

Article

Measuring Accessibility Based on Improved Impedance and Attractive Functions Using Taxi Trajectory Data

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Abstract: Accessibility has attracted wide interest from urban planners and transportation engineers. It is an important indicator to support the development of sustainable policies for transportation systems in major events, such as the COVID-19 pandemic. Taxis are a vital travel mode in urban areas that provide door-to-door services for individuals to perform urban activities. This study, with taxi trajectory data, proposes an improved method to evaluate dynamic accessibility depending on traditional location-based measures. A new impedance function is introduced by taking characteristics of the taxi system into account, such as passenger waiting time and the taxi fare rule. An improved attraction function is formulated by considering dynamic availability intensity. Besides, we generate five accessibility scenarios containing different indicators to compare the variation of accessibility. A case study is conducted with the data from Shenzhen, China. The results show that the proposed method found reduced urban accessibility, but with a higher value in southern center areas during the evening peak period due to short passenger waiting time and high destination attractiveness. Each spatio-temporal indicator has an influence on the variation in accessibility.

Keywords: accessibility; impedance and attractive functions; COVID-19; temporal variation; taxi GPS data; potential measures



Citation: Huang, H.; Wu, J.; Liu, F.; Wang, Y. Measuring Accessibility Based on Improved Impedance and Attractive Functions Using Taxi Trajectory Data. *Sustainability* **2021**, *13*, 112. <https://dx.doi.org/10.3390/su13010112>

Received: 11 October 2020

Accepted: 20 December 2020

Published: 24 December 2020

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1. Introduction

Accessibility is a key indicator to evaluate travel convenience in urban planning and transport geography. With the rapid urbanization and population growth, accessibility improvement can enhance the quality of urban transport services, reduce social segregation, and provide improved benefits for the whole society [1,2]. Measuring accessibility has attracted great attention from researchers and policymakers, not only for detecting the social inequalities of accessibility [3–5], but also for policies assessment and the evaluation of transportation system construction [6–8]. Accessibility studies can also support the formulation of emergency plans for the transportation system in major events, especially in the period of the COVID-19 pandemic. Some researchers recently found that transport accessibility is a key factor to detect the relationship between human behavior and the spread of COVID-19, to establish effective travel restriction policies [9,10].

With the development of the transportation system, availability of multiple modes, and increasing travel demands in the last several decades, evaluating dynamic urban accessibility became essential. Accessibility analysis has focused more on detecting the ease to opportunities by means of transport mode(s). Taxi as a competitive travel mode can provide comfortable, 24-h, and door-to-door services in most large cities. The services may fill the gaps of other travel modes from space and time [11–14]. Shaaban [15] also listed several reasons for relying on taxis for different travel purposes instead of using public transport services. Dynamic taxi-based accessibility was evaluated to assess the

service level of the taxi system and identify the regions with low efficiency for individuals taking social activities. Besides, taxi trajectory data can be easily collected from GPS (global positioning system) devices installed in taxi vehicles without the additional cost incurred [16].

This study proposes a method to evaluate dynamic taxi-based accessibility by improving two core components of the conventional location-based accessibility measures—impedance attractive functions. The suggested method depends on the characteristics of the taxi system and dynamic destination attractiveness. Furthermore, we generate five accessibility scenarios to identify the variation of accessibility influenced by different indicators. The study measures accessibility from two parts:

1. We propose an improved impedance function consisting of passenger waiting time and piecewise distance decay function. Passenger waiting time represents taxi availability, which is calculated by the queuing theoretic approach. Taxi fare rule, taking an example in China, comprised of minimum fare and fare per kilometer, which influence traditional distance decay function. The piecewise distance decay function is proposed to reflect these effects.
2. We construct a new attractive function by considering the indicator named dynamic availability intensity. Since choosing a taxi mode to perform activities at a location is constrained by time period (e.g., urban rail transit would be a better choice during the peak hours), space (e.g., destination's location), and individual's preference (e.g., individual's value of travel time or services quality).

In general, this study contributes to a new method incorporated with the spatio-temporal indicators that evaluate a realistic dynamic taxi-based accessibility to opportunities, differentiating from private vehicle accessibility measures. The study analyzes the variation of accessibility by comparing five accessibility scenarios, in which each scenario considers one or more indicators. To verify this method's applicability, we take Shenzhen as a case study area to conduct an experiment based on a grid-division method. Taxi trajectory data and POI (point of interest) data are utilized to support the study.

The remainder of the paper is organized as follows. Section 2 presents the literature review. Section 3 introduces the methodology utilized to measure taxi-based dynamic accessibility to opportunities. Section 4 describes the study area and data used. Five accessibility scenarios are introduced for the comparative analysis. The results and discussions are presented in Section 5. In Section 6, we conclude the paper and present possible follow-up study topics.

2. Literature Review

Accessibility was originally defined as “the potential of opportunities for interaction” by Hansen [17]. Four components have an important influence on measuring accessibility: land-use, transportation, time, and individual [18]. Depending on the perspectives of components, researchers differently defined what accessibility is [19–21]. The evaluation of accessibility to opportunities depends on two common measures: individual-based measures and location-based measures [18]. Individual-based measures can conceptualize individuals' ability to participate in activities under several space–time constraints. The methods spend high costs to gather large samples of individuals' activity information in large-scale study areas [22]. Location-based measures analyze the level of accessibility at a location to spatial opportunities typically on a macroscopic level [18], such as the number of restaurants within 15 min travel times from original locations. The current study defines taxi-based accessibility as the ease for individuals taking taxis from original locations to opportunities or destinations based on the definition of location-based measures. Common types of location-based measures include the minimum distance between two locations (i.e., distance measures), the cumulative number of opportunities within cut off distance (i.e., contour measures), and gravity measures in which the opportunities express decreasing effects with an increasing distance from the origin (i.e., potential measures) [23]. Potential accessibility measures (also called gravity-based measures) can estimate the com-

bined effect of transport components and land-use, and also take individuals' perceptions into account, overcoming the disadvantages of the other two measures [18].

In most previous location-based accessibility studies, researchers have conducted a static analysis without considering fluctuation in accessibility [24–26]. They utilized average travel times or a fixed speed to measure ease of access and other static indicators (e.g., population, employment) to present the destination attractiveness [11,27]. The static data obtained depend on traditional social questionnaire survey, census, in-depth interviews, and other data acquisition methods [28–30]. Järv [31] regarded that the lack of time-sensitive spatial data limits the location-based accessibility modeling incorporated with the time dimension. With the rapid development of information and communication technologies (ICT), more accurate and real-time spatio-temporal data sources can be acquired, such as GPS, mobile phone, and social media data. The spatio-temporal large-scale data enable data-driven approaches to extract dynamic information such as dynamic traffic conditions and dynamic mobility patterns, and provide a new opportunity to study dynamic accessibility [31–33].

In the recent decade, the perspective has shifted from static to dynamic, which is mainly manifested in improving components of location-based measures to obtain real-time accessibility data. Researchers improved time-sensitive accessibility analyses based on accurate evaluation of travel times or costs from new data sources. Several studies estimated public transport accessibility to destination using General Transit Feed Specification (GTFS) files to calculate transit travel times at all periods of the day [34–36]. Considerable case studies estimated urban network accessibility dynamically depending on the evaluation of travel times by motor vehicles. The common data includes floating car data collected from mobile GPS embedded in vehicles [16,37], the data recorded by embedded loop detectors [38], or data collected from TomTom database [39]. Furthermore, under the support of big data analytics and location technologies, researchers emphasized the influence of dynamic traffic conditions on accessibility analysis. The impact of traffic congestion on accessibility has gradually become a research focus in recent years [39–42].

In addition, dynamic accessibility analysis also depends on the measurement of temporal destination attractiveness. As the core component of dynamic accessibility, available activities were constrained by opening hours, temporal schedules, or the spatial distribution of given activity locations [21]. Researchers measured destination attractiveness considering dynamic intensities for performing activities due to activity type and temporal individuals' facility choice behaviors [22,29]. Furthermore, Wang et al. quantified the degree of satisfaction derived from performing activities to present attractiveness by using rich facility information collected from Baidu Maps [22]. In general, the existed studies utilized a proxy to measure destination attractiveness from the dimension of time, space, and individuals' degree of desire to access available activities. Typical representatives in dynamic accessibility researches were the number of trips ending in zones [27], the spatial distribution of population [43,44], and drop-offs in the spatial unit [11].

Great numbers of taxi-related research have been carried out, including customers' satisfaction assessment of taxi service [15,45], evaluating the performance of the overall taxi system [46], taxi route selection [25], and so on. Generally, travel time and taxi fare were considered in taxi-related studies. Shaaban et al. took 'time' as a significant factor to evaluate customers' satisfaction with taxi service, which included access time to home/work station, passenger waiting time, and in-vehicle travel time [15]. They adopted SEM (structured equation modeling) to get the result that passenger waiting time was the most contributing variable on customers' satisfaction. Alonso et al. also regarded passenger waiting time as the most critical factor for frequent users among the time spent. Uncertainty will be the main barrier against using taxis as a transport mode [45]. Zhang et al. established a queueing-based SM/M/1 modeling structure to estimate passenger-vehicle matching time in the new taxi system [47]. Zhang et al. proposed that taxi-coming probability was an important taxi availability index influencing the customers' satisfaction, in which the probability of taxi-coming was assumed to satisfy the Poisson distribution [46]. Taxi fare is another essential

variable in taxi system assessment, affecting service quality, travel demand, or individuals' benefits. Zhang et al. built the drivers' satisfaction index by explicitly considering taxi fare rule [46]. They separately calculated drivers' daily profits since taxi fares consist of two parts: starting fare and fare per mile. Starting fare changes during day and night.

