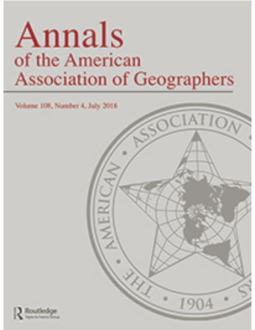

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Understanding the Impacts of Human Mobility on Accessibility Using Massive Mobile Phone Tracking Data

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Many existing accessibility studies ignore human mobility due to the lack of large-scale human mobility data. This study investigates the impacts of human mobility on accessibility using massive mobile phone tracking data collected in Shenzhen, China. In this study, human mobility information is extracted from mobile phone tracking data using a time-geographic approach. The accessibility of each phone user is evaluated using fine spatial resolution across the entire city. The impacts of human mobility on accessibility are quantified by using relative accessibility ratios between phone users and a virtual stationary user in the same residential location. Results of this study enrich understandings of how land use influences relationships between human mobility and accessibility. For resource-poor regions with sparse service facilities, human mobility can greatly enhance individual accessibility. In contrast, for resource-rich regions with dense service facilities, human mobility can even reduce individual accessibility. Overall, human mobility can reduce spatial inequity of accessibility for people living in different regions of the city. The results of this study also have several important methodological implications for including human mobility and time dimension in accessibility evaluations. *Key Words: accessibility, activity spaces, human mobility, spatiotemporal big data, time geography.*

诸多既有的可及性研究, 因为缺乏大尺度的人类移动数据而忽略了人类移动。本研究运用在中国深圳所搜集的大规模手机追踪数据, 探讨人类移动对于可及性的影响。在本研究中, 运用时间地理学取径, 从手机追踪数据取得人类移动信息。每位手机使用者的可及性, 通过整座城市的细微空间解析度进行评估。人类移动对于可及性的影响, 运用同一住宅区位中的手机使用者和虚拟的静止使用者之间的相对可及性比率进行量化。此一研究成果, 丰富了我们对于土地使用如何影响人类移动和可及性之间的关系之理解。在资源贫瘠且服务设施缺乏的区域, 人类移动能够大幅增进个人的可及性。反之, 在资源丰沛且服务设施密集的区域, 人类移动甚至会降低个人的可及性。总体而言, 人类移动能够减少生活在城市不同区域中的人们的可及性之空间不均。本研究之成果, 对于包括可及性评估中的人类移动和时间面向, 同时具有若干重要的方法论意涵。 *关键词: 可及性, 活动空间, 人类移动, 时空大数据, 时间地理学。*

Gran parte de los estudios existentes sobre accesibilidad ignoran la movilidad humana debido a la falta de datos sobre este fenómeno a gran escala. Este estudio investiga los impactos de la movilidad humana sobre la accesibilidad con el uso de gran un volumen de datos de rastreo de teléfonos móviles, recogidos en Shenzhen, China. En este estudio, la información sobre la movilidad humana es extraída de datos del rastreo de teléfonos móviles, a través del uso de un enfoque geográfico del tiempo. La accesibilidad de cada usuario de teléfono es evaluada con resolución espacial fina aplicada a toda la ciudad. Los impactos de la movilidad humana sobre la accesibilidad son cuantificados a partir de ratios de accesibilidad relativa entre los usuarios del teléfono y un usuario virtual estacionario en la misma localización residencial. Los resultados de este estudio enriquecen el entendimiento de cómo influye el uso del suelo las relaciones entre movilidad humana y accesibilidad. Para las regiones pobres en recursos con facilidades de servicios de baja densidad, la movilidad humana puede fortalecer fuertemente la accesibilidad individual. Por contraste, para las regiones ricas en recursos con facilidades de servicios muy densas, la movilidad humana puede incluso reducir la accesibilidad individual. En general, la movilidad humana puede reducir la injusticia espacial de accesibilidad para gente que reside en diferentes regiones de la ciudad. Los resultados de este estudio tienen también varias implicaciones metodológicas importantes para incluir la movilidad humana y la dimensión tiempo en las evaluaciones de accesibilidad. *Palabras clave: accesibilidad, espacios de actividad, movilidad humana, big data espacio-temporales, geografía del tiempo.*

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The paramount goal of urban planning is to provide sufficient opportunities for citizens to access urban services, such as jobs, food, shopping, and recreational services. High-level accessibility to urban services is crucial for urban life viability. Equitable access to urban services is also strongly related to social exclusion issues, with the aim to avoid barriers to participating in normal activities (Stanley et al. 2011; van Wee and Geurs 2011). Evaluating accessibility of urban services over different regions and social groups has been a major issue in the geography and urban planning literature (Kwan and Weber 2003; Geurs and van Wee 2004; Langford and Higgs 2010; Páez et al. 2010; B. Y. Chen et al. 2013; Farber et al. 2013; Horner and Wood 2014; Niedzielski and Boschmann 2014).

Accessibility of urban services depends on three components: urban service spatial distribution (i.e., land use), transportation network efficiency, and individual socioeconomic characteristics (Kwan 1998; Geurs and van Wee 2004; Niedzielski and Boschmann 2014). Traditionally, accessibility has been evaluated by place-based accessibility measures, which are conceptualized mainly in terms of locational proximity to individuals' residential areas. Place-based accessibility measures, such as cumulative opportunity and gravity-based measures, are valuable and require only a few aggregated data (Geurs and van Wee 2004; B. Y. Chen, Yuan, et al. 2017; Yang et al. 2017). These place-based measures, however, consider only land use and transportation components and have been criticized for ignoring distinct individual human mobility patterns of different socioeconomic groups. Obviously, people move around a range of places in the course of their daily lives, and residential areas might not adequately represent a real individual's activity spaces (Kwan 2012; Jones and Pebley 2014). Thus, ignoring human mobility might obfuscate what people actually experience in their everyday lives and might introduce significant bias to accessibility studies (Kwan 2012, 2013).

With the availability of activity diary data since the 1990s, considerable research efforts have been made to develop individual-based (or space–time) accessibility measures by explicitly considering individual mobility of different socioeconomic groups (Kwan 1999; Miller 1999; Kim and Kwan 2003; Kwan and Weber 2003; Neutens, Schwanen, and Witlox 2011). An activity diary data set records detailed information of every activity conducted by sample individuals within a particular time period, such as activity location, type, beginning and ending times, and so on (J. Chen et al. 2011). With this activity diary data set, human mobility of sample individuals can be well quantified by using time-geographic approaches (Hägerstrand 1970), in terms of daily potential path area (DPPA) or daily space–time prism (DSTP). The DPPA represents the individual's potential activity space in two-dimensional (2D) geographical space, whereas the DSTP extends this by capturing the individual's time available for activity participation. The number of opportunities within the DPPA (called CUM measure) and the cumulative activity durations at opportunities with the DSTP (called DUR measure) are two commonly used individual-based measures. These individual-based measures have been widely recognized as powerful indicators to evaluate accessibility of individuals in different socioeconomic groups and geographical regions (Kwan and Weber 2003; Miller 2007). Only a few studies, however, have compared results obtained from DUR and CUM measures to evaluate the impacts of including the time dimension in accessibility studies (Neutens et al. 2010; Kwan 2013).

Due to the key role of human mobility in accessibility evaluation, much attention in the literature has been given to evaluating human mobility impacts on accessibility. Many transport-related social exclusion studies have evaluated accessibility for disadvantaged people living in resource-poor regions with sparse service facilities, such as female (McCray and Brais 2007), disabled (Casas 2007), and low-income individuals (Rogalsky 2010; Stanley et al. 2011; Kamruzzaman and Hine 2012). Poor mobility, in terms of small DPPA, has been identified as a key factor making it difficult or impossible for disadvantaged people to access certain urban services outside their activity spaces. These transport-related social exclusion studies have provided significant evidence to support that provision of adequate mobility to disadvantaged people can significantly enlarge their DPPA and thereby improve their accessibility in terms of the CUM measure. Few studies, however, have investigated impacts of human mobility on accessibility in terms of the DUR measure by explicitly considering individual time available for activity participation. Most previous studies were restricted to a relatively small geographical area with few samples, due to the difficulty of collecting large-scale human mobility data through traditional activity diary surveys. Therefore, it remains unclear how human mobility affects accessibility for people living in different areas with distinct land use characteristics, including resource-poor and resource-rich regions.

