ADVANCING SPATIAL ACCESSIBILITY MEASUREMENTS TO URBAN INFRASTRUCTURE: UNCOVERING TEMPORAL DYNAMICS AND UNCERTAINTY

A Dissertation

by

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ABSTRACT

Measurement of spatial accessibility is useful for the assessment of the ease of access to an infrastructure of interest from the interactions of supply, demand, and mobility. Spatial accessibility measures are essential in the investigation of the geospatial problem, as they explain the spatial disparity of access between inter- and intra-regions and suggest that locations of poor accessibility should be supplemented with additional resources. However, the conventional approach used in spatial accessibility studies underexamined the temporal dynamics embedded in the three input variables, overestimating accessibility and decreasing the accuracy of measurements. To address these concerns, the implementation of temporal dynamics in spatial accessibility is thoroughly investigated in three aspects as follows: 1) examining the stochastic distribution of spatial accessibility from the uncertainty underlying the temporal changes, 2) enhancing the accuracy of accessibility measurements by leveraging the temporal changes of supply, demand, and mobility, and 3) promoting the reproducibility of temporal dynamics by prioritizing the use of time-dependent variables in accessibility measurements.

The analyses performed in this dissertation provided three major findings. First, it revealed that the uncertainty embedded in the temporal dynamics dramatically changes the degree of accessibility and intensifies the inequality of access in the worst-case scenario. This indicates that the temporal changes should be considered in assessing accessibility, given their notable impact. Second, incorporating time-dependent variables

into measurements would uncover the 24-hour variation of spatial accessibility. The enhanced temporal granularity of the measurement provides an improved understanding of the time-dependent spatial disparity of access and supports a better allocation of supplementary infrastructures at a specific space and time. Third, the implementation of time-dependent mobility, rather than time-dependent supply and demand, should be prioritized to maximize the temporal variations of the measurements, and the partial use of time-dependent variables may fail to predict accessibility during the daytime. These findings shed light on the benefits of utilizing time-dependent variables and suggest possible strategies to promote policy implications. Therefore, the dissertation would provide insights on how to take advantage of the current data-rich environment to understand the temporal dynamics of geospatial problems for the discipline of Geographic Information Science and Systems.

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Contributors

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1. INTRODUCTION

Spatial accessibility is defined as the ease of access from a particular region to an infrastructure of interest (Hansen 1959, Shen 1998, Radke and Mu 2000). In spatial accessibility measurements, three input variables (supply, demand, and mobility) are used, and their interactions are considered in the assessment of the level of accessibility of geographical regions (Luo and Wang 2003). Spatial accessibility measures allow for the identification of different levels of accessibility across locations; typically, urban areas have higher accessibility, and rural areas have low accessibility (McGrail and Humphreys 2014, Chen and Jia 2019, Gong *et al*. 2021). Therefore, they improve the understanding of geospatial issues by reflecting spatial disparity of access (Dony *et al*. 2015) and address the disparity by suggesting locations of poor accessibility should have supplementary resources (Kang *et al*. 2020). Given that measures of spatial accessibility provide significant policy implications, much attention has been paid to spatial accessibility across various disciplines such as geography or urban planning (Dai 2010, Bell *et al*. 2012, Wang *et al*. 2020).

Since its introduction in 2003, the two-step floating catchment area (2SFCA), has become the most well-known method of spatial accessibility measurement (Luo and Wang 2003). The method addresses the shortcomings of previous approaches (Hansen 1959, Shen 1998, Radke and Mu 2000) by considering threshold travel time (i.e., the will of people to visit facilities) and the nature of demand (i.e., the dynamic distribution of people). As implied by its name, the method measures accessibility in two steps as follows (Wang 2012): 1) calculation of the supply-to-demand ratio from supply locations and 2) calculation of the total ratio for demand locations. With its increasing popularity, the method has been constantly complemented to enhance the accuracy of measurements in numerous studies, categorized into three groups as follows: The first group includes studies about the use of various threshold travel times, as rural residents may travel further than urban residents to overcome the low density of infrastructure (Luo and Whippo 2012, McGrail and Humphreys 2014). The second category includes studies that investigated the impact of various distance decay functions on the measures and determined the distribution that best predicted the travel behavior of people to access supply facilities based on different contexts (i.e., diverse region or infrastructure) (Luo and Qi 2009, Dai 2010, Dai and Wang 2011, Tang *et al*. 2017). The third category is the use of an extra step (Wan *et al*. 2012) or distance decay (Delamater 2013) to prevent a possible exaggeration issue of accessibility.

Despite the methodological advancements of spatial accessibility measurements, previous studies underexamined the temporal dynamics embedded in the three input variables (Neutens 2015, Park and Goldberg 2021). This could decrease the accuracy of measurements, as the temporal changes over time are not taken into account in the measurements (Hu and Downs 2019). Previous studies used the three input variables in their static forms, under the assumption that they have no temporal variation; however, the variables dynamically change over time, especially within a day (Park *et al*. 2021). Each infrastructure (i.e., supply) has operating hours, allowing people to obtain services only when it is open (Järv *et al*. 2018, Wang *et al*. 2018). In addition, people access infrastructures not only from their residential locations but also from school, work, or even during travel. Given that demand describes the locations of people traveling to infrastructures, the time-dependent variation in the number of people should be incorporated into the measurement (Lee *et al*. 2018, Xia *et al*. 2019). Furthermore, mobility is a variable that shows the most dynamic changes over 24 hours because of the time-variant traffic condition (Chen *et al*. 2017, 2020, Lee and Miller 2018). The degree of mobility is typically maximized during the nighttime and minimized during rush hours, greatly influenced by daily commute.

The aim of this dissertation was to investigate the impacts of the temporal uncertainty and changes on the measures of spatial accessibility by using time-dependent supply, demand, and mobility. Given that the degrees of these three variables fluctuate over time (Järv *et al*. 2018, Park *et al*. 2021), this dissertation elucidates how the degree and inequality of accessibility could be changed owing to the uncertainty in its input variables. In addition, the enhanced temporal granularity of measurement would uncover the 24-hour variation of spatial accessibility, which the conventional approaches could not reveal (Neutens 2015). The research questions motivating this dissertation are as follows: First, how can we leverage the time-dependent variables in measuring spatial accessibility? Second, how can we provide improved policy implications by taking advantage of the time-dependent variables?

This dissertation consists of a literature review (Chapter 2) and three analyses (Chapters 3–5). The literature review was conducted to investigate the recent advancements of spatial accessibility measurements that benefitted from the current data-rich environment (Park and Goldberg 2021). Previous studies in the last 10 years focused on the implementation of time-dependent variables (Järv *et al*. 2018, Lee *et al*. 2018, Hu and Downs 2019, Xia *et al*. 2019) and multimodal transportation (Langford *et al*. 2016, Lin *et al*. 2018, Tao *et al*. 2018, Hu *et al*. 2020). They considered the dynamic aspects of spatial accessibility measurements to reflect the behavior of people accessing infrastructure better. From the thorough review, the following gaps were found: 1) the underexamined influence of the uncertainty of the input variables attributed to their temporal changes, on the measures of spatial accessibility, 2) the weak linkage between the enhanced temporal granularity of measurements and policy implications, and 3) the limited reproducibility of temporal dynamics in spatial accessibility due to the lack of data.

To address the gaps, three analyses using the 2SFCA method were performed in this study, focusing on 1) investigating the impact of the temporal uncertainty underlying the input variables on the measures of spatial accessibility, 2) enhancing the policy implications of spatial accessibility by leveraging the temporal changes of the inputs, and 3) promoting the reproducibility of temporal dynamics in spatial accessibility by prioritizing inputs that should implement time-dependent variables.

In Chapter 3, the influence of the temporal uncertainties of input variables on the measure is examined, focusing on the spatial accessibility to intensive care unit (ICU) beds in the Greater Houston area. In detail, the Monte-Carlo simulation was used to investigate how the stochastic distribution of accessibility varies by locations under the temporal uncertainty of the availability of ICU beds (i.e., supply) and the estimated travel time (i.e., mobility) observed during the coronavirus disease (COVID-19) pandemic. Furthermore, in the chapter, regions are clustered spatially according to their stochastic distributions, and the relationship between the attributes of the accessibility of ICU beds and the case-fatality ratio of COVID-19 is compared.

Chapter 4 proposes a framework leveraging temporal changes of spatial accessibility measurements for better policy implications and presents a case study on the accessibility to electric vehicle (EV) charging stations in Seoul, South Korea (Park *et al*. 2021). In the analysis, a complete set of time-dependent supply, demand, and mobility was used to maximize the temporal dynamics in spatial accessibility. In addition, two temporal clustering methods (K-means and hierarchical clustering) were utilized to summarize the 24-hour variation of accessibility and provide improved policy implications of accessibility.

Chapter 5 presents an investigation of the importance of the temporal dynamics of each input in estimating the temporal changes of spatial accessibility that would be obtained from a full implementation of time-dependent variables. A sensitivity analysis was conducted with eight scenarios of accessibility measurements, including every possible combination of the static and dynamic forms of supply, demand, and mobility. With the spatial accessibility of health-care resources in New York City, two correlation analyses were performed to determine the priority of the three inputs for maximizing the temporal variation and predict the hours that would have low accuracy when time-dependent variables are partially implemented.

Chapter 6 sheds light on the significance of the use of time-dependent variables for spatial accessibility measurements and discusses the potential contribution of this dissertation to the field of geography and urban planning. In addition, it illustrates the limitations of the analyses performed in the study and proposes future research agenda.

2. A REVIEW OF RECENT SPATIAL ACCESSIBILITY STUDIES THAT BENEFITTED FROM ADVANCED GEOSPATIAL INFORMATION: MULTIMODAL TRANSPORTATION AND SPATIOTEMPORAL DISAGGREGATION*

2.1. Introduction

Spatial accessibility explains the ease of access from a geographical unit to an infrastructure of interest (Hansen 1959). The measures of spatial accessibility are calculated based on the interaction of three input variables (Shen 1998, Luo and Wang 2003): supply (i.e., locations of infrastructure), demand (e.g., locations of people who are expected to utilize the infrastructure), and mobility (i.e., travel costs from demand locations to supply locations). Occasionally, supplementary variables, such as distance decay functions and threshold travel time, are incorporated into measurements to reflect the will of the people to visit infrastructure (Wang 2012, Chen and Jia 2019). The measures provide an improved understanding of geographical issues in two aspects. The first is to illustrate the spatial disparity of accessibility (Weiss *et al*. 2018, 2020) and examine the relationship between socioeconomic conditions and accessibility. The second aspect is to identify areas of poor accessibility, and in it, it is proposed that those

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locations should be supplemented with additional resources (Kang, Michels, *et al*. 2020). Therefore, measuring spatial accessibility may address the spatial mismatch between supply and demand and promote sufficient and equalized accessibility. Thanks to these insightful policy implications, much attention has been paid to spatial accessibility studies for various infrastructures, such as health care resources (Luo and Wang 2003, Luo and Whippo 2012, McGrail and Humphreys 2014, Tao, Cheng, *et al*. 2020), job opportunities (Shen 1998, Hu and Downs 2019), food outlets (Järv *et al*. 2018, Chen and Jia 2019), other urban infrastructures (Delafontaine *et al*. 2012, Lee *et al*. 2018, Kelobonye *et al*. 2020).

In several reviews, the extensive number of accessibility-related studies were summarized focusing on empirical findings (Handy and Niemeier 1997, Shi *et al*. 2020), methodological developments of metrics (Guagliardo 2004, Neutens 2015), and the impact of supplementary variables (i.e., distance decay or threshold travel time) (McGrail 2012, Wang 2012, Chen and Jia 2019). As most reviews were conducted more than a decade ago (Handy and Niemeier 1997, Guagliardo 2004, Wang 2012), it was out of their scope to investigate how spatial accessibility measurements took advantage of dynamic variables (i.e., multimodal transportation and the enhanced granularity of spatiotemporal information). In addition, it was suggested in some reviews that incorporating dynamic variables into measurements would increase accuracy and predictability (Neutens 2015, Shi *et al*. 2020). Therefore, it is essential to follow up on how recent studies have adopted this suggestion and enhanced the performance of measurements.

In this decade, the availability of dynamic geospatial data has increased significantly through big-data analysis and open-data policy, particularly the implementation of multimodal transportation and spatial and temporal disaggregation. Specifically, the advent of sophisticated transportation databases, such as general transit feed specification (GTFS) and Uber Movement (https://movement.uber.com/), enables the estimation of various travel times per different transportation modes (e.g., public transit, private car) and dynamic travel times under time-variant traffic conditions. In addition, the advent of GPS-equipped devices (e.g., smartphones) facilitates the tracing of an anonymized movement of individuals (Yoo *et al*. 2020) and enhances the space and temporal granularity of data (Benenson *et al*. 2017). With improved granularity, it is empowered to further investigate the nonhomogeneous distribution of people within conventional coarser geographical units (e.g., neighborhood, census tract) and to systematically estimate the time-variant distribution of floating populations.

Recently, dynamic variables, such as multimodal transportation and spatial and temporal disaggregation, have been incorporated into the measurements of spatial accessibility studies, which have benefitted from advancements in geospatial data. The studies were classified into two groups based on the dynamic variables they implemented. The first group is related to multimodal spatial accessibility measurements, in which investigations on the impact of various transportation modes on the disparity of spatial accessibility are developed. For instance, in a series of studies, researchers accounted for more than one alternative transportation modes (e.g., public transit, bicycles, or walks) besides private car travel, improving the predictability of the measures (Mao and Nekorchuk 2013, Dony *et al*. 2015, Lin *et al*. 2018). The second group is related to the examination of temporal changes in spatial accessibility. Given that the inputs of the measures are time-variant, studies have measured spatial accessibility hourly within a day and examined how the measures change over time. This form of advancement is aligned with "high-frequency cities," which indicates 24-hour variations of urban phenomena repeated every day (Batty 2020). The big data analysis and real-time data mining facilitated the investigation of temporal changes. For example, Järv *et al*. (2018) considered temporal dynamics of supply and demand from the opening hours of grocery stores and time-variant distribution of floating populations, illustrating temporal changes in food accessibility over 24 hours. Hu and Downs (2019) demonstrated how to employ census data (i.e., census transpiration planning products; CTPP) to populate temporal dynamics of the variables (i.e., supply and demand) and measured space-time job accessibility within a day.

In this review, we aim to systematically scrutinize the methodological advancements and empirical findings of spatial accessibility measures. We took advantage of Web of Science Core Collection (https://webofknowledge.com/WOS) as a literature database and searched for accessibility studies with the author keywords "accessibility" or "access." Because the initial result was voluminous (92,579), we refined the literature as articles published in geography and urban studies between 2011 and 2021 to focus on recent advancements in accessibility literature. Consequently, we obtained 1,447 studies. By reading their abstracts, we investigated methodological improvements regarding accessibility measurements and recent trends in dynamic variable implementation (i.e., multimodal transportation and spatial and temporal disaggregation of measures). We assigned the reviewed studies to two sections to distinguish between conventional approaches and recent advancements. In the second section, we investigate methodological advances in traditional place-based accessibility. In the third section, we cover the recent dynamic spatial accessibility, focusing on their methodological improvements and the empirical finding. The advancements in dynamic spatial accessibility consist of multimodal accessibility and temporal changes of spatial accessibility. From the exhaustive reviews, in the fourth section, we propose a future research agenda and potential ways to promote the accuracy and predictability of measures, furnishing policy implications beyond the implementation of dynamic variables. In particular, this paper focuses on place-based accessibility measures, which assess accessibility based on geographical units (e.g., census tracts, traffic analysis zones), and excludes people-based accessibility measures (i.e., accessibility of individual trajectories) (Miller 1991, Kwan 1998).

2.2. Methodological Advancements in Measuring Spatial Accessibility

Methodological advancements in spatial accessibility measurement have proceeded in three steps: the gravity model, Shen's model, and the two-step floating catchment area (2SFCA) method. First, in the gravity model, also referred to as the cumulative opportunity model, the number of opportunities (i.e., supply facilities) accessible from a given location, considering spatial impedance, is measured (Hansen 1959). The model is defined as follows:

$$O_i = \sum_j S_j f\left(d_{ij}\right)$$ **Equation 2.1**

where O_i is the cumulative opportunity of location i; S_j is the weight of supply facility (e.g., the number of physicians in the case of healthcare resources) at location j; d_{ij} is the travel cost (i.e., time or distance) between location i and location j; $f()$ is a distance decay function reflecting the spatial impedance of the travel cost (i.e., d_{ij}).

Second, Shen (1998) improved the accuracy of spatial accessibility measurement by introducing an additional variable (i.e., demand), whereas a homogeneous distribution of people is assumed in the gravity model. He adopted the consideration of demand from the Huff model (Huff 1963, 1964), in which the geographical units based on the probabilities of customers visiting a shopping center are delineated and defined Shen's model as follows:

$$\mathrm{A}_i = \sum_j \frac{S_j f(d_{ij})}{\sum_k D_k f(d_{kj})}$$ **Equation 2.2**

where A_i is the accessibility at location i; S_j is the weight of supply facility at location j; d_{ij} is the travel cost between location i and j; $f()$ is an impedance function by which the travel cost is constrained. D_k is the number of people (i.e., demand) at location k.

Finally, the limitation of Shen's model, in which every supply facility is considered to provide service to every demand location in the case of an inappropriate distance decay function, is addressed in the 2SFCA method (Luo and Wang 2003, Wang 2020). A threshold travel time is employed in the model to reflect the will of the customer and to define the locations accessible within the threshold travel time, such as a catchment area. In this method, spatial accessibility is measured in two steps using the following formulas:

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \leq d_0\}} D_k f(d_{kj})} \qquad \textbf{Equation 2.3}$$

$$\mathrm{A}_i = \sum_{j \in \{d_{ij} \leq d_0\}} R_j f(d_{ij}) = \sum_{j \in \{d_{ij} \leq d_0\}} \frac{S_j f(d_{ij})}{\sum_{k \in \{d_{kj} \leq d_0\}} D_k f(d_{kj})} \qquad \textbf{Equation 2.4}$$

where R_j is the supply-to-demand ratio of the supply facility at location *j*; S_j is the weight of supply facility at location *j*; D_k is the demand (e.g., population) in location *k*; d_{kj} or d_{ij} is the travel cost from location *k(or i)* to location *j*; $f()$ is an impedance function by which the travel cost is constrained; d_0 is the threshold travel cost, by which the catchment area is created; A_i is the accessibility measure of location *i*.

As its name implies, the 2SFCA method consists of two steps (Figure 2.1). In the first step of the method (Equation 2.3), the supply-to-demand ratio of each supply facility is calculated; the weight of the supply facility is divided by the sum of demand, in which locations fall into the catchment area (i.e., accessible within the threshold travel time). For instance, assume hospital A in Figure 2.1(a) has five census tracts accessible within a predefined threshold travel time. Therefore, the supply-to-demand ratio of hospital A (i.e., R_A) is obtained by dividing the weight of supply (i.e., S_A) by the sum of every accessible demand location (i.e., $D_1 + D_2 + D_5 + D_6 + D_7$). In the second step (Equation 2.4), the supply-to-demand ratio of supply facilities is summed up where the locations are accessible within the threshold travel time from each demand location. For example, assume census tract 7 in Figure 2.1(b) can access both hospitals in the area within the threshold travel time; therefore, the accessibility measure of the location (i.e., A_7) is the sum of the supply-to-demand ratio of both hospitals (i.e., $R_A + R_B$).

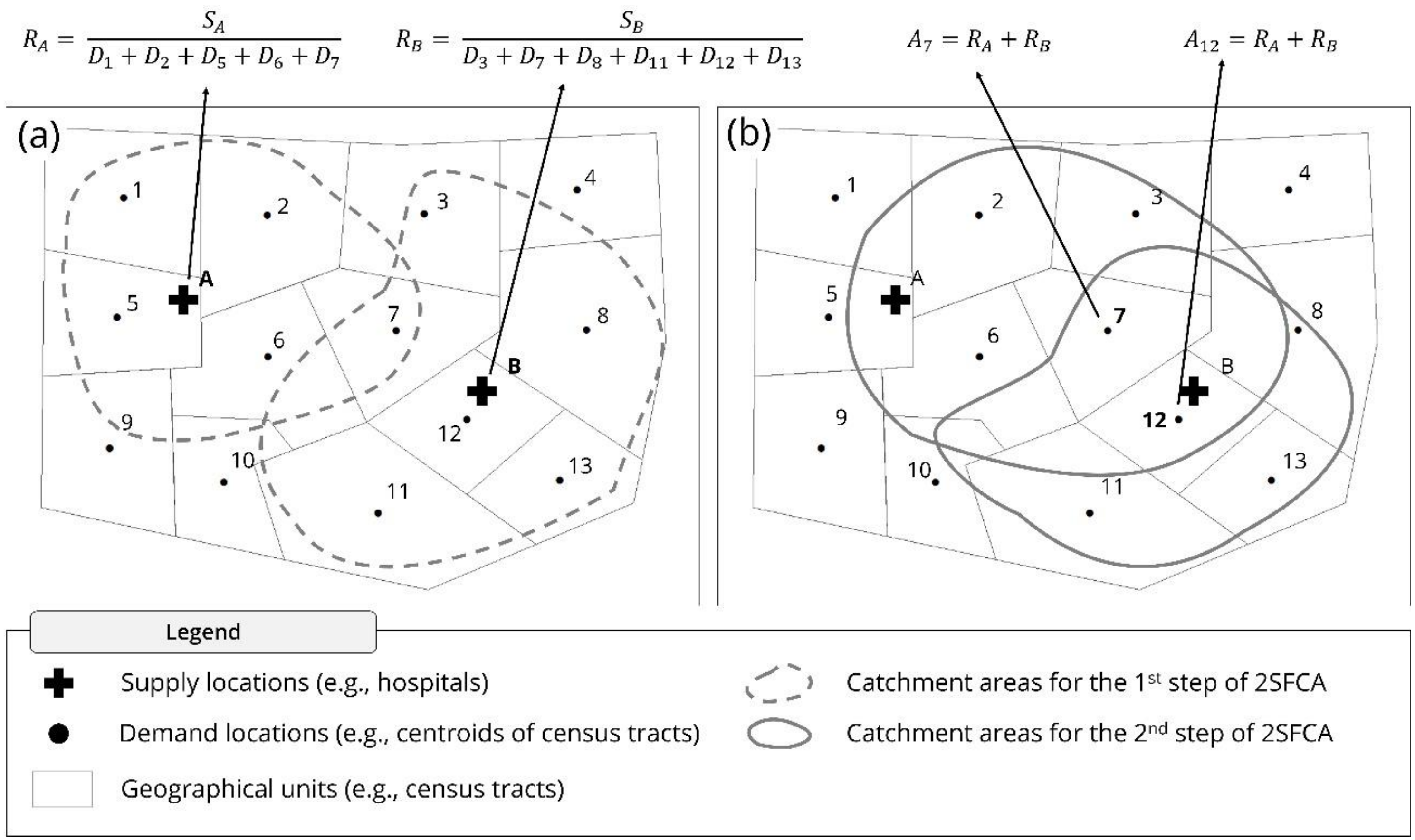

Figure 2.1. Conceptual diagram of the two-step floating catchment area (2SFCA) method: (a) the first step of 2SFCA—calculating a supply-to-demand ratio of each supply facility accessible within the threshold travel time; (b) the second step of the 2SFCA method—summing up the supply-to-demand ratio of all supply facilities accessible from each demand location within the threshold travel time.

