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Understanding travel time uncertainty impacts on the equity of individual accessibility

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ABSTRACT

Most current accessibility equity studies ignore travel time uncertainties. This study investigates the travel time uncertainty impacts on the equity of individual accessibility. Travel time distributions of the road network and mobility data for a large number of individual samples across the entire study area are extracted using comprehensive big datasets of taxi trajectories and mobile phone tracking data. Two reliability-based individual accessibility measures are proposed to evaluate individual accessibility by explicitly considering individual's on-time arrival probability concern for activity participations. The proposed measures are further applied to quantify travel time uncertainty impacts on the equity of individual accessibility to shopping services. Results of this study demonstrate the capabilities of using spatiotemporal big data to examine the equity of accessibility in a disaggregated individual level. The results also suggest that travel time uncertainties have negative impacts on accessibility of all people groups, but more serious impacts on disadvantaged people groups with a lower accessibility level.

1. Introduction

Accessibility is a key concept in urban and transport planning (Cao et al., 2010; Geurs et al., 2010; Hu et al., 2015; Owen and Levinson, 2015; Xu et al., 2016). Sufficient levels of accessibility to urban services, such as job, healthcare, and shopping services, are essential for quality of life and wellbeing. Conversely, the lack of accessibility could significantly increase the amount of effort individuals need to exercise to organize their daily life (Lucas, 2012; El-Geneidy et al., 2016). Therefore, it is crucial for policymakers to evaluate distributive equity of accessibility among people in different socio-spatial groups, and identify disadvantaged people with an extreme low level of accessibility (van Wee and Geurs, 2011; Delbosc and Currie, 2011; Lucas et al., 2016; Hu et al., 2017; Pereira et al., 2017).

Theoretically, accessibility level of an individual should be evaluated by using individual accessibility measures to capture interactions between land use, transport, and people components (Geurs and van Wee, 2004). Most existing individual measures are built upon the time geographic concept of space-time prism (Miller, 2005; Hägerstrand, 1970) to represent individual potential activity spaces under various space-time constraints. The cumulative number of urban services and the activity durations at reachable

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urban services within the individual's potential activity space are two commonly used individual measures (Kwan, 1998). However, the individual accessibility measures has rarely been fully operationalized in accessibility equity studies for large study areas (Kwan and Weber, 2003; Miller, 2007), because it is very time-consuming and expensive to collect huge samples of individual-level data by using traditional activity-diary surveys. Most existing accessibility equity studies have been conducted by using aggregated approaches based on place-based accessibility measures, which ignore distinct activity-travel behaviors of people in different socio-spatial groups (Delbosc and Currie, 2011; Su et al., 2017). Such place-based measures, however, produce an identical accessibility level to all people living in the same residential area, leading to considerable bias on the evaluation of individual accessibility and the associated equity issue (Miller, 2007; Pereira et al., 2017).

Further, previous accessibility studies build on a deterministic assumption of travel times in transport networks (Kwan, 1998; Miller, 1999; Neutens et al., 2010; Hu et al., 2018; Xu et al., 2017). In reality, travel times inherently fluctuate, due to various interruptions caused by traffic signal controls, traffic incidents, and road constructions, adverse weather, etc. (Lam et al., 2008; Shi et al., 2017). Individuals in face of travel time uncertainties do not know with certainty about the on-time arrival for activity participations, but only a probability. Many empirical studies found that the on-time arrival probability, termed travel time reliability, is the most important factor considered by individuals in their activity-travel scheduling (Bates et al., 2001; Carrion and Levinson, 2012; Liao et al., 2014). Majority of individuals under travel time uncertainties are risk-averse for being late. They tend to budget extra time as a safety margin to ensure a high on-time arrival probability, leading to a reduction of their activity spaces and accessibility levels (Chen et al., 2013). Therefore, ignoring travel time uncertainties could overestimate individuals' activity spaces and the accessibility levels to urban services. Because different people tend to have distinct activity space patterns and road networks in different city regions have various degrees of travel time uncertainties, it is still unknown how travel time uncertainties affect the accessibility equity among people in different socio-spatial groups.

Recent advances in information and communication technologies have made it possible to collect huge amounts of spatiotemporal big data, such as mobile phone data, social media data, taxi trajectories, etc. (Miller and Goodchild, 2015; Bertone and Burghardt, 2017; Wang et al., 2018). These spatiotemporal big data record very detailed individual movements across changing urban environments; and widely recognized as ideal data sources for estimating individual activity spaces of a large samples (Xu et al., 2016; Chen et al., 2018; Weiss et al., 2018) and for monitoring traffic conditions in large-scale transport networks (Shi et al., 2017; Ma et al., 2018). Such spatiotemporal big data have offered unprecedented opportunities to move beyond aggregated place-based accessibility studies towards disaggregated individual accessibility studies (Kwan and Weber, 2003; Miller, 2007). Chen et al. (2018) conducted one of the first individual accessibility studies using individual activity spaces extracted from mobile phone big data instead of traditional activity-diary survey data. They examined spatial equity of accessibility by aggregating accessibility of all users in cellular towers, and found that human mobility can mitigate spatial inequality for people living in different geographical regions. Nevertheless, the equity of accessibility was not investigated at a disaggregated individual level, and travel time uncertainties were completely ignored.

With spatiotemporal big data, much attention has been given to quantify temporal variation (Fransen et al., 2015; Wessel et al., 2017) and service reliability of public transport systems (Chakrabarti, 2015; Chen et al., 2009). Nevertheless, a few previous studies have employed spatiotemporal big data to explicitly investigate travel time uncertainty impacts on accessibility. Chen et al. (2017) proposed reliable place-based accessibility measures by considering reliability constraints for performing activities at facilities under travel time uncertainties. Zhang et al. (2018) and Conway et al. (2018) extended those proposed measures to public transport networks. However, these reliable accessibility measures were to evaluate place-based accessibility rather than individual accessibility and the associated equity issue.

This study aims to fill two gaps in accessibility equity studies: extend previous studies by using spatiotemporal big data to evaluate accessibility equity of a large number of individual samples across a large study area; and examine travel time uncertainty impacts on accessibility equity of people in different socio-spatial groups. To achieve these research objectives, comprehensive datasets of taxi trajectories and mobile phone tracking data are collected in Shenzhen, China. Link travel time distributions and mobility patterns for over 5 million phone users are extracted across the entire study area. Two reliability-based individual accessibility measures are proposed to evaluate individual accessibility by explicitly considering individual concerns on travel time reliability. The proposed measures are applied to quantify travel time uncertainty impacts on equity of accessibility to shopping services. The results will advance methodologies to evaluate accessibility equity under travel time uncertainties, and enrich our understanding of how transport network uncertainties shape accessibility of people in different socio-spatial groups.

2. Reliability-based individual accessibility measures under travel time uncertainties

Traditional individual accessibility measures, such as cumulative number of facilities (denoted by CUM) and the cumulative time durations at accessible facilities (denoted by DUR), adopt the deterministic travel time assumption but ignore travel time uncertainties (Kwan, 1998). To address this issue, we extend CUM and DUR measures in this section by explicitly incorporating the individual's concerns on travel time reliability.

