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Examining income segregation within activity spaces under natural disaster using dynamic mobility network

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ABSTRACT

Rising income segregation perpetuates socioeconomic inequalities, preventing us from developing more sustainable environments. In the literature, little is known about the spatiotemporal dynamics of income segregation under natural disaster. To address this gap, this paper aims to quantify how people experience income segregation in the context of a disaster through their mobility patterns. Specifically, we propose a generalized framework to construct a dynamic mobility network that describes the footprint of residents within their activity spaces, leveraging large-scale mobile phone data. The construction of this network is formulated as a nonlinear programming model and solved by the Lagrangian relaxation and numerical iterative method. A case study is presented to examine income segregation of residents in Harris County (Texas) in access to various critical facilities before, during, and after the winter storm Uri. Our results indicate that income segregation behaviors vary at different critical facilities, as facilities with smaller catchment areas are found to have higher degrees of segregation. We also highlight the disparities in access to critical facilities between low-income and high-income neighborhoods. This paper provides a new venue to better understand income segregation behavior under natural disaster through human mobility networks, which could inform equitable resource allocation in disaster management.

1. Introduction

With an increase in urbanization and migration, population diversity and social equity play a pivotal role in the development of sustainable and resilient cities and society (Bibri & Krogstie, 2017; Komeily & Srinivasan, 2015). One of the pressing social issues that communities are still experiencing is income segregation, which refers to disparate neighborhoods being separated from each other based on their income (Van Ham, Tammaru, Ubarevičienė, & Janssen, 2021). Especially in the United States, neighborhoods are becoming more segregated and less diverse according to socioeconomic status (Reardon, Bischoff, Owens, & Townsend, 2018). A high degree of income segregation not only undermines people's quality of life and opportunities (Levy, Vachuska, Subramanian, & Sampson, 2022), but also erodes social cohesion and equity that are fundamental towards sustainable urban development (Buck, Summers, & Smith, 2021). Additionally, income segregation can further lead to inequalities in social, economic, political and physical outcomes between low-income and high-income households (Reardon & Bischoff, 2011). Thus, it is of critical importance to better understand and characterize the pattern of income segregation in a region.

Traditionally, income segregation is often analyzed by mapping the geographic distribution of residential neighborhoods (Iceland, Weinberg, & Steinmetz, 2002). From the top populous U.S. cities, evidence suggests that lower-income households in the metropolitan area tend to situate in a majority lower-income residential areas (Taylor & Fry, 2012), and experience significant isolation from non-poor neighborhoods (Massey, Rothwell, & Domina, 2009). Studies that focus primarily on residential spaces in understanding income segregation assume that people of the same neighborhood do not further sort themselves by their socioeconomic status in the places they visit (Reardon & Bischoff, 2011), which is often not true (Owens, Reardon, & Jencks, 2016). Recent research suggests that people can further experience income segregation in various spaces such as workplace and leisure venue that are beyond the residential space (Mijs & Roe, 2021). Individuals are often found at specific places that are more socially and culturally attractive to them, making these places segregated in their own way (Dong et al., 2020). Restricting analysis to residential contexts may give rise to the uncertain geographic context problem, which states that the observation of segregation behaviors could be

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affected by how neighborhoods are geographically delineated (Kwan, 2012). In addition, failure to consider the segregation occurring in the non-residential space could lead to an incomplete examination of the full spectrum of segregation that residents experience in their daily lives (Milias & Psyllidis, 2022). In this context, to holistically study income segregation, the concept of activity space is proposed in the literature to encompass all different kinds of locations where people conduct socioeconomic activities and interact with other population groups (Wong & Shaw, 2011). A recent study demonstrates that 45% of the residents' income segregation is due to where they live, and the rest of 55% is attributed to where they move in the activity space (Moro, Calacci, Dong, & Pentland, 2021).

Although much effort has been devoted to assessing income segregation through either residential space or activity space, most of the studies were conducted at a coarse spatiotemporal resolution, due to data unavailability (Iceland et al., 2002; Sun, Axhausen, Lee, & Huang, 2013). Conventionally, researchers utilize travel survey data to understand how people experience income segregation at different locations through travel time and distance (Farber, O'Kelly, Miller, & Neutens, 2015; Wang, Li, & Chai, 2012). Survey data is valuable for providing individual information, but suffers a series of drawbacks such as low population coverage, coarse spatial resolution, and high implementation cost (Barbosa et al., 2018). Some studies make use of Twitter data to capture both geographic and contextual segregation behavior of users associated with their historical tweets (Huang & Wong, 2015; Mirzaee & Wang, 2020). Social media data is often criticized by high selection bias and low spatial resolution, as some users fail to provide the accurate content or location (Hecht, Hong, Suh, & Chi, 2011). To this end, characterizing the residential and activity spaces at finer spatial resolution could provide more accurate assessment of income segregation. Empirical evidence indicates the temporal variation of segregation throughout the day is not uniformly distributed across spatial areas, highlighting the importance of income segregation assessment at a finer spatial and temporal scale (Park & Kwan, 2018; Zhang, Wang, & Kan, 2022).