With the 2SFCA method, significant insight into spatial accessibility studies is provided, considering spatial impedance and local competition (i.e., supply-to-demand ratio) within catchment areas. Thanks to its straightforward and compelling characteristics, not only has the method been predominantly adopted in spatial accessibility studies, but it also entailed numerous follow-ups (i.e., the 2SFCA family), complementing to improve accuracy. The methodological advancements in the descendants can be classified into three categories: various distance decay functions, various sizes of catchment areas, and reflection of the preference of the customer. In the first category, various types (e.g., discrete, continuous, or hybrid) of distance decay functions were examined to address dichotomous measures of the original 2SFCA and enhance the prediction of the spatial impedance. As the spatial impedance differs by region and facility (Wan *et al.* 2012), researchers incorporated a diverse range of distance decay functions: Gaussian distribution (Luo and Qi 2009, Dai 2010), Kernel density (Dai and Wang 2011), Log-logistic distribution (Delamater *et al.* 2013), exponential function (Tang *et al.* 2017), and hybrid function (Gong *et al.* 2021). The second category involves using different catchment sizes to reflect that rural residents travel further than city residents to offset the low density of infrastructures (McGrail and Humphreys 2009). Given that an inappropriate catchment size may underestimate spatial accessibility measures, either diverse threshold travel time based on a spatial setting (McGrail and Humphreys 2014) or predefined supply-to-demand ratio (Luo and Whippo 2012) were implemented in studies. In studies associated with the third category, either an additional step (Wan *et al.* 2012) or an additional distance decay function (Delamater

2013) were introduced to consider the tendency of people to a closer one when multiple facilities are available.

2.3. Dynamic Spatial Accessibility: Incorporating Dynamic Variables into the Measurements

With the enhanced availability of dynamic variables, they were incorporated into the measurements in studies in two aspects: multimodal spatial accessibility and temporal changes of spatial accessibility. They adopted advancements in people-based accessibility measurements (e.g., space-time accessibility), taking advantage of the different velocities of movements and finer space and time granularities (Miller 1991, Kwan 1998). In the meantime, the downside of people-based accessibility was addressed, which is challenging to adopt for policymaking (Neutens 2015). The measures of people-based accessibility vary by the trajectory of each person, which requires a substantial amount of information (e.g., trajectory data for each person) and entails a substantial computational intensity (Kwan 1998, O'Sullivan *et al.* 2000). Besides, the enhanced granularity of space and time is subject to be compromised when the measures are generalized for geographical units, given that decision-making is frequently made based on a place, not people (Neutens 2015).

2.3.1. Multimodal Spatial Accessibility

The first group of dynamic spatial accessibility involves multimodal spatial accessibility measurements (Mao and Nekorchuk 2013, Langford *et al.* 2016, Lin *et al.* 2018). In previous studies, the use or preference of people of various kinds of transportation modes, such as public transit, bicycles, walks, and private cars, was considered (Figure 2.2). They were aimed to reflect the different travel distances or speeds of each transportation mode and its impact on the measures. Specifically, equations 2.5–2.7 estimate the number of people (i.e., D_k^m) at a geographical location (i.e., k) who are likely to take a type of transportation (i.e., m) to access an infrastructure. In addition, separate threshold travel times and distance decay functions were implemented in each transportation mode. Consequently, the supply-to-demand ratio (i.e., R_j^m) and accessibility measures (i.e., A_i^m) of a location per mode are obtained. Equation 2.7 aggregates each accessibility measure per mode, based on the ratio of the riders utilizing each transportation mode to produce a synthesized accessibility measure. The equations of multimodal spatial accessibility are defined as follows:

$$R_j^m = \frac{S_j}{\sum_{k \in \{d_{kj}^m \leq d_0^m\}} \sum_m^n D_k^m f(d_{kj}^m)}$$ **Equation 2.5**

$$A_i^m = \sum_{j \in \left\{d_{ij}^m \leq d_0^m\right\}} \sum_m^n R_j^m f\left(d_{ij}^m\right) = \sum_{j \in \{d_{ij}^m \leq d_0^m\}} \sum_v^n \frac{S_j f(d_{ij}^m)}{\sum_{k \in \{d_{kj}^m \leq d_0^m\}} \sum_m^n D_k^m f(d_{kj}^m)}$$

Equation 2.6

$$A_i = \frac{\sum_k \sum_m D_k^m A_i^m}{\sum_k \sum_v D_k^m}$$ **Equation 2.7**

where m refers to transportation mode; R_j^m represents the supply-to-demand ratio of the supply facility j of the people who are likely to utilize a transportation mode m; A_i^m

denotes the accessibility measures of location i with a transportation mode m; A_i is the integrated accessibility measures of every transportation mode at location i.

Multimodal spatial accessibility enhances the accuracy and predictability of measurements, reflecting real-world dynamics. Implementing multimodal mobility was proposed to address the limitation of conventional spatial accessibility measurements, which assumed only a single mode (i.e., car) for mobility. Alternative transportation modes (e.g., public transportation, bicycles, and walks) may be essential for people with poor socioeconomic conditions, given that they may not have access to private vehicles (Mao and Nekorchuk 2013). Additionally, a significant portion of travelers, particularly for big cities or the elderly, is accounted for in public transportation (Kawabata 2009, Tao and Cheng 2019, Lee and Miller 2020).

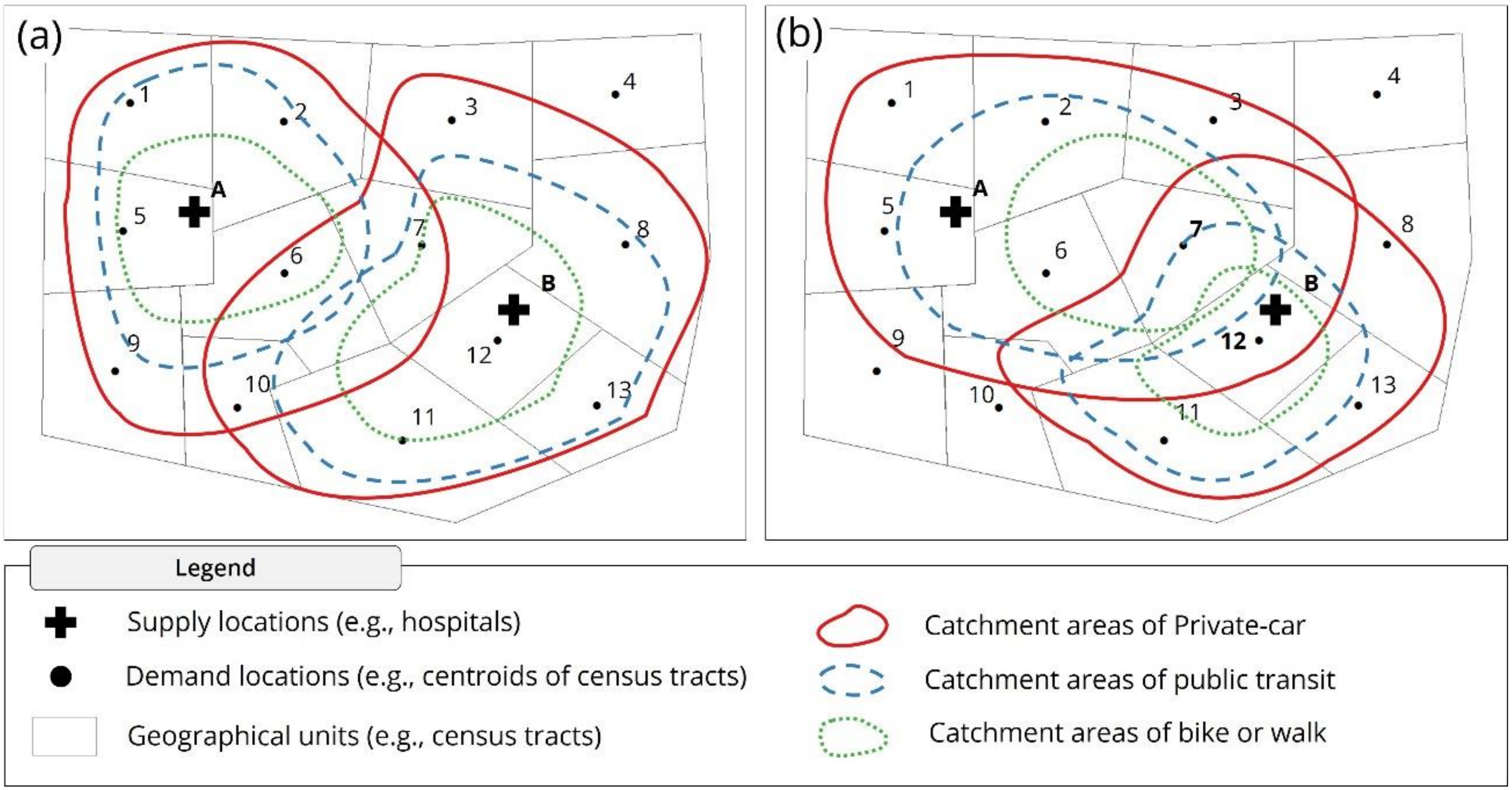

Figure 2.2. Conceptual diagram of the multimodal spatial accessibility: (a) the first step of the multimodal 2SFCA, calculating the supply-to-demand ratio of each supply facility to each transportation mode; (b) the second step of multimodal 2SFCA method, summing up the supply-to-demand ratio of all supply facilities to each transportation mode.

Since the initial proposal of multimodal spatial accessibility by Mao and Nekorchuk (2013), the methodological advancements could be summarized into two groups: (i) a simple comparison of spatial accessibility between different transportation modes, and (ii) synthesized measures of spatial accessibility considering multimodal mobility. In the first group of studies, it was demonstrated that the accessibility gap was attributed to different transportation modes. The characteristics of each transportation mode were incorporated into their measurements by assigning different travel speeds (e.g., 10 mph for a bus, 40–70 mph for a private car (Mao and Nekorchuk 2013, Zhang and Mao 2019)) and allocating longer threshold travel times for alternative modes (e.g., 60 min for a bus, 30 min for a private car; (Lin *et al.* 2018)). Alternative transportation modes are frequently slower than private cars because public transit (e.g., bus or subway) travels along a designated route (Langford *et al.* 2016), whereas bicycles or walks are nonmotorized modes of transport (Dony *et al.* 2015). To implement multimodal transportations, researchers either configured a separate layer for alternative transportations in addition to generic transportation network for private car travel or employed a sophisticated database (i.e., general transit feed specification; GTFS) (Apparicio *et al.* 2017) or third-party web APIs (application programming interface) (Zhou *et al.* 2020), such as Google (Dony *et al.* 2015, Tao *et al.* 2018, 2020). This improved analysis accuracy, as they reflected door-to-door travel with walking from an origin, riding along a predefined route, and walking to a destination (Langford *et al.* 2016, Lin *et al.* 2018).

The multimodal spatial accessibility studies of the second group had their accuracy of measurements improved with synthesized measures of accessibility by considering several transportation modes. In these studies, either the ratio of travelers per transit mode per location (Langford *et al.* 2016, Lin *et al.* 2018, Tao *et al.* 2018, Hu *et al.* 2020) or the preference for transit mode (Xing *et al.* 2018, Xiao *et al.* 2021) were employed. In this feature, the competition between people using different transportation modes but sharing the same facility is reflected. The advantage of census data (e.g., car ownership) was considered, assuming that households without a car would only take public transportation only (Mao and Nekorchuk 2013, Hu *et al.* 2020, Tao *et al.* 2020). It was also assumed in these studies that people would prefer to walk to green spaces over bicycling and driving when they could walk to a park within a given threshold travel time (Xing *et al.* 2018). The partitioning of people with transportation modes is critical for a synthesized index of accessibility with various transportation modes (Lin *et al.* 2018, Hu *et al.* 2020) and intermodal competition for each transportation mode (Langford *et al.* 2016, Tao *et al.* 2018).

Multimodal spatial accessibility studies have resulted in several empirical findings, such as significant interregional and intermodal accessibility disparities. Whereas sufficient accessibility in downtown areas and insufficient accessibility in peripheral areas persisted (Tao and Cheng 2019, Tao *et al.* 2020), the most critical finding is that conventional single-mode (i.e., car) measurements would overestimate accessibility in rural or suburban regions (Dony *et al.* 2015, Apparicio *et al.* 2017, Hu *et al.* 2020). Due to the disadvantages of alternative transportation modes (i.e., slower speed and predefined routes), only travel with cars allowed access from peripheral to downtown areas, where most infrastructures were located (Langford *et al.* 2016). The accessibility by car provided a dispersed pattern of measures due to a larger catchment area, whereas the accessibility by the alternative methods produced only a few clustered regions with sufficient values (Dony *et al.* 2015, Tao *et al.* 2018). Unfortunately, this interregional disparity would persist; many cities put efforts into providing additional public transportation for downtown areas, whereas they frequently disregard the demand in rural/suburban areas (Kawabata 2009). Therefore, the scholars emphasized that the inter-region disparity would be correlated to the socioeconomic conditions of regions (Chang *et al.* 2019), and policymakers should pay attention to public transit in peripheral regions (Mao and Nekorchuk 2013, Tao *et al.* 2020).

2.3.2. Temporal Changes in Spatial Accessibility

In the second group of dynamic spatial accessibility studies, the dynamics of temporal changes in spatial accessibility were centered (Figure 2.3). Whereas in a few studies the temporal differences (i.e., over the years) of spatial accessibility measures were investigated (Jamtsho *et al.* 2015, Yang and Mao 2018, Moya-Gómez and Geurs 2020), in the majority of them, researchers took advantage of the enhanced granularity of space and time, examining how spatial accessibility changes over 24 h (Lee *et al.* 2018, Hu and Downs 2019, Xia *et al.* 2019). As the inputs of spatial accessibility measurements (i.e., supply, demand, and mobility) vary over time (Xu *et al.* 2015), temporal dynamics were populated from input attributes, such as operating hours, time-variant distribution of floating population, in the studies, and time-variant traffic condition. They then measured the spatial accessibility of each hour with the 2SFCA method over 24 h with the following equations:

$$R_j^t = \frac{S_j^t}{\sum_{k \in \{d_{kj}^t \leq d_0\}} D_k^t f(d_{kj}^t)} \qquad \textbf{Equation 2.8}$$

$$A_i^t = \sum_{j \in \{d_{ij}^t \leq d_0\}} R_j^t f(d_{ij}^t) = \sum_{j \in \{d_{ij}^t \leq d_0\}} \frac{S_j^t f(d_{ij}^t)}{\sum_{k \in \{d_{kj}^t \leq d_0\}} D_k^t f(d_{kj}^t)} \qquad \textbf{Equation 2.9}$$

where t refers to an hour within a day, R_j^t represents the supply-to-demand ratio of the supply facility j at an hour t, and A_i^t denotes the accessibility measures of location i at hour t.

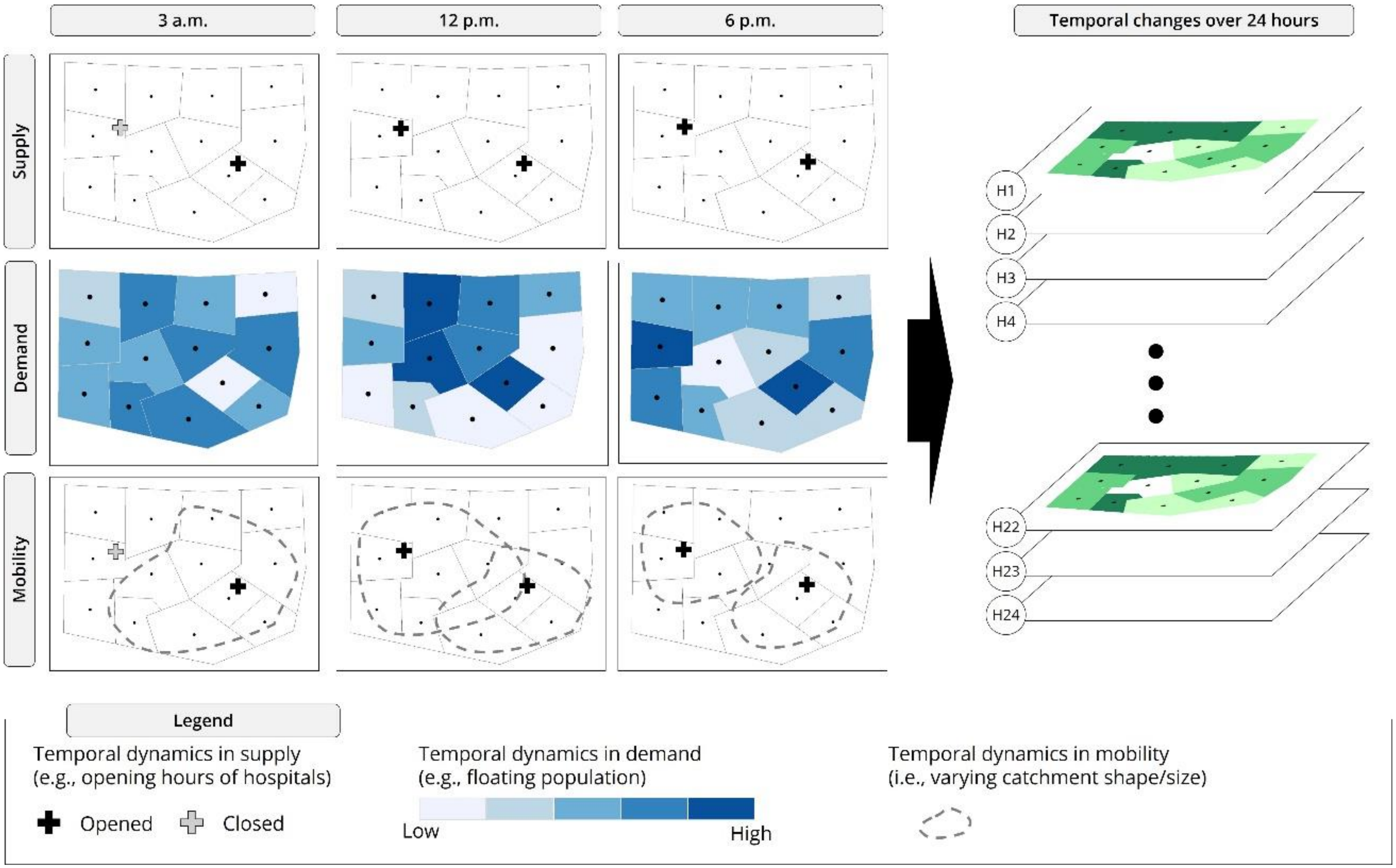

Figure 2.3. Conceptual diagram of temporal changes in spatial accessibility: temporal dynamics in the input variables (i.e., supply, demand, and mobility) and hourly spatial accessibility measurements over 24 h.

Temporal changes in spatial accessibility were aimed to enhance the accuracy of the measurements by taking advantage of the enhanced resolution of space and time in geospatial data. Researchers utilized more than one time-dependent input variables (i.e., supply, demand, and mobility) and employed finer geographical units (Table 2.1). Although the targets are the same, this advanced form is referred to by various names, such as space-time accessibility (Hu and Downs 2019), spatiotemporal accessibility (Xia *et al.* 2019), temporal variation of location-based accessibility (Wang *et al.* 2018), and dynamic location-based accessibility (Järv *et al.* 2018).

Researchers tackled the limitations of conventional approaches of spatial accessibility and enhanced resolutions in both space and time. Regarding temporal resolution, the conventional approach may fail to explain the temporal dynamics of accessibility, given that the generalized input did not reflect temporal variation within a day. However, the input variables change over time (e.g., operating hours, floating population, and time-variant traffic conditions), influencing spatial accessibility measures. The researchers also tried to address spatial resolution, which is strongly tied to the modifiable areal unit problem (MAUP), with the implementation of finer geographical units. As the 2SFCA method determines whether the location is accessible based on the inclusion of the centroids of geographical units, this may be affected by MAUP. In studies where dynamic spatial accessibility was assessed with micro-level geographic units, such as census tracts (Boisjoly and El-Geneidy 2016) or grids (Järv *et al.* 2018, Wang *et al.* 2018, Hu and Downs 2019), this implementation increased accuracy of the measurements.

Table 2.1. Studies in which temporal changes in spatial accessibility were investigated.

	Method	**Target**	**Supply (Variable; Source)**	**Demand (Variable; Source)**	**Mobility (Variable; Source)**	**Geographical Unit**
Boisjoly & El-Geneidy (2016)	Gravity	Job	Dynamic (number of jobs; census data)	N/A	Dynamic (estimated travel time via public transportation; GTFS)	Census tracts
Chen *et al*. (2017)	Gravity	Food (restaurants)	Static	N/A	Dynamic (estimated travel time via road network; taxi trajectory data)	Not specified
Lee *et al*. (2018)	2SFCA + Huff	Bus stops	Static	Dynamic (floating population; mobile phone usage data)	Static	Grids
Järv *et al*. (2018)	Not specified	Food (grocery)	Dynamic (operating hours; website of supplier)	Dynamic (floating population; mobile phone usage data)	Dynamic (estimated travel time via public transportation; GTFS)	Grids

Table 2.1. Continued.

	Method	Target	Supply (Variable; Source)	Demand (Variable; Source)	Mobility (Variable; Source)	Geographical Unit
Wang *et al*. (2018)	Gravity	Food (restaurants)	Dynamic (operating hours; map API)	N/A	Dynamic (estimated travel time via road network; taxi trajectory data)	Grids
Hu & Downs (2019)	2SFCA	Job	Dynamic (number of jobs; CTPP)	Dynamic (number of job seekers; CTPP)	Static	Grids
Xia *et al*. (2019)	2SFCA	Healthcare (emergency services)	Static	Dynamic (floating population; GPS-enabled mobile phone)	Static	Grids
Chen *et al*. (2020)	2SFCA	Healthcare (hospitals)	Static	Static	Dynamic (estimated travel time via road network; taxi trajectory data)	Thiessen polygon (cellular tower coverage)

Given that the same objectives (i.e., temporal changes in spatial accessibility over 24 h) in every study in this category are shared, we investigated how temporal dynamics were populated in them, based on which attributes. We categorized the studies into three groups according to the three input measurement variables: supply, demand, and mobility. First, studies in which researchers populated temporal dynamics in supply based on the opening hours of facilities (Järv *et al.* 2018, Wang *et al.* 2018) or the work hours of job opportunities (Boisjoly and El-Geneidy 2016, Hu and Downs 2019). Because people cannot access infrastructures outside their opening hours (e.g., 8 a.m.–5 p.m. or 24 h), the degree of available supply facilities is time-dependent (Widener and Shannon 2014, Järv *et al.* 2018). Also, jobs have a specified time that requires employees to work. Second, floating population was utilized to estimate the time-variant distribution of the people (Järv *et al.* 2018, Lee *et al.* 2018, Hu and Downs 2019, Xia *et al.* 2019). The floating population is critical to improving the accuracy of measurements, as people access infrastructures not only from their residential locations, but also from work, school, or even while traveling. In other words, it reflects the nature of the daily activities of people who travel and conduct various activities across regions within a day. In these studies, researchers took advantage of census data (Kobayashi *et al.* 2011, Hu and Downs 2019) or GPS-enabled mobile phone usage data (Järv *et al.* 2018, Lee *et al.* 2018, Xia *et al.* 2019) to incorporate floating populations into the measurements. Third, studies in which researchers furnished temporal dynamics in mobility from taxi trajectory data (Chen *et al.* 2017, 2020, Wang *et al.* 2018) or sophisticated transportation databases (Boisjoly and El-Geneidy 2016, Järv *et al.* 2018). The advent of GPS-enabled devices (e.g., taxi trajectories or cell phones) has significantly facilitated the estimation of time-dependent mobility. It is empowered to provide anonymized individual movements (Yoo *et al.* 2020) and predict the mobility of a particular space and time based on historical travel time data (Gong *et al.* 2020). Particularly, temporal dynamics in mobility are the most important variable for measuring temporal changes in spatial accessibility (Chen *et al.* 2017, Lee and Miller 2020). Although the locations of supply and demand are stationary, the longer travel time diminishes the size of catchment areas, prevents ease of access to supply facilities, and increases the disparity of measures between demand locations.

