Journal of Transport & Health 15 (2019) 100675

Contents lists available at ScienceDirect

Journal of Transport & Health

journal homepage: http://www.elsevier.com/locate/jth

Incorporating multiple travel modes into a floating catchment area framework to analyse patterns of accessibility to hierarchical healthcare facilities

Xiangyuan Ma[a], Fu Ren[a,b,*], Qingyun Du[a,b], Pengcheng Liu[c,d], Langjiao Li[a], Yuliang Xi[a], Peng Jia[e,f]

[a] *School of Resources and Environmental Science, Wuhan University, Wuhan, 430079, China*
[b] *Key Laboratory of Geographic Information Systems, Ministry of Education, Wuhan University, Wuhan, 430079, China*
[c] *College of Urban and Environment Sciences, Central China Normal University, Wuhan, 430079, China*
[d] *Hubei Province Key Laboratory for Geographical Process Analysis& Simulation, Central China Normal University, Wuhan, 430079, China*
[e] *Faculty of Geo-Information Science and Earth Observation, University of Twente, Enschede, 7500, the Netherlands*
[f] *International Initiative on Spatial Lifecourse Epidemiology (ISLE), the Netherlands*

ARTICLE INFO

Keywords:
Healthcare facilities
Patterns of accessibility
Multiple travel mode
Three-step floating catchment area approach
Gaussian function
Wuhan

ABSTRACT

Introduction: The existing healthcare-services-related literature tends to examine accessibility under a single travel mode, and measurement approaches are remaining limited for several inherent deficiency. This paper proposed a methodological enhancement of the three-step floating catchment area approach.
Methods: First, we incorporates real-time travel time and trip distance of private car and public transport obtained from open-source route planning API into model, which aims to differentiate the impact of multiple travel costs on spatial accessibility outcomes; next, an arithmetic mean-based Gaussian weight algorithm was introduced for achieve stable accessibility index; then, exploratory factor analysis was further employed to evaluate healthcare capacity, with the total score as the healthcare supply indicator to calculate the provider-to-population ratios; finally, an empirical study was conducted to verify the model's advantages. We investigate accessibility to three tiers of healthcare facilities (including 22 tertiary hospitals, 88 secondary hospitals, and 55 community healthcare centres), and reveal disparities between supply and demand, via conjoint analysis of the accessibility of facilities and the population density under four associate patterns in the district of Wuhan at community scale (total 830 communities). Results: The results suggest that in terms of travel modes, the travel time and trip distance under the private car mode are shorter than these calculated under the public transport mode. Highly accessible communities are more concentrated in the central urban areas and distributed near a healthcare service centre, and community healthcare center have the greatest accessibility among the three tiers of healthcare. Moreover, statistical analysis highlights that distinct polarized differentiation appears in the number of communities with low and high accessibility, and more than half of the communities have accessibility levels that are inappropriate for their population size.
Conclusions: These findings may have important policy implications for health planners and decision-makers who must reasonably allocate public health resources.

* Corresponding author. School of Resource and Environmental Science, Wuhan University, 129 Luoyu Road, Wuhan, 430079, PR China.
E-mail addresses: maxiangyuan@whu.edu.cn (X. Ma), renfu@whu.edu.cn (F. Ren), qydu@whu.edu.cn (Q. Du), liupc3000@qq.com (P. Liu), lilangjiao299@163.com (L. Li), yuliangwh@163.com (Y. Xi), jiapengff@hotmail.com (P. Jia).

https://doi.org/10.1016/j.jth.2019.100675
Received 29 May 2019; Received in revised form 22 October 2019; Accepted 28 October 2019
Available online 18 November 2019
2214-1405/

1. Introduction

Public healthcare facilities, as the main body of medical systems, play a vital role in health security for city dwellers and have been a primary focus of policy planning, service provision, and health research for over forty years. In China, the acceleration of urbanization and the excessive centring of the population in urban areas have placed enormous pressure on the provision of medical resources and the functioning of the healthcare system (Dong and Phillips, 2010). Hence, since 2009 and the new medical reform, the Ministry of Health has actively explored feasible policies; in particular, establishing a hierarchical diagnosis mechanism and improving the treatment of referral systems are viable solutions to these issues with healthcare provision (Xu et al., 2016; Yang et al., 2018). Specifically, to meet different patients' demand for treatment, various tiers of healthcare facilities undertake corresponding diagnosis or treatment tasks based on their specialized function and service capabilities. For instance, for prevalent or common illnesses, patients are encouraged first to go to a primary hospital for treatment, while those with chronic diseases or who are convalescing receive a dual referral after diagnosis from a tertiary hospital to a secondary hospital; this process alleviates the predicament in which the different reasons for hospitalization overly concentrate patients in tertiary hospitals, optimizing the allocation of medical resources and realizing the orderly flow of patient groups across all levels of healthcare facilities (Chen et al., 2013).

In Wuhan, as the most important metropolis in Central China, health authorities have carried out a battery of measures to practice these policies. In Wuhan, 52% of outpatient and emergency treatment tasks were undertaken by primary hospitals, and 57% of inpatient services were supplied by tertiary hospitals. In contrast, only 9% of outpatients and emergency patients and 14% of inpatients opted for secondary hospitals. This means that Wuhan is still far from establishing a rational hierarchical diagnosis and dual referral treatment scheme. It is necessary to clarify the mechanisms behind this imbalance in hospitalization behaviour at the population group level from the perspective of geographical spatial analysis(Jia et al., 2019a). Indeed, numerous specific factors may influence the patients' choice of hospital: the provision of healthcare services (e.g., location, healthcare number, facility size, service capacity), the distribution of the demand population (e.g., population scale and composition, attractiveness of alternative facilities), and the travel cost (time or distance, geographic impedance) between such pairs are the most pivotal factors(Jia and Xierali, 2015). These factors can be discussed together by integrating them into an analytical framework for measuring spatial accessibility.

In a more general sense, the spatial accessibility of healthcare facilities, as an important potential driver of health equality, is at the heart of public health policy and is internationally recognized as a primary target for meeting the essential health demands of individuals (Barbara et al., 2010). Hence, reducing the barriers to access to healthcare facilities and revealing distribution disparities are becoming a greater priority for planners, especially among developing countries with increasing populations (Chan, 2013; Xi et al., 2014). Moreover, measuring the spatial accessibility of healthcare facilities in residential areas at a fine scale (e.g., neighbourhood and community scales) helps to provide a better understanding of the linkage between the distribution patterns of healthcare facilities (supply side) and the characteristics of health needs (demand side) and provides crucial knowledge to inform health policy in terms of planning service provision (Jia et al., 2017a, b; Jiang et al., 2017; Johan et al., 2015).

Thus, in response to the above-mentioned challenges, we attempt to hierarchically measure the spatial patterns of accessibility to different tiers of healthcare facilities for help better implement the hierarchical diagnosis and dual referral treatment policy in Wuhan. This work was built upon previous efforts to further this field, and our study aims are three-fold:

(1) We apply a floating catchment area framework algorithm, which uses the three-step floating catchment area (3SFCA) approach, to investigate the hierarchical accessibility patterns of three tiers of healthcare facilities and analyse the spatial disparities between supply and demand under the private car travel mode (PCTM) and public transport travel mode (PTTM) at a community scale in the urban districts of Wuhan, China.
(2) We propose an arithmetic mean-based Gaussian weight instead of the previously used changing geographic impedance-based Gaussian weight to address the native deficiency of the 3SFCA approach, in which the accessibility values exhibit unstable variations with changes of the geographic impedance coefficient and obtain stable accessibility values.
(3) We employ exploratory factor analysis (EFA) to calculate the service capacity score of healthcare facilities, and the generated comprehensive indicator was added into the 3SFCA models to calculate provider-to-population ratios (PPRs), which may be more persuasive than a one-sided indicator, such as the number of physicians or hospital beds.

The remainder of this paper is organized as follows: Section 2 reviews the main approaches of previous studies and illustrates the novelty of our work. Section 3 introduces the study area and data preparation and provides the details of the methodology used in this paper. Section 4 describes the research results in detail. Finally, the advantages of the modified methods, limitations, and future work are discussed in section 5.

2. Literature review

2.1. Potential spatial accessibility of healthcare facilities: previous approaches

The potential accessibility of healthcare services refers to the possibility or opportunity for an individual to easily utilize facilities based on existing transportation conditions. Scholars have proposed many approaches to spatial accessibility metrics in the early literature, which broadly fall into two categories: 'container-based' and 'travel-cost-based' approaches (Lin et al., 2018; Souliotis et al., 2016; Wang and Onega, 2015). The former metric comprises counting the number of healthcare facilities within the census unit, calculating the number of consumers within a given cost to travel to the demand site, and then calculating the PPR within the boundaries of a fixed administrative region. However, the fundamental weaknesses of this ratio are well recognized: the inability to reveal spatial details inside the census unit, such as potential cross-border hospitalization behaviours, and an innate assumption that no interaction effects occur within administrative boundaries (Albert and Butar, 2005; Mcgrail and Humphreys, 2009). Furthermore, container-based approaches are vulnerable to the effects of the modifiable areal unit problem, whereby the results may be influenced by scale effects (e.g., the sizes of the spatial unit and the container object) and zone effects (e.g., the aggregation of attribute data from small spatial units results in uncertain variation in the areas and boundaries of the merged spatial units)(Delamater, 2013).

2.2. Gravity model-derived floating catchment area approaches

To address these inherent limitations of the container-based approach, some elaborate analysis approaches have been proposed, such as the gravity model and the floating catchment area framework (Schuurman et al., 2010; Wang and Luo, 2005). The gravity model, as a typical travel-cost-based approach, has been broadly used to measure spatial accessibility since the 1980s, and it assumes that the attractiveness of a service facility diminishes with the increase in travel cost and the associated increasing traffic impedance. Likewise, the spatial accessibility of nearby healthcare facilities decreases with increasing travel time or trip distance in a gravitational manner. However, similar to the PPR approach, only pre-defined administrative boundaries or census units are used as the container objects (Fransen et al., 2015; Wang, 2012).

To solve this defect, the two-step floating catchment area (2SFCA) approach was proposed by Wang and Luo (2005), which builds upon the PPR framework and represents a specialized variant of the gravity model. In the first step, a trip distance or travel time catchment is set around each healthcare facility as a maximum travel threshold, and a PPR is computed within the threshold. In the second step, a similar floating catchment is defined around each population site (e.g., the population-weighted centroid of census units), and the spatial accessibility values are calculated by summing all PPRs within the zone (JohnRadke, 2000; Wang and Luo, 2005). In contrast to a gravity model, the catchment size was based on fixed administrative units but could be adjusted for the service capacities of the facilities and the travel or access abilities of the residents. The greatest improvement of the 2SFCA approach is overcoming the restriction of using only pre-defined boundaries and providing a metric that is more refined to interpret the potential to seek healthcare across boundaries (Langford et al., 2012). However, the original 2SFCA approach has drawn some criticism because of its dichotomous approach. In brief, this approach retained the fallacious assumption that all residents have identical accessibility within the same catchment and that the distance decay effect is roughly disposed of as 0 (within catchment) and 1 (outside catchment).

To address this concern, Luo and Qi (2009) worked on the limitations of the 2SFCA approach and proposed an enhanced two-step floating catchment area (E2SFCA) approach by embedding a distance decay function into the floating catchment of both steps (Luo and Qi, 2009). This extension approach segments the catchment area into several continuous travel time sub-zones (zones 1–3 at time intervals of 10, 20 and 30 min, respectively) and weighs the distance decay in each sub-zone via a mathematical function, with the decay curve presenting a discrete stepped model (Jing et al., 2018). The advantage of the E2SFCA approach is that the accessibility values within the catchment area are differentiated via multiple distance decay weights instead of the dichotomous 0 and 1 used in the 2SFCA approach.

There are several deficiencies in the E2SFCA approach that have emerged: (1) it assumes people access facilities via a single travel mode, (2) it does not incorporate competition between neighbourhood facilities, and (3) it fails to quantitatively capture the impacts of facility scale and the ability of different population groups to use the facility based on the availability of facility resources. Thus, this analytical approach provides a one-dimensional view of spatial accessibility (Delamater, 2013). At present, a great deal of research is being conducted to address both concerns.

