mathrm{ND}(k,j)\le d\}} D_k} \tag{1}$$

where ND(k, j) is the distance between the demand location k and the supply location j, S_j is the capacity of supply j (i.e., the number of beds), and D_k is the demand (i.e., the population) at location k within the catchment. In our research, the distance is calculated as the shortest-path length along the street network between the locations k and j. Thus, the network expansion procedure is employed in our algorithm (Steps 7-19 and Steps 24-36).

(2) Second, construct a catchment with distance d for each demand location k (census tract centroid), searching all health services within such catchment and summing up all the supply-to-demand ratios at these service locations to obtain the final accessibility A_k^F at the demand location k(Steps 22-39 in Algorithm ***2SFCA***). The accessibility measure A_k^F is calculated as follows:

$$A_k^F = \sum_{j\in\{\mathrm{ND}(k,j)\le d\}} R_j \tag{2}$$

where ND(k, j) is the network distance between the demand location k and the supply location j, and R_j is the supply-to-demand ratio at supply location j within the catchment of k.

As presented above, the 2SFCA method adopts an intuitive way to address the supply-demand issue. Its steps are also easy to be implemented in a GIS environment. Although there are many successful works on the 2SFCA method and related applications, they mainly focus on the accessibility in the current urban environment, and there are few research work on the potential effects of the urban planning policies on changing 2SFCA accessibility. The reason could be due to the difficulty of simulating the new urban environment under the context of policies. The policy concerned, i.e., the community opening policy, has been expected to improve the poor accessibility conditions in China's cities through increasing the spatial density of public street network. However, empirical research on this issue remains scarce. It is important to employ GIS techniques (e.g., Delaunay triangulation model) to assess the community opening policy to support policy decisions about health service accessibility.

For Algorithm I, the first step of constructing the Delaunay triangular network (Step 1) is based on the incremental method, and thus it has the computational complexity of O(n log n) [31], where n is the number of points on the boundaries of buildings; then since Steps 3-9 needs to traverse all the triangles, it has the complexity of O(m), where m is the number of triangles. In addition, for generating skeleton lines from the triangles, each triangle side would be evaluated in Steps 10-12. Thus, Steps 10-12 have the complexity

Algorithm 2 2SFCA

```
Inputs:
{$j$}: the set of health service points
{$k$}: the set of census tract points
$N = \{\{n\},\{e\}\}$: the street network consisting of nodes {$n$ } and edges {$e$ }
$d$: the threshold distance for catchment
Outputs:
the accessibility values {$A_k^F$ } for the census tracts {$k$}
Steps:
(1)  for each health service point $j$ do
(2)      $n_j$ ←Project($j$) // project $j$ to the nearest node $n_j$
             on the network $N$ using the Euclidean
             distance measure Distance($j$,$n_j$) ≦Distance($j$,$n$),
             where $n \in N$.
     end for
(3)  for each census tract point $k$ do
(4)      $n_k$ ←Project($k$) // project $k$ to the nearest node $n_k$
             on the network $N$ using the Euclidean distance
             measure Distance($k$, $n_k$) ≦ Distance($k$, $n$),
             where $n \in N$.
     end for
(5)  for each node $n_j$ in {$n_j$ } do
(6)      Initialize the min-heap $H$ and insert $n_j$ into $H$ with
         key (i.e., $n_j.dis$) set to 0
(7)      while $H$ is not empty do
(8)          Deheap the top node $n_{min}$ from $H$ with minimum
             key and mark it as visited
(9)          for each edge $e$ connected to $n_{min}$ do
(10)             if the start-node $n_{start}$ of $e$ is unvisited and
                 $n_{min}.dis+e.length \leqq d$ then //$e.length$ is the
                 weight of the street segment $e$.
