Measuring Place-based Accessibility under Travel Time Uncertainty

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Abstract

Travel time uncertainty has significant impacts on individual travel-activity scheduling, but at present these impacts have not been considered in most accessibility analyses. This study proposes an accessibility evaluation framework for urban areas with uncertain travel times. In this study, a reliable space-time service region (RSTR) model is introduced to represent the space-time service region of a facility under travel time uncertainty. Based on the RSTR model, four reliable place-based accessibility measures are proposed to evaluate accessibility to urban services by incorporating the effects of travel time reliability. To demonstrate the applicability of the proposed framework, a case study using large-scale taxi tracking data and social media data is carried out. The results of case study indicate that the proposed accessibility measures can evaluate large-scale place-based accessibility well in urban areas with uncertain travel times. Conventional place-based accessibility indicators ignoring travel time reliability can significantly overestimate the accessibility to urban services.

Keywords: Place-based accessibility; service area analysis; travel time uncertainty; reliability

1. Introduction

Accessibility is a fundamental concept in transport geography, urban planning and other related fields. It refers to the ease with which activity locations or urban services can be reached from a particular location or by individuals at that location (Kwan and Weber, 2008). The concept of accessibility has been widely applied to many applications, such as evaluating transportation systems performance, appraising access to job opportunities and health care facilities, investigating social equity and segregation, and etc. (Miller and Wu, 2000; Huang and Wu, 2008; Wang and Chai, 2009; Richardson et al., 2013; Lubamba et al., 2013; Schwanen and Wang, 2014).

In the literature, various measures have been developed to quantify accessibility for different

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application contexts. Roughly, accessibility measures can be classified into two categories: place-based and individual-based measures (Geurs and van Wee, 2004). Conventional place-based measures conceptualized accessibility largely in terms of the proximity to urban opportunities. Commonly used measures include distance to the nearest opportunity (Ingram, 1971; Kirby, 1976), cumulative-opportunity accessibility (Breheny, 1978) and gravity-based accessibility (Hansen, 1959). Such conventional measures are easily implemented and interpreted, needing few aggregated data and computational efforts. However, they are often criticized for their inadequate description of the complexity of individual space-time constraints and urban environments (Kwan and Weber, 2003; Miller, 2007).

Individual-based accessibility metrics were developed to measure the opportunities available to an individual given her detailed activity travel diary, subject to various space-time constraints (Kwan, 1998; Miller, 1999; Neutens et al., 2012). The volume of the space-time prism and the number of opportunities within the space-time prism are well-known individual-based accessibility measures. Although individual-based accessibility measures can full capture the complexities of individual activity travel behaviors, they require individual-level activity travel diary data which can be very expensive and difficult to acquire large number of samples. In-depth discussions of the pros and cons of these various accessibility measures can be referred to Geurs and van Wee (2004), Kwan and Weber (2003) and Miller (2007).

Accessibility to urban services depends on transportation networks for overcoming the friction of distances between individuals and activity locations. In most previous accessibility studies, travel times of transportation networks were assumed to be deterministic (Geurs and van Wee, 2004). Travel times are commonly fixed and measured as mean travel times if the traffic data are available (Li et al., 2011), or free flow travel times if the traffic data are unavailable (Neutens et al., 2010). However, travel times in urban road networks are highly stochastic, due to random supply degradations and demand fluctuations (Lam et al., 2008; Du et al., 2012; Fu et al., 2014a, 2014b). Figure 1 highlights the variation of travel times at the Cross Harbor Tunnel in Hong Kong, based on 1,975 observation samples taken on weekdays between 4:00 to 7:00 P.M. As shown in the figure, a single mean value (i.e., 16.2 min) is insufficient to fully represent travel times at this typical site, which are varying from 5.4 min to 29.2 min. Due to this variation of travel times, the accessible space-time extents of individuals at a particular location are not deterministic but rather stochastic.

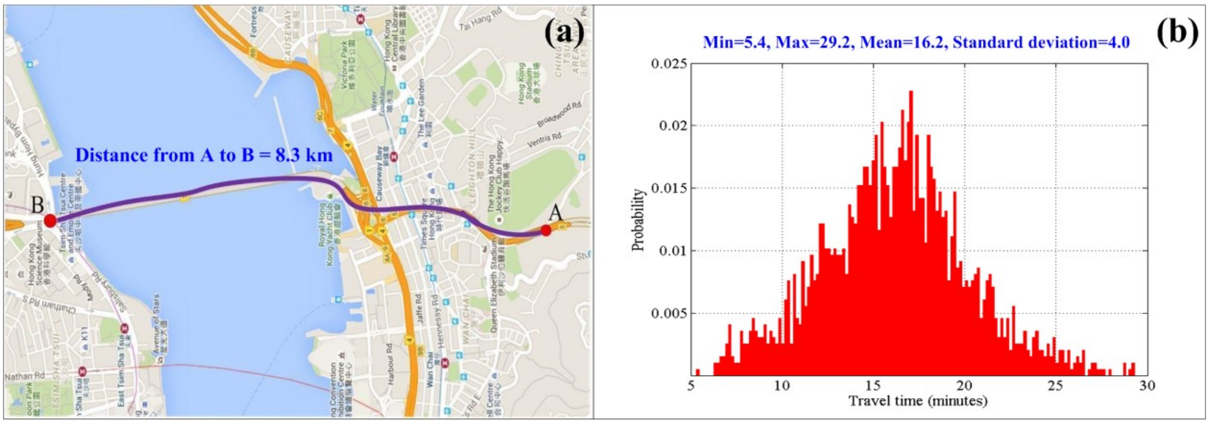

Figure 1. An illustrative travel time distribution (a) Cross Harbor Tunnel in Hong Kong (source: Google Map) (b) Travel time distribution during 4:00-7:00 P.M.

Many empirical studies have found that travel time uncertainty has significant impacts on individuals' travel-activity scheduling (Carrion and Levinson, 2012; Taylor, 2013). For example, Abdel-Aty et al. (1995) identified that travel time uncertainty is either the most important or the second-most important factor for commuters' travel decision-making. Bates et al. (2001) found that for most commuters a one minute reduction of travel time standard deviation is equally valued as two minutes on mean travel time. Previous empirical studies (Tam et al., 2008a; Carrion and Levinson, 2012) have shown that individuals facing travel time uncertainty tend to become risk-averse to being late, and allow extra travel time 'safety margin' (Hall, 1983), to ensure a desirable on-time arrival probability for activity participations (also known as travel time reliability in the literature). Therefore, travel time reliability concerns are necessary inclusions in accessibility analyses.

The issue of uncertainty in recent years has become increasingly recognized in geography and GIScience fields (Kobayashi et al., 2011; Kuijpers et al., 2010; Kwan, 2012). Particularly, Chen et al. (2013a) have proposed a reliable space-time prism model to incorporate travel time reliability concept into the classical space-time prism model. Nevertheless, the effects of travel time reliability have not been considered in existing accessibility studies.

To fill the gap, this study proposes a place-based accessibility evaluation framework for large-scale urban areas with uncertain travel times. Inspired by the reliable space-time prism model (Chen et al., 2013a), a reliable space-time service region (RSTR) model is introduced to analyze service area of a facility under travel time uncertainty. This RSTR model generalizes the conventional service area analysis (e.g., the ArcGIS network analysis module) by considering customers' travel time reliability constraint. In addition, several temporal constraints of the facility (such as opening hours and minimum activity duration) can be explicitly formulated. Based on the RSTR model, four reliable place-based accessibility measures are developed to evaluate accessibility to urban services under travel time uncertainty. The effects of travel time reliability on the friction of distances between customers and facilities are explicitly formulated and incorporated. Therefore, the proposed accessibility evaluation framework would enhance the validity and realism of accessibility studies in large-scale urban areas with uncertain travel times.

To demonstrate the applicability of the proposed accessibility evaluation framework, a comprehensive case study is conducted in Wuhan, China. Large-scale taxi tracking data are collected to estimate link travel time distributions in the Wuhan road network. Check-in data of a popular social media site are extracted to represent the attractiveness of food service facilities. The results of the case study indicates that the proposed accessibility measures can evaluate food service accessibility well in situations of travel time uncertainty. Conventional place-based accessibility measures ignoring customers' travel time reliability constraint can significantly overestimate the accessibility to urban services. The impacts of travel time reliability on accessibility are highly spatially uneven.