Recent advances in information and communication technologies offer new sources of spatiotemporal big data for collecting human mobility information, such as social media data, taxi trajectories, smart card data, and so on (Miller 2005b; Li et al. 2013; Miller and Goodchild 2015; B. Y. Chen et al. 2016; Kwan 2016). Among various technologies, mobile phone tracking is a promising technique to collect human mobility information for large numbers of individuals over the entire region. The mobile phone tracking data sets are generated by the business operations of mobile telecommunication networks. The locations of phones in terms of connected cellular towers are automatically recorded without contacting the users being tracked. These data sets are a by-product generated for network management purposes and theoretically available at no cost for data analyses. In recent years, mobile phone tracking data have been widely used for human mobility studies (Gonzalez, Hidalgo, and Barabasi 2008; Ahas, Aasa, et al. 2010; Song et al. 2010; Ahas et al. 2015; Xu et al. 2015; Xu et al. 2016) and transportation applications (Caceres et al. 2012; Iqbal et al. 2014; Pei et al. 2014). Nevertheless, there has been little attention in the literature on using mobile phone tracking data for accessibility studies.

This study seeks to fill two gaps in human mobility and accessibility studies. It extends previous studies by investigating human mobility impacts on accessibility for the entire region of a megacity with diverse land use characteristics, providing new insights on how land use influences relationships between human mobility and accessibility. It also examines human mobility impacts on accessibility in terms of the DUR measure, to explicitly consider the critical time dimension with respect to individual time available for activity participation. To fulfill these research objectives, a large-scale mobile phone tracking data set is collected, including twenty-four-hour trajectories of more than 6 million phone users, across the entire region of Shenzhen, China. This collected data set offers an effective means to extract human mobility information, in terms of DPPA and DSTP, for a massive number of individuals across the whole study region. Individual accessibility to typical urban services for all collected phone users is evaluated using CUM and DUR measures at a fine resolution of cellular tower. To quantify human mobility impacts on accessibility, virtual users stationary within their residential area are constructed for each cellular tower as the reference user group. Relative accessibility ratios between actual and stationary virtual users at the same

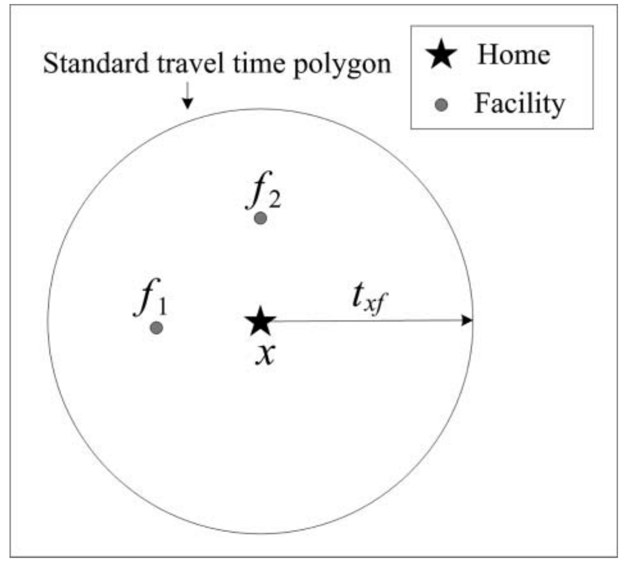

Figure 1. Standard travel time polygon concept.

cellular tower are derived to derive human mobility impacts on accessibility in terms of both CUM and DUR measures. Results of this study will enrich our understanding of how land use influences relationships between human mobility and accessibility and also provide methodological implications for incorporating human mobility and time dimension into accessibility evaluations.

Traditional Place-Based Accessibility Measures

This section briefly introduces traditional place-based accessibility measures to provide necessary background. Accessibility has traditionally been evaluated by place-based accessibility measures, which ignore human mobility and only consider an individual's residential area as the relevant geographic context. For instance, the widely used cumulative opportunity measure (Breheny 1978; denoted by *CUM*) can be expressed as

$$CUM = \sum_{f} R_f \tag{1}$$

$$R_f = \begin{cases} 1, & t_{xf} \leq \gamma \\ 0, & \text{otherwise}, \end{cases} \tag{2}$$

where t_{xf} is the travel time between residential location x and facility f and γ is a fixed cutoff distance parameter representing an individual's capability (or willingness) to travel for activity participations. An underlying assumption in this accessibility measure is that

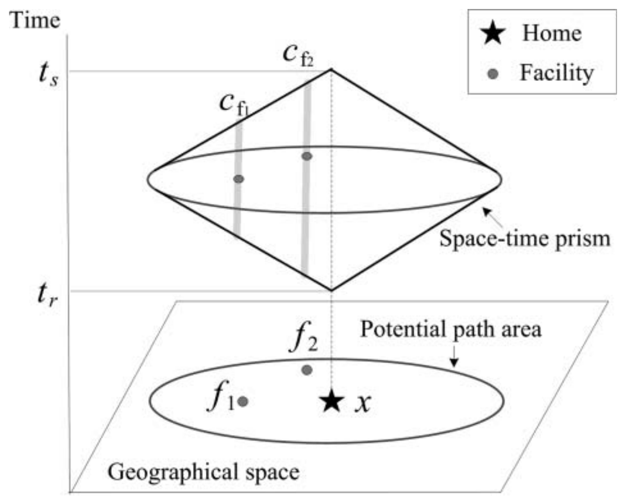

Figure 2. Space–time prism concept.

potential activity spaces of all people living in location x is the standard travel time polygon centered at their residential location (Sherman et al. 2005; see Figure 1). The accessibility of people living at location x is evaluated by the cumulative number of facilities within the potential activity space. $R_f = 1$ indicates that facility f is within the potential activity space. This cumulative opportunity measure is valuable and easily interpretable but often criticized for ignoring human mobility, hence oversimplifying individuals' potential activity spaces.

As an extension, Delafontaine, Neutens, and Weghe (2012) proposed a set of place-based space–time accessibility measures incorporating the time dimension from individual-based perspectives. In the proposed measures, a round trip from residential location x to facility f was considered to construct the space–time service area centered at the facility. The accessibility of people at location x was evaluated by the number of reachable facilities whose service area covers the location x. This formulation was equivalent to the assumption that all potential activity spaces of people living at location x were the space–time prism (denoted by STP) with both origin and destination located at x. The space–time prism concept (Miller 2005a) is illustrated in Figure 2 in three-dimensional (3D) space and can be expressed as

$$\mathrm{STP}(\mathrm{r}, s, t_r, t_s, c_{\min}) = \{(t_{rf} \le t - t_r) \wedge (t_{fs} \le t_s - t) \wedge (t_{rf} + t_{fs} \le t_s - t_r - c_{\min}) \wedge (t_r \le t < t_s)\}, \quad (3)$$

where r and s are origin and destination, respectively; t_r and t_s are departure time and preferred arrival time, respectively; t_{rf} and t_{fs} are travel time from origin r to facility f and travel time from facility f to destination s, respectively; and $c_{\min}$ is the minimum activity time required for activity participation. The height of the space–time prism at f represents the maximum activity duration, c_f. The effect of facility opening hours can also be represented by intersecting the activity duration with facility opening, t_p, and closing, t_q, times:

$$c_f = \min(t_f^-, t_q) - \max(t_f^+, t_p), \quad (4)$$

where $t_f^- = t_r + t_{rf}$ and $t_f^+ = t_s - t_{fs}$ are the earliest arrival and latest departure times, respectively, at facility f. Accessible facilities, $\forall f \in STP$, can be determined according to constraint $c_f \ge c_{\min}$.

The projection of the space–time prism onto 2D geographical space is the potential path area (denoted by PPA). If the travel time budget $b = t_s - t_r - c_{\min}$ is set as 2γ, then the potential path area is equivalent to the standard travel time polygon defined in Figure 1. Using potential path area as an individual's potential activity space, the cumulative opportunity measure can be expressed as

$$CUM^{STP} = \sum_f R_f^{PPA} \quad (5)$$

$$R_f^{PPA} = \begin{cases} 1, & f \in PPA \\ 0, & \text{otherwise}, \end{cases} \quad (6)$$

where R_f^{PPA} is a binary variable indicating whether facility f is within the potential activity space. Incorporating activity durations at accessible facilities, Delafontaine, Neutens, and Weghe (2012) proposed an activity duration weighted accessibility measure, DUR^{STP}:

$$DUR^{PPA} = \sum_f c_f R_f^{PPA}. \quad (7)$$

These place-based space–time accessibility measures have made substantial improvements to the conventional cumulative opportunity measure by incorporating the time dimension. They consider residential location as a single reference location, however, and ignore other key places, such as workplaces and recreational locations. Furthermore, they do not allow for interpersonal heterogeneity in human mobility, assuming the same level of accessibility for all people at a residential location. In this study, we extend these place-based space–time accessibility measures to incorporate human mobility information derived from mobile phone tracking data.

