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ORIGINAL ARTICLE

An integrated approach to analyze equitable access to food stores under disasters from human mobility patterns

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Abstract
Limited access to food stores is often linked to higher health risks and lower community resilience. Socially vulnerable populations experience persistent disparities in equitable food store access. However, little research has been done to examine how people's access to food stores is affected by natural disasters. Previous studies mainly focus on examining potential access using the travel distance to the nearest food store, which often falls short of capturing the actual access of people. Therefore, to fill this gap, this paper incorporates human mobility patterns into the measure of actual access, leveraging large-scale mobile phone data. Specifically, we propose a novel enhanced two-step floating catchment area method with travel preferences (E2SFCA-TP) to measure accessibility, which extends the traditional E2SFCA model by integrating actual human mobility behaviors. We then analyze people's actual access to grocery and convenience stores across both space and time under the devastating winter storm Uri in Harris County, Texas. Our results highlight the value of using human mobility patterns to better reflect people's actual access behaviors. The proposed E2SFCA-TP measure is more capable of capturing mobility variations in people's access, compared with the traditional E2SFCA measure. This paper provides insights into food store access across space and time, which could aid decision making in resource allocation to enhance accessibility and mitigate the risk of food insecurity in underserved areas.

KEYWORDS
equitable access, floating catchment area, food stores, human mobility, natural disaster

1 | INTRODUCTION

Lack of access to healthy food is closely associated with various social problems such as food insecurity and health risks, including obesity, poor nutrition, and heart failure (Kelli et al., 2019; Powell et al., 2007; Wei et al., 2022). Globally, the number of people lacking consistent access to healthy food is estimated at 1.3 billion in 2022, which has increased around 10% from the 2021 estimate (Zereyesus et al., 2022). In the United States, there were 10.2% (13.5 million) of people experiencing a lack of access to affordable nutritious food in 2021 (USDA, 2023). Notably, a lack of access to food disproportionately affects rural and socioeconomically disadvantaged populations. For example, low-income African Americans often face a significantly higher risk of food insecurity, ranging from 20.7% to 36.9%, compared to the general population (Dubowitz et al., 2021). Thus, addressing the lack of food access has become one of the nation's prominent health and nutrition challenges (Gundersen & Ziliak, 2015).

The growing intensity and frequency of extreme weather disasters could further disrupt people's access to food (Davis et al., 2021; Wheeler & von Braun, 2013). Natural disasters, such as hurricanes, floods, and droughts, can destroy the normal functioning of the food supply chain, leading to food shortages and/or food insecurity (Perdana et al., 2022). In Latin America and the Caribbean, the estimated disaster impacts between 2008 and 2018 caused an equivalent loss of 975 calories per capita per day, accounting for 40% of recommended daily allowance (United Nations, 2021). Natural disasters can even pose more significant risks to socially vulnerable populations suffering from food accessibility issues. People living in poverty or marginalized communities constantly experience heightened challenges in accessing food stores during disaster events (Drake et al., 2023;

Esmalian et al., 2022). For example, following Hurricane Katrina, around 71% African American neighborhoods in New Orleans experienced limited access to supermarkets, which had increased from 40% before Hurricane Katrina (Rose et al., 2011). Better access to food stores is integral for building resilient and sustainable communities, especially in the face of disruptive events (Gillespie-Marthaler et al., 2019; Logan & Guikema, 2020). However, limited research has been dedicated to examining how the accessibility of food stores is affected by natural disasters, particularly across neighborhoods of different socioeconomic backgrounds. Thus, there is a need to advance our understanding of the dynamics in access to food stores across different neighborhoods at multiple stages of natural disasters.

Measuring how people access food stores is the first and foremost step toward better understanding and mitigating the disparities in food store access, thereby reducing food insecurity within a community (Jiao & Azimian, 2021). However, measuring accessibility is challenging due to its multifaceted nature, which can be conceptualized in multiple dimensions such as proximity, availability, acceptability, affordability, adequacy, and awareness (Penchansky & Thomas, 1981; Saurman, 2016). For example, the proximity is often measured by travel distance to the nearest available facility, where travel distance can be calculated through the existing road networks such as driving and walking networks (Jiao & Azimian, 2021). To conjointly account for proximity and availability—the two important aspects in measuring spatial accessibility, the traditional two-step floating catchment area (2SFCA) method and its variants are widely used (Luo & Wang, 2003). However, these conventional methods focus mainly on measuring the *potential access* of people to food stores, without explicitly considering the *actual access* of people to these facilities (Miller, 2018). Here, potential access refers to the theoretical or physical proximity/availability of food stores in an area. In contrast, actual access indicates the practical or realized utilization of those stores by people in the area (Zahnd et al., 2022). Specifically, the actual access reveals people's travel preferences in visiting different facilities, which may not necessarily be the one with the nearest travel distance. For example, people are more likely to travel to certain facilities, taking into account multiple factors such as safety, social interactions, and economic segregation (Moro et al., 2021). Thus, it is of critical importance to incorporate actual access in characterizing how people access food stores.

The actual access of people can be captured by their mobility patterns. Traditionally, human mobility behaviors are analyzed through surveys, call detailed records, and public transport systems (Choi et al., 2014; Sun et al., 2013; Zhang et al., 2018). However, those data sources often fall short of capturing dynamic mobility patterns at finer spatial scales, which are crucial for examining neighborhoods' variations in access to different facilities (Barbosa et al., 2018; Wei & Mukherjee, 2022). Recently, with the burgeoning of Geographic Information System (GIS) technology, mobile phone data provide unique opportunities to reveal the detailed mobility behaviors in visiting various places at finer spatiotemporal resolutions (Podesta et al., 2021; Washington et al., 2024; Wei et al., 2023). For example, mobility patterns from mobile phone users illustrate income segregation behaviors between low-income and high-income neighborhoods in visiting a variety of critical facilities including hospitals, gas stations, and grocery stores under natural disaster (Wei & Mukherjee, 2023). Mobile phone data can also be used to infer facility closures following a hazard event by examining the mobility changes, which is useful to identify areas with the loss of access to critical facilities after a disaster (Swanson & Guikema, 2024). Even though mobile phone data have emerged as a valuable resource for understanding human movement behaviors in recent studies, there is still a lack of research on how to incorporate fine-grained human mobility patterns into characterizing the accessibility of food stores.

Therefore, in this paper, we aim to quantitatively examine the people's actual access to food stores in the face of a natural disaster, leveraging human mobility data. Specifically, we examined the accessibility of both grocery stores and convenience stores across neighborhoods before, during, and after the unprecedented winter storm Uri. To better capture people's actual access, we utilized human mobility patterns from large-scale mobile phone data to characterize people's travel preferences. Our analysis is conducted at the census block group (CBG) level to reveal spatiotemporal variations in people's access. This study could benefit city planners and disaster responders by identifying the underserved areas and evaluating inequalities in access to food stores, and help in mitigating the risk of food insecurity in underserved communities. In a nutshell, the contribution of our study to the extant literature is summarized as follows.

