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Measuring temporal variation of location-based accessibility using space-time utility perspective

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ABSTRACT

Conventional location-based accessibility measures are static and cannot represent accessibility fluctuations at different times of day. To fill this gap, this study proposes location-based space-time accessibility measures to capture the temporal variation of location-based accessibility. Using the space-time utility perspective, the accessibility of a location is conceptualized as the space-time utility offered by a set of facilities accessible from the location. Individuals' facility choice behaviors among multiple alternatives are explicitly considered. A time-dependent facility attractiveness function is introduced to represent the temporal variation of individuals' needs to perform activities at a certain facility. The introduced function is formulated as two components: a time-invariant component representing individual satisfactions derived from activity participation at the facility, and a time-varying component expressing individuals' dynamic intensities to perform a certain type of activities at different times of day. To demonstrate the applicability of these proposed measures, a comprehensive case study has been carried out in Wuhan, China. The results of the case study show that the proposed measures can well capture the temporal variation of accessibility, due to the dynamics both of traffic conditions and of individuals' intensities in performing activities at different times of day. The proposed measures require moderate level of data, in terms of rich facility information; and most of these data could be extracted from social media applications.

1. Introduction

Accessibility is a core concept in transport geography, urban planning, and other related fields. It is defined as the ease with which activity locations or facilities can be reached from a particular location (or by individuals at that location) using a particular transport system (Kwan and Weber, 2008). Accessibility to various facilities (e.g., food, healthcare, park, and shopping facilities) has been intensively studied in the literature, not only for policy evaluation purposes (Páez et al., 2012; Shaw et al., 2014), but also for being an explanatory factor in many geographic phenomena analyses (e.g., social equity and justice) (Neutens et al., 2010; Lucas, 2011; van Wee and Geurs, 2011; Neutens, 2015; Giuffrida et al., 2017; Higgs et al., 2017).

The evaluation of accessibility to urban services depends on accessibility measures. In the literature, various measures have been developed and can be broadly classified into two categories: location-based (or place-based) and individual-based (or people-based) measures (Geurs and van Wee, 2004). Conventional location-based measures conceptualize accessibility largely in terms of the proximity to urban services from an individual's residential location or workplace. Common examples of location-based measures include travel distance to the nearest service location, the cumulative number of services within a specified cut-off distance, and gravity-type measures in which the attractiveness of services decreases with distance from the origin (Neutens et al., 2010). These location-based measures require small amounts of aggregated data and have been widely applied to many applications in large-scale study areas. However, a major inadequacy of such conventional location-based measures is that they are static and fail to account for the fact that accessibility levels may fluctuate at different times of day, because of the dynamic nature of human activity-travel behaviors and traffic conditions (Miller, 2007; Neutens et al., 2012a; Kwan, 2013).

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The importance of including the critical time dimension in accessibility studies has been well acknowledged in the literature by developing individual-based measures (Kwan and Weber, 2003; Miller, 2007; van Wee, 2016). Most individual-based measures are built upon the time-geographic framework (Hägerstrand, 1970), which captures the complexities of individual activity-travel behaviors under various space-time constraints. The number of reachable urban services and the cumulative activity durations at reachable urban services are two well-known individual-based measures (Kwan, 1998). A theoretically better measure is the space-time utility approach, which directly measures the individual space-time utilities of activity participation (Miller, 1999). All these individual-based measures are well suited to evaluate the accessibility of people in different social groups at different times of day (Kwan and Weber, 2008). However, such individual-based measures are difficult to generalize to large study areas (Páez et al., 2010; Horner and Downs, 2014), because it is generally very expensive to acquire a large number of samples of individual-level activity diary data in large study areas.

With the recent development of information and communication technologies (ICTs), it has become technically and economically feasible to collect and assemble huge amounts of spatiotemporal data, such as taxi trajectories, mobile phone tracking data, and social media data (Liu et al., 2015; Miller and Goodchild, 2015; de Bruijn et al., 2018; Yuan et al., 2018). These spatiotemporal Big Data enable data-driven approaches to extract information about human activity and travel behaviors and dynamic traffic conditions, thereby providing new data sources to improve conventional location-based accessibility studies (Järv et al., 2018). In the literature, considerable progress has recently been made in location-based accessibility studies by explicitly considering dynamic traffic conditions (Li et al., 2011; Tenkanen et al., 2016; Chen et al., 2017; Benenson et al., 2017; Widener et al., 2017; Yang et al., 2017; Kujala et al., 2018; Zhang et al., 2018; Moya-Gómez et al., 2018). In addition, increasing attention has been paid in the literature to improving conventional location-based accessibility measures by incorporating human mobility patterns. Páez et al. (2010) improved the conventional cumulative-opportunity measure by using distinct travel distances for people in different social groups and geographical regions. Widener et al. (2015) and Fransen et al. (2015) extended conventional location-based measures by using interaction potential metrics (Farber et al., 2013) and considering inter-zonal commuting patterns. Chen et al. (2018) improved location-based accessibility measures by using individual mobility patterns extracted from mobile phone tracking data. Järv et al. (2018) proposed a generic framework for integrating the time dimension in location-based accessibility measures, and illustrated its application in a food accessibility study by considering facilities' opening hours and temporal variation of population distributions and traffic conditions.

Along the line of data-driven geographical research (Miller and Goodchild, 2015), this study aims to incorporate the time dimension in location-based accessibility measures by explicitly considering individuals' dynamic intensities for performing activities at facilities using rich facility information. In recent years, rich facility information has become publicly available through many social media (and location-based service) applications, e.g., Foursquare, Twitter, and Google Map. For example, the Foursquare application enables users to post their location in a "check-in" to record, track, and share their life moments with friends. In the application, a user's geographical location is matched to nearby facilities such as restaurants, shopping malls, cinemas, and coffee shops. After checking into a facility, users can share their activity participation experiences through advice, photographs, and ratings of service quality. Beyond the facilities stored in the application, users are encouraged to check into new facilities, for which they earn additional rewards. These user-generated social media data provide an effective means for researchers to collect and update rich information about dynamically changing urban facilities. Such rich facility information could be a useful data source for accessibility studies because it records not only the detailed characteristics of urban facilities (e.g., facility location, type, opening hours and price), but also customers' behaviors (or experiences) in choosing and using urban facilities. However, little attention has been paid in the literature to using such rich facility information for accessibility studies.

By using rich facility information, this study proposes new location-based space-time accessibility measures to evaluate the temporal variation of location-based accessibility in large-scale study areas. The proposed accessibility measures reconciles conventional location-based accessibility measures with the space-time utility perspective (Miller, 1999; Delafontaine et al., 2012). In this study, the accessibility of a location is conceptualized as the space-time utility offered by a set of facilities that are accessible from the location. Individuals' facility choice behaviors among multiple alternatives are explicitly considered. A time-dependent facility attractiveness function is introduced to represent the temporal variation of individuals' needs to perform activities at a certain facility. The introduced function is further formulated as two components: an activity satisfaction component, and an activity intensity component. The former represents the degree of satisfaction that individuals derive from performing activities at a facility. It is time-invariant, depending on the facility's qualities. The latter represents individual intensities when participating in a particular type of activity at different times of day. It is time-varying, related to activity type and individual needs to perform this type of activity during a certain time period. Such a formulation of space-time utility reflects the observation that individuals' activity utility is related to the satisfaction of performing the activity itself and to the intensity with which the activity is performed (Axhausen and Gärling, 1992; Lam and Yin, 2001). Therefore, the proposed measures enable realistic evaluation of temporal variation of location-based accessibility at different times of day. More importantly, the proposed measures only required a moderate level of data with respect to rich facility information, and most of these data could be extracted from social media data.