Large-scale taxi trajectory data make dynamic accessibility research a great development. However, taxis as an essential mode attract less attention to measure the taxi-based accessibility. Existing research provides a limited assessment of taxi-based accessibility. In the previous work of [37], Jiang et al. measured taxi accessibility using trajectory data with the cumulative opportunity measures. They considered a real travel time to calculate the impedance function and adopted three types of opportunities (constant POIs, total drop-offs, and dynamic drop-offs) to compare the effects on taxi accessibility. No one takes the characteristics of the taxi system (e.g., taxi availability and fares) into consideration to measure taxi-based accessibility. The current study will fill the gap to build an appropriate method to capture a more accurate taxi-based accessibility. The proposed method will integrate various accessibility indicators into conventional location-based measures. Moreover, using taxi trajectory data, we will get real-time accessibility to represent the whole city's operational efficiency and reveal significant spatial heterogeneity.

3. Methodology

This section proposes an improved dynamic potential accessibility measure to estimate the temporal variation of accessibility to opportunities based on taxi travel mode. First, conventional potential accessibility measures are in short introduced to supply the necessary background knowledge. Then, to get a more accurate and targeted dynamic taxi-based accessibility measure, passenger waiting time, taxi travel time, taxi fare rules, and dynamic availability intensity of opportunities are considered to reconstruct impedance and attractive functions of conventional potential accessibility measure. On the whole, based on traditional potential accessibility measures, two works will be completed in this paper:

1. Restructuring a new impedance function by combining passenger waiting time and travel times influenced by taxi fare rules.
2. Considering the influence of variation in destination attractiveness on potential opportunities achieved, forming an attractive function from static and dynamic perspectives.

3.1. Conventional Potential Accessibility Measures

In order to effectively measure accessibility in a specific location to surrounding opportunities by using a certain transportation mode, several types of location-based measures are widely adopted in past accessibility studies. Two essential accessibility components compose the location-based measures: trip costs (determined by the transport network conditions) and attractiveness (the quality/quantity of opportunities) [20,43]. The general formula of conventional location-based measures is expressed as follows [22]:

$$A_i = \sum_{j=1}^n D_j \cdot f(c_{ij}) \quad (1)$$

where, A_i presents the accessibility in unit i , D_j is the size of attraction in unit j to individuals in unit i , e.g., the number of opportunities, $f(\cdot)$ is the impedance function, c_{ij} is the trip costs between unit i and unit j . As mentioned in the literature review, location-based measures contain three common methods: distance measures, contour measures, and potential measures. The definition of the impedance function can distinguish each accessibility measure.

Potential accessibility measures (also called gravity-based measures) are appropriate for analyzing accessibility to opportunities from residents or workplaces, which can estimate the combined effects of transport components and land-use, also taking individuals' perceptions into account [18]. Potential accessibility measures can be defined as the sum of the products of an attractive function and a negative exponential function, which estimate the accessibility of individuals in spatial unit i to opportunities in all units (n) where

smaller or more distant opportunities provide decreasing influences [17,48]. The negative exponential impedance function is mostly used in location-based accessibility measures in the present studies due to the correlation to travel behavior theory [49]. Then, we get the conventional potential measure as follows [17]:

$$A_i = \sum_{j=1}^n D_j e^{-\beta c_{ij}} \quad (2)$$

where $\beta \geq 0$ is the cost sensitivity parameter—the larger the value, the stronger the distance decay effect on accessibility will be [22].

The potential accessibility measures have the advantage of simple structure and easy calculation, which are used to assess accessibility to different types of opportunities (jobs, medical facilities, recreation facilities, social services, etc.). Furthermore, considering space-time constraints, individuals' dynamic perception, and dynamic traffic conditions, space-time potential accessibility measures are in quantities studied in the field of transport geography. However, these measures are not combined with the characteristics of the taxi system. Thus it is difficult to accurately estimate and analyze the dynamic accessibility to opportunities using taxis.

3.2. Dynamic Taxi-Based Potential Accessibility Measure

(1) Impedance function:

In this section, the competition effect (i.e., passenger waiting time) between demand and supply of origin, and the trip costs (i.e., travel times) between origin and destination are considered as the impedances when individuals travel by taxis. Thereby, the product of two decay functions, which depends on passenger waiting time and travel time influenced by taxi fare rules respectively, constructs a new impedance function.

Spending less passenger waiting time means the ease to take available vacant taxis, which represents high accessibility for individuals to destination. Note that passenger waiting time exists a variation in space (e.g., center areas, peripheral areas) and time (e.g., traffic congestion period). Also, taxi drivers' aimless driving path and passengers' arrival randomness will result in an uncertain passenger waiting time [46]. Two assumptions are defined to calculate expected passenger waiting time: (1) The passenger and vacant taxi arrival processes are Poisson processes and that the service times are exponentially distributed [47]; (2) passengers and vehicles are matched on a first-come-first-served (FCFS) basis in the taxi system [47]. Thereby, this paper utilizes the simple M/M/1 queue, which belongs to queuing theoretic approaches, to estimate expected passenger waiting time (wt_i) in each spatial unit i in different time intervals of the day. Passenger waiting time wt_i is expressed as:

$$wt_i = \frac{1}{\mu_i - \lambda_i} \quad (3)$$

where, μ_i is the service rate defined as the average number of vacant taxis per unit time in spatial unit i , λ_i is the arrival rate defined as the average number of pick-ups per unit time in spatial unit i .

The fare rule of taxis is distinct from other travel modes like bus and urban rail transit. Meanwhile, different countries have their taxi fare rules to charge fees per trip. For example, in China, the fare is divided into two parts: a starting fare (minimum fare) and fare per kilometer [46]. The starting fare is fixed within the specified kilometer range (e.g., 1.5 \$ within 2 km), and fare increases per kilometer over the specified kilometers (e.g., 0.7 \$ per mile over 2 km). On the basis of the taxi fare rule, we assume that if travel time is less than or equal to the threshold, that is the time when the fare is just beginning to increase from the starting fare, the impedance in travel would not change, or if travel time is more than the threshold, the impedance in travel would increase with travel time. Finally, a piecewise

distance decay function based on the taxi fare rule is proposed to illustrate the influence of the trip cost on taxi-based accessibility. The function can be defined as follow:

$$k(c_{ij}) = \begin{cases} 1, & c_{ij} \leq TH_T \\ e^{-\beta(c_{ij}-TH_T)}, & c_{ij} > TH_T \end{cases} \quad (4)$$

where, $k(\cdot)$ represents piecewise distance decay function depending on travel time, TH_T is the travel time threshold, c_{ij} is the travel time between unit i and unit j . The cost sensitivity parameter (i.e., β) of the function should be estimated with recent empirical data of spatial travel behavior in the study area [18].

Then, an improved impedance function can be defined as:

$$f(wt_i, c_{ij}) = e^{-\alpha wt_i} \cdot k(c_{ij}) \quad (5)$$

where the new impedance function $f(\cdot)$ is the product of the decay function of passenger waiting time and the piecewise distance decay function, α is the time-sensitivity parameter.

(2) Attractive function:

In this section, a time-dependent attractive function is proposed to indicate the dynamic demand of passengers at a destination, i.e., destination attractiveness. From a perspective of the dynamic demand, destination attractiveness to potential passengers in each spatial unit is determined by the static number of opportunities as well as the dynamic availability of opportunities (e.g., operating hours of the day) [50–52]. Furthermore, the availability of opportunities has a temporal fluctuation related to land-use and opportunity type (e.g., trips to workplace predominate in the morning, whereas trips to shopping malls or return to home predominate in the evening) [22,27]. We consider the concept of time-dependent attractiveness and formulate a new attractive function as follows:

$$D_j(t) = p_j \cdot g_j(t) \quad (6)$$

where, $D_j(t)$ represents the time-dependent attractive function at unit j , p_j is the number of POIs representing ideally maximum number of opportunities passengers can obtain at unit j , $g_j(t)$ is a time-dependent availability intensity function representing the intensity of individuals' access to opportunities at unit j at a certain time t . In this study, the number of drop-offs at a unit is used to estimate the availability intensity function. The value of availability intensity is normalized into a range from zero to one.

Thus, a dynamic taxi-based potential accessibility measure A_i^T is proposed consisting of a new attractive function and an improved impedance function mentioned above. The formula is presented as:

$$A_i^T = \sum_{j=1}^n D_j(t) \cdot f(wt_i, c_{ij}) \quad (7)$$

This new measure can enhance the ability to estimate realistic fluctuating accessibility to opportunities based on taxi travel mode, along with considering taxi characteristics (passenger waiting time and taxi fare rule) and dynamic availability intensity in each spatial unit. For the convenience of readers, we put the description of terms in functions in Appendix A.

4. Case Study

4.1. Study Area

The case study is conducted in Shenzhen, China. The city located in South China consists of ten administrative districts. The southern parts of the city are central areas with rapid development, containing Futian, Luohu, and Nanshan districts. To ensure a more accurate result of accessibility research, we utilize a grid division method to divide spatial regions. The whole city is discretized into a set of grid cells with the size of $1 \times 1 \text{ km}^2$.

Totally, there are 1705 grid cells cover Shenzhen. Figure 1 presents the road network for the whole city. The southern areas are covered with dense road networks. Besides, many areas are not covered with road network due to the hills or lakes.

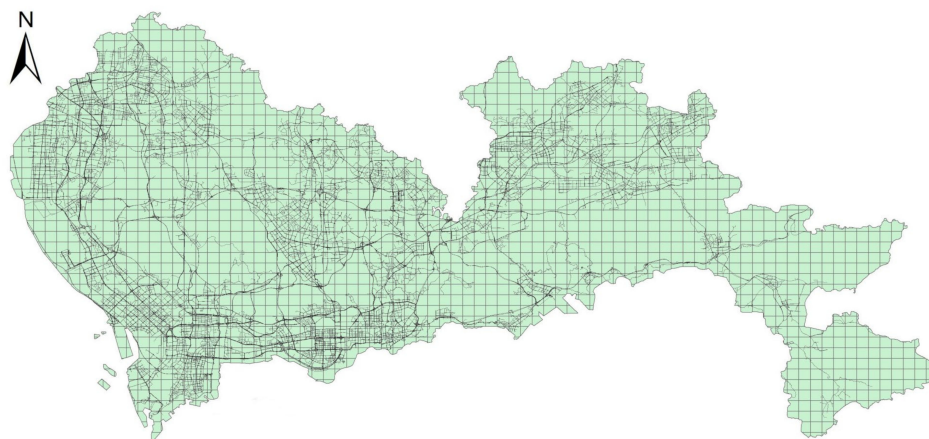


Figure 1. Road network in Shenzhen.