- This paper presents a new perspective to characterize people's access through human mobility patterns from mobile phone data. This point of view centers on how people *actually* access essential services, which is distinct from previous studies that mainly focus on how people would *potentially* access them.
- We develop a novel enhanced two-step floating catchment area model integrating travel preferences (E2SFCA-TP) to measure accessibility across both space and time. This model extends the traditional E2SFCA method by explicitly accounting for the people's travel preferences, which are derived from human mobility data.
- We present a case study to analyze people's access to grocery and convenience stores in the face of natural disaster at finer spatiotemporal resolutions. The analysis highlights the value of using actual access by leveraging the mobile phone data to better reflect people's access behaviors.

The remainder of this paper is organized as follows. Section 2 summarizes the related studies on spatial accessibility and accessibility measures that motivate and support the importance of our study. Section 3 presents the methodological framework of the proposed E2SFCA-TP method to measure accessibility. Section 4 describes the results of a case study that demonstrates the applicability of the proposed framework. Section 5 provides discussion and policy implications of this study. Finally, Section 6 concludes the paper.

2 | LITERATURE REVIEW

In this section, we summarize the concept of spatial accessibility and provide a short description of how spatial accessibility is measured. The existing research gaps in the literature on spatial access to service facilities are also discussed.

2.1 | Spatial accessibility

Accessibility is a widely used concept that describes the ease of reaching desired facilities from a particular place (Dalvi & Martin, 1976). It has been applied in various domains such as urban planning, transportation modeling, and emergency management (Aboolian et al., 2016; Ermagun & Tilahun, 2020; Lewis et al., 2023). Despite the widespread use of accessibility, there is still no universal consensus on how it should be characterized due to its multifaceted nature (Novak & Sullivan, 2014; Page et al., 2018). Spatial accessibility mainly focuses on availability and proximity, which are the two crucial dimensions in understanding the accessibility of facilities.

Availability describes a proportion or ratio of a particular type of facility or service in a region, often measured by the prevalence of facilities or the supply–demand ratio (Guagliardo et al., 2004; Morland et al., 2002). For instance, Morland et al. (2002) examined the access to food stores by measuring the prevalence of places from where people can obtain food and found that fewer supermarkets are located in economically disadvantaged areas. The availability measure is widely used due to the ease of calculation and interpretation; however, it is often measured at coarser spatial units (e.g., county, state), ignoring geographical variations at the finer levels (e.g., CBG) (Geurs & van Wee, 2004). In addition, the availability measure fails to consider the impedance that may prevent people from fully accessing facilities (McGrail & Humphreys, 2009). Here, the impedance refers to the difficulty level encountered by people when traveling between places, which can be represented by the function of travel distance (Jiao & Azimian, 2021).

Proximity describes travel distance to the nearest available facility. The widely adopted concepts to characterize proximity include the nearest measure and cumulative measure of the facility (Jiao & Azimian, 2021). The nearest measure captures the minimum travel distance required to reach the nearest facility. Logan et al. (2021) evaluated the travel distance to the nearest grocery stores, and demonstrated spatial inequality in how people access to groceries across 10 cities in the United States. Similarly, the cumulative measure describes the number of facilities within a predefined travel distance. Ermagun and Tilahun (2020) investigated and compared the accessibility metrics across different facilities including grocery stores, hospitals, and schools by counting the number of these facilities within various travel distance thresholds.

Even though availability and proximity are essential in understanding the accessibility of facilities, each of them only provides a partial assessment of accessibility (McGrail & Humphreys, 2009). To put it differently, close proximity may not guarantee high accessibility, since the potential demand may be substantial to compete with available services. Similarly, high availability may not result in high accessibility, especially when the distribution of facilities is highly skewed toward urban areas over rural communities. In addition, previous studies mainly focus on potential access in measuring accessibility, which refers to the potential utilization of facilities by people (Ermagun & Tilahun, 2020; Jiao & Azimian, 2021; Logan et al., 2021). However, potential access does not guarantee realized access (Zahnd et al., 2022). The realized access (also known as actual access) describes the actual utilization of facilities, which reflects the true accessibility experienced by people (Miller, 2018). To address this gap, this paper provides a practical perspective on how to characterize accessibility based on people's actual access, leveraging human mobility patterns obtained from large-scale mobile phone data.

2.2 | Accessibility measures

The standard 2SFCA method has been widely used to quantify the spatial accessibility of facilities across administrative boundaries (Luo & Wang, 2003; Wang, 2000). In short, the first step of 2SFCA method is to calculate the availability within a specific catchment area, where the catchment area is defined by the acceptable travel distance. Then, the second step is to aggregate the availability measures obtained in the first step, for all facilities that fall within the catchment area around the population location (Luo & Wang, 2003). However, the conventional 2SFCA method does not distinguish distance impedance within a catchment area, meaning that people within the catchment area are assumed to have equal accessibility to critical facilities. This assumption ignores the heterogeneity of neighborhoods with varying travel distances (McGrail & Humphreys, 2009). To mitigate this limitation, the E2SFCA is developed by introducing a decay function to distinguish areas with different travel distances (Luo & Qi, 2009). The decay function is used to demonstrate the diminishing effect of service facility as travel distance increases, meaning that areas closer to the facility are weighted more in computing the spatial accessibility. Various forms of travel distance decay functions have been investigated including the Gaussian function (Wu et al., 2020) and the exponential function (Chen et al., 2017). McGrail (2012) evaluated the effectiveness of various decay functions and varying sizes of the catchment area based on the E2SFCA framework, and highlighted that the selection of decay function and catchment size depends on the type of facilities and communities being considered.

Recently, a growing attention has been paid to examine the impact of natural disasters on people's access to crucial services. For example, Anderson et al. (2022) evaluated the direct and indirect impacts on communities under natural disasters in a transportation network, and analyzed how access changes following various simulated scenarios of tsunami and earthquake events. Kar et al. (2022) investigated the changes in potential access to primary care at the census tract level following a hurricane, using the E2SFCA method. The authors further highlighted that a significant variation exists in this potential access between the high and low socioeconomic status groups. Jasour et al. (2022) examined people's ability to access the key local amenities under different sea-level rise scenarios, highlighting that limited access could pose a potential risk of household inundation. In addition to the risk of inundation, people may also experience the risk of isolation as a result of flooding, due to a lack of physical connectivity to essential services (Logan et al., 2023). Despite the growing attention paid to evaluating access to services, it is of critical importance to ensure the equitable aspect of access to essential services, in order to foster community resilience under disruptive events (Logan & Guikema, 2020). To improve people's equitable access, Svirsko et al. (2022) formulated an integer programming model to determine an optimal repair and reopening schedule for supermarkets following a disaster. These studies adopted the road network to measure the proximity (distance) to operational facilities. The road network is more realistic than other distance measures such as Euclidean distance (i.e., straight line) or Haversine distance (i.e., great circle) to construct the catchment area of service facilities. Because road network accounts for topological structures of the transportation system, which is more realistic to reveal how people travel to different places (Delamater et al., 2012).