2.3. Floating catchment area-based multiple travel mode approaches

A growing body of literature focuses on incorporating multiple travel modes into the FCA framework and aims to reveal the differences in accessibility patterns at various scales of spatial units (Chao et al., 2017; Pan et al., 2018). Following the 2SFCA analysis framework, Mao and Nekorchuk (2013) proposed a multi-mode 2SFCA approach that was the first to incorporate multiple travel modes for measuring the accessibility of healthcare in Florida, USA. The population of each demand site was divided into several subpopulations according to the car and bus travel modes at the block level of the census tracts, and multiple catchments were generated at each facility location using one per transport mode. The weights were determined according to the sizes of the subpopulations within each service area. Both car and bus travel modes were assigned different travel speeds in one network dataset in the model. The results suggest that multiple travel modes resulted in low mean accessibility but high variability, and a smaller under-served area and population were identified when multiple travel modes were considered than when single travel modes were evaluated (Jia et al., 2019b; Mao and Nekorchuk, 2013).

Langford et al. (2016) enhanced the sophistication of the 2SFCA approach by integrating multiple travel modes, private cars and public transport using a dedicated network dataset, which is a multi-modal 2SFCA approach, and conducted an empirical study to examine the accessibility of primary healthcare facilities in South Wales, UK. The accessibility score for each travel mode was separately generated at each demand and supply location based on the combined population using the modelled travel modes. The results suggest that each census tract has much lower accessibility scores than identified under a single travel mode (car only) and that accessibility via the car travel mode may also be miscalculated in an undifferentiated model because they may potentially benefit from low demand for service points from bus passengers (Langford et al., 2016).

In another case, Higgs et al. (2017) examined the impact of different travel modes on the association between different measures of general practitioner supply and shortage at the area level in South Wales, UK. The accessibility score was separately calculated for the car and bus travel modes based on the E2SFCA method, and these scores were input into a multivariate regression model to illustrate the relationship between service needs and the potential accessibility of general practitioners under different travel modes. The results indicated that the strength of the association between health deprivation and accessibility varies under different travel modes (Higgs et al., 2017).

However, the calculation of the travel times via car and public transport in these studies relied on a geographic information system (GIS)-based weighted road network. The essential component of the weighted road network was the average speed of different road grades (generally four grades: expressway, arterial road, secondary trunk road and branch way), which were assigned to the road network as a weight to calculate the shortest travel path (Hu et al., 2018). In reality, as traffic situations will obviously differ across different areas (e.g., generally urban centre areas are more congested than outskirt areas with low population densities) and some road conditions (e.g., traffic congestion and traffic control), some biases in computed travel time would occur if these influential coefficients were not added to the simulation of real traffic situations (Langford et al., 2012).

Later, open datasets such as general transit feed specifications and volunteered geographic information initiatives such as Open Street Map enabled the use of advanced shortest travel path modelling (Rehrl et al., 2013; S. et al., 2017). In China, Baidu Map and Auto Navi Map are prevalent online mapping service providers that are already sharing open and easy-to-use live data on route planning by calling API services and supporting the computation of travel time and trip distance considering multiple travel modes, and compared with OD data, these shortest travel time and distance data have been acknowledged as high-precision travel data. These services facilitate a more elaborate measurement of accessibility under multiple travel modes.

In their latest study, Gang et al. (2016) considered travel time to hospitals to be the main factor restricting individuals' access to healthcare and derived travel time data by calling the API services of Baidu using a distance-weighted road network based on vector maps. The travel times for both car and public transport were calculated between sub-districts and high-level hospitals, and the kernel density-2SFCA method was applied to analyse the spatial accessibility of high-level hospitals in Shenzhen, China under different travel modes and based on multiple time thresholds (Gang et al., 2016). Later, in another study, Tao et al. further modified the multi-modal 2SFCA method and utilized the API of Baidu Maps to calculate travel time and trip distance to model accessibility of healthcare via multiple travel modes in Shenzhen (Tao et al., 2018).

2.4. Metrics of multiple travel mode

As stated above, multiple travel modes have been widely introduced into the floating catchment area family of approaches and applied to more accurately measure health-related accessibility, especially in the field of healthcare facilities services. It is also useful to reveal the differences in outcomes under different travel modes in detail, as has been repeatedly verified by numerous scholars in China and other countries (Langford et al., 2016; Lin et al., 2018; Tenkanen et al., 2016). However, a number of aspects can be further improved.

Travel cost plays an important role in terms of the impact of transport conditions on accessibility outcomes and especially affects health at the individual level as well as opportunities to access healthcare facilities (Dony et al., 2015; Neutens, 2015). Specifically, in hospitalization behaviours, travel cost has a significant effect on delivery efficiency, and population groups must overcome the constraints of geographic barriers to enter the healthcare system (Widener et al., 2015). Generally, travel time and trip distance are used as proxies for the travel cost between the origin point and the destination point. However, almost all scholars in previous studies adopt only one of these proxies as the travel cost to depict the distance decay effect and capture the potential for competition between facilities. In fact, both proxies have different connotations and features for representing the travel cost of hospitalization behaviour and may result in a variety of accessibility outcomes.

The factors in common between travel time and trip distance are both relevant to the plan and the choice of the shortest travel path. In short, these two proxies under the optimal travel path are the 'shortest outcomes' among all journey schemes. Even so, travel time comprises the start time from the origin point and the duration of the journey and changes at any time in a real traffic scenario, it is the critical factor that influences an individual's choice of whether and when to go to healthcare facilities for treatment. Also, which is closely related to traffic impedance.(Fang et al., 2014; Farber et al., 2014). For instance, sufficient capacity of the transportation system, effective traffic control, sparse pedestrian flow, no congestion and other factors lead to short travel times. Additionally, the travel time depends on the travel mode (e.g., vehicle) that people choose, and in line with lived experience, it is common sense that cars take less time than buses and other transit vehicles. Distinct from this, trip distance reflects the physical length of the route between the origin and destination points, which depends on the trip objective and association with the location and attraction of facilities (Salonen and Toivonen, 2013). Taking the trip distance to hospitals as an example, the size of the healthcare facility, the treatment level of the specialists, the number of general practitioners and the hospital bed capacity are potential factors that will all influence a person's decision-making around, where and whether to seek healthcare within the tolerance threshold range. The considerations of these factors will be mapped via the trip distance.

Thus, in our study, we adopt a so-called 'multiple-type travel cost' that consists of both travel time and trip distance, which were derived from the shortest travel path under the PCTM and PTTM via the API services of the Baidu Map developer platform.

3. Methods

3.1. Study area

Wuhan is the capital of Hubei Province and is located in Central China (113°41′E to 115°05′E and 29°58′N to 31°22′ N). The world's third-longest river, the Yangtze River, and its largest branch, the Hanshui River, flow across the centre of the city. Wuhan currently contains a total of 13 districts, including seven central urban districts and six suburban districts; the latter have a total area of 8596 km^2, while the central urban area is 863 km^2. Wuhan is the most populous city in Central China, with a population of 10.66 million, and its central urban districts contained approximately 56% of the total population in 2015. In this study, the central urban districts of Wuhan (Appendix Fig. 1), which include 830 communities, are selected as the basic statistical units.

Wuhan has comparatively a more than sufficient number of medical resources than the national level. By the end of 2015, there were a total of 5341 health-related institutions, 80,726 hospital beds and 94,653 medical professionals in Wuhan, with an average of 7.6 hospital beds, 8.9 medical workers and 3.1 practising doctors per thousand people. However, Wuhan has also faced some persistent problems; for example, for the people per thousand beds, some districts have more than 15, while others have fewer than 3. Per capita medical resources also vary greatly across different regions. In addition, high-quality medical resources are mainly concentrated within the second ring road, and the new urban area is relatively weak in these. Thus, local governments have been concentrating not only on socio-economic growth but also on investing in health benefits and have proposed policies to promote basic public health services equalization.

3.2. Data preparation

3.2.1. Population data

In Wuhan, the urban administrative region is hierarchically organized into four different levels: the community, subdistrict, zone, and city levels. The community level is directly under the subdistrict level as the lowest-level basic census unit. The population data for the 830 communities were obtained from the household registration of the public security departments in 2015, and it is used as an indicator to represent healthcare demand in the following calculation of accessibility.

3.2.2. Healthcare facility data

Healthcare facilities in China are mainly organized into three tiers: primary hospitals, secondary hospitals and tertiary hospitals. The attribute information of the original variable data of different healthcare facilities was collected from the registration catalogue of the hospital information statistics service system provided by the Health and Family Planning Commission of Hubei Province in 2015 (Appendix Table 1).All the healthcare facilities analysed in the study are public medical institutions; therefore, the basic indices, such as hospital scale, medical workers, technical force, medical devices, and clinical and paramedical departments, of the 22 tertiary hospitals and 55 secondary hospitals that we selected meet the corresponding qualification assessment standards and hold nameplates issued by the Ministry of Health and provincial health departments (Appendix Fig. 2). Furthermore, more than half of outpatient and emergency treatment tasks were undertaken and a vast majority of inpatient services were supplied by these healthcare facilities; these hospitals are well known at the provincial and even the national levels. The private hospitals and specialized hospitals in the central urban area, and few hospitals for which some attribute information was missing were excluded from this study list. Moreover, due to the limitation of the datasets, there are only 88 CHCs with complete attribute records; in fact, as the primary nursing facilities in communities and neighbourhoods, the number of CHCs in the urban centre is greater. In future work, we will proceed to supplement this dataset. In the following calculation of accessibility, we use 16 variables based on the EFA approach to synthesize a comprehensive evaluation score for these healthcare facilities as an indicator of their service capability.

3.2.3. Travel path data

Baidu Maps is a professional location-based service provider in China that primarily functions to provide navigation, real-time and dynamic route planning services for the public's daily travel. The opened public version of Baidu Maps offered three route planning schemes for users' daily travel, namely, recommended routes, shorter time routes, and least transfer routes. The travel path data are open-source floating car data that utilize probe cars consisting of taxis, buses and volunteers' private cars as the transmission media to gather real-time traffic information. The collection of real-time traffic information considers the traffic impedance of roads, such as the property and quality of a road, the traffic load, time required to swerve, congestion during rush hour, traffic lights, and traffic control. The travel path data were derived from the URL (http://lbsyun.baidu.com/index.php?title=uri) of the open platform via request to access the API, recursively read the geographic coordinates and feedback the resulting shortest path. The route planning program was iterated every 10 min and obtained a total of 136,950 attribute records consists of travel times and trip distances over a 24-h period. The corresponding shortest travel paths between the 830 communities and the 88 CHCs, 55 secondary hospitals and 22 tertiary hospitals comprised 73,040, 45,650 and 18,260 records, respectively. After processing this information, the corresponding travel time and trip distance data can be generated.

3.3. Methodology

The integrated methodological framework of this study is shown in Fig. 1. The computational process involves four major steps: (1) calculating the service capacity scores of the different healthcare facilities using the EFA approach; (2) calculating the geographic impedance and corresponding Gaussian weight to capture the distance decay effect; (3) measuring the accessibility of healthcare facilities using the 3SFCA approach, and comparing the outcomes from travel time and trip distance under PCTM and PTTM visually and statistically; and (4) analysing the spatial disparity between facility supply and population demand considering the supply-to-demand match.

3.3.1. Three-step floating catchment area approach

Building on previous research, this work presents a 3SFCA approach that was first proposed by Wan et al. and uses the following three-step procedure to calculate the accessibility of healthcare facilities:

Step 1: Determine the hospital catchment size and calculate the selection weight.

In this study, the travel threshold is determined based on the results of the frequency count of travel time and trip distance, and the catchment area is defined as the 'hospital catchment' (Wan et al., 2012). It should be noted that in many previous studies, scholars segment the catchment area into several continuous travel time sub-zones and add the weigh coefficient into each sub-zone to represent the distance decay effect (Dony et al., 2015; Luo and Qi, 2009; Page et al., 2017; Wan et al., 2012; Wei and Whippo, 2012).