A road network can be represented as a directed graph, $G = (V, E)$, consisting of a set of vertices, V, and a set of edges (or links), E, where each link $e \in E$ has randomly distributed travel time, T_e. Let p_i^{ox} be a path from an individual's origin, o, to a network location, x, consisting of a set of consecutive links. The path travel time distribution, T_i^{ox}, can be calculated by the summation of corresponding travel times of links along the path:

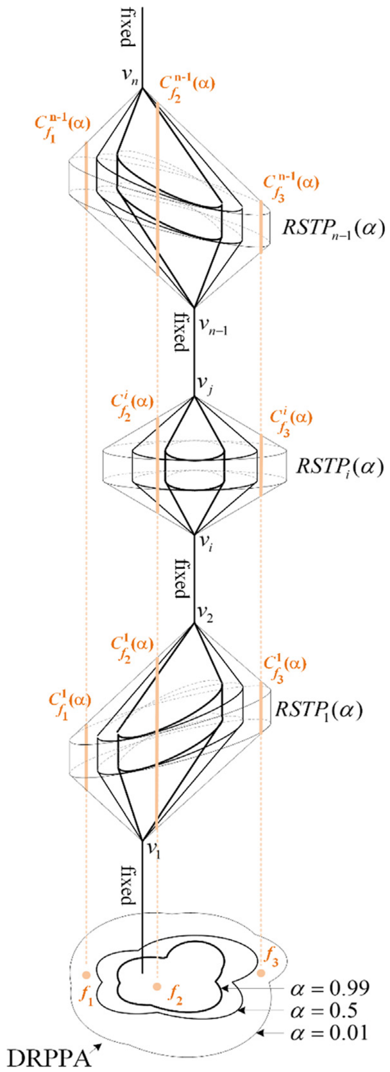

Fig. 1. Daily reliable space-time prism and related concepts.

$$T_i^{ox} = \sum_{\forall e} T_e \delta_e^{ox,i} \tag{1}$$

where $\delta_e^{ox,i}$ is the path-link incidence, i.e., $\delta_e^{ox,i} = 1$ means that link e is on the path, and $\delta_e^{ox,i} = 0$ otherwise. Since path travel time is random, the on-time arrival probability, α, of an individual reaching the facility within travel time budget, b, can be expressed as

$$\alpha = \Phi_{T_i^{ox}}(b) \tag{2}$$

where $\Phi_{T_i^{ox}}(b)$ is the cumulative distribution function (CDF) of T_i^{ox}. This on-time arrival probability, $\alpha \in (0, 1)$, reflects the individual's risk attitude for being late to perform activities at the facility (Lam et al., 2008; Chen et al., 2013). Generally, an individual can pre-determine α as a reliability constraint for activity participation according to the activity type. Therefore, the travel time budget b required for satisfying α reliability constraint can be expressed as

$$b = \Phi_{T_i^{ox}}^{-1}(\alpha) \tag{3}$$

where $\Phi_{T_i^{ox}}^{-1}(\alpha)$ is the inverse CDF of T_i^{ox} at α confidence level. Let $\bar{P}^{ox}$ be the set of all paths from o to x. The path with the least travel time budget is defined as the reliable shortest path, p^{ox} (Chen et al., 2012). This least travel time budget of reliable shortest path, $\Phi_{T^{ox}}^{-1}(\alpha)$, well quantifies the distance impedance for the individual's activity scheduling in face of travel time uncertainties.

Since the path travel times are stochastic, individual potential activity space is also stochastic. As shown in Fig. 1, individual potential activity space relies on his/her daily activity schedule, consisting of n fixed (or mandatory) activities, denoted as $\{v_1, \cdots, v_i, \cdots, v_n\}$, which are also referred as anchor points in time geography literature. Between each two subsequent anchor points, v_i and v_j, a flexible (or discretionary) activity could be scheduled. Building on the reliable shortest path concept, Chen et al. (2013)

proposed a reliable space-time prism (RSTP) model to delimit all feasible space-time locations to perform the flexible activity by explicitly considering individual reliability constraints. Suppose one fixed activity has been completed by the individual at v_i and time instance t_i, and another fixed activity is scheduled at destination v_j and t_j (Fig. 1). Between two fixed activities, a flexible activity might be scheduled at location x and t_x with minimum duration c_{min}. The RSTP model delimits feasible space-time locations, (x, t_x), for performing the flexible activity and return to v_j with at least α probability of on-time arrival, and can be expressed as Chen et al. (2013):

$$\mathrm{RSTP}_i(\alpha) = \{(x, t_x)|\Phi_{T^{ix}}^{-1}(\alpha) \le t_x - t_i,\ \Phi_{T^{xj}}^{-1}(\alpha) \le t_j - t_x,\ \Phi_{T^{ix}}^{-1}(\alpha) + \Phi_{T^{xj}}^{-1}(\alpha) \le t_j - t_i - c_{min},\ t_i \le t_x \le t_j\} \tag{4}$$

where $\Phi_{T^{ix}}^{-1}(\alpha)$ is the least travel time budget from v_i to x; and $\Phi_{T^{xj}}^{-1}(\alpha)$ is the least travel time budget from x to v_j. The height of RSTP at x represents the maximum activity duration, $c_x^i(\alpha)$, and can be expressed as

$$c_x^i(\alpha) = t_j - t_i - \Phi_{T^{ix}}^{-1}(\alpha) - \Phi_{T^{xj}}^{-1}(\alpha) \tag{5}$$

Projecting RSTP onto two-dimensional (2D) geographical space forms a reliable potential path area (RPPA).

Given an individual's activity schedule, a series of RSTPs, $\mathrm{RSTP}_1(\alpha),\ \cdots, \mathrm{RSTP}_i(\alpha),\ \cdots, \mathrm{RSTP}_{n-1}(\alpha)$ can be constructed for $n - 1$ successive pairs of fixed activities. These constructed RSTPs can be superimposed to create a daily reliable space-time prism (DRSTP) to represent the 3D potential activity space for activity participation. Projecting DRSTP onto 2D geographical space forms the daily reliable potential path area (DRPPA) of the individual's 2D potential activity space. Fig. 1 shows that the potential activity space size depends on not only traffic conditions but also the individual's reliability constraint α. When $\alpha = 0.5$, DRSTP and DRPPA are equivalent to traditional daily space-time prism and daily potential path area, respectively, which consider only median travel time and ignore travel time uncertainties. With increasing α, individual's reserve larger travel time safety margins to ensure higher probability of arriving on time, hence reducing the potential activity space size.

Based on the above DRSTP and DRPPA concepts, two reliability-based individual accessibility measures are proposed to evaluate individual accessibility under travel time uncertainties. Let $F = \{\cdots f,\ \cdots\}$ be the set of service facilities for individuals to perform activities. The first measure, denoted by $\mathrm{RCUM}(\alpha)$, is the number of facilities within the individual's DRPPA as

$$\mathrm{RCUM}(\alpha) = \sum_{\forall f} \delta_f \tag{6}$$

$$\delta_f = \begin{cases} 1, & \text{if } f \in DRPPA \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where δ_f is a binary variable, $\delta_f = 1$ indicates facility f is within DRPPA, and $\delta_f = 0$ otherwise. The second measure, denoted by $\mathrm{RDUR}(\alpha)$, is the cumulative activity durations at accessible facilities within the individual's DRSTP as

$$\mathrm{RDUR}(\alpha) = \sum_{\forall f} \sum_{\forall RSTP_i} c_f^i(\alpha)\delta_f \tag{8}$$

This measure extends $\mathrm{RCUM}(\alpha)$ by incorporating time availability for activity participations.