However, these studies fall short of capturing people's travel preferences, which are crucial for understanding their actual access to different essential services. For example, people are more likely to visit places that share similar socioeconomic characteristics to their own neighborhoods during a disaster (Deng et al., 2021; Wei & Mukherjee, 2023). Thus, it is critical to account for travel preferences when measuring people's access. To this end, this paper develops a novel method to measure accessibility to facilities leveraging human mobility patterns.

3 | METHODOLOGICAL FRAMEWORK

The overview of our methodological framework for measuring accessibility is displayed in Figure 1. In what follows, we first present the data collection and processing, and then provide details on the proposed E2SFCA-TP method for calculating accessibility.

3.1 | Data collection and processing

3.1.1 | Human mobility data

Human mobility data are collected from SafeGraph, which is a company that provides geographic location information of mobile phone users (SafeGraph, 2020). The data are anonymous and aggregated at the population level to ensure privacy. The collected data record the home locations of mobile phone users, which are determined by the modal locations where the users have spent their nights (between 6 pm and 7 am) over the course of 6 weeks (Klise et al., 2021). The collected data also capture the foot traffic patterns at each facility. Here, the term "facility" broadly describes business establishments that people can access to get services, such as food stores and banks. To estimate the population flow from people's home neighborhood to each facility, we constructed the human mobility network using the approach developed in the previous study (Wei & Mukherjee, 2023). Based on the human mobility network, the travel preference $P_{ij}^{(t)}$ is then characterized as the likelihood of people from neighborhood i to visit facility j on day t, which is given by

$$P_{ij}^{(t)} = \frac{w_{ij}^{(t)}}{\sum_j w_{ij}^{(t)}}, \tag{1}$$

where $w_{ij}^{(t)}$ denotes the number of people traveling from neighborhood i to facility j on day t in the mobility network. Here, we choose the CBG to represent the neighborhood (i.e., residential area of individuals). Because CBG provides a high level of detail in revealing geographic variations in access to various locations, compared to coarser spatial units such as census tract and county (Nelson & Brewer, 2017). The higher values of $P_{ij}^{(t)}$ indicate that people living in CBG i are more likely to visit facility j on day t. We also collected the descriptive information about the facilities from SafeGraph. Each facility contains the geographic location information including longitude and latitude, and is labeled by the North American Industry Classification System (NAICS) code. The NAICS code is the standard used by Federal agencies in classifying business establishments relevant to the US business economy, which is helpful to filter the facilities of interest.

3.1.2 | Street network data

We extracted the street network from OpenStreetMap (OSM) that describes various geographic features of roads such as physical layout, speed limits, and railway stations (OpenStreetMap, 2022). The street network is represented as a directed graph consisting of nodes and edges, where nodes represent intersections and edges indicate road segments. Each edge is associated with the travel distance. This street network can capture the spatial characteristics and topology

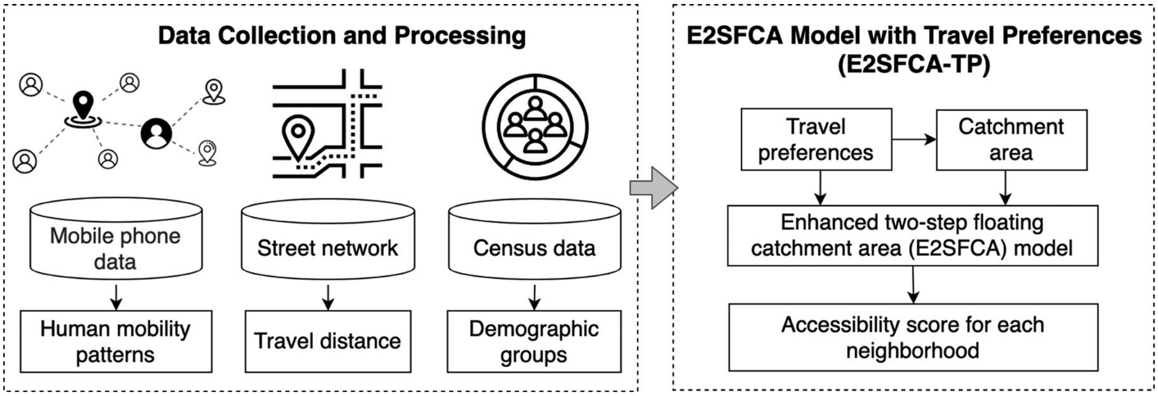


FIGURE 1 Overview of the framework.

of a road system, allowing us to analyze people's travel behaviors such as travel distance on the network (Boeing, 2017).

The travel distance is calculated using the following two steps. First, we identified the origin (destination) node in the network that is closest to a given origin (destination) location. The given geographic location consists of longitude and latitude of a facility. Second, the travel distance is computed by the shortest path between the identified origin and destination nodes in the street network, where the shortest path is determined by Dijkstra's algorithm (Johnson, 1973). For more details on routing with OSM data, readers may refer to the previous studies (Boeing, 2017; Luxen & Vetter, 2011).

3.1.3 | Census data

We obtained census data from the American Community Survey (ACS) 5-year estimates (2016–2020) of the US Census Bureau (2020). The census data include demographics and socioeconomic characteristics of each CBG, and it is the primary source of detailed population data in the United States. Specifically, the collected census data provide detailed information on the demographic and socioeconomic composition at each CBG. The census data could assist in addressing the issue of unavailable demographic data for sampled mobile phone users due to privacy concerns. Thus, we use the sociodemographic information of a CBG to represent the sociodemographic characteristics of sampled mobile phone users living in that CBG, which is a widely adopted method in the literature (Jay et al., 2020).

3.2 | The E2SFCA model with travel preferences

We introduce E2SFCA-TP to measure accessibility to facilities (e.g., food stores). This proposed E2SFCA-TP is constructed based on the standard 2SFCA method proposed by Luo and Wang (2003) and Luo and Qi (2009), and it generates accessibility score through the following two steps.

The first step is to calculate the time-dependent availability metric, which is defined as the ratio of store capacity to demand at each facility j on day t given by

$$R_j^{(t)} = \frac{S_j}{\sum_{i \in \{i: d_{ij} \le d_0\}} P_{ij}^{(t)} N_i F_{ij}}. \tag{2}$$

In Equation (2), S_j indicates the capacity of facility j. In general, the capacity information at each store is often not publicly available due to privacy concerns and decentralized inventory management. Thus, we use the average foot traffic over the first week of February 2021 to estimate the capacity of each food store, as the foot traffic is highly correlated with the capacity of each food store (Kumar & Karande, 2000). The average foot traffic also reflects the general trend of people's visiting patterns. The notation N_i represents the population demand of the neighborhood i. In this study, the neighborhood is represented as CBG, but it can be generalized to other spatial units (e.g., census track) as well. The probability of people from neighborhood i going to facility j on day t is represented by $P_{ij}^{(t)}$, which describes their preferences in visiting different food stores. The weight F_{ij} is measured by the distance decay function, to reflect that the longer travel distance is associated with a smaller weight. The widely used Gaussian formula is adopted here to characterize the decay function with respect to travel distance (Bryant & Delamater, 2019; Wan et al., 2012), which is expressed as

$$F_{ij} = f(d_{ij}) = \mathrm{e}^{-d_{ij}^2/d_0^2}. \tag{3}$$

In Equation (3), d_0^2 controls the level of impedance or difficulty in accessing facilities from different locations within the catchment area. The catchment area, denoted as $\{i : d_{ij} \le d_0\}$, describes all neighborhoods where the centroids fall within a predefined travel threshold d_0 from facility j. The travel distance metric d_{ij} is calculated through the actual road network obtained from OSM data. The use of the actual road network provides a more accurate estimate of travel distance, compared with other distance measures (e.g., Euclidean, Haversine) in most previous studies (Luo & Qi, 2009; Sun et al., 2017).