2. Conventional location-based accessibility measures

This section briefly introduces conventional location-based accessibility measures to provide necessary background. Most location-based accessibility measures in the literature can be defined generically as the sum of products of an attractiveness and a distance decay function (Kwan, 1998; Páez et al., 2010):

$$A(i) = \sum_{f} (W_f)^{\alpha} K(c_{if}) \tag{1}$$

where $A(i)$ is the accessibility of individuals living at location i; W_f is the individual perception of the attractiveness of facility f; α is the sensitivity parameter with respect to facility attractiveness; and $K(\cdot)$ is a distance decay function that depends on the time (or distance) c_{if} required to travel from location i to facility f. Depending on how $K(\cdot)$ is defined, different accessibility measures can be obtained. Using a negative exponential (or power) function leads to the gravity measure (Hansen, 1959):

$$A(i) = \sum_{f} (W_f)^{\alpha} \exp(-\beta_i c_{if}) \tag{2}$$

where $\beta_i \geq 0$ is the sensitivity parameter with respect to travel time c_{if}. The larger the value of β_i, the stronger will be the distance decay effect on $A(i)$. By using a binary cutoff function $R_i(f)$, a measure of cumulative opportunities (Breheny, 1978) can be defined as follows:

$$A(i) = \sum_{f} (W_f)^{\alpha} R_i(f)$$
$$R_i(f) = \begin{cases} 1, & \text{if } c_{if} \leq \gamma_i \\ 0, & \textit{otherwise} \end{cases} \tag{3}$$

where $R_i(f) = 1$ if travel time c_{if} is less than or equal to threshold γ_i and $R_i(f) = 0$ otherwise. Smaller values of γ_i can be interpreted as lower mobility for people living in location i (i.e., a stronger distance decay

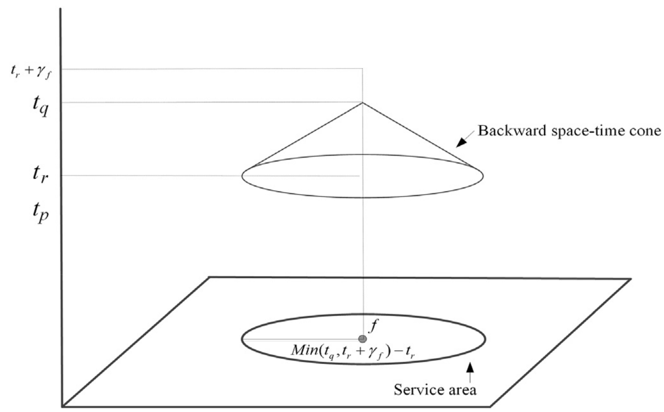

Fig. 1. Service area concept of a facility.

effect). Spatially varying values of γ_i or β_i could be used for people living in different locations (Páez et al., 2010).

These conventional location-based accessibility measures are easy to implement and require only a small amount of data. However, they are static and are often criticized for their neglect of dynamics in human behavior and traffic conditions (Kwan and Weber, 2003; Miller, 2007).

3. Proposed location-based space-time accessibility measures

This section presents the proposed location-based space-time accessibility measures to evaluate the temporal variation of location-based accessibility. Unlike conventional location-based measures, the proposed measures centered at facilities rather than individuals' residential locations. The service area of facility f delimits all possible space-time locations from which individuals can travel to the facility within the given travel-time threshold γ_f. Fig. 1 illustrates this service area concept in three-dimensional (3D) space, where the z-axis represents time and the x- and y-axes represent two-dimensional (2D) geographic space. Given a facility f, a time instant t_r, and a travel-time threshold γ_f, the facility's service area, denoted by $SA(f, t_r, \gamma_f)$, can be expressed as following a backward space-time cone (Miller, 2005) in the time geographic literature:

$$SA(f, t_r, \gamma_f) = \{(i, t) \mid Min(t_q, t_r + \gamma_f) - Max(t_p, t_r + c_{if}(t_r)) \geq 0; t_r \leq t \leq t_r + \gamma_f\} \quad (4)$$

where t_p and t_q are the facility's opening and closing times respectively and $c_{if}(t_r)$ is the time-varying travel time required to reach the facility from location i. A location i within the facility's service area, $SA(f, t_r, \gamma_f)$, can be determined by the binary function, $R_f(i)$, as.

$$R_f(i) = \begin{cases} 1, & \text{if } i \in SA(f, t_r, \gamma_f) \\ 0, & otherwise \end{cases} \quad (5)$$

Thus, this service area model can consider the facility's open hour constraint and the dynamics of traffic conditions at different time instants (i.e., the sizes of the service area can vary by different times of day).

Following the space-time utility accessibility approach (Miller, 1999), the utility of individuals living in residential location $i \in SA(f, t_r, \gamma_f)$ and performing activities at facility f is denoted by $U_f(i)$ and formulated generically as:

$$U_f(i) = (W_f(t_r))^{\alpha} K(c_{if}(t_r)) \quad (6)$$

where $K(\bullet)$ is the generic distance decay function and $W_f(t_r)$ is the time-dependent attractiveness of the facility. Using $R_f(i)$ as the distance decay function, $U_f(i)$ can be defined as:

$$U_f(i) = (W_f(t_r))^{\alpha} R_f(i) \quad (7)$$

Similarly, using the negative exponential function, $U_f(i)$ becomes:

$$U_f(i) = (W_f(t_r))^{\alpha} \exp(-\beta_f c_{if}(t_r)) \quad (8)$$

where β_f is the distance decay parameter of facility f. Given β_f, the travel-time-threshold γ_f for generating $SA(f, t_r, \gamma_f)$ can be simply determined as:

$$\gamma_f = -\lg(\varepsilon)/\beta_f \quad (9)$$

where $\varepsilon \approx 0$ is a small tolerance (e.g., $\varepsilon \approx 0.001$).

To represent the temporal variation of activity utility at different times of day, the time-dependent attractiveness, $W_f(t_r)$, is formulated in this study as follows:

$$W_f(t_r) = s_f g_f(t_r) \quad (10)$$

where s_f is a static "activity satisfaction" parameter representing the degree of individual satisfaction gained from performing activities at the facility and $g_f(t_r)$ is a time-varying "activity intensity" function representing the intensity of an individual's participation in activities at a certain time instant t_r. This formulation of attractiveness reflects the observation that the activity utility is related to the satisfaction of performing the activity itself and the intensity with which the activity is performed (Axhausen and Gärling, 1992; Lam and Yin, 2001). The activity satisfaction function is time-invariant and depends on an ensemble of facility qualities. In practice, this parameter can be directly estimated from user rating information provided by social media applications.

The intensity of an individual performing an activity is related to the activity type and to individual physiological and/or psychological needs of performing this type of activities (Lam and Yin, 2001; Liao et al., 2013). In most cases, these physiological and/or psychological needs depend on the time of day in the context of daily activity-travel scheduling, and hence activity intensity is represented in this study as a time-dependent function. Note that the intensities of participation in activities at facility f may be different from one individual to another. The $g_f(t_r)$ function represents the average intensities of all individuals performing activities at the facility and can be estimated from the number of customers at the facility throughout the day (i.e., the temporal profile of the number of customers). Fig. 2 illustrates an activity intensity function for a typical McDonald's restaurant. In the figure, the number of customers is normalized into a range from zero to one. The zero value of $g_f(t_r)$ indicates that no people would participate in activities at the facility at time instant t_r (e.g., a time instant outside the opening hours of the facility). Within the opening hours, the $g_f(t_r)$ value can vary at different times of day.

Three location-based space-time accessibility measures are then developed to evaluate the accessibility of individuals living at location i. A location i may be covered by the service areas of several facilities of the same type. Note that various sizes of service area can be used for facilities with different qualities. These accessible facilities constitute the facility choice set for an individual's activity participation, denoted

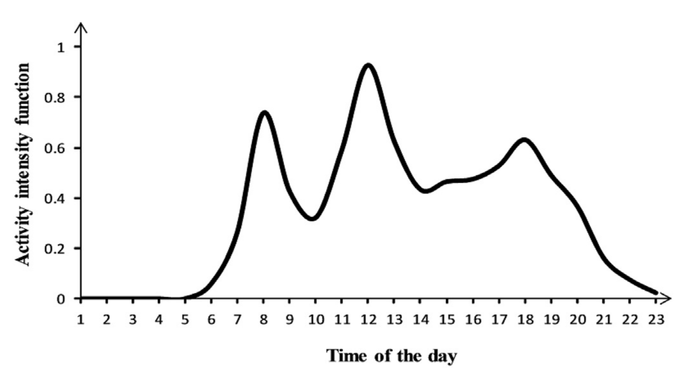

Fig. 2. Illustrative example of a time-dependent activity intensity function.

by $F_i = \{f_1, \cdots, f_n\}$. The first proposed measure, denoted by $CWA(i)$, expresses the consumer welfare aggregation (CWA) principle used in conventional location-based accessibility measures. It is the sum of the activity utilities provided by all facilities in the choice set F_i:

$$A(i) = CWA(i) = \sum_{\forall f \in F_i} U_f(i) \tag{11}$$

where $U_f(i)$ is the utility derived from activity participation at facility $f \in F_i$ as defined in Eq. (6). This accessibility measure represents all possible activity utilities (amounts of welfare) enjoyed by an individual at location i.