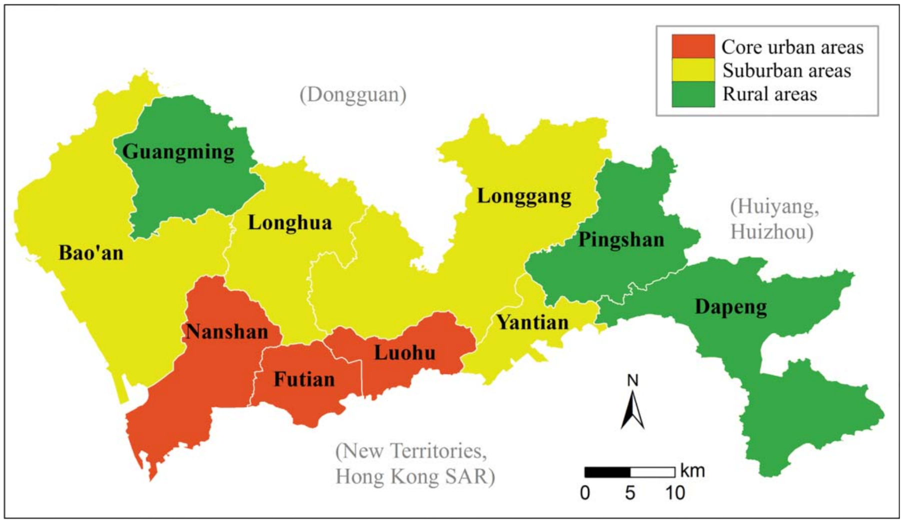

Figure 3. Administrative districts of Shenzhen city. (Color figure available online.)

Study Area and Data Collection

Shenzhen is a major economic center in south China. It is located within the Pearl River Delta, bordering Hong Kong to the south. During the past thirty years, Shenzhen has been considered one of the fastest growing cities in the world in terms of population growth and economic development. The city covers an area of approximately 1,996 km^2 and had a total population of approximately 10.54 million in 2012, with a density of over 5,282 inhabitants/km^2. Immigrant population accounts for more than 70 percent of the total city population. Figure 3 shows that Shenzhen city consists of ten administrative districts. Luohu, Futian, and Nanshan districts are core urban areas with highly developed economies, dense population, and service facilities. Bao'an, Longhua, Longgan, and Yantian districts are suburban areas, including some new towns and a concentration of electronics factories. The remaining districts (Guangming, Pingshan, and Dapeng) are rural areas with large hilly and agriculture lands and a few industrial parks. The unique socioeconomic and demographic status of Shenzhen makes it an interesting area for accessibility studies (Xu et al. 2015).

Three data sets were collected in the city of Shenzhen, including mobile phone tracking data, road network data, and facility data of urban services. The mobile phone tracking data set was collected on 23 March 2012 (Friday), consisting of 174.6 million positioning records of 6.21 million users (approximately 58.92 percent of the total population). In this data set, the location of a phone user μ, in terms of connected cellular tower, was tracked at the time instance when a call was placed or received or a short message was sent or received. If the users were not on a call, their locations were also tracked at regular or irregular time intervals for network operating purposes. The average sampling frequency of users' trajectories was one hour and users with missing data (i.e., fewer than twenty-four position records) were excluded in the data analysis. To protect user privacy, the data set had been anonymized by the mobile phone carrier before it was made available for this study. Actual phone numbers and other personal information were not included in the tracking data set.

This mobile phone tracking data set consists of 5,930 cellular towers in Shenzhen. Any mobile phone located inside the Thiessen polygon is closest to the corresponding cellular tower. Because the phone location was set as its connected cellular tower, polygon size has a significant impact on positioning accuracy of mobile phone locations. In this data set, Thiessen polygons varied from 0.001 km^2 to 14.5 km^2 and were smaller in core urban areas than rural areas. The average size of the Thiessen polygons was 0.33 km^2, and over 93.74 percent of Thiessen polygons are less than 1 km^2. The average positioning error of this mobile positioning was approximately 300 m in core urban areas and suburban areas and approximately 2 km in rural areas, which seems reasonable given the large study area of this case study.

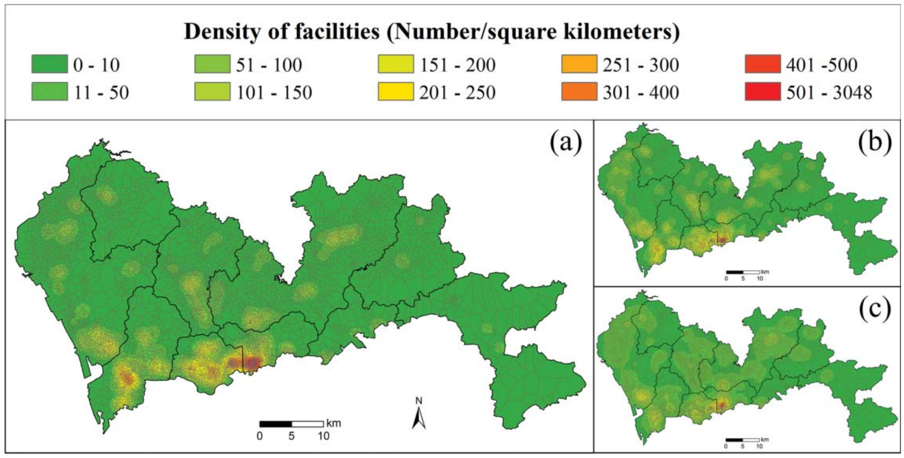

Figure 4. The spatial distributions of facilities: (A) foodservice facilities; (B) recreational facilities; (C) shopping facilities. (Color figure available online.)

The Shenzhen road network data set included the major roads in the city and consisted of 14,414 nodes and 16,723 links. The traffic conditions of the road network were estimated by a real-world floating car data set for the same day as the mobile phone tracking data set. The floating car data set included trajectories of 17,406 taxis in Shenzhen city. The Global Positioning System (GPS) sampling interval for each taxi is about thirty seconds. All taxi trajectories were matched onto the road network using the multicriteria dynamic programming map-matching algorithm proposed by B. Y. Chen et al. (2014) and then separated into link segments to estimate the hourly travel times for all network links. These estimations of hourly traffic conditions were explicitly used for analyzing human mobility and individual accessibility.

The facility data set consisted of three types of facilities in Shenzhen, including 6,899 foodservice facilities (mainly restaurants), 8,807 recreational facilities (including cinemas, bars, gymnasiums, cybercafes, etc.), and 3,705 shopping facilities (including shopping malls and grocery stores). Figure 4 shows that these facilities are not evenly distributed but rather are clustered in the three core urban areas, particularly in Luohu and Futian districts.

Method

In this study, four steps are designed to investigate human mobility impacts on accessibility using mobile phone tracking data. The first step is to estimate residential location of each phone user. Because residential locations of phone users are not explicitly provided in the mobile phone tracking data sets, they are estimated based on user trajectories. For each phone user, cellular towers between 22:00 and 06:00 are considered their candidate residential locations, based on the reasonable assumption that most people would stay at their home through overnight. Then, the user's residential location is determined if five hourly records (of eight possible) are at the same cellular tower over the eight-hour period. Because the location records of a phone user could jump among several adjacent cellular towers even though the user is stationary, a spatial tolerance can be adopted (i.e., 500 m used in this study). Previous studies (Ahas, Silm, et al. 2010; Xu et al. 2015) have shown that this method can identify residential locations for most phone users (i.e., over 99 percent of all users). In addition, no residential location might be identified in cellular towers in remote rural areas or in urban areas with very small sizes. To address this issue, cellular towers without data are merged with the nearest cellular tower that had valid data. Accordingly, the merged cellular towers are used as the basic analysis units, and further analyses are restricted to phone users with identified residential locations.