The remainder of this paper is structured as follows. In the next section, the RSTR model is then presented. Four reliable place-based accessibility measures are introduced in Section 3. The case study in Wuhan using real data is reported in Section 4. Finally, the conclusions and future research recommendations are given in Section 5.

2. Reliable service area analysis under travel time uncertainty

The service area of a facility is generally defined by a geographical region, in which potential customers can reach a facility within a given distance or time threshold (e.g. a 15-minute service area of a facility). This service area concept has been implemented by the service area analysis tool in ArcGIS network analysis module, and widely used in many accessibility studies (Kim and Kwan, 2003; Wan et al., 2012). However, such service area concept, built on the deterministic travel time assumption, cannot well represent the service area of a facility under travel time uncertainty.

Inspired by the reliable space-time prism concept (Chen et al., 2013a), this study proposes a reliable space-time service region (RSTR) model to analyze the facility's service area under travel time uncertainty. Figure 2 illustrates this RSTR model in 3D space, where the z axis represents time, and the x and y axes represent 2D geographic space. As shown in the figure, a facility f_i provides a specific service to customers during its opening time slot from t_p to t_q; and its minimum activity duration for providing the service to customers is denoted by $c_{f_i}^{\min} \geq 0$.

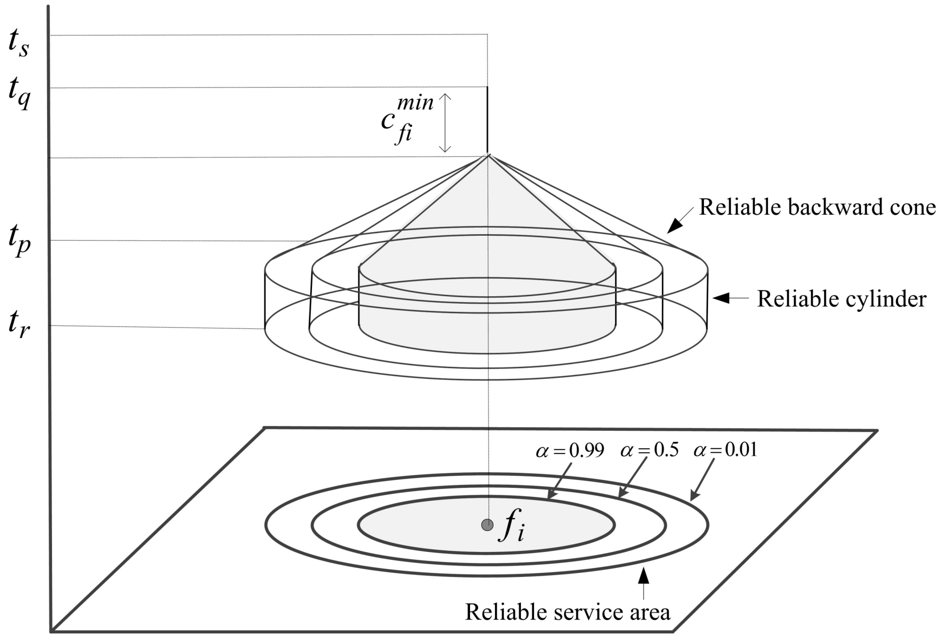

Figure 2. Reliable space-time service region model and related concepts

Given a customer at location x, the available time resource for the customer is from time instant t_r to time instant t_s. Then, time budget for travelling, denoted by b, can be calculated by

$$b = t_s - t_r - c_{f_i}^{\min} \tag{1}$$

Let T^{xf_i} be travel time from location x to the facility and assumed to be stochastic. As the travel time T^{xf_i} is a random variable, it is not certain that the individual can arrive at the facility on-time for activity participation, but only probable. This probability of on-time arrival (denoted by α) is expressed as the following cumulative distribution function (CDF):

$$\alpha = \Phi_{T^{xf_i}}(b) = \int_0^b f(t)dt \tag{2}$$

where $\Phi_{T^{xf_i}}(b)$ and $f(t)$ respectively are the CDF and probability density function (PDF) of travel time T^{xf_i}. Such on-time arrival probability $\alpha \in (0,1)$ is referred as 'travel time reliability' in the literature (Bell and Iida, 1997). $\alpha = 0.9$ can be interpreted as the frequency (i.e., 27 out of 30 days) that a trip can be successfully made within a desirable time budget b. This α parameter represents customers' travel time reliability constraint in activity-travel scheduling and can be pre-determined based on the individual's activity purposes and socioeconomic characteristics.

To achieve a pre-determined α probability of on-time arrival at the facility, the required effective travel time can be expressed as the inverse of CDF of T^{xf_i} at α confidence level, denoted by $\Phi_{T^{xf_i}}^{-1}(\alpha)$. Thus, the earliest arrival time at the facility with α probability of on-time arrival can be calculated as $t_r + \Phi_{T^{xf_i}}^{-1}(\alpha)$. By considering the facility's opening hours, the maximum time duration for activity participations (denoted by $C_{f_i}^{x}(\alpha)$) can be expressed as:

$$C_{f_i}^{x}(\alpha) = Min\left(t_q, t_s\right) - Max\left(t_p, t_r + \Phi_{T^{xf_i}}^{-1}(\alpha)\right) \tag{3}$$

where $Min\left(t_q, t_s\right)$ represents the latest activity completion time, and $Max\left(t_p, t_r + \Phi_{T^{xf_i}}^{-1}(\alpha)\right)$ represents the earliest activity starting time with α probability of on-time arrival. To guarantee α probability of successfully completing activities at the facility, the maximum activity duration should satisfy the following constraint:

$$C_{f_i}^{x}(\alpha) = Min\left(t_q, t_s\right) - Max\left(t_p, t_r + \Phi_{T^{xf_i}}^{-1}(\alpha)\right) \geq c_{f_i}^{\min} \tag{4}$$

where $c_{f_i}^{\min}$ is the required minimum activity duration. Therefore, all geographic locations satisfying this constraint form the facility's reliable service area (denoted by $\mathrm{RSA}(\mathrm{f_i}, \alpha)$) as

$$\mathrm{RSA}(\mathrm{f_i}, \alpha) = \{x \mid Min\left(t_q, t_s\right) - Max\left(t_p, t_r + \Phi_{T^{xf_i}}^{-1}(\alpha)\right) \geq c_{f_i}^{\min}\} \tag{5}$$

Accordingly, the RSTR delimits all space-time points, from which customers can visit the facility and guarantee α probability of successfully completing activities at the facility. It can be defined as

$$\mathrm{RSTR}(\mathrm{f_i}, \alpha) = \mathrm{RBC}(\mathrm{f_i}, \alpha) \cap \mathrm{RC}(\mathrm{f_i}, \alpha) \tag{6}$$

$$\mathrm{RBC}(\mathrm{f_i}, \alpha) = \left\{(x,t) \mid \Phi_{T^{xf_i}}^{-1}(\alpha) \leq Min(t_q, t_s) - c_{\min} - t, t \geq t_r\right\} \tag{7}$$

$$\mathrm{RC}(\mathrm{f_i}, \alpha) = \left\{(x,t) \mid Min\left(t_q, t_s\right) - Max\left(t_p, t_r + \Phi_{T^{xf_i}}^{-1}(\alpha)\right) \geq c_{f_i}^{\min}, t_r \leq t \leq t_s\right\} \tag{8}$$

where $\mathrm{RBC}(\mathrm{f_i}, \alpha)$ is the reliable backward cone encompassing all space-time points, from which customers can travel to the facility in remaining time budget $Min(t_q, t_s) - c_{\min} - t$ with α probability of on-time arrival. $\mathrm{RC}(\mathrm{f_i}, \alpha)$ is the reliable cylinder including all space-time locations within the reliable service area. The projection of RSTR into the 2D geographical space is the reliable service area (i.e., $\mathrm{RSA}(\mathrm{f_i}, \alpha)$).

As shown in Figure 2, by varying input α parameter ($\forall \alpha \in (0,1)$), the proposed RSTR can represent space-time service regions of a facility under various travel time reliability constraints. When $\alpha = 0.5$, the RSTR is constructed based on only median travel time but ignores travel time variation. In this scenario, the RSTR delimits the space-time service region, in which customers can visit the facility and guarantee 50% probability of successfully completing activities at the facility. With the decrease of α parameter (e.g., $\alpha = 0.1$), the size of RSTR is enlarged. In this scenario, more customers in larger geographic areas can be served by the facility, but a lower (e.g., 10%) probability can be guaranteed for customers to successful complete activities at the facility. When the α value approaches to zero (e.g., $\alpha = 0.01 \approx 0$), the upper bound is reached. Customers outside the upper bound are impossible to participate in activities at the facility during the available time budget. Conversely, with the increase of α parameter (e.g., $\alpha = 0.9$), the size of RSTR decreases, while a higher (e.g., 90%) probability can be guaranteed for customers to successful complete activities at the facility. The size of RSTR reaches its lower bound when the α value approaches to one (e.g., $\alpha = 0.99 \approx 1$). This lower bound delineates space-time service regions, within which customers can visit the facility and complete activities at the facility with certainty.