Fig. 1 shows that $\mathrm{RCUM}(\alpha)$ and $\mathrm{RDUR}(\alpha)$ measures can well capture individual various reliability constraints, $\forall\ \alpha \in (0, 1)$. With increasing α, the individual becomes more risk-averse, tending to reserve more time budget to ensure a higher probability of on-time arrival at locations to perform fixed activities. This reduces individual potential activity space, in terms of DRPPA and DRSTP, consequently reducing individual accessibility level. Thus, $\mathrm{RCUM}(\alpha)$ and $\mathrm{RDUR}(\alpha)$ provide a flexible means to evaluate individual accessibility considering travel time uncertainties. These proposed $\mathrm{RCUM}(\alpha)$ and $\mathrm{RDUR}(\alpha)$ measures generalize traditional CUM and DUR measures (Kwan, 1998), respectively, by incorporating individual reliability constraint, $\forall\ \alpha \in (0, 1)$. The traditional measures, CUM and DUR, ignore travel time uncertainties can be regarded as special cases of $\mathrm{RCUM}(\alpha)$ and $\mathrm{RDUR}(\alpha)$, respectively, for $\alpha = 0.5$.

We will apply the proposed reliability-based accessibility measures to investigate travel time uncertainty impacts on individual accessibility of different people groups and the associated equity issue in the following sections.

3. Study area and data collection

The study area is Shenzhen, a mega-city in Southern China, adjacent to Hong Kong. By the end of 2013, Shenzhen covered 1996 km^2; with approximately 10.54 million inhabitants, more than 70% being migrants. It had a highly developed road transport system with 1659 km of highways, major roads and arterial streets. There were 2.59 million private cars accounting for 47% of daily travels, while taxis, buses and subways accounted for 7%, 32% and 14%, respectively, of daily travels. Therefore, road transport modes (i.e., private cars and taxis) played a key role in Shenzhen. As shown in Fig. 2, Shenzhen comprises 10 administrative districts with diverse land use characteristics. Nanshan, Futian and Luohu are core urban areas with dense service facilities and population; Yantian, Bao'an, Longgang, and Longhua are suburban areas with several electronics factories and new towns; and Dapeng, Pingshan and Guangming are rural areas with many agriculture and hilly lands (Chen et al., 2018). People in different regions have distinct income levels. Per capita disposable income for people living in the core urban, suburban, and rural areas was 49,873, 39,944 and 30,220 Chinese Yuan, respectively, in 2013 (Shenzhen Statistical Yearbook, 2013). The diverse socioeconomic population and land use characteristics make Shenzhen an interesting area for accessibility equity studies.

Three datasets are collected for this study: mobile phone tracking, and shopping facilities, and traffic conditions. The mobile

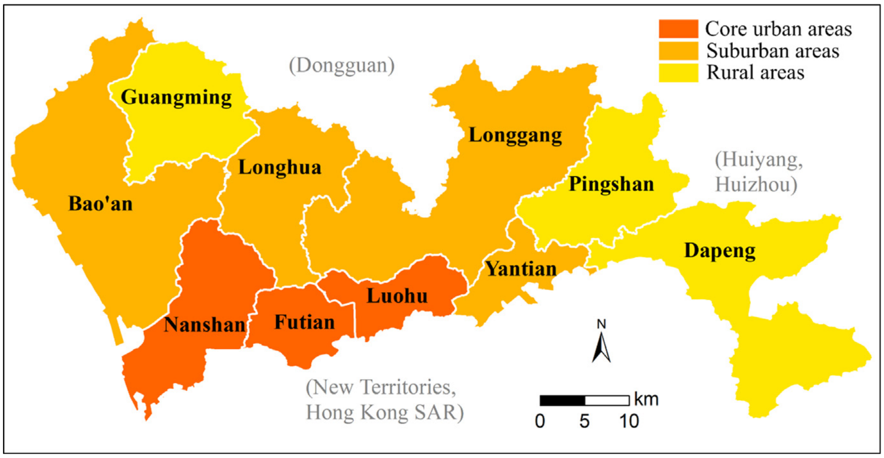

Fig. 2. Shenzhen administrative districts.

phone tracking dataset consists of 5.33 million phone users collected on a typical Friday (23 March 2012). Location for each phone user is recorded approximately every hour, hence each phone user has 24 records, with each record including an anonymized ID, timestamp, and longitude and latitude coordinates of the cellular tower the mobile phone is connected with. The original dataset includes 5930 cellular towers. All cellular towers have records of more than 50 phone users, except for 72 cellular towers in remote areas or in core urban areas with very small sizes. To address this issue, such 72 cellular towers are merged with their nearest cellular towers that had valid data. Service area for each cellular tower is represented by the tower's Thiessen polygon (see light yellow polygons in Fig. 3). The average size of the service areas is 0.3 km^2, and over 93% of service areas are less than 1 km^2.

The facility dataset consists of 3705 shopping facilities, including department stores, shopping malls, furniture shops, and supermarkets. Fig. 3 shows that shopping facilities are unevenly spatially distributed across the study region, being somewhat clustered in the core urban areas confirming spatial inequity of shopping service provision.

The Shenzhen road network includes 32,066 vertices and 40,809 links, as shown in Fig. 4(b). Hourly link travel time distributions of the Shenzhen road network are estimated from trajectories of 17,406 taxis on the same day as the mobile phone dataset collection. Sampling frequency for the taxi trajectories is approximately 30 s. Collected trajectories are matched to the road network using map matching algorithm developed by Chen et al. (2014). Link travel time distributions are estimated using weighted moving average technique proposed by Shi et al. (2017).

Fig. 4(a) shows estimated 24 hourly traffic conditions at different times of the day. It can be seen that traffic conditions are more congested and uncertain during the morning (8:00–10:00) and evening (17:00–19:00) peak hours. Fig. 4(b) shows mean travel speeds for all links during an evening peak hour, 18:00–19:00. It can be seen that 20.49% of links in Shenzhen are congested, mostly around core urban and suburban areas. Fig. 4(c) shows link travel time variations during the same evening peak hour using the coefficient of variation (CV), i.e., the ratio of the standard deviation to the mean. Larger CV indicates larger link travel time variation and hence more uncertain of the link travel time. Average CV = 0.33, and 13.82% of red links have CV greater than 0.5. Therefore, travel times

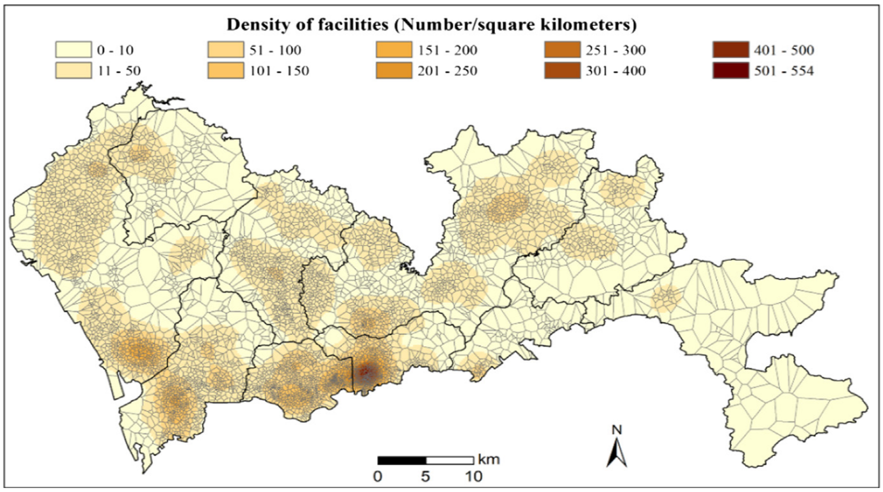

Fig. 3. Spatial distributions of shopping facilities in Shenzhen.