The second step is to estimate potential activity spaces of each phone user. In this study, the potential activity spaces of user μ are estimated using a time-geographic approach to construct a chain of space–time prisms along the user trajectory during time periods of interest, as $STP_1^{\mu},\ldots, STP_i^{\mu},\ldots, STP_{n-1}^{\mu}$. The time budget for each space–time prism is the time duration between two corresponding sample points (i.e., one hour in this study). The parameter $c_{\min}\geq 0$ can be used in the space–time prism construction to

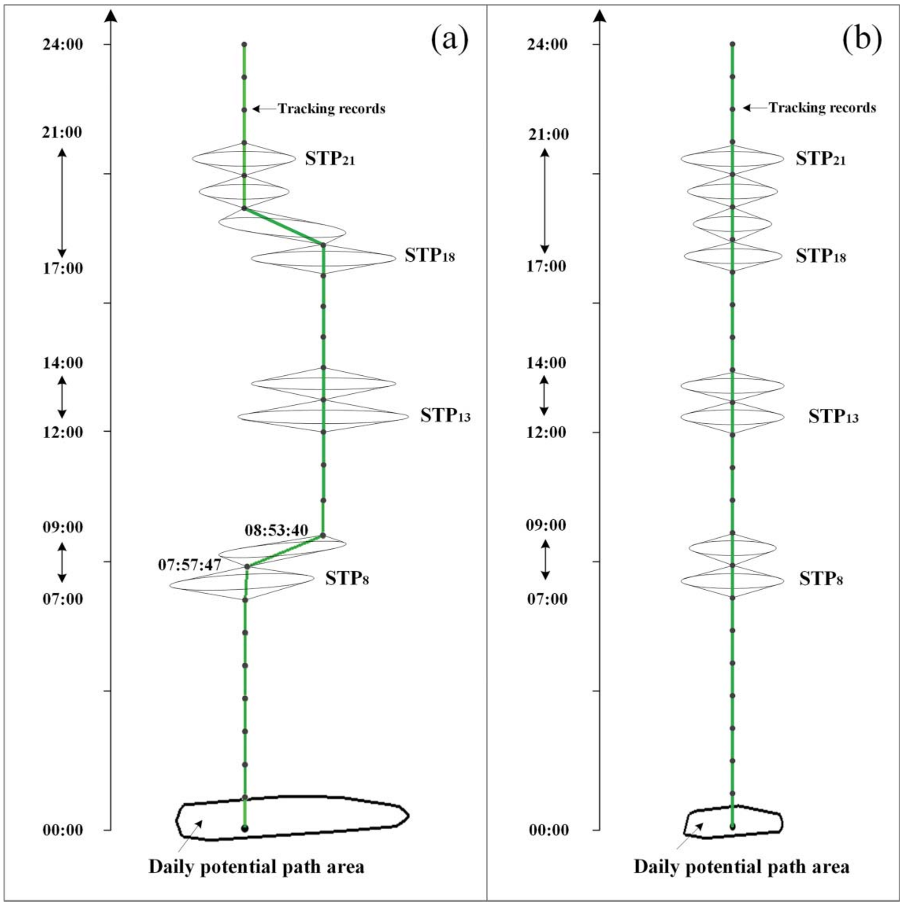

Figure 5. Potential activity spaces derived from mobile phone tracking data: (A) typical sampled user; (B) reference stationary user. (Color figure available online.)

consider the minimum activity duration constraint. Figure 5A illustrates this concept using a typical user trajectory during three time periods (i.e., 07:00–09:00, 12:00–14:00, and 17:00–21:00) for a weekday. The users' working hours (i.e., 09:00–12:00 and 14:00–17:00) and sleeping hours (i.e., 21:00–07:00) for conducting nondiscretionary activities (i.e., working, sleeping, and in-home activities) are excluded in the analysis. During time periods of interest, each space–time prism delimits all possible unobserved space–time locations between two adjacent samples. The constructed space–time prisms can be superimposed to create a daily space–time prism (denoted by $DSTP^{\mu}$). This $DSTP^{\mu}$ delimits all possible unobserved space–time locations for the user's movements or activity participations, constrained by the tracked locations along the user trajectory. Projection of such space–time prisms onto 2D geographical space forms a series of potential path areas, PPA_1, $PPA_2, \ldots$, PPA_{n-1}, which can be aggregated to create a daily potential path area (denoted by $DPPA^{\mu}$). These $DPPA^{\mu}$ and $DSTP^{\mu}$ can be regarded as 2D and 3D approaches for representing the phone user's mobility, respectively (Patterson and Farber 2015).

It should be noted that these $DSTP^{\mu}$ and $DPPA^{\mu}$ concepts, to some extent, are different from the classical concepts based on activity diary data (Kwan 1998). As shown in Figure 5B, however, the constructed $DSTP^{\mu}$ can be regarded as a generalization of previous potential activity space concept shown in Figure 2, which is the DSTP of a stationary user. Compared with the previous concept (see Figure 5B), the constructed $DSTL^{\mu}$ and $DPPA^{\mu}$ (see Figure 5A) can fully capture mobility of the phone user from multiple reference points in the course of their daily life, rather than a single residential location. In addition, the constructed $DSTP^{\mu}$ and $DPPA^{\mu}$ can capture different mobility patterns of people living within the same residential locations. Further, empirical studies have shown that the phone user's potential activity space can be well represented by standard travel time polygons centered at multiple reference points (i.e., top N locations, such as home, workplaces, schools, etc.; Zang and Bolot 2011; B. Y. Chen, Wang, et al.

2017). Typically, these top N locations could be recorded by sample points of user trajectories during three periods of interest (i.e., 07:00–09:00, 12:00–14:00, and 17:00–21:00). Therefore, we believe that $DSTP^{\mu}$ and $DPPA^{\mu}$ can be valuable proxies for phone users' potential activity spaces. Based on results of empirical studies (Zang and Bolot 2011; B. Y. Chen, Wang, et al. 2017), $c_{\min} = 20$ minutes is set (i.e., to construct standard travel time polygons of twenty minutes around the top N locations).

Consequently, the mobility pattern for any user, μ, can be measured using the sizes of extracted 2D and 3D potential activity spaces; that is, DPPA size and DSTP volume. They are expressed, respectively, as cumulative lengths of accessible links (Kwan 1998) and cumulative activity durations on all accessible links (Neutens et al. 2008; H.-P. Chen et al. 2016). In addition to these 2D and 3D indicators, traveled distance along the user's trajectory during three time periods of interest is also calculated, as it is a commonly used one-dimensional (1D) indicator in the literature.

Following Kwan (1998), different human mobility patterns of phone users using 1D, 2D, and 3D indicators are quantified using Spearman's rank correlation coefficients (Spearman 1904; B. Y. Chen et al. 2012). This correlation coefficient (denoted by p) quantifies the statistical dependence between rankings of two indicators. For example, the correlation coefficient between DPPA sizes and DSTP volumes can be expressed as

$$P = 1 - \frac{6\sum_{\mu=1}^{m}\left(rank^{\mu}_{\mathrm{DPPA}} - rank^{\mu}_{\mathrm{DSTP}}\right)^2}{m(m^2-1)}, \quad (8)$$

where $rank^{\mu}_{\mathrm{DSTP}}$ and $rank^{\mu}_{\mathrm{DPPA}}$, respectively, are the rankings of DSTP volume and DPPA size for user μ among all phone users, and m is the total number of phone users in the data set. Because only the rankings are used, this correlation coefficient can assess relationships between measures with different dimensions. The value of p is between –1 and 1, where $p = -1$ indicates a perfect negative correlation and $p = 1$ indicates a perfect positive correlation.