4.2. Data Collection

In this study, we measure taxi-based accessibility to opportunities constrained by land-use and real traffic conditions. Two major categories of data (taxi trajectory data and POI data) are collected to compute dynamic accessibility in Shenzhen.

Taxi trajectory data is technically and economically feasible to collect, which can extract more information about individuals' travel behaviors and real-time traffic conditions [22]. The original taxi trajectory data used for this study was collected from five typical weekdays in 2017. Each GPS record contains such information: car ID, speed, recording times, longitude and latitude, and operational status messages ('0' represents no passenger, '1' means the vehicle is occupied). To improve the quality, we removed abnormal GPS records differentiating from the actual traffic conditions. Several types of records were filtered out, such as records outside the city boundary and records with a velocity higher than the road section's speed limit. Moreover, we removed the anomalous trajectory data if the duration was less than 1 min or more than 120 min since it is abnormal for a passenger to take a taxi for such a short or long duration [11].

Travel times were calculated by using GPS trajectories according to the hour division. Through data processing, we obtained the temporal variations of the average travel speed of urban networks at different hours of the day (see Figure 2). We selected three typical periods for dynamic accessibility research: the morning peak period (8:00–9:00), the evening peak period (17:00–18:00), and the off-peak period (12:00–13:00).

Occupied taxis can better reflect the actual traffic conditions, and drop-offs can be supposed as the attractiveness of the grid cell [11]. We got pick-ups and drop-offs based on a common method. We regarded the trajectory points where the operational status changes from '1' to '0' as drop-offs. Similarly, points where the taxi status changed from '0' to '1', were supposed to be pick-ups. In addition, quantities of operational vacant taxis in the grid cell will reflect the taxi service capacity. To gather the number of vacant available vehicles in grids, we extracted all the GPS records with the '0' operational status and deleted inappropriate records (collected from the vehicles parked at a certain place for a long time). Moreover, we removed the repeat records of the same vacant vehicles in the grid cell, ensuring that operational vacant taxis in the grid cell have a unique license plate number.

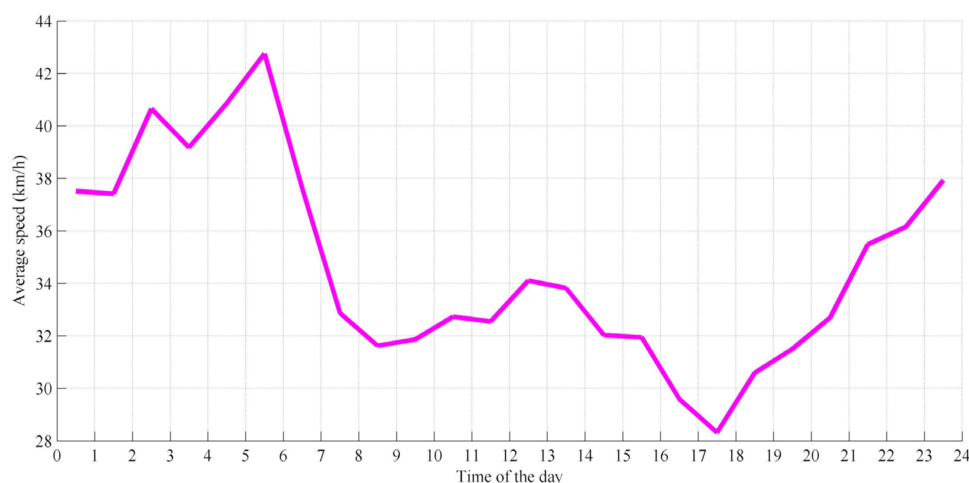


Figure 2. Temporal variations of average travel speed.

POI is widely used in accessibility research, presenting the potential opportunities individuals can access. According to previous classification experience [11], POI data containing 170,619 facilities in Shenzhen were classified into 12 categories by definition of different facilities. Through the statistics, shopping services (45.3%), restaurants (15.8%), and entertainment services (11.2%) account for the top three of total facilities. The spatial distribution of POI is showed in Figure 3. From the figure, POIs are concentrated in the center areas and some suburban areas (Baoan district, Longhua district, and Longgang district); fewer gathered in rural areas located in the east of city.

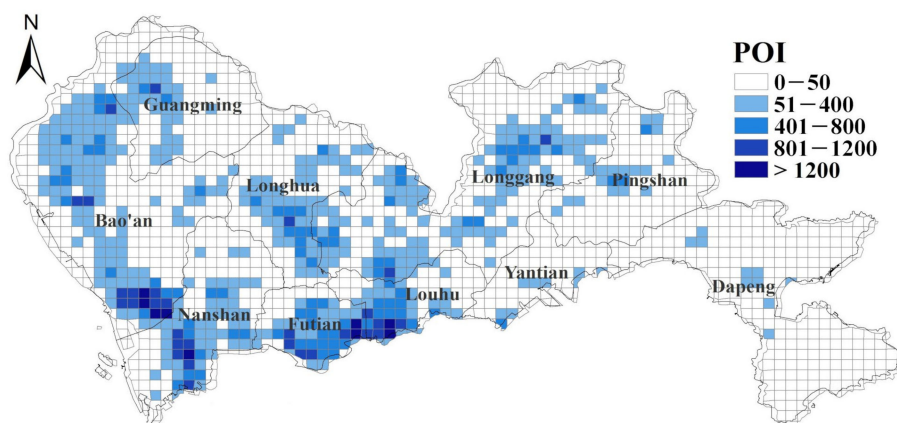


Figure 3. Spatial distribution of points of interest (POI).

The sensitivity parameters of the impedance function—the time-sensitivity parameter α and the cost sensitivity parameter β are respectively set to be 0.5 and 0.3 according to empirical data of spatial travel behavior in the study region.

4.3. Scenarios Setup

We generated five scenarios for analysis (Table 1) in line with the proposal proposed by Pedro [27] to identify the variation of accessibility in different periods influenced by each accessibility scenario. These five scenarios are described as follows:

- Scenario 1 is the reference scenario. Accessibility was calculated based on Equation (2) considered with static destination attractiveness (i.e., $g_j(t) = 1$) and conventional impedance function (i.e., only considering travel time). We will take the scenario as a reference to compare differences in accessibility with other scenarios with different indicators.

- Scenario 2 is the dynamic attractiveness scenario. Accessibility was calculated considering time-varying attractiveness based on the reference scenario, while taxi characteristics were not considered.
- Scenario 3 is the scenario considering passenger waiting time. This scenario combined passenger waiting time with conventional impedance function based on the reference scenario. The destination attractiveness remained static, and the taxi fare rule was not considered.
- Scenario 4 is the scenario considering taxi fare rules. The new piecewise distance decay function was calculated with travel times influenced by taxi fare rule. Destination attractiveness remained static, and passenger waiting time was not considered.
- Scenario 5 is the taxi-based dynamic accessibility scenario. Accessibility was calculated with dynamic destination attractiveness and improved impedance function.

Table 1. Five accessibility scenarios.

	Constant POIs	Conventional Impedance Function ¹	Dynamic Availability Intensity	Passenger Waiting Time	Piecewise Distance Decay Function
Scenario 1	✓	✓			
Scenario 2	✓	✓	✓		
Scenario 3	✓	✓		✓	
Scenario 4	✓				✓
Scenario 5	✓		✓	✓	✓

¹ Conventional impedance function is expressed as $e^{-\beta c_{ij}}$, where c_{ij} is the travel time between unit i and j .

5. Results and Discussions

5.1. Descriptive Analysis of the Combined Data Sources

In this section, we first give a detailed description of data processing results when building the new taxi-based accessibility measure. We used taxi trajectory data collected on two days for analysis. Figure 4 presents the spatial distribution of passenger waiting times in Shenzhen in three time periods. This figure shows a center-periphery pattern since passengers can quickly get the vehicles in regions with high-density road networks and developed commercial centers. Conversely, passengers will spend more waiting times in regions the vehicle cannot access (e.g., forests or lakes). Figure 5 presents the spatial distribution of pick-ups representing individuals' needs to take taxis in different time periods. The figure shows a high taxi demand in rapidly developed areas located in Futian district and Nanshan district, and low taxi demand in the north and east areas with slow development. Two grids located in suburb regions with more pick-ups are the airport in Baoan district and the Shenzhen railway station in Longhua district. Figure 6 presents the spatial distribution of vacant taxis in different time periods. We can infer that taxi drivers tend to search for passengers in center areas with high demands. Passenger waiting time in each grid is influenced by the number of vacant vehicles and pick-ups.