We also set the maximum travel time to 45 min and trip distance to 60 km as the travel threshold in the PCTM; similarly, 120 min and 60 km are set as the travel threshold in the PTTM. As shown in the Appendix Table 2, the frequency count of the number of shortest paths under the PCTM indicated that significant portions of the shortest paths between communities to hospitals are concentrated within the range of 45 min, compared with the few paths outside this threshold range. A similar trend appears at approximately 120 min in the PTTM (Appendix Table 3). Accordingly, we determined that the maximum travel time is approximately 45 min for private cars and 120 min for public transit, and the maximum travel distances are determined refer similar principles. Thus, we consider these thresholds to be appropriate because there are few paths outside this threshold range.

Thus, we consider these thresholds to be appropriate because there are few paths outside this threshold range, and they can help

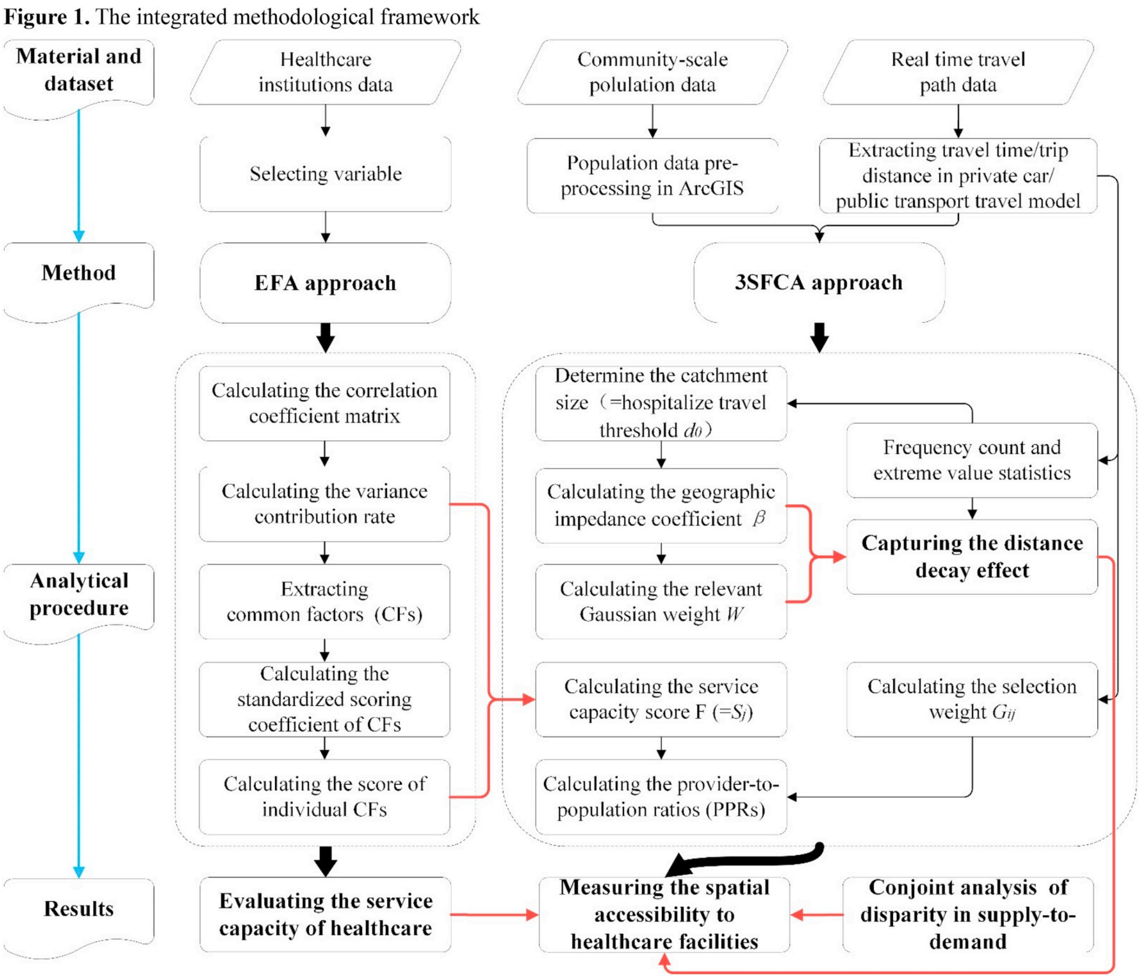


Fig. 1. The integrated methodological framework.

make a well-founded assumption in our computational model that hospitalization behaviour will seldom occur beyond these travel thresholds.

The formula used to express the hospital selection weight is defined as follows:

$$A_{ij} = \frac{T_{ij}}{\sum_{j\in\left\{d_{ij}\leq d_o\right\}} T_j} \tag{1}$$

where A_{ij} is the selection weight between the population location *i* and facility site *j*, d_{ij} is the travel cost from *i* to *j*, and d_o is the travel threshold ($d_{ij} \leq d_0$). T_{ij} is the assigned weight of the Gaussian decay function for *j*, and T_j is the total sum weight of the Gaussian decay functions of all healthcare facility sites within the hospital catchment.

Step 2: Search for all healthcare locations within the hospital catchment and calculate the PPR of facility site *j*. This formula is given as follows:

$$R_j = \frac{S_j}{\sum_{r=1,2,3,4}\sum_{j\in\left\{D_r, d_{ij\leq} d_o\right\}} A_{ij}P_kW_r} = \sum_{j\in\left\{D_1, d_{ij\leq} d_o\right\}} A_{ij}P_kW_1 + \sum_{j\in\left\{D_2, d_{ij\leq} d_o\right\}} A_{ij}P_kW_2 + \sum_{j\in\left\{D_3, d_{ij\leq} d_o\right\}} A_{ij}P_kW_3 + \sum_{j\in\left\{D_4, d_{ij\leq} d_o\right\}} A_{ij}P_kW_4 \tag{2}$$

where S_j is the healthcare service capacity of site *j*; W_r is the geographic impedance coefficient of the rth sub-zone D_r within the hospital catchment, which is expressed as a generalized function $g(d_{ij})$; and P_k is the population size of site *k*, which represents the population demand.

Step 3: Calculate the accessibility of the population at location *i* using the following formula:

$$\begin{aligned} A_i &= \frac{S_j}{\sum_{r=1,2,3,4}\sum_{i\in\left\{D_r, d_{ij\leq} d_o\right\}} A_{ij}R_jW_r} \\ &= \sum_{j\in\left\{D_1, d_{ij\leq} d_o\right\}} A_{ij}R_jW_1 + \sum_{j\in\left\{D_2, d_{ij\leq} d_o\right\}} A_{ij}R_jW_2 + \sum_{j\in\left\{D_3, d_{ij\leq} d_o\right\}} A_{ij}R_jW_3 + \sum_{j\in\left\{D_4, d_{ij\leq} d_o\right\}} A_{ij}R_jW_4 \end{aligned} \tag{3}$$

where R_j is the PPR of site *j*, and W_r is the sum of the geographic impedance coefficient β of the rth sub-zone D_r within the hospital catchment. Note that the complete calculation process can be realized by space modelling in the toolbox of ArcGIS 10.3.

3.3.2. Spatial disparity in supply and demand

In a community, the higher A_i is, the better the healthcare accessibility. If a community with a large population also has high accessibility, the potential utilization of healthcare facilities services is likely to be high. If residents in communities with low population density are provided with high facility accessibility, there may be a surplus of healthcare facilities services. The accessibility values and population densities in communities are standardized as follows:

$$Z_{A_i} = \frac{A_i - \overline{A}}{\sigma_{A_i}} \tag{4}$$

$$Z_{PopD_i} = \frac{PopD_i - \overline{PopD}}{\sigma_{PopD}} \tag{5}$$

where Z_{Ai} is the Z-score of A_i of community *i*; $\overline{A}$ denotes the ratio of the total service capacity scores (sum S_j) of healthcare facilities to the total population. *PopDi* is the population density of community *i*; Z_{PopDi} is the Z-score of $PopD_i$;$\overline{PopD}$ is the population density in the study area;σ_{PopD} is the standard deviation of the population density. By joining Z_{Ai} and Z_{PopDi}, four association patterns were derived for comparing the spatial disparity of accessibility between facility supply and population demand from the perspective of the degree of supply and demand match in community *i*:

(1) If $Z_{Ai} > 0$ and $Z_{PopDi} > 0$, community *i* has high accessibility and high population density.
(2) If $Z_{Ai} > 0$ and $Z_{PopDi} < 0$, community *i* has high accessibility and low population density.
(3) If $Z_{Ai} < 0$ and $Z_{PopDi} > 0$, community *i* has low accessibility and high population density.
(4) If $Z_{Ai} < 0$ and $Z_{PopDi} < 0$, community *i* has low accessibility and low population density.

3.3.3. Distance decay effects of hospitalization patterns

The Gaussian function is introduced to account for the distance decay effect. The formula is defined as follows:

$$f(d_{ij}) = \begin{cases} g(d_{ij}) = e^{\frac{-d^2}{\beta}}, d_{ij} \le d_o \\ 0, otherwise \end{cases} \tag{6}$$

The generalized function $g(d_{ij})$ of geographic impedance and the corresponding Gaussian weight W of the segmented sub-zones within the hospital catchment are expressed as follows:

$$g(d_{ij}) = \begin{cases} W_1, d_{ij} \in D_1 \\ \cdots, \cdots \\ W_r, d_{ij} \in D_r \end{cases} \tag{7}$$

3.3.4. Service capacity scores of healthcare facilities

EFA is a multivariate statistical approach designed to achieve dimension reduction and handle multicollinearity in raw data. In this study, we utilized EFA to change multiple variables into a few common factors (CFs) and then compute a score to represent healthcare service capacity.

4. Results

4.1. Travel time and trip distance

The travel times and trip distances between the 830 communities to the 88 CHCs, 55 secondary hospitals and 22 tertiary hospitals were statistically classified, and the results are shown in Table 1.

From a travel time perspective, these statistics suggest that in PCTM, the average travel time to CHCs, secondary hospitals and tertiary hospitals is approximately 8 min, with minimum values of 0.02, 0.03, and 0.03 min and maximum values of 61, 55, and 49 min, respectively. In PCTM, the average travel time is greater than 60 min, and the minimum travel time is approximately 10 min. The difference in maximum travel time between PCTM and PTTM is significant, e.g., in PTTM, the maximum travel time is greater than 260 min. Overall, it is obvious that PCTM results in a lower travel time than PTTM. Meanwhile, the statistics indicate that in both PCTM and PTTM, the average trip distances to the three tiers of healthcare facilities are both approximately 15 km, whereas the minimum is less than 1.5 km in PTTM, which may be consistent with the actual use of healthcare facilities. In addition, the lower the healthcare level is, the shorter the minimum travel times and trip distances are in both travel modes.

Next, the travel time and trip distance in PCTM and PTTM are grouped statistically in intervals of 5 min and 10 km, respectively, and the resulting frequency count histograms and cumulative percentages are shown in Fig. 2. The results indicate that travel time is most commonly distributed in the range of 0 to 35 min (in PCTM) and 0 to 120 min (in PTTM), while the trip distances are mainly distributed from 0 to 40 km (in PCTM) and 0 to 50 km (in PTTM).

4.2. Distance decay effects

Utilizing formulas 6 and 8 and based on the value range of β in equations (9)–(20), the calculated relevant Gaussian weights W in different travel modes are listed in Table 2. For instance, when the minimum travel time d_{ij} is set as 1 min and the W value is set as 0.01, the obtained β value is 45. By continuously increasing the β value until it reaches 795, we can determine that the Gaussian weight W is 0.9922. This value is the maximum weight of the Gaussian function, and the corresponding travel time is 61 min, which is also the maximum travel time between a population location and a CHC. The β value was set to 795 because at this point, the value of Gaussian weight W reached convergence, and the decaying trend of the curve is relatively flat at 0.9922. The remaining values of the geographic impedance coefficient β and relevant Gaussian weight W in different travel modes are calculated using this procedure, and the results are shown in Table 3. These constant values were then visualized as Gaussian decay curves, which are shown in Fig. 3. Compared to other forms of decay functions (inverse power, exponential and kernel density functions), the Gaussian curve presents a slow rate of declination, and its changes in distance decay match the normal distribution curve.