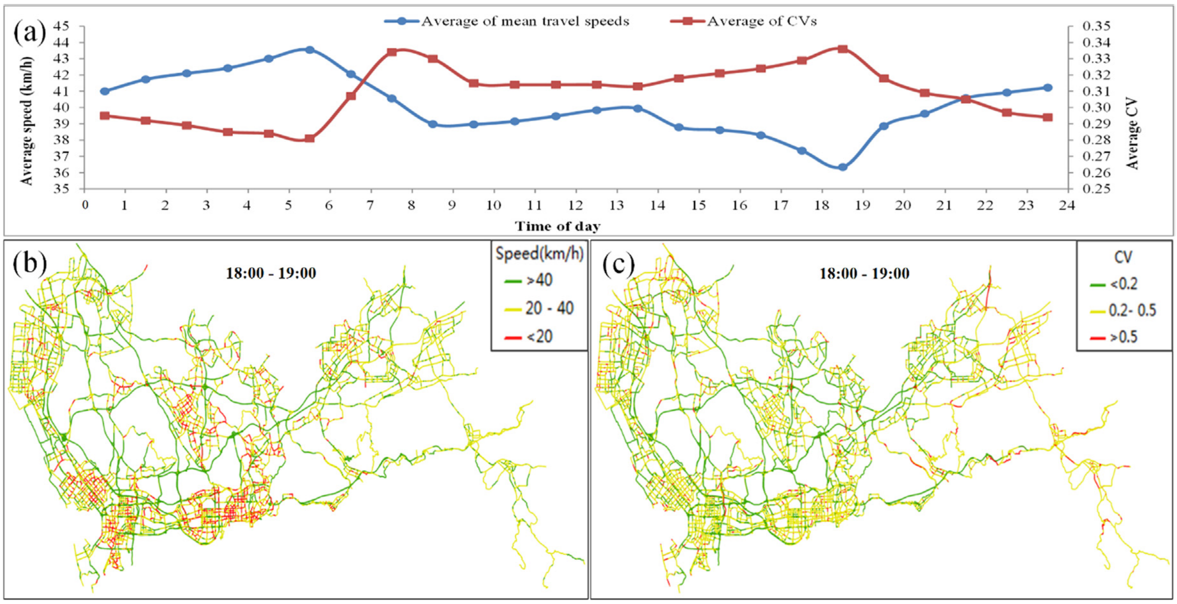

Fig. 4. Shenzhen traffic conditions: (a) temporal variation of traffic conditions (b) mean travel speeds during 18:00–19:00; (c) CV (coefficient of variation) of link travel times during 18:00–19:00.

are highly stochastic in the Shenzhen road network, and impacts of travel time uncertainties are necessary inclusions to evaluate individual accessibility equity.

4. Analysis methods

Based on the above collected datasets, we apply following four steps to investigate travel time uncertainty impacts on phone users' accessibility to shopping services.

1. Identify home location for each phone user.
2. Estimate individual accessibility for each identified phone user.
3. Evaluate accessibility equity among phone users.
4. Investigate impacts of travel time uncertainties on individual accessibility and associated equity issues.

4.1. Home location identification

Because phone users' home locations are not provided, they are estimated based on user location records. The locations during 22:00–06:00 are considered to be users' candidate home locations according to a reasonable assumption that most people would state at their residential locations during this period (Ahas et al., 2010; Chen et al., 2018). The home location is determined where 5 records are at the same location over the 8 h period. Spatial tolerance of 500 m is adopted to address the mobile phone positioning issue, where location records for a stationary phone can jump among several adjacent cellular towers.

4.2. Individual accessibility calculation

Previous studies (Chen et al., 2018) have shown that incorporating time duration for activity participation can better quantify spatial inequity of accessibility. Therefore, we use the proposed RDUR(α) measure to evaluate individual accessibility.

Fig. 5(a) shows the approach to calculate accessibility of a typical user using the RDUR(α) measure. Following Chen et al. (2018), phone hourly records during 07:00–09:00, 12:00–14:00, and 17:00–21:00 are considered anchor points to estimate individual DRSTP. We exclude sleeping hours (21:00–07:00) and working hours (09:00–12:00 and 14:00–17:00) for conducting mandatory activities, i.e. sleeping, in-home activities and working, from the analysis. Thus, we construct a chain of RSTPs, i.e., $RSTP_8(\alpha)$, $\cdots$,$RSTP_{14}(\alpha)$, $\cdots$,$RSTP_{21}(\alpha)$, based on the corresponding hourly traffic conditions (i.e., 7:00–8:00, …, 13:00–14:00, …, 20:00–21:00) to determine individual potential activity spaces, in terms of DRSTP. We set the reliability constraint $\alpha = 0.95$ for all RSTPs, following empirical evidence that most people are risk-averse regarding travel time uncertainties (Carrion and Levinson, 2012), e.g. the Federal Highway Administration suggested 95% on-time arrival probability as the benchmark for transport network performance (FHWA, 2006). Minimum activity duration for shopping services is set $c_{min} = 20$ min. Hence travel time threshold for a one-way trip from the anchor point to the activity location is 20 min, i.e., $(60 - 20)/2$. This threshold (i.e., 20 min) was also used by

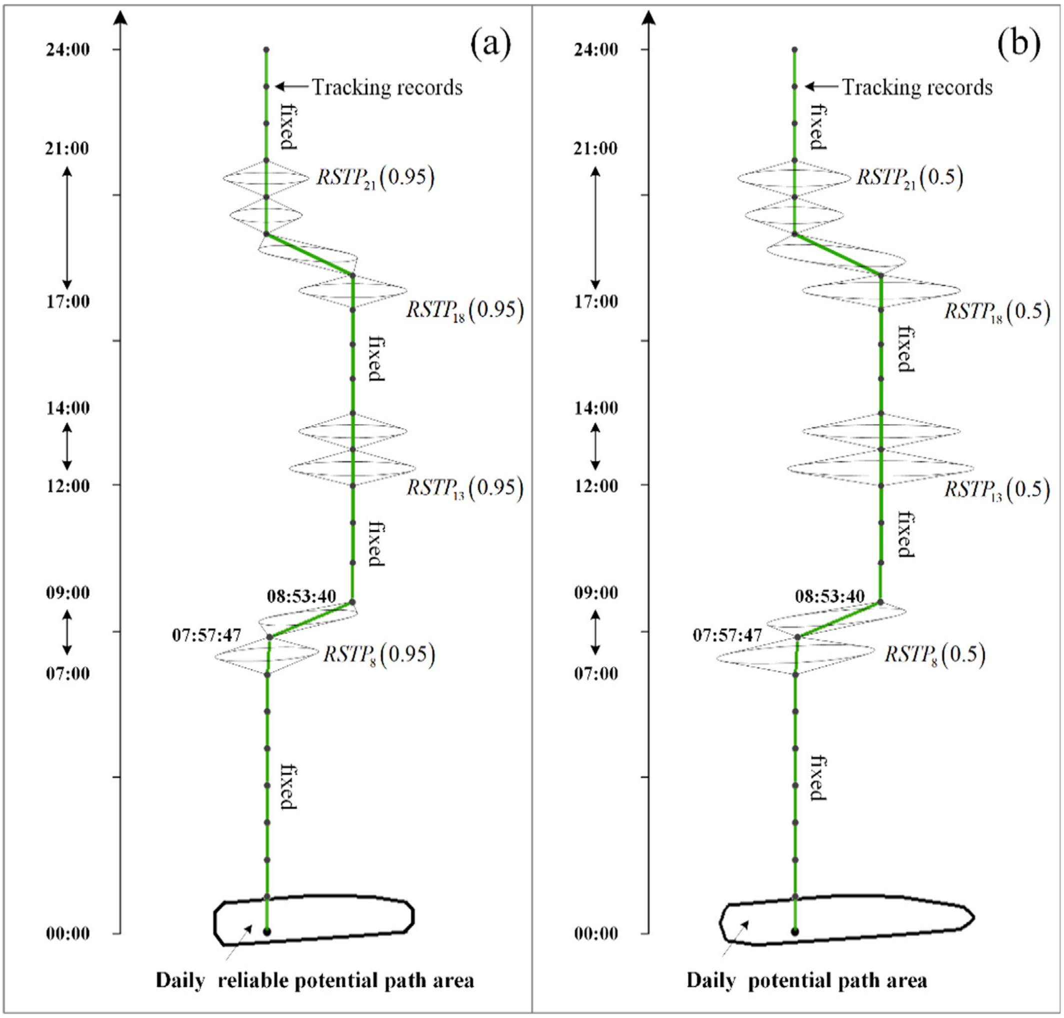

Fig. 5. Typical individual accessibility: (a) reliability-based and (b) traditional individual accessibility measures.