The third step is to evaluate accessibility for each phone user by using the user's estimated 2D and 3D potential activity spaces. In this study, two accessibility measures are proposed to evaluate the user's accessibility to urban services. The first proposed measure, denoted by CUM^{μ}, is the cumulative number of accessible facilities within the user's 2D potential activity space in terms of $DPPA^{\mu}$,

$$CUM^{\mu} = \sum_{f} R_f^{DPPA} \quad (9)$$

$$R_f^{DPPA} = \begin{cases} 1, & f \in DPPA^{\mu} \\ 0, & \text{otherwise,} \end{cases} \quad (10)$$

where $R_f^{DPPA} = 1$ indicates that facility f is within the user's potential activity space $DPPA^{\mu}$; $R_f^{DPPA} = 0$ otherwise. The second measure, denoted by DUR^{μ}, is the cumulative activity durations at facilities within the user's 3D potential activity space in terms of $DSTP^{\mu}$,

$$DUR^{\mu} = \sum_{f}\sum_{STP_i} c_f R_f^{DPPA}, \quad (11)$$

where c_f is the cumulative activity durations at f derived from all STP_i of $DSTP^{\mu}$. This DUR^{μ} measure extends the CUM^{μ} measure by incorporating time dimension (in terms of time available for activity participation) in the accessibility evaluation.

Following Neutens et al. (2010), the Gini coefficient is adopted to evaluate spatial inequity of accessibility. The Gini coefficient, denoted by GC, can evaluate the inequality among accessibility values for different cellular towers. The Gini coefficient is expressed as the average absolute difference of all pairs of accessibility values divided by the average value:

$$GC = \left(\sum_{i=1}^{n}\sum_{j=1}^{n} |x_i - x_j|\right) \Big/ \left(2n\sum_{i=1}^{n} x_i\right), \quad (12)$$

where x_i is the accessibility value (e.g., mean DUR^{μ} value) at cellular tower i and n is the total number of cellular towers in the study area. The GC value ranges from 0 (i.e., complete equality) to 1 (i.e., complete inequality). A larger GC value implies more unequal spatially distributed accessibility.

The final step is to investigate mobility impacts on accessibility of each phone user using the relative accessibility concept. In this study, a virtual user h who is stationary at home for the whole day is constructed for each residential location (i.e., cellular tower) as a reference user (see Figure 5B). Note that the variation of space–time prism sizes in Figure 5B is due to the variation of traffic conditions in different times of the day. The two proposed accessibility measures are calculated for the reference stationary user h, denoted by CUM^{h} and DUR^{h}, respectively. These

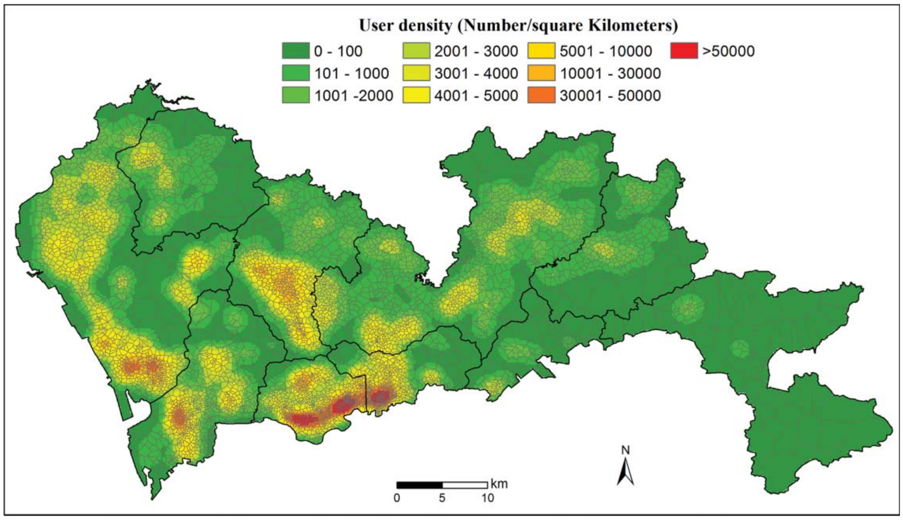

Figure 6. Spatial distribution of mobile phone users. (Color figure available online.)

CUM^h and DUR^h measures can be regarded as the previous place-based space–time accessibility measures defined in Equations 5 through 7, which ignore human mobility.

A comparison of CUM accessibility measures between phone user μ and reference stationary user h provides the relative CUM accessibility measure:

$$R^{\mu}_{CUM} = CUM^{\mu}/CUM^{h}. \tag{13}$$

This relative accessibility measure is interpreted as a proportion, the number of facilities available to user μ, with respect to the number of facilities available to reference user h at the same resident location. Similarly, a comparison of DUR accessibility measures between μ and h provides the relative DUR accessibility measure

$$R^{\mu}_{DUR} = DUR^{\mu}/DUR^{h}. \tag{14}$$

These R^{μ}_{CUM} and R^{μ}_{DUR} indicators reflect the impacts of human mobility on the phone user's accessibility. $R^{\mu}_{DUR} > 1$ indicates that mobility enhances accessibility of user μ, whereas $R^{\mu}_{DUR} < 1$ indicates that mobility reduces the user's accessibility. Human mobility impacts on accessibility spatial inequity, in terms of CUM^{μ} or DUR^{μ}, can be quantified through the differences of corresponding Gini coefficients between phone and reference stationary users.

Results

Human Mobility Patterns

Reported first are the results of residential location estimation for all collected phone users. Residential locations of 6.16 million users (approximately 99.2 percent) were identified based on phone user trajectories. The identified residential locations were distributed over 5,858 cellular towers; the other seventy-two cellular towers without data were merged to their nearest cellular tower. Figure 6 shows the density of mobile phone users in terms of their identified residential locations. Phone users were concentrated in the three core urban areas, particularly the Luohu and Futian districts. Two suburban areas, Bao'an and Longhua, close to the core urban areas also showed relatively dense concentrations of phone users.

Human mobility patterns of all phone users were then investigated using 1D, 2D, and 3D indicators (i.e., traveled distance, DPPA size, and DSTP volume). Figures 7A and 7B show extracted traveled distances for all phone users across the study area. Human movements in Shenzhen city were dominated by short distance travel, with average travel distance approximately 8.79 km. The coefficient of variation (CV; ratio of standard deviation to mean) showed significant interpersonal variation of user traveled distances. Larger CV implies larger interpersonal variation among phone users. People in suburban and rural areas tend to have higher inhomogeneity (i.e., larger CV).

Spearman's rank correlation coefficients for the 1D, 2D, and 3D indicators are quantified and summarized in Table 1. A very weak positive correlation

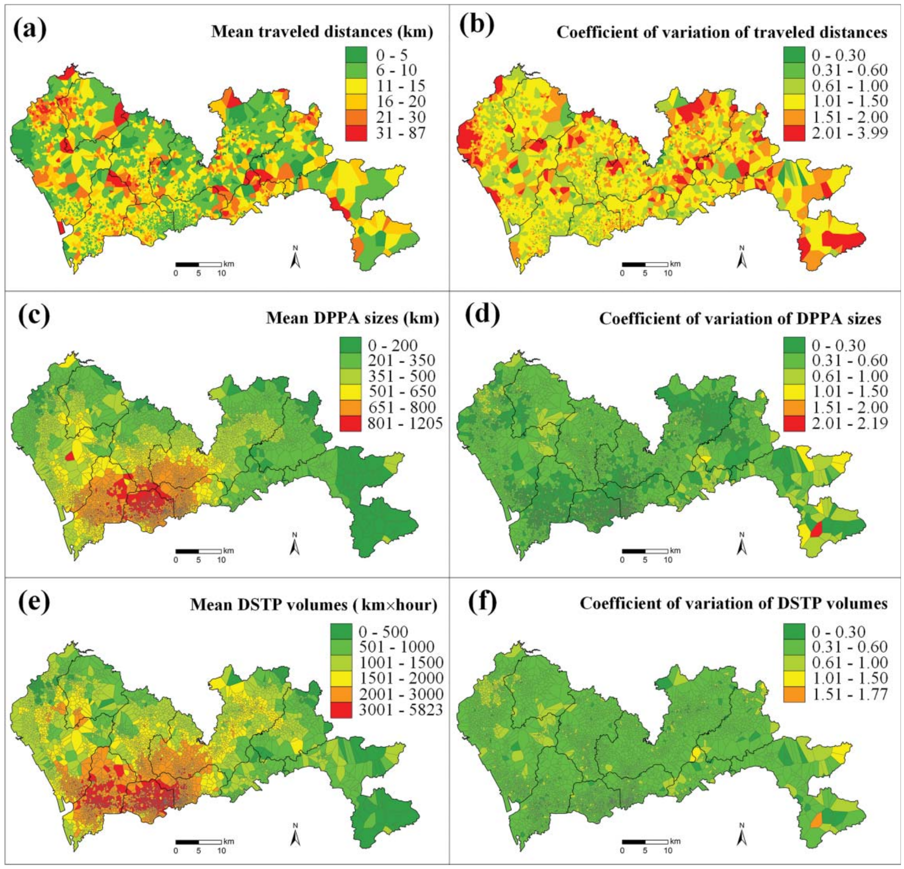

Figure 7. Extracted human mobility patterns using 1D, 2D, and 3D indicators: (A) and (B) traveled distance; (C) and (D) daily potential path area; and (E) and (F) daily space–time prism. DPPA = daily potential path area; DSTP = daily space–time prism. (Color figure available online.)