The second step is to calculate the temporal accessibility score $A_i^{(t)}$ for each neighborhood i on day t, which can be written as

$$A_i^{(t)} = \sum_{j \in \{j: d_{ij} \le d_0\}} R_j^{(t)} F_{ij}. \tag{4}$$

The temporal accessibility score $A_i^{(t)}$ aggregates the weighted ratios of all facilities j that fall within the catchment area of the neighborhood i. Note that the accessibility score $A_i^{(t)}$ is a relative measure and it is always nonnegative. A higher value of $A_i^{(t)}$ indicates better access to facilities (Wan et al., 2012).

The introduced accessibility measure $A_i^{(t)}$ generalizes the traditional E2SFCA method by incorporating people's temporal travel preferences. The people's travel preferences are captured by real human mobility patterns, indicating how people actually utilize facilities. This is where our method is distinct from most previous studies that focus on measuring the potential access. In a special case when $P_{ij}^{(t)} = 1$, the proposed accessibility measure reduces to the traditional E2SFCA model.

4 | RESULTS

To illustrate the applicability of the proposed framework, in this section, we examine how people access food stores in the face of a natural disaster. First, we describe our study region and the settings of the case study. Then, we present a descriptive analysis of human mobility patterns. Finally, the accessibility scores are calculated to reveal people's actual access patterns across space and time, where we highlight the importance of using the human mobility patterns in the measure of actual access to food stores.

4.1 | Case study

We selected Harris County in Texas, the United States, as our study region. The county seat of Harris County is Houston, the largest city in Texas and the fourth largest city in the United States, which offers a rich and varied demographic landscape. Two common types of food stores are selected: grocery stores (NAICS code: 445110) and convenience stores (NAICS code: 445120). Even though both are classified as food stores, they are different from the perspective of the type of food they provide. Grocery stores offer a broader assortment of fresh foods, including fruits, vegetables, and meat, whereas convenience stores sell staple food that is packaged (Larson et al., 2009).

We analyze how people access both types of food stores under the historical winter storm Uri occurred in the middle of February 2021. The winter storm Uri is the deadliest winter storm in the history of Texas (Svitek, 2022). More than two out of three Texans lost electricity for an average of 42 hours. Particularly, Harris County suffered the worst, with roughly 91% of residents experiencing power outages. This number was significantly higher than the average of 64% in other counties in Texas. Snow and ice coupled with record-low temperatures caused widespread road closures and dangerous travel conditions (Lee et al., 2022). Thus, this situation presents a unique case to study people's access to food stores in the face of such an extreme weather event. To summarize, in our study region, approximately 0.32 million mobile phone users were recorded across 2142 CBGs during February 2021, representing around 7% of the total census population.

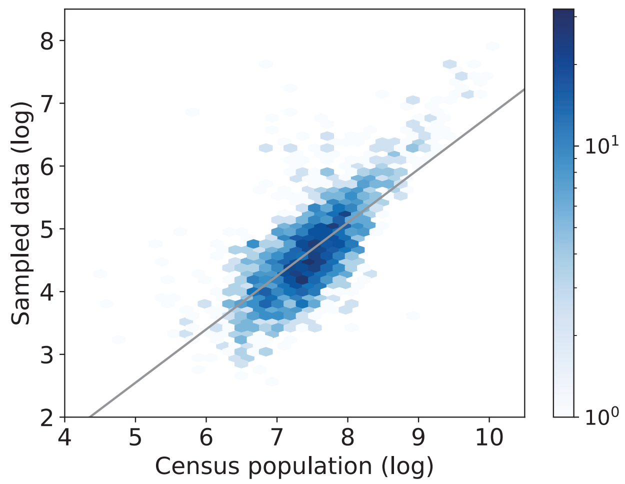
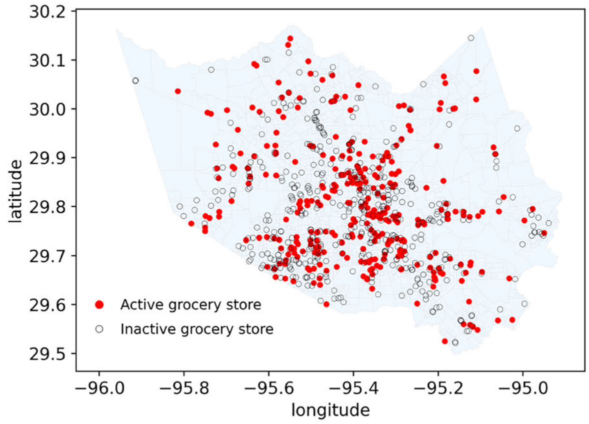


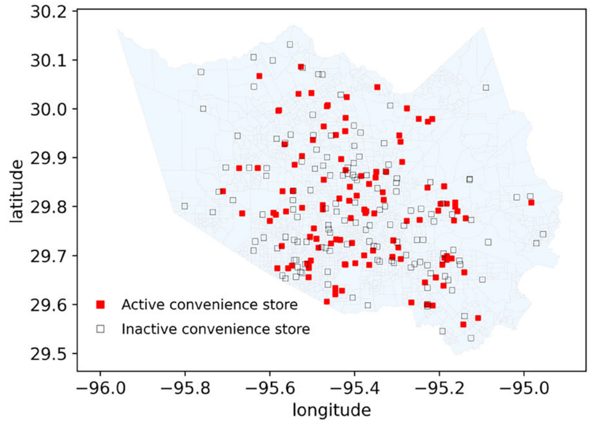
FIGURE 2 The hexbin plot showing the representation test between the sampled mobile phone users and the census population.

Before proceeding with the analysis, verifying whether the sampled mobile phone users are representative of the population data is essential. To achieve this, we implemented the representation test by examining the relationship between the number of observed samples from our data and the number of residents from the census data. We found that the associated Pearson correlation is 0.81 with $p < 0.05$, indicating that the sampled data do not have significant bias in population coverage. In addition, the hexbin plot is displayed in Figure 2, showing the strong correlation between the sampled data and the census data. In Figure 2, the darker colors indicate the higher densities of the CBGs that fall within each bin. To summarize, throughout the representation test, the sampled data are well representative of the census population. This aligns with the previous study showing that SafeGraph data generally reflect the census population (Brelsford et al., 2022).