many previous accessibility studies (Wang et al., 2018; Farber et al., 2014; Kwan, 1998). Thus, we represent individual potential activity space by space-time regions of 20 min around multiple anchor points. After DRSTP construction, individual accessibility is calculated using Eqs. (6)–(8).

It should be noted that the used anchor points may not exactly match fixed activity locations collected from activity diary surveys (Kwan, 1998; Patterson and Farber, 2015), which may introduce some bias when calculating individual potential activity spaces. However, several empirical studies found that phone user activity spaces can be well represented by multiple space-time regions of 20 min around top N most visited locations (Zang and Bolot, 2011; Chen et al., 2018). Further, Chen et al., (2018) demonstrated that this approach could well capture interpersonal variation of individual accessibility among phone users with distinct mobility patterns even living in the same cellular tower. Therefore, the calculated DRSTP provides valuable proxies for phone user activity spaces for shopping activities under travel time uncertainties.

4.3. Accessibility inequity evaluation

Inequity of individual accessibility among phone users is evaluated using three types of measures, including CV, Gini coefficient and percentile ratio. *CV* is a dimensionless positive number, where larger *CV* implies larger inequity among individual accessibility of phone users.

The Gini coefficient has been widely used in accessibility equity studies due to its easy interpretation by using Lorenz curves (Delbosc and Currie, 2011; Lucas et al., 2016), as shown in Fig. 6. The Lorenz curve is the cumulative distribution of people ordered from low to high for an indicator (horizontal axis), and cumulative distribution of the indicator (vertical axis). The Gini coefficient can be expressed as the ratio of the area between the equal distribution line and Lorenz curve, divided by the area under the triangle between equal distribution line, the horizontal axis and the vertical axis. The Gini coefficient is dimensionless; and thereby various

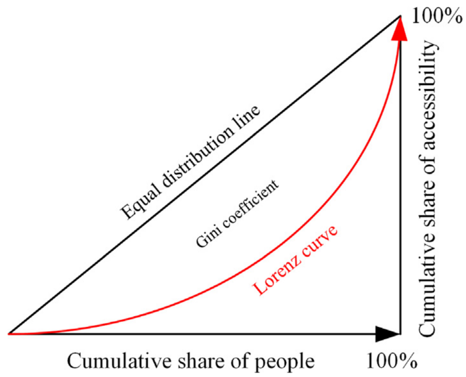

Fig. 6. Gini coefficient and Lorenz curve concepts.

accessibility measures (including RDUR(α)) can be used as the indicator. Mathematically, the Gini coefficient, denoted by GC, can be expressed as:

$$GC = \left(\sum_{i=1}^{m} \sum_{j=1}^{m} |z_i - z_j|\right) \Big/ \left(2m \sum_{i=1}^{m} z_i\right) \tag{9}$$

where z_i is the accessibility value for user i; and m is the total number of phone users. Larger GC ($0 \le GC \le 1$) implies more unequal distributed accessibility among phone users, with $GC = 0$ being complete equality and $GC = 1$ being complete inequality.

Although the Gini coefficient is an effective inequity measure, it is very sensitive to the differences in the middle portion of the distribution but not very sensitive to the bottom tail. Capturing such sensitivity is critical to accessibility equity studies, because individuals at the bottom tail of the distribution can be interpreted as the disadvantaged people group with a low level of accessibility to urban services. To this end, a percentile ratio (denoted by PR) (Mussida and Parisi, 2018) is also adopted to quantify the accessibility inequity on disadvantaged people group as

$$PR = \Phi_{RDUR}^{-1}(50\%)/\Phi_{RDUR}^{-1}(\beta) \tag{10}$$

where $\Phi_{RDUR}^{-1}(50\%)$ is the median level of accessibility, and $\Phi_{RDUR}^{-1}(\beta)$ is the accessibility level at β percentile. In this study, $\beta = 1\%$ is set to consider the disadvantaged people group with an extreme low accessibility level. The larger PR value indicates the more vulnerable disadvantaged people group compared to the majority ordinary people.

4.4. Travel time uncertainty impact evaluation

Travel time uncertainty impacts on individual accessibility and associated equity issues are quantified by comparing accessibility results using the proposed RDUR(0.95) and traditional DUR measures. Fig. 5(b) shows the DUR measure for the same user as Fig. 5(a). As discussed above, DUR is calculated following the same method as for RDUR(0.95), i.e., Eqs. (6)–(8), but with $\alpha = 0.5$ instead of 0.95.

As discussed in Section 2, increasing α would reduce individual potential activity space and accessibility. Therefore, to quantify travel time uncertainty impacts on individual i, we use following activity space and accessibility reduction rates:

$$R_{DRSTP}^{i} = (1 - \mathrm{DRSTP}(0.95)/\mathrm{DSTP}) \times 100\% \tag{11}$$

and

$$R_{RDUR}^{i} = (1 - \mathrm{RDUR}(0.95)/\mathrm{DUR}) \times 100\% \tag{12}$$

where DRSTP(0.95) and DSTP are the individual 3D potential activity spaces when $\alpha = 0.95$ and $\alpha = 0.5$, respectively; and RDUR(0.95) and DUR are the individual accessibility values when $\alpha = 0.95$ and $\alpha = 0.5$, respectively.

Since travel time uncertainty can have various impacts on different individuals, it may misidentify the disadvantaged people group within the bottom 1% (i.e., β). Such impacts on disadvantaged people group identification are evaluated using the misidentification rate:

$$MIR = (N_e/N_g) \times 100\% \tag{13}$$

where N_g is the number of people identified being in the disadvantaged group when $\alpha = 0.95$ (as ground true); and N_e is the number of people in ground true who are not identified when $\alpha = 0.5$. Travel time uncertainty can further affect the accessibility inequity among different people groups and can be quantified by the change of three above inequity measures, i.e., CV, GC and PR.

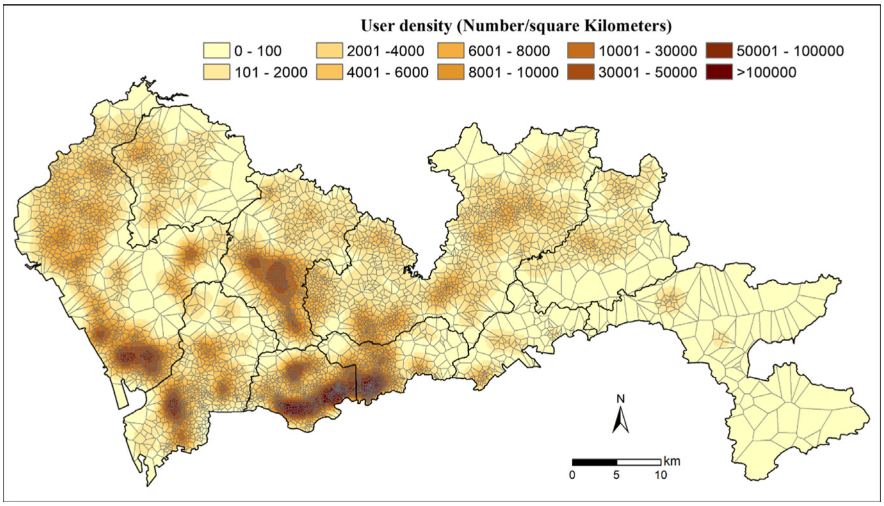

Fig. 7. Spatial distribution of mobile phone users.