(11)                 $n_{start}.dis \leftarrow n_{min}.dis+e.length$
(12)                 insert $n_{start}$ into $H$
(13)             end if
(14)             if the end-node $n_{end}$ of $e$ is unvisited and
                 $n_{min}.dis+e.length \leqq d$ then
(15)                 $n_{end}.dis \leftarrow n_{min}.dis+e.length$
(16)                 insert $n_{end}$ into $H$
(17)             end if
(18)         end for
(19)     end while
(20)     $R_j \leftarrow \frac{S_j}{\sum_{k\in\{n_k.dis\leq d\}} D_k}$ // calculate the supply-to-
         demand ratio R$_j$ according to Equation (1)
(21) end for
(22) for each node $n_k$ in {$n_k$ } do
(23)     Initialize the min-heap $H$ and insert $n_k$ into $H$
         with key (i.e., $n_k.dis$) set to 0
(24)     while $H$ is not empty do
(25)         Deheap the top node $n_{min}$ from $H$ with
             minimum key and mark it as visited
(26)         for each edge $e$ connected to $n_{min}$ do
(27)             if the start-node $n_{start}$ of $e$ is unvisited and
                 $n_{min}.dis+e.length \leqq d$ then
```

Algorithm 2 *(Continued.)* 2SFCA

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(28)                 $n_{start}.dis \leftarrow n_{min}.dis+e.length$
(29)                 insert $n_{start}$ into $H$
(30)             end if
(31)             if the end-node $n_{end}$ of $e$ is unvisited and
                 $n_{min}.dis+e.length \leqq d$ then
(32)                 $n_{end}.dis \leftarrow n_{min}.dis+e.length$
(33)                 insert $n_{end}$ into $H$
(34)             end if
(35)         end for
(36)     end while
(37)     $A_k^F = \sum_{j\in\{n_j.dis\leq d\}} R_j$ //calculate the accessibility
         measure $A_k^F$ according to Equation (2)
(38) end for
(39) return {$A_k^F$ }
```

of O($3m$). In sum, the computational complexity of Algorithm I is O(n log n) + O(m) + O($3m$). Since the number of points on the building footprints is larger than the number of triangles, the complexity of Algorithm I is O(n log n).

For Algorithm II, the complexity of Steps 1-4 is O(c_jc_v) + O(c_kc_v), where c_j, c_k and c_v are the number of health service points, the number of census tract points and the number of nodes on the network, respectively. Since the catchments of census tract points and health service points are constructed based on the network distance, the computational complexity of Steps 5-39 depends on the classic Dijkstra's algorithm (Steps 6-19 and Steps 23-36). Dijkstra's algorithm has the complexity of O(c_v log c_v), and thus the complexity of Steps 5-39 is O(c_jc_v log c_v) + O(c_kc_v log c_v). In sum, Algorithm II has the time complexity of O(c_jc_v) + O(c_kc_v) + O(c_jc_v log c_v) + O(c_kc_v log c_v), and that can be simplified as O(c_jc_v log c_v) + O(c_kc_v log c_v). Therefore, our proposed algorithms have the complexity of O(n log n) + O(c_jc_v log c_v) + O(c_kc_v log c_v).

IV. SETTINGS, RESULTS AND DISCUSSION

A. SETTINGS, RESULTS AND ANALYSIS

Our algorithms were implemented in ArcGIS 10.1 using C# language. We calculated the spatial accessibility measure values at 1000 m, 3000 m, and 5000 m network shortest-path distance. These threshold distances were set according to Apparicio *et al.* [2], which suggests to use 2000-m threshold to calculate the 2SFCA measure values. Since our census tract polygons have a larger variation in size than those of Apparicio *et al.* [2] (please see Figure 2a), we chose the thresholds of 1000 m, 3000 m, and 5000 m to fully reflect the catchment areas of health services at different scales. In addition, as presented in Apparicio *et al.* [2], most of the transportations (e.g., car and bicycle) that the people use to move to the suppliers depend on the street network layout; and thus our catchment sizes were calculated based on the shortest path of the street network. Furthermore, in order to present more details of accessibility in local areas, we break down the census tracks into smaller subsets, i.e., 300 m × 300 m grid. The population of each census tract is assigned to its cells equally. The total number of cells in the study region is 1367.

Figure 4 presents that the spatial distributions of accessibility scores have a significant clustering tendency from the current network system to the simulated network system under the community opening policy. Specifically, the central and eastern parts have the highest accessibility scores in the study region, while the other parts have a relative low accessibility score. The reason could be that the central and eastern parts are located within the Central Business District (CBD) of Shenzhen, in which street infrastructures and public services are more than those in other areas. Although opening private intra-community streets will increase the spatial density of street network in all the areas, some parts of the study region could obtain a higher density of public network than the other parts, because they have more local intra-community streets (please see Figure 3). In addition to the "supply" and "demand", the public network infrastructures can also affect the accessibility change under the community opening policy by reducing the travel impedance between "supply" and "demand". As presented in Figures 4b, d and f, the spatial access disparity to health services is still a major problem in the simulated environment, and thus an effective strategy is needed for improving the health care system in the city.