In addition, it is obvious that at different travel threshold ranges, the extent of decay of the multiple Gaussian curve drawn from the

Table 1
The statistics of travel time and trip distance.

Travel mode	Healthcare	Max		Mean		Min		S.D.	
		PCTM	PTTM	PCTM	PTTM	PCTM	PTTM	PCTM	PTTM
Travel time	CHC	60.52	289.30	8.80	80.91	0.02	9.48	6.04	88.44
	Secondary hospital	54.88	272.78	8.31	68.00	0.02	10.35	4.70	26.32
	Tertiary hospital	49.25	262.07	7.79	64.54	0.03	11.68	4.67	25.7
Trip distance	CHC	86.86	98.516	14.07	17.31	0.01	1.27	9.63	13.02
	Secondary hospital	87.81	90.84	13.28	15.74	0.03	1.44	7.49	8.08
	Tertiary hospital	78.82	90.13	12.46	14.60	0.07	1.47	7.45	8.03

Note that: CHC is the community healthcare centres; PCTM is the private car travel mode, and PTTM is the public transport travel mode.

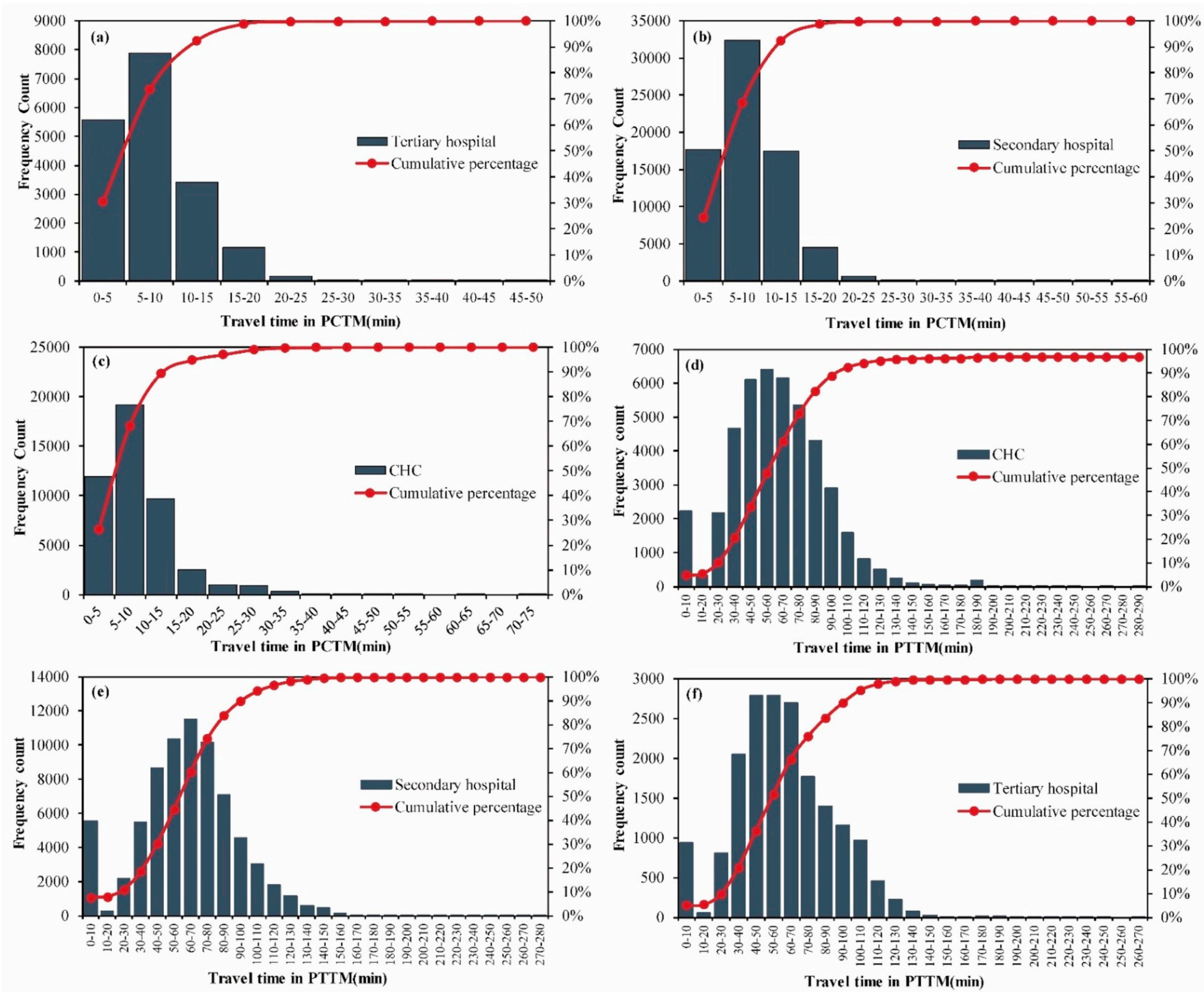


Fig. 2. The frequency count histograms and cumulative percentage of the travel times and trip distances.

non-convergence state is inconsistent. For instance, the PCTM-based decay curve is shown in Appendix Fig. 3(a1); at a travel time of 10 min, the curve with the smallest β value becomes flat first, and as a result, the Gaussian weight W and decay effect reach zero within sub-zones 10 to 60. In contrast, after this point, the other curves (dotted line) continue to exhibit the decay effect. Thus, we applied Eq. (21) to calculate the mean W values of sub-zones D_1 to D_4 within the catchment area (Table 3); under different travel modes, the smooth full lines are the convergent Gaussian distance decay curves of the three tiers of healthcare facilities. The arithmetic mean-based Gaussian weight W is the optimal and the only decay weight, which addresses the problem in which the accessibility value variations follow applied multiple non-convergence Gaussian weights.

4.3. Service capacity scores

By summarizing the EFA results, the Kaiser-Meyer-Olkin value reached approximately 0.8, and Bartlett's test was significant at the 0.01 level. The correlation coefficient matrix clearly reveals that there is a strong correlation between most paired original variables (Appendix Fig. 4), which suggests that the 16 original variables were feasible when applied to the EFA.

The initial eigenvalues of the first three CFs are >1, and the cumulative variance contribution rate of the first three factors explains 82% of the total variance (Appendix Table 4). Thus, the first three factors are selected as the CFs for the subsequent analysis; these values are used as independent variables to calculate the scores of individual CFs using regression analysis. In addition, the variance contribution rates of CFs with common weights $W\,(0.50, 0.23, 0.09)^T$ are used to compute the total F score. Finally, the total F score was used as the parameter S_j in the 3SFCA formula to calculate the accessibility values.

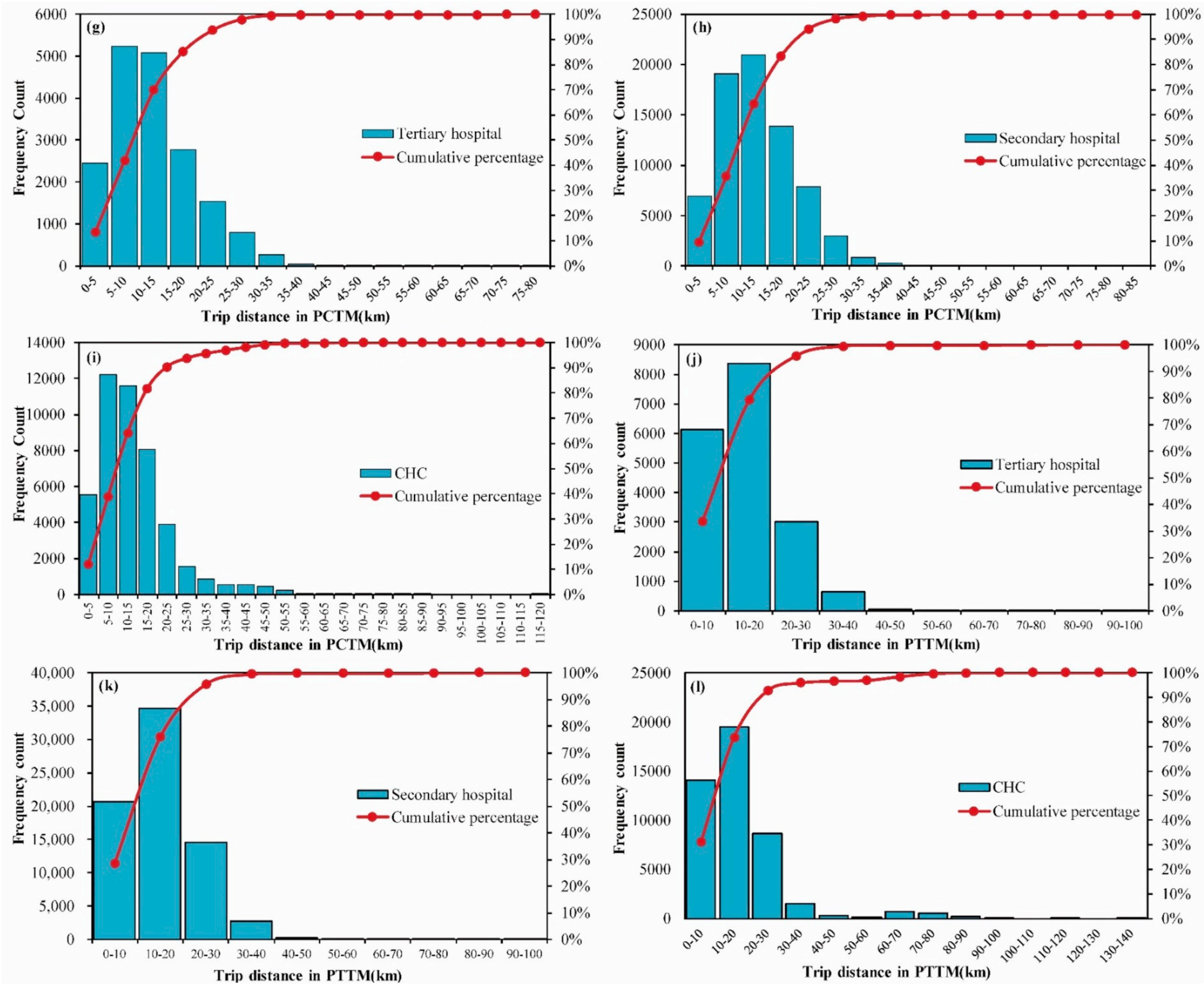


Fig. 2. (*continued*).

Table 2
The critical β and relevant weights.

Travel mode	Healthcare	Travel time (minutes)				Trip distance (km)			
		Max		Min		Max		Min	
		w	β	w	β	w	β	w	β
PCTM	CHC	0.9922	795.34	0.01	45.34	0.9994	1638.11	0.01	38.11
	Secondary hospital	0.9905	653.89	0.01	3.89	0.9994	1674.45	0.01	74.45
	Tertiary hospital	0.9882	526.709	0.01	26.70	0.9993	1349.01	0.01	49.01
PTTM	CHC	0.9986	18174.03	0.01	174.03	0.9995	2107.50	0.01	7.50
	Secondary hospital	0.9985	16158.09	0.01	158.09	0.9994	1791.96	0.01	91.96
	Tertiary hospital	0.9983	14913.44	0.01	413.44	0.9994	1764.10	0.01	64.10

Note that: CHC is the community healthcare centres; PCTM is the private car travel mode, and PTTM is the public transport travel mode.

4.4. Outcomes of healthcare accessibility

4.4.1. Spatial accessibility patterns of the three tiers of healthcare facility

The natural breaks method of ArcMap 10.3 was utilized to classify the accessibility values into seven properties, as shown in Fig. 4. This suggest that for all metrics used for travel costs, no apparent variations in spatial accessibility exist between the three tiers of healthcare facilities, and the communities with different levels of accessibility tend to exhibit staggered distribution. Meanwhile, joint analysis and a comparison of the distribution patterns of different tiers of healthcare facilities (Fig. 5) indicate that high values of accessibility are observed near healthcare service centres, and low values are observed at the periphery. Moreover, communities have

Table 3
The statistic of average Gaussian weights.