2.4. Research Agenda

Although it is acknowledged that implementing dynamic variables enhanced the accuracy of measurements, we found in the exhaustive review in the previous section that dynamic spatial accessibility has not been applied to its fullest. We propose two research agendas worthy of investigating beyond the current accomplishments: (i) enhance the predictability and accuracy of accessibility measurements and (ii) examine temporal changes in spatial accessibility to furnish policy implications.

2.4.1. Improving the Predictability and Accuracy of Measurements with Dynamic Variables

This section provides three suggestions that could improve the predictability and accuracy of the measurement. First, measurement accuracy is significantly enhanced when implementing a complete set of temporal dynamic inputs. Despite the significance of reflecting realistic temporal changes, in none of the previous studies there was the complete incorporation of a set of temporal dynamic inputs into the measurements (Table 2.1); they were limited to partially implementing time-dependent variables (Boisjoly and El-Geneidy 2016, Chen *et al.* 2017, 2020, Lee *et al.* 2018, Wang *et al.* 2018, Hu and Downs 2019, Xia *et al.* 2019). Employing a complete set of temporally dynamic variables would benefit from continuously enhancing high temporal granularity data (Benenson *et al.* 2017). For instance, dynamics in supply could be populated from operating hours, which are easily accessible through the websites of suppliers or third-party search engines. Time-dependent demand (i.e., floating population) is also published through municipal government or third-party companies. Mobility has the vastest sources to populate dynamics: open street maps (OSM), GTFS, or map APIs. Volunteered geographic information systems, such as OSM, provide precise network datasets because many users constantly create road segments and reviews. Because the data are available via the Python package (Boeing 2017, 2020), the dataset can easily be combined with nonspatial traffic data and populate traffic dynamics (Kang, Michels, *et al.* 2020). Additionally, GTFS is specifically designed for public transportation and consists of static GTFS and real-time GTFS (GTFS 2005, Google 2020). Static GTFS calculates travel time via public transportation based on the schedule, whereas real-time GTFS provides the current position of vehicles and the delay information. Furthermore, commercial map services provide estimated travel time via their Maps API, but the temporal dynamics employing the source have only been examined in a few studies (Rong *et al.* 2020). As high temporal resolution data are widely available, it is straightforward but powerful to integrate the dynamics of the three inputs and to measure temporal changes in spatial accessibility. Besides the rich temporal data sources, the advancement of an open-source geocomputational framework would boost the implementation. Until now, many studies have relied on a commercial GIS platform (e.g., Esri ArcGIS). However, the advent of CyberGIS would be an alternative for analysis with computational intensity (Wang 2010, Kang, Aldstadt, *et al.* 2020).

Second, the combination of time-dependent mobility and multimodal spatial accessibility measurements would advance the predictability of the measures (Stępniak *et al.* 2019). In the current approaches of multimodal studies, researchers have taken advantage of predefined timetables of public transportation to estimate travel time and have compared accessibility with free-flow private car travel (i.e., no traffic congestion considered) (Mao and Nekorchuk 2013, Lin *et al.* 2018, Tao *et al.* 2020). This disparity may reduce the realistic projection of spatial accessibility, since people use public transit due to limited access to private vehicles and avoid traffic congestion in big cities. As described above, the estimated travel time under traffic congestion for both car and public transit is available through various APIs, such as GTFS or Google (Lee and Miller 2018). Therefore, implementing sophisticated mobility data for both modes would increase the accuracy of measurements and provide an improved understanding of the spatial disparity in accessibility attributed to different transit modes.

Third, it would be noteworthy to investigate resource availability uncertainties, as accessibility is meaningless if no resources are available at facilities. Whereas every spatial accessibility variable is uncertain, uncertainty in supply is the most critical. For example, in hospital accessibility, the number of beds is often implemented as the supply weight to predict the service capacity. However, every hospital has some beds already utilized for hospitalization, so the degree of service they provide is not static and fluctuates over time. For these cases, the Monte-Carlo simulation may be a solution, and it was implemented in several studies to examine the stochastic distribution of on-time arrival considering the traffic congestion and unexpected delay (Ertugay and Duzgun 2011, Chen *et al.* 2020, Lee and Miller 2020). Lee and Miller (2020) compared how the accessible area changed according to the preference for the risk of the traveler (i.e., risk-averse or risk-seeking) from the perspective of people-based accessibility. Chen *et al.* (2020) measured place-based accessibility by incorporating the chance of on-time arrival. Given that they only focused on uncertainties in mobility, incorporating supply uncertainties would quantify accessibility reliability and delineate the region with robust accessibility.

2.4.2. Furnish Policy Implications from Temporal Changes in Spatial Accessibility

Because the significance of spatial accessibility studies is rooted in their policy implications (i.e., identifying spatial inequality of access to urban infrastructure and proposing locations that require additional resources), it is crucial to provide policymakers with refined and summarized information for their understanding of problems (Neutens 2015). In this context, the 24-hour spatial accessibility measurements in previous studies (Järv *et al.* 2018, Lee *et al.* 2018, Wang *et al.* 2018, Hu and Downs 2019, Xia *et al.* 2019) may be voluminous for stakeholders to examine notable temporal changes in the accessibility measures. As soon as the temporal dynamics are fully incorporated into the measurements, this issue can be addressed in two ways: temporal clustering and sequence analysis.

The first suggestion is to group the 24-hour measurements into a few temporal clusters with a homogenous distribution of measurements. Although the implementation of dynamic variables resulted in dynamic temporal changes in the measurements, the measures may have provided relatively similar patterns for some periods. For example, the accessibility of 2 p.m. may be more similar to 4 p.m., compared to that of 4 a.m. (Järv *et al.* 2018). Researchers have subjectively picked hours in previous studies that tended to show distinctive patterns to demonstrate temporal changes (Lee *et al.* 2018, Xia *et al.* 2019), possibly resulting in a biased interpretation. However, temporal clustering could systematically summarize the temporal variation and provide only distinctive changes of the measures (Rogerson and Yamada 2008). Therefore, temporally synthesized measures can produce an improved understanding of temporal changes by identifying which locations have limited access to infrastructure for a particular duration of time. In addition, the clustered measures would furnish policymaking on where to provide additional resources if the expected usage time data were provided (Widener *et al.* 2015).

As a second suggestion, sequence analysis could be implemented to identify how the accessibility of each location changes over time and illustrate the trends of temporal changes in a study area. Compared to the first suggestion, in which spatiotemporal accessibility was temporally summarized, in this suggestion, the regions are spatially clustered based on their possible temporal changes (i.e., sequence) in the accessibility

(Delmelle 2015, 2016). Therefore, the temporal sequence would facilitate the examination of the socioeconomic phenomenon related to accessibility (Gong *et al.* 2021, Liu *et al.* 2021) and propose how the spatial disparity of access can be addressed. For example, assume that the temporal changes in accessibility are summarized as follows: Region A has sufficient accessibility in the morning and limited accessibility during the day, Region B has consistent and sufficient accessibility, and Region C consistently has insufficient accessibility. These sequences would indicate that more attention is necessary for Regions A and C; furthermore, they enable investigation of what causes poor accessibility of Region A during the daytime. Consequently, with this approach, it would be possible to propose a way to furnish better policy implications stemming from the enhanced temporal granularity of spatial accessibility.

2.5. Conclusion

We thoroughly examined the methodological advancements and empirical findings of dynamic spatial accessibility, incorporating dynamic variables into the measurements. Specifically, dynamic spatial accessibility is aimed to improve the accuracy of the assessments by taking advantage of the enhanced availability of dynamic variables. The topic has been developed in two different ways: multimodal accessibility and temporal changes of spatial accessibility. Multimodal accessibility incorporated alternative transit into conventional private car travel and examined the disparity in accessibility attributed to transit mode. Accessibility with alternative modes illustrated was limited compared to that with car travel, and the gap was more significant in peripheral regions due to insufficient public transportation infrastructure. Time-dependent variables for the measurement inputs (i.e., supply, demand, and mobility) were used in the spatial accessibility temporal changes, increasing the temporal granularity of measurements into an hour. It was demonstrated that accessibility changes both space and time. Despite these advancements from dynamic variable employments, two research agendas are worthy of investigating. Considering the enhanced availability of high granularity spatiotemporal data, in this study, we highlighted the importance of dynamic variables to increase the accuracy and predictability of measures and provide practical implications from sophisticated results, which are the critical merits of spatial accessibility.

3. AN EXAMINATION OF THE STOCHASTIC DISTRIBUTION OF SPATIAL ACCESSIBILITY TO INTENSIVE CARE UNIT BEDS DURING THE COVID-19 PANDEMIC: A CASE STUDY OF THE GREATER HOUSTON AREA OF TEXAS

3.1. Introduction

In addition to sufficient access to healthcare resources, the provision of reliable healthcare is critical to promote the overall health of the public (Chen *et al*. 2020, Lee and Miller 2020). The merit of high accessibility to hospitals would be depreciated if the available resources in hospitals are depleted, even if several hospitals exist around residential locations. This issue is particularly emphasized during the global pandemic; particularly, the state of Texas has been suffering from the limited availability of hospitals, which resulted in high fatality from the coronavirus disease (COVID-19) (Walters *et al*. 2020). For example, Texas was hit hard by the second wave of the COVID-19 spread, where approximately 10,000 new cases daily and a total of 350,000 confirmed cases were reported. Owing to the extraordinary outbreak of COVID-19, the US Department of Health and Human Services (2020) estimated that 70.1% of inpatient beds (95% confidence interval [CI]: 70.2%–71.1%) and 77.9% of intensive care unit (ICU) beds (95% CI: 76.9%–78.9%) were occupied in the state of Texas as of July 14, 2020. Therefore, the limited availability of healthcare resources should be taken into account in spatial accessibility measurement to promote policy implications such as identification of spatial disparity or effective allocation of infrastructures (Park and Goldberg 2021).

In spatial accessibility measurements, three variables (supply, demand, and mobility) are used, and spatial accessibility is measured on the basis of their interactions (Shen 1998, Luo and Wang 2003, Wang 2012). Here, supply refers to the infrastructure of interest, such as hospitals or grocery stores; demand represents the spatial distribution of people who are expected to use the facility; and mobility is the travel cost (i.e., distance or time) to access the supply location from the demand location. Since the advent of the two-step floating catchment area (2SFCA) method (Luo and Wang 2003), two significant trajectories have emerged to advance the accuracy of spatial accessibility measurements. First, studies pursued to enhance the prediction of people traveling to infrastructures based on various distance decay functions (Dai 2010, Dai and Wang 2011, Delamater *et al*. 2013, Tang *et al*. 2017, Gong *et al*. 2021) and threshold travel time (Luo and Whippo 2012, McGrail and Humphreys 2014). In addition, they introduced either an extra step (Wan *et al*. 2012) or distance decay (Delamater 2013) to improve the prediction. Second, studies investigated the 24-hour variation of spatial accessibility, along with the argument of high-frequency cities (Batty 2020, Kandt and Batty 2021). Given that the supply, demand, and mobility statuses are subject to change over 24 hours (Järv *et al*. 2018, Park *et al*. 2021), much attention has been paid to the temporal dynamics of spatial accessibility caused by the temporal changes of the three input variables (Chen *et al*. 2017, Lee *et al*. 2018, Hu and Downs 2019, Xia *et al*. 2019).

Compared with the notable trajectories for accuracy improvements, the impact of uncertainty on the spatial accessibility measurement is underexamined. To our knowledge, only a few research studies have examined uncertainty in the context of spatial accessibility. However, these studies still focused on the influence of uncertain mobility on accessibility measures. Ertugay and Duzgun (2011) were among the first to develop an approach for investigating how the service area was mutated on the basis of the probability distribution of the observed travel speed. They drew the shape and size of catchment areas randomly through Monte-Carlo simulation and concluded that the locations consistently included in the catchment areas had sufficient and reliable accessibility. In addition, Lee and Miller (2020) incorporated the notions of risk-seeking and risk-averse on the arrival probability into the measurement and defined robust accessibility as the accessibility of a location regardless of uncertain mobility. Whereas Ertugay and Duzgun (2011) and Lee and Miller (2020) only examined the characteristics of catchment areas, Chen *et al*. (2020) proposed a reliability-based 2SFCA method and assessed the impact of uncertain mobility with their interaction with supply and mobility. They underscored that uncertain mobility had a notable impact on the accessibility measures, as it could provide mixed consequences depending on the location. A reduction in catchment area could prevent facilitated access to infrastructures from a location but could be beneficial to other locations, as it could lower the local competition for the same facility.

Given that spatial accessibility is measured on the basis of the interactions between supply, demand, and mobility, the uncertainty of both supply and mobility should be incorporated to spatial accessibility measurements. The dynamic changes of supply and mobility would possess uncertainty so that they could impact the measures of spatial accessibility (Park and Goldberg 2021). To be specific, the uncertainty of supply would change the amount of available resources, while static supply would assume that the total capacity is readily available (Kang *et al*. 2020). For instance, the percentage of available ICU beds in Harris County was maximized (21.3%, 344 of 1614 operational ICU beds) on May 25, 2020, and minimized (1.4%, 24 available beds) on July 15, during the second COVID-19 outbreak in Texas (from May 1 to September 30, 2020). An increase in availability would alleviate local competition (i.e., more resources and high supply-to-demand ratio), whereas a decrease in availability would worsen it (i.e., fewer resources; low supply-to-demand ratio). In addition, the uncertainty of mobility would change the size and shape of the service area that a facility provides (Sahebgharani and Haghshenas 2021). By contrast, static mobility would maximize the service area, as it assumes no traffic congestion on roads (Luo and Qi 2009). Travel speed tends to be fastest during the nighttime and slowest during the daytime because of time-dependent traffic congestion (Houston Transtar 2020). High mobility would expand the service area of supply, whereas low mobility would shrink it.

In this study, we aimed to examine the stochastic distribution of spatial accessibility to ICU beds during the COVID-19 pandemic in the Greater Houston area. In addition, we aimed to address the uncertainties of two variables (availability of supply and degree of mobility) in the measurement of spatial accessibility with the 2SFCA method. As availability is one of the essential criteria of access (Penchansky and Thomas 1981), the significance of our study would be acknowledged. To be specific, our analysis proceeded with the following three steps: First, we calculated the probability distribution of supply and mobility based on their historical changes in the Greater

Houston area. Second, we used the Monte-Carlo simulation to randomize the levels of supply and mobility for the 2SFCA method and measure spatial accessibility to ICU beds more than 999 times. Given that the stochastic distribution of accessibility provided by the simulation varied by location, we conducted hierarchical clustering to delineate areas of adequate (i.e., sufficient and reliable) accessibility and inadequate (i.e., insufficient and unreliable) accessibility. Our study focuses on the following three research questions: 1) How does spatial accessibility stochastically vary under the temporal uncertainty of supply and mobility? 2) Where are locations of adequate accessibility and inadequate accessibility indicated by the stochastic distribution? 3) Are the characteristics of accessibility related to the case fatality ratio of COVID-19?

3.2. Research workflow

We used the following three steps to measure spatial accessibility to ICU beds under the temporal uncertainty of supply and mobility (Figure 3.1): calculation of probability distribution, accessibility measurement with Monte-Carlo simulation, and spatial clustering. The first step to calculate the probability distribution of supply and mobility, which would be used as the randomized input variables in the Monte-Carlo simulation in the next step. The second step was to assess spatial accessibility to ICU beds 999 times (i.e., Monte-Carlo simulation) to investigate the impacts of the two randomized variables on the measures. The simulation provided the stochastic distribution of the measures for each location. Spatial clustering was implemented in the last step to group locations based on the measures and to demonstrate which locations had sufficient and reliable accessibility.

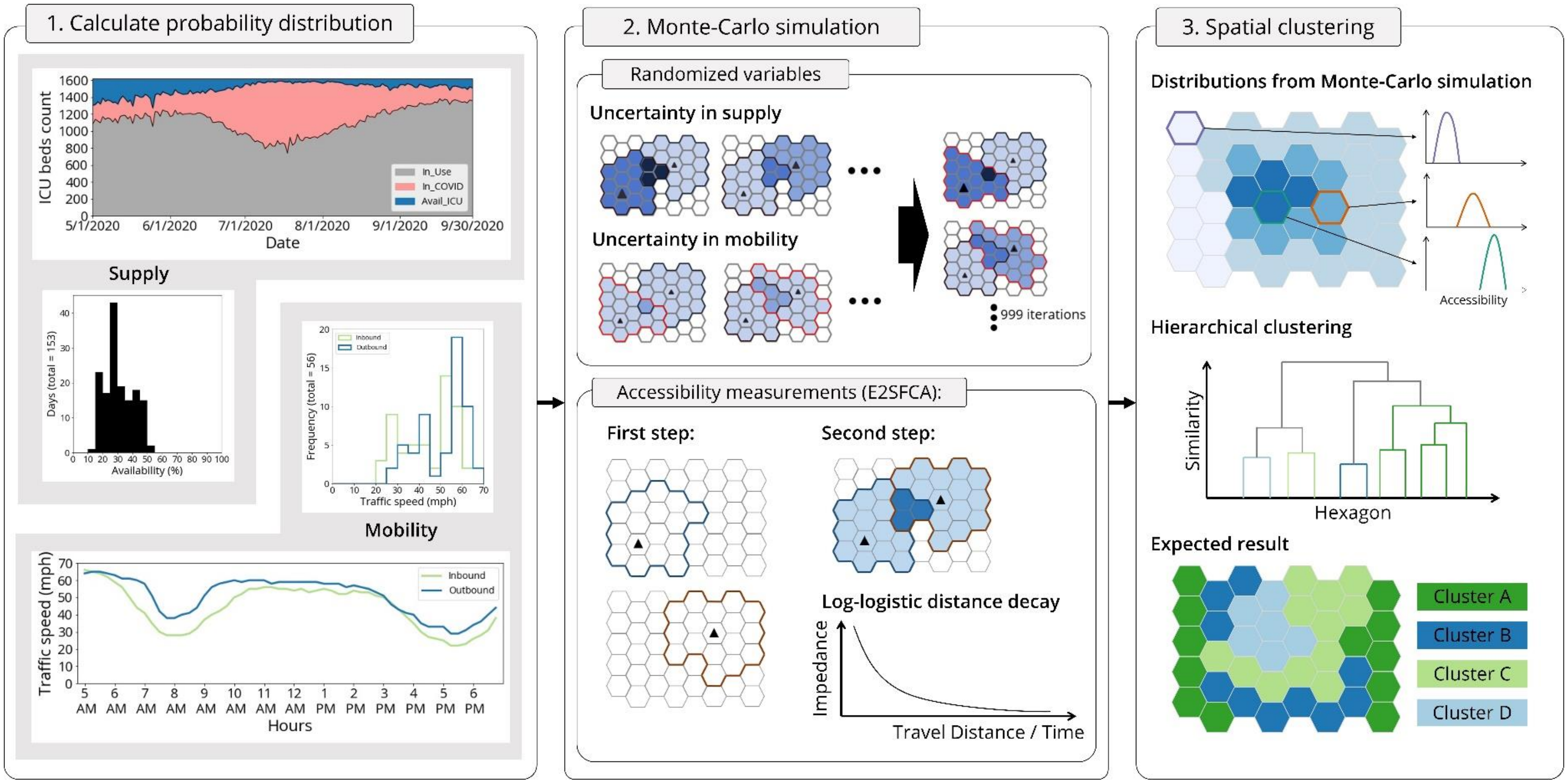

Figure 3.1. Research workflow

3.2.1. Study area and data

Our study area is the Greater Houston area (Figure 3.2), which consists of nine counties (Harris, Fort Bend, Brazoria, Galveston, Chambers, Liberty, Montgomery, Waller, and Austin) in the state of Texas. The study area is the fifth largest metropolitan area in the United States, with more than 7 million residents (U.S. Census Bureau 2021). When the second wave of the COVID-19 spread hit the state of Texas in July 2020, the study area was suffering from a limited availability of ICU beds. In addition, the case fatality ratio of COVID-19 was significantly high during the period even though the number of cases during the second peak was lower than those during the third (December 2020) and fourth waves (August 2021). This may be attributed to the limited availability of beds. Moreover, the city of Houston has notorious traffic congestions, which may prevent on-time arrival to healthcare resources. Therefore, the study area would be an excellent example for investigating the impacts of the uncertainties of supply and mobility on the measures of spatial accessibility.