Our results at different threshold distances also show that the spatial variations of accessibility scores become less significant with the increase of the distance. From the 5000-m catchment to the 1000-m catchment, the standard deviation of accessibility scores in the current network system increases from 0.006071 to 0.020492 (Table 1). Accessibility scores estimated in the simulated system show smaller variability than those in the current system with the decrease of the distance. This indicates that by travelling a shorter distance the capacity of residents to reach a health service shows a larger spatial variation among the areas. This will become less obvious in the simulated network system. Therefore, whether the government opens the intra-community streets or not, the spatial access disparity to health services should be given more attention from the local scale than from the global scale in Shenzhen.

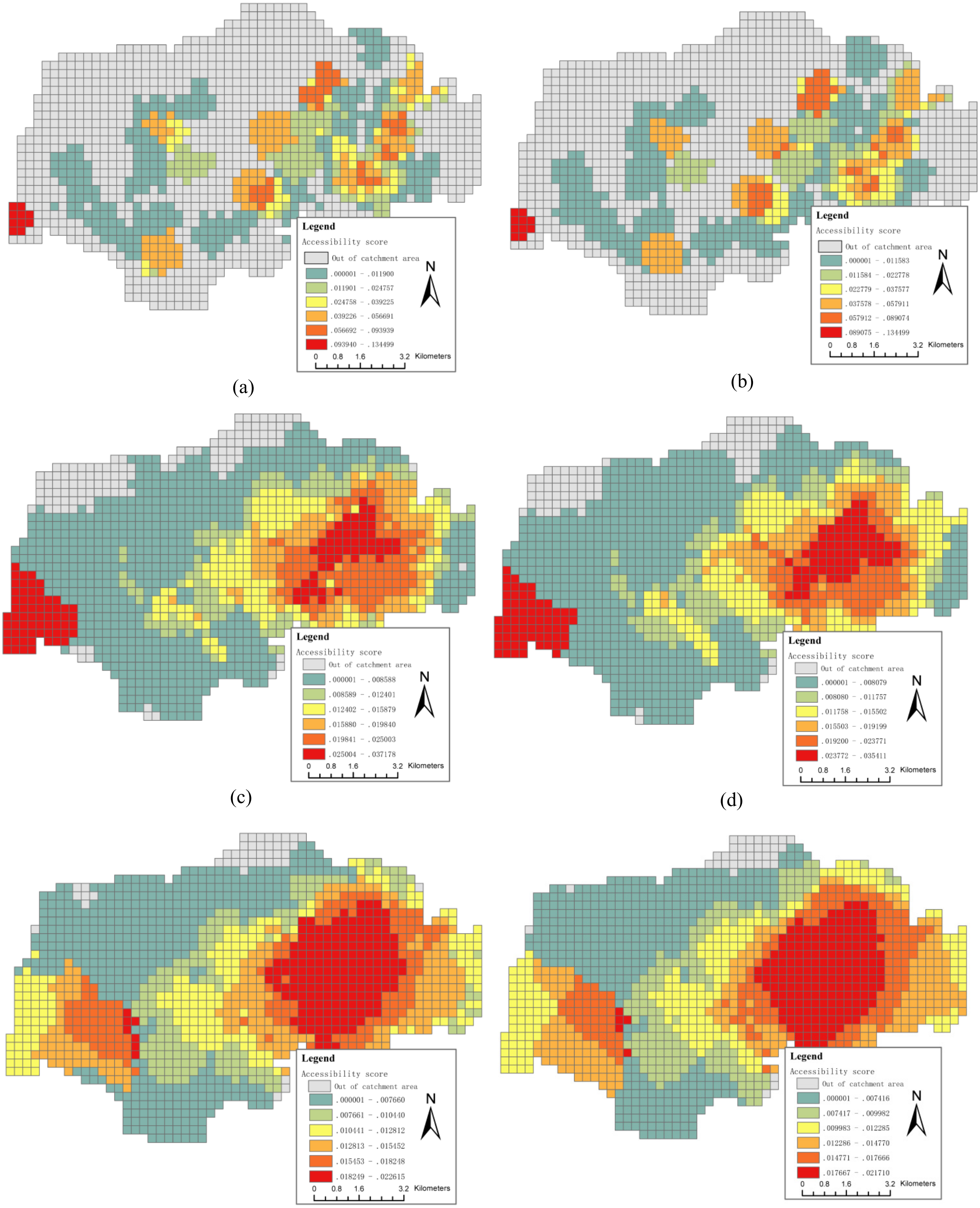
In order to better understand the change of the accessibility to health services in the simulated system, we also mapped the differences of the accessibility scores in the study region. Results are presented in Figure 5 and Table 2. A positive score in Figure 5 and Table 2 indicates an improvement of accessibility from the current urban system to the simulated urban system, and a negative score indicates a worsening of accessibility in this process. It can be observed that the potential impacts of the community opening policy on accessibility have spatial variations, and for all the three threshold distances there always exists positive scores and negative scores in the study region. That means when some residents enjoy the benefits brought by the community opening policy, some other residents also suffer from the worsening of accessibility to health services. More specifically, both of the most positively affected areas and the most negatively affected areas are detected in the central part of the region. With the increase of distance, more areas obtain a non-zero score and they are distributed in the CBD and its surroundings. In general, the number of the areas that are negatively affected by the policy increases with the distance. The accessibility differences brought by the policy is maximum at 1000 m distance (please see Table 2). Therefore, the change of public street infrastructures caused by the community opening policy can affect the health services both in terms of accessibility score magnitude and accessibility score distribution.