The proposed RSTR model extends the classical deterministic service area model by considering several space-time constraints under travel time uncertainty. In the proposed RSTR model, the customers' travel time reliability constraint is formulated. The size of space-time service region is determined by not only available time budget but also customers' travel time reliability constraint. In addition, temporal constraints of the facility, including facility opening hours and minimum activity duration, is formulated.

3. Reliable place-based accessibility measures under travel time uncertainty

Based on the RSTR model, four reliable place-based accessibility measures are proposed to evaluate accessibility to urban services under travel time uncertainty. Let $F = \{f_1, ..., f_n\}$ be a set of facilities for providing the same type of urban services. A location x can be covered by the reliable space-time service regions of several facilities with α probability of on-time arrival. These facilities constitute the facility choice set (denoted by $F_x(\alpha)$) for serving customers at location x as

$$F_x(\alpha) = \{x \in RSTR(f_i, \alpha), \forall f_i \in F\} \tag{9}$$

The first measure (denoted by $MINT(\alpha)$) is related to the minimum effective travel time required to reach an accessible facility f_i from location x:

$$MINT(\alpha, x) = \min_{\forall f_i \in F_x(\alpha)} \Phi^{-1}_{T^{xf_i}}(\alpha) \tag{10}$$

where $\Phi^{-1}_{T^{xf_i}}(\alpha)$ is the required effective travel time from location x to the nearest facility f_i with α probability of on-time arrival. This $MINT(\alpha)$ measure is a stochastic extension of the classical accessibility measure in terms of distance to the nearest opportunity (Ingram, 1971; Kirby, 1976).

The second measure (denoted by $CUM(\alpha)$) is the cumulative number of accessible facilities with α probability of on-time arrival:

$$CUM(\alpha, x) = \sum_{\forall f_i \in F_x(\alpha)} 1 \tag{11}$$

This $CUM(\alpha)$ measure is a stochastic extension of classical cumulative-opportunity accessibility measure (Breheny, 1978), which is often used as a measure of the freedom to participate in activities.

The third measure (denoted by $DUR(\alpha)$) is the cumulative activity durations at accessible facilities:

$$DUR(\alpha, x) = \sum_{\forall f_i \in F_x(\alpha)} C^x_{f_i}(\alpha) \tag{12}$$

where $C^x_{f_i}(\alpha)$ is the possible activity duration at the facility f_i with α probability of on-time arrival. This $DUR(\alpha)$ measure extends the $CUM(\alpha)$ measure by incorporating activity durations at accessible facilities. It can be regarded as a stochastic extension of the place-based space-time accessibility measure (Delafontaine et al., 2012).

The forth measure (denoted by $GRAV(\alpha)$) is a gravity-type measure as

$$GRAV(\alpha, x) = \sum_{\forall f_i \in F_x(\alpha)} (W_{f_i})^{\lambda} \exp(-\beta \Phi^{-1}_{T^{xf_i}}(\alpha)) \tag{13}$$

where W_{f_i} is the attractiveness of the facility f_i. This parameter differentiates facilities with various levels of service quality, and can be represented by a function related to one or multiple attributes of facilities (Miller and Wu, 2000). λ and β are sensitive parameters to facility attractiveness and the distance decay effect respectively. This $GRAV(\alpha)$ measure extends $CUM(\alpha)$ by considering the facility service quality (expressed by W_{f_i}) and distance decay effect (expressed by the negative exponential decay function of $\Phi^{-1}_{T^{xf_i}}(\alpha)$). Such $GRAV(\alpha)$ measure can be regarded as a stochastic extension of the classical gravity accessibility measure (Hansen, 1959).

4. Case study

This section presents a case study using real-world data collected in Wuhan, China, to demonstrate the applicability of the proposed reliable place-based accessibility evaluation framework. In this study, a GIS toolkit was developed for constructing RSTRs in road networks and calculating the proposed accessibility measures. The GIS toolkit was developed using Visual C# programming language and integrated with the ArcGIS software. The detailed algorithm for constructing RSTRs is given in Appendix 1.

4.1. Data collection

The data collected in this case study included a detailed digital road network, a large-scale taxi tracking data set for estimating travel time distributions, and information about food service facilities (mainly restaurants) extracted from an online social media application.

As shown in Figure 3(a), the Wuhan road network consisted of 19,306 nodes and 46,757 links. Real-world floating car data (FCD) was collected on a typical Thursday (September 3, 2009) to estimate traffic conditions of the Wuhan road network. This dataset consisted of 10,741,837 GPS observations from 11,248 taxis. Each observation included the taxi identifier, geographical location and timestamp. The GPS sampling interval for all taxis is about 40 s. Firstly, these GPS observations to the road network and reconstruct taxi trajectories using multi-criteria dynamic programming map matching algorithm (Chen et al., 2014). After the map-matching process, the taxi trajectories were separated into link segments. Then, travel time experienced by a taxi on link l_{ij} was obtained by the time difference between the taxi entering node i and exiting node j. Finally, normal distribution was adopted to fit travel time distribution of each link l_{ij} through travel times experienced by all taxis on the same link.

Figure 3 illustrates the estimated traffic conditions of the Wuhan network during a typical evening peak period (6 p.m. – 7 p.m.). Figure 3(a) shows the mean travel speeds of all network links. In the figure, links shown in red represent congested links (< 20 km/h); yellow represents slightly congested links (20–40 km/h); and green represents uncongested links (> 40 km/h). The figure shows that 9.7% of links in the Wuhan network were congested, mostly around seven commercial centers (Yue et al., 2012), especially the Wuguang center. This reflects the high travel demand in commercial areas during the evening peak period.

Figure 3(b) illustrates travel time uncertainty in the Wuhan network. The level of travel time uncertainty was measured by coefficient of variation (CV), which is defined as the ratio of the standard deviation to the mean. The CV is always positive. Larger values of CV obviously indicate more uncertain in the link travel time. A CV value of zero would imply the validity of classical deterministic travel time assumption. As illustrated in Figure 4(b), link travel times in the Wuhan network are highly stochastic, with the average CV value equal to 0.39. Of these, 19.2% of links represented in red color with a CV value larger than 0.5. This high degree of travel time uncertainty implies that link travel times in the urban road network should be represented as stochastic variables during the peak hour.

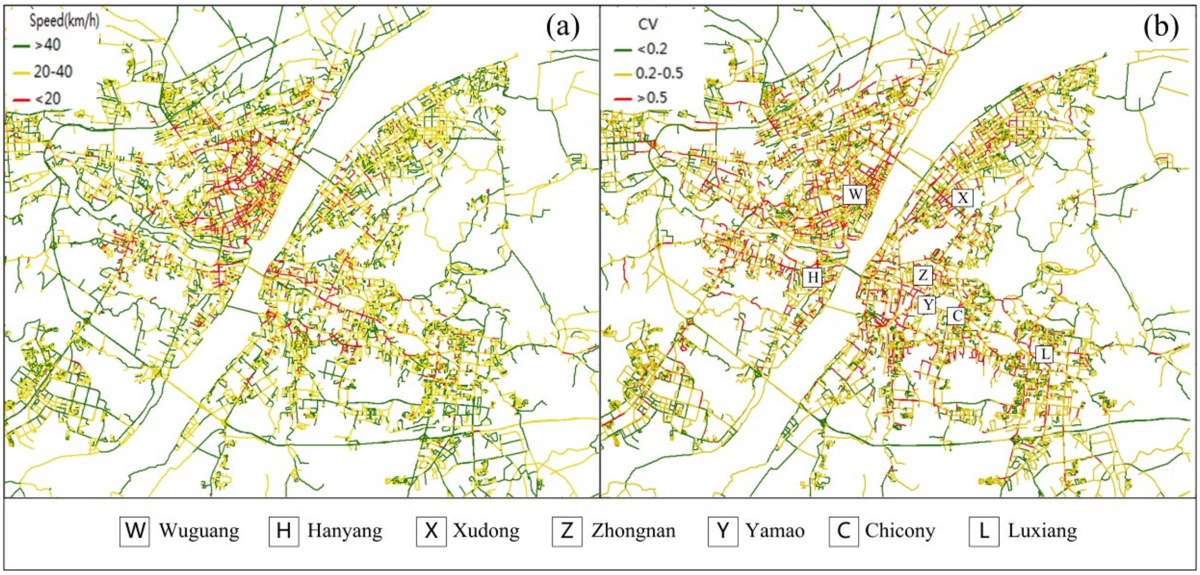

Figure 3. Traffic condition of the Wuhan network: (a) mean link speed; (b) coefficient of

variation of link travel time distributions

The temporal variations of traffic conditions of the Wuhan network are illustrated in Figure 4. Blue lines represent mean link speeds and red lines represent the average CV at different times of day. As expected, traffic flows in the Wuhan city go smoothly during the off-peak period from 10 p.m. to 6 a.m. Traffic conditions become more congested and uncertain during the morning peak periods (7 a.m. – 9 a.m.) and evening peak periods (5 p.m. – 7 p.m.).