($\rho = 0.06$) was observed between traveled distance and DPPA size. This result was confirmed by their distinct mobility patterns (see Figures 7A and 7C). People in core urban areas with dense road networks have large mean DPPA sizes, whereas those in rural areas, despite long traveled distances, tend to have relatively small mean DPPA sizes. Such distinct patterns arise because individual DPPA depends not only on individual traveled distance but also on the area's built-up density (measured by road network density). This is consistent with previous studies that have shown that traveled distance is incapable of representing complete human mobility patterns and is not relevant to individual geographic context (Sherman et al. 2005; Kamruzzaman and Hine 2012; Patterson and Farber 2015). Such a result was also supported by the weak negative correlation ($\rho = -0.2$) between traveled distance and DSTP volume indicators.

A modest positive correlation ($\rho = 0.75$) was found between DSTP volume and DPPA size indicators. This positive correlation was consistent with the similar spatial patterns shown in Figures 7C and 7E. A distinctive spatial disparity of DSTP volumes was observed, however, between people from different regions. As summarized in Table 1, the CV of DSTP volumes for all phone users was 0.64, approximately 30 percent larger than that of DPPA sizes (0.49). From this perspective, it might suggest that $DSTP^{\mu}$, which considers individual time available for activity partici-

Table 1. Correlation coefficients and coefficient of variation for mobility indicators and accessibility measures

	Spearman's rank correlation coefficient					
	Traveled distance	$DPPA^{\mu}$	$DSTP^{\mu}$	CUM^{μ}	DUR^{μ}	CV
Traveled distance	1	0.06	–0.20	0.06	–0.06	1.35
$DPPA^{\mu}$		1	0.75	0.88	0.72	0.49
$DSTP^{\mu}$			1	0.68	0.83	0.64
CUM^{μ}				1	0.90	0.88
DUR^{μ}					1	1.16

Note. CV = coefficient of variation.

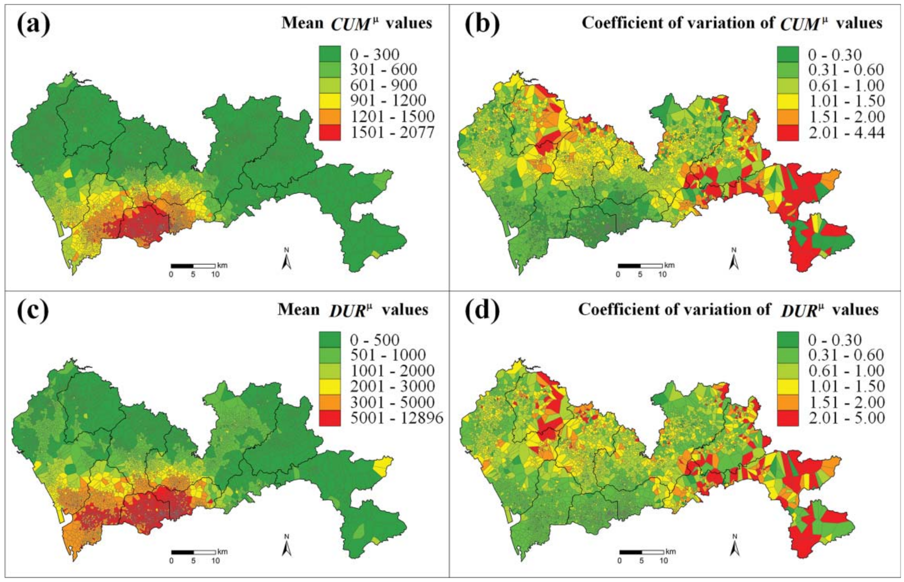

Figure 8. Accessibility to food services based on CUM^{μ} and DUR^{μ} measures. (Color figure available online.)

pation, can better articulate heterogeneity of human mobility across individuals than $DPPA^{\mu}$.

Individual Accessibility Patterns

Individual accessibility (CUM^{μ} and DUR^{μ}) measures were calculated for all phone users across the whole study area using the extracted potential activity spaces ($DPPA^{\mu}$ and $DSTP^{\mu}$).

Figures 8A and 8B show accessibility to foodservice facilities based on the CUM^{μ} measure (i.e., cumulative number of foodservice facilities within the user's $DPPA^{\mu}$). As illustrated in Figure 8A, mobile phone tracking data allow accessibility of a massive number of phone users to be generated at fine resolution across a large study area. People in various regions of the city have significantly different patterns of accessibility, in terms of the number of foodservice facilities available. People in resource-rich regions with dense service facilities (mainly in the core urban areas) tend to have a higher level of accessibility than those in the resource-poor regions with sparse service facilities (mainly in suburban and rural areas). It was found in Figure 8B that the CUM^{μ} measure can well capture the interpersonal variation for phone users living in

Figure 9. CUM^{μ} and DUR^{μ} rankings for the largest 1,000 daily potential path area phone users. DPPA = daily potential path area. (Color figure available online.)

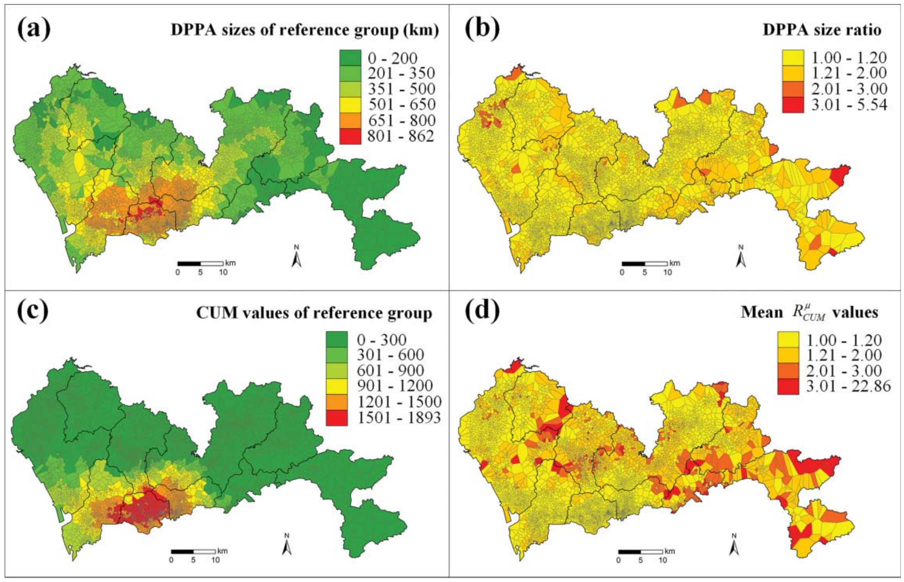

Figure 10. Human mobility impacts on accessibility in terms of CUM^{μ} measure. DPPA = daily potential path area. (Color figure available online.)

the same residential area. A significantly larger interpersonal variation of accessibility was found for phone users in suburban and rural areas than core urban areas.

Figures 8C and 8D illustrate the calculated individual accessibility to food service facilities using the DUR^{μ} measure. As illustrated, a similar spatial pattern of accessibility can clearly be observed between DUR^{μ} and CUM^{μ} measures. Compared to CUM^{μ} defined in 2D activity space, DUR^{μ} evaluates accessibility in terms of the cumulative activity durations at all accessible facilities within the user's 3D activity space (i.e., $DSTP^{\mu}$). A strong positive correlation ($\rho = 0.90$) was found between DUR^{μ} and CUM^{μ} (see Table 1). It also can be observed from the figures that the DUR^{μ} measure produced more differentiated spatial patterns of accessibility than the CUM^{μ} measure. The CV of DUR^{μ} was 1.16, approximately 31.8 percent larger than that of the CUM^{μ} measure (0.88). This result could suggest that inclusion of time available for activity participation is more suitable to capture individual accessibility spatial patterns across various regions.