In addition to the CWA principle, the consumer welfare maximization (CWM) principle and the random utility maximization (RUM) principle, which are used in the space-time utility accessibility approach (Miller, 1999), are adopted. The second proposed measure, denoted by $CWM(i)$, follows the CWM principle. Assuming that the individual is a rational utility maximizer, he/she chooses only one facility $f \in F_i$ which provides the maximum activity utility for performing an activity. Accordingly, the accessibility of individuals at location i is measured as the maximum utility provided by a particular facility $f \in F_i$:

$$A(i) = CWM(i) = \max_{\{f \in F_i\}} (U_f(i)) \tag{12}$$

The third proposed measure, denoted by $RUM(i)$, adopts the RUM principle. Unlike the CWM principle, the RUM principle builds on random utility theory, adding an unobservable random error component to the activity utility measure, i.e., Eq. (6). The error components of all facilities $\forall f \in F_i$ are assumed to follow independently and identically distributed Gumbel distributions. Accordingly, the mechanism of choosing a facility to maximize activity utilities can be formulated as a logit discrete-choice model. Accessibility based on the RUM principle can therefore be expressed as the following logsum accessibility measure (van Wee, 2016):

$$A(i) = RUM(i) = \frac{1}{\lambda} \ln\left\{ \sum_{\forall f \in F_i} \exp(U_f(i)) \right\} \tag{13}$$

Unlike $CWM(i)$, this measure is a summary indicator representing the expected maximum utility of the full facility choice set.

By using facility-specific parameters ($\beta_f$or γ_f), these three proposed accessibility measures can capture distinct distance decay effects for facilities with different qualities. Fig. 3 gives a simple illustrative example. Suppose that f_1 is a famous restaurant and perceived by most citizens, whereas f_2 is a local fast-food shop and perceived only by local residents. As shown in Fig. 3, using conventional location-based measures, both facilities, f_1 and f_2, within travel-time threshold γ_i are identified as accessible facilities for people living at location i. This implies that both facilities have an identical service area of γ_i. In reality, the service area of f_1 can be much larger than that of f_2. People may drive 20 min to f_1, but may not be willing to drive 10 min to f_2. Using the proposed measures, facility-specific parameters, γ_{f_1} and γ_{f_2}, can be used to capture different distance decay effects for these two facilities.

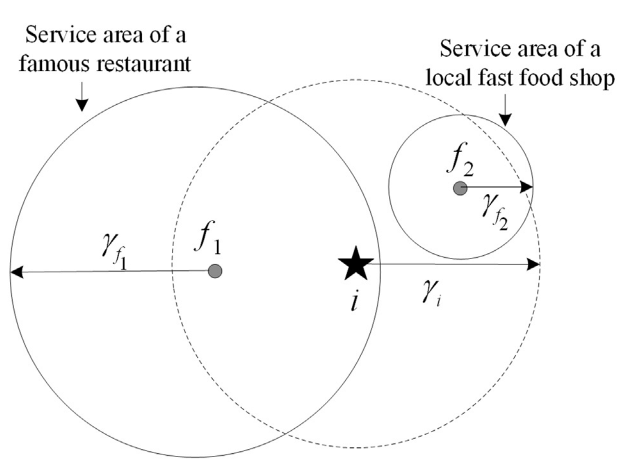

Fig. 3. Illustrative example of various distance decay effects for facilities at different levels.

Therefore, the proposed measures generalize conventional location-based accessibility measures in several aspects. First, the proposed measures can well represent the temporal variation of location-based accessibility at different times of day using the introduced time-dependent attractiveness function, $W_f(t_r)$. The facility's opening hour constraints and the dynamics of traffic conditions are also explicitly considered in the service-area model, $SA(f, t_r, \gamma_f)$. Second, the proposed measures can well capture various distance decay effects for facilities of different qualities using facility-specific parameters, γ_f or β_f. Finally, the proposed measures can explicitly consider individuals' facility choice behaviors among multiple alternatives using the CWA, CWM, and RUM principles. Conventional location-based accessibility measures can be regarded as special cases of $CWA(i)$, using a static attractiveness and assigning the same distance decay parameter (γ_f or β_f) to all facilities. Nevertheless, compared to conventional location-based accessibility measures, the proposed measures require extra rich facility information data, including facility type, opening hours, user rating (i.e., activity satisfaction parameter) and the temporal profiles of the number of customers (i.e., activity intensity function).

4. Study area and methods

4.1. Study area

This section presents a case study in a mega-city (Wuhan, China) to demonstrate the applicability of the proposed accessibility measures. As shown in Fig. 4, Wuhan is located in central China and lies in the middle reaches of the Yangtze River at the intersection of the Yangtze and Han Rivers. It consists of thirteen administrative districts, including seven districts in core urban areas and six districts in suburban and rural areas. The city is the economic, educational, and transportation center of central China, covering approximately 8594 km^2 with a population of 10.6 million. Wuhan is the world's largest “college town”, with a total of 1.2 million university-level students across 85 institutions of higher learning. In recent years, Wuhan has been considered as one of the fastest-growing cities in China and the world. Its gross domestic product (GDP) exceeded 210 billion USD in 2017 and is growing at an annual rate of 8.0%. The unique economic and demographic status of Wuhan makes it an interesting area for accessibility studies.

4.2. Data collection

Two datasets were collected, including a taxi-tracking dataset and a rich facility information dataset. The taxi-tracking dataset was collected to estimate hourly traffic conditions in the Wuhan road network, which consists of 19,306 nodes and 46,757 links. The taxi-tracking dataset was collected on a typical Thursday (September 3, 2009), including 11,248 taxis' trajectories. The method for estimating hourly mean travel times using this taxi-tracking dataset has been documented in Chen et al. (2017). Fig. 5(a) illustrates the estimated traffic conditions of the road network during a morning peak period (7:00–8:00). Links shown in red represent congested links (speed < 20 km/h); orange represents slightly congested links (speed 20–40 km/h); and yellow represents uncongested links (speed > 40 km/h). As illustrated, 18.24% of the links in the Wuhan network were congested in the morning peak hour. Fig. 5(b) shows the temporal variations of average travel speed on all network links. Traffic conditions became more congested during the morning (7:00–9:00) and evening (17:00–18:00) peak periods.

The rich facility information dataset was collected from *Baidu Map*, which is one of the largest open platforms of location-based services in China. Similarly to many social media applications, *Baidu Map* allows