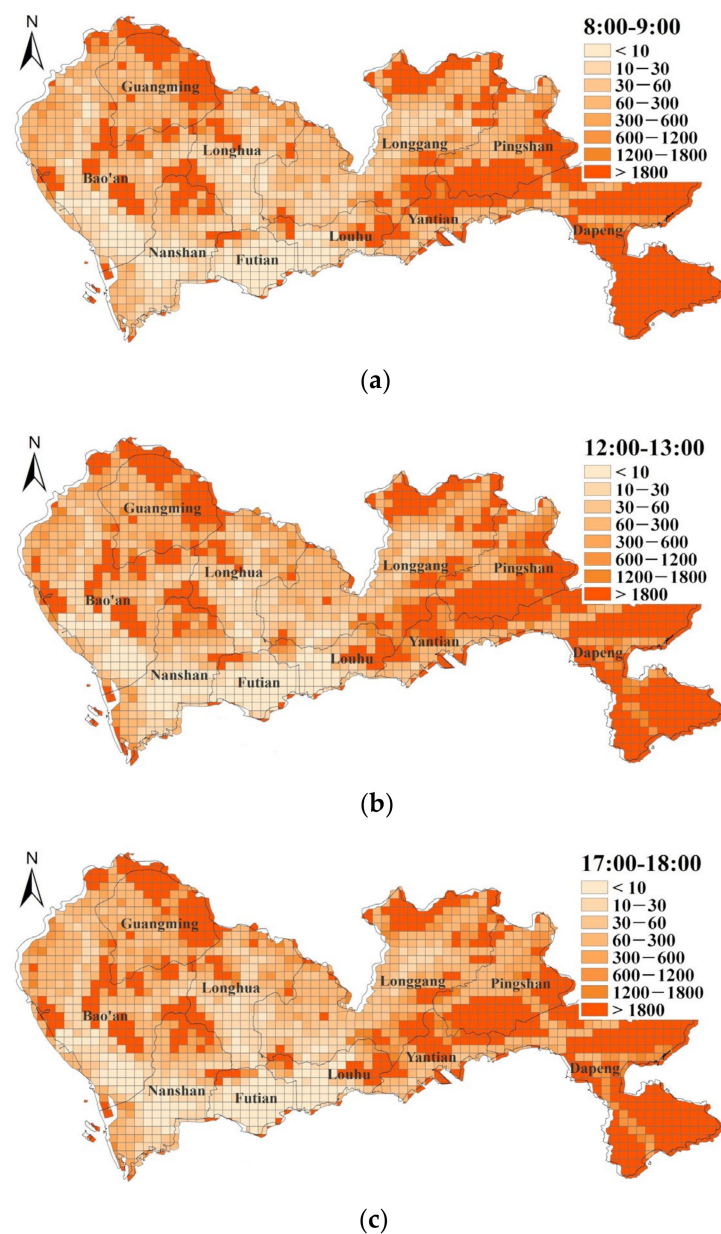
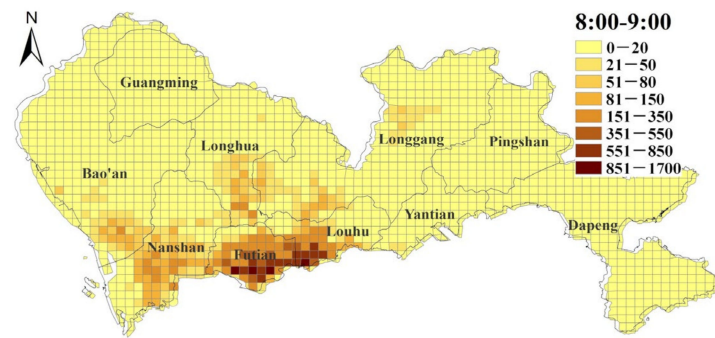
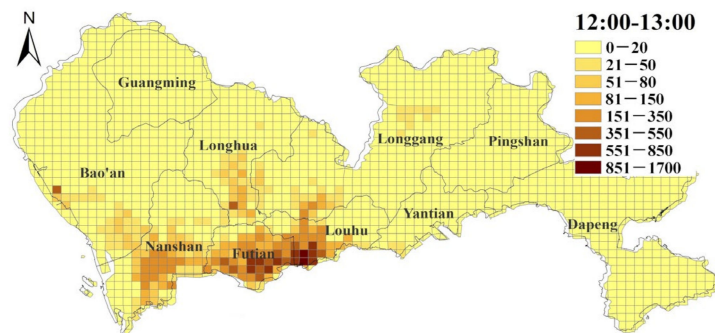


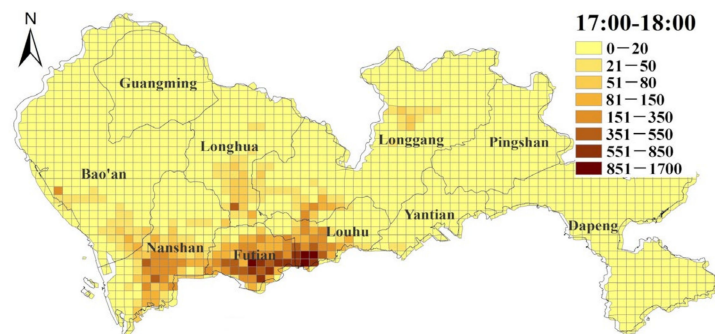
Figure 4. Spatial distribution of passenger waiting time (s) in three time periods. (a) The morning peak period; (b) The off-peak period; (c) The evening peak period.



(a)



(b)



(c)

Figure 5. Spatial distribution pick-ups in three time periods. (a) The morning peak period; (b) The off-peak period; (c) The evening peak period.

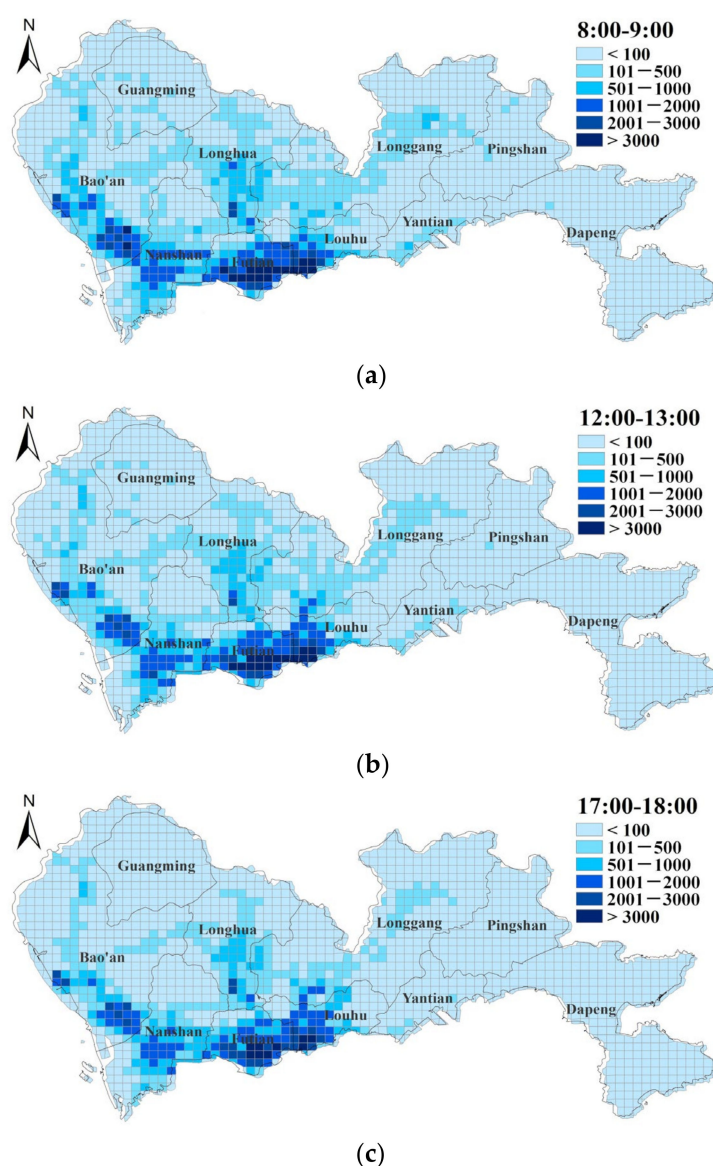


Figure 6. Spatial distribution of operational vacant taxis in three time periods. (a) The morning peak period; (b) The off-peak period; (c) The evening peak period.

Figure 7 presents the dynamic availability intensity of six representative grids with different facility types. The facilities selected contain Baoan airport, Luohu shopping mall, Shenzhen North railway station, Futian bus station, Peking University Shenzhen Hospital, and Shenzhen University. We counted dynamic drop-offs in these grids in each hour of the day, respectively. The number of drop-offs is normalized into a range from zero to one. The zero value indicates no passengers drop off the vehicle to participate in the activities at that time. The figure shows that these grids' availability intensity reaches the lowest during 5:00–6:00 period, which is in line with individuals' psychological/physiological needs to participate in activities. The availability intensity of grids tended to display a different variation in time of the day due to the diverse demands to perform various activities. Therefore, we can note that it is reasonable to consider the time-varying availability intensity in different grids.

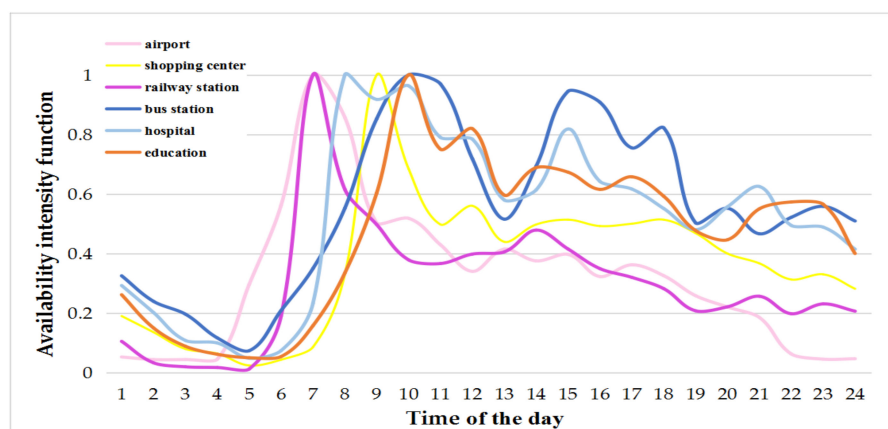


Figure 7. Availability intensity function for six types of facilities.