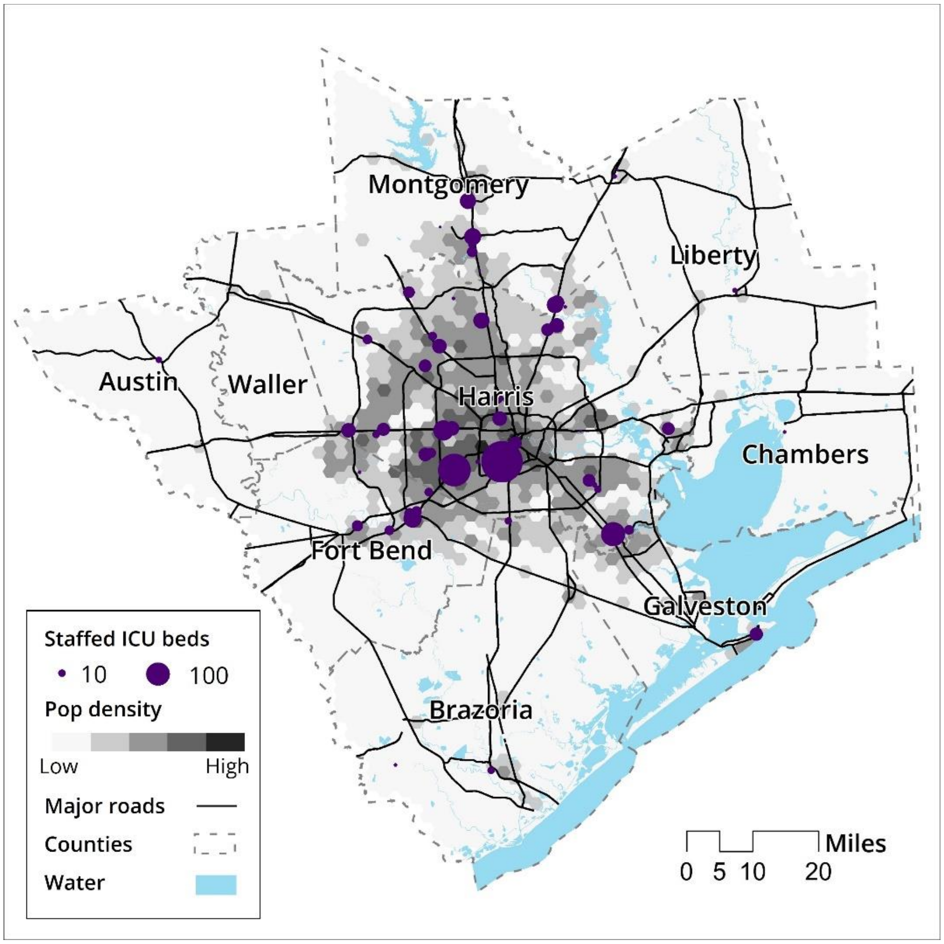

Figure 3.2 The study area

We utilized three spatial data sources to obtain the necessitated inputs (supply, demand, and mobility) for spatial accessibility measurements. For the supply facilities, we first used healthcare resources data provided by Definitive Healthcare (Definitive Healthcare 2020); it included the locations of hospitals and number of staffed ICU beds. The study area has 83 hospitals equipped with ICU beds among 115 hospitals and a total of 2,039 staffed ICU beds. Second, to represent demand, we used LandScan, a database of estimated global population distribution data (Rose *et al*. 2020). The dataset would enhance the accuracy of measurements given its finer spatial resolution (1 × 1 km) (Luo and Qi 2009, Kobayashi *et al*. 2011). As LandScan data were provided as points, we aggregated the population with 2000-acre hexagons (i.e., the average size of the census block group in the study area) to incorporate them into the accessibility measurement. Lastly, the mobility data were obtained from OpenStreetMap with a Python package (OSMnx) (Boeing 2017). The road networks provided by the dataset were used to calculate the travel time from a demand location to hospitals (i.e., ICU beds).

3.2.2. Calculating the probability distributions of supply and mobility

To prepare the randomized input for the Monte Carlo simulation, we first computed the probability distributions of supply and mobility on the basis of the historical temporal changes of the number of ICU beds in use and the travel speed of freeways, respectively (Figure 3.1). Given that the amount of service and ease of mobility are temporally dynamic, the levels of supply and mobility at a certain time would be ambiguous. Therefore, we used the historical variations of supply and mobility to determine the probability that each variable has a particular value.

We generated the probability distribution of supply in three steps as follows: Data on the temporal variation of ICU beds in use (i.e., supply) was collected from the South East Texas Regional Advisory Council within the period from May 1, 2020, and September 30, 2020 (SETRAC 2020). Given that the second wave of the COVID-19 spread peaked in July 2020 in Texas, the duration was chosen to cover the surge and decline of the number of ICU beds in use. First, we summed the numbers of empty beds and those occupied by patients with COVID-19 (i.e., confirmed and suspected), as our focus was on the available resources for patients with COVID-19. We then divided these by the total number of staffed ICU beds. Second, the percentages of ICU beds available for patients with COVID-19 were divided into 10 classes (0–10%, 10–20%, … 90%–100%). Third, we calculated the frequency of a certain availability rate from the entire period (from May 1 to September 30, 2020). For example, in Harris County, 312 ICU beds were empty and 221 ICU beds were occupied with COVID-19-related patients as of May 1, 2020, and the total number of staffed ICU beds was 1,614. Hence, the availability rate of ICU beds was 33% (i.e., [312 + 221]/1,614) at that moment. The rate (33%) was classified as an availability group of 30–40%. We repeated the calculation of availability over 153 days (from May 1 to September 30, 2020) and computed the frequency of the groups. We also applied this process for six (Harris, Fort Bend, Brazoria, Galveston, Chambers, and Montgomery) of the nine counties in the study area. The historical usage data for Austin and Liberty counties were missing, so we assumed that the probability distributions in the counties follow the overall variation in the other six counties. In addition, Waller County did not have any staffed ICU beds.

The probability distribution of mobility was calculated in four steps as follows: Its temporal variation was retrieved from the historical travel speed of freeways in 2019 (Houston Transtar 2020). The temporal granularity of the data was 15 minutes, from 5:00 a.m. to 7:00 p.m. We first matched the historical travel speed of a chunk of a freeway to the corresponding edges on the road network obtained from OpenStreetMap. Second, we divided the travel speed measured every 15 minutes into the fastest travel speed within a day, given the ratio to the free flow. We then divided the ratios into four classes (1–0.75: free flow, 0.75–0.5: light congestion, 0.5–0.25: moderate congestion, and 0.25–0.0: severe congestion) and estimated the delay in travel time compared with the free flow. Lastly, we determined the frequency of having a certain degree of mobility for each road. For example, the fastest travel speed on Interstate Highway 10 from Beltway 8 to downtown Houston was 66 mph at 5:00 a.m. The travel speed at 8:00 a.m. was 28 mph. Therefore, the ratio to the free flow is 0.42, indicating moderate congestion. As a result, the interstate highway has a 50% chance of free flow, a 21% chance of light congestion, and a 29% chance of moderate congestion. In addition, we assumed that non-freeway roads would have a 25% chance of having light congestion to maximize the impact of the uncertainty in mobility (Wang *et al*. 2018).

3.2.3. Monte Carlo simulation: measurement of spatial accessibility under uncertainty

Monte Carlo simulation was used to incorporate the temporal uncertainties of supply and mobility into the spatial accessibility measurements. The simulation is useful for investigating the impact of the ambiguity of inputs on the output, as it takes randomized variables for each measurement and processes with 999 iterations (Ertugay and Duzgun 2011). As the spatial accessibility requires three input variables (supply, demand, and mobility), we produced randomized supply and mobility from their probability distribution, computed on the basis of their historical changes. To be specific, in each iteration, the number of available ICU beds for each hospital (i.e., supply) fluctuated, and the estimated travel time via the road network (i.e., mobility) varied.

With the randomized inputs, we assessed the spatial accessibility to ICU beds, implementing the E2SFCA method (Luo and Qi 2009, Kang *et al*. 2020) to evaluate spatial accessibility in two steps as follows: 1) calculate the supply-to-demand ratio for each facility and 2) aggregate the ratio of reachable facilities. Distance decay was considered in the method by assigning different weights for subzones. Whereas the original E2SFCA method determined spatial impedance on the basis of the Gaussian distribution, we used log-logistic distribution given that it provided a good prediction of the travel behavior of people visiting healthcare resources both in urban and rural areas (Luo and Qi 2009, Delamater *et al*. 2013, Jia *et al*. 2017). In detail, in the first step of the E2SFCA method, the supply-to-demand ratio of a hospital (R_j) was computed. Then, the product between the number of staffed ICU beds in each hospital (S_j) and their availability rate (E_j) was divided by the number of residential populations within its service area (D_k), where the facility is accessible within a threshold travel time. The first step is defined in the following equation:

$$\mathrm{R}_j = \frac{S_j E_j}{\sum_{k \in \{t_{kj} \le t_0\}} D_k f(t_{kj}, t_0)} \qquad \textbf{Equation 3.1}$$

where supply and demand locations are represented by j and k, and the log-logistic distance decay function is denoted by $f\left(t_{kj}, t_0\right)$.

The second step of the E2SFCA method summed the supply-to-demand ratio of hospitals (R_j) that were accessible from a demand location, providing the accessibility measure (A_i), computed using the following equation:

$$\mathrm{A}_i = \sum_{j \in \{t_{ij} \le t_0\}} R_j f\left(t_{ij}, t_0\right) = \sum_{j \in \{t_{ij} \le t_0\}} \frac{S_j E_j f(t_{ij}, t_0)}{\sum_{k \in \{t_{kj} \le t_0\}} D_k f(t_{kj}, t_0)} \qquad \textbf{Equation 3.2}$$

where a demand location is presented by i.

The log-logistic distance decay function was implemented in both steps to depreciate the influence from either demand (Equation 3.1) or supply (Equation 3.2). The distance decay function is based on the cumulative distribution function of log-logistic distribution and is defined as follows:

$$f(\mathrm{t}_{ij}, t_0) = \begin{cases} \frac{1}{1+\left(\frac{t_{ij}}{\theta}\right)^{\beta}} & if\ t_{ij} \leq t_0 \\ 0 & if\ t_{ij} > t_0 \end{cases} \qquad \textbf{Equation 3.3}$$

where t_{ij} and t_0 represent the travel time from demand location i to supply location j and the threshold travel time, respectively; and θ and β indicate the scale and shape parameters, respectively. In our implementation, we defined threshold travel time, θ, and β, as 60 minutes, 13.89, and 1.82, respectively, on the basis of the actual travel pattern of patients (Delamater *et al*. 2013). Consequently, the following weights for 10 subzones were incorporated into the E2SFCA method to represent spatial impedance: 0.9459 for the 0- to 5-minute subzone; 0.7544 for the 5- to 10-minute subzone; 0.5511 for the 10- to 15-minute subzone; 0.3993 for the 15- to 20-minute subzone; 0.2957 for the 20- to 25-minute subzone; 0.2253 for the 25- to 30-minute subzone; 0.1765 for the 30- to 35-minute subzone; 0.1417 for the 35- to 40-minute subzone; 0.1161 for the 40- to 45-minute subzone; and 0.0832 for the 45- to 60-minute subzone.

3.2.4. Spatial clustering

In the final step, hierarchical clustering was implemented to spatially cluster hexagons according to their stochastic distributions of accessibility as determined from the Monte Carlo simulation. We used agglomerative hierarchical clustering, which is initiated with the accessibility distribution of each hexagon and aggregates the hexagons into a higher cluster on the basis of the similarities of distribution. The representative value of the distributions per hexagon was computed with Ward's method, given that it minimizes within-cluster variance (Ward 1963). In addition, the silhouette method was used to indicate the optimal number of spatial clusters (Rousseeuw 1987), which is expected to delineate spatial segregation the most.

3.3. Results

3.3.1. Stochastic distribution of accessibility to ICU beds

The implementation of the Monte Carlo simulation provided a stochastic distribution of accessibility that varies depending on the temporal uncertainties in supply and mobility (Figure 3.3). Given that the levels of supply and mobility dynamically change among the 999 iterations, the hexagons of the different locations showed distinctive distributions of accessibility (Figure 3.3a). Overall, the accessibility to ICU beds tended to be high in the center of the study area and was gradually decreased to the peripheral regions. For example, a site in Waller County (blue point) had a sharp distribution of poor accessibility (mean: 3.55; standard deviation [SD]: 0.27). By contrast, a location in Harris County (red point) had a smooth distribution of sufficient accessibility (mean: 21.51; SD: 1.67).

The pattern of spatial accessibility was greatly affected by the different levels of reliability (i.e., the probability that a location has a certain degree of accessibility). The three maps in Figure 3.3 illustrate the spatial accessibility that can be obtained at probability rates of 50% (Figure 3.3b), 5% (Figure 3.3c), and 95% (Figure 3.3d). The gradation of the maps indicates the available ICU bed count per 100,000 people that residents in the hexagon have access to. An inverse correlation was observed between the reliability level and the number of available ICU beds. For instance, 10 ICU beds per 100,000 people are assumed to be sufficient, given the median number of available ICU beds for patients with COVID-19. The ratio of all staffed ICU beds to the population in the study area was 28.94 per 100,000 people, and the median availability rate of ICU beds for patients with COVID-19 in the study period was 35%. For 5% reliability, 474 hexagons with 5.1 million people had sufficient access to ICU beds. However, the numbers were limited to 368 hexagons of 4.4 million people and 262 hexagons of 3.6 million people in the case of 50% and 95% reliability rates, respectively.

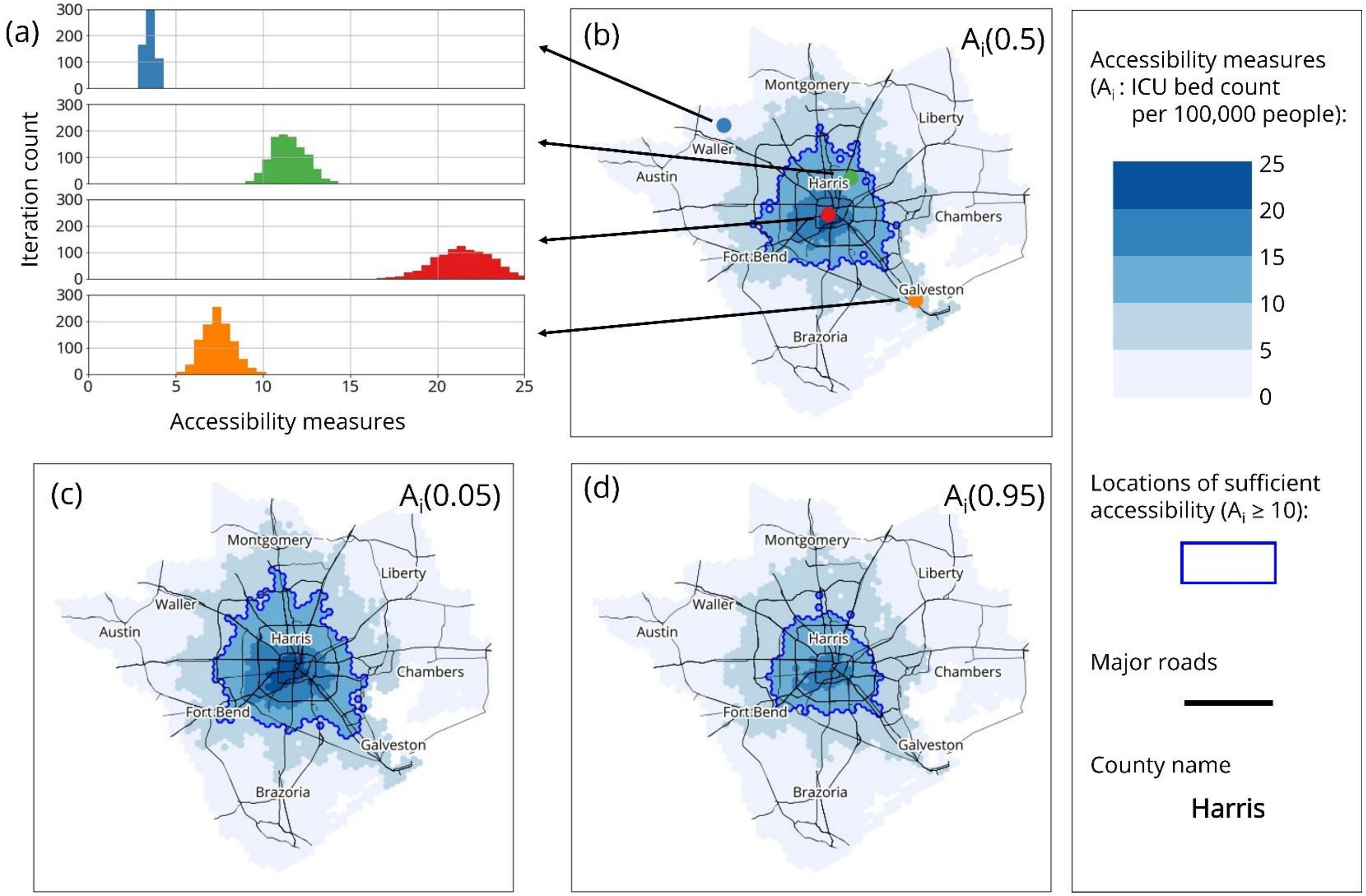

Figure 3.3. Stochastic distributions of accessibility to ICU beds: (a) distinctive distribution of each hexagon and the accessibility for probability rate of (b) 50%, (c) 5%, and (d) 95%.

3.3.2. Spatial clustering

The agglomerative hierarchical clustering produced two major spatial clusters (Figure 3.4b), one with adequate (i.e., sufficient and reliable) access to ICU beds and the other with inadequate (i.e., insufficient and unstable) accessibility. Although the optimal number of clusters as determined by the silhouette method was two clusters (silhouette coefficient: 0.619; Figure 3.4c), we further divided the two major clusters into a couple of subgroups, given that the five clusters provided the second highest silhouette coefficient (0.523). The cluster of inadequate accessibility was broken down into two subclusters (clusters L1 and L2), and the other cluster consisted of three partitions (clusters H1, H2, and H3).

The five spatial clusters were delineated in Figure 3.4a. They had different characteristics for the sufficiency (mean) and reliability (coefficient of variation [CV]) of accessibility (Figure 3.4d). Given that the scatterplot has sufficiency of accessibility as x-axis and unreliability of accessibility as y-axis, the upper-left corner indicates inadequate accessibility, and the lower-right corner presents adequate accessibility. The first cluster (L1) was at the outermost region in the study area, covering 720 hexagons with 0.1 million residents. It had very poor ($\overline{A_\iota} \leq 2.0$) and unreliable ($\overline{CV} \approx 0.58$) accessibility. The second cluster, L2, was mainly in the rural area (1030 hexagons with 0.5 million residents), having low accessibility ($2.0 < \overline{A_\iota} \leq 5.7$) and reliability ($\overline{CV} \approx 0.10$). The third cluster (H3) overlaid the suburban areas of Greater Houston, such as the city of Galveston, Galveston County, the Woodlands, Montgomery County, and the city of Sugar Land, Fort Bend County. It included 485 hexagons of 1.4 million people and presented moderate ($5.7 < \overline{A_i} \leq 9.3$) and stable ($\overline{CV} \approx 0.08$) accessibility. Cluster H3 was extruded to the southwest of the study area because of the freeway (Interstate 45) toward Galveston County, while the other directions of the cluster were constrained in a circular shape. The fourth cluster was an urbanized area and a group of peripheral neighborhoods in Houston (369 hexagons with 3.3 million residents), with sufficient ($9.3 < \overline{A_i} \leq 15.0$) and reliable ($\overline{CV} \approx 0.07$) accessibility. The last cluster was the urban core of Houston. It produced outstanding ($15.0 < \overline{A_i}$) and solid ($\overline{CV} \approx 0.07$) accessibility, although it was the most populous area (1.8 million residents in 85 hexagons). The cluster was slightly extended southwest, as a colossal hospital cluster (Texas medical center) was located in the direction.

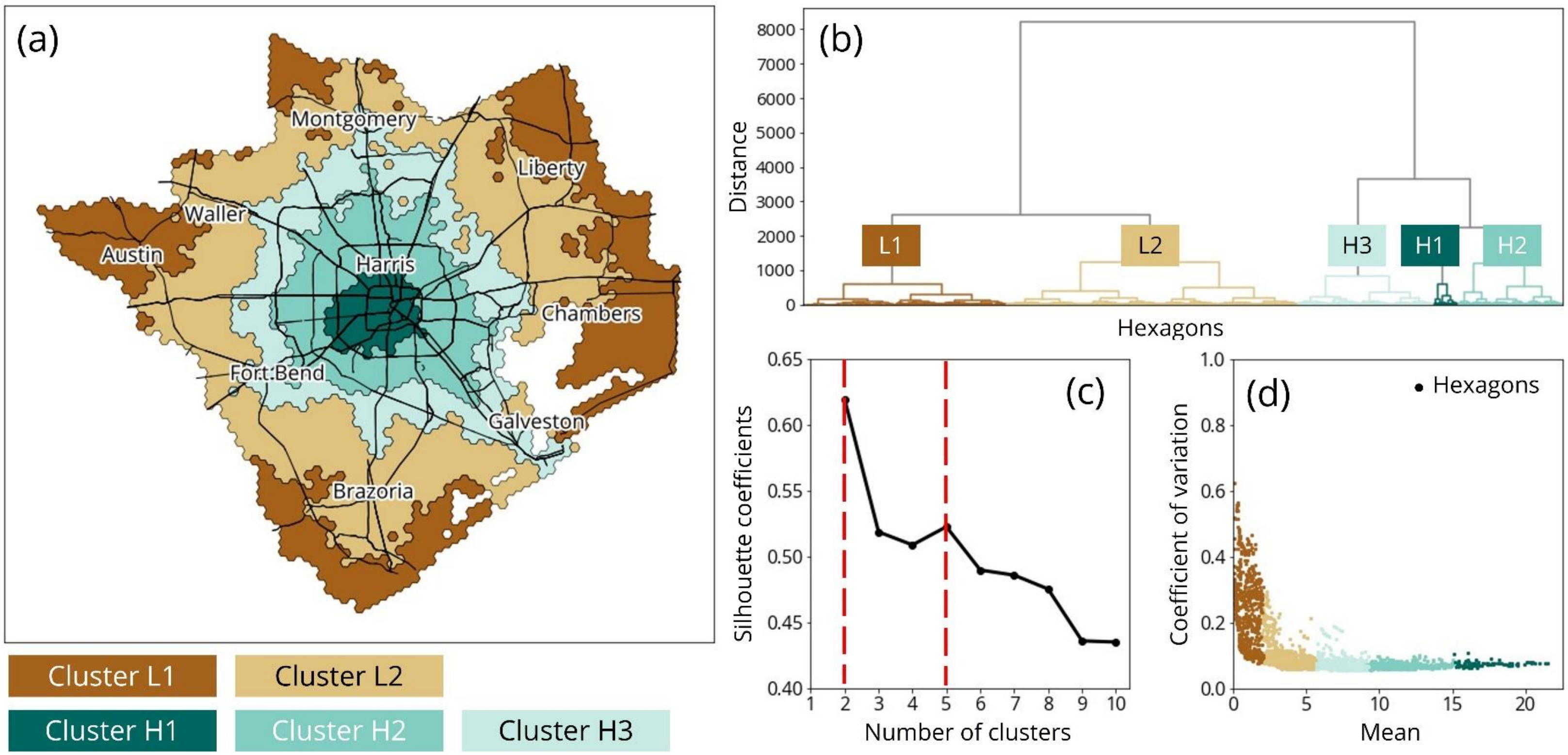

Figure 3.4. Hierarchical clustering results based on the stochastic distribution of accessibility: (a) spatial distribution of clusters, (b) dendrogram of hierarchical clustering, (c) silhouette method for determining the optimal number of clusters, and (d) the attributes of the hexagon classified in each cluster.

**Note: Hexagons with excessive coefficient of variation (CV > 1) were omitted at (d).

3.3.3. Impact of accessibility to ICU beds on COVID-19 and its spatial inequality

We observed a trend where the case fatality ratio of COVID-19 can be attributed to unsatisfactory accessibility even though it may not be statistically significant because of the limited number of samples (n = 9 counties; Figure 3.5a). Three of nine counties showed a higher case fatality rate than the average in the study area. While 18‰ (18 fatalities per 1,000 people) of the case fatality rate was observed as of September 30, 2020, Liberty, Austin, and Harris counties had case fatality rates of 23‰, 20‰, and 19‰, respectively. Liberty and Austin counties had insufficient (mean accessibility: 2.09 and 1.64) and unreliable (mean CV of accessibility: 0.13 and 0.27) accessibility. Therefore, their high rates can be related to the attributes of their accessibility. However, Harris County had a robust accessibility (mean accessibility: 10.39, and mean CV: 0.07). Its casualty could be caused by the intensive transmission of the virus within a short period, which was often reported in a high-density city such as New York.