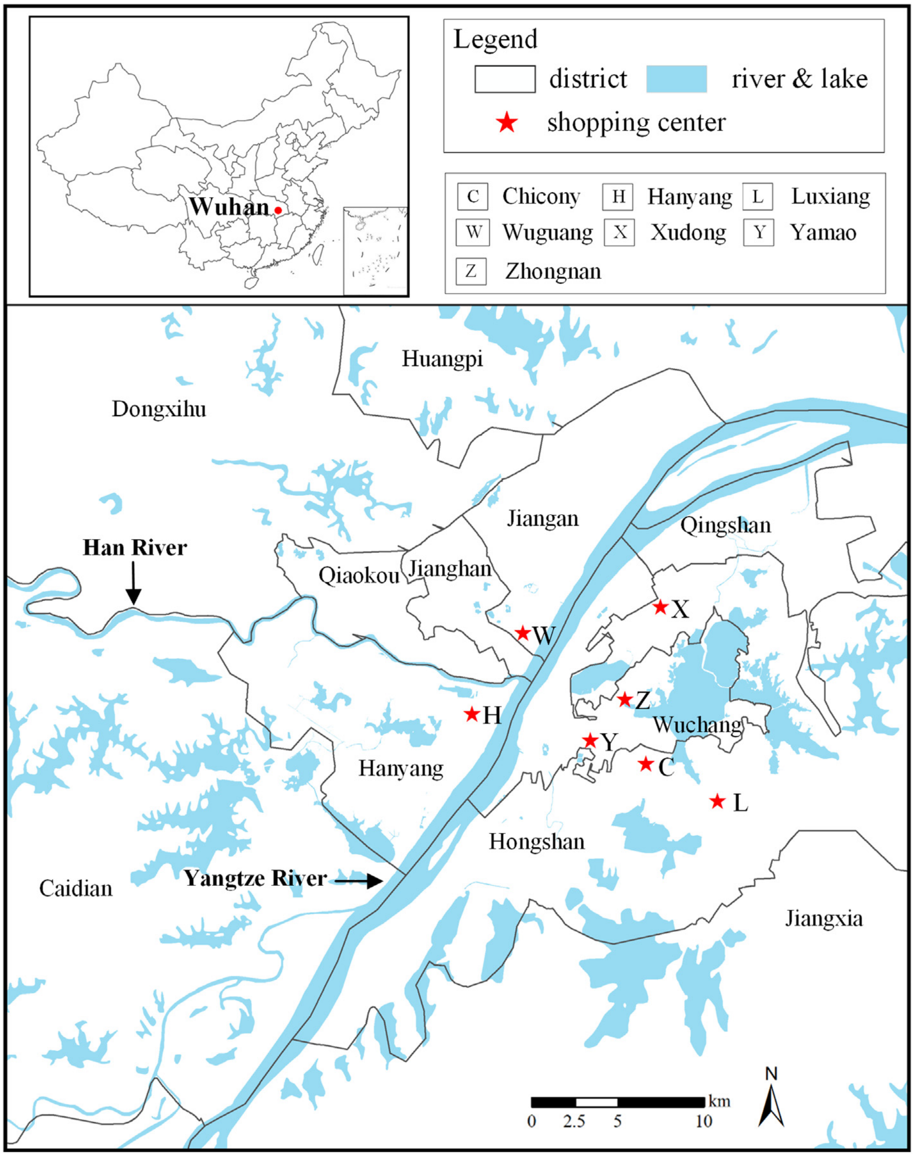

Fig. 4. Study area in Wuhan, China.

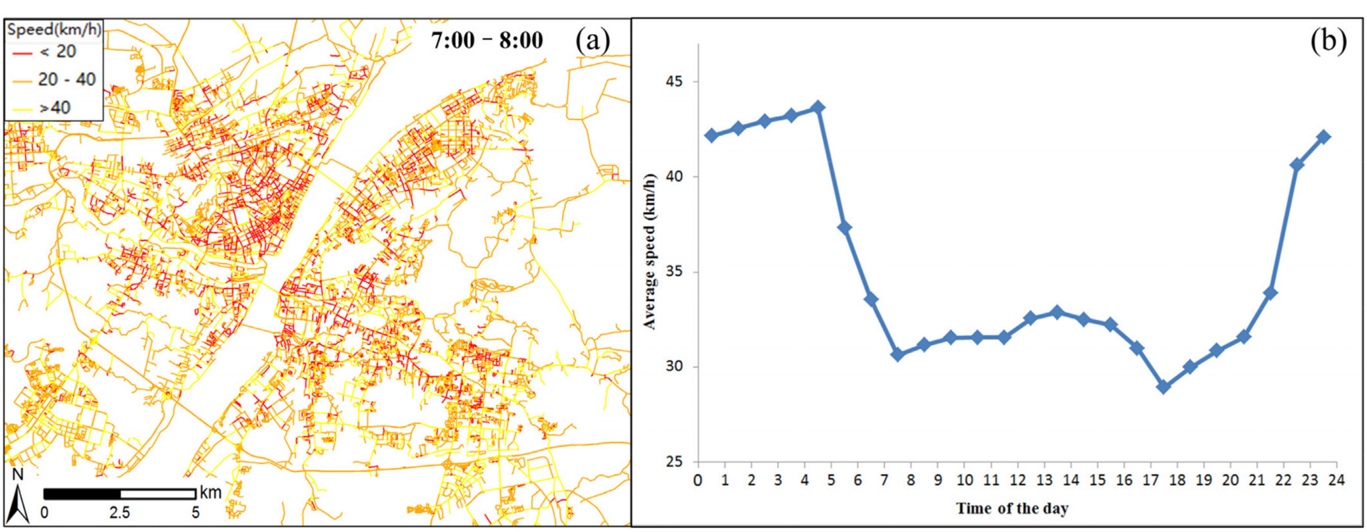

Fig. 5. Estimated traffic conditions in the Wuhan network: (a) a morning peak hour; (b) temporal variation of average travel speed.

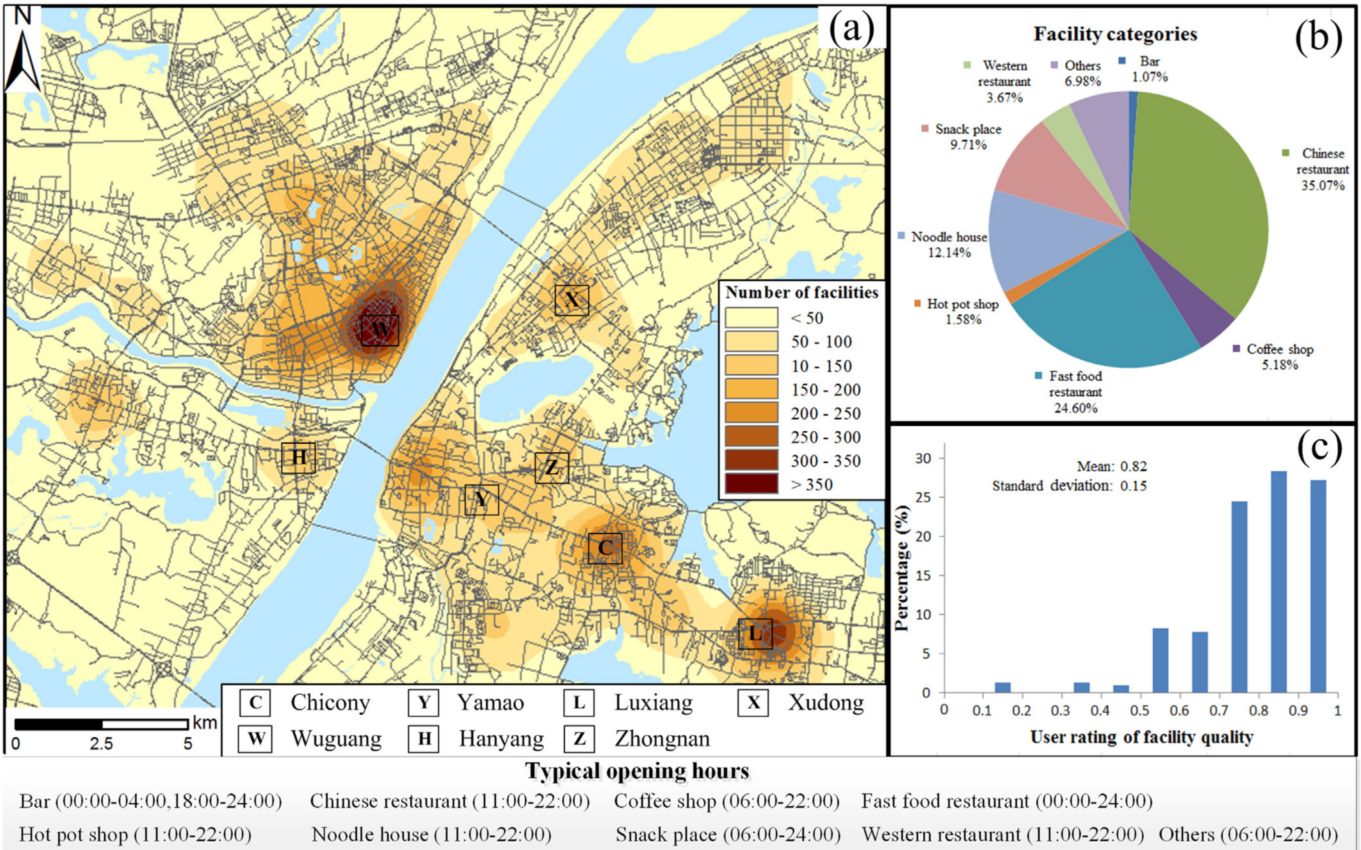

Fig. 6. Food service facilities in Wuhan City: (a) facility spatial distribution; (b) facility type distribution; (c) user rating distribution.