The geographic distribution of grocery and convenience stores in our study region is shown in Figure 3A,B, respectively. The stores are classified as active during the winter storm Uri if at least one customer is observed visiting the store on February 15, 2021, or inactive if no customer is



(A) Grocery stores



(B) Convenience stores

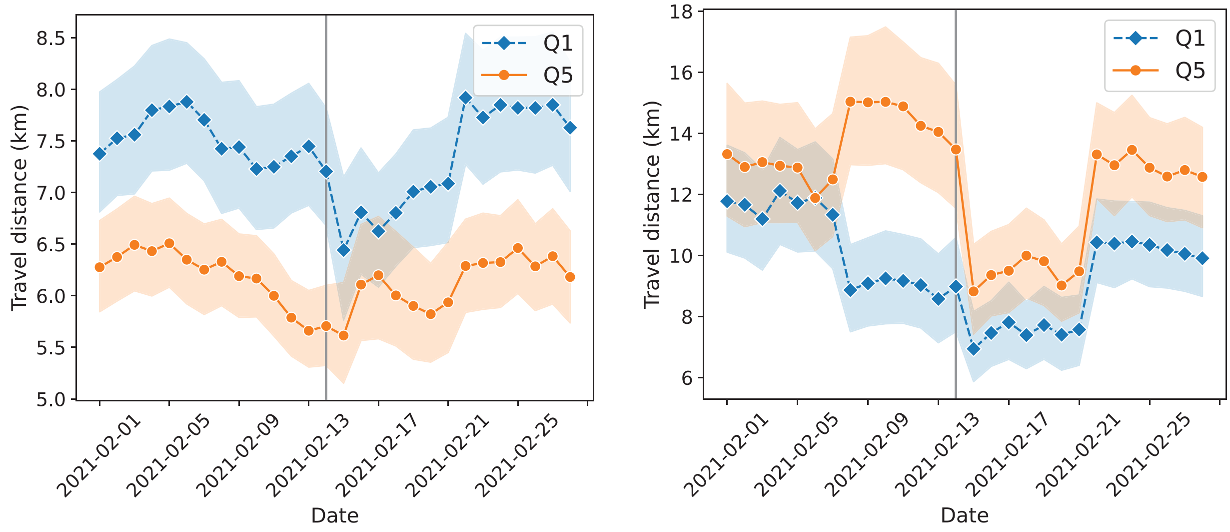
FIGURE 3 The distribution of grocery stores and convenience stores in the study area.

observed on that day. For visualization, the maps only display active stores that had a minimum foot traffic of 20 people, and the inactive stores. It can be observed that the density of food stores is spatially heterogeneous. Specifically, the central part of Harris County, where the city of Houston is located, has a higher concentration of grocery and convenience stores. In contrast, the remaining areas in Harris County, such as the north-western fringe areas, have a low density of food stores. In addition, the food stores are considered active during the winter storm Uri if they still have active customers. Overall, there are 1063 grocery stores and 535 convenience stores, with only 479 (45%) of the grocery stores and 268 (50%) of the convenience stores active during the winter storm Uri.

4.2 | Human mobility patterns

We analyzed the time series of human mobility patterns at grocery and convenience stores for different economic groups. Specifically, we use income quintiles to represent the economic status of CBGs, where each CBG is assigned an income quintile based on the median household income. Each income quintile contains approximately 20% of the CBGs. We use Q1 (first quintile) to represent the low-income groups, comprising CBGs located within the bottom 20% of the distribution of median household income. Similarly, we use Q5 (fifth quintile) to represent the high-income groups with CBGs in the top 20% of income distribution (Jay et al., 2020).

Figure 4 illustrates the average travel distances to grocery and convenience stores of the low-income (Q1) and high-income (Q5) neighborhoods, as reflected by human mobility patterns. Here, we use the driving network to calculate people's travel distance to food stores, which is described in Section 3.1. The average travel distances are around 7 km (i.e., 4.35 miles) and 11 km (i.e., 6.84 miles) to grocery and convenience stores, respectively. Specifically, grocery stores' average travel distances are 7.4 km (i.e., 4.6 miles) and 6.2 km (i.e., 3.85 miles) for residents of Q1 and Q5 neighborhoods, respectively. On the contrary, the average travel distances to convenience stores are 9.7 km (i.e., 6.03 miles) and 12.4 km (i.e., 7.71 miles) for residents of Q1 and Q5 neighborhoods, respectively. From Figure 4, we also observe that low-income neighborhoods typically have more considerable travel distances to grocery stores compared to high-income neighborhoods. In contrast, high-income neighborhoods tend to have more considerable travel distances to convenience stores than low-income neighborhoods. Such disparity in access to grocery and convenience stores is consistent before, during, and after the winter storm. This human mobility behavior could help explain why people living in economically disadvantaged neighborhoods often have an increased risk of various health conditions (e.g., diabetes). For example, this societal problem can be attributed to these socially disadvantaged people being less likely to have easy access to grocery stores that offer a variety of fresh and healthy food products (Sharkey, 2009). The variation in mobility patterns is likely a result of a combination of various factors such as awareness and preparation (Jay et al., 2020). For example, before the storm, we observe a jump in travel distance for high-income communities (Q5) and a drop in travel distance for low-income communities (Q1), as shown in Figure 4B. This may be because high-income neighborhoods are more aware of and better prepared for the impending disaster, compared to people from low-income neighborhoods. Another observation is a drop in travel distance on the day of the storm. This mobility reduction indicates the storm impact on people's access to food stores. Particularly, in access to convenience stores, low-income communities consistently showed a decline in travel distance, whereas high-income communities experienced an increase in travel distance before the storm and a subsequent decline on the day of the storm. These observations highlight that human mobility patterns can reflect how people access different types of food stores in their daily lives.



(A) Grocery stores (B) Convenience stores

FIGURE 4 The average travel distance in access to (A) grocery stores and (B) convenience stores between low-income (Q1) and high-income (Q5) neighborhoods. The shaded areas around the mean represent a 95% confidence interval. The gray vertical line indicates the onset of the winter storm Uri.