The importance of incorporating time available for activity participation in the accessibility valuation was further investigated. Figure 9 shows the CUM^{μ} (yellow) and DUR^{μ} (green) rankings for the largest 1,000 DPPA phone users. Both rankings of CUM^{μ} and DUR^{μ} are shown in Figure 9 using a logarithm scale. Among these phone users, 331, 666, and 3 of them were living in urban, suburban, and rural areas, respectively. As shown, users with large DPPA sizes tend to also have large CUM^{μ} values. More than half (56.8 percent), including 92.7 percent of users in core urban areas, were ranked within the top 1,000 and almost all (95.9 percent) within the top 10^5 CUM^{μ} values. This suggests that large DPPA size implies high accessibility with respect to the CUM^{μ} measure. This observation was supported by the strong positive correlation ($\rho = 0.88$) between CUM^{μ} and DPPA (see Table 1) and is consistent with Kwan (1998).

However, the situation is somewhat different for the DUR^{μ} measure, with only a modest correlation ($\rho = 0.72$) between DUR^{μ} and DPPA (see Table 1). As shown in Figure 9, very few phone users with large DPPA size (1.4 percent) were ranked within the top 1,000 DUR^{μ} values. The majority of users (87.6 percent), including 98.5 percent of users in suburban and rural areas, were ranked outside the top 10^5 DUR^{μ} values. Thus, it reveals that large DPPA size does not imply high accessibility with respect to the DUR^{μ} measure. In fact, large DPPA size can also indicate significant time

Table 2. Average relative accessibility ratios for different city regions and service types

Region service type		Core urban areas	Suburban areas	Rural areas
Foodservice	R^{μ}_{CUM}	1.05	1.36	1.53
	R^{μ}_{DUR}	0.82	1.04	1.17
Recreational service	R^{μ}_{CUM}	1.05	1.29	1.49
	R^{μ}_{DUR}	0.81	1.01	1.16
Shopping service	R^{μ}_{CUM}	1.03	1.16	1.55
	R^{μ}_{DUR}	0.78	0.89	1.15

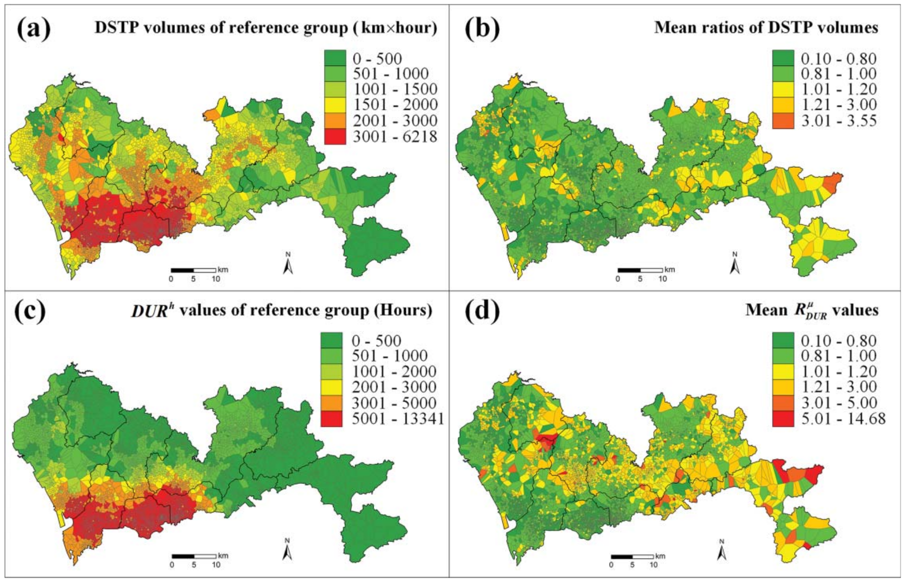

Figure 11. Human mobility impacts on accessibility in terms of DUR^{μ} measure. DSTP = daily space–time prism. (Color figure available online.)

resource allocation for traveling, reducing the time resource for activity participation and hence reducing DUR^{μ} accessibility. This suggests that time available for activity participation is a critical factor for accessibility evaluation, and ignoring this factor could lead to biased individual accessibility patterns.

Human Mobility Impacts on Accessibility

Human mobility affects accessibility with respect to both CUM^{μ} and DUR^{μ} measures that were quantified using the relative accessibility measures; that is, the ratio of actual users against the stationary user in the same cellular tower, R^{μ}_{CUM} and R^{μ}_{DUR}, respectively. The DPPA and DSTP ratios are similarly defined.

Figures 10A and 10C show the calculated DPPA sizes and CUM^h values for stationary users in all cellular towers, respectively. Figures 10B and 10D show the DPPA ratios and R^{μ}_{CUM} values, respectively. It can be observed from Figure 10D that human mobility significantly enhances accessibility in terms of CUM^{μ} measure for all phone users across the entire city, but the impacts are highly spatially uneven. As summarized in Table 2, human mobility has more positive impacts on people in rural areas (average $R^{\mu}_{CUM} = 1.53$) and suburban areas (average $R^{\mu}_{CUM} = 1.36$) than in core urban (average $R^{\mu}_{CUM} = 1.05$) areas. This result is expected. As shown in Figure 10B, human mobility can significantly enlarge individuals' DPPA sizes, especially for people in those resource-poor regions. Such a result, that human mobility can significantly enhance CUM^{μ} accessibility for disadvantaged individuals in resource-poor regions, is consistent with previous transport-related social exclusion studies (Casas 2007; Preston and Rajé 2007; Stanley et al. 2011; Kamruzzaman and Hine 2012).

Figures 11A and 11C show the calculated DSTP volumes and DUR^h values for stationary users in all cellular towers, respectively. Figures 11B and 11D show the DSTP ratios and R^{μ}_{DUR} values, respectively. It can be seen from Figure 11D that human mobility impacts on DUR^{μ} accessibility are spatially uneven and largely influenced by the richness of service facilities. For resource-rich regions with dense service facilities (including most core urban areas), mean R^{μ}_{DUR} values were less than 0.8, suggesting that human mobility can significantly reduce DUR^{μ} accessibility for people living in resource-rich regions. This seems reasonable and is confirmed by Figure 11B, which shows that human mobility reduced DSTP volumes for people living in resource-rich regions. The situation is significantly different, however, for people living in resource-poor regions with sparse facilities, largely suburban and rural areas. Figure 11D shows that average R^{μ}_{DUR} ratios were larger than 1.2 for many cellular towers in rural areas and larger than 3.0 for several remote rural areas. It reveals that human mobility can greatly enhance DUR^{μ} accessibility for people living in resource-poor regions. In contrast to resource-rich regions, although human mobility might also reduce individual DSTP volumes (Figure 11B), trips by

Table 3. Gini coefficients for different accessibility measures and service types

Measure service type	CUM^{μ}	CUM^{h}	DUR^{μ}	DUR^{h}
Foodservice	0.43	0.47	0.50	0.52
Recreational service	0.40	0.43	0.46	0.48
Shopping service	0.34	0.36	0.40	0.42

people from resource-poor regions enable them to enjoy urban services provided by other regions of the city. Therefore, human mobility impacts on accessibility in terms of the DUR^{μ} measure are spatially uneven. Human mobility can significantly enhance accessibility for people living in resource-poor regions, while reducing accessibility for people living in resource-rich regions.

Interestingly, this result that human mobility impacts on accessibility are either positive or negative contradicts the earlier outcome using the CUM^{μ} measure that human mobility impacts are positive for all regions. Although people living in resource-poor regions showed a significant positive impact of human mobility for both DUR^{μ} and CUM^{μ} measures, as shown in Table 2, the CUM^{μ} measure tends to overestimate 30.8 percent (i.e., 1.53/1.17 – 1) of human mobility impact on accessibility. This contradiction shows that ignoring time available for activity durations could lead to bias or even erroneous conclusions of human mobility impacts on accessibility and also suggests that time available for activity durations should be explicitly incorporated in accessibility studies.