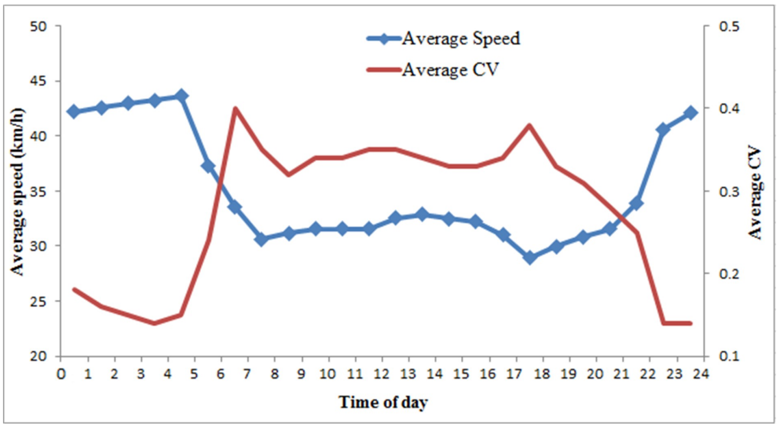

Figure 4. Temporal variations of traffic conditions

Food service facilities in Wuhan were collected from a location-based social networking website in China, named *Jiepang* (http://jiepang.com/). Jiepang, launched in 2010, is a popular web and mobile application, with five million users. Similar to *Foursquare*, Jiepang allows registered users to post their location at a "check-in" to record, track and share their life moments with friends. User geographical location was based on smartphone positioning software which was then matched to nearby points of interest (POIs) given by the application: restaurants, shopping malls, cinemas, coffee shops etc. After checking into a POI, users share their activity participation experiences through advice, photographs and ratings of the service quality of the POI.

Based on application programming interfaces (APIs) provided by the Jiepang application, a toolkit was developed to extract POI data for Wuhan City in September 2013. Each collected POI has several attributes, including the name, latitude and longitude, category, total number of check-in records, total number of check-in users, user rating of facility quality, and etc. In this study, totally 4,407 POIs (facilities) were collected from 37 categories related to food service (mainly restaurants). By merging similar categories, collected facilities were grouped into 10 categories (Figure 5). The spatial distribution of facilities is illustrated in Figure 5(a), which shows that food service facilities are not evenly distributed in the city but rather clustered at six commercial centers, especially in the Wuguang area.

The collected user rating of facility quality was used in this case study to measure the facility attractiveness to customers (i.e., W_{f_i} in Eq. (13)). The user rating of facility quality is a direct measure of user satisfaction after performing activities at the facility. Figure 5(c) illustrates the Jiepang user ratings for all collected facilities in Wuhan City. The user ratings, as collected, ranged from 1 to 10. They were normalized into a scale of 0 to 1. The larger W_{f_i} value indicates a higher level of user satisfaction to the facility service quality. It can be seen in the figure that the average of W_{f_i} values was 0.72, but these values vary significantly between facilities. More than half of collected facilities (52.01%) in the Wuhan city are satisfactory ($W_{f_i} \geq 0.8$); of these, about 16.72% were very satisfactory ($W_{f_i} \geq 0.9$). The percentage of unsatisfactory facilities ($W_{f_i} < 0.6$) was low, accounting for about 9% of the total. Those in the 'ordinary facility' category ($0.6 \leq W_{f_i} < 0.8$) accounted for about 39%.

The facility's opening hour information was not included in the POI dataset. In this study, the same opening hours were set for all facilities in a category based on field observations. For each category, three facilities were randomly selected to collect their opening hour information. The collected opening hour information for 10 categories was shown in the legend of Figure 5a.

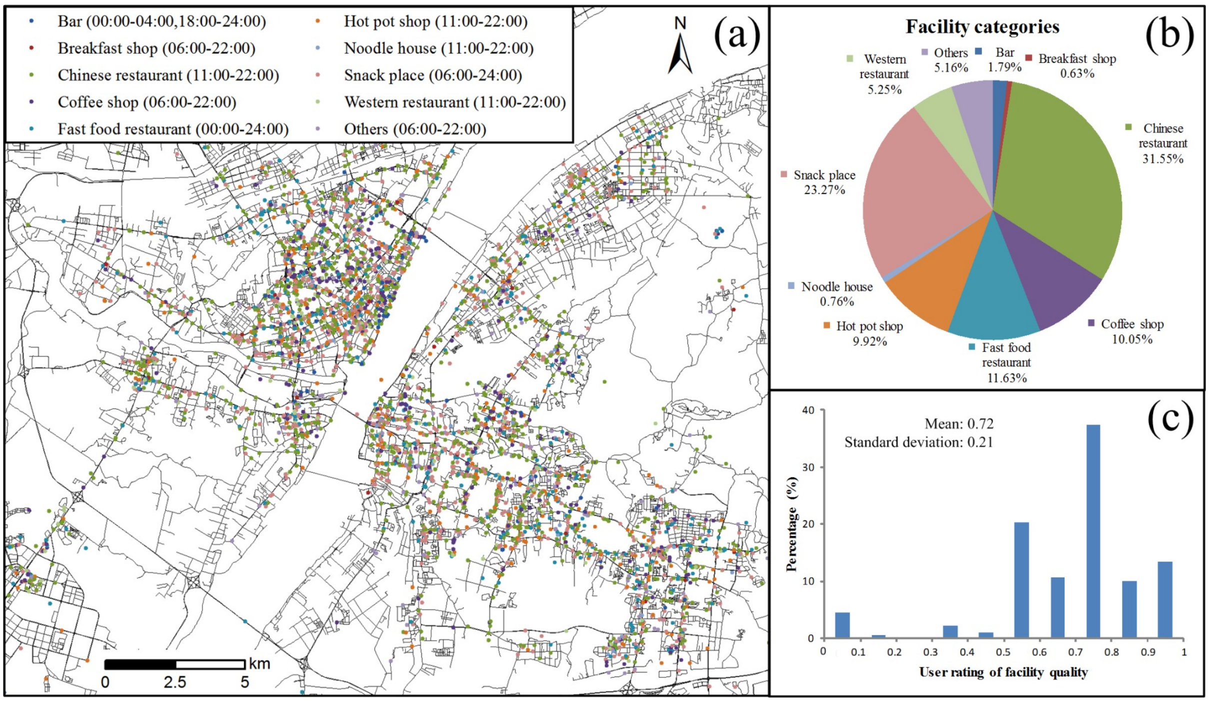

Figure 5. Collected food service facilities in Wuhan City: (a) spatial distribution; (b) categories; (c) user ratings of facility quality

4.2. Analysis of facility service areas under travel time uncertainty

In this section, RSTRs of all collected facilities were constructed and analyzed. To facilitate the presentation of the essential ideas, the available time budget was set as $t_s - t_r = 60$

minutes and the minimum activity duration was set as $c_{f_i}^{\min} = 45$ minutes throughout the case study.

Figure 6 illustrates the constructed RSTRs of three typical facilities during the evening peak hour (6 p.m. – 7 p.m.) when travel time reliability constraint was set as $\alpha = 0.9$. As shown in Figure 6(a), each constructed RSTR delimits the facility's space-time service region, in which customers can visit the facility and guarantee 90% probability of successfully completing activities. The projection of these RSTRs onto the 2D geographical space are three reliable service areas (i.e., $\mathrm{RSA}(f_i, \alpha)$).