Travel time-based weights	PCTM				PTTM			
	Sub-zone1	Sub-zone2	Sub-zone3	Sub-zone4	Sub-zone1	Sub-zone2	Sub-zone3	Sub-zone4
	≤15	15–30	30–45	>45	≤60	60–90	90–120	>120
CHC	0.7483	0.2597	0.0540	0.0063	0.8140	0.4469	0.2656	0.0476
Secondary hospital	0.7223	0.2005	0.0325	0.0040	0.7988	0.4146	0.2348	0.0424
Tertiary hospital	0.7134	0.1806	0.0249	0.0024	0.7993	0.3995	0.2183	0.0382
Trip distance-based weights	PCTM				PTTM			
	Sub-zone1	Sub-zone2	Sub-zone3	Sub-zone4	Sub-zone1	Sub-zone2	Sub-zone3	Sub-zone4
	≤15	15–45	45–60	>60	≤15	15–45	45–60	>60
CHC	0.8132	0.2695	0.0466	0.0080	0.8221	0.3267	0.0780	0.0129
Secondary hospital	0.8277	0.2805	0.0500	0.0081	0.8322	0.2998	0.0586	0.0097
Tertiary hospital	0.7940	0.2265	0.0290	0.0050	0.8220	0.2914	0.0558	0.0090

Note that: CHC is the community healthcare centres; PCTM is the private car travel mode, and PTTM is the public transport travel mode.

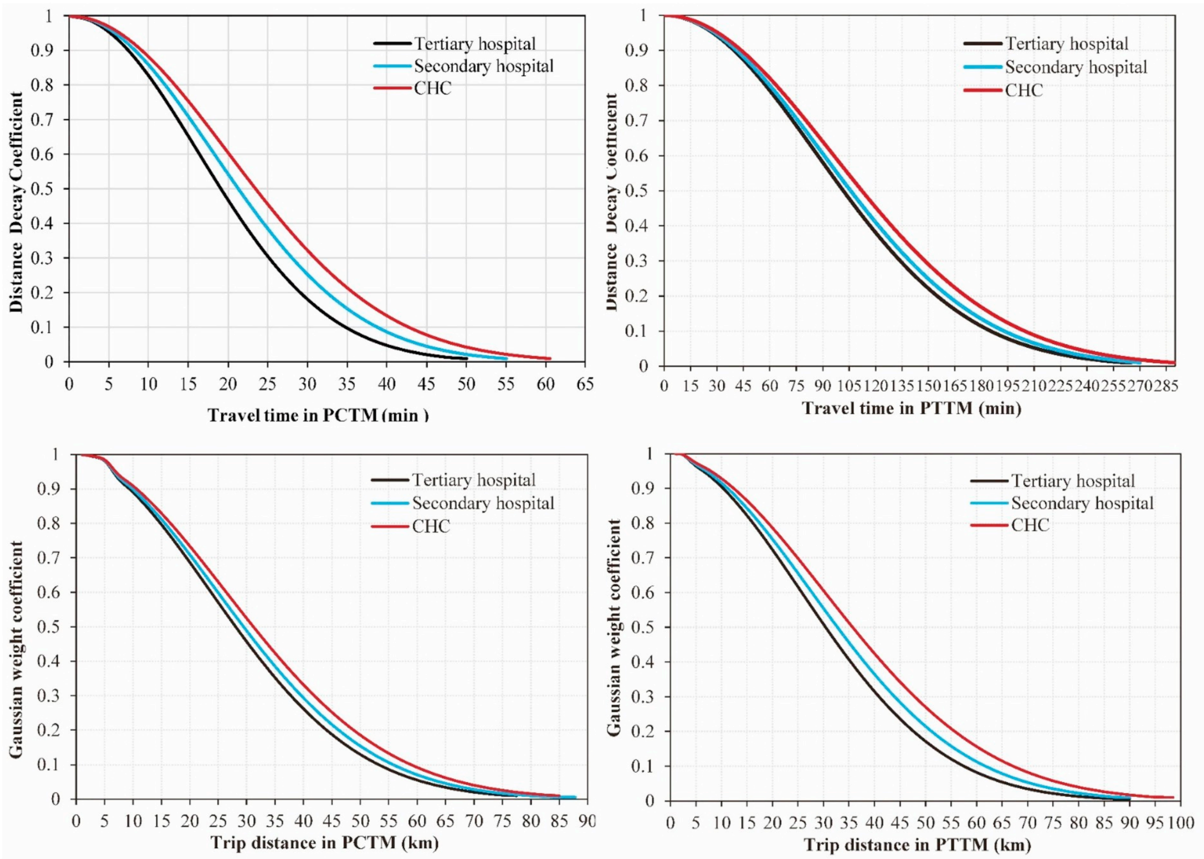


Fig. 3. The Gaussian decay curves of the three tiers of healthcare facilities.

relatively better access to CHCs and secondary hospitals than to tertiary hospitals. The closer a community is to being adjacent to downtown, the more obvious this trend is. The accessibility of tertiary hospitals is significantly higher in some communities of the Hongshan, Qiaokou and Wuchang districts than in other communities. In contrast, the communities that showed relatively low accessibility of tertiary hospitals are mainly scattered in the Hanyang, Jianghan and Qingshan districts.

From the view of the extreme statistical values, both in PCTM and PTTM, the mean values for the accessibility of CHCs are largest from among the three tiers of healthcare facilities, which may demonstrate that CHC services are more accessible than tertiary and secondary hospitals and closely related to the dense distribution of CHCs near most communities in the city. In particular, the standard deviations of the accessibility of tertiary and secondary hospitals are greater than that of CHCs. In a statistical sense, most accessibility values for CHCs are significantly different from the mean value, and the degree of dispersion is obvious. In reality, this result suggests

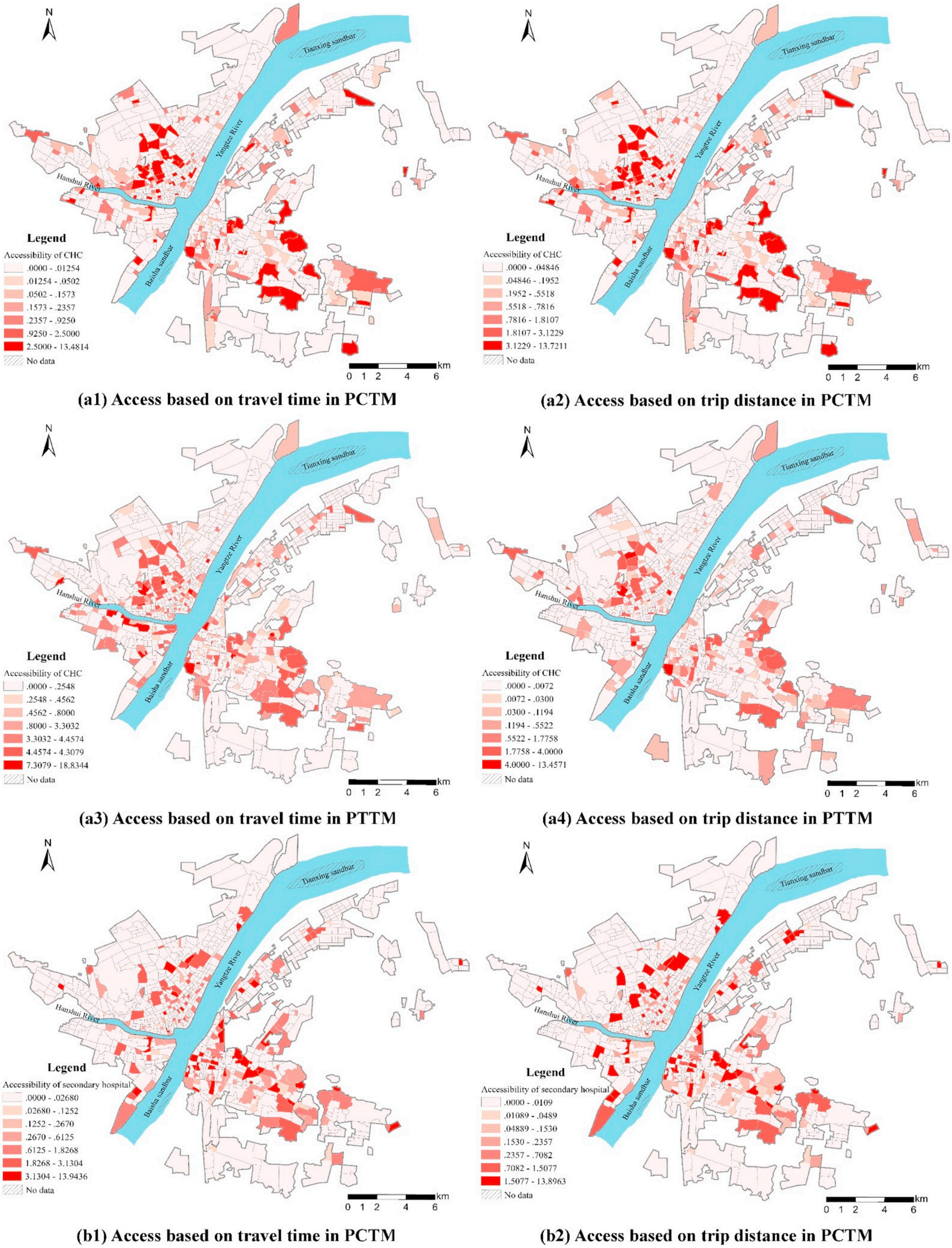
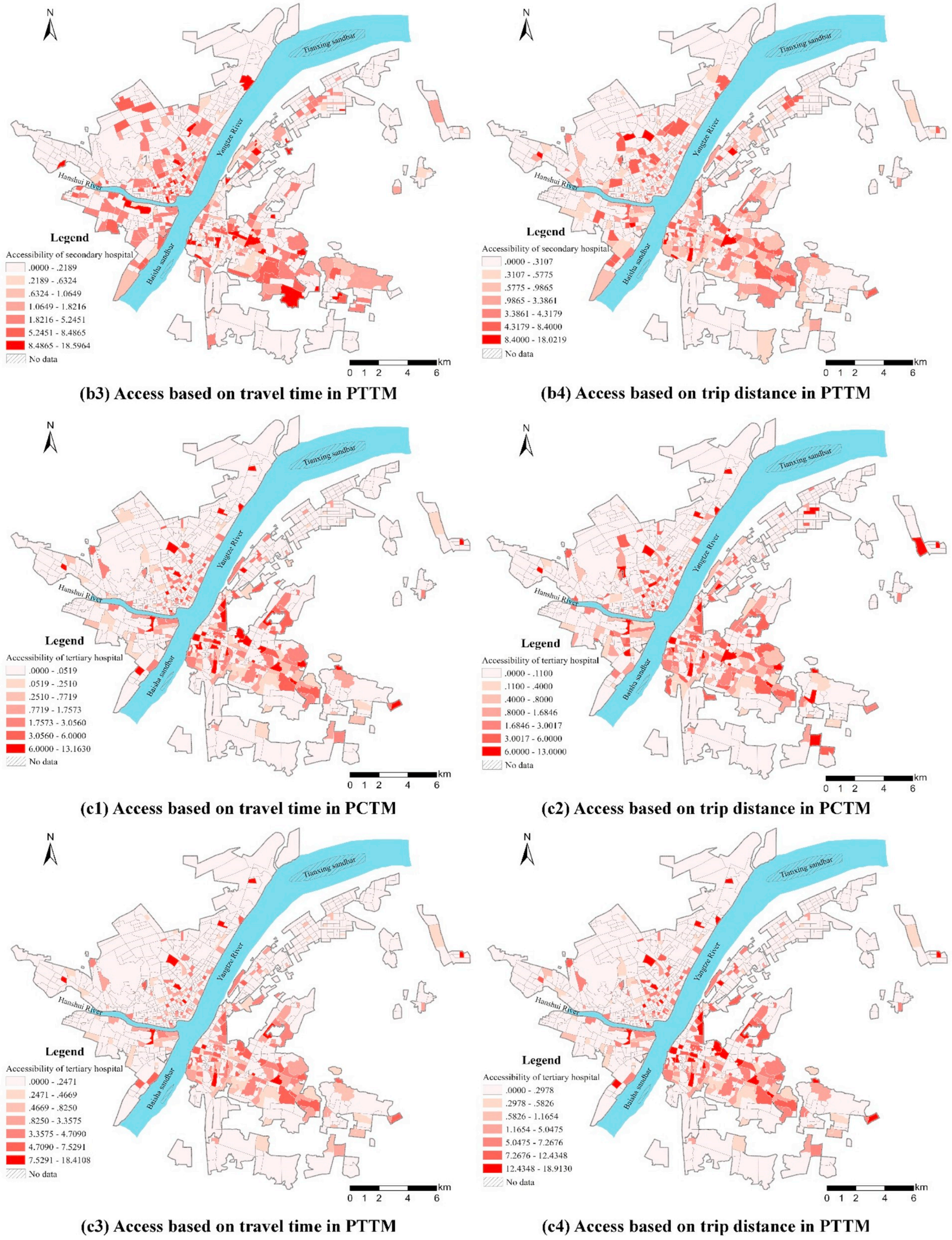


Fig. 4. Health accessibility to healthcare facilities: CHCs (a1-4), secondary hospitals (b1-4), and tertiary hospitals (c1-4).