The spatial disparity of accessibility would deteriorate as the reliability level increases (i.e., the probability that a location has a certain degree of accessibility), which possibly impacts the inequity of the case fatality rate of COVID-19. Stochastic distributions obtained from the Monte Carlo simulation provided that the degree of accessibility would be changed according to the reliability level. The Gini index values of accessibility for the reliability levels of .05%, .50%, and .95% were 0.43, 0.45, and 0.47, respectively (Figure 3.5b). Despite the fact that the difference was marginal, the spatial inequality of access was intensified as the reliability level increased. This alluded that the inequality of fatality may deteriorate in the future if the spatial disparity continues.

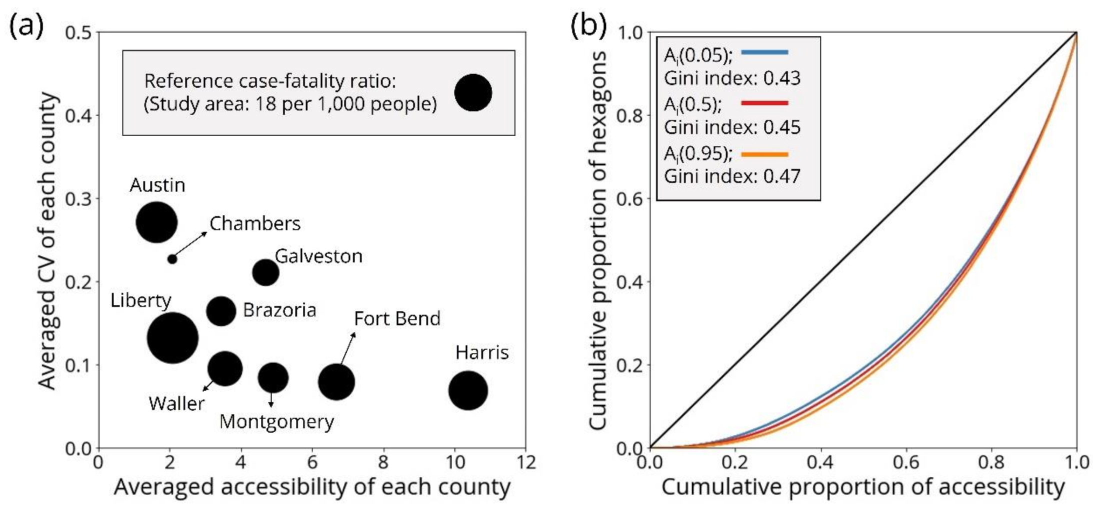

Figure 3.5. Attributes of accessibility to ICU beds: (a) relationship to the case fatality ratio of COVID-19 and (b) Gini index per various reliability level

3.4. Discussion

A direct relationship was observed between sufficient and reliable accessibility. That is, the center of the study area (cluster H1; downtown Houston) had adequate accessibility with sufficiency and reliability. However, the peripheral locations had inadequate accessibility (cluster L1), showing insufficient and unreliable characteristics. Our result was consistent with that of previous studies that showed spatial disparity of access between urbanized and rural areas (Luo and Whippo 2012, McGrail and Humphreys 2014, Kim *et al*. 2021). In addition, we uncovered that the spatial inequality of access would persist or intensify under the uncertainties of supply (availability of resources) and mobility (travel time for accessing hospitals). If a policymaker focuses on a spatial accessibility distribution that would be consistently obtained [i.e., $A_i(0.95)$], compared with the distribution obtained for the probability rate of 50% [i.e., $A_i(0.5)$], not only does measurement have a low overall accessibility but also the disparity between locations would also be severe.

As claimed by previous studies, sufficient access to healthcare resources, particularly ICU beds, is critical to patients with COVID-19, and insufficient accessibility may result in a higher case fatality rate (Kang *et al*. 2020, Ghorbanzadeh *et al*. 2021, Kim *et al*. 2021). Our comparison for nine counties presented direct relationships between the characteristics of accessibility and the case fatality rate of COVID-19. Our results are considered significant because they show that the higher fatality rate of COVID-19 could be expected to the locations of inadequate (i.e., insufficient and unreliable) accessibility. Whereas previous studies investigated a direct relationship between a snapshot of spatial accessibility to healthcare and COVID-19 fatality, our study concluded that the higher fatality could be attributed to the unreliable availability and insufficient accessibility.

The disparity in accessibility may be attributed to the different densities of hospitals across the study area. For example, if a hospital is running out of vacant ICU beds, a downtown resident could access other hospitals close to their locations, but this may not be the case for rural residents because of the sparse density of hospitals. As shown in our results, rural areas are more susceptible to the effects of unreliable availability of ICU beds; thus, more attention should be paid to the location. The measure of spatial accessibility typically indicates that locations need additional infrastructure; however, the cost of a new hospital installation is significant. Therefore, policymakers could enhance the number of operational beds in the rural area to prevent rural residents from unstable reliability of the availability of ICU beds.

3.5. Conclusion

Our study examined the stochastic distributions of the spatial accessibility to ICU beds and investigated the impact of accessibility on the case fatality rate of COVID-19. To be specific, we aimed to address uncertainties in the availability of ICU beds and travel time to healthcare resources in the Greater Houston area. As far as we know, our study is the first to discover the uncertainties of supply and mobility for spatial accessibility measurements. We used the Monte Carlo simulation to examine the stochastic distribution of accessibility granted from the randomized supply and mobility. Hierarchical clustering grouped locations according to stochastic distribution and discovered the locations of adequate (i.e., sufficient and reliable) and inadequate (i.e., insufficient and unreliable) accessibility. Our results demonstrate that the reliability of accessibility is proportional to the sufficiency of accessibility, indicating that spatial disparity of access would persist regardless of uncertainty. In addition, our results show that the high case fatality rate of COVID-19 in the peripheral counties may be attributed to the inadequate accessibility of the locations.

Our study has the following limitations: First, it would be challenging to reproduce and replicate because of the issue of computational intensity. Given that we used the Monte Carlo simulation with 999 iterations, the analysis took 3 months even though we conducted parallel computing of four computers with 16 cores. Second, we addressed the uncertainties of supply and mobility, neglecting the nature of demand. As the confirmed cases of COVID-19 were both spatial and temporally dynamic, the dynamic distribution of patients would have a significant impact on the availability of supply resources. Third, our comparison was not statistically significant because of the limited number of counties included. Our next step is to implement the CyberGIS approach to address computational intensity, incorporate uncertainty of demand, and expand the study area. High-performance computing capability would enable us to produce a meaningful relationship between accessibility and the disease. As the pandemic continues, it would help policymakers effectively allocate additional infrastructures and possibly reduce the fatality of COVID-19.

4. LEVERAGING TEMPORAL CHANGES OF SPATIAL ACCESSIBILITY MEASUREMENTS FOR BETTER POLICY IMPLICATIONS: A CASE STUDY OF ELECTRIC VEHICLE (EV) CHARGING STATIONS IN SEOUL, SOUTH KOREA*

4.1. Introduction

Spatial accessibility explains the ease for people in a particular region (i.e., demand) to access infrastructures of interest (i.e., supply) based on the interaction of supply, demand, and mobility (Hansen 1959, Shen 1998, Luo and Wang 2003). The measures of spatial accessibility identify the spatial mismatch between supply and demand, which in turn provides an improved understanding of spatial impedance and inequality issues (McLafferty 2015). Particularly, the measures play an important role in decision-making processes (Langford *et al*. 2012, Wan *et al*. 2012, Hu and Downs 2019, Chen *et al*. 2020) because they help policymakers to investigate where additional supply should be provided. Due to these useful policy implications, the approach has been applied to various urban infrastructures, such as healthcare resources (McLafferty *et al*. 2012, Kang *et al*. 2020), food outlets (Widener *et al*. 2013, Chen and Jia 2019), and green space (Dony *et al*. 2015, Xing *et al*. 2018, Liu *et al*. 2021).

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Although the significance of temporal dynamics for enhancing the accuracy of the spatial accessibility measurements (Boisjoly and El-Geneidy 2016, Hu and Downs 2019), it is often neglected to leverage such temporal dynamics for better decision-making. Here, temporal dynamics refer to the use of time-variant data, such as operating hours (Järv *et al*. 2018, Wang *et al*. 2018), floating population (Lee *et al*. 2018, Xia *et al*. 2019), and estimated travel time with traffic congestion (Chen *et al*. 2017, 2020, Wang *et al*. 2018). In specific, Hu and Downs (2019) emphasized that measuring space-time accessibility over 24 hours would provide insightful suggestions for policymaking; however, it is still challenging to identify which particular regions need additional supply at a particular time. It would cause policymakers to provide supplements only for regions with persistent low accessibility and not benefit from the enhanced temporal granularity. Given the importance of allocating limited resources to alleviate the inequality issues of spatial accessibility (Dony *et al*. 2015, Kang *et al*. 2020), it would be a timely matter to examine specific space and time to place supplemental resources.

In this sense, temporal clustering of spatial accessibility over 24 hours would help to address such issues. Clustering methods examine the similarity between/within distributions, assign several units into a small number of clusters, and result in a few distinctive patterns (Rogerson and Yamada 2008, Hohl *et al*. 2016, Yang and Mao 2018, Wu *et al*. 2020). Therefore, temporal clustering would also improve the understanding of remarkable temporal fluctuation of the measures and support policymakers to focus on a particular period of time. Assume that, for example, a temporal clustering of 24-hour spatial accessibility measurement for grocery stores presents three notable patterns (i.e., morning, afternoon, and midnight). This may suggest that policymakers should pay attention to the afternoon cluster and place extra services to regions with limited accessibility at the period, considering people tend to visit grocery stores when returning home from work (Widener *et al*. 2015).

Our study proposes a conceptual framework that takes advantage of temporal changes of spatial accessibility for better policy implications. We first measure 24-hour spatial accessibility (i.e., each hour's spatial accessibility over 24 hours) with Gaussian two-step floating catchment area (G2SFCA) method. We then temporally cluster the measures through K-means clustering method. Finally, we validate the temporal clustering results with Pearson's correlation coefficient. The outcomes of the framework would describe significant temporal transitions of the measures and provide policymakers with a new insight that allocates resources based on space and time. As a case study, we assess spatial accessibility to electric vehicle (EV) charging stations located in Seoul, South Korea, to demonstrate our framework. Sufficient accessibility to public EV charging stations is essential in the city because it is limited to equip private chargers at residential locations due to a high percentage of multi-unit residents. Specifically, our study focuses on the following three research questions: 1) How does spatial accessibility change over 24 hours from the interaction of all time-dependent input variables (i.e., supply, demand, and mobility)? 2) What are the distinctive temporal fluctuations in the 24-hour spatial accessibility measurements that temporal clustering indicates? 3) Which aspect does policy implication benefit from the temporally clustered measures?

4.2. Research framework

Our conceptual framework consists of the following four steps: data preparation, accessibility measurement, temporal clustering, and validation (Figure 4.1). Inspired by the framework of dynamic accessibility modeling (Järv *et al*. 2018), we first populate the temporal dynamics of supply, demand, and mobility based on their corresponding attributes (i.e., operating hours, time-variant distribution of floating population, and estimated travel time with traffic congestion, respectively).

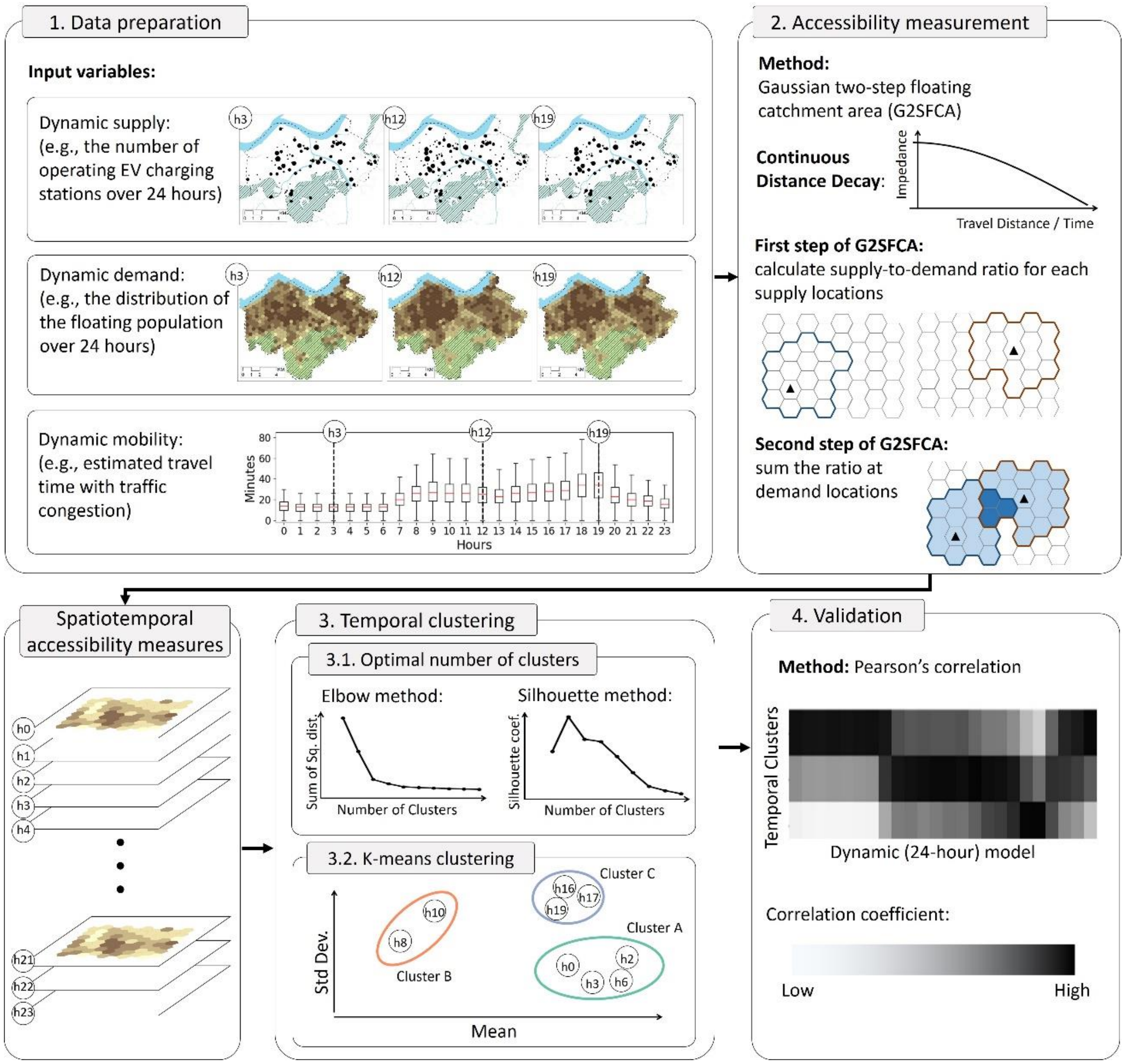


Figure 4.1. A conceptual framework for leveraging temporal fluctuation of spatial accessibility.

Second, we measure 24-hour spatial accessibility using the Gaussian two-step floating catchment area (G2SFCA) method. The method considers the interaction between supply and demand and employs the Gaussian function for continuous distance decay of the mobility (Dai 2010). In detail, the method assesses spatial accessibility in two steps. The first step of G2SFCA calculates the supply-to-demand ratio at each supply location at each hour using the following equation:

$$R_j^h = \frac{S_j^h}{\sum_{k\in\{t_{kj}^h \le t_0\}} D_k^h G(t_{kj}^h, t_0)} \qquad \textbf{Equation 4.1}$$

where *j* and *k* refer to supply location and demand location, respectively; *h* represents an hour out of 24 hours; R_j^h denotes the supply-to-demand ratio at a supply location *j* at hour *h*; S_j^h indicates the supply provided at location *j* at hour *h*; and D_k^h represents the degree of demand at location *k* at hour *h*. $G(t_{kj}^h, t_0)$ illustrates the distance decay function shown in Equation 4.3 and takes the following two variables as input: threshold travel time (t_0) and estimated travel time (t_{kj}^h) from a demand location *k* to a supply location *j* at hour *h*.

The second step of G2SFCA aggregates the accessibility measures at a demand location with the following equation:

$$A_i^h = \sum_{j\in\{t_{ij}^h \le t_0\}} R_j^h G(t_{ij}^h, t_0) = \sum_{j\in\{t_{ij}^h \le t_0\}} \frac{S_j^h G(t_{ij}^h, t_0)}{\sum_{k\in\{t_{kj}^h \le t_0\}} D_k^h G(t_{kj}^h, t_0)} \qquad \textbf{Equation 4.2}$$

where *i* indicates a demand location; A_i^h represents the accessibility measures at location *i* at hour *h*. R_j^h (Equation 4.1) explains the supply-to-demand ratio at supply location *j* at hour *h*, and $G(t_{ij}^h, t_0)$ denotes the distance decay function (Equation 4.3). This step measures the accessibility at location *i* at hour *h* by aggregating the supply-to-demand ratio of each supply location *j* that is accessible from demand location *i* within the threshold travel time (t_0).

Both steps depreciate the influence of supply and demand as the distance increases with distance decay function G. The function G calculates the friction-of-distance based on the Gaussian distribution, which is defined as follows:

$$G(t_{ij,}t_0) = \begin{cases} \dfrac{e^{-\frac{1}{2}*\left(\frac{t_{ij}}{t_0}\right)^2} - e^{-\frac{1}{2}}}{1-e^{-\frac{1}{2}}} & if\ t_{ij} \leq t_0 \\ 0 & if\ t_{ij} > t_0 \end{cases}$$ **Equation 4.3**

where t_{ij} indicates estimated travel time from demand location *i* to supply location *j*, and t_0 refers to the threshold travel time. If the estimated travel time (t_{ij}) is smaller than the threshold travel time (t_0), the distance decay function *G* calculates the distance decay based on the upper equation, otherwise, the function returns in 0. For example, when t_0 is set to 15 minutes, the t_{ij} set to 5 minutes, 10 minutes, and 15 minutes returns 0.8626…, 0.4935…, and 0, respectively.

Third, we take advantage of K-means clustering method to temporally cluster the 24-hour spatial accessibility measurement. This step examines the significant temporal changes in the pattern of spatial accessibility. Among clustering methods (e.g., K-means, Dendrogram, DBSCAN), K-means clustering is one of the uncomplicated but compelling approaches (Jain 2010). The method allocates observations into a predefined K number of clusters based on the distances between the observations (MacQueen 1967). As Wang (2020) exclaimed, spatial accessibility put efforts into the straightforwardness of its method (e.g., the family of two-step floating catchment area).

Given K-means clustering is also straightforward, it would maintain the simplicity of 2SFCA and be suitable for application in accessibility studies.

The quality of K-means clustering is tied to the number of clusters (i.e., K); therefore, we first determine the optimal number of clusters with the elbow method and the silhouette method. The elbow method plots a line graph with the number of clusters as an x-axis and the sum of squared distances as a y-axis and indicates the optimal number of clusters when the slope of the line graph changes the most. Given that the elbow method is a heuristic approach and sometimes provides ambiguous results, it is often supplemented with the silhouette method (Rousseeuw 1987). The silhouette method evaluates the partitioning of distribution using the following formula:

$$S = \frac{1}{N}\sum_{i}^{N} \frac{b(i)-a(i)}{\max\{a(i),b(i)\}} \qquad \textbf{Equation 4.4}$$

where S represents the average silhouette coefficients of current partitioning, N demonstrates the number of points, $a(i)$ is a cohesion indicator of a point i (i.e., distances from point i to all other points in the same cluster), and $b(i)$ is a separation indicator of a point i (i.e., distances from point i to all points in the other clusters). As described, the silhouette method considers both within-cluster variation and between-cluster variation, and a higher average silhouette coefficient (i.e., S) means that the current clustering is well classified.

We then utilize K-means clustering method to classify the each hour's measures, out of 24-hour spatial accessibility measurement, into a predefined number (i.e., K) of temporal clusters (MacQueen 1967; Jain 2010). We locate the 24-hour measures into a two-dimensional plane using the mean and standard deviation of each hour's measures, because the mean and standard deviation represents distributions the most. The objective of K-means clustering method is to minimize the sum of the squared distances between the observations and the centroids of clusters:

$$\sum_{k=1}^{K} \sum_{x_i \in C_k} \|x_i - \mu_k\|^2 \qquad \textbf{Equation 4.5}$$

where x_i and μ_k indicate the locations of observations (i.e., x-coordinate: the mean of each hour's measures; y-coordinate: the standard deviation of each hour's measures) and centroid of a cluster C_k, respectively, and K denotes the number of predefined clusters. The outcome of K-means clustering would summarize the temporal fluctuation in the measures of 24-hour spatial accessibility and demonstrate the notable temporal variation.

Last, we employ Pearson's correlation to examine whether each hour's measurement is properly assigned to its corresponding temporal cluster. For example, assume that temporal clustering allocates 2 p.m. to temporal cluster B. If the correlation coefficient between the measures at 2 p.m. and temporal cluster B shows the highest value, compared to other temporal clusters, it indicates that the hour's measures are properly assigned to a temporal cluster.

4.3. Case study: Accessibility to EV charging stations

To demonstrate the framework, we take EV charging stations in Seoul, South Korea, as a case study. EVs are eco-friendly transportation, so many countries put efforts into promoting their usage (Mahmoudi *et al*. 2019). The usage of EVs is highly correlated with sufficient and easy access to charging stations, and it makes EV owners equip personal chargers in their homes (Lee *et al*. 2019, 2020). However, given the high percentage of multi-unit residents in Seoul, it is not the case. Moreover, insufficient access to EV charging stations is the major barrier to prospective owners (Park, Kim, *et al*. 2017). Therefore, it is highlighted that the accessibility of public EV charging stations is particularly important for Seoul to enhance its sustainability.

4.3.1. Study area and period

Our study area is a section of Seoul (i.e., Seocho-gu, Gangnam-gu, and Songpa-gu) in South Korea (Figure 4.2). It largely consists of both residential and commercial areas. The study period was isolated to January 15, 2020, which is a Wednesday. A weekday was chosen since it was thought to have an increased temporal variation in the floating population (i.e., demand) and mobility. The population density in the study area becomes substantially greater during the daytime due to the influx of commuters. Also, the study area may have increased traffic congestion during rush hour, given its location between the Central Business District (CBD) of Seoul and a large residential area in the suburbs.