5.2. Comparison between Scenarios

Five accessibility scenarios with different indicators are generated and compared to identify the influence of these indicators on taxi accessibility. To conduct a comparative analysis between scenarios, the spatial distribution of accessibility in reference scenario is presented, i.e., considering the number of POIs as static destination attractiveness and the conventional impedance function (see Figure 8). Due to dynamic traffic conditions, the figure shows a distinct variation of accessibility in three time periods. The off-peak period (12:00–13:00) displays a higher accessibility than the other two periods since the smooth traffic conditions made individuals get more opportunities at a certain time. On the contrary, the morning and evening peak periods show a lower accessibility in three time periods due to the congested traffic. Figure 8 shows a distinctive higher accessibility in the urban center areas (especially in Futian and Nanshan district), and lower accessibility in eastern and northern suburbs, which shows a typical center-periphery pattern. Furthermore, some grids in center areas that are not covered by road networks (e.g., parks or lakes) present a lower accessibility than other grids nearby. Conversely, some suburbs in the north show a high accessibility due to the concentration of economic activity facilities (e.g., offices, shopping malls) or residential areas.

The variation of differences between the reference scenario and the other four scenarios in three time periods are presented in Figure 9. Note that the value of the variation of difference is expressed in percentage and the grids, that the variation of differences is zero, meaning that accessibility value of these grids is zero, i.e., taxis cannot arrive at these grids (e.g., forests or lakes).

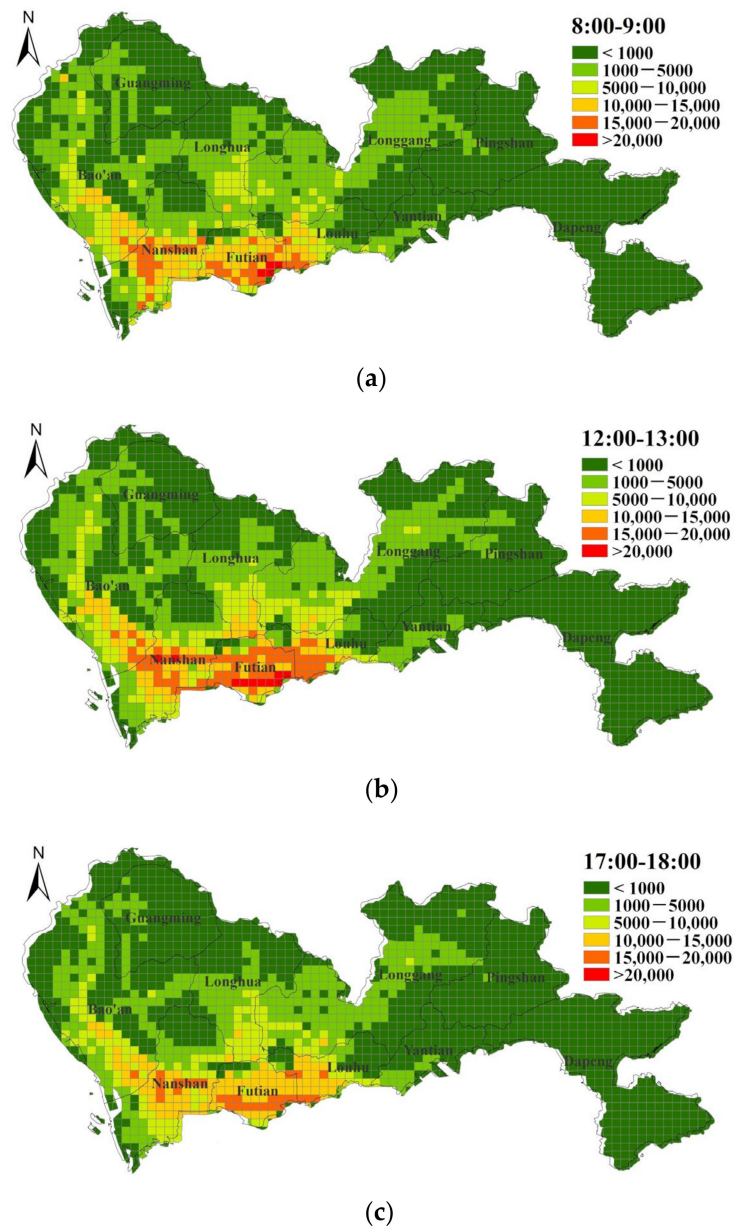


Figure 8. The spatial distribution of accessibility in the reference scenario. (a) Accessibility in the morning peak period; (b) Accessibility in the off-peak period; (c) Accessibility in the evening peak period.

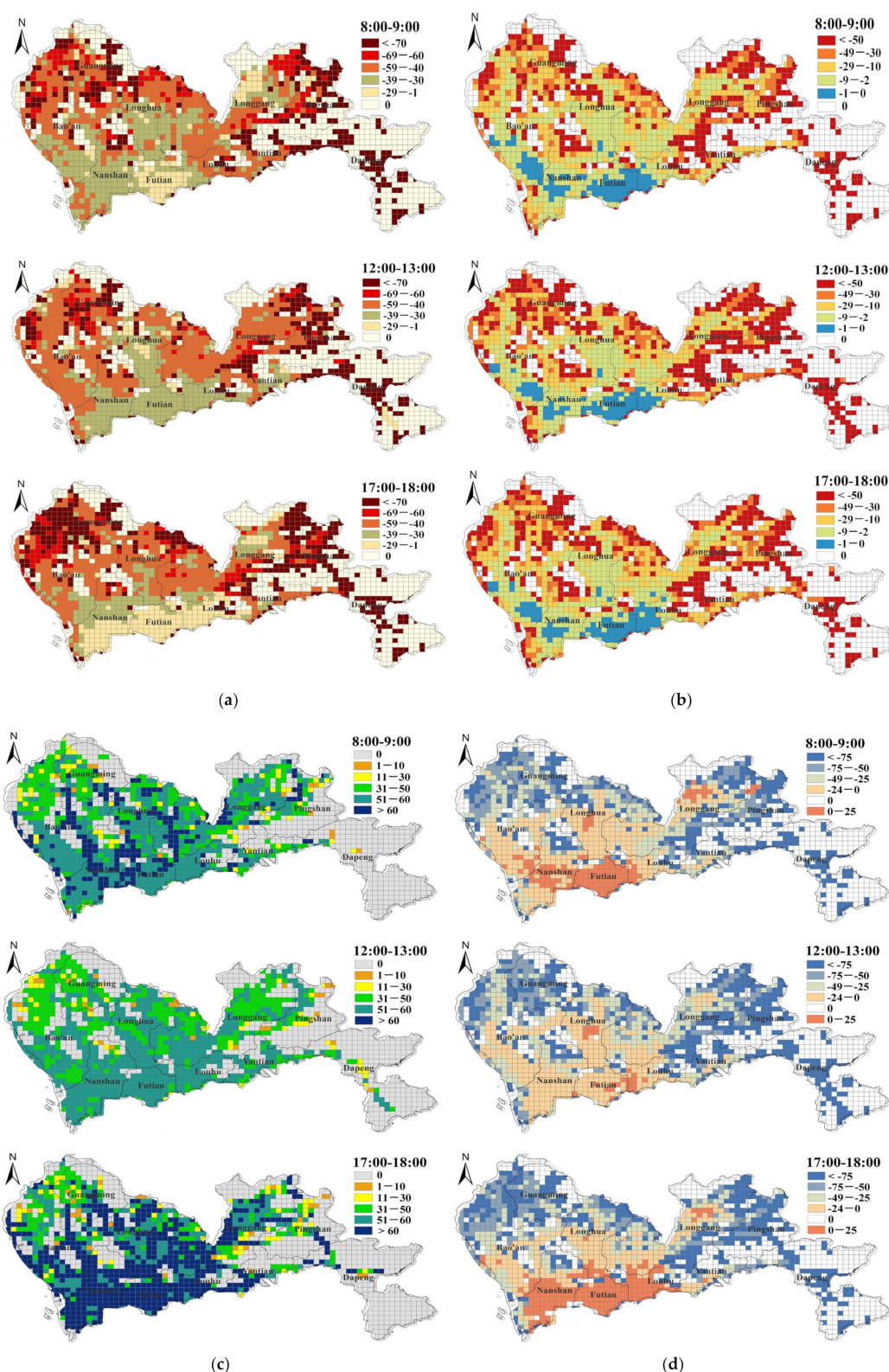


Figure 9. Differences (%) in accessibility throughout the day according to scenario: (a) Scenario 2; (b) scenario 3; (c) scenario 4; (d) scenario 5.

The distribution of differences between scenario 5 (taxi-based dynamic accessibility scenario) and the reference scenario shows dynamic taxi-based accessibility exerted a distinct effect on each grid (see Figure 9d). In morning and evening peak periods, the accessibility of center areas has an apparent increase compared with the reference scenario,

especially in Futian district and Nanshan district, because of the higher density of POI and shorter waiting times. In the off-peak period, except for the weak increase in accessibility in the southern center, other areas have shown a sharp decline in accessibility, which is due to the low attractiveness intensity during this period.

We list the accessibility results in each scenario in three time periods and the differences between the reference scenario and other scenarios in Table 2. As shown in the table, adding dynamic attractiveness indicator makes a negative contribution to accessibility compared with scenario 1 that is considered a static attractiveness (i.e., availability intensity function equals 1), which is especially obvious in 12:00–13:00 (−40.17%). Scenario 3 (considering passenger-waiting time) shows a negative impact on accessibility in three time periods due to the increasing travel costs by considering the passenger waiting time, which is particularly marked in 12:00–13:00 (−9.79%). Scenario 4 (considering the taxi fare rule) shows that the new proposed piecewise distance decay function makes a positive contribution to dynamic accessibility, which is marked in evening peak hours (+62.4%). The dynamic taxi-based accessibility scenario (scenario 5) shows variation in accessibility in three time periods. These accessibility values show a negative effect depending on the characteristics of the taxi system and dynamic attractiveness. The lowest mean accessibility difference is recorded during the off-peak hour (−16.82%).

Table 2. Accessibility in five scenarios and difference between scenario 1 and other scenarios (n = 1705).