(b3) Access based on travel time in PTTM

(b4) Access based on trip distance in PTTM

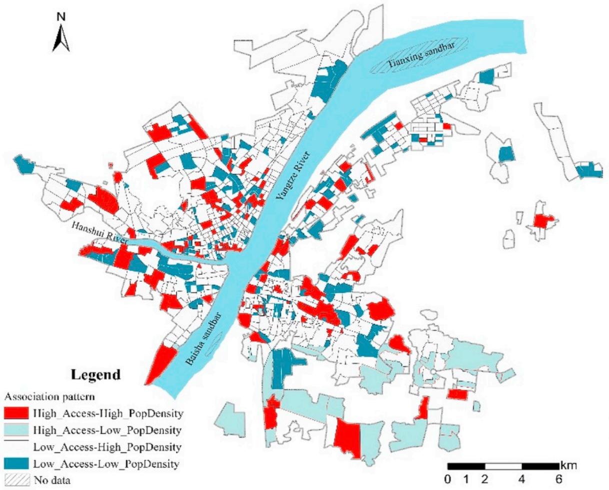
(c1) Access based on travel time in PCTM

(c2) Access based on trip distance in PCTM

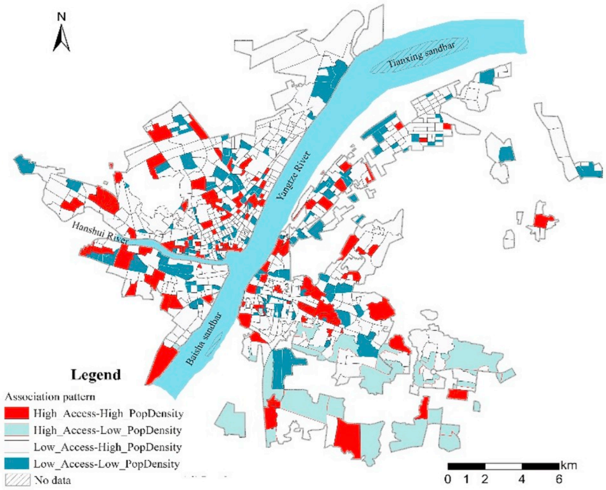
(c3) Access based on travel time in PTTM

(c4) Access based on trip distance in PTTM

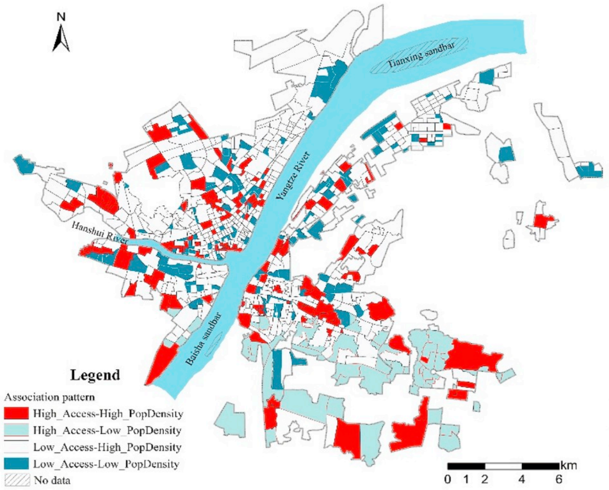
Fig. 4. (*continued*).



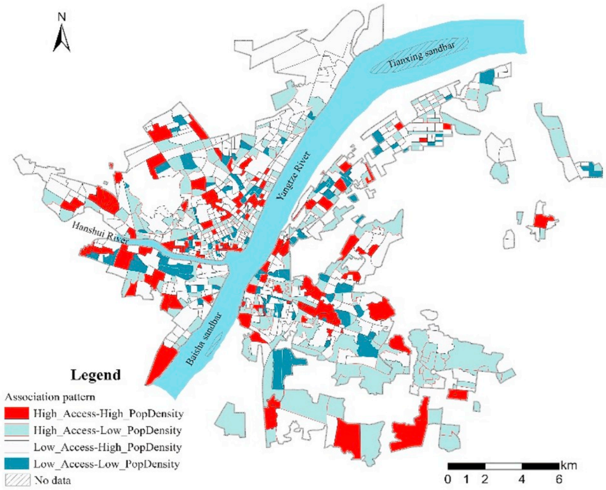
(a1) Disparities based on travel time in PCTM



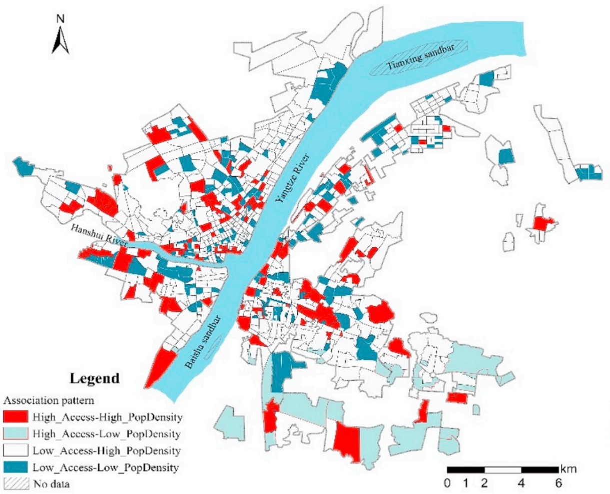
(a2) Disparities based on trip distance in PCTM



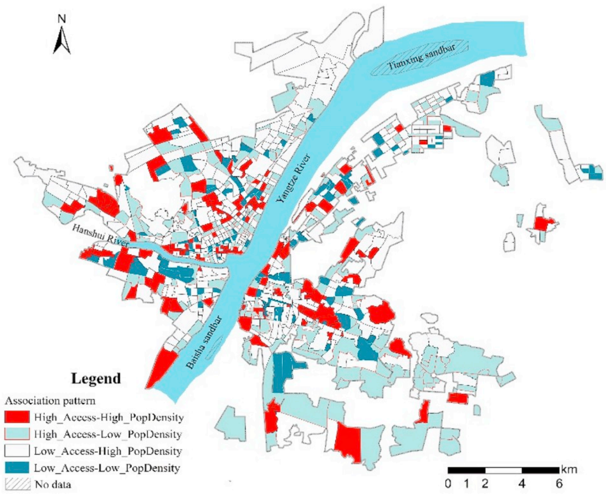
(a3) Disparities based on travel time in PTTM



(a4) Disparities based on trip distance in PTTM

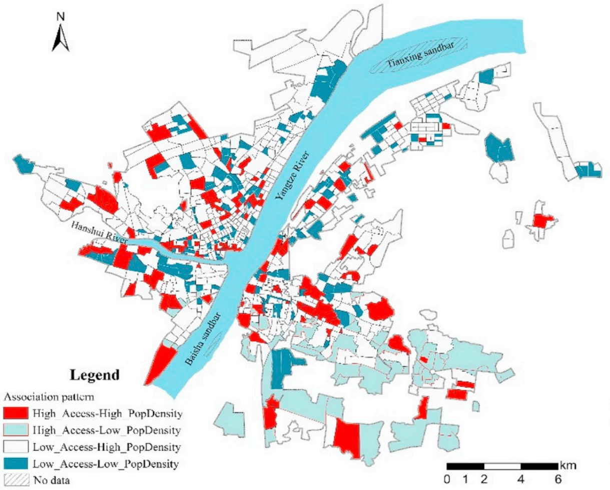


(b1) Disparities based on travel time in PCTM

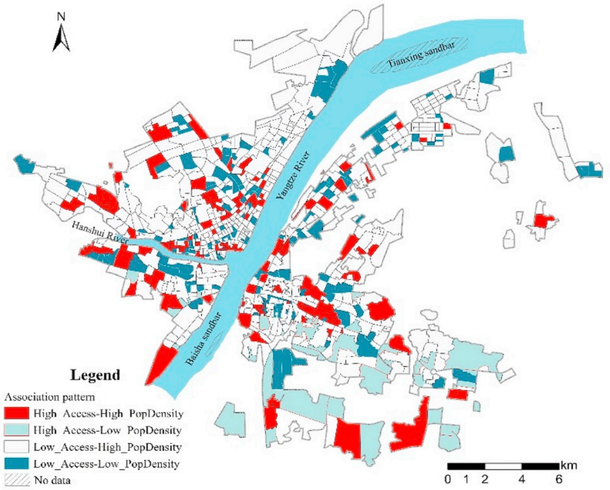


(b2) Disparities based on trip distance in PCTM

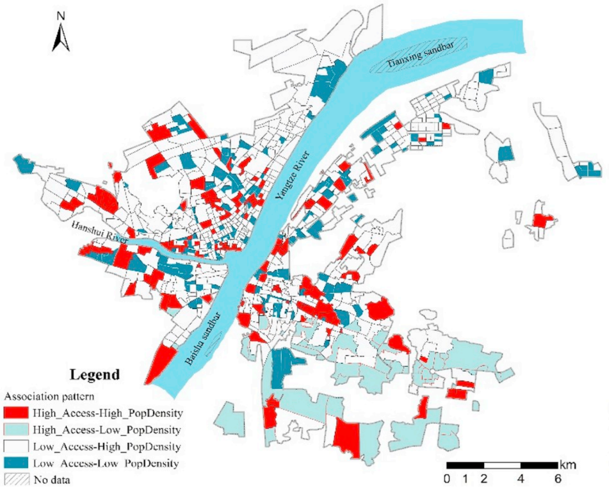
Fig. 5. Healthcare accessibility and its associations with population density: CHCs (a1-4), secondary hospitals (b1-4), and tertiary hospitals (c1-4).