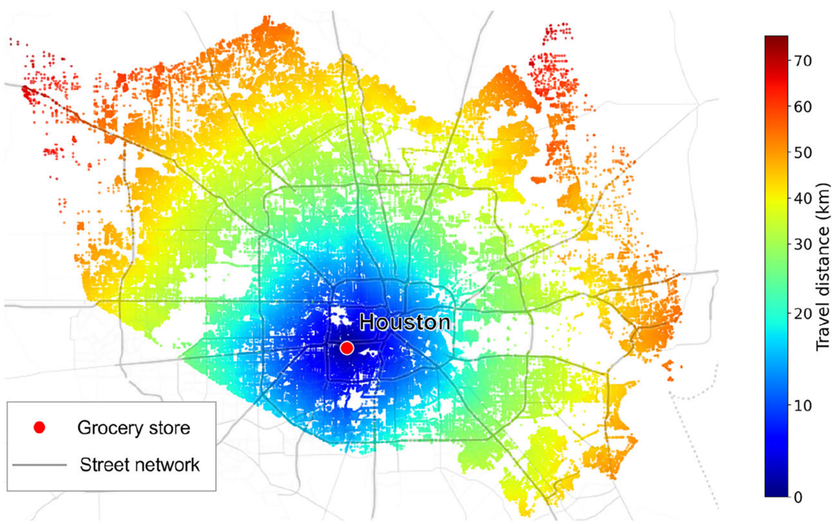


FIGURE 5 Illustration of the catchment area defined by driving distance. The gradient color represents the distances traveled from the grocery store (marked as the red dot) to other locations in the street network.

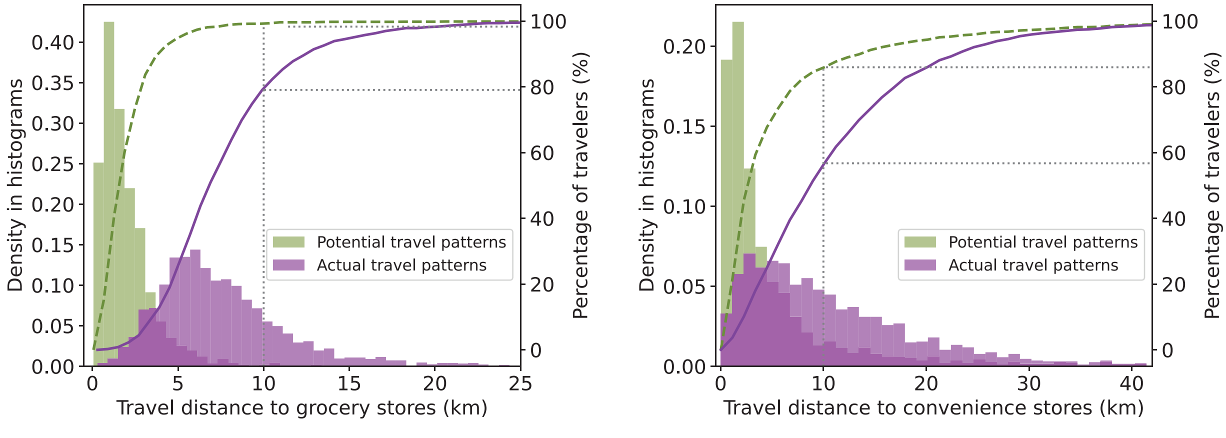
4.3 | Spatial accessibility

4.3.1 | Illustration of catchment area

Figure 5 displays the catchment area of one grocery store (marked as the red dot in the map), where the travel distance is calculated using the underlying street network (marked as gray lines). This map is often referred to as the isodistance map, where regions with the same color have equal travel distances to the origin location. It can be observed that the areas with the same travel distance do not fall within the circular area, which is often derived from the Euclidean distance measure. The catchment area measured by Euclidean distance does not account for the street topology and thus cannot reflect people's actual travel distances. The travel distances to the chosen store are primarily within 60 km (i.e., 37.28 miles), meaning that people in our study region are more likely to reach the marked grocery stores less than 60 km (i.e., 37.28 miles).

4.3.2 | Comparison between potential and actual travel patterns

Figure 6 demonstrates people's potential and actual travel patterns to grocery and convenience stores throughout our study period. The potential travel patterns are measured by the residents' distance from road networks to their nearest grocery/convenience store. In contrast, the actual travel patterns are measured by residents' actual travel distances



(A) Grocery stores

(B) Convenience stores

FIGURE 6 Comparison between potential and actual travel patterns. The potential travel patterns are measured by the residents' distance to their nearest grocery/convenience store. The actual travel patterns are measured by residents' actual travel distance revealed from human mobility data.

accounting for their travel preferences, as revealed from human mobility data.

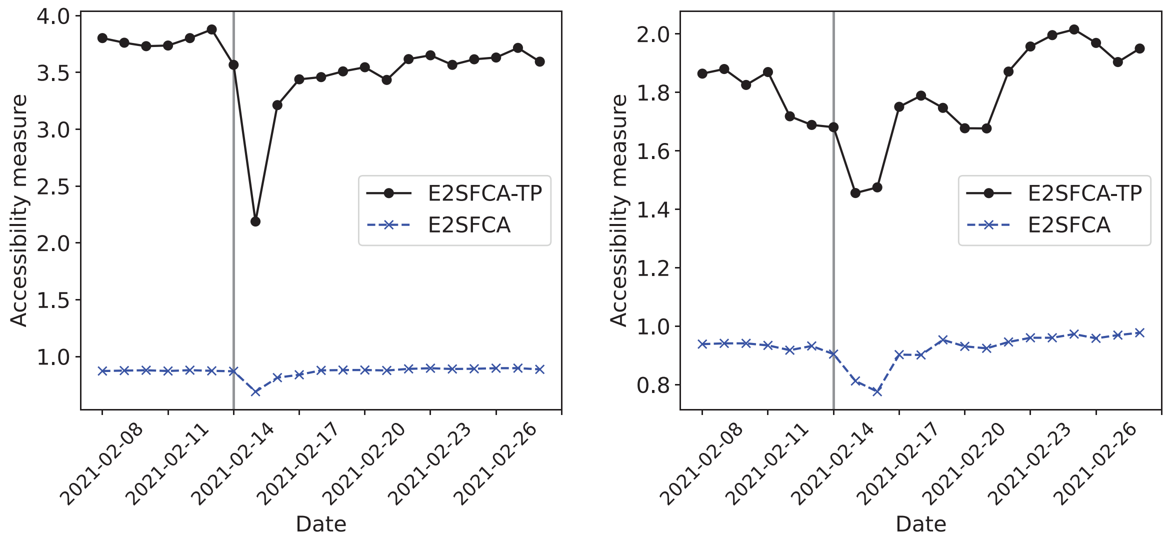
From Figure 6A, we observe that even though almost 100% of residents live within 10 km of the nearest grocery store, only around 80% of them visited the store within this radius, as revealed by their actual mobility patterns. This indicates that people prefer visiting a different grocery store, which may not be the one with the shortest travel distance. Similar patterns can be found in people's access to convenience stores in Figure 6B. We also implemented the statistical Kolmogorov–Smirnov test (KS test) to examine whether the actual travel pattern is statistically different from the potential one. Results show that there is a significant difference in their empirical cumulative distribution functions (ECDFs), as indicated by $p < 0.05$. These analyzes highlight the importance of considering human mobility patterns when examining people's access to critical facilities. This is because the traditional way of measuring the people's potential access (i.e., by considering the nearest facility) falls short of capturing people's actual mobility in reaching more distant facilities.