Scenario 1	Count	Minimum	Maximum	Sum	Mean	Standard Deviation
8:00–9:00	1705	0	21,147.53	3,887,898.71	2280.29	3964.16
12:00–13:00	1705	0	21,820.24	4,566,265.52	2678.16	4631.75
17:00–18:00	1705	0	19,482.96	3,693,045.85	2166.01	3875.31
Scenario 2	Count	Minimum	Maximum	Sum	Mean	Standard deviation
8:00–9:00	1705	0	15,680.50	2,431,589.68	1426.15	2670.50
12:00–13:00	1705	0	14,365.55	2,732,044.73	1602.37	2929.05
17:00–18:00	1705	0	13,533.87	2,363,108.56	1385.99	2739.05
Differences between scenario 1 and 2		Minimum	Maximum	Sum	Mean	Standard deviation
8:00–9:00		0	−5467.03	−1,456,309.03	−854.14	−1293.66
12:00–13:00		0	−7454.69	−1,834,220.80	−1075.79	−1702.70
17:00–18:00		0	−5949.09	−1,329,937.29	−780.02	−1136.26
Differences (%) between scenario 1 and 2		Minimum	Maximum	Sum	Mean	Standard deviation
8:00–9:00		0	−25.85	−37.46	−37.46	−32.63
12:00–13:00		0	−34.16	−40.17	−40.17	−36.76
17:00–18:00		0	−30.53	−36.01	−36.01	−29.32
Scenario 3	Count	Minimum	Maximum	Sum	Mean	Standard deviation
8:00–9:00	1705	0	20,845.47	3,556,847.34	2086.13	3869.22
12:00–13:00	1705	0	21,691.07	4,119,342.58	2416.04	4532.01
17:00–18:00	1705	0	19,166.07	3,396,523.29	1992.10	3800.40
Differences between scenario 1 and 3		Minimum	Maximum	Sum	Mean	Standard deviation
8:00–9:00		0	−302.06	−331,051.37	−194.17	−94.93
12:00–13:00		0	−129.17	−446,922.95	−262.12	−99.74
17:00–18:00		0	−316.89	−296,522.56	−173.91	−74.91
Differences (%) between scenario 1 and 3		Minimum	Maximum	Sum	Mean	Standard deviation
8:00–9:00		0	−1.43	−8.51	−8.51	−2.39
12:00–13:00		0	−0.59	−9.79	−9.79	−2.15
17:00–18:00		0	−1.63	−8.03	−8.03	−1.93

Table 2. Cont.

Scenario 4	Count	Minimum	Maximum	Sum	Mean	Standard deviation
8:00–9:00	1705	0	32,621.86	6,018,893.09	3530.14	6199.37
12:00–13:00	1705	0	33,255.76	6,934,102.02	4066.92	7096.81
17:00–18:00	1705	0	32,711.16	5,998,152.25	3517.98	6379.09
Differences between scenario 1 and 4		Minimum	Maximum	Sum	Mean	Standard deviation
8:00–9:00		0	11,474.33	2,130,994.38	1249.85	2235.21
12:00–13:00		0	11,435.52	2,367,836.50	1388.76	2465.06
17:00–18:00		0	13,228.19	2,305,106.41	1351.97	2503.78
Differences (%) between scenario 1 and 4		Minimum	Maximum	Sum	Mean	Standard deviation
8:00–9:00		0	54.26	54.81	54.81	56.39
12:00–13:00		0	52.41	51.85	51.85	53.22
17:00–18:00		0	67.90	62.42	62.42	64.61
Scenario 5	Count	Minimum	Maximum	Sum	Mean	Standard deviation
8:00–9:00	1705	0	23,354.53	3,496,023.99	2050.45	4078.43
12:00–13:00	1705	0	21,689.77	3,798,243.71	2227.71	4384.05
17:00–18:00	1705	0	22,312.11	3,604,799.85	2114.25	4413.78
Differences between scenario 1 and 5		Minimum	Maximum	Sum	Mean	Standard deviation
8:00–9:00		0	2207.00	−391,874.72	−229.84	114.27
12:00–13:00		0	−130.46	−768,021.81	−450.45	−247.69
17:00–18:00		0	2829.15	−88,245.99	−51.76	538.48
Differences (%) between scenario 1 and 5		Minimum	Maximum	Sum	Mean	Standard deviation
8:00–9:00		0	10.44	−10.08	−10.08	2.88
12:00–13:00		0	−0.60	−16.82	−16.82	−5.35
17:00–18:00		0	14.52	−2.39	−2.39	13.90

Figure 10 shows the spatial distribution of dynamic taxi-based potential accessibility (scenario 5) based on A_i^T as defined in Equation (7) in three time periods. From the figure, the results are similar to those in Figure 8. However, accessibility of urban center areas in scenario 5 expresses a distinctive increase, and accessibility of other areas have a decline, especially during the evening peak period (see Figure 10c), which reveals that at night a large number of trips to center areas (e.g., leisure, shopping) make a high activity intensity.

From the temporal perspective, the fluctuation of accessibility of scenario 1 and scenario 5 forms different performances during the day (see Figure 11), in which the ordinate is the sum of accessibility in grids and the abscissa is time of the day. The blue line in Figure 11 shows the temporal variation of taxi-based accessibility (scenario 5). The accessibility reaches its maximum value during night time (22:00–23:00) due to the high availability intensity and the good traffic conditions in this period. The accessibility reaches its minimum value during the early morning period (5:00–6:00). That result is more reasonable than that of the red line because the availability intensity during 5:00–6:00 is lowest (see Figure 8), and individuals make few trips to perform activities at these times of day (e.g., sleeping at home). Therefore, the new taxi accessibility measure, considering dynamic availability intensity and taxi characteristics, is more appropriate to estimate the actual temporal accessibility to opportunities based on the taxi mode.

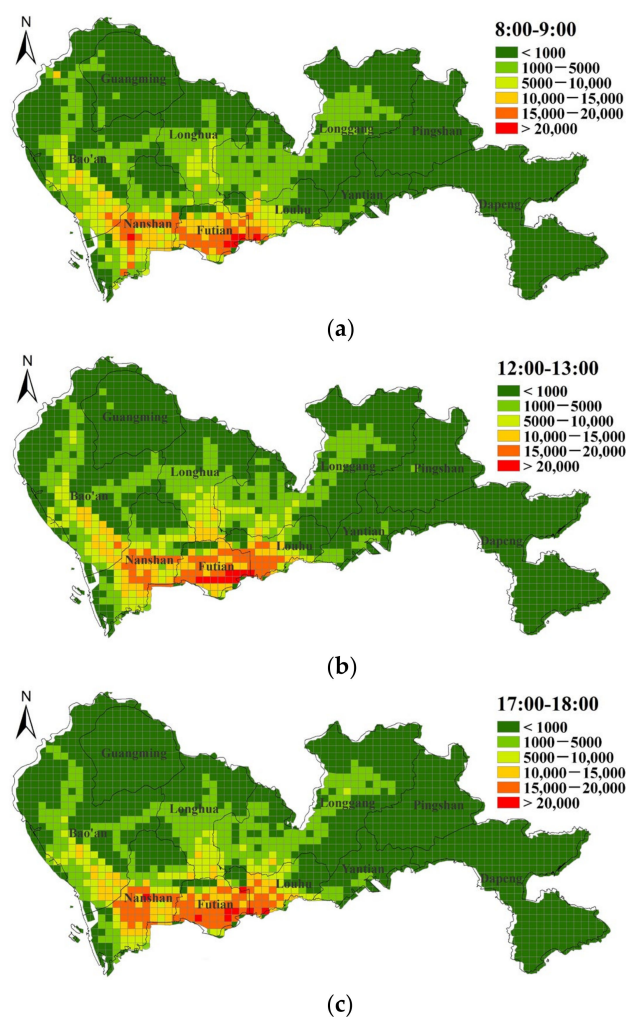


Figure 10. Results of dynamic taxi-based potential accessibility. (a) Accessibility in the morning peak period; (b) Accessibility in off-peak period; (c) Accessibility in the evening peak period.

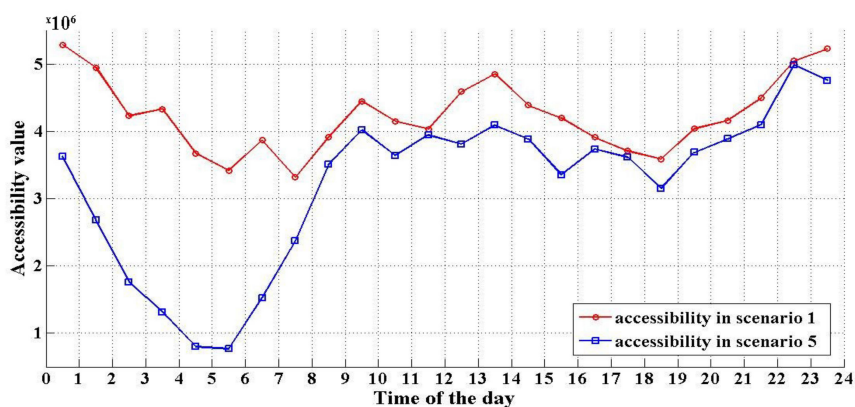


Figure 11. Temporal variation of accessibility.

5.3. Discussions

From the results above, we found that the conventional potential accessibility measures may overestimate or underestimate taxi accessibility. Thus, this study's purpose is to present a new method to evaluate taxi accessibility more accurately and to provide reference resources for relevant managers and planners. Three indicators affecting taxi ac-

cessibility are considered: dynamic availability intensity, passenger waiting time, and taxi fare rule. Moreover, the scenarios were compared to analyze these indicators.

Figure 9a shows that after considering dynamic availability intensity, the accessibility in southern center areas has no obvious change, but the accessibility in periphery areas has a distinct decrease. The southern areas of Shenzhen are closer to Hong Kong, which leads to the earlier and faster development of these areas than periphery areas. That is to say, the facilities in southern areas may have a higher dynamic availability intensity. As displayed in Figure 9a, two conclusions are drawn: (1) Developed areas are less affected by availability intensity indicator; (2) if we neglect dynamic availability intensity of facilities in accessibility measures, the accessibility results would be overestimated. The overestimation would be higher from midnight to early morning (0:00 to 7:00), especially in developing or underdeveloped areas.