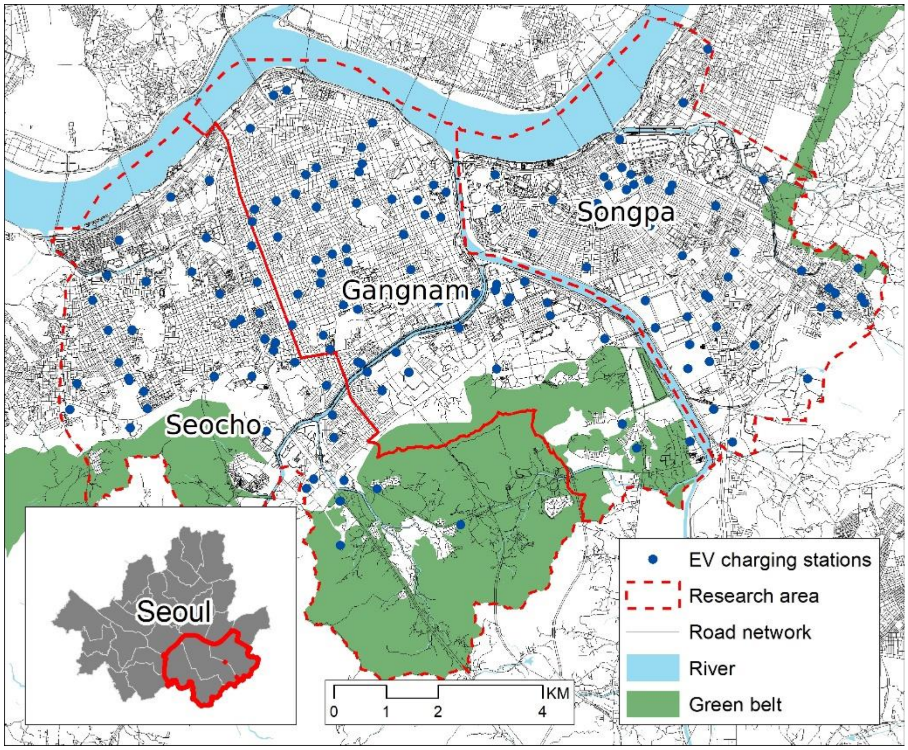


Figure 4.2. Study area.

4.3.2. Data

We employed three major data sources to furnish temporal dynamics in supply, demand, and mobility. First, the information of EV charging stations (i.e., supply) were obtained from Korea Environment Corporation (2020). It provides the locations, operating hours, the number of equipped chargers of EV charging stations. We utilized operating hours to furnish the temporal fluctuation of the supply, provided by operating EV charging stations. Weights of charging stations were applied based on the number and types of chargers that each station has. Considering a fast charger charges ten times faster than a slow charger (Korea Environment Corporation 2020), weights of ten and one were assigned to the faster chargers and slower chargers, respectively. Second, floating population data (i.e., demand) was collected from Seoul Open Data Plaza (Seoul

Metropolitan Government 2020). The data were estimated from the interactions among cell phone transaction data, public transportation usage data, and census data. The floating population is expected to be a more accurate distribution of the population during the daytime (Järv *et al.* 2018) as it includes the non-residential population commuting to Seoul, which is disregarded in the census data. Third, the estimated travel time with traffic congestion (i.e., mobility) was called from iNavi Maps API (https://docs.toast.com/en/Application%20Service/Maps/en/Overview/), which was approximated based on users' empirical wayfinding usage data. To reflect the flow of traveling to supply, the origin and the destination were set to demand locations and supply locations, respectively.

4.3.3. Geographical unit of reference and threshold travel time

We determined 250m hexagons as the geographical unit of reference in the case study. Given that the G2SFCA method assesses spatial accessibility based on the inclusion of the centroid of the geographical unit (Luo and Wang 2003, Dai 2010), the method may be susceptible to have the modifiable areal unit problem (MAUP) (Neutens 2015, Rong *et al*. 2020). Hexagons would alleviate the issue because they have constant distances between the edge and the centroids. We set the size of the hexagons based on the speed limit of non-primary roads within Seoul (i.e., 30km/h); the size of hexagons (i.e., 250m) corresponds to the distance traveled in a minute.

Implementing proper threshold travel time is tied to the accuracy of the spatial accessibility measurements because it reflects people's willingness to travel for service (Chen and Jia 2019). However, the threshold travel time for EV charging stations is under-investigated given the early stage of EVs. Hence, we determined threshold travel time for the 24-hour spatial accessibility measurements with preliminary analysis and utilized it as a sensitivity analysis of our framework. The analysis took various threshold travel times (i.e., 5 minutes, 10 minutes, 15 minutes, 20 minutes, 25 minutes, and 30 minutes) into static G2FCA method (i.e., static variables for supply, demand, and mobility). The result showed that some of the threshold travel times may not be eligible for the 24-hour measurement (Figure 4.3), since they either underestimated (i.e., 5 minutes) or overestimated (i.e., 25 minutes and 30 minutes) the size of the catchment area. 5-minute threshold travel time produced an excessive number of hexagons with low accessibility, indicating the threshold travel time should be enlarged. In contrast, 25-minute and 30-minute threshold travel times produced monotonous distribution, indicating the threshold travel time should be reduced.

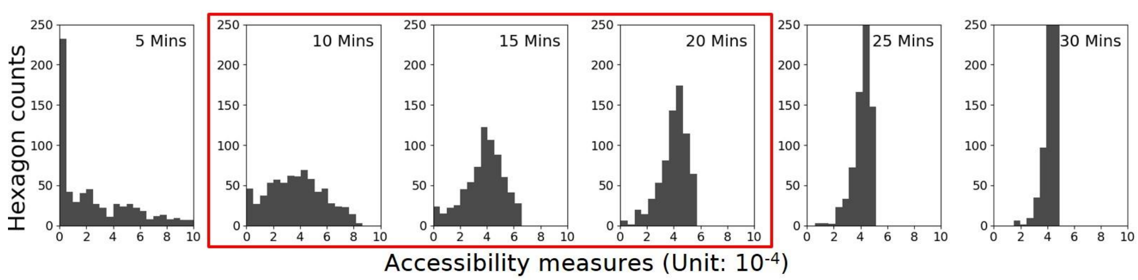


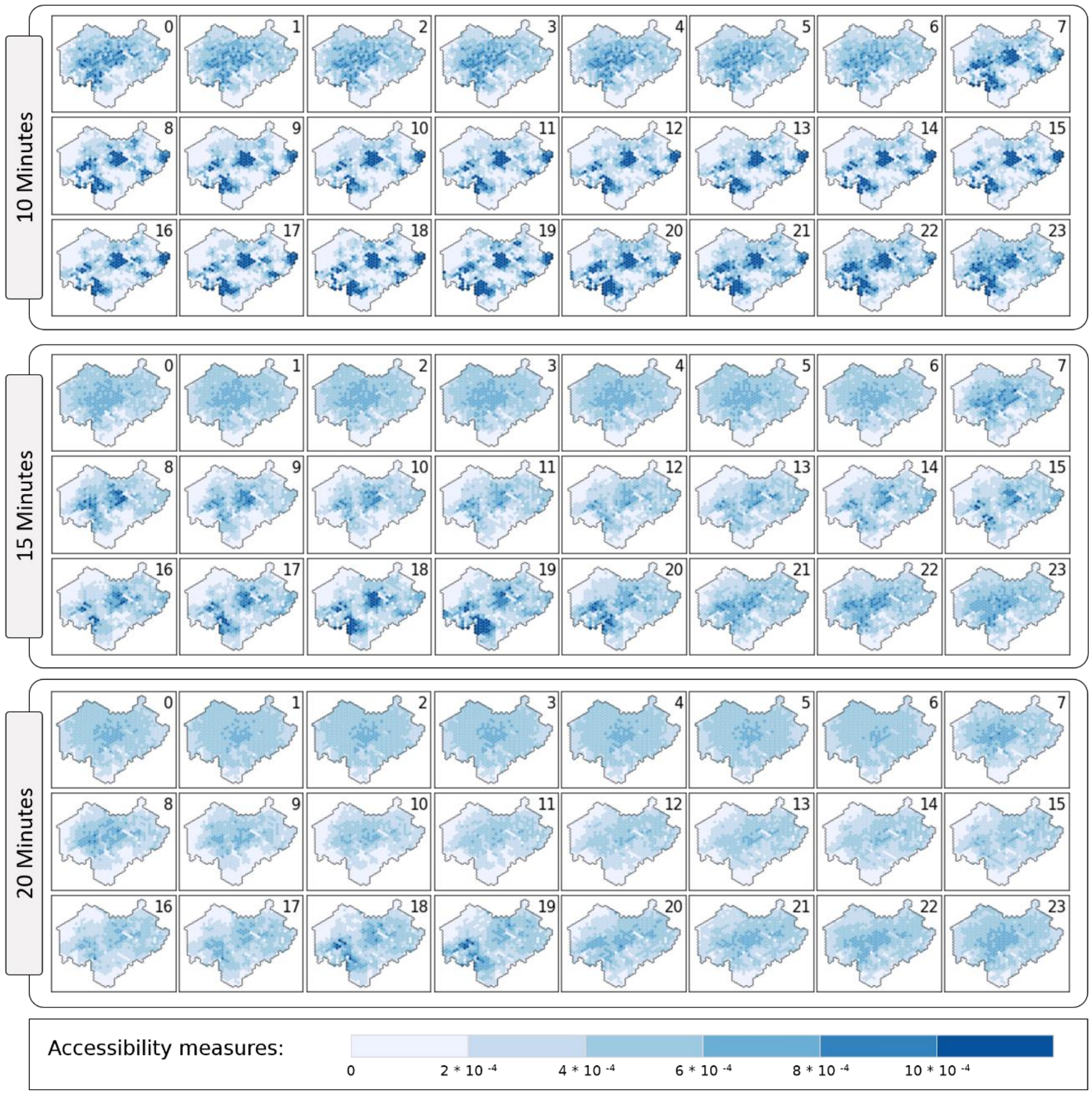
Figure 4.3. A preliminary analysis to determine the proper threshold travel times.

4.4. Results

4.4.1. Measuring 24-hour spatial accessibility

The spatial accessibility to EV charging stations dynamically varied both spatially and temporally over 24 hours, regardless of different threshold travel times (i.e., 10 minutes, 15 minutes, and 20 minutes). Hexagons with high value were spatially clustered at specific hours, as shown in Figure 4.4. In other words, the accessibility measures were not significantly different in nighttime, whereas the inequality in accessibility increased in daytime.

With shorter threshold travel time, the measures tend to be more spatially clustered. Specifically, spatial clusters of 10-minute threshold travel time measurement were noticeably presented from 7 to 23 time period. In 15-minute threshold travel time measurement, the spatial clusters were shown at the following hours: 8, 9, 16, 17, 18, and 19. Spatial clusters of 20-minute threshold travel time measurement were presented at only 18 and 19.



* Note: The numbers in the panel represent the hours when the measurements were taken.

Figure 4.4. Spatial distribution of 24-hour spatial accessibility measures.

4.4.2. Temporal clustering

The results from both elbow and silhouette methods indicated that three clusters are optimal for temporal clustering for every measurement (Figure 4.5). The elbow method produced a decreasing trend; the sum of the squared distances (i.e., y-axis) decreased as the number of clusters (i.e., x-axis) increased. The obvious slope change points of the elbow method were at three clusters (i.e., 10 minutes: -12.84 to -1.83, 15 minutes: -3.83 to -0.58, 20 minutes: -1.77 to -0.26). The silhouette method also resulted in the highest average silhouette coefficients at three clusters: 0.65, 0.65, and 0.64 for 10-minute, 15-minute, and 20-minute threshold travel times, respectively.

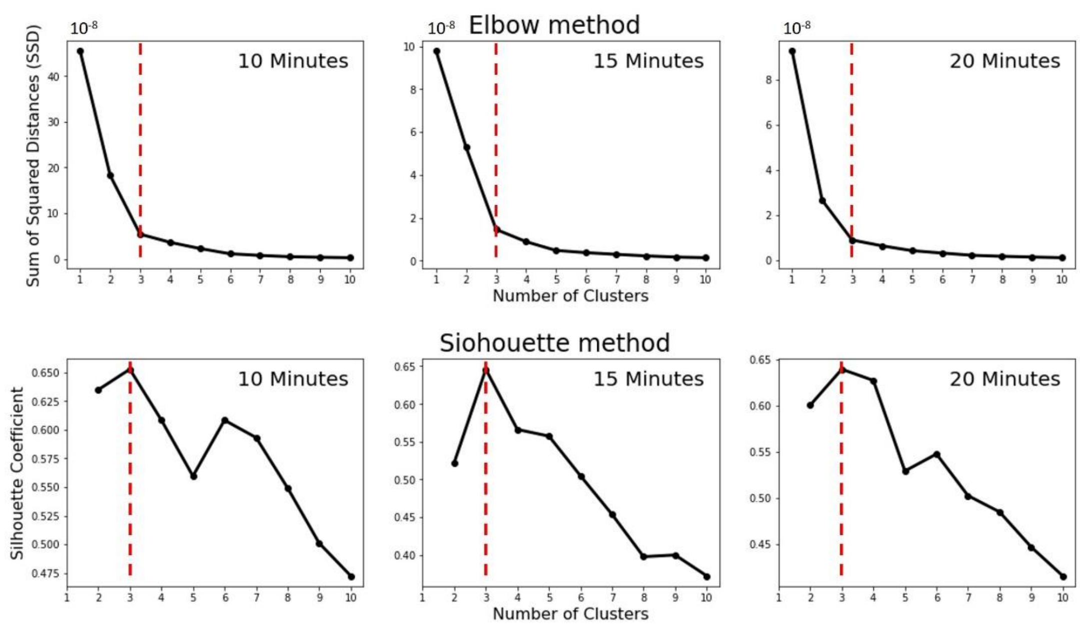
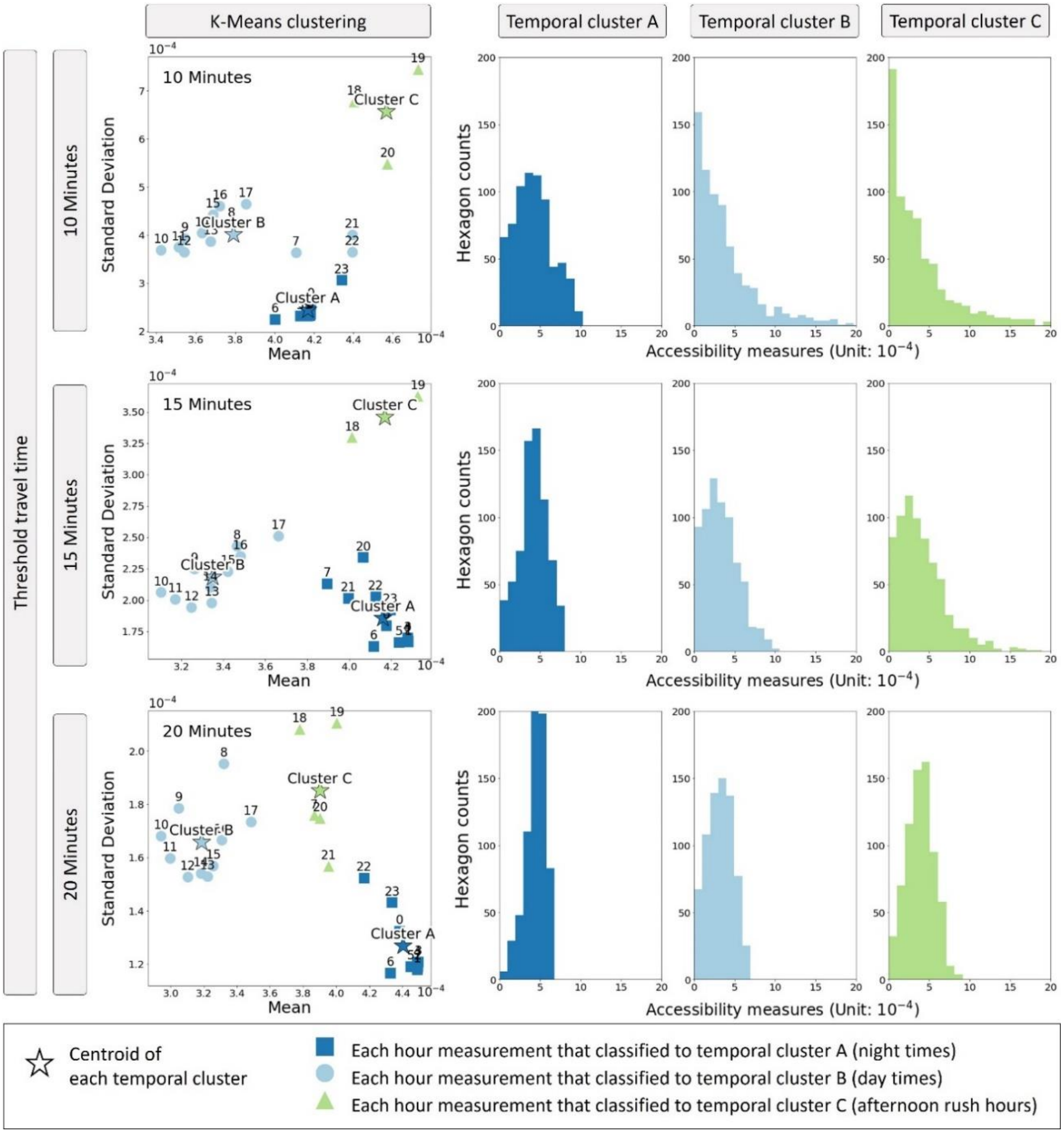


Figure 4.5. Determining the optimal number of temporal clusters.

K-means clustering allocated the hours of 24-hour spatial accessibility measurements into three temporal clusters as shown in Figure 4.6: temporal cluster A (named nighttime cluster), temporal cluster B (named daytime cluster), and temporal cluster C (named afternoon rush hour cluster). Since the accessibility measures were distributed on a microscopic scale, we defined the scales of the x-axis (i.e., mean of each hour's measurement) and the y-axis (i.e., standard deviation of each hour's measurement) as 10-4 for better representation. Despite the disparity in distributions, the clustering results for three threshold travel time measurements were largely similar. Temporal cluster A had high mean and low standard deviation. Low mean and moderate standard deviation were showed in temporal cluster B. Temporal cluster C presented high mean and high standard deviation.

Histograms demonstrated distinctive distribution for each temporal cluster (Figure 4.6). The histogram was drawn from the mean of accessibility of the hours associated with a temporal cluster. For example, in histogram, the temporal cluster A of 10-minute threshold travel time measurement were calculated from the mean of accessibility from 11 p.m. to 6 a.m. Histograms of each temporal cluster A (i.e., nighttime cluster) were close to the normal distribution, presenting equalized accessibility across the study area. In contrast, histograms of each temporal cluster B (i.e., daytime cluster) and cluster C (i.e., afternoon rush hour cluster) were right-skewed. This illustrated notable inequality of accessibility during daytime and afternoon rush hour, that many hexagons had limited accessibility whereas only some hexagons had sufficient accessibility.



* Note: (Clustering) the numbers in each plot indicate the hour the measurement is taken. (Histogram) Extreme accessibility measures beyond 20*10-4 are omitted.

Figure 4.6. Results of temporal clustering and corresponding histograms.

Each temporal cluster presented different spatial distributions, regardless of threshold travel times (Figure 4.7). X, Y, and Z in Figure 4.7 denoted the Central Business District (CBD), greenbelt, and a park, respectively. Temporal cluster A showed the spatial distribution of accessibility gradually decreased from the center of study area to the peripheral regions. Especially, CBD (X) had moderate accessibility. Temporal clusters B and C indicated a significant inequality in accessibility. Only a few locations presented sufficient accessibility (e.g., greenbelt (Y) and park (Z)), whereas people in most regions had the limited accessibility to EV charging stations.

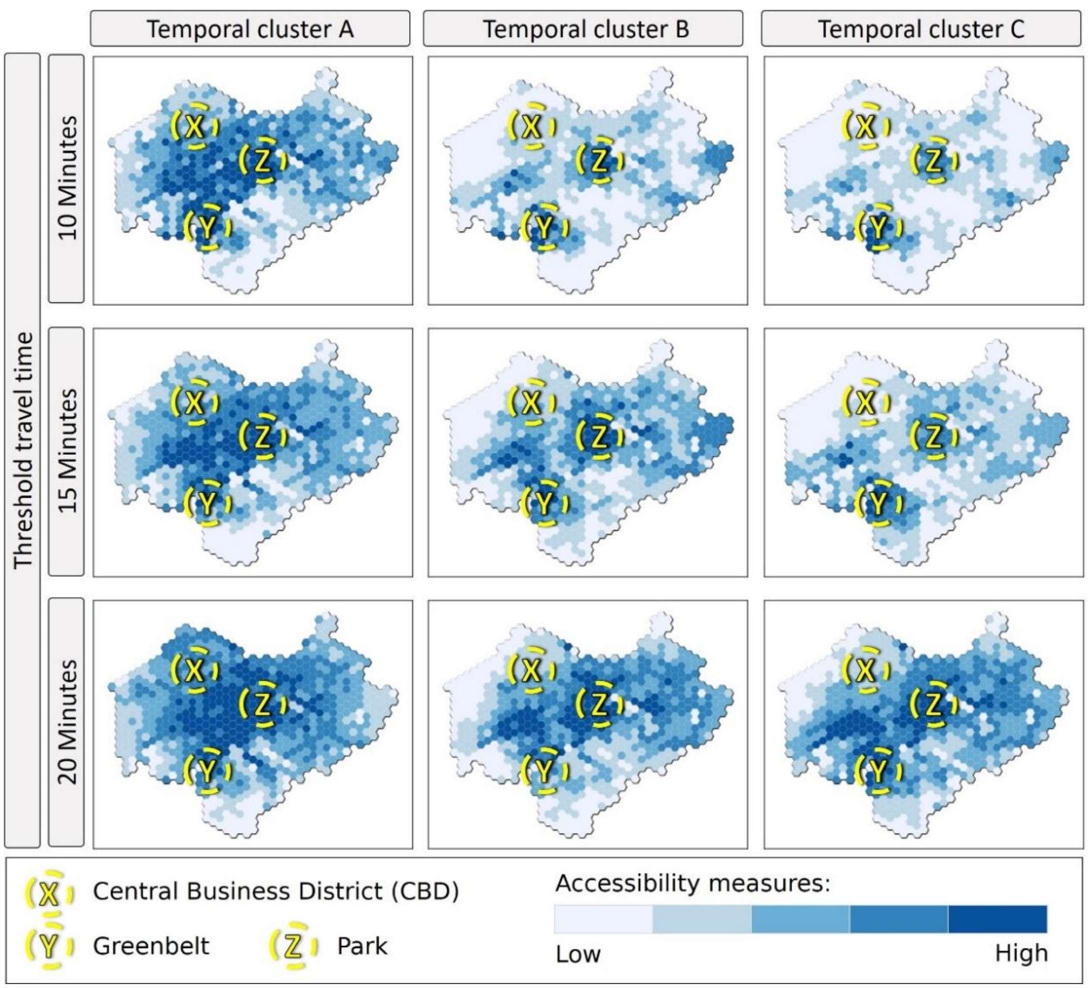
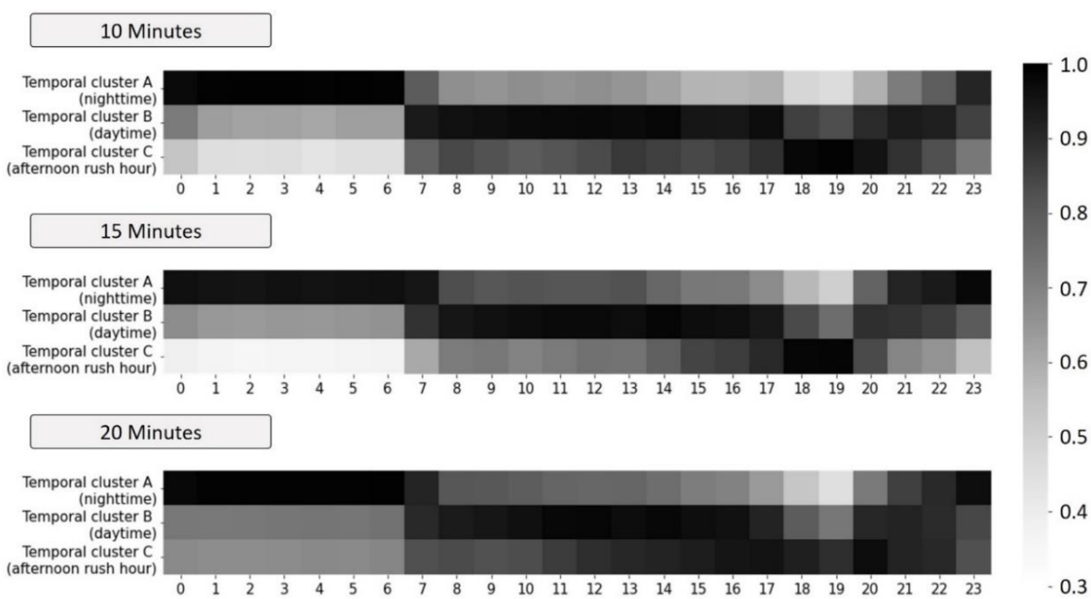


Figure 4.7. Spatial distribution of the measures of each temporal cluster.