5. Results

5.1. Residential location distribution

Fig. 7 shows the identified residential locations for the 5.32 million users, accounting for approximately 99% of total phone users. About 34% of total users (1.82 million users) lived in three urban areas, with very high user densities, particularly Luohu and Futian districts. Approximately 58% of users (3.10 million) lived in four suburban areas; and Longhua and Bao'an districts adjacent to the urban areas with relatively dense users. In contrast, three rural areas had very low user density, accounting for only approximately 8% of total users (0.40 million). This spatial distribution of phone users is consistent with census data regarding population distribution by administrative districts, with Pearson's coefficient equal to 0.99 (Xu et al., 2016).

5.2. Inequity of phone user accessibility to shopping facilities

Individual accessibility, RDUR(0.95), to shopping facilities for all collected phone users in the study area, is calculated to investigate accessibility equity among different people groups. Fig. 8 reports the histogram and Lorenz curve of all calculated accessibility values. The histogram in the figure shows a long tail distribution of individual accessibility, indicating significant accessibility inequity among phone users. The median level of individual accessibility is equal to 2634.2. The bottom 1% individual accessibility < 72.2 (2.7% of the median), whereas the top 1% individual accessibility > 10558.0 (400.8% of the median). This significant level of accessibility inequity is reflected in the Lorenz curve with $GC = 0.43$, $CV = 0.77$ and $PR = 36.5$.

Fig. 9 shows spatial distribution of individual accessibility at a fine spatial resolution, i.e. cellular towers. Highest levels of accessibility occur for people living in three urban areas, particularly Futian and Luohu districts, where there is higher density of shopping facilities. In contrast, lowest levels of accessibility occur for people in three rural areas, particularly Dapeng and Pingshan

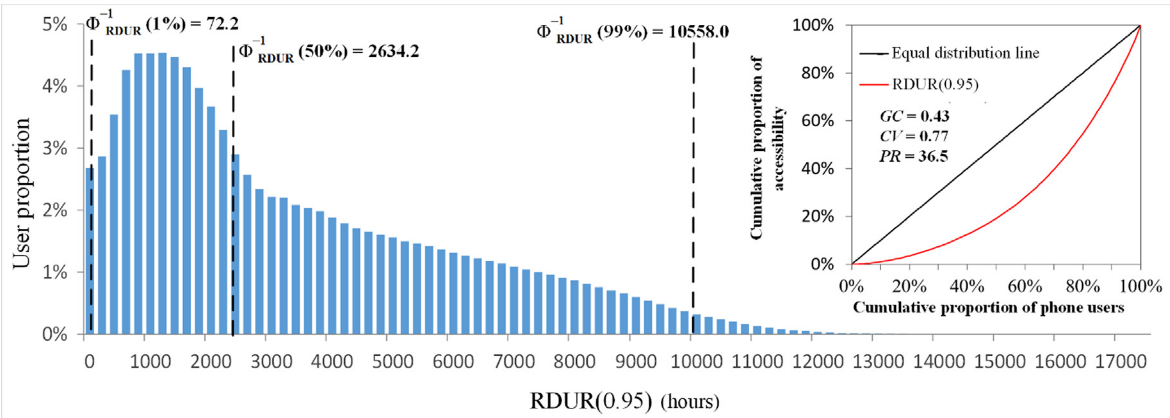

Fig. 8. Distribution and Lorenz curve of individual accessibility in Shenzhen (GC: Gini coefficient; CV: coefficient of variation; PR: percentile ratio).

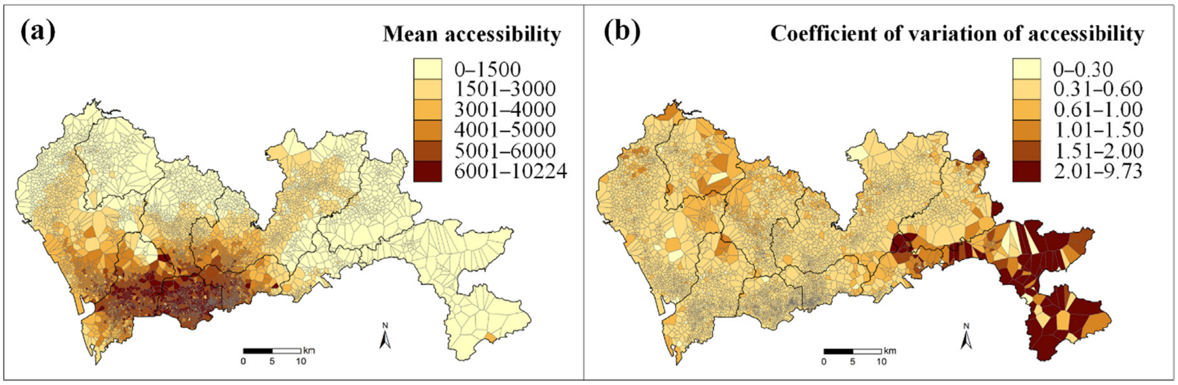

Fig. 9. Spatial distribution of individual accessibility across the study area: (a) mean and (b) coefficient of variation (CV) of accessibility.

districts, where there is lower density of shopping facilities. Fig. 9(b) shows inter-personal variations of accessibility for people at the same home location caused by their different mobility patterns. People living in most urban areas exhibit lower inter-personal variation with $CV < 0.3$, whereas people in most rural areas and suburban exhibit higher inter-personal variation with $CV > 0.6$.

Given the significant accessibility disparities for people living in different city regions, accessibility distribution patterns are further investigated for each city region separately. Phone users are divided into urban, suburban, and rural groups according to their residential locations, and then users of each group are classified into seven categories based on their accessibility ranking across complete dataset, as summarized in Fig. 10. The three different groups exhibit distinct distribution patterns of accessibility to shopping services. Most people living in core urban areas have advantageous access to shopping services, with more than 83% of them ranked in the top 50% (Categories 5–7), and about 26% in the top 10% (Category 7). Nevertheless, only few (0.29%) people living in the corners of Luohu and Nanshan districts rank in the bottom 1% (Category 1), due to the boundary effect. The CV value for users in the urban group is 0.50, approximately 35% less than the overall CV for the dataset (0.77). In contrast, people living in rural areas tend to be disadvantaged in terms of accessibility to shopping services, with more than 99% ranking in the bottom 50% (Categories 1–4), and 5.21% ranking in bottom 1%. However, accessibility levels for people in suburban areas is relatively equal distributed in seven categories, with $CV = 0.74$, approximately 4% lower than the overall value.

In this study, 53,237 phone users within the bottom 1% (Category 1) are identified as disadvantaged people with an extreme low level of accessibility to shopping facilities. Fig. 11 shows this people group clustered at five communities (i.e., Jiedao in Chinese) in Songgang and Shiyan suburban areas; and Kengzi, Kuiyong, and Dapeng rural areas. Census data (Su et al., 2017) show that these five communities are poverty areas with high unemployment rate and large proportion of elder and less educated residents. This suggests a strong association between individual accessibility and disadvantaged social-economic conditions, which is consistent with previous social exclusion studies (Lucas, 2012; Su et al., 2017).