According to Figure 9b, the unbalanced spatial distribution of the difference value indicates that accessibility in peripheral areas is more affected by waiting time during three periods. One of the reasons is that the supplement of vacant taxis in the peripheral areas is insufficient, which makes individuals need to spend more time waiting for a vacant taxi. It was also implied that a well-distributed supplement of vacant taxis can reduce passenger waiting times and improve taxi accessibility of the transportation system in the peripheral areas. Another reason is that the taxi trajectory data used in this study is incomplete, which might lead to the overestimation of the waiting time in peripheral areas. We only collected the taxi trajectory data of license plates belonging to Shenzhen. These taxis mainly operate in the southern areas of Shenzhen. However, some taxis from surrounding cities (e.g., Dongguan, Guangzhou) also operate in Shenzhen, and the Shenzhen government only allows these taxis to operate in the peripheral areas (e.g., Guangming district and the part regions of Baoan district). Therefore, due to the lack of these taxis' trajectory data, we may underestimate accessibility in the peripheral areas. If data from more sources are available in the future, it is expected that more accurate measurement and evaluation of taxi accessibility would be obtained.

Figure 9b also shows that the difference value of blue grids is less than 1%, which indicates that considering the passenger waiting time hardly affects the accessibility of these areas. According to Equation (3), the above results are mainly because the number of vacant taxis is far greater than the number of passengers in the blue grids. This serious imbalance between supply and demand may lead to the waste of taxi resources and unnecessary environmental pollution. Hence, we suggest that the taxi company could dispatch some of the vacant taxis in blue grids to the neighboring green grids to search for passengers, producing profit by reducing competition among vacant taxis and improving the operational efficiency.

The influence of the taxi fare rule on impedance function is shown in Equation (4). If the impedance function of scenario 1 is replaced by Equation (4) (i.e., scenario 4), the accessibility value of the grids, where taxis can reach more facilities under the travel time threshold TH_T , will increase. In Figure 9c, we find that the increase of accessibility in the southern areas or the areas near the primary road is larger than that in the northern suburb areas. In other words, if individuals travel by taxi, the individuals in the southern areas or the areas near the primary road may spend less travel time to arrive at destinations, while the individuals in the northern suburb areas (especially in the northwest areas) may need to spend more travel time due to the concentration of facilities in the southern areas. Thus, we can expect that the urban structure with multiple sub-centers is more convenient and accessible for taxi mode.

Although this study revealed important findings, the study is not without limitations that should be addressed in follow-up studies. First, to the estimation of passenger waiting time, this study calculated ideal waiting times by assuming a first-come-first-served basis and neglected the searching time when a vacant taxi picks up the next passenger after entering the grid. Therefore, more complex situations about passenger-vehicle matching should be considered to estimate passenger waiting time. Second, recent new on-line taxi systems provide real-time on-demand services with smartphone applications (e.g., Uber,

Lyft, Didi), which were not considered in this study. If the on-line taxi system data is available, the results would be more accurate and reliable. Third, heterogeneity between individuals is also an important factor for taxi accessibility, including socioeconomic status (e.g., income) and individual perception towards taxis. The heterogeneity should be taken into consideration in attractive functions in future studies.

6. Conclusions

This study developed a dynamic taxi-based potential accessibility measure to estimate spatio-temporal accessibility to opportunities by improving the conventional potential accessibility measure. Previously, existing studies provided a limited assessment of taxi-based accessibility. Researchers extracted travel times from taxi trajectory data to measure accessibility, neglecting other taxi-related information obtained from the data. This study filled the research gap by proposing a methodological framework to measure taxi-based accessibility. We took taxi availability (i.e., passenger waiting time) and taxi fare rule into account in the construction of impedance function. A dynamic attractive function was proposed at the perspective of temporal variation. We combined the static size of opportunities (i.e., the constant POIs) and dynamic availability intensity (i.e., dynamic drop-offs) to present the destination attractiveness. Furthermore, we generated five accessibility scenarios in the case study to analyze the influence of each indicator on variation in accessibility at different times of the day.

Taking dynamic availability intensity into consideration can obtain two main conclusions. First, developing and underdeveloped areas are more likely to be influenced by availability intensity indicators, whereas developed areas are less affected. Second, the accessibility would be overestimated if dynamic availability intensity is not taken into consideration. These phenomena are more obvious for the nighttime period (0:00 to 7:00), as well as in developing or underdeveloped areas. The consideration of passenger waiting time index can identify that the accessibility level of different regions varies greatly due to the unbalanced supplement of vacant taxis, especially in suburb areas. We also find that many vacant taxis are gathered in the core area, leading to the decline of accessibility in the surrounding areas. Moreover, in the construction of the impedance function, the taxi fare rule has a positive impact on accessibility, especially in the city's southern areas and the areas near the primary road. Single-central city structure makes suburban residents spend more to participate in social and economic activities. A multi-center city structure may enable residents to save travel costs and balance the urban development structure.

The proposed measure can provide the idea of taxi-based dynamic accessibility research for existing research and the realistic accessibility fluctuation at different time periods of the day. In addition, we expect that a more in-depth analysis of the results and policy implications of different scenarios will enable traffic managers and planners to generate profound thinking on transport and land-use policies, as well as a reliable basis for taxi operation companies to carry out dispatching management.

Author Contributions: Conceptualization, H.H. and F.L.; methodology, J.W.; supervision, H.H.; validation, Y.W.; visualization, J.W., Y.W.; writing—original draft, F.L., H.H., and J.W.; writing—review and editing, F.L. and Y.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded in part by the National Natural Science Foundation of China (No. 71701215), Natural Science Foundation of Hunan Province (No. 2020JJ4752), Innovation-Driven Project of Central South University (No. 2020CX041), Innovation-Driven Project of Central South University (No. 2020CX013), National Key R&D Program of China (No. 2020YFB1600400), Foundation of Central South University (No. 502045002), Postdoctoral Science Foundation of China (No. 2018M630914 and 2019T120716), Science and Innovation Foundation of the Transportation Department in Hunan Province (No. 201725).

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to the privacy reason.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Appendix A

Table A1. Description of terms in function.

Terms	Description
$A(i)$	The accessibility in unit i
D_j	The size of attraction in unit j to individuals in unit i
$f(.)$	The impedance function of conventional location-based measures
c_{ij}	The trip costs between unit i and unit j
β	The cost sensitivity parameter
wt_i	Passenger waiting time
μ_i	The service rate defined as the average number of vacant taxis per unit time in spatial unit i
λ_i	The arrival rate defined as the average number of pick-ups per unit time in spatial unit i
$k(c_{ij})$	Piecewise distance decay function depending on travel time c_{ij}
TH_T	The travel time threshold
a	The time-sensitivity parameter
$D_j(t)$	The time-dependent attractive function at unit j
p_j	The number of POIs representing ideally maximum number of opportunities passengers can obtain at unit j
$g_j(t)$	The time-dependent availability intensity function representing the intensity of individuals' access to opportunities at unit j at a certain time t
A_i^T	Taxi-based accessibility in unit i

References

1. Basso, F.; Frez, J.; Martínez, L.; Pezoa, R.; Varas, M. Accessibility to opportunities based on public transport gps-monitored data: The case of Santiago, Chile. *Travel Behav. Soc.* **2020**, *21*, 140–153. [\[CrossRef\]](#)
2. Blumenberg, E.; Shiki, K. How Welfare Recipients Travel on Public Transit, and Their Accessibility to Employment Outside Large Urban Centers. *Transp. Q.* **2003**, *57*, 25–37.
3. Chen, B.; Wang, Y.; Wang, D.; Li, Q.; Lam, W.H.K.; Shaw, S. Understanding the Impacts of Human Mobility on Accessibility Using Massive Mobile Phone Tracking Data. *Ann. Am. Assoc. Geogr.* **2018**, *108*, 1115–1133. [\[CrossRef\]](#)
4. Martin, D.; Jordan, H.; Roderick, P. Taking the bus: Incorporating public transport timetable data into health care accessibility modeling. *Environ. Plan. A* **2008**, *40*, 2510–2525. [\[CrossRef\]](#)
5. Chang, Z.; Chen, J.; Li, W.; Li, X. Public transportation and the spatial inequality of urban park accessibility: New evidence from Hong Kong. *Transp. Res. Part D Transp. Environ.* **2019**, *76*, 111–122. [\[CrossRef\]](#)
6. Papa, E.; Silva, C.; Brömmelstroet, M.T.; Hull, A. Accessibility instruments for planning practice: A review of European experiences. *J. Transp. Land Use* **2015**, *9*, 1–20. [\[CrossRef\]](#)
7. Boisjoly, G.; El-Geneidy, A.M. How to get there? A critical assessment of accessibility objectives and indicators in metropolitan transportation plans. *Transp. Policy* **2017**, *55*, 38–50. [\[CrossRef\]](#)
8. Juan, P.B.S.; Daniel, R.O.H. Transport accessibility and social inequities: A tool for identification of mobility needs and evaluation of transport investments. *J. Transp. Geogr.* **2012**, *24*, 142–154.
9. Carteni, A.; Francesco, L.D.; Martino, M. The role of transport accessibility within the spread of the Coronavirus pandemic in Italy. *Saf. Sci.* **2020**. [\[CrossRef\]](#)
10. Carteni, A.; Francesco, L.D.; Martino, M. How mobility habits influenced the spread of the COVID-19 pandemic: Results from the Italian case study. *Sci. Total Environ.* **2020**. [\[CrossRef\]](#)
11. Jiang, S.; Guan, W.; He, Z.; Yang, L. Measuring Taxi Accessibility Using Grid-Based Method with Trajectory Data. *Sustainability* **2018**, *10*, 3187. [\[CrossRef\]](#)
12. Wong, K.I.; Wong, S.C.; Yang, H. Modeling urban taxi services in congested road networks with elastic demand. *Transp. Res. Part B Methodol.* **2001**, *35*, 819–842. [\[CrossRef\]](#)
13. Tang, J.; Liang, J.; Zhang, S.; Huang, H.; Liu, F. Inferring driving trajectories based on probabilistic model from large scale taxi GPS data. *Phys. A Stat. Mech. Appl.* **2018**, *506*, 566–577. [\[CrossRef\]](#)
14. Zong, F.; Tian, Y.; He, Y.; Tang, J.; Lv, J. Trip destination prediction based on multi-day GPS data. *Phys. A* **2019**, *515*, 258–269. [\[CrossRef\]](#)