4.4.3. Validation

The correlation analysis between the measures of temporal clusters and the measures of 24-hour spatial accessibility validated the clustering results (Figure 4.8). The measures of each cluster were highly correlated with the measures at its associated hours (i.e., $r > 0.9$), whereas they had relatively low correlation coefficient with the measures of other hours (i.e., $r < 0.5$). For instance, the correlation coefficients at the hours (from 8 a.m. to 5 p.m.; temporal cluster B of 15-minute threshold travel time measurement) with temporal cluster A, B, and C were ranged from 0.677 to 0.831, from 0.942 to 0.984, and from 0.699 to 0.904, respectively. As the hours showed the highest correlation coefficient with their assigned temporal cluster, it proved that temporal clustering properly allocated the measures of 24-hour spatial accessibility.



* Note: Every Pearson's correlation analysis is significant at level of 0.01, and the brightness of each cell indicates the correlation coefficient (Pearson's r).
Figure 4.8. Correlation analysis between the measures of temporal clusters and the measures of 24-hour spatial accessibility.

4.5. Discussion

Our conceptual framework could facilitate better decision-making on infrastructure allocation. As our result shows, 24-hour spatial accessibility measurements can be summarized into a few temporal clusters. Namely, the temporally clustered measures can point out a particular space and time requiring additional supply. For example, the spatial accessibility in the case study fluctuated as of the three temporal phases (i.e., nighttime, daytime, and afternoon rush hour). Considering people tend to use public EV charging stations from 12 p.m. to 5 p.m.(Park, Jeon, *et al*. 2017), the measures of temporal cluster B would be more prioritized than others in the context of decision-making. This would address a potential vagueness granted from the 24-hour measurements and may recommend the regions near the CBD for placing supplementary EV charging stations.

In addition, the framework could be beneficial in examining the attributes (i.e., inequality and spatial mismatch) of spatial accessibility focusing on a particular time period. As the temporally clustered measures represent the accessibility of a series of hours, it would support further investigation of how the interaction of inputs (i.e., supply, demand, and mobility) impacts the temporal fluctuations of the measures. In our case study, the sufficient and equalized accessibility of the nighttime cluster (i.e., temporal cluster A) may be attributed to low supply, low demand, and high mobility. High mobility facilitated people to travel further to access EV charging stations and alleviated the negative impact of most non-24-hour charging stations operated from 9 a.m. to 5 p.m. However, daytime cluster (i.e., temporal cluster B) illustrated insufficient and imbalanced accessibility, due to the interaction among high supply, high demand, and low mobility. Whereas most EV charging stations were operating, high demand (i.e., the influx of commuters) caused high competition of supply, and low mobility deteriorated access to peripheral charging stations, especially near the CBD (marked X in Figure 4.7). Low supply, high demand, and low mobility may be responsible for the inequality of accessibility intensified in the afternoon rush hour cluster (i.e., temporal cluster C). While high demand and low mobility persisted, most non-24-hour EV charging stations were closed after 5 p.m.

The proposed framework can be applied to any type of infrastructure and region. With the improved availability of time-sensitive data, previous studies have expanded the temporal granularity of spatial accessibility to diverse domains, such as healthcare resources (Chen *et al*. 2020, Wang *et al*. 2020) and food outlets (Chen *et al*. 2017, Wang *et al*. 2018). In this context, our study would contribute by extracting meaningful information from spatial/spatiotemporal/space-time accessibility measurements. For instance, our framework is applicable to synthesize the 24-hour variation of emergency medical service accessibility (Xia *et al*. 2019). On top of the enhanced accuracy with the 24-hour spatial accessibility measurements, our framework would provide a better understanding of accessibility issues persisting for a particular time period. To be specific, the framework would tackle potential issues by demonstrating the notable changes of spatial accessibility, identifying a particular space and time with limited access, and proposing locations to place additional infrastructures.

4.6. Conclusion

Our study proposes a conceptual framework for leveraging temporal changes of spatial accessibility to furnish better policy implications. With temporal clustering, our framework helps in extracting valuable implications from spatial accessibility measurements, which is potentially voluminous to examine temporal variation of the measures. As demonstrated in the case study, our framework synthesizes the 24-hour spatial accessibility measurements into a few distinctive temporal clusters, which in turn improve the understanding of temporal fluctuations of accessibility and facilitate policymaking of infrastructure allocation. Therefore, our finding shows that temporal clustering would provide an insight for policy implications, whereas 24-hour measurements may be redundant and superfluous. Our study extensively contributes to forthcoming accessibility studies by proposing a new framework to comprehend temporal changes embedded in their measures.

Our study has limitations. First, the empirical usage data of EV charging station was not utilized in our analysis. Unlike other facilities (e.g., hospital; Wang 2020), it is challenging to keep track of a user's origin (i.e., demand location) traveling to a supply facility, in the case of EV charging stations. Second, we only considered a single temporal clustering method. Given that different clustering methods may not provide identical results (Jain 2010), our result may vary according to clustering method. Our next step is to measure spatial accessibility to EV charging stations using empirical data, once the data is available. With the empirical data, it would also be worthwhile to investigate which clustering method would be more suitable for our framework.

5. AN APPROACH TO ENHANCE THE REPRODUCIBILITY OF TEMPORAL CHANGES IN SPATIAL ACCESSIBILITY: PRIORITIZING THE TEMPORAL DYNAMICS OF SUPPLY, DEMAND, AND MOBILITY

5.1. Introduction

Measurement of 24-hour changes in spatial accessibility is critical to enhancing the accuracy of measurements (Hu & Downs, 2019; Järv *et al*., 2018). It not only improves the temporal granularity of spatial accessibility measurements but also uncovers the temporal dynamics of accessibility within a day, which may not be taken into account in the conventional measurement based on deterministic variables (Park *et al*., 2021). In addition, it promotes the policy implications of spatial accessibility measurement. In general, spatial accessibility improves the understanding of spatial inequality of access and proposes locations that require additional infrastructures (Kang *et al*., 2020; Neutens, 2015). Owing to enhanced temporal granularity, 24-hour measurements of spatial accessibility are useful in examining how spatial disparity of access changes over time and identifying a specific space and time for placing additional resources (Järv *et al*., 2018; Park *et al*., 2021).

With the recent advancements in computational platforms and big data analysis methods (Griffith, 2021), the enhanced granularity of time-dependent variables facilitates the examination of temporal changes in spatial accessibility (Boisjoly & El-Geneidy, 2016; Hu & Downs, 2019). In spatial accessibility measurements, supply, demand, and mobility are treated as input variables, and their interactions are considered in the assessment of the ease of access to an infrastructure of interest. The current approaches used time-variant attributes such as operating hours (Järv *et al*., 2018; Y. Wang *et al*., 2018), floating population (Järv *et al*., 2018; Lee *et al*., 2018; Xia *et al*., 2019), and estimated travel time (Chen *et al*., 2017, 2020; Y. Wang *et al*., 2018) to represent temporal changes of supply, demand, and mobility, respectively. The operating hours of supply facilities depict that people only can access and obtain service when facilities are open (Park & Goldberg, 2021). The demands represented with the floating population illustrates that people want to obtain services not only from their residential locations but also from their schools or jobs (Lee *et al*., 2018). The estimated travel time indicates that the travel costs between two locations could significantly differ within a day according to the time-dependent congestion (Chen *et al*., 2020; Sahebgharani & Haghshenas, 2021).

Despite the substantial benefit of improved temporal granularity, the limited availability of time-dependent variables restricts broader applications (Neutens, 2015). Time-dependent data are only available in a few locations. For example, Uber movement data (https://movement.uber.com/), which provide time-dependent mobility and have been utilized for numerous studies on geographic information systems, are only available for 13 cities in the United States. In addition, the floating population are difficult to identify because of privacy concerns, as their data are frequently obtained by tracing GPS (global positioning system)-enabled devices (Park *et al*., 2021). Therefore, full implementation of time-dependent variables could be practically challenging; thus, it has been a constraint in the incorporation of temporal dynamics in previous studies and reduced the accuracy of measurements. To our knowledge, only two previous studies considered all the temporal dynamics of spatial accessibility measures (Järv *et al*., 2018; Park *et al*., 2021). Most studies were limited to incorporating several temporal dynamic variables into the measurements of demand (Lee *et al*., 2018; Xia *et al*., 2019), mobility (Chen *et al*., 2020), supply and demand (Hu & Downs, 2019), or supply and mobility (Y. Wang *et al*., 2018).

To enhance the reproducibility and expand the applications of spatial accessibility studies, the limited availability of time-dependent variables should be overcome. While the commercial data on temporal dynamics have been claimed to have high accuracy, the temporal changes in supply, demand, and mobility could be estimated with public data such as census data. For example, Census Transportation Planning Products (CTPP) provides commute information with the residential and work locations of people; thus, this data set could be used to estimate the commuter-adjusted population (Hu & Downs, 2019; Kobayashi *et al*., 2011). In addition, taxi or for-hire vehicles in big cities share their historical travel time information, which is an excellent sample data set for predicting the entire mobility pattern throughout a day (Chen *et al*., 2020). Not only the time-dependent information obtained from public data sets but also three inputs (i.e., supply, demand, and mobility) prioritized according to their contributions to temporal changes could be useful for facilitating the examination of temporal dynamics of measures. Given that the input variables may show different patterns over 24 hours, they may have various weights on the prediction of the temporal changes of spatial accessibility granted from the full implementation.

To address the issue, our study used publicly available data sets and examined the importance of temporal dynamics for each input (i.e., supply, demand, and mobility) in the case of accessibility to healthcare resources in New York City. Specifically, we conducted a sensitivity analysis with eight scenarios of inputs (i.e., every possible combination of the dynamic or static forms of three input variables) that are required by the two-step floating catchment area (2SFCA) method (Luo & Wang, 2003; F. Wang, 2012). For example, in the first scenario, all variables were taken in their static forms, and in the eighth scenario, all the variables were taken in their dynamic (time-dependent) forms. We then compared the measures of spatial accessibility produced by the eight scenarios to determine the priority of temporal dynamics that each variable possesses. When the correlation coefficient between a scenario and the complete set of time-dependent variables (i.e., scenario 8) is high, the variables implemented in the scenarios would be critical for estimating temporal changes. Furthermore, we investigated the period that was likely to have a spatial accessibility that could not be predicted if the time-dependent variables are partially incorporated. Our study was conducted to address the following research questions: 1) How can the temporal dynamics of spatial accessibility be estimated with a broadly available data set (e.g., census data)? 2) Which input should be prioritized to maximize the accuracy of measurement from the limited availability of time-dependent data? 3) Which hour is the most susceptible, resulting in low accuracy, if the time-dependent variables are partially implemented?

5.2. Analytical framework

Our analytical framework consisted of the following three steps (Figure 5.1): data preparation, sensitivity analysis, and correlation analysis. The first step was to populate the temporal dynamics of the input variables (i.e., supply, demand, and mobility) and determine their static forms from publicly available data sets. We estimated the 24-hour variations of supply, demand, and mobility on the basis of their operating hours (Y. Wang *et al*., 2018), commuter-adjusted population (Kobayashi *et al*., 2011), and historical travel time of taxi trip records (Gong *et al*., 2020), respectively. In detail, the time-dependent supply was determined on the basis of the operating hours of each healthcare resource, as people may not obtain services when facilities are closed. We also considered commute to estimate the floating population, given that commute takes a significant portion of the daily movement of people. The temporal dynamics of mobility were granted from the taxi trip data, as these are a good sample to represent time-dependent traffic congestion. In the meantime, we defined the static forms of the three inputs as follows: The static form of supply was defined as all healthcare resources open for 24 hours, regardless of individualized operating hours. The static demand was defined as the residential population, assuming that people travel to the facility only from their homes. Static mobility was computed with a network data set obtained from OpenStreetMap (OSM), presuming no traffic congestion throughout a day.

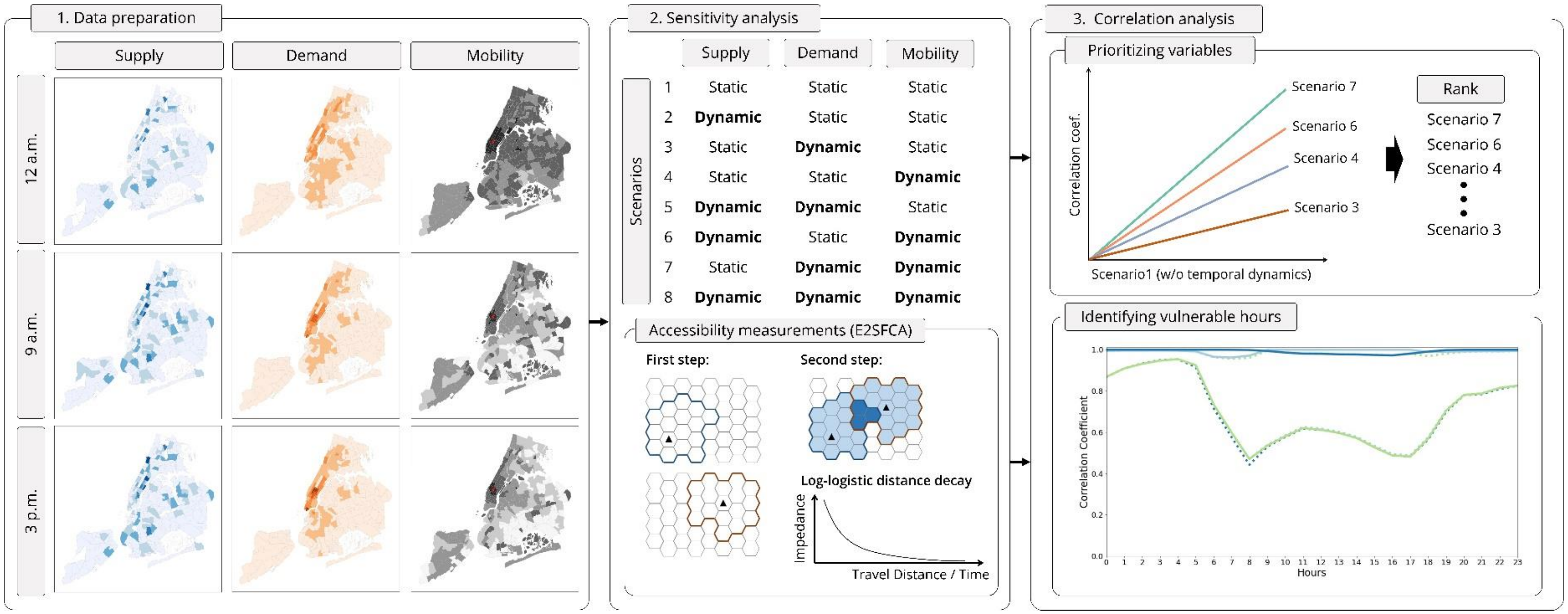


Figure 5.1. Analytical framework

The second step is the sensitivity analysis of spatial accessibility measurements based on eight scenarios that take either the static or dynamic inputs. To determine the impacts of the dynamic variables on the measures of spatial accessibility (i.e., 2SFCA method), we defined eight scenarios, representing every possible combination of static or dynamic use of the three inputs (i.e., supply, demand, and mobility) (Figure 5.1). In detail, scenario 1 used only the static variables, scenarios 2–4 used one dynamic variable and two static variables, scenarios 5–7 used two dynamic variables and one static variable, and scenario 8 represented the use of all dynamic variables.

With these combinations of inputs, we measured the spatial accessibility to healthcare resources in New York City with the enhanced 2SFCA method (Delamater *et al.*, 2013; Luo & Qi, 2009). The method is the best-known approach for spatial accessibility measurement (Luo & Wang, 2003; F. Wang, 2012) and has been applied for various urban infrastructures such as healthcare resources (Kang *et al.*, 2020), job opportunities (Hu & Downs, 2019), and service utilities (Fu *et al.*, 2017). As its name implies, the 2SFCA method consists of two steps. In the first step (Equation 5.1), the local supply-to-demand ratio of each supply facility is calculated. In the second step (Equation 5.2), the supply-to-demand ratios of the facilities that are accessible from each demand location are summed. Given that our study focused on the temporal changes of spatial accessibility, we appended the time variable (t) at each input, defining each step as follows:

$$\mathrm{R}_j^t = \frac{S_j^t}{\sum_{k\in\{d_{kj}^t \leq d_0\}} D_k^t f(d_{kj}^t)}$$ **Equation 5.1**

$$A_i^t = \sum_{j \in \{d_{ij}^t \leq d_0\}} R_j^t f(d_{ij}^t) = \sum_{j \in \{d_{ij}^t \leq d_0\}} \frac{S_j^t f(d_{ij}^t)}{\sum_{k \in \{d_{kj}^t \leq d_0\}} D_k^t f(d_{kj}^t)}$$ **Equation 5.2**

where A_i^t and R_j^t represent the accessibility and local supply-to-demand ratio of locations *i* and *j* at hour *t*, respectively. S_j^t denotes the degree of supply facility (e.g., the number of physicians) at location *j* at hour *t*, D_k^t refers to the degree of demand (e.g., the number of people) at location *k* at hour *t*, d_{kj}^t is the travel cost from location *k* to location *j* at hour *t*, and $f()$ is the distance-decay function to depreciate the value of supply and demand based on travel cost.

In our implementation, we specified the threshold travel time and distance-decay function as 60 minutes and log-logistic function, respectively. While the E2SFCA method uses the Gaussian function with a 30-minute threshold travel time to estimate the travel behavior of people accessing healthcare resources (Ghorbanzadeh *et al*., 2021; Luo & Qi, 2009), the log-logistic function with a 60-minute threshold travel time provided a more accurate prediction (Delamater *et al*., 2013; Jia *et al*., 2017). In detail, we divided the 60-minute catchment area into 10 subzones based on travel times (5, 10, 15, 20, 25, 30, 35, 40, 45, and 60 minutes) and assigned corresponding weights (0.946, 0.754, 0.551, 0.340, 0.296, 0.226, 0.177, 0.142, 0.116, and 0.083, respectively).

In the third step of the analytical framework, the Pearson correlation analysis was used to determine the priority of temporal dynamics in inputs and investigate which hours are likely to provide low accuracy in partially implementing time-dependent variables. To be specific, the first correlation analysis investigated the relationship between each scenario (i.e., scenarios 1–7; partial implementation of dynamic variables) and scenario 8 (i.e., the full implementation of dynamic variables). The correlation coefficient indicated if or how each scenario was impacted by missing dynamic variables. For example, if scenario 4 provided a higher correlation coefficient than did scenarios 2 and 3, the dynamic variable implemented in scenario 4 (i.e., mobility) would be essential to investigate the temporal changes in spatial accessibility. Thus, the temporal dynamics in mobility would be prioritized over the inputs used in the other scenarios (i.e., scenario 2: supply and scenario 3: demand). The second correlation analysis further examined the correlations of each hour between each scenario and scenario 8. If scenario 5 results in a low correlation coefficient during the daytime, this indicates that the dynamic variables implemented in the scenario (i.e., supply and demand) were not effective enough to predict the temporal changes during the daytime, and the dynamic variable omitted in the scenario (i.e., mobility) would be critical to complement the gap.

5.3. Study area and data

We measured spatial accessibility to healthcare resources in New York City (Figure 5.2). Given that the location had a high fatality rate from the COVID-19 pandemic, the importance of sufficient hospital access should be acknowledged. The study area consists of five counties (New York, Bronx, Queens, Kings, and Richmond), 29,678 physicians (i.e., 11,749 healthcare facilities), and 8,457,737 residents. Both hospitals and residents were concentrated in New York County (i.e., Manhattan borough) but had the lowest densities in Richmond County (i.e., Staten Island borough). In addition, we selected the neighborhood tabulation area (NTAs) as the geographic unit of analysis because it was the finest geographical unit where all variables were available time-dependently.

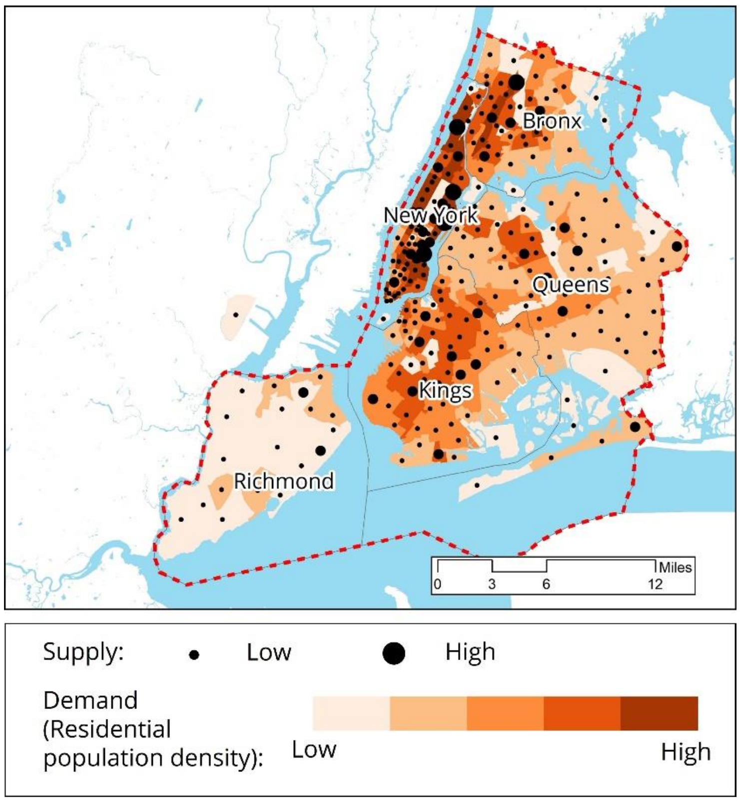


Figure 5.2. Study area

We used the following three databases to obtain the geospatial information of supply, demand, and mobility. First, we used Data Axle Reference Solutions (https://referenceusa.com/) to get the addresses and numbers of hospital physicians and summed their numbers for each neighborhood tabulation area (NTA). Second, we used data from the American Community Survey (ACS) to obtain the number of residents in each census tract and aggregate it for NTAs. Third, we took advantage of OSM to calculate the travel time from the centroid of demand NTA to the centroid of supply NTA.