4.3.3 | Comparison between E2SFCA and E2SFCA-TP

We compared the traditional E2SFCA method and the proposed E2SFCA-TP approach in measuring people's access to analyze the value added by the proposed one. Note that our E2SFCA-TP approach generalizes E2SFCA by incorporating travel preferences into the access measure. The travel preferences reflect people's actual travel patterns in accessing different service locations, revealed from human mobility patterns. The traditional E2SFCA measure can be achieved by setting $P_{ij}^{(t)} = 1$ in Equation (2).

Figure 7 illustrates the time series of the accessibility values obtained from the traditional E2SFCA method and the proposed E2SFCA-TP approach. The temporal distributions of two accessibility measures are found to be significantly different as indicated by the statistical t-test with $p < 0.05$. We observe that the E2SFCA-TP yields higher accessibility values than the traditional E2SFCA. This is because, the traditional E2SFCA method assumes that each point of interest (POI) attracts the demand of all CBGs that fall within its catchment area (see Equation 2 with $P_{ij}^{(t)} = 1$). This often overestimates the actual demand, as people may have preferences in accessing other service locations. When it comes to overestimating the demand, the resulting accessibility score tends to be low (see Equation 4), as more demands are competing with the limited resources. In this view, our proposed E2SFCA-TP method that accounts for travel preferences better captures the actual demand of people, which helps to accurately measure the access.

We also observe from the figure that people's actual access to grocery and convenience stores is sensitive to disasters, which is reflected by a drop in the values of access in the aftermath of the disaster Uri. This is because some stores are closed during the disaster (illustrated in Figure 3), which leads to a drop in the accessibility scores. Thus, our proposed E2SFCA-TP method is more sensitive to time/disaster in contrast to the E2SFCA measure that has less variations over time. This highlights the fact that people's actual travel patterns in access to stores are time-dependent, which are captured adequately in the E2SFCA-TP measure. This temporal variation is crucial to reveal the dynamics in people's access to essential services, particularly under natural disasters.



(A) Grocery stores (B) Convenience stores

FIGURE 7 Comparison between enhanced two-step floating catchment area (E2SFCA) and E2SFCA method with travel preferences (E2SFCA-TP) in measuring the access to grocery stores (A) and convenience stores (B). The gray vertical line indicates the onset of the winter storm Uri.

4.3.4 | Changes in people's access during the disaster

We also quantified the changes in people's access for each CBG, which is then used to understand the variation in accessibility across various population groups. To achieve this, we adopted the following mathematical formulation:

$$\Delta_i = \frac{E_i^{\text{during}} - E_i^{\text{before}}}{E_i^{\text{before}}}. \tag{5}$$

Here, E_i^{before} is the baseline of people's access from the CBG i before the disaster, which represents the average values of accessibility value $A_i^{(t)}$ between February 8, 2021 and February 13, 2021, that is, the 1-week period before the disaster event considered in our study. The notation E_i^{during} indicates the average of people's access $A_i^{(t)}$ from the CBG i during the disaster event (from February 14, 2021 to February 17, 2021).

We then examined how the disaster impacts the areas with consistent low access to food stores. First, to identify the areas with low access to food stores, we classified CBGs into three groups based on the quantiles of the accessibility distribution prior to the disaster, that is, $\{E_i^{\text{before}}, \forall i\}$. The CBG considered as having low access is situated in the first quantile of the accessibility distribution. Then, we further divided the identified low access areas into three groups based on the quantiles of the distribution of change in access, that is, $\{\Delta_i, \forall i\}$. The CBG considered as having low (high) access is situated in the first (third) quantile of the distribution of access change. Through the above two procedures, we examine the demographic composition of the two groups: (1) the "L-L" group which indicates the people living in CBGs that have *low* access to food stores before the disaster and *low* change in access to these food stores during the disaster, and (2) the "L-H" group which indicates the people living in CBGs that have *low* access to food stores before the disaster and *high* change in access to these food stores during the disaster. Based on this setting, we hypothesize that the "L-H" group is more vulnerable compared to the "L-L" group, as the "L-H" group is more sensitive to the disaster with high changes in people's access.

To test our hypothesis, we compared the demographic composition of the "L-L" and the "L-H" groups. The distributions of the three demographic variables (i.e., high-school degree or below, non-White population, and 65 years and above) and one socioeconomic variable (i.e., income per capita) in these two groups are compared in Figures 8 and 9, respectively. The statistical significance codes[1] are indicated in the plots as well. From Figure 8, we observe the variations in access to the grocery stores for the two groups. It can be noticed that the "L-H" group has higher percentages of people with low educational attainment, high non-White representation, and low per capita income, compared to the "L-L" group. These differences are also statistically significant ($p < 0.1$). Note that, the difference of the elderly population (65 years and above) between the "L-L" and "L-H" groups is not statistically significant. Similar patterns can be observed for the access to convenience stores in Figure 9.

To summarize, we illustrated that the "L-H" group is indeed the vulnerable communities with limited access to grocery and convenience stores, and is disproportionately impacted by the disaster. Such findings are also aligned with previous studies showing minority groups such as non-White and low-income population groups are disproportionately

[1] Significance codes: "**" if $p < 0.01$; "*" if $p < 0.05$; "·" if $p < 0.1$; "ns" indicates not significant if $p \geq 0.1$.

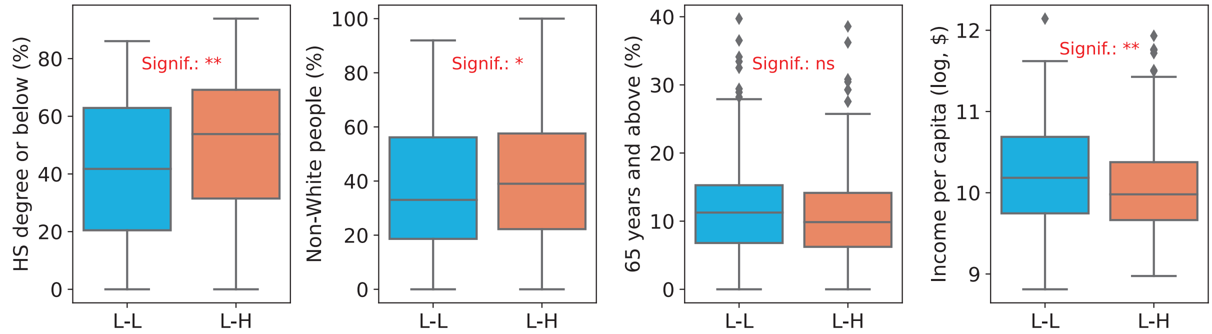


FIGURE 8 The distribution of sociodemographic variables between the "L-L" and the "L-H" groups in access to grocery stores.