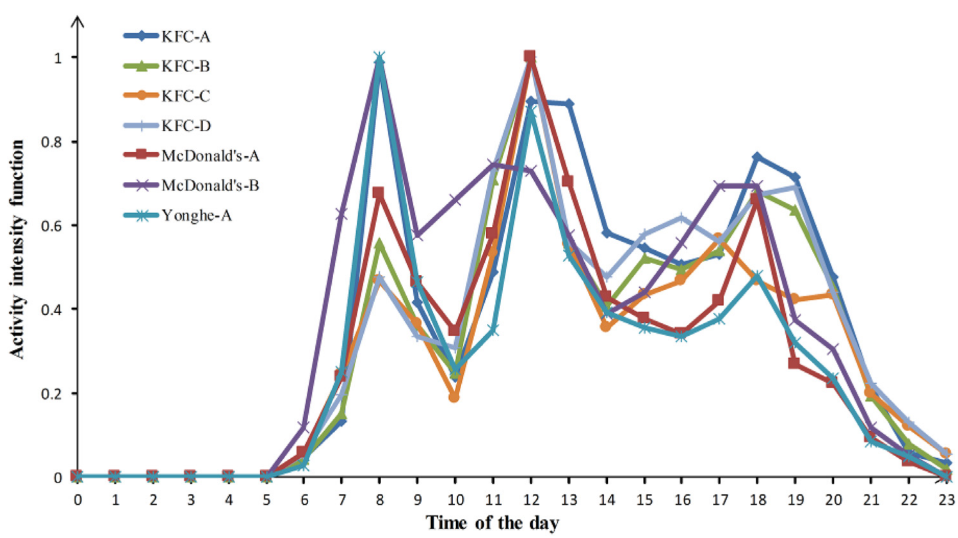

Fig. 7. Activity intensity functions for seven fast-food restaurants.

registered users to post their location at a "check-in" to share their experiences of using various facilities, such as restaurants, shopping malls, cinemas, coffee shops, etc. Based on application programming interfaces (APIs) provided by *Baidu Map* (http://lbsyun.baidu.com/index.php?title=jspopular), a toolkit was developed to extract rich facility information about food services in Wuhan City during September 2017. Each collected facility had several attributes, including its name, latitude and longitude, type, opening hours, total number of check-in records, user rating of service level, and price. Among these attributes, the *type* attribute gives the detailed type of food service facilities among 40 types. By merging similar types (e.g., Chinese restaurants serving Sichuan and Guangdong cuisines), the 27,256 facilities collected were grouped into nine types, as shown in Fig. 6(b). Chinese restaurants are dominant in Wuhan City, accounting for 35.1% of overall food service facilities. Following those are fast-food restaurants (24.1%) and noodle houses (12.1%). Fig. 6(a) shows the spatial distribution of the facilities collected in Wuhan. As shown, food service facilities are not evenly distributed in Wuhan City, but rather are clustered at seven shopping centers. The bottom of Fig. 6 gives the opening hours for most facilities in each category.

The user ratings of service level attribute were used in this case study to measure individual activity satisfaction directly, i.e., s_f in Eq. (10). Fig. 6(c) illustrates the 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. A larger s_f value indicates a higher degree of individual satisfaction with the service offered by the facility. The average s_f value was 0.82, but the values varied significantly among facilities. More than half the collected facilities (55.73%) in Wuhan City were satisfactory ($s_f \geq 0.8$); of these, 27.29% were very satisfactory ($s_f \geq 0.9$). The percentage of unsatisfactory facilities ($s_f < 0.6$) was low, accounting for 11.93% of the total. The "ordinary facility" category ($0.6 \leq s_f < 0.8$) accounted for 32.34%.

To generate the activity intensity function, i.e., $g_f(t_r)$ in Eq. (10), a survey was carried out to perform a manual count of customer numbers for nine collected facility types. Forty-seven representative facilities were randomly selected within the study area. Fig. 7 shows the resulting activity intensity functions for seven fast-food restaurants (two McDonald's restaurants, four KFC restaurants, and one Yonghe King restaurant). The figure shows that the activity intensity functions of all facilities of the same type tended to display a very similar pattern. This was due to the similar physiological needs of performing the same type of activities at different facilities. The activity intensity functions for the other eight types were also generated and are shown in Fig. 8. For these eight types of facilities, each activity intensity function was generated by the average of five representative facilities, which also had a very similar pattern of the activity intensity function. Therefore, we argue that it is reasonable to use a representative activity intensity function to approximate the activity intensity functions of all facilities in the same type.

In this case study, to capture distinct distance decay effects for facilities of different quality, facilities were classified into three levels: city, district, and local. Food service facilities classified at the city level were well-known and could be perceived by most citizens; facilities at the district level were relatively well-known and could be perceived by many people living in the same district; and other facilities at the local level could be perceived only by local residents. In this study, $R_f(i)$, as calculated in Eq. (5), was used as the distance decay function, and a larger value of the γ_f parameter (i.e., a larger service area) was assigned to facilities at a higher level. This classification of facilities was consistent with the behavioral perspective of accessibility (Cascetta et al., 2016) that an accessible facility should be perceived by individuals as a potential location to perform their activities.

According to a survey of eight experienced local residents, all collected facilities were classified, and facilities at the city, district, and local levels accounted for 1.54%, 45.04%, and 53.43% respectively of all facilities. City-level facilities were generally located at seven shopping centers in Wuhan City. Local-level facilities were typically snack places, noodle houses, and fast-food restaurants, whereas district-level facilities were large Chinese or Western restaurants with a relatively high rating and price. According to the survey, the threshold parameters (i.e., γ_f) were set to 30 min by car for city-level facilities, 15 min by car for district-level facilities, and 20 min on foot for local-level facilities. The walking speed was set as 5 km/h for the whole period of interest.

4.3. Data analysis

Based on the collected data, accessibility to food services in core urban areas of Wuhan City are evaluated using three proposed measures. To calculate the proposed measures, a GIS toolkit is developed. The detailed information of the developed GIS toolkit is given in the Appendix A.

In this case study, three steps are designed to demonstrate unique characteristics of the proposed measures. The first step is to examine the capabilities of proposed measures (using $CWA(i)$ for illustration) to capture temporal variation of location-based accessibility, due to both dynamic traffic conditions and time-varying activity intensity functions. To distinguish their distinctive effects, the $CWA(i)$ measure is also calculated for the scenario that the values of all activity intensity functions to be 1 (i.e., $g_f(t_r) = 1$) throughout the day. All accessibility measures are calculated for every hour of the day. The second step is to investigate facilities' various distance decay effects on accessibility spatial disparities using the $CWA(i)$ measure for illustration. For comparison, $CWA(i)$ accessibility values is also calculated for the scenario that classified all facilities in the study area into the district level. In another word, the same γ_f parameter (i.e., 15 min by car) is used for all facilities. The third step is to investigate the individuals' facility choice behavior effects on the evaluation of location-based accessibility. The spatial distributions of three proposed measures, i.e., $CWA(i)$, $CWM(i)$ and $RUM(i)$, are compared and analyzed.

Throughout the case study, $U_f(i)$ defined in Eq. (7) is used to calculate the space-time utility based on the distance decay function, $R_f(i)$. The sensitivity parameter for facility attractiveness (i.e., α) is set to 0.49, according to a previous study (Chen et al., 2017) that calibrated this parameter in Wuhan City. The whole study area is discretized into a set of grid cells with the size of 300 m × 300 m.