TABLE 1. Statistics of accessibility scores in the current urban system and simulated urban system after sharing the intra-community streets with the public.

Statistics	Current urban system			Simulated urban system		
	1000 m	3000 m	5000 m	1000 m	3000 m	5000 m
Mean	0.009741	0.010222	0.010692	0.009854	0.010243	0.010749
Std. Dev.	0.020492	0.008716	0.006071	0.020446	0.008298	0.005735
Min	0	0.000628	0.002746	0	0	0
Max	0.134499	0.037178	0.022615	0.134499	0.035411	0.021710

TABLE 2. Differences of accessibility score between the current urban system and the simulated urban system after sharing the intra-community streets with the public.

Bandwidth	Mean	Std. Dev.	Min	Max	Number of positive scores	Number of negative scores
1000 m	0.000113	0.006763	-0.045982	0.074401	247	335
3000 m	0.000021	0.002439	-0.026213	0.024328	339	943
5000 m	0.000057	0.001802	-0.013013	0.012525	383	946



(a)

(b)

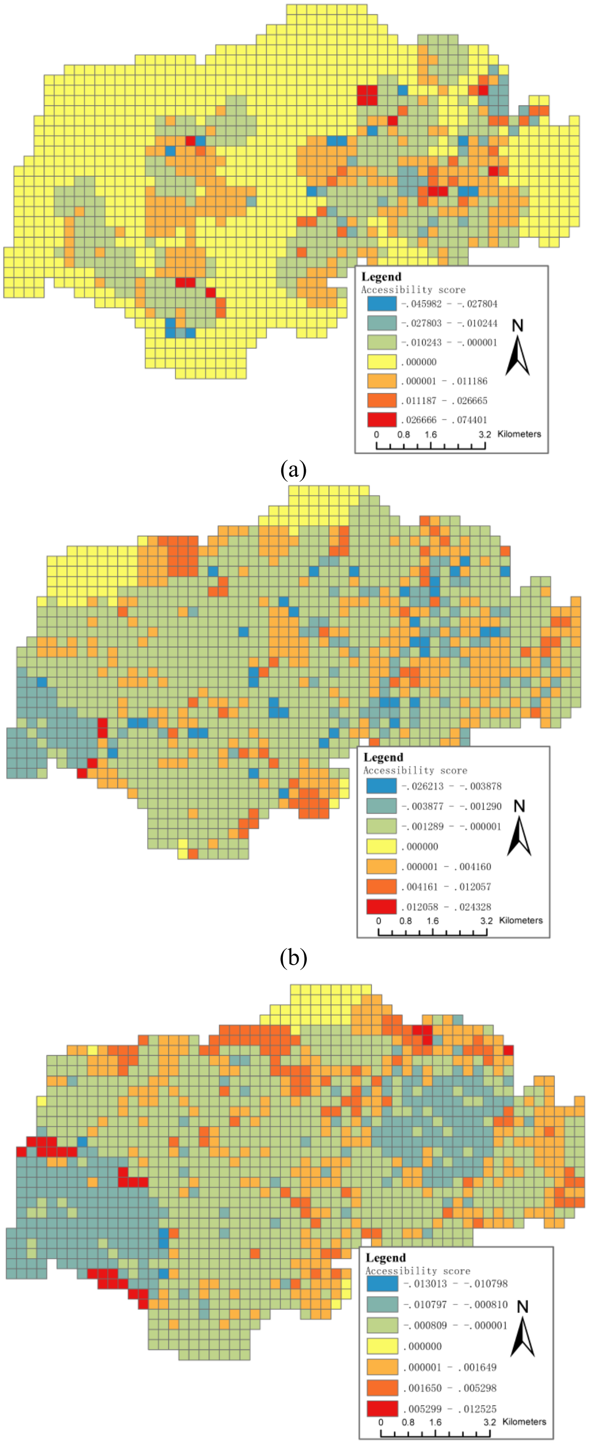
(c)

(d)

(e)

(f)

FIGURE 4. **Accessibility scores of 2SFCA method at different threshold distances within the current street network system and the simulated street network system: the current street network at 1000 m (a), the simulated street network at 1000 m (b), the current street network at 3000 m (c), the simulated street network at 3000 m (d), the current street network at 5000 m (e), and the simulated street network at 5000 m (f).**



(a)

(b)

(c)

FIGURE 5. **Differences of accessibility scores between the current street network system and the simulated street network system at different threshold distances: the catchment of 1000 m (a), the catchment of 3000 m (b), and the catchment of 5000 m (c). A positive score indicates an improvement of accessibility from the current urban system to the simulated urban system, and a negative score indicates a worsening of accessibility in this process.**

We also evaluated the behavior of the algorithm when the input data size varies. Figure 6 presents the result. The computational cost of the algorithm increases with the increase of building data size. The reason could be that the size of the Delaunay triangular network to be analyzed is closely related to the number of building footprints. Nevertheless, our algorithm achieves satisfying effect in efficiency when applied to a large data set (Figure 6).

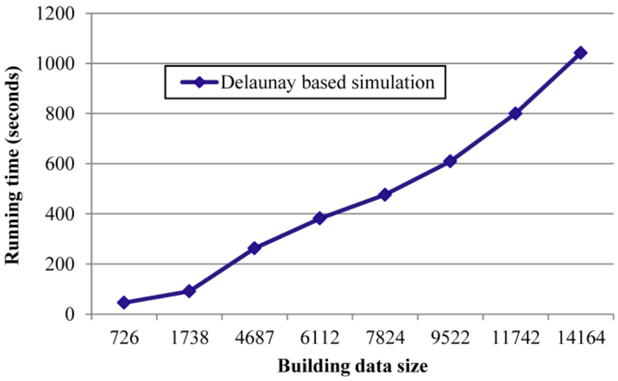


FIGURE 6. **Performance of the algorithm with the building data size.**

B. DISCUSSION