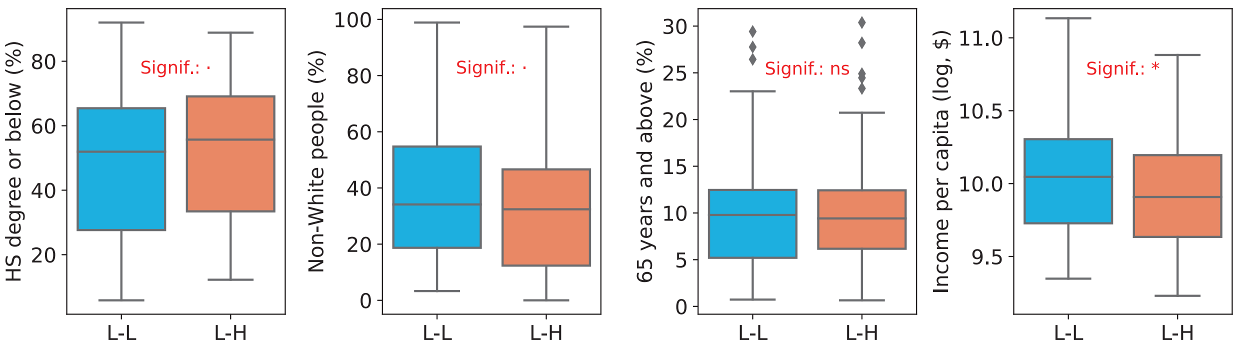


FIGURE 9 The distribution of sociodemographic variables between the "L-L" and the "L-H" groups in access to convenience stores.

impacted by natural disasters in access to grocery stores (Esmalian et al., 2022).

5 | DISCUSSION

In this study, we aim to advance the understanding of people's actual access to essential services like the food stores using human mobility patterns obtained from mobile phone data. Previous studies mainly focus on examining how people potentially access services considering the travel distance to the nearest facility, which often fall short of capturing the actual access patterns of people. Therefore, to fill this gap, this paper considers people's travel preferences to investigate how people actually access different facilities, and develops a method to quantify the accessibility of essential services. In particular, we demonstrated the changes in people's access to food stores across time and space in response to a natural disaster. Following this, we also showed that the disaster had the disproportionate impacts on socially vulnerable people's access to food stores. The methods proposed in this study could be generalized to analyze the actual access of people to other types of essential services as well, such as healthcare.

Our results indicate that there is a significant value in considering the actual access of people using the mobile phone data. This is because mobile phone data reflect people's actual travel patterns and preferences in visiting different service locations, which may not necessarily be the one with the shortest travel distance/time that is mostly considered in the previous studies. Our results also indicate that statistically significant differences exist between the potential access and the actual access, as the former neglects actual travel patterns of people. Most importantly, using the potential access may result in inaccurate assessments of people's access to essential services, consequently leading to suboptimal resource allocation.

5.1 | Policy implications

Our approach enables identifying regions that suffer from limited access to food stores, particularly in the face of natural disasters. People living in these areas could have a high risk of being isolated from essential food services. The risk of isolation, which describes the potential that residents may be cut off from accessing essential services, provides crucial information for evaluating adaptation strategies to enhance community resilience (Logan et al., 2023). By recognizing which regions are more likely to have limited access, this paper could help local planners for capital investments in building more accessible transport network or adding more facilities, allowing residents to access the services they need (Leitch & Wei, 2024). For example, over the last decade, federal and state governments in the United States have invested significant financial resources to incentivize the establishment of food stores and the improvement of transportation infrastructure. Particularly, the Healthy Food Financing Initiative (HFFI) by the federal governments has allocated more than $22.6 million for 134 projects through the year of 2021. These funds are aimed to improving food accessibility by establishing grocery stores and supermarkets in the underserved communities (America's Healthy Food Financing Initiative, 2021).

In addition, our work could also empower government officials or disaster responders to keep track of at-risk communities across space and time during disasters, ensuring that resources can be effectively and promptly allocated to these communities to guarantee equitable access to essential services. People with easier access to food stores are more likely to achieve higher levels of disaster preparedness and short-term recovery effort, which can be linked to a higher disaster resilience of the community (Esmalian et al., 2022). To determine availability that is based on the daily visit patterns, advanced predictive modeling techniques can be applied to forecast human mobility patterns from the historical data, such as a two-stage mobility predictive model (Wei & Mukherjee, 2024). In this view, our method can be further applied to real-time analysis by identifying communities that might be vulnerable to the disasters. Note that, while real-time access to mobile phone data facilitates quicker and more effective responses to crises (e.g., disasters and pandemics), this data access depends on various factors, such as user permissions and the service provider's willingness to share data. Particularly, the data from mobile phones are often collected and processed (e.g., through aggregation and anonymization) with certain delays, which may limit its ability to undergo real-time analysis. Thus, it is crucial to establish regulatory guidelines to protect individual's privacy while leveraging the potential benefits of such data for public good. Striking the right balance between public welfare and individual privacy is a key to better build resilient communities.

5.2 | Limitations and future research directions

In this study, we constructed the catchment areas using the travel distance rather than travel time. This is because travel distance is considered a more explicit and stable measure, compared to the travel time that depends on multiple factors such as travel mode and traffic conditions (Burkey et al., 2012; Miller, 2018). The travel time can also be examined in the measure of accessibility in the future. Furthermore, the acceptable travel distance threshold is determined based on the average travel distance derived from actual human mobility patterns. In practice, each community may have a different view on what travel threshold can be considered acceptable, depending on the size of the community and the type of service facilities. Thus, to determine the best acceptable travel threshold requires community engagement to ensure alignment with the actual needs of the community.

Another limitation of this study is that it uses the driving network to calculate the travel distance. Accessibility to food stores can also be affected by other transportation networks, such as pedestrian walkways, which were not considered in this study. Future research could further extend our proposed framework by incorporating walking routes extracted from OSM data, into the accessibility measures. This could help in building an x-minute city, which has gained increasing attention in countries such as New Zealand and the United States (Logan et al., 2022). The concept of the x-minute city aims to achieve the goal that residents can fulfill most of their daily needs within the x-minute walk (e.g., $x = 15$) (Logan et al., 2022). In this case, the street network for walking, rather than driving, could be more suitable for measuring accessibility within a city. Future work could further investigate inequality measures to better evaluate disparities in people's access across various population groups and disaster phases, where the advanced statistical equity-based tools such as the Kolm–Pollak equally distributed equivalent (EDE) can be utilized (Logan et al., 2021; Sheriff & Maguire, 2020).

6 | CONCLUSION

This study examined the spatial access to two main food stores (grocery and convenience stores) in the face of the winter storm Uri, leveraging human mobility data. We also analyzed variations in accessibility across neighborhoods with diverse demographic backgrounds. The incorporation of real human mobility patterns in measuring accessibility provides a new perspective to understand how people actually utilize food stores. From this point of view, this study is distinct from most previous studies that focus primarily on potential access to service facilities, without fully considering human movement behaviors. All analyzes are conducted at CBG level, which provides the high level of detail in revealing spatial access patterns of people. The accessibility analysis could help city planners or disaster responders identify the food desert areas at finer spatial resolutions. This can be incorporated into urban planning (e.g., incentivize the development of new service facilities) to enhance overall food store accessibility as well as ensure equitable access, thus mitigating the risk of food insecurity across different population groups.

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