Figure 6(b) illustrates these three reliable service areas in the 2D geographical space using different values of the α parameter. In the figure, three reliable service areas in α = 0.3, 0.5 and 0.9 scenarios are respectively represented as polygons in blue, yellow and red. When $\alpha = 0.5$, the reliable service areas were constructed based only the median travel times. It should be noted that median travel times are identical to mean travel times when travel times following normal distributions. In this scenario, totally 9,722 links were identified by three reliable service areas in which customers can traveled to facilities for activity participations with at least 50% probability guarantee. When $\alpha = 0.3$, the reliable service areas of these facilities were increased by 14.8% to 11,161 links. In this scenario, more geographical areas can be served by these facilities but with only 30% probability guarantee. When $\alpha = 0.9$, the reliable service areas of three restaurants were reduced by 18.6% (only 7,913 links), while customers can visit these facilities for activity participations with 90% probability guarantee.

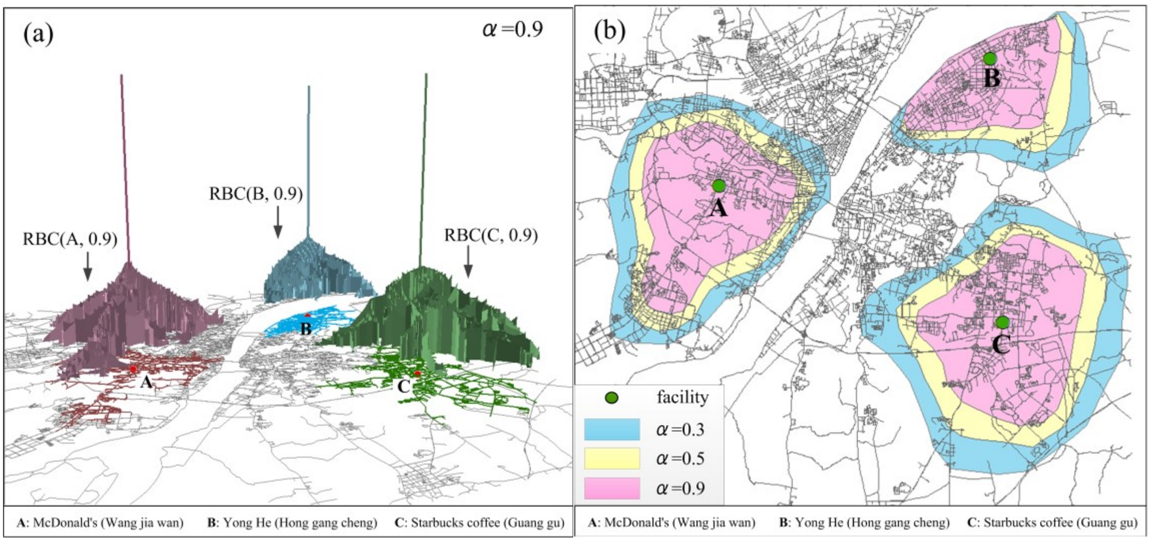

Figure 6. Reliable space-time service regions under various travel time reliability constraints (a) 3D space; (b) 2D geographical space

Figure 7 shows the average size of constructed RSTRs for all 4,407 collected facilities under various α values. As shown in the figure, it can be easily observed that the size of constructed RSTRs significantly reduces with the increase of α value. This result confirms that the proposed RSTR model can well represented space-time service regions of facilities under various travel time reliability constraints.

Figure 7 also reports the average computational times required for constructing RSTRs. It can be seen from the figure that RSTRs can be efficiently constructed within 26 milliseconds for all α values. The results of computational experiments indicates that the proposed RSTR model is applicable for service area analysis in large-scale road networks under travel time uncertainty.

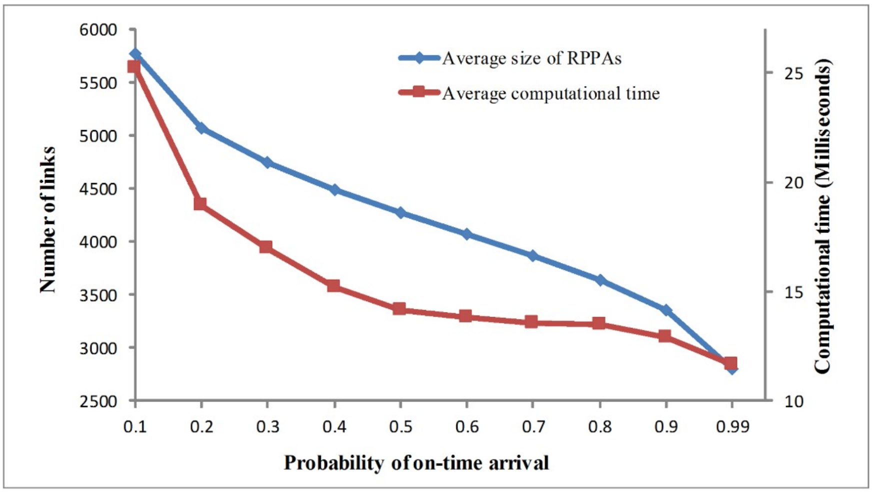

Figure 7. Average size of RSTRs constructed under various travel time reliability constraints

4.3. Analysis of reliable place-based accessibility measures

This section investigates accessibility to food service facilities under travel time uncertainty. For using $GRAV(\alpha)$ measure, the collected user rating of facility quality was used to represent the facility attractiveness to customers (i.e., W_{f_i}). Two parameters were set as $\lambda = 0.360$ and $\beta = 0.313$, according to recent empirical study conducted in the same study area using the gravity model (Yue et al., 2012). The sensitive analysis of these two parameters were given in the Appendix 2.

Figure 8 illustrates the spatial distribution of $GRAV(\alpha)$ values during the evening peak hour (6 p.m. - 7 p.m.) when travel time reliability constraint was set as $\alpha = 0.9$. As shown, the accessibility to food service facilities was not evenly distributed in the Wuhan City. Compared to suburban areas, the values of $GRAV(0.9)$ were relatively high (over 120) in seven commercial centers. The Wuguang area had the highest value of $GRAV(0.9)$ (over 160) due to its large number of restaurants.

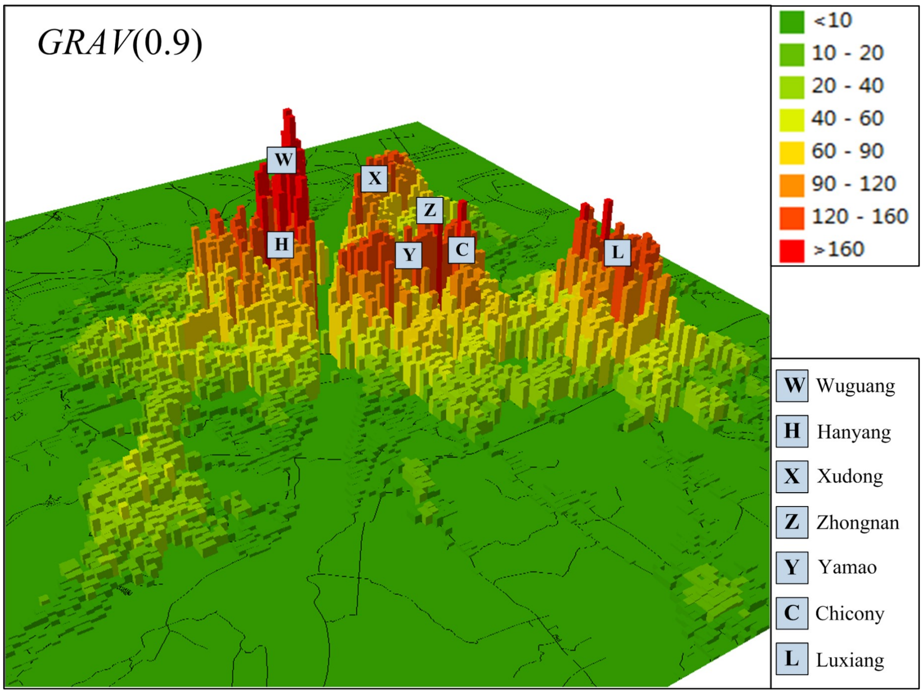

Figure 8. Food service accessibility in Wuhan City

The effects of travel time reliability on food service accessibility were investigated by using the same $GRAV(\alpha)$ measure. Figure 9 shows the spatial distribution of $GRAV(\alpha)$ values under various α values. When $\alpha = 0.5$, the effects of travel time uncertainty were ignored in the accessibility evaluation. In this scenario, mean travel time was adopted to construct the space-time service regions of facilities and to evaluate the distance decay effects between customers and facilities. The average value of $GRAV(0.5)$ measure for the whole city was 52.41.