Our study is under the context of "opening community", which can be traced back to the "New Urbanists" by Benevolo [34], Crane [35] and Katz *et al.* [36]. The "New Urbanists" that aim at developing ecological practices from community is popular in the modern urban planning domain. It tries to "calm" the traffic, straighten the streets and optimize the land uses through re-developing built environments. As a supporter of the accessible public space, the "New Urbanists" suggest to re-develop the landscape of communities for open space. In this regard, the movement of "opening community" can be considered as an example of the planning idea of "New Urbanists". It is believed that a sustainable neighborhood environment can promote the interactions between residents. Specifically, the streets within communities have a large impact on the mobility, physical and mental health, neighborhood safety and demographics (e.g., gender and income). For example, Oakes *et al.* [37] prove that improving street connectivity is able to affect the walking activities within neighborhood. Giles-Corti *et al.* [38] find that high-density street network benefits the children to walk to school. In addition, connected street network can increase the potential for residents to access local services [39], [40].

As presented in Figure 4, the simulated results allowed us to assess the potential impacts of the community opening policy on spatial accessibility to health services. This can be valuable for policy decision because previous research mainly focus on the theoretical aspects of the community opening policy [41]. Actually, our case study also reveals the key to understanding it. First, high accessibility scores were found to be clustered in the CBD of the study region, whether in the current network system or in the simulated network system. This is understandable because of the following two reasons: first, both the inter-community streets and the intra-community streets have a higher spatial density in the central part than the other parts; second, many hospitals with high capability are crowded into the CBD area. Since the accessibility level in the simulated network system varies across the space, some efforts are still needed to reduce the spatial access disparity to health services. For example, it may be feasible to add new infrastructures to the health service shortage areas. In addition, in the current urban system of Shenzhen, government agencies consumes large amounts of land and open space, and it would be beneficial to transfer some of these lands to the health service land, as suggested by Chen and Li [41].