15. Shaaban, K.; Kim, I. Assessment of the taxi service in Doha. *Transp. Res. Part A Policy Pract.* **2016**, *88*, 223–235. [\[CrossRef\]](#)
16. Cui, J.X.; Liu, F.; Janssens, D.; An, S. Detecting urban road network accessibility problems using taxi GPS data. *J. Transp. Geogr.* **2016**, *51*, 147–157. [\[CrossRef\]](#)
17. Hansen, W.G. How accessibility shapes land use. *J. Am. Inst. Plan.* **1959**, *25*, 73–76. [\[CrossRef\]](#)
18. Geurs, K.T.; Wee, B.V. Accessibility evaluation of land-use and transport strategies: Review and research directions. *J. Transp. Geogr.* **2004**, *12*, 127–140. [\[CrossRef\]](#)
19. Cascetta, E. *Transportation Systems Analysis: Models and Applications*; Springer: Berlin, Germany, 2009.
20. Páez, A.; Scott, D.M.; Morency, C. Measuring accessibility: Positive and normative implementations of various accessibility indicators. *J. Transp. Geogr.* **2012**, *25*, 141–153. [\[CrossRef\]](#)
21. Wee, B.V. Accessible accessibility research challenges. *J. Transp. Geogr.* **2016**, *51*, 9–16.
22. Wang, Y.; Chen, B.Y.; Yuan, H.; Wang, D. Measuring temporal variation of location-based accessibility using space-time utility perspective. *J. Transp. Geogr.* **2018**, *73*, 13–24. [\[CrossRef\]](#)
23. Neutens, T.; Schwanen, T.; Witlox, F.; De Maeyer, P. Equity of urban service delivery: A comparison of different accessibility measures. *Environ. Plan. A* **2010**, *42*, 1613–1635. [\[CrossRef\]](#)
24. Gutierrez, J.; Gomez, G. The impact of orbital motorways on intra-metropolitan accessibility: The case of Madrid's M-40. *J. Transp. Geogr.* **1999**, *7*, 1–15. [\[CrossRef\]](#)
25. Martín, J.C.; García-Palomares, J.C.; Gutiérrez, J.; Román, C. Impacts of orbital motorways in metropolitan areas on accessibility: Efficiency and equity. A case study in Madrid. *Transp. Land Use* **2010**, *3*, 67–84.
26. Chiarazzo, V.; dell'Olio, L.; Ibeas, Á.; Ottomanelli, M. Modeling the Effects of Environmental Impacts and Accessibility on Real Estate Prices in Industrial Cities. *Proc. Soc. Behav. Sci.* **2014**, *111*, 460–469. [\[CrossRef\]](#)
27. Pedro, G.A.; Picornell, M.; Salas-Olmedo, M.H.; Gutiérrez, J. Exploring the potential of mobile phone records and online route planners for dynamic accessibility analysis. *Transp. Res. Part A* **2019**, *125*, 294–307.
28. Liu, Y.; Liu, X.; Gao, S.; Gong, L.; Kang, C.; Zhi, Y.; Chi, G.; Shi, L. Social Sensing: A New Approach to Understanding Our Socioeconomic Environments. *Ann. Assoc. Am. Geogr.* **2015**, *105*, 512–530. [\[CrossRef\]](#)
29. Miller, H.J.; Goodchild, M.F. Data-driven geography. *GeoJournal* **2015**, *80*, 449–461. [\[CrossRef\]](#)
30. Yuan, H.; Chen, B.Y.; Li, Q.Q.; Shaw, S.-L.; Lam, W.H.K. Toward space-time buffering for spatio-temporal proximity analysis of movement data. *Int. J. Geogr. Inf. Sci.* **2018**, *32*, 1211–1246. [\[CrossRef\]](#)
31. Järv, O.; Tenkanen, H.; Salonen, M.; Ahas, R.; Toivonen, T. Dynamic cities: Location-based accessibility modelling as a function of time. *Appl. Geogr.* **2018**, *95*, 101–110. [\[CrossRef\]](#)
32. Tang, J.; Wang, Y.; Hao, W.; Liu, F.; Huang, H.; Wang, Y. A mixed path size logit based taxi customer-search model considering spatio-temporal factors in route choice. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 1347–1358. [\[CrossRef\]](#)
33. Zhang, S.; Tang, J.; Wang, H.; Wang, Y.; An, S. Revealing intra-urban travel patterns and service ranges from taxi trajectories. *J. Transp. Geogr.* **2017**, *61*, 72–86. [\[CrossRef\]](#)
34. Farber, S.; Morang, M.Z.; Widener, M.J. Temporal variability in transit-based accessibility to supermarkets. *Appl. Geogr.* **2014**, *53*, 149–159. [\[CrossRef\]](#)
35. Fransen, K.; Neutens, T.; Farber, S.; de Maeyer, P.; Deruyter, G.; Witlox, F. Identifying public transport gaps using time-dependent accessibility levels. *J. Transp. Geogr.* **2015**, *48*, 176–187. [\[CrossRef\]](#)
36. Farber, S.; Fu, L. Dynamic public transit accessibility using travel time cubes: Comparing the effects of infrastructure (dis) investments over time. *Comput. Environ. Urban Syst.* **2017**, *62*, 30–40. [\[CrossRef\]](#)
37. Li, Q.; Zhang, T.; Wang, H.; Zeng, Z. Dynamic accessibility mapping using floating car data: A network-constrained density estimation approach. *J. Transp. Geogr.* **2011**, *19*, 379–393. [\[CrossRef\]](#)
38. Owen, A.; Levinson, D.M. Modeling the commute mode share of transit using continuous accessibility to jobs. *Transp. Res. Part A* **2015**, *74*, 110–122. [\[CrossRef\]](#)
39. Dingil, A.E.; Schweizer, J.; Rupi, F.; Stasiskiene, Z. Transport indicator analysis and comparison of 151 urban areas, based on open source data. *Eur. Transp. Res. Rev.* **2018**, *10*, 58. [\[CrossRef\]](#)
40. Zhang, S.; Liu, X.; Tang, J.; Cheng, S.; Qi, Y.; Wang, Y. Spatio-temporal modeling of destination choice behavior through the Bayesian hierarchical approach. *Phys. A Stat. Mech. Appl.* **2018**, *512*, 537–551. [\[CrossRef\]](#)
41. Tang, J.; Bi, W.; Liu, F.; Zhang, W. Exploring urban travel patterns using density-based clustering with multi-attributes from large-scaled vehicle trajectories. *Phys. A Stat. Mech. Appl.* **2020**. [\[CrossRef\]](#)
42. Tang, J.; Zhang, S.; Chen, X.; Liu, F.; Zou, Y. Taxi Trips Distribution Modeling Based on Entropy-maximizing Theory: A Case Study in Harbin City-China. *Phys. A Stat. Mech. Appl.* **2018**, *493*, 430–443. [\[CrossRef\]](#)
43. Chen, J.; Ni, J.; Xi, C.; Li, S.; Wang, J. Determining intra-urban spatial accessibility disparities in multimodal public transport networks. *J. Transp. Geogr.* **2017**, *65*, 123–133. [\[CrossRef\]](#)
44. Stpnjak, M.; Goliszek, S. Spatio-Temporal Variation of Accessibility by Public Transport—The Equity Perspective. *Rise Big Spat. Data* **2017**. [\[CrossRef\]](#)
45. Alonso, B.; Barreda, R.; Dell'Olio, L.; Ibeas, A. Modelling user perception of taxi service quality. *Transp. Policy* **2018**, *63*, 157–164. [\[CrossRef\]](#)
46. Zhang, D.Z.; Sun, D.; Peng, Z.R. A Comprehensive Taxi Assessment Index Using Floating Car Data. *J. Harbin Inst. Technol.* **2014**, *21*, 7–16.

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47. Zhang, W.; Honnappa, H.; Ukkusuri, S.V. Modeling urban taxi services with e-hailings: A queueing network approach. *Transp. Res. Part C* **2020**, *113*, 332–349. [[CrossRef](#)]
 48. Kwan, M.P. Space-time and integral measures of individual accessibility: A comparative analysis using a point-based framework. *Geogr. Anal.* **1998**, *30*, 191–216. [[CrossRef](#)]
 49. Handy, S.L.; Niemeier, D.A. Measuring accessibility: An exploration of issues and alternatives. *Environ. Plan. A* **1997**, *29*, 1175–1194. [[CrossRef](#)]
 50. Delafontaine, M.; Neutens, T.; Schwanen, T.; Weghe, N.V.D. The impact of opening hours on the equity of individual space-time accessibility. *Comput. Environ. Urban Syst.* **2011**, *35*, 276–288. [[CrossRef](#)]
 51. Tenkanen, H.; Saarsalmi, P.; Järv, O.; Salonen, M.; Toivonen, T. Health research needs more comprehensive accessibility measures: Integrating time and transport modes from open data. *Int. J. Health Geogr.* **2016**, *15*, 23. [[CrossRef](#)]
 52. Widener, M.J.; Minaker, L.; Farber, S.; Allen, J.; Vitali, B.; Coleman, P.C.; Cook, B. How do changes in the daily food and transportation environments affect grocery store accessibility? *Appl. Geogr.* **2017**, *83*, 46–62. [[CrossRef](#)]