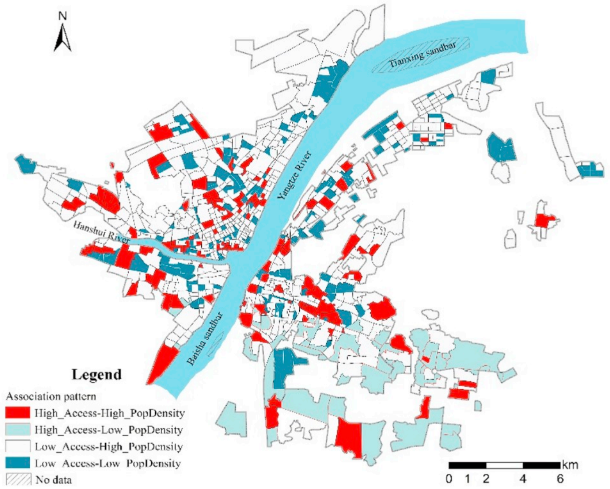
(b3) Disparities based on travel time in PTTM



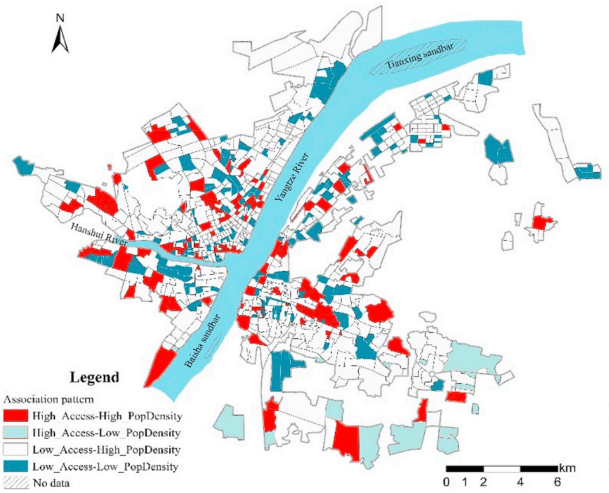
(b4) Disparities based on trip distance in PTTM



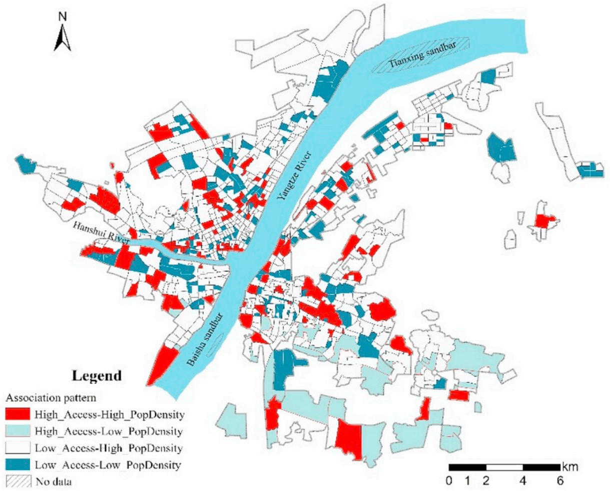
(c1) Disparities based on travel time in PCTM



(c2) Disparities based on trip distance in PCTM



(c3) Disparities based on travel time in PTTM



(c4) Disparities based on trip distance in PTTM

Fig. 5. (*continued*).

that there is a significant polarized differentiation in the number of communities with low and high accessibility, which may further remind us that both potentially under-served and potentially over-supplied communities may exceed the average. In addition, except for the mean values, the maximum, minimum and standard deviation of accessibility in PCTM is smaller than those in PTTM. However, the comparison shows that there are no significant differences in these extreme values in the accessibility outcomes between travel time-based and travel distance-based metrics.

4.4.2. Disparity analyses of access to healthcare facilities

The ratios of the service capacity scores of healthcare facilities to the population at the three tiers of healthcare facilities are 0.4 for CHCs, 4 for secondary hospitals and 22 for tertiary hospitals. Meanwhile, the accessibility values are positively correlated with the service capacity scores of healthcare facilities and negatively correlated with the population size.

The accessibility values of the three tiers of healthcare facilities were summed separately, and the total accessibility (A_i) was then standardized using formulas 5 and 6 to conduct a conjoint analysis with the standardized population density using formula 8 (Appendix text 1). The associated spatial patterns between the total accessibility of facilities and the population density are shown in Fig. 5, combining the statistics for the number of communities and their population under four association patterns (Fig. 6). At first glance, various association patterns are interlaced and discretely distributed in the communities, but some communities with the same association patterns are centralized in local areas. In different travel modes, there is a slight difference in the four association patterns of communities that were based on travel time and travel distance among the three tiers of healthcare facilities; these indicate the following.

(1) The high-high association pattern communities are both outnumbered in PCTM. This result suggests that healthcare facilities are less likely to be underutilized under PCTM than under PTTM, which may result from the well-developed public transit system helping shorten the travel cost (especially the travel time) of a city dweller engaging in hospitalization behaviour.
(2) The high-low association pattern communities are fewest, with a variety of results, and the spatial distributions are limited under different travel modes across the three tiers of healthcare facilities, which are mostly concentrated in Hongshan and Wuchang districts in the south-eastern part of the city. Of particular note, in terms of CHC services, the communities with high-low association patterns under PTTM, which may be related to the intensive distribution of CHCs and the high coverage of public transit systems in urban areas.
(3) Low-high association pattern communities are concentrated in the Qingshan, Hanyang, Qiaokou and Jiangan districts. Compared with other association patterns, the largest number of communities and populations have these patterns. In addition,

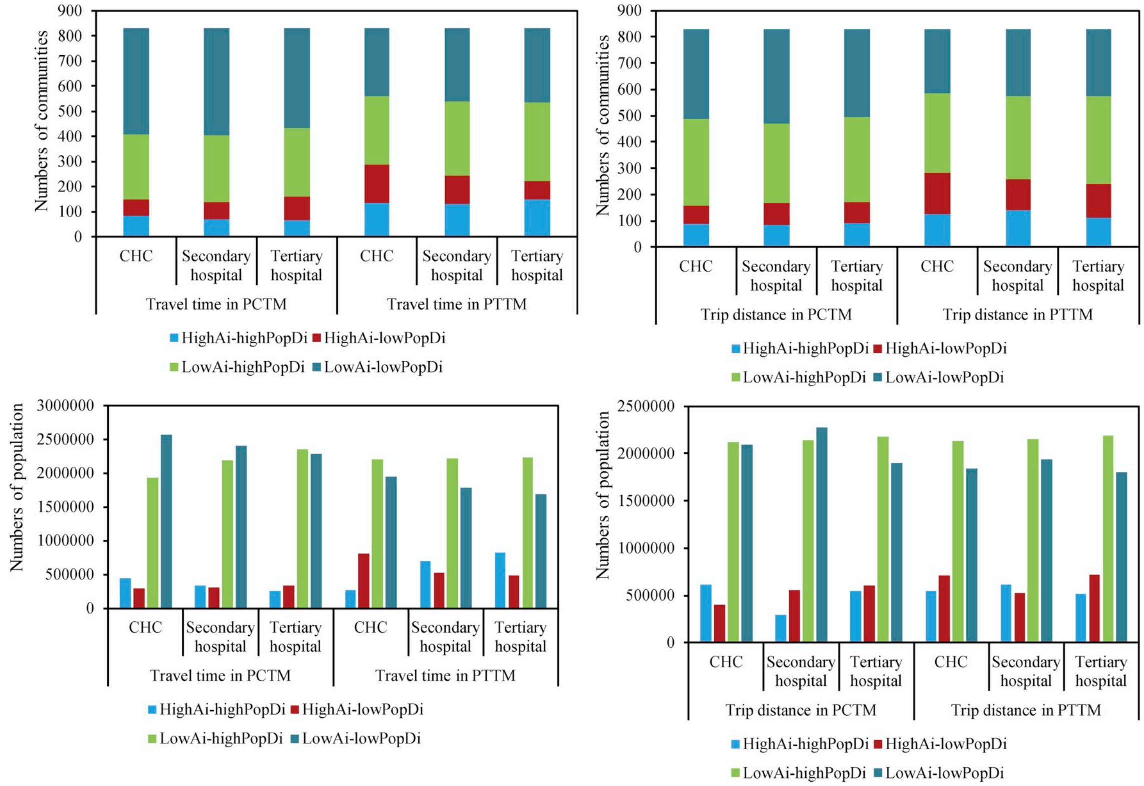


Fig. 6. Summary of the associations between healthcare accessibility and population density.

for all travel cost metrics, the number of PTTM-based communities is less than the number of PCTM-based communities, which may also benefit from the extension of public transit systems to residential areas in distant suburbs. This extension would effectively shorten people's travel barriers and distances, improve the potential utilization of healthcare facilities, and decrease the number of areas with professional healthcare shortages identified under PTTM. Meanwhile, the number of low-low association pattern communities is close to that of the low-high patterns, which suggests that such areas may urgently need high-quality healthcare facilities services.

In summary, the variation in association patterns between total healthcare accessibility and population density under the different travel costs of PCTM and PTTM is relatively unapparent in the number of communities. Approximately 13% of the communities had high population density and high healthcare accessibility, while an average of more than 39% of the communities are low-density census areas with low health accessibility levels. That is, more than half of the communities have an accessibility level that is incommensurate with their population size. The percentage of communities with high population density but low healthcare accessibility exceeded 36% (equivalent to approximately 55% of the total population).

5. Discussion and conclusions

5.1. Summary of findings

In this paper, as exploratory research, we attempted to use a multiple-type travel cost that consists of both the travel time and trip distance; the purpose was to compare the differences in spatial distribution patterns between time accessibility and distance accessibility across multiple travel modes. The findings of this study suggest the following.

(1) As far as travel costs are concerned, the average travel time and travel distance under PCTM are shorter than those under PTTM, and the average trip distances from communities to the three tiers of healthcare facilities are approximately 15 km for both travel modes, which is consistent with the actual use of healthcare facilities. However, regardless of the travel cost metric, no apparent variations in spatial accessibility exist between the three tiers of healthcare facilities. We think that maybe travel time and trip distance each have their own traits and merits in assessing spatio-temporal access, and perhaps comparisons between such pairs may confront the obstacle of incommensurability.
(2) In total, less than one-seventh of the communities have a high population density and high healthcare access, which were defined as over-serviced areas. On average, more than one-third of the communities are areas with a low population density and low health access level. That is, more than half of the communities have an access level that is inappropriate for their population size. The percentage of communities with a high population density but low healthcare access exceeded one-third (equivalent to nearly 55% of the total population). These communities were defined as under-serviced areas.

5.2. Implications for policy and further research

Regardless of the travel mode, the statistics of the association patterns indicate that a certain number of communities (approximately 10%–15%) have a high population size and a high access score among the three tiers of healthcare facilities. Although the types of communities with high access and a high population are relatively lower than the other association patterns across the overall areas, the underlying cause is still worth probing. Combined with the distribution of healthcare facilities, it is apparently that most of these communities are located in central urban districts or are near high-level healthcare facilities, both of which result in the current high accessibility. Additionally, it may be that these communities benefit from areas with relatively dense medical institutions at all levels, which raises the coverage of facility services, shortens the travel time/distance to hospital, and results in increased service capacity scores. Compared to communities in suburban areas, for the association patterns that have a large population size but that provide low accessibility; that means the government's layout planning for new public health facilities has not yet been implemented in practice. At present, the existing healthcare facility resources, which include but are not only confined to these 165 hospitals in these high-accessibility areas or communities in the city centre, are still relatively sufficient. However, when looking at the situation of whole cities, the degree of correspondence between resource supply and population demand in most areas is still not optimistic. Hence, to better assist in implementing the hierarchical diagnosis and dual referral treatment policy, a multi-hierarchical healthcare system needs to be established to provide a variety of healthcare service choices and raise the access opportunity of available facilities.

Furthermore, travel time is a dynamic factor, and as an idiosyncratic proxy of travel cost, is used to assess the availability of facilities and to capture the spatial interactive effect between healthcare facilities and demanders. And, trip distance has a significant impact on residents' hospitalize choices, e.g., residents who own private cars are more likely to take a trip with a longer distance to visit and access facilities than those who rely on public transit; additionally, the maximum travel threshold that individuals can tolerate is different across different travel modes. Once the locations of facilities fall beyond a proleptical trip distance that individuals can move and reach, the access opportunities for these services facilities will be diminished. In addition, in our study, the accessibility values of the three tiers of healthcare facilities verified that a low travel cost tends to result in high proximity and accessibility values, and this result is consistent with our knowledge of the actual situation in Wuhan. Hereby, it would be a feasible plan to construct a developed transit system with more connectivity and fewer impedances. Such a system is an essential public infrastructure and would provide benefits by facilitating the convenience of city dwellers' trips and lowering the travel cost of hospitalization behaviour.

5.3. Strengths and limitations

Based on previous research, our work has improved several aspects of accessibility measurement. The first aspect is applied the real-time travel time and trip distance to improve the accuracy of accessibility outcomes. Numerous specific factors influence the measurement of the spatial accessibility of healthcare facilities, and travel cost is a pivotal metric. In previous studies, Euclidean distance, topological distance and other techniques used GIS-based road network analyses to reflect travel costs. Limited to the access of research data and for ease of calculation, these model-based travel costs simplify the complexity of real road networks and traffic environments and may result in biased accessibility values at different scales of spatial units. Thus, in this study, the real-time multiple travel costs were used instead of GIS-based OD travel costs, which more accurately represented the actual travel costs of different population groups.