As shown in the figure, when customers' travel time reliability constraint (i.e., α parameter) was increased to 0.9, the average value of $GRAV(0.9)$ measure was significantly reduced by 24.4% to 39.63. The reduced $GRAV(\alpha)$ values were due to following two reasons. Firstly, as reported in Figure 7, the facilities' space-time service regions were reduced with the increase of α parameter. Accordingly, the number of accessible facilities was significantly reduced, resulting in the decrease of accessibility level. Secondly, customers with higher travel time reliability constraint were required to budget larger effective travel times (i.e., $\Phi^{-1}_{T^{xf}}(0.9)$) to overcome the friction of distance between customers and facilities, leading to the decrease of accessibility level.

As illustrated in the figure, when customers' travel time reliability constraint was reduced to 0.3, the total value of $GRAV(0.3)$ measure was increased by 13.6% to 59.56. This result is expected. When travel time reliability constraint was reduced, larger space-time service regions can be covered by facilities; and thus more facilities were accessible to customers. In addition, smaller effective travel times (i.e., $\Phi^{-1}_{T^{xf}}(0.3)$) are required by customers with lower travel time reliability constraint, contributing to the increase of accessibility level. Therefore, travel time reliability (i.e., α parameter) had a significant impact on accessibility studies in urban areas with travel time uncertainty.

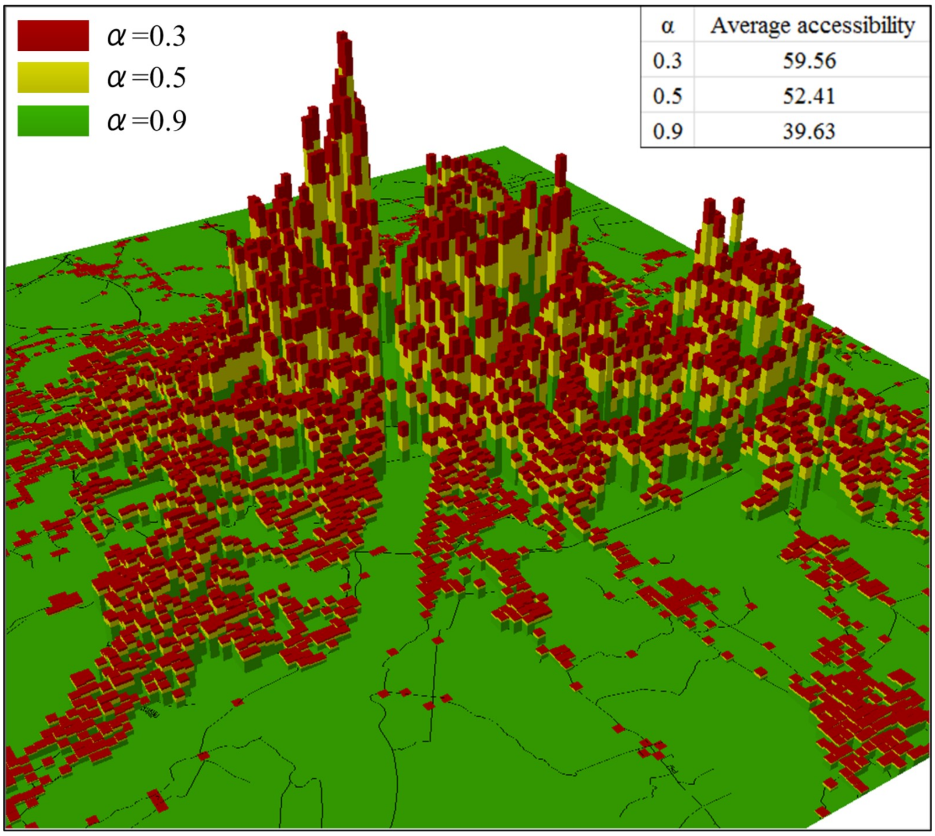

Figure 9. Food service accessibility under various travel time reliability constraints

According to empirical studies that have been reported in the literature, most individuals facing travel time uncertainty are risk-averse (Carrion and Levinson, 2012). For example, based on a stated-preferences survey, de Palma and Picard (2005) observed that the groups of risk-averse ($\alpha > 0.5$), risk-neutral ($\alpha = 0.5$) and risk-seeking ($\alpha < 0.5$) commuters respectively account for about 60%, 6%, and 33% of total commuters. Individuals' risk-averse behaviors have long been recognized by transportation authorities and planners. Travel time reliability is widely considered as a key network performance measure to ensure a high on-time arrival probability for all network users (Taylor, 2013). Therefore, we argue that accessibility measures should be calculated for the risk-averse scenario (e.g., $\alpha = 0.9$) to enable city planners and decision-makers to implement reliable land-use and transport development. Conventional place-based accessibility measures that ignore travel time reliability significantly overestimated accessibility (e.g., 24.4% for $GRAV(\alpha)$ measure).

Incorporating travel time reliability not only reduces average accessibility level, but also produces a very different geography of accessibility. Figure 10 shows the accessibility reduction (i.e., $1-GRAV(0.9)/GRAV(0.5)$) after incorporating travel time reliability. It shows that the effects of travel time reliability on accessibility are highly spatially uneven. When α increases from 0.5 to 0.9, the accessibility measures at seven commercial centers were slightly reduced, below the average of 24.4% reduction. The degree of accessibility reduction becomes more marked with distance from the seven commercial centers, and is over 40% for many suburban areas. Such a result is to be expected, since customers in these areas have to travel long distances to food service facilities at commercial centers. With increasing travel time reliability constraint, space-time service regions of facilities are significantly reduced. Consequently, these facilities are no longer accessible, leading to a sharp accessibility reduction.