The Gini coefficient concept was also employed to quantify human mobility impacts on the spatial pattern of DUR^{μ} accessibility. Table 3 shows the Gini coefficient of DUR^{h} measure to be 0.52, indicating high accessibility spatial inequality among reference stationary users living in different regions of the city. This significant spatial inequity of accessibility is due to the uneven distribution of urban services in Shenzhen city. Incorporating human mobility, the Gini coefficient of DUR^{μ} measure was reduced by 3.4 percent to 0.50. This outcome is reasonable, because human mobility impacts are negative for people in resource-rich regions with a higher level of accessibility but positive for people in resource-poor regions with a lower level of accessibility. This result suggests that human mobility could help mitigate spatial inequity of accessibility to urban services for people living in different regions of the city.

In addition to foodservices, the impacts of human mobility on accessibility were generalized to recreational and shopping services. Table 2 shows that human mobility has very similar impacts on DUR^{μ} for these three urban services in Shenzhen city. Similar to the foodservice case, human mobility impacts on accessibility to recreational and shopping services are also spatially uneven. For people living in urban areas, human mobility can reduce accessibility to both recreational and shopping services by approximately 20 percent ($R^{\mu}_{DUR} = 0.81$ and $R^{\mu}_{DUR} = 0.78$, respectively). For people living in rural areas, human mobility can enhance accessibility to both recreational and shopping services by approximately 15 percent ($R^{\mu}_{DUR} = 1.16$ and $R^{\mu}_{DUR} = 1.15$, respectively). For people living in suburban areas, human mobility impacts can be either slightly positive ($R^{\mu}_{DUR} = 1.01$ for recreational services) or slightly negative ($R^{\mu}_{DUR} = 0.89$ for shopping services). As summarized in Table 3, human mobility can also reduce the Gini coefficients of accessibility, in terms of DUR^{μ} measure, to recreational and shopping services by 4.2 percent and 4.8 percent, respectively. These consistent results for the different urban services, to some extent, confirmed the observed human mobility impacts on accessibility to urban services.

Discussion and Conclusions

This study investigated the impacts of human mobility on accessibility using a massive mobile phone tracking data set including more than 6 million users collected in Shenzhen, China. Phone users' mobility data were extracted using 2D and 3D potential activity spaces (i.e., $DPPA^{\mu}$ and $DSTP^{\mu}$), and phone users' accessibility to urban services was evaluated using CUM^{μ} and DUR^{μ} measures. It was shown that the mobile phone tracking data allowed individual accessibility to be evaluated for all phone users across the whole study area at fine resolution (cellular tower), and interpersonal accessibility variation could be identified for phone users within the same residential locations. This result illustrated that massive mobile phone tracking data could be a very useful data source for large-scale, individual-based accessibility studies (Kwan and Weber 2003; Miller 2007).

Mobility impacts on accessibility for people living in various regions were quantified using relative accessibility ratios between actual and virtual stationary phone users in the same residential location. Results of this study provided several new insights on relationships between human mobility and accessibility.

First, this study extended previous human mobility studies (Schönfelder and Axhausen 2003; Casas 2007; Stanley et al. 2011; Kamruzzaman and Hine 2012; Patterson and Farber 2015) by investigating human mobility impacts on accessibility for the entire region of a megacity with diverse land use characteristics (i.e., spatial distribution of service facilities). This study found that human mobility impacts on accessibility, in terms of the DUR^{μ} measure, can be positive or negative, depending on land use characteristics. For resource-rich regions with dense service facilities (i.e., most core urban areas in this case study), human mobility can significantly reduce individual accessibility. In these regions, long individual traveled distance indicates allocation of significant time resources for traveling, which reduces individual time available to participate in activities, leading to reduced accessibility. For resource-poor regions with sparse service facilities (i.e., most suburban and urban areas in this case study), human mobility can greatly enhance individual accessibility. Although long traveled distance also reduces individual time available to participate in activities, longer trips enable people in these resource-poor regions to enjoy urban services provided by other regions and hence enhances their accessibility. Therefore, these findings enrich our understanding of how land use influences the relationships between human mobility and accessibility.

Second, this study extended previous spatial equity studies (Omer 2006; Delbosc and Currie 2011; van Wee and Geurs 2011) by showing that human mobility can mitigate spatial inequity of accessibility for people living in various regions of the city. This result is pertinent to the statement of space–time convergence, which describes the dramatic impact of space-adjusting technologies on the organization of human activities in geographic space (Janelle 1969; Miller 2007). Mobility provided by transportation technologies has reduced the friction of distance for people to access urban services at other places from their residential locations. Human mobility thus contributes to the reduction of spatial inequality of accessibility to urban services among people living in different regions of the city. Therefore, this finding deepens our understanding of the influence of human mobility on spatial equity of accessibility.

Based on these findings of human mobility impacts on the accessibility, several policy implications can be made regarding improving accessibility for people living in different city regions. For resource-rich regions, it would be beneficial to provide a balanced mix of living, service, and working opportunities within individuals' neighborhoods, reducing their mobility in terms of traveled distance and DPPA size, for conducting mandatory out-of-home activities. This would increase individual time available for participating in discretionary activities at surrounding service facilities, enhancing their accessibility. This could also contribute to reduced travel demands in core urban areas (Timmermans, Arentze, and Joh 2002), as well as sustainable and compact development of the city (Levine and Frank 2007; van Wee and Handy 2016; Stevens 2017). For resource-poor regions, however, provision of adequate mobility would be an effective means to improve accessibility of disadvantage people. Sufficient mobility (i.e., large DPPA size) via private and public transportation can enable disadvantaged people to access basic service facilities located in other city regions, helping reduce their risk of transport-related social exclusion (McCray and Brais 2007; Stanley et al. 2011; van Wee and Geurs 2011).

Results of this study also have several important methodological implications in the accessibility evaluation. The DUR^{h} measure of the reference stationary group can be regarded as a place-based accessibility measure ignoring human mobility. Comparing DUR^{μ} and DUR^{h} accessibility suggests that place-based accessibility measures ignoring human mobility can introduce significant bias on spatial distribution of accessibility and overestimate spatial inequity of accessibility by overestimating accessibility for people living in resource-rich regions while underestimating accessibility for those living in resource-poor regions. In addition, comparing DUR^{μ} and CUM^{μ} results shows that the DUR^{μ} measure, incorporating time available for activity participation, is more suitable to capture spatial inequity of individual accessibility across various regions, consistent with the findings from previous studies (Kwan 1998; Neutens et al. 2010; Ren, Tong, and Kwan 2014). More important, comparing DUR^{μ} and CUM^{μ} rankings (see Figure 9) clearly shows that ignoring time available for activity participation can lead to biased accessibility results, particularly for individuals with large DPPA sizes. This study clearly reveals that ignoring time available for activity duration could lead to erroneous conclusions of human mobility impacts on accessibility (i.e., that human mobility impacts are positive for all city regions). Therefore, these methodological implications provide strong evidence supporting the assertion (Kwan 2013) that human mobility and time dimension (in terms of time available for activity participation) are critical factors that should be explicitly considered in accessibility studies. Such methodological implications also underscore the significant influence of algorithms (e.g., accessibility measures in this study) on geographic research in the era of big data, termed algorithmic geographies by Kwan (2016).

There are several fruitful directions for future research. First, this study estimated the potential activity spaces of massive numbers of mobile phone users by constructing space–time prisms along sample points of user trajectories. This activity space estimation method, however, differs to some extent from the classical approach of constructing space–time prisms along anchor points collected by activity diary surveys (Kwan 1998). Further studies are required to investigate the effective methods for estimating individuals' activity spaces through mobile phone tracking data (B. Y. Chen, Wang, et al. 2017). Second, this study only considered a single flexible activity in the accessibility evaluation and ignored the individual's trip-chain behavior (i.e., multiple flexible activities; Fang et al. 2011; X. Chen and Kwan 2012). The incorporation of trip-chain behavior in accessibility research is a topic for further study. Third, to protect user privacy, this study collected only the trajectories of mobile phone users, omitting any personal information, such as gender, age, occupation, income, car ownership, mode choice, trip purpose, and so on. How these personal attributes might affect the relationships between human mobility and individuals' accessibility requires further investigation. How to impute personal attributes from user trajectories and context information by using spatiotemporal data mining techniques is another interesting direction for further study (Bohte and Maat 2009; Biljecki, Ledoux, and van Oosterom 2013; Feng and Timmermans 2013; Shen and Stopher 2013). Finally, this study included only mobile phone tracking data from the Shenzhen city region. It would be helpful to use similar data sets collected in other cities to verify the identified relationships between human mobility and accessibility.

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