Second, another finding is that in the simulated environment the spatial access disparity to health services is more significant at low distance than at large distance. We realized that for balancing the local accessibility variations the urban planners may consider measures to improve the capacity of branch roads and achieve traffic microcirculation. In addition, since the elders are very dependent on the health services at low distance, the large spatial access disparity in the simulated environment could have a larger impact on the wellbeing of the elders [2]. Anyway, our results confirm that although the community opening policy could increase the spatial density of street network, it cannot ease the problems of accessibility inequality of health services in Shenzhen.

Finally, results of comparing the accessibility scores pre the planning and post the planning indicate that the community opening policy can have both positive and negative impact on increasing accessibility to health services. As the distance increases, more places have a different accessibility level of health services in the simulated environment, compared with the current urban environment. The largest differences between the current environment and the simulated environment are concentrated in the CBD and its surrounding. Besides, the most positively and negatively affected areas are always located together in close proximity with the increase of the distance. There are two possible ways to reduce this disparity after opening private communities. Since the northern areas are less affected by the policy, the first way is to add new public street infrastructures in these areas to promote accessibility of health services. The second way is to consider the areas with health service shortage for new health service facilities. To the best of our knowledge, this is the first work that analyzes the health services in a potential urban environment under the context of the community opening policy.

V. CONCLUSIONS

Spatial accessibility to health services has always been a hot issue in health geography. In the past decades, there are many successful applications on this problem, especially in developed countries. As the main focus of this paper, the cities in developing countries are undergoing a rapid development of economy and society. It is believed that the governments should pay more attention to the public health problems (e.g., spatial access disparities to health services) in these changing cities. China, just like many other developing countries around the world, is experiencing a massive migration from rural to urban. This economic and demographic growth process have led to numerous social and health-related problems in Chinese cities especially in megacities. The Chinese government is also exploring the policies which can be implemented to optimize available resources in crowded urban space. Recently, the State Council of the People's Republic of China [8] raised the community opening policy which requires gated communities to share their private streets with the public in cities. The implementation of this policy will change the urban landscape, especially the way people travel. It is then important to assess the potential effects of the community opening policy on increasing spatial accessibility of health services. Nonetheless, empirical research on validating the community opening policy for accessibility remains scarce. Our research develops an effective method to simulate the potential street network system under the community opening policy and compare the differences of accessibility between the current urban system and the potential urban system. The proposed method combining the computational geometry technique and the 2SFCA measures enables the quantitative analysis of the community opening policy from the perspective of health service.

Our application results have also revealed that the community opening policy can have both positive and negative impacts on accessibility of health services in Shenzhen, China, and needs to be implemented carefully. After private streets are shared with the public, the most significant changes of accessibility exist in the CBD of Shenzhen, and the most positively and negatively affected areas are located together in close proximity. Further analysis found that the community opening policy can provide the biggest accessibility difference for the whole study region when the distance is equal to 1000 m. In addition, our results demonstrate that the spatial access disparities to health services still exist in the potential urban environment under the policy of concern. Nevertheless, future works investigating the improvement of the 2SFCA method are needed. For example, this paper only used the non-spatial data of population density because Chinese government limits access to other private data such as health status, financial status, and perception about health. But the idea underlying our framework, i.e., using Delaunay triangulation skeleton model and 2SFCA measure, is applicable to other types of non-spatial data. This can be implemented by integrating other non-spatial variables into the adopted accessibility function [42]–[45]. Besides, since the community opening policy is available for all other cities in China, it may be interesting to investigate the contribution of the proposed method in other urban contexts. Because GIS topographic data is confidential to the public in China, our research only considers the city area in which topographic data is available. In this regard, future applications need to take into account the edge effects—health services and transport infrastructures outside of the region also have an effect on the way people travel near the borders. Nevertheless, our research is a new attempt to use GIS techniques to predict health service accessibility under the context of government policies. With the rapid development of crowdsourcing techniques, lots of geospatial data have been accessible to the public. For example, from the website of the OpenStreetMap, we can easily obtain the up-to-date data of building footprints and inter-community street networks in different cities. In addition, although the intra-community street segments are difficult to be generated from the remote sensing images (please see Figure 1), we can use other public data sources such as taxi trajectory data to automatically detect and update the inter-community street segments [36]. The proposed method is also useful in other fields such as urban planning, transportation, and spatial epidemiology.

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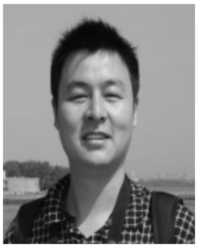

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