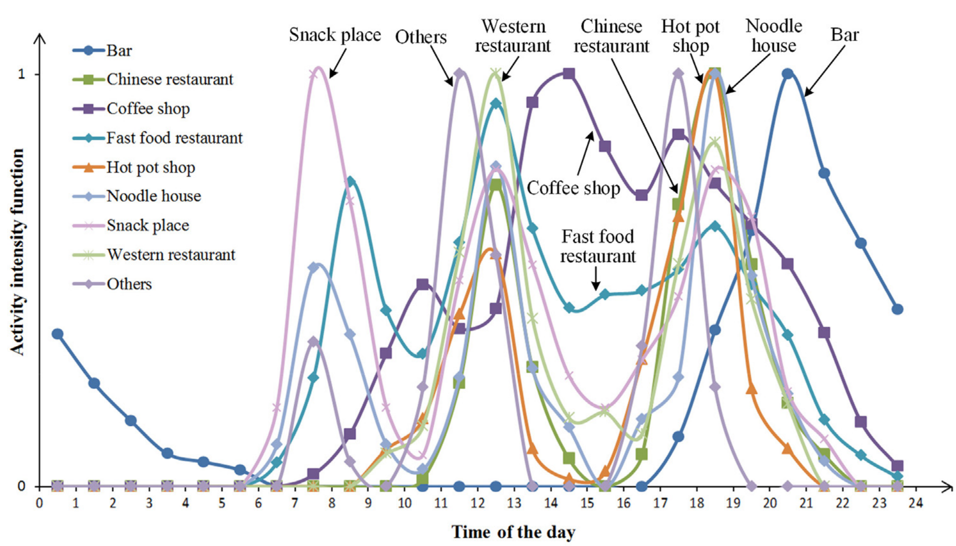

Fig. 8. Activity intensity functions for nine types of food service facilities.

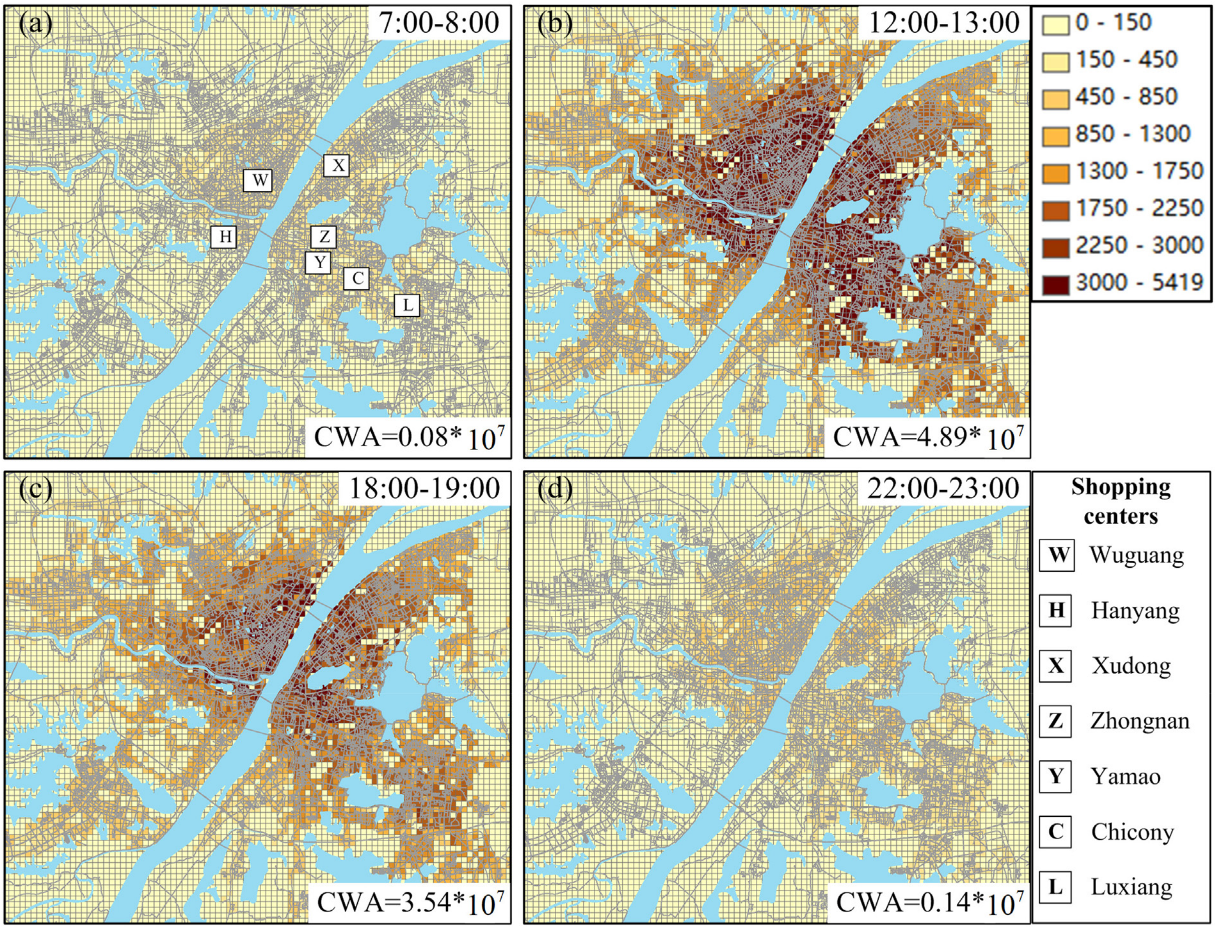

Fig. 9. Accessibility to food services at different times of day.

5. Results

5.1. Accessibility temporal variation

This section reports the results of case study. Fig. 9(b) shows the calculated spatial distribution of food service accessibility in terms of $CWA(i)$ as defined in Eq. (11) during lunch time (12:00–13:00). As shown, food service accessibility, in terms of $CWA(i)$, was not evenly distributed. Distinctive peaks were found near the seven shopping centers, especially Wugang and Xudong.

Fig. 10 shows the temporal variation of accessibility to food services in Wuhan City. The blue line in this figure shows the total $CWA(i)$ value for the whole city at different times of day, and reveals that accessibility varied significantly. The accessibility value reached its peak values during lunch time (12:00–13:00) and dinner time (18:00–19:00). This was due to the high values of the activity intensity function, $g_f(t_r)$, during these time periods (see Fig. 8). The spatial distributions of the accessibility value for the two periods are illustrated in Figs. 9(b) and 9(c), which show that the total $CWA(i)$ value during lunch time were 38.14% (i.e., (4.89–3.54) / 3.54) larger than during dinner time. This result was due to the better traffic conditions during lunch time than during dinner time in Wuhan City. Fig. 9(a) shows the accessibility value during the breakfast time period (7:00–8:00). Although traffic conditions in Wuhan City during breakfast time are as congested as at dinner time, individual intensities for having breakfast at food service facilities were not as high as those for having dinner at these facilities. In fact, the accessibility value during breakfast time was only 2.26% (0.08/3.54) of those during dinner time. Fig. 9(d) gives the accessibility value for the off-peak period from 22:00–23:00. During this period, traffic flows smoothly in Wuhan City. However, most restaurants (e.g., Chinese restaurants) are closed, with the exception of some fast food restaurants, coffee shops, and bars. In addition, individual intensities for eating at fast-food restaurants and coffee shops during this period are relatively low. All these factors contribute to low accessibility value during this off-peak period, accounting for only 2.86% of the value during lunch time. Therefore, the proposed accessibility measures can well capture the temporal variation of location-based accessibility, due to the dynamic traffic conditions and individuals' intensities of performing activities at different times of day.

The red line in Fig. 10 shows the temporal variation of accessibility (i.e., total $CWA(i)$ value) when $g_f(t_r) = 1$ was set throughout the day. In this case, the accessibility value fluctuated due to only dynamic traffic conditions and the opening hours of facilities. The accessibility value reach its peaks when traffic conditions become smooth during the periods of 13:00–14:00 and 21:00–22:00. However, this result of peak accessibility values, particularly during the period of 21:00–22:00, was not reasonable from the perspective of individuals' space-time utilities; because the intensities for individuals having dinners during that period are low. Conversely, by incorporating individuals' time-varying activity intensities (see the blue line), the periods with peak accessibility to food services were well shifted to the lunch (12:00–13:00) and dinner (18:00–19:00) time periods. Therefore, the introduced activity intensity function, $g_f(t_r)$, can enhance the ability to evaluate the temporal variation of accessibility at different times of day.