The increasing frequency and severity of natural disasters can further perpetuate income segregation and inequality, as socially vulnerable populations (e.g., the poor, racial minorities, the elderly, and people with disabilities) are being affected in a disproportionate manner (Fatemi, Ardalan, Aguirre, Mansouri, & Mohammadfam, 2017; Ogie & Pradhan, 2019). For instance, wealthier populations are more likely to have the means to obtain critical goods such as food almost immediately, while lower-income households often have difficulties in satisfying their needs during a natural disaster (Dargin, Berk, & Mostafavi, 2020). In addition, people living in underprivileged areas with low-quality and insecure housing have limited access to essential services, leading to higher mortality and morbidity rates (Sandoval & Sarmiento, 2020). In the literature, little is known about the impact of natural disaster on income segregation across both spatial and temporal scales. However, it is of critical importance to understand how people experience income segregation in response to and recovery from a natural disaster, such that resources can be allocated in an informed and optimal way to minimize the impact on the marginalized populations.

Therefore, in this paper, we aim to assess how people experience income segregation by integrating both residential areas and activity spaces at a higher spatiotemporal granularity, and examine the segregation behaviors before, during, and after a natural disaster. Specifically, we propose a generalized framework to develop a dynamic human mobility network that characterizes the daily footprint of people in their residential neighborhoods and activity spaces leveraging large-scale mobile phone data. The construction of such a network is first formulated as a nonlinear programming model. Then, we apply Lagrangian relaxation technique and design a numerical iterative method to obtain the most probably population flow in the network. To demonstrate the use of the proposed framework, a case study is presented where we build a time-dependent mobility network of residents from Harris County–in the U.S. state of Texas–under Winter Storm Uri 2021. Based on the mobility network, income segregation patterns in access to various critical facilities (e.g., hospitals) are analyzed before, during and after the disaster. Finally, practical insights are also provided to illustrate how our findings can be used in disaster management and regional planning to potentially mitigate the pre-existing economic segregation and inequalities in communities.

The remainder of the paper is structured as follows. Section 2 summarizes the related literature which motivates and supports the importance of this paper. Section 3 introduces the methodological framework including mobility network construction, income segregation assessment, and mobility behaviors illustration. Section 4 presents a case study demonstrating the applicability of the framework with a description of data collection and pre-processing. Results and discussion are provided in Section 5 and Section 6 respectively. Finally, Section 7 concludes the paper.

2. Literature review

2.1. Income segregation

Income segregation can broadly refer to the sorted pattern of population groups into various neighborhoods according to their economic characteristics (Reardon & Bischoff, 2011). It has attracted considerable attention around the globe, and especially has a long history in the U.S. (Pendall & Carruthers, 2003). On the one hand, high degree of income segregation is associated with detrimental consequences on residents' quality of life, including low access to essential services and resources (e.g., health centers) (Quick & Revington, 2022), limited social interactions (Echenique & Fryer, 2007), and high concentration of poverty (Quillian, 2012). On the other hand, income segregation is often entangled with other types of segregation in terms of race, age and education, leading to a cascading effect on sustainable development of a community (Brasington, Hite, & Jauregui, 2015). Therefore, a better understanding of income segregation plays a crucial role in building a more inclusive society.

A large body of literature on income segregation focuses heavily on the geographic distribution of residential neighborhoods (Iceland et al., 2002). The uneven sorting of households by income in a neighborhood reveals unequal opportunities to access services and resources (Massey et al., 2009). Specifically, people living in the low-income neighborhoods become spatially separated from essential resources (e.g., employment opportunities, elite schools) that are usually situated in the high-income areas (Ross, Houle, Dunn, & Aye, 2004). These conventional studies often assume a random mixing in non-residential spaces, suggesting that residents living in the same neighborhood do not confront extra sorting by their socioeconomic status in the places where they conduct daily social activities (Browning, Calder, Krivo, Smith, & Boettner, 2017). Some empirical studies contradict this assumption by showing that people living in the same residential areas may not experience the same level of segregation (Wong, 2016). This is because most people are likely to spend a sufficient amount of time at places outside of home to interact with various income groups (Wang, Phillips, Small, & Sampson, 2018). Focusing solely on residential space could fall short of revealing the holistic picture of income segregation that spans over divergent socio-geographical spaces (Ta, Kwan, Lin, & Zhu, 2021).

In reality, besides residential spaces, people further experience income segregation through daily activities and interactions occurred in the other types of spaces such as schools, workplaces, and leisure venues (Mijs & Roe, 2021; Owens et al., 2016). These non-residential places may exhibit socioeconomic characteristics that are different from visitor's residential areas (Zhang et al., 2022). The concept of activity space is adopted to consolidate all relevant non-residential spaces in the literature, and it encompasses all locations where residents have direct social interactions with others from different economic backgrounds (Wong & Shaw, 2011). Analyzing activity spaces of people can advance our understanding of income segregation on how residents are exposed to or isolate from other groups at a variety of places during their day-to-day activities (Echenique & Fryer, 2007).

Income segregation could also be influenced by natural disaster. Although disasters do not discriminate among different socioeconomic groups, studies often suggest that low-income households experience more disaster losses and have the limited access to essential services and resources to secure their daily needs in the face of the disaster (Ogie & Pradhan, 2019; Yabe, Rao, & Ukkusuri, 2021). This leads to inequalities in exposure to disaster impact and unequal social and physical outcomes, rendering