Secondary, we should admit that any debates over the correct sizes of catchment areas cannot be settled without analysing real-world healthcare utilization patterns (Jia, 2016; Wang, 2012). More specifically, a sophisticated hospital catchment size involves numerous factors, such as patient surveys, resident knowledge of local healthcare facilities, the scale of facilities, the actual demand and characteristics of the population groups. In fact, this procedure is difficult to implement because it depends on intensive computations and is constrained by the data. Thus, in this study, according to the results for the frequencies of travel times and trip distances, the maximum travel times and trip distances between the 830 communities and 165 healthcare facilities sites were roughly defined as the tolerable travel cost thresholds, and the extreme travel costs of the different travel modes were set as the hospital catchment size. The experiment shows that these thresholds to be appropriate because there are few paths outside this threshold range, and they can help make a well-founded assumption in our computational model that hospitalization behaviour will seldom occur beyond these travel thresholds. Furthermore, the hospital catchment size could vary according to the characteristics of the population and the specific type of healthcare facility in demand. In the different steps of the 3SFCA method, the optimal size can be determined by incrementally increasing the catchment size until it matched the population demand or the service capacity score of the facility, which would prevent the hospital catchment size from having to remain constant for the three tiers of healthcare facilities. Hence, this is a key domain that we will attempt to improve in a future study.

However, the approach taken in this paper has clear limitations and biases. Upon closer inspection, household income, the location of residences and other attributes of socio-economic status will indirectly affect the travel time of consumers of different ages and genders. In addition, in healthcare-seeking behaviour, different genders, age brackets, and professions will have differences with respect to individual vehicles, preferences for facilities and the travel routes chosen, which will together indirectly affect the spatial accessibility patterns. However, our dataset includes only the population quantity aggregated at the community scale, and information on the demographic attributes is lacking. Conducting a questionnaire survey on the hospitalization information and socioeconomic status of residents in such a large-scale (830 communities) is not easy. Thus, it is difficult to conduct analysis in a demographic data-driven manner; and cannot ensure that these various user attribute data are combined to analyse and distinguish the differences in residents' travel time, trip distance and spatial accessibility patterns to the three tiers of healthcare facilities. However, we think that this domain can be a further explored in future work.

Author contributions

FR and QD conducted the study and obtained research funding for the study. XM and JL introduced the research idea. XM analysed the data and drafted the manuscript. PL and YX secured research data. PJ critically commented on the study design and revised the manuscript. All authors read and approved the final manuscript.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgements

We thank Miss Siying He and Ziwen Liu for their help. In addition, this work was supported by the National Key Research and Development Programme of China (2016 YFC 0803106) and the National Natural Science Foundation of China (Project No. 41571438).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jth.2019.100675.

References

Albert, D.P., Butar, F.B., 2005. Estimating the de-designation of single-county HPSAs in the United States by counting naturopathic physicians as medical doctors. Appl. Geogr. 25, 271–285.

S, K.F.S., Liu, X.C., Zhang, G., 2017. An efficient General Transit Feed Specification (GTFS) enabled algorithm for dynamic transit accessibility analysis. PLoS One 12, e0185333.
Barbara, S., Leiyu, S., James, M., 2010. Contribution of primary care to health systems and health. Milbank Q. 83, 457–502.
Chan, M., 2013. WHO | the Contribution of Primary Health Care to the Millennium Development Goals. World Health Organization.
Chao, W., Ye, X., Du, Q., Ping, L., 2017. Spatial effects of accessibility to parks on housing prices in Shenzhen, China. Habitat Int. 63, 45–54.
Chen, W., Keqin, R., Sinan, W., Qian, L., 2013. Health care in China: improvement, challenges, and reform. Chest 143, 524–531.
Delamater, P.L., 2013. Spatial accessibility in suboptimally configured health care systems: a modified two-step floating catchment area (M2SFCA) metric. Health Place 24, 30–43.
Dong, Z., Phillips, M.R., 2010. Evolution of China's health-care system. Lancet 372, 1715–1716.
Dony, C.C., Delmelle, E.M., Delmelle, E.C., 2015. Re-conceptualizing accessibility to parks in multi-modal cities: a Variable-width Floating Catchment Area (VFCA) method. Landsc. Urban Plan. 143, 90–99.
Fang, R., Tong, D., Kwan, M.P., 2014. Space–time measures of demand for service: bridging location modelling and accessibility studies through a time-geographic framework. Geogr. Ann. 96, 329–344.
Farber, S., Morang, M.Z., Widener, M.J., 2014. Temporal variability in transit-based accessibility to supermarkets. Appl. Geogr. 53, 149–159.
Fransen, K., Neutens, T., Maeyer, P.D., Deruyter, G., 2015. A commuter-based two-step floating catchment area method for measuring spatial accessibility of daycare centers. Health Place 32, 65–73.
Gang, C., Zeng, X., Lian, D., Lu, X., Sun, H., Tao, J., Li, Y., 2016. Spatial difference analysis for accessibility to high level hospitals based on travel time in Shenzhen, China. Habitat Int. 53, 485–494.
Higgs, G., Zahnow, R., Corcoran, J., Langford, M., Fry, R., 2017. Modelling spatial access to General Practitioner surgeries: does public transport availability matter? J. Transp.Health 6, 143–154.
Hu, W., Dong, Q., Huang, B., 2018. Effects of distance and rescue time to medical facilities on traffic mortality utilizing GIS. Int. J. Inj. Control Saf. Promot. 25, 329–335.
Jia, P., 2016. Developing a flow-based spatial algorithm to delineate hospital service areas. Appl. Geogr. 75, 137–143.
Jia, P., Xierali, I.M., 2015. Disparities in Patterns of Health Care Travel Among Inpatients Diagnosed with Congestive, vol. 12. Heart Failure, Florida, p. E150, 2011.
Jia, P., Wang, F., Xierali, I.M., 2017. Delineating hierarchical hospital service areas in Florida. Geogr. Rev. 107.
Jia, P., Wang, F., Xierali, I.M., 2017. Using a Huff-Based Model to Delineate Hospital Service Areas. Professional Geographer, pp. 1–9.
Jia, P., Wang, F., Xierali, I.M., 2019. Differential effects of distance decay on hospital inpatient visits among subpopulations in Florida, USA. Environ. Monit. Assess. 191, 381.
Jia, P., Wang, F., Xierali, I.M., 2019. Teaming up census and patient data to delineate fine-scale hospital service areas and identify geographic disparities in hospital accessibility. Environ. Monit. Assess. 191, 303.
Jiang, B., Liang, S., Peng, Z.R., Cong, H., Levy, M., Cheng, Q., Wang, T., Remais, J.V., 2017. Transport and public health in China: the road to a healthy future. Lancet 390, 1781–1791.
Jing, L., Chen, G., Chang, L., Xia, B., Xuan, S., Chen, S., 2018. Use of an E2SFCA method to measure and analyse spatial accessibility to medical services for elderly people in wuhan, China. Int. J. Environ. Res. Public Health 15, 1503.
Johan, H., Groenewegen, P.P., Boerma, W.G.W., Kringos, D.S., 2015. Living in a country with a strong primary care system is beneficial to people with chronic conditions. Health Aff. 34, 1531–1537.
JohnRadke, LanMu, 2000. Spatial decompositions, modeling and mapping service regions to predict access to social programs. Geogr. Inf.Sci. 6, 105–112.
Langford, M., Fry, R., Higgs, G., 2012. Measuring transit system accessibility using a modified two-step floating catchment technique. Int. J. Geogr. Inf. Sci. 26, 193–214.
Langford, M., Higgs, G., Fry, R., 2016. Multi-modal two-step floating catchment area analysis of primary health care accessibility. Health Place 38, 70–81.
Lin, Y., Wan, N., Sheets, S., Gong, X., Davies, A., 2018. A multi-modal relative spatial access assessment approach to measure spatial accessibility to primary care providers. Int. J. Health Geogr. 17, 33.
Luo, W., Qi, Y., 2009. An enhanced two-step floating catchment area (E2SFCA) method for measuring spatial accessibility to primary care physicians. Health Place 15, 1100–1107.
Mao, L., Nekorchuk, D., 2013. Measuring spatial accessibility to healthcare for populations with multiple transportation modes. Health Place 24, 115–122.
Mcgrail, M.R., Humphreys, J.S., 2009. Measuring spatial accessibility to primary care in rural areas: improving the effectiveness of the two-step floating catchment area method. Appl. Geogr. 29, 533–541.
Neutens, T., 2015. Accessibility, equity and health care: review and research directions for transport geographers. J. Transp. Geogr. 43, 14–27.
Page, N., Langford, M., Higgs, G., 2017. Measuring spatial accessibility to services within indices of multiple deprivation: implications of applying an enhanced two-step floating catchment area (E2SFCA) approach. Appl.Spatial. Anal.Policy 1–28.
Pan, X., Kwan, M.P., Yang, L., Zhou, S., Wan, B., 2018. Evaluating the accessibility of healthcare facilities using an integrated catchment area approach. Int. J. Environ. Res. Public Health 15, 2051.
Rehrl, K., Gröechenig, S., Hochmair, H., Leitinger, S., Steinmann, R., Wagner, A., 2013. A conceptual model for analyzing contribution patterns in the context of VGI. J. Aerosol Sci. 66, 96–110.
Salonen, M., Toivonen, T., 2013. Modelling travel time in urban networks: comparable measures for private car and public transport. J. Transp. Geogr. 31, 143–153.
Schuurman, N., Bérubé, M., Crooks, V.A., 2010. Measuring potential spatial access to primary health care physicians using a modified gravity model. Can. Geogr. 54, 29–45.
Souliotis, K., Hasardzhiev, S., Agapidaki, E., 2016. A conceptual framework of mapping access to health care across EU countries: the patient Access initiative. Public Health Genomics 19, 153–159.
Tao, Z., Yao, Z., Kong, H., Duan, F., Li, G., 2018. Spatial accessibility to healthcare services in Shenzhen, China: improving the multi-modal two-step floating catchment area method by estimating travel time via online map APIs. BMC Health Serv. Res. 18, 345.
Tenkanen, H., Saarsalmi, P., Järv, O., Salonen, M., Toivonen, T., 2016. Health research needs more comprehensive accessibility measures: integrating time and transport modes from open data. Int. J. Health Geogr. 15, 23.
Wan, N., Zou, B., Sternberg, T., 2012. A three-step floating catchment area method for analyzing spatial access to health services. Int. J. Geogr. Inf. Sci. 26, 1073–1089.
Wang, F., 2012. Measurement, optimization, and impact of health care accessibility: a methodological review. Ann. Assoc. Am. Geogr. 102, 1104–1112.
Wang, F., Luo, W., 2005. Assessing spatial and nonspatial factors for healthcare access: towards an integrated approach to defining health professional shortage areas. Health Place 11, 131–146.
Wang, F., Onega, T., 2015. Accessibility of cancer care: disparities, outcomes and mitigation. Geogr. Inf.Sci. 21, 119–125.
Wei, L., Whippo, T., 2012. Variable catchment sizes for the two-step floating catchment area (2SFCA) method. Health Place 18, 789–795.
Widener, M.J., Farber, S., Neutens, T., Horner, M., 2015. Spatiotemporal accessibility to supermarkets using public transit: an interaction potential approach in Cincinnati, Ohio. J. Transp. Geogr. 42, 72–83.
Xi, Y., Ren, F., Liang, S., Zhang, J., Lin, D.N., 2014. Spatial analysis of the distribution, risk factors and access to medical resources of patients with hepatitis B in Shenzhen, China. Int. J. Environ. Res. Public Health 11, 11505–11527.
Xu, B., Yang, J., Zhang, Y., Gong, P., 2016. Healthy cities in China: a lancet commission. Lancet 388, 1863–1864.
Yang, J., Siri, J.G., Remais, J.V., Cheng, Q., Zhang, H., Chan, K.K.Y., Sun, Z., Zhao, Y., Cong, N., Li, X., 2018. The tsinghua– lancet commission on healthy cities in China: unlocking the power of cities for a healthy China. Lancet 391, 2140–2184.