5.2. Facilities' various distance decay effects

Fig. 11 shows the spatial accessibility according to the $CWA(i)$ measure during dinner time (18:00–19:00) by classifying all facilities at the district level. In this setting, the $CWA(i)$ measure approaches the

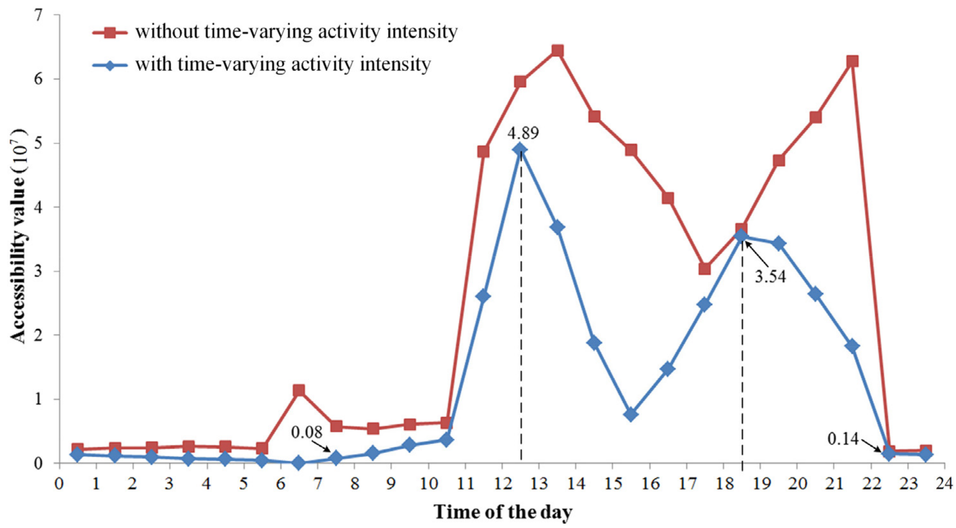

Fig. 10. Temporal variation of location-based accessibility.

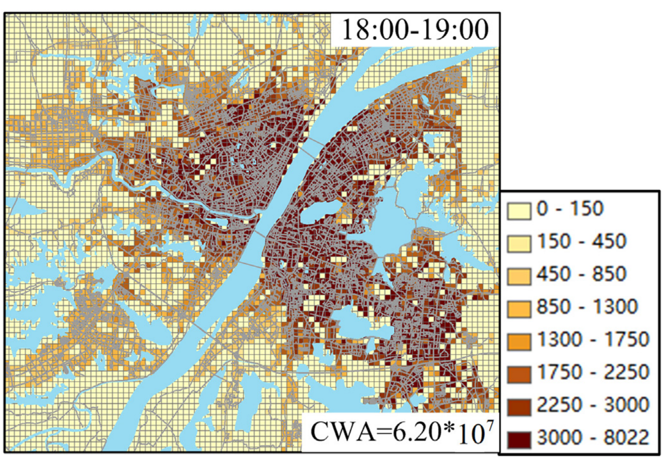

Fig. 11. Accessibility to food service using a single distance decay parameter.

conventional location-based accessibility measure (i.e., cumulative opportunities). The total *CWA*(*i*) value was significantly overestimated by 75.14% (i.e., 6.20/3.54–1) compared to that shown in Fig. 9(c). This result is reasonable because local-level facilities accounted for 53.43% of total facilities in Wuhan City, and their service areas were overestimated by classifying them at the district level. Therefore, using a single distance decay effect for facilities with different qualities can introduce considerable bias into the evaluation of location-based accessibility.

5.3. Individuals' facility choice behavior effects

Fig. 12 shows the accessibility spatial patterns of *RUM*(*i*) and *CWM*(*i*) measures during dinner time (18:00–19:00). It is apparent that the *RUM*(*i*) and *CWM*(*i*) measures had very different spatial patterns of food service accessibility than the *CWA*(*i*) measure shown in Fig. 9(c). The *CWA*(*i*) measure expresses the CWA (consumer welfare aggregation) principle used in conventional location-based accessibility measures, and the space-time utilities provided by all facilities within the choice set of location *i* were aggregated to form the location's accessibility. Because food service facilities were clustered in Wugang and Xudong, distinctive peaks were observed in these two areas (see Fig. 9(c)). Unlike *CWA*(*i*), the *RUM*(*i*) measure expresses the RUM (random utility maximization) principle. It accommodates the law of diminishing marginal utility from microeconomic theory, meaning that inclusion of the first facility in the choice set yields more utility than inclusion of the second and subsequent facilities, with a continuing reduction for more facilities. Accordingly, as shown in Fig. 12(a), distinctive peaks did not form at Wugang and Xudong, and the seven shopping centers had similar accessibility levels, which were still higher than those of other areas with fewer facilities. The *CWM*(*i*) measure expresses the CWM (consumer welfare maximization) principle, and only the facility providing the maximum utility was considered in evaluating the location's accessibility. Hence, the seven shopping centers as well as their closest neighboring areas had similar levels of accessibility in terms of the *CWM*(*i*) measure, as shown in Fig. 12(b). Therefore, how individuals' facility choice behaviors among multiple alternatives were modeled had a significant impact on accessibility evaluation. Compared to the *CWA*(*i*) measure, the *RUM*(*i*) and *CWM*(*i*) measures, using the CWM and RUM principles, could be useful alternatives to evaluate the accessibility of urban service delivery.

6. Discussion

The analysis presented above demonstrates the capabilities of the proposed location-based space-time accessibility measures to capture temporal variation in accessibility over the course of the day. Consistently with previous literature (Li et al., 2011; Neutens et al., 2012b; Tenkanen et al., 2016; Widener et al., 2017; Kujala et al., 2018; Järv et al., 2018), the analysis highlights the roles of dynamic traffic conditions and facilities' opening hours in evaluating accessibility at different times of day. More importantly, the analysis contributes to the existing literature by showing how individuals' time-varying intensities for performing activities at different types of facilities shape accessibility fluctuations over 24 h. It suggests that planners and policymakers should be aware of the time-varying accessibility (or utility) provided by various types of facilities at different times of day. For example, a location with clustered Chinese restaurants may have a high level of food service accessibility at dinner time, but a low accessibility at breakfast time. From this perspective, we argue that examining accessibility over a specific time period alone will yield only a partial understanding of dynamic spatial accessibility patterns over the course of the day, particularly for study areas with heterogeneous distributions of facilities of different types. Substantial improvements on facilities' service level could be achieved by adopting a dynamic allocation of resources (e.g., employees) in accordance with the individuals' time-varying intensities for performing activities at facilities.

The analysis underscores the significance of facilities' various distance decay effects for accessibility studies. It suggests that using a

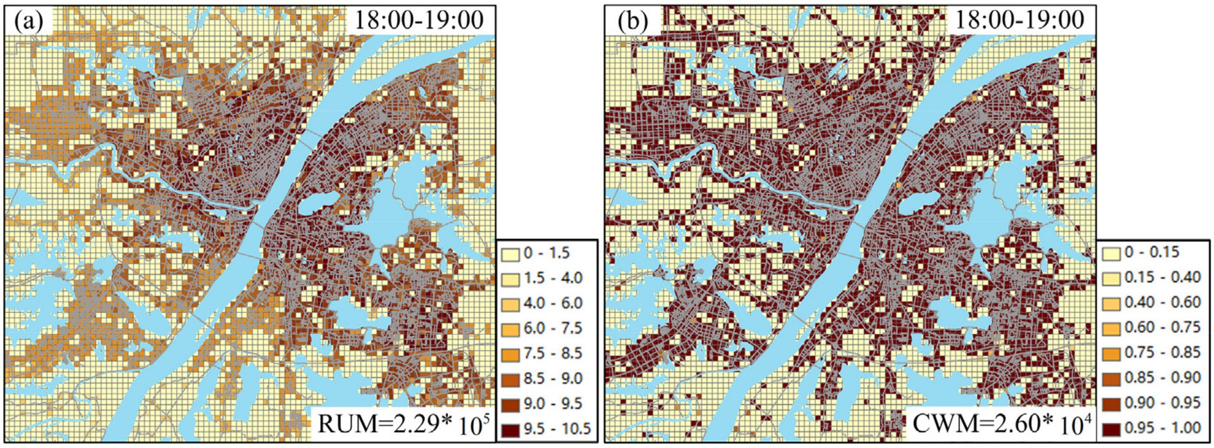

Fig. 12. Accessibility to food services using the *RUM*(*i*) and *CWM*(*i*) measures.