5.3. Travel time uncertainty impacts on individual accessibility

Travel time uncertainty impacts on individual accessibility are investigated for the three user groups and seven accessibility ranking categories defined above. As shown in Fig. 12, negative impacts of travel time uncertainties on user activity space are spatially inhomogeneous, with more serious impact for rural and suburban users than urban users. For example, average R^{i}_{DRSTP} of

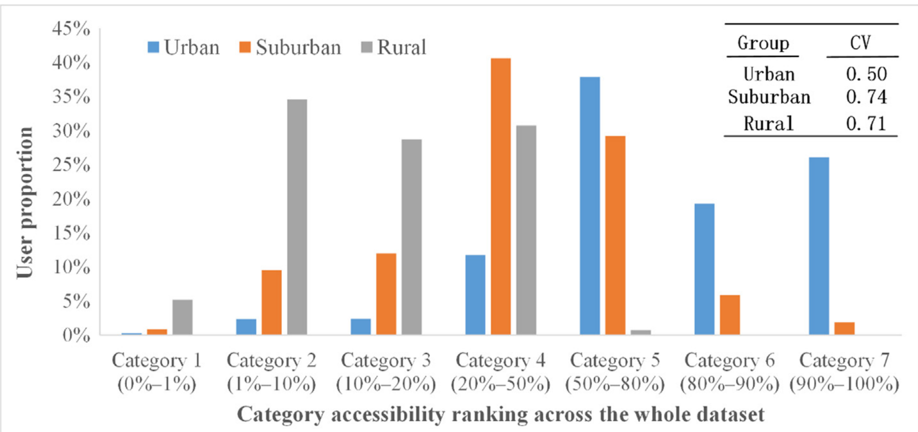

Fig. 10. Location group ranking distribution. (CV: coefficient of variation).

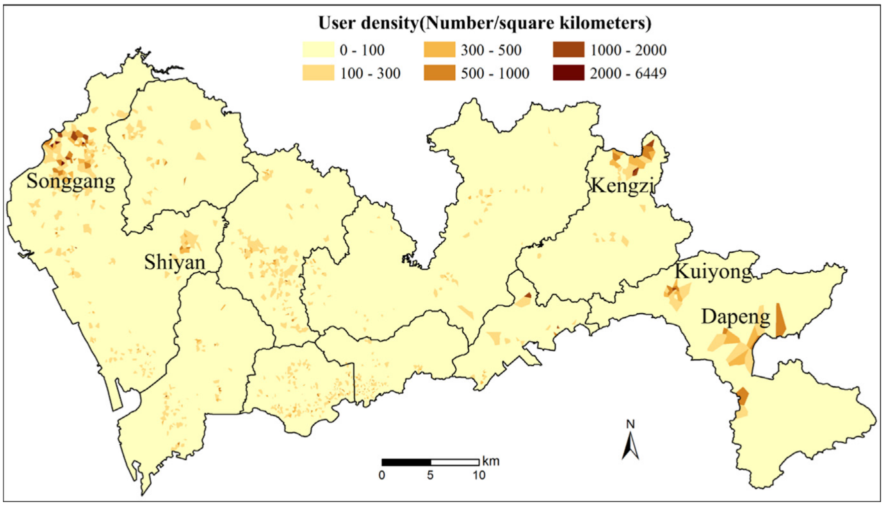

Fig. 11. Spatial density of identified disadvantaged people using RDUR(0.95) measure.

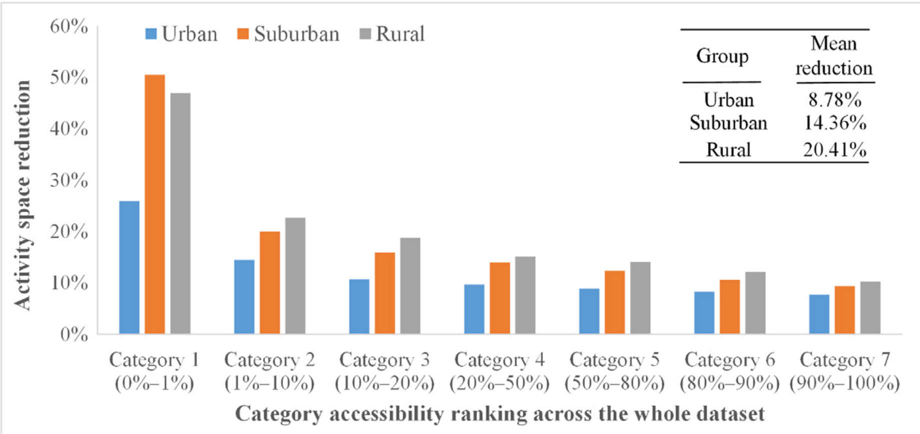

Fig. 12. Individual activity space reduction.

rural users is 20.41%, 1.32 times larger than that of urban users (8.78%). This is mainly due to lower network density in suburban and rural areas. It can be clearly observed that travel time uncertainties have significantly more severe impacts on users in lower accessibility categories for all urban, suburban, and rural subgroups. For example, R^i_{DRSTP} of urban users in the bottom 1% category is 25.94%, which is significantly larger than R^i_{DRSTP} of all users in the top 10% category not only for urban areas (7.72%) but also suburban (9.38%) and rural areas (10.22%).

Fig. 13 shows average accessibility reduction rates, R^i_{RDUR}, for users in different accessibility ranking categories and geographical regions. A similar pattern is observed between R^i_{RDUR} and R^i_{DRSTP} among users in different accessibility ranking categories and regions, because reduction of individual activity space directly degraded individual accessibility to shopping facilities. Comparing Figs. 12 and 13 shows that $R^i_{RDUR} < R^i_{DRSTP}$ for most users ranking in the top 50% (i.e., categories 5–7), whereas $R^i_{RDUR} > R^i_{DRSTP}$ for most users ranking in the bottom 50% (i.e., categories 1–4). This indicates that users in lower accessibility categories are more sensitive to the activity space reduction.

Travel time uncertainty impacts on the identification of disadvantaged phone users with an extreme low level of accessibility (i.e., within the bottom 1%) are investigated using the misidentification rate, *MIR*. As calculated, using DUR can misidentify up to 18.88% of disadvantaged users compared to RDUR(0.95). Fig. 14 shows that the DUR measure can miss many disadvantaged users in Songgang and Kengzi communities (red rectangles), due to significant over estimation of accessibility in these suburban areas. Several users in Kuiyong, Dapeng, Shajin, and Dalang communities (blue rectangles) are also falsely identified. This result highlights that travel time uncertainty impacts should be explicitly considered to identify disadvantaged people with an extremely low accessibility.