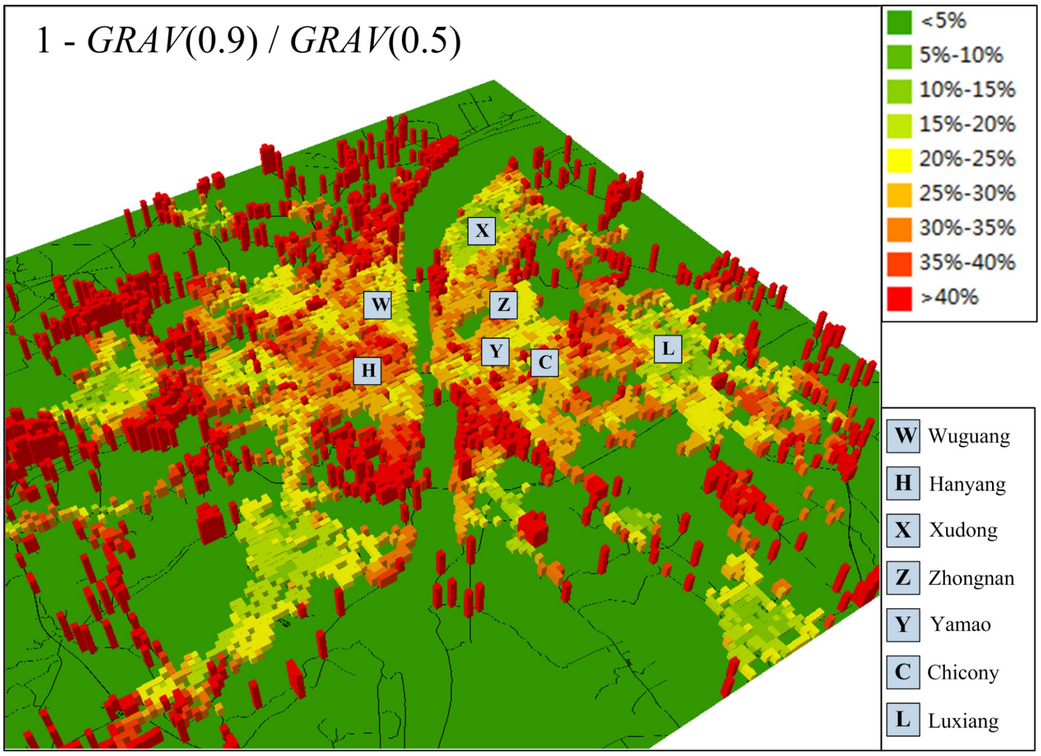

Figure 10. Impacts of travel time reliability on accessibility in Wuhan City

The effects of travel time reliability were also investigated for other three reliable place-based accessibility measures (i.e., $MINT(\alpha)$, $CUM(\alpha)$ and $DUR(\alpha)$). As can be seen from Table 1, ignoring effects of travel time reliability can overestimate all these accessibility measures. The $CUM(0.9)$ measure evaluated the food service accessibility based on the number of accessible facilities under $\alpha = 0.9$ scenario. If the $CUM(0.5)$ measure was adopted, it can overestimate accessibility level by 21.3% (i.e., 1 - 532.93/677.49). The $DUR(0.9)$ measure extends the $CUM(0.9)$ measure by incorporating activity durations at accessible facilities. Since the average number of accessible facilities was overestimated by the $\alpha = 0.5$ scenario, the $DUR(0.5)$ measure can overestimate the accessibility level by 21.5% (i.e., 1 - 444.94/566.54). The $MINT(0.9)$ measure evaluated the accessibility level by the effective travel time (i.e., $\Phi^{-1}_{T^{xf}}(0.9)$) from customers to their nearest facilities. When $\alpha = 0.5$ was used, the $MINT(0.5)$ measure would adopt travel time median instead of $\Phi^{-1}_{T^{xf}}(0.9)$. In this case, the friction of distance between customers and facilities was underestimated by 16.7% (i.e., 2.21/1.89 - 1), leading to the overestimation of accessibility level. Therefore, these results confirmed that travel time reliability has significant impacts on accessibility evaluation and ignoring travel time reliability can significantly overestimate the level of accessibility.

Table 1. Impacts of travel time reliability on four reliable place-based accessibility measures

Travel time reliability (α)	Average $MINT(\alpha)$	Average $CUM(\alpha)$	Average $DUR(\alpha)$	Average $GRAV(\alpha)$
0.3	1.75 minutes	752.50	629.91 hours	59.56
0.5	1.89 minutes	677.49	566.54 hours	52.41
0.9	2.21 minutes	532.93	444.94 hours	39.63

The temporal variation of food service accessibility in Wuhan city was also investigated using the $GRAV(\alpha)$ measure. Figure 11 illustrates the average $GRAV(0.9)$ values at different times of day, and shows that the accessibility measures varied significantly. This accessibility temporal variation is due to the opening hours of facilities and dynamic traffic conditions in road networks. For example, the sharp raise of accessibility measure during the noon period (11:00 - 12:00) was mainly due to the opening of Chinese and western restaurants. Then, the accessibility measure dropped during 12:00–18:00 and raised during 18:00-22:00, because of the traffic condition changes during these time periods (see Figure 4). Therefore, the proposed reliable place-based accessibility measures can well capture the accessibility temporal variation due to both dynamic traffic conditions and the opening hours of facilities.

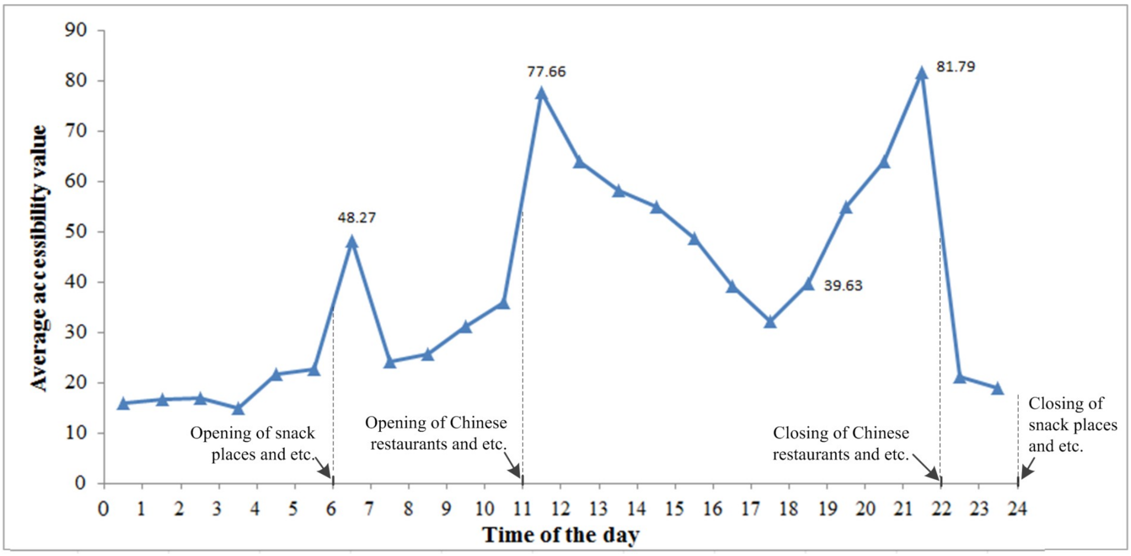

Figure 11. Temporal variation of food service accessibility

5. Conclusions and further studies

This study established a reliable place-based accessibility evaluation framework to measure accessibility to urban services under travel time uncertainty. A reliable space-time service region (RSTR) model was proposed to delimit all space-time points, from which potential customers can visit the target facility and guarantee α probability of successfully completing activities at the facility. The proposed RSTR model generalized the classical deterministic service area model by considering customers' travel time reliability constraint and the facility's temporal constraints (i.e., opening hours and minimum activity duration). Based on the RSTR model, four reliable place-based accessibility measures were proposed to evaluate the accessibility to urban service with explicitly consideration of travel time reliability effects.

The applicability of the proposed accessibility evaluation framework was demonstrated through a case study in Wuhan, China. The results of the case study indicate that the RSTR model represents facilities' space-time service regions under various customers' travel time reliability constraints (i.e. $\forall \alpha \in (0,1)$). The proposed reliable place-based accessibility measures can evaluate large-scale accessibility well in situations of travel time uncertainty. Conventional place-based accessibility measures ignoring customers' travel time reliability constraint can significantly overestimate the accessibility to urban services; and the impacts of travel time reliability on accessibility are highly spatially uneven.

The results of this study imply that travel time uncertainty should be incorporated in measuring accessibility for urban planning and policy decision-making. Whereas such inclusion may be prohibited in the past by the lack of data, in recent years large-scale traffic information has become increasing available (Miller, 2005; Li et al., 2013; Chen et al., 2016a). In addition to taxi-tracking data used in this study, travel time distributions can be obtained by using spatiotemporal big data collected from other techniques; for example loop detectors, automatic vehicle identification, electronic license plate matching, video-imaging techniques, etc. (Tam and Lam, 2008b). Travel time distributions can also be indirectly estimated from traffic assignment models (Lam et al., 2008; Chen et al., 2011). Therefore, there are no practical reasons not to address the travel time uncertainty issue in accessibility studies. Incorporating travel time reliability in accessibility analysis may lead to better decision making built on more valid and reliable data. Urban planning policies could be made for different social groups with various travel time reliability constraints.

Several directions for future research are worth noting. Firstly, the proposed accessibility measures consider only private car mode. The extension of the proposed accessibility evaluation framework to multi-modal networks is an interesting topic for further research work. Secondly, the accessibility to food services was examined mainly based on restaurants and other dining facilities. It is interesting to apply the proposed method for evaluating accessibility to other types of urban opportunities, such as job and health-care services. Last but not least, completing demands can have negative impacts on the accessibility to urban services. Similar to two-step floating catchment area (2SFCA) methods (Luo and Wang, 2003; Wan et al., 2012), the proposed reliable place-based accessibility measures can be extended to incorporate demand completion effects by calculating the physician-to-population ratio in the space-time service regions of facilities.

Appendix 1. Algorithm for constructing reliable space-time service region

This appendix presents a geo-computational algorithm for constructing RSTRs in real-world road networks. A road network with uncertain travel times can be represented as a directed graph $G(N,L,\Psi)$ comprising a set of nodes N, a set of links L and a set of movements Ψ. Each link $l_{ij} \in L$ has a tail node i, a head node j, and a random travel time distribution T_{ij}. Link travel times could be represented by normal, log-normal, gamma or Burr distributions (Kaparias et al., 2008; Chen et al., 2016b). The mean and standard deviation of link travel time are denoted by $\overline{t_{ij}}$ and σ_{ij} respectively. A movement $\psi_{ijk} = (l_{ij}, l_{jk}) \in \Psi$ represents an allowed movement at node j (e.g., through-movement), while $\psi_{ijk} \notin \Psi$ means a restricted movement at node j (e.g., left-turn).