single service-area size for all facilities at different levels could introduce a considerable bias into evaluating spatial accessibility disparities. This result is consistent with previous accessibility studies performed using the floating catchment area approach (Luo and Whippo, 2012; McGrail and Humphreys, 2014; Dony et al., 2015; Bauer and Groneberg, 2016). The analysis also demonstrates how individuals' facility choice behaviors among multiple alternatives influence the spatial distribution of accessibility. It suggests that incorporating a space-time utility approach (Miller, 1999) provides a flexible framework for modeling individuals' facility choice behaviors to evaluate location-based accessibility. Other principles, i.e., RUM (random utility maximization) and CWM (consumer welfare maximization), can be useful alternatives to the conventional CWA (consumer welfare aggregation) principle commonly used in location-based measures. This result supports van Wee's assertion (2016) that individuals' facility choice behaviors, as an important option value, should be considered when evaluating location-based accessibility.

The case study results suggest that the proposed measures require a moderate level of data with respect to rich facility information, including facility locations, types, opening hours, user ratings, and temporal profiles of numbers of customers. Most of these data (i.e., locations, types, opening hours, and user ratings) can be extracted from social media applications, such as Baidu Map, Foursquare, Twitter, TripAdvisor, Yelp, and etc. The check-in records for a facility may be a potential data source from which to collect temporal profiles of numbers of customers. However, in the collected dataset, the frequency of user check-ins was not sufficient to obtain reasonable activity intensity functions. Field surveys were therefore carried out. Nevertheless, the case study showed that facilities of the same type tend to have very similar patterns of activity intensity functions, an observation that can be used to generate a representative activity intensity function for all facilities of the same type. Therefore, we suggest that conventional location-based accessibility can be greatly enriched by incorporating the critical time dimension and the individual behavioral preferences extracted from such rich facility information.

Several directions for future research are worth noting. First, the proposed accessibility measures did not consider the congestion effects on facilities. Further studies are required to extend the proposed measures to incorporate competitions from both demand and supply sides using floating catchment area approach (Neutens, 2015). Dynamics in customer demands at different times of day can also be incorporated using mobile phone big data (Chen et al., 2018; Järv et al., 2018). Second, the CWA, CWM, and RUM principles were used in this study to evaluate spatial accessibility to a single type of facilities (i.e., food services). The extension of the proposed measures to systematically evaluate accessibility to multiple types of urban services (e.g., job, healthcare, park, and shopping facilities, etc.) using discrete choice models, such as nested logit models, is another interesting topic for further research. Third, the proposed measures only consider the road transportation model. Extension of the proposed measures to multi-mode transportation network is another topic for further investigation. Last but not least, in the case study, a survey was carried out to determine the service areas of facilities at the three levels. In recent years, several studies have investigated the problem of shopping-center service area delineation by using taxi-trajectory Big Data (Yue et al., 2012; Chen et al., 2017). The delineation of service areas for different types of urban facilities using emerging spatiotemporal Big Data and the incorporation of the results into accessibility studies need further investigation.

7. Conclusion

This study has proposed three location-based space-time accessibility measures by reconciling conventional location-based accessibility measures with the space-time utility perspective. The dynamic accessibility of a location was conceptualized as the temporal variation of space-time utility offered by facilities accessible from the location. The temporal variation of individuals' intensities to perform activities at facilities was explicitly formulated. The facilities' opening hour constraints and the dynamics of traffic conditions were also considered. To demonstrate the capability of the proposed measures, a comprehensive case study was performed in Wuhan, China. The case study results indicated that the proposed measures can well capture the temporal variation of location-based accessibility, due to the dynamic nature of traffic conditions and individuals' intensities of performing activities at different times of day.

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Appendix A. Appendix

This appendix presents the developed GIS toolkit for calculating the proposed location-based space-time accessibility measures. The GIS toolkit was implemented using Visual C# programming language and integrated with the ArcGIS 9.3 software.

As shown in Fig. 13, the toolkit comprises two types of input: road network and rich facility information. Rich facility information is organized by a GIS point layer, an intensity function table, and a service area table. The GIS point layer stores a bundle of attributes, including facility's geographical location, type_ID, level_ID, opening time t_p, closing time t_q and user rating s_f. The type_ID is a foreign key of intensity function table, which stores the time-dependent activity intensity function, $g_f(t)$. The level_ID is a foreign key of service area table, which specifies the type of distance decay function (i.e., exp(•) or $R_i(f)$) and distance decay parameter (i.e., β_i or γ_i). The road network information is formulated as a GIS polyline layer with the road geometries, and a speed table with node-link topologies.

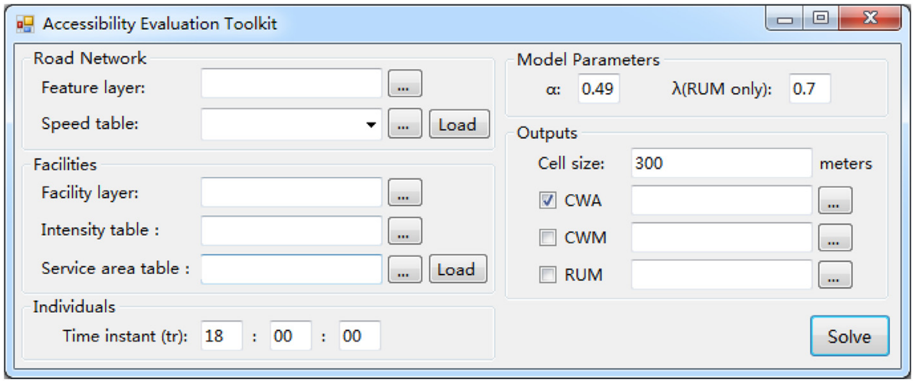

Fig. 13. User interface of the developed toolkit.

The outputs are the calculated location-based space-time accessibility measures, i.e., $CWA(i)$, $CWM(i)$ and $RUM(i)$. To store the calculation results, the whole study area is discretized into grid cells of equal size and stored in a GIS raster layer. The detailed steps for calculating accessibility measures are described below (using $RUM(i)$ for illustration).

Step 1. Initialization.
01: For each cell i.
02: $A(i) = 0$.
03: End For.
Step 2. Accessibility measure calculation.
04: For each facility $f \in F$.
05: Construct the service area $SA(f, t_r, \gamma_f)$.
06: For each cell $i \in SA(f, t_r, \gamma_f)$.
07: Retrieve $c_{if}(t_r)$ (travel time from facility f to cell i).
08: Calculate utility $U_f(i)$ using Eq. (6).
09: Set $A(i) = A(i) + Exp(U_f(i))$.
10: End For.
11: End For.
12: For each cell i.
13: Set $A(i) = \frac{1}{\lambda}\ln(A(i))$.
14: End For.

Step 1 is the initialization by setting $A(i) = 0$ for all cells. Step 2 is to calculate accessibility measures for each cell $f \in F$. Firstly, the service area of the facility is constructed by using backward space-time cone algorithm (Chen et al., 2016), allowing all accessible cells $i \in SA(f, t_r, \gamma_f)$ of the facility to be determined. Then, travel time from facility f to accessible cell i, $c_{if}(t_r)$, can be retrieved. The utility of activity participations at facility f for individuals at cell i is calculated from $U_f(i) = (W_f(t_r))^{\alpha} K(c_{if}(t_r))$. The utility derived for different facilities are added iteratively as $A(i) = A(i) + Exp(U_f(i))$. After utilities from all facilities are added, the $RUM(i)$ value is obtained by $\frac{1}{\lambda}\ln(A(i))$.

This algorithm can be readily modified for calculating $CWA(i)$ and $CWM(i)$ measures by respectively using $A(i) = A(i) + U_f(i)$ and $A(i) = Max(A(i), U_f(i))$ on Line 09. Lines 12–14 are not needed for both $CWA(i)$ and $CWM(i)$ measures.

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