Travel time uncertainty impacts on the overall accessibility inequity are evaluated by comparing three inequity measures (i.e., *CV*, *GC* and *PR*) between RDUR(0.95) and DUR. As shown in Table 1, all three measures of RDUR(0.95) increased compared to that of DUR. Particularly, the *PR* value increased by about 40%. It suggests that travel time uncertainties exacerbates the inequity of

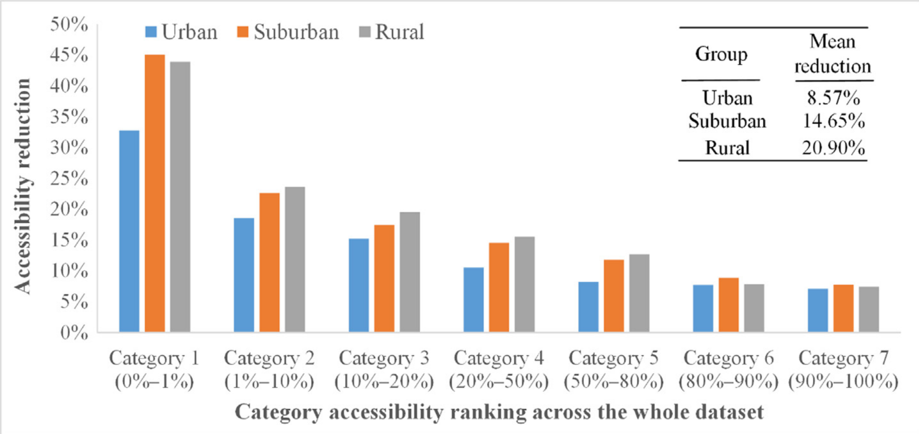

Fig. 13. Individual accessibility reduction.

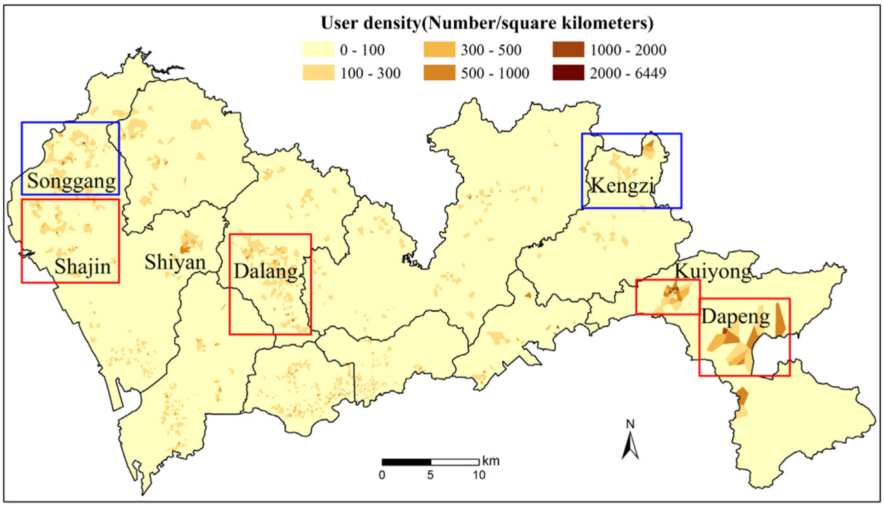

Fig. 14. Spatial density of identified disadvantaged people using DUR measure. (Blue rectangle: missed identified area compared to Fig. 10; Red rectangle: false identified area compared to Fig. 11). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Travel time uncertainty impacts on accessibility inequity.

Reliability constraint	GC	CV	PR
0.95	0.43	0.77	36.5
0.5	0.41	0.74	26.0

GC: Gini coefficient; CV: coefficient of variation; PR: percentile ratio.

accessibility among different people groups. This observation is supported by the above finding that travel time uncertainties have more serious impacts on disadvantaged users with lower accessibility to shopping facilities. It also confirms that the *PR* value is sensitive to the accessibility differences at the bottom tail.

6. Discussion

The analysis presented above provide several new insights on the accessibility equity studies. Firstly, it demonstrates the capabilities of mobile phone big data to examine accessibility equity from a disaggregated individual perspective. It can fully capture the inter-personal accessibility variation within the same residential area due to their distinct mobility patterns, and provide a clear accessibility distributive pattern for all people groups in the entire study area. Subsequent analysis highlights the feasibility of using a distributive approach, e.g. bottom 1% of accessibility, to identify disadvantaged people with an extreme low level of accessibility.

Therefore, this study provides strong evidence supporting the assertion that accessibility equity issues should be carefully examined using disaggregated individual approaches to incorporate individual distinct mobility and socio-spatial characteristics (Pereira et al., 2017; Di Ciommo and Shiftan, 2017).

Secondly, it highlights distinct impacts of travel time uncertainties on accessibility equity among different people groups. Consistent with previous studies (Chen et al., 2017; Zhang et al., 2018), the analysis shows spatially inhomogeneous impacts of travel time uncertainties on accessibility, with more serious impacts for rural and suburban than urban areas. More importantly, the analysis extends previous studies by identifying significantly more severe impacts of travel time uncertainties on all disadvantaged people with lower accessibility level for various city regions (including rural, suburban and urban areas). Travel time uncertainties can exacerbate overall accessibility inequity among people groups. Therefore, the analysis enrich our understanding of how transport network uncertainties shape accessibility equity of people in different socio-spatial groups.

Thirdly, it has important methodological implications in the evaluation of accessibility equity under travel time uncertainties. Traditional individual accessibility measures (e.g., CUM and DUR) build on a deterministic assumption of travel times, but ignore corresponding uncertainties (Kwan 1998; Miller, 1999; Neutens et al., 2010; Chen et al., 2018). However, the results of this study found that ignoring travel time uncertainties can overestimate accessibility of all people groups, and cause more serious impact for disadvantaged peoples with lower accessibility level. Equity evaluation using traditional individual accessibility measures can underestimate accessibility inequity among different people groups across the entire study area. Therefore, the proposed reliability-based individual accessibility measures, i.e., $\mathrm{RCUM}(\alpha)$ and $\mathrm{RDUR}(\alpha)$, contribute to existing individual accessibility evaluation methods by explicitly considering the travel time uncertainty impacts.

Although this study is among the first to investigate accessibility equity issue under travel time uncertainties, several limitations remain. First of all, phone user transport mode choice behaviors were not considered in this study by assuming that all users had equal access to private cars or taxis. Further studies should be conducted to allow users make their trips by multiple transport modes, including not only private car and taxi but also walking, bicycling and bus and subway modes. In addition, individual activity spaces in this study were estimated by using one day tracking of mobile phone users. Further researches are needed to conduct a more robust estimation of individual activity spaces by using multi-day mobile phone tracking data.

There are a number of opportunities for related future study. To protect individual privacy, this study collected only individual geo-locations and omitted any personal information, such as income, age, gender, etc. Further studies should incorporate relevant personal socioeconomic characteristics into individual accessibility studies to provide deeper insights into how travel time uncertainties affect accessibility of different people groups, particularly those individuals with disadvantaged socioeconomic conditions. In addition, this study highlights the important role of transport network reliability to improve accessibility of different people groups. Future studies could incorporate the proposed reliability-based individual accessibility measures into transport network design models for maximizing total accessibility while reducing accessibility inequity among different people groups (Martens and Di Ciommo, 2017).

7. Conclusions

In this study, travel time uncertainty impacts on equity of individual accessibility was investigated using a spatiotemporal big data analysis approach. Two reliability-based individual accessibility measures were proposed to generalize traditional individual accessibility measures by explicitly considering various individual reliability constraints for activity-travel travel time uncertainties. A case study applying the proposed measures to comprehensive datasets of taxi trajectories and mobile phone tracking data was performed to investigate individual accessibility to shopping services in Shenzhen, China. The results demonstrated the capabilities of using spatiotemporal big data to investigate accessibility equity across large study areas using a disaggregated individual approach, and highlighted distinct impacts of travel time uncertainties on accessibility for different people groups. Specially, travel time uncertainties had more severe impacts on disadvantaged people with lower accessibility and exacerbated overall accessibility inequity among all people groups. These results highlighted considerable bias of using traditional deterministic individual accessibility measures to evaluate the accessibility equity under travel time uncertainties.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2019.08.027.

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