While the three data sets represent static supply, demand, and mobility, we also used three additional databases to populate their temporal dynamics (Table 5.1). First, the operating hour information of each hospital (i.e., dynamic supply) was retrieved from Google Maps API, with Wednesday as the day of reference, given that operating hours may differ within a week. If the operating hour information was missing, we assumed the healthcare facility was open from 9:00 am to 5:00 pm, as these were the most common operating hours within the study area. Second, the time-dependent demand was calculated on the basis of the commuter information obtained from CTPP. It provides information on the time and number of workers leaving their residential locations and arriving at work, thereby enabling the computation of the commuter-adjusted population (Kobayashi *et al*., 2011). Third, dynamic mobility was estimated on the basis of taxi and for-hire vehicle (e.g., Uber) trip records. The trip data stored information on travel time and the distance between the NTAs of each transaction. We collected the travel records for May 2019, and missing information was filled with travel time calculated with OSM.

Table 5.1. Static and dynamic forms of inputs

	Supply	Demand	Mobility	Geographic unit
Static	Every health care	Residential population	Travel time via OSM network	Neighborhood tabulation areas (NTAs)
Dynamic	Time-variant operating health care	Commuter-adjusted population	Taxi trip records between NTAs	

5.4. Results

The temporal changes of accessibility measurements in the eight scenarios were divided into two groups (Figure 5.3). The first group included scenarios 2, 3, and 5, and their temporal changes were close to scenario 1 (i.e., static measurement). They showed high accessibility in New York County (Manhattan borough) and poor accessibility in Richmond County (Staten Island borough), which is the pattern often explained with the conventional accessibility measurements. Negligible temporal changes were observed; accessibility measures only differed for a couple of NTAs in New York and Queens counties. On the other hand, the second group consisted of scenarios 4, 6, and 7 and provided significant temporal changes in the accessibility measures close to scenario 8 (i.e., full dynamic measurement). While their accessibility measures at 3:00 a.m. showed a similar pattern with the conventional measurement (i.e., high value in the center and low value in the peripheral locations), the spatial distribution of measures at 9:00 a.m., 2:00 p.m., and 8:00 p.m. varied substantially. In detail, the accessibility at 9:00 a.m. and 2:00 p.m. were spatially dispersed, illustrating high accessibility not only in New York

County but also in Queens and Kings counties. The accessibility at 8:00 p.m. indicated that high values were more clustered in New York County.

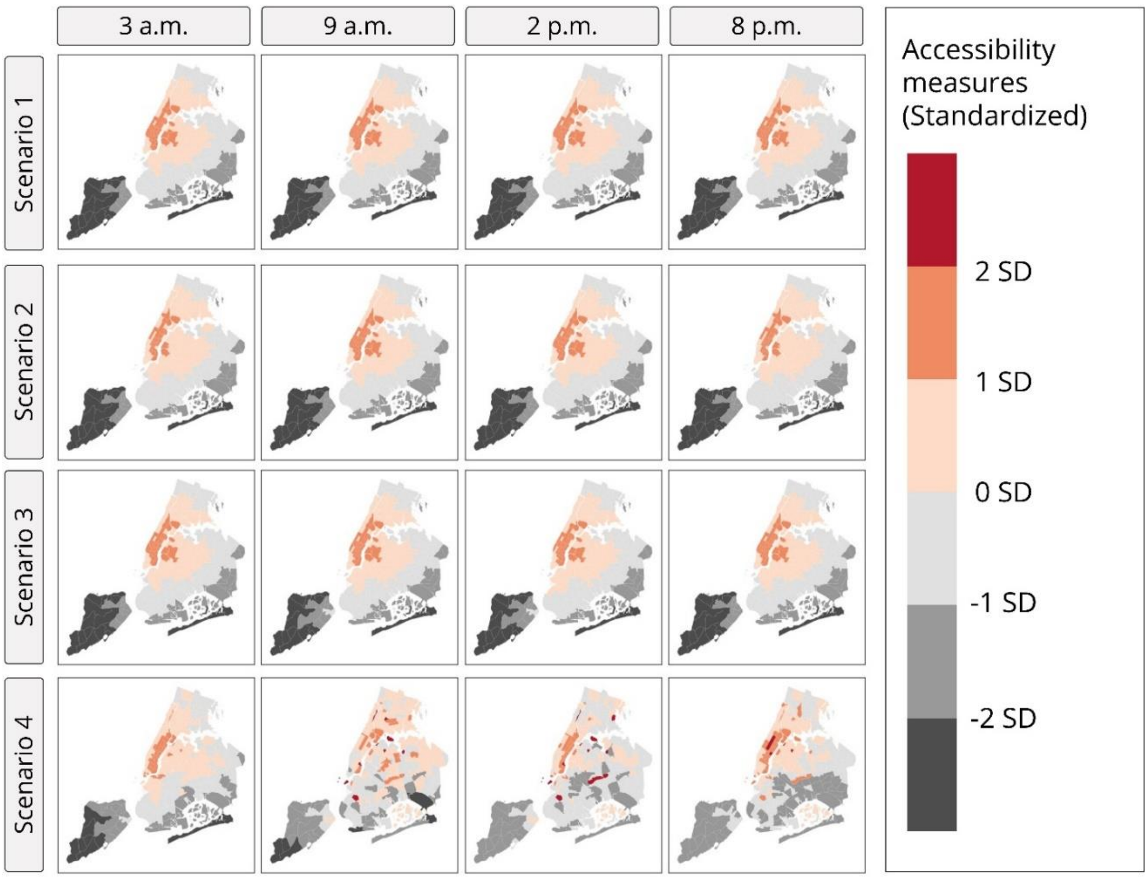


Figure 5.3. Temporal changes in the accessibility measures for the eight scenarios.

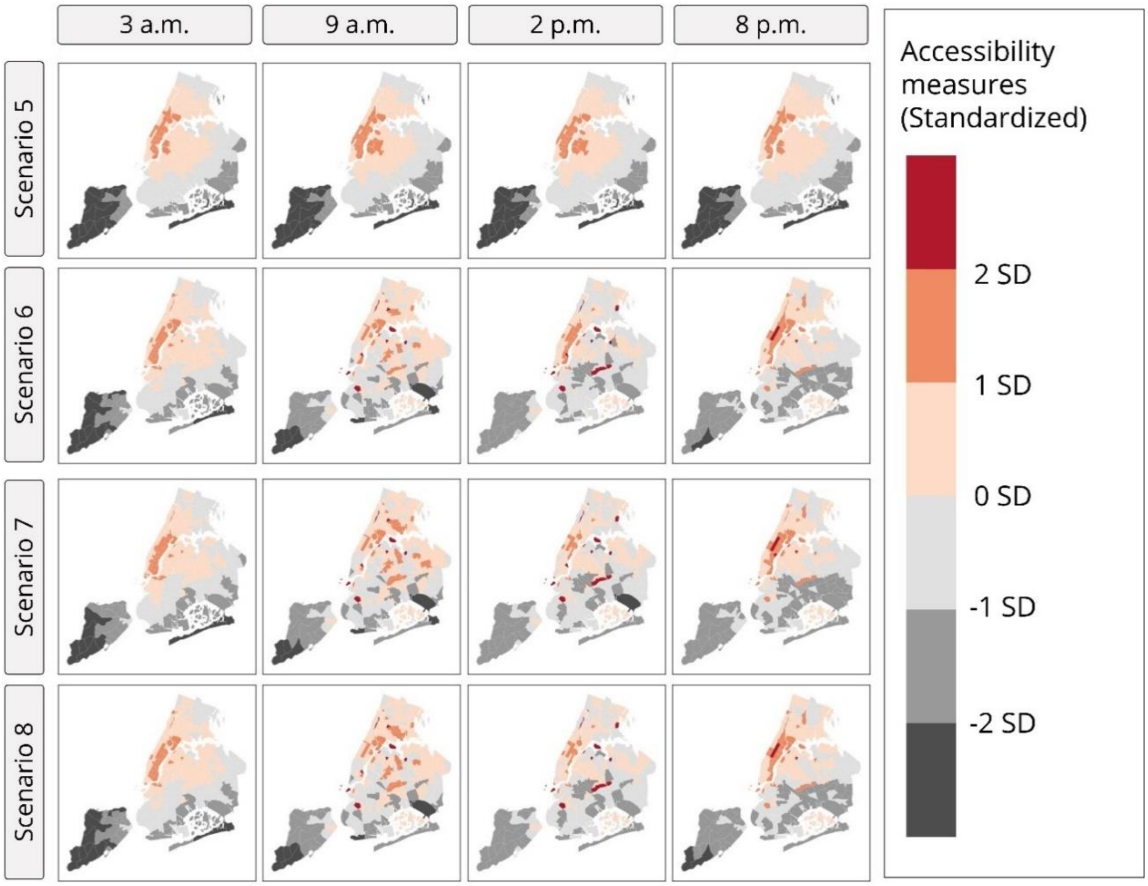


Figure 5.3. Continued.

The correlation analysis between scenarios 1–7 and scenario 8 (Table 5.2) resulted in high correlation coefficients with scenarios 4, 6, and 7 ($r > 0.9$; $p \leq 0.05$) and low correlation coefficients with scenarios 2, 3, and 5 ($r < 0.7$; $p \leq 0.05$). The analysis provided high correlation coefficients in the following order: scenarios 7 (0.991), 6 (0.99), 4 (0.979), 2 (0.679), 5 (0.676), and 3 (0.669). To be specific, the scenarios with time-dependent mobilities (i.e., scenarios 4, 6, and 7) produced substantially higher correlation coefficients, whereas the scenarios with static mobilities (i.e., scenarios 2, 3, and 5) presented lower correlation coefficients. Scenario 3 (i.e., static supply, dynamic demand, and static mobility) had a lower correlation coefficient than the scenario with static measurement (i.e., scenario 1 [0.672]). In addition, the correlation analysis result proved the spatial pattern of accessibility provided by each scenario. Scenarios 2, 3, and 5 presented a pattern similar to that of scenario 1 (i.e., static measurement); however, the temporal changes of accessibility of scenarios 4, 6, and 7 aligned with those of scenario 8 (i.e., full dynamic measurement).

Table 5.2. Correlation analysis between scenarios 1–7 and scenario 8

Scenario	Correlation coefficient	Rank
1	0.672	6
2	0.679	4
3	0.669	7
4	0.979	3
5	0.676	5
6	0.99	2
7	0.991	1

Further correlation analysis of each hour accessibility measurement between scenarios 1–7 and scenario 8 (Figure 5.4) revealed that scenarios 2, 3, and 5 had significantly low correlation coefficients ($r < 0.7$; $p \leq 0.05$) during the daytime. They provided similar patterns of correlation coefficient; the correlation coefficients started to decrease from 5:00 a.m., were minimized at 8:00 a.m., and increased from 5:00 p.m. Although they produced relatively higher correlation coefficients during the night ($r > 0.8$; $p \leq 0.05$), these scenarios do not reflect the temporal changes of spatial accessibility over 24 hours. On the other hand, scenarios 4, 6, and 7 showed high correlation coefficients throughout a day, with marginal variation, although they partially implemented time-dependent variables. Scenarios 4 and 6 presented slightly low correlation coefficients between 9:00 a.m. and 5:00 p.m., whereas scenario 7 showed a lower value in the early morning (6:00 a.m.–9:00 a.m.).

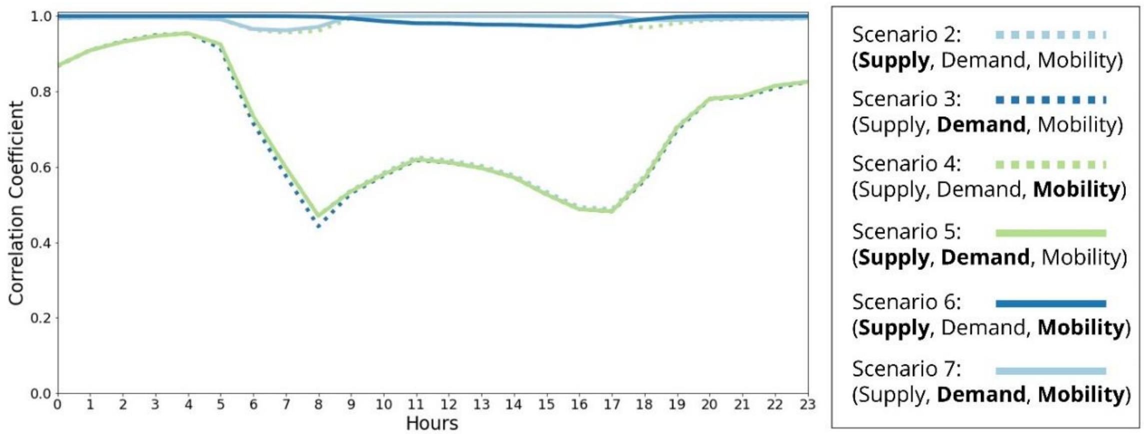


Figure 5.4. Hourly correlation between scenarios 1–7 and scenario 8.

5.5. Discussion

Our results indicate that the implementation of time-dependent mobility should be prioritized over the use of time-dependent supply and demand to examine temporal changes of spatial accessibility over 24 hours. The higher correlation coefficient indicates that the measures of spatial accessibility and their temporal changes obtained in two different scenarios were similar (Park *et al.*, 2021). In both spatial accessibility measurements and correlation analysis, the scenarios with time-dependent mobility (i.e., scenarios 4, 6, and 7) provided high correlation coefficients to the full dynamic implementation than the other scenarios; the top three correlation coefficients were observed from scenario 7 (dynamic demand and mobility), scenario 6 (dynamic supply and mobility), and scenario 4 (dynamic mobility). Scenario 4 produced a higher coefficient than scenario 5, in which two dynamic variables were used (supply and demand). This result indicates that time-dependent mobility should be incorporated into measurements to examine the temporal changes of spatial accessibility, particularly in 24-hour investigations.

The roles of input variables (i.e., supply, demand, and mobility) in spatial accessibility measurements may explain their different influences on temporal changes. As shown in our results, time-dependent mobility is considered the most critical element for estimating temporal changes of spatial accessibility. In general, the degree of mobility determines the size and shape of catchment areas. Therefore, the temporal fluctuation of mobility dynamically changes the number of people who have access to infrastructures and the number of facilities that are accessible from a particular location. However, supply and demand regulate the supply-to-demand ratio in catchment areas defined by mobility; thus, they may have a relatively more minor impact than mobility on temporal changes of spatial accessibility. In addition, their marginal effect on the measures may be attributed to the fact that our study used the operating hours of hospitals and a commuter-adjusted population to populate their temporal dynamics. Their temporal changes in the study area were simple; most hospitals operate either during the daytime or for 24 hours, and most commuters move in the morning and evening rush hours.

5.6. Conclusion

To promote the reproducibility of temporal changes in spatial accessibility measurement, in this study, we assessed the priority of three inputs (mobility, demand, and supply) when applying temporal dynamics. We used publicly available data sets to populate the temporal dynamics of the inputs and conducted a sensitivity analysis of eight scenarios to determine whether the inputs were used in their static and dynamic forms for the 2SFCA method. Our results show that the temporal dynamics of mobility were critical for estimating the temporal changes in spatial accessibility that resulted from the full implementation of time-dependent variables. Therefore, the use of time-dependent mobility would enhance the reproducibility of temporal changes in spatial accessibility measurements. In other words, the lack of time-dependent mobility would decrease the accuracy of measurements during the daytime. Consequently, our study provided insight into the input that should be prioritized as a dynamic form, and this will help overcome the current lack of data in forthcoming spatial accessibility studies.

Despite our results, this study has the following limitations. First, the results may not be generalizable, considering that the temporal changes of the input variables would be different depending on the location. For example, the typical working hours vary across the world, which may affect the temporal changes of the floating population. In the United States, most people work from 8:00 a.m. to 5:00 p.m., whereas Koreans work from 9:00 a.m. to 6:00 p.m. Second, the spatial granularity of the mobility data set was coarse. Owing to privacy concerns, the origin and destination of the taxi trip data were available as units of NTAs, whereas the estimated travel time was subject to vary within an NTA. Third, the temporal granularities of supply and demand should be increased. For the time-dependent supply, we used the operating hours of hospitals weighted with the number of physicians. However, physicians would have different working hours and may not be available during operating hours; therefore, this warns of the weight of hospitals being exaggerated. The time-dependent demand only reflects the variation caused by the commute; however, a megacity would have a more dynamic fluctuation of people due to the influences of schools or tourists.

6. CONCLUSIONS

This dissertation sheds light on the significance of the use of time-dependent variables for spatial accessibility measurements to provide better policy implications. By focusing on the 2SFCA method, the aim was to 1) examine the impact of the uncertainty attributed to the temporal dynamics on the measures; 2) increase the accuracy of measurement with the observed temporal changes of supply, demand, and mobility; and 3) improve the reproducibility of the temporal dynamics from limited time-dependent variables. In summary, the outcomes presented in Chapter 3 reveal that the temporal uncertainty of the inputs would dynamically change the degree of accessibility and intensify the inequality of access in the worst-case scenario. In Chapter 4, the present author indicated that the enhanced temporal granularity of the measurements would provide an improved understanding of the time-dependent spatial disparity of access and support a better allocation of supplementary infrastructure at a specific space and time (Park *et al*. 2021). To take advantage of the benefits from the time-dependent variables, the sensitivity analysis discussed in Chapter 5 revealed that implementing time-dependent mobility, rather than time-dependent supply and demand, should be prioritized. Consequently, this dissertation would help address geographical problems by presenting advanced spatial accessibility measurements. It would provide better insights into the disciplines of geography and urban planning along with the current data-rich environment, considering that the significance of the geographic information science and system is rooted in decision support systems.

This dissertation proceeded to address the following two main research questions: 1) How can we leverage the time-dependent variables in the measurement of spatial accessibility? 2) How can we provide improved policy implications by taking advantage of the time-dependent variables?

The temporal changes of supply (i.e., availability of ICU beds) and mobility (i.e., time-dependent travel time) were taken into account in Chapter 3 to address the temporal uncertainties of the spatial accessibility of ICU beds in the Greater Houston area, Texas, during the COVID-19 pandemic. The stochastic distributions of accessibility confirmed the persistence of the spatial disparity of adequate (i.e., sufficient and reliable) and inadequate (i.e., insufficient and unreliable) accessibility between the urban (i.e., downtown Houston) and rural areas (i.e., surrounding counties) under the uncertainty of the inputs. It also provides awareness that the inequality may become severe under the worst-case scenario. In addition, the comparison between the accessibility of ICU beds and the case-fatality ratio of COVID-19 indicated that the high fatality in the rural regions might be attributed to the inadequate accessibility to ICU beds.

In Chapter 4, a complete set of time-dependent variables (supply, demand, and mobility) is used, and the 24-hour changes in spatial accessibility to EV charging stations in Seoul, South Korea, are investigated (Park *et al*. 2021). The chapter presents the importance of using time-dependent variables, as it could uncover the temporal dynamics of accessibility within a day, which may remain concealed when the conventional measurements are used. In addition, the chapter takes advantage of temporal clustering, presenting two aspects thereby 24-hour changes of accessibility could help decision makers. Given that temporal clustering produced a few distinctive patterns of accessibility over time, it would, first, support the examination of temporal changes of access inequality (e.g., evening cluster in this research work). Second, it would have a strength in proposing a specific space and time for placing additional EV charging stations (e.g., afternoon cluster in this research work).

The aim of the investigation presented in Chapter 5 was to increase the reproducibility of temporal changes in spatial accessibility measurements by using publicly available datasets. To pursue the benefits of the time-dependent variables presented in Chapter 4, the priority of the inputs (supply, demand, and mobility) was examined to maximize the temporal changes of spatial accessibility when partially implementing temporally dynamic variables. From the measurements of the spatial accessibility of health-care resources in New York City, time-dependent mobility was found to be critical in estimating the temporal dynamics of accessibility, while time-dependent supply and mobility had negligible impacts. In addition, the hourly correlation analysis indicated that the underestimation of time-dependent mobility would show a lower accuracy of measurement in the daytime. Therefore, the chapter highlights that the use of time-dependent mobility would possibly result in significant policy implications even if not all inputs are available as temporally dynamic.

Two barriers must be overcome to pursue the benefits from the implementations of the time-dependent variables and further promote the policy implications of spatial accessibility measurements. The first issue is the limited availability of the time-dependent variables. Although time-dependent data from public databases were used to estimate the temporal dynamics presented in Chapter 5, commercial databases, such as Google Maps API, provide more accurate and higher granularity information of time-dependent variables. However, taking advantage of commercial databases is challenging owing to the substantial cost. This prevents easy access of researchers to produce the significant policy implications presented in chapters 3 and 4 and reduces the extent of application of the temporal changes in spatial accessibility. With the trend of reproducibility and replicability of geospatial studies (Wilson *et al*. 2020), investigating the temporal dynamics in high-frequency cities would be helpful once more data are made available to the public. The second issue is computational intensity, which frequently entails a spatiotemporal analysis. For example, as mentioned in Chapter 3, the assessment of the stochastic distribution of spatial accessibility took 3 months owing to the Monte-Carlo simulation, despite the multiprocessing with a Python package. Chapter 4 reveals that the travel time matrix of each origin and destination over 24 hours required 2 months to obtain. In addition to the data availability issue, this also possibly limits the broader applications owing to the significant processing time. The availability of high-performance computing to the geospatial analysis platform (Wang 2010) would greatly advance the applications of spatial accessibility measurements.

The following are the proposed subsequent research agenda: 1) spatial accessibility measurement at scale and 2) the use of multimodal transport along with the time-dependent variables. Given that the spatial accessibility of health-care resources may have a direct relationship to the fatality of COVID-19, expanding Chapter 3 to a larger scale such as to the state or national level would be essential to prove the correlation statistically. The spread of COVID-19 showed various patterns of space and time; that is, different locations suffered from the virus at different periods. Therefore, the sequence of the temporal changes of spatial accessibility of ICU beds would enhance the understanding of the impact of the current pandemic and possibly prevent fatality from the next pandemic. In addition, the other future plan is to reproduce the temporal dynamics in a high-frequency city by using both time-dependent variables and multimodal transports. As demonstrated in the literature review (Chapter 2), previous studies were limited to partially incorporating the dynamic variables, either time-dependent variables or multimodal transportation, into measurements. Given the dynamic interaction of time-dependent and multimodal transportation, this would reflect how people travel within a city and how the accessibility changes accordingly by uncovering their full dynamics. Therefore, this agenda will also be helpful in constructing digital twin cities.

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