Given a facility f_i in the road network, its location (denoted by $Pos(f_i)$) is represented by $Pos(f_i) = (l_{ij}, \theta)$ by using linear reference technique (Miller and Shaw, 2001; Chen et al., 2016a). $\theta \in [0,1]$ indicates the facility's relative position on link l_{ij}, and $\theta = 0$ and $\theta = 1$ represent the beginning and end of the link respectively. The travel time of the partial link l_{fj} from facility f_i to head node j is assumed to be proportional to the link length, and is calculated from $T_{fj} = (1-\theta)T_{ij}$.

Let p_1^{xf} be a path from location x to the facility f_i. The path travel time T^{xf} is the summation of corresponding (partial) link travel times along the path:

$$T^{xf} = \sum_{\forall l_{ij} \in p_1^{xf}} T_{ij} \tag{14}$$

It is assumed in this study that path travel time follows normal distributions and link travel times are mutually independent. Using real-world traffic data, Chen et al. (2016b) also empirically found that normal distributions can well approximate path travel time distributions by achieving 98.3% and 94.9% of accuracy at 10th and 90th percentiles (i.e., $\alpha = 0.1$ and $\alpha = 0.9$). The assumption of independent link travel time distributions can be relaxed by using two-level hierarchical network model (Chen et al., 2012). Using these two assumptions, the mean and standard deviation of path travel time T^{xf} can be calculated by

$$\bar{t}_1^{xf} = \sum_{\forall l_{ij} \in p_1^{xf}} \bar{t}_{ij} \tag{15}$$

$$\sigma_1^{xf} = \sqrt{\sum_{\forall l_{ij} \in p_1^{xf}} \sigma_{ij}^2} \tag{16}$$

Through the p_1^{xf} path, the effective travel time (denoted by $\Phi^{-1}_{T_1^{xf}}(\alpha)$), required for achieving α probability of on-time arrival, can be expressed as

$$\Phi^{-1}_{T_1^{xf}}(\alpha) = \bar{t}_1^{xf} + z_\alpha \sigma_1^{xf} \tag{17}$$

where z_α is the inverse CDF of the standard normal distribution at α confidence level and it can be obtained from the standard normal table or calculated by numerical approximation.

Let $P^{xf} = \{p_1^{xf}, ..., p_n^{xf}\}$ be the path set consisting of all paths from location x to the facility f_i. The path p^{xf} with minimum effective travel time $\Phi^{-1}_{T^{xf}}(\alpha)$ is said to be the reliable shortest path if it satisfies $\Phi^{-1}_{T^{xf}}(\alpha) \le \Phi^{-1}_{T_1^{xf}}(\alpha)$ for any path $p_1^{xf} \in P^{xf}$ (Chen et al., 2013b). Due to the non-linear structure of effective travel time, defined in Eqs. (15-17), the reliable shortest path cannot be determined by classical shortest path algorithm (e.g., Dijkstra's algorithm) (Li et al., 2015; Huang and Zhan, 2007). Reliable shortest path algorithms, such as the multicriteria label-setting algorithm (Chen et al., 2013b), can be utilized to efficiently determine the reliable shortest path in road networks with travel time uncertainty.

Using the reliable shortest path algorithm, a solution algorithm is presented in this study to construct $\mathrm{RSTR}(\mathrm{f_i},\alpha)$ of a facility f_i with its opening hour time slot from t_p to t_q. The constructed $\mathrm{RSTR}(\mathrm{f_i},\alpha)$ delimits space-time service regions in which customers can visit the facility and guarantee α probability of successfully completing activities at the facility. The detailed steps of the algorithm are described below.

Step 1: A backward reliable shortest path tree is constructed. The reliable shortest path tree centered at facility f_i is to determine effective travel times from each node j to the facility (i.e. $\Phi^{-1}_{T^{jf}}(\alpha)$). To complete this task, the RBC-LS procedure (see appendix in Chen et al., 2013a) modified from the multicriteria label-setting algorithm (Chen et al., 2013b) is adopted.

Step 2: The $\mathrm{RSA}(\mathrm{f_i},\alpha)$ is generated. For each link l_{jk}, activity durations of tail node j and head node k are respectively determined by $C^j_{f_i}(\alpha) = Min\left(t_q, t_s\right) - Max\left(t_p, t_r + \Phi^{-1}_{T^{jf}}(\alpha)\right)$ and $C^k_{f_i}(\alpha) = Min\left(t_q, t_s\right) - Max\left(t_p, t_r + \Phi^{-1}_{T^{kf}}(\alpha)\right)$. If both $C^j_{f_i}(\alpha) \ge c^{\min}_{f_i}$ and $C^k_{f_i}(\alpha) \ge c^{\min}_{f_i}$ hold, then add link l_{jk} into $\mathrm{RSA}(\mathrm{f_i},\alpha)$.

Step 3: The $\mathrm{RSTR}(\mathrm{f_i}, \alpha)$ is constructed. For each link $l_{jk} \in RSA(f_i, \alpha)$, the latest departure times from tail node j and head node k are respectively determined by $t_j^+ = Min\left(t_q, t_s\right) - c_{f_i}^{\min} - \Phi_{T^{jf}}^{-1}(\alpha)$ and $t_k^+ = Min\left(t_q, t_s\right) - c_{f_i}^{\min} - \Phi_{T^{kf}}^{-1}(\alpha)$. Then, a 3D space-time polygon along link l_{jk} is created as $\left\{\left(x_j, y_j, t_r\right), \left(x_j, y_j, t_j^+\right), \left(x_k, y_k, t_k^+\right), \left(x_k, y_k, t_r\right)\right\}$, where $\left(x_j, y_j\right)$ and $\left(x_k, y_k\right)$ are the geographical coordinates of tail node j and head node k respectively. If link l_{jk} has other intermediate vertexes, their 3D coordinates in $\mathrm{RSTR}(\mathrm{f_i}, \alpha)$ can be interpolated from those of the tail and head nodes based on their length proportions.

Appendix 2. Reliable gravity model calibration

This appendix describes the method for calibrating λ and β parameters in Eq. (13) used for case study in Section 4.3. Following the work of Yue et al. (2012), customer shopping location choices to seven commercial centers (see Figure 8) were extracted from the collected FCD (see Section 4.1). Firstly, a buffer zone r_{f_i} based on the anchor store (i.e., a shopping mall) was constructed for each commercial center f_i. A 500 meters buffer radius was adopted to generate the buffer zone. Secondly, customer shopping demands q_{xf_i} to the commercial center f_i were obtained by selecting taxi trips, whose drop-off points located within the generated buffer zone r_{f_i}. The origins of customer shopping demands q_{xf_i} are identified according to pick-up points of the selected taxi trips. Finally, the observable probability (denoted by ω_{xf_i}) of customers at location x shopping at commercial center f_i can be obtained by

$$\omega_{xf_i} = \frac{q_{xf_i}}{\sum_{i=1}^{7} q_{xf_i}} \tag{18}$$

The Huff model was also used to compute the theoretical probability of customer's shopping center choices. The Huff Model has been recognized as one of the most widely accepted market forecasting models in economic geography (Huff 1963). It estimates people's choice on a service site considering the attraction of the service site and the distance decay effects on interactions between customers and services. In this study, the effective travel time (i.e., $\Phi_{T^{xf_i}}^{-1}(\alpha)$) was adopted to model the distance decay effects in stochastic networks under travel time uncertainty. Accordingly, the theoretical probability of customer shopping location choice (denoted by $\hat{\omega}_{xf_i}$) can be expressed as

$$\hat{\omega}_{xf_i} = \frac{(W_{f_i})^{\lambda} \exp(-\beta \Phi^{-1}_{T^{xf_i}}(\alpha))}{\sum_{\forall f_i} (W_{f_i})^{\lambda} \exp(-\beta \Phi^{-1}_{T^{xf_i}}(\alpha))} \tag{19}$$

The λ and β parameters can be calibrated by minimizing the square error between observable and theoretical probabilities of customer's shopping center choices as

$$\min \sum_{\forall x, \forall f_i} (\hat{\omega}_{xf_i} - \omega_{xf_i})^2 \tag{20}$$

	λ	β
Kwan (1998)	1	0.12
Kwan (1998)	1	0.15
Kwan (1998)	1	0.22
Kwan (1998)	1	0.45
Miller (1998)	0.5	0.9
Neutens et al. (2010)	1	0.1
Yue et al. (2012)	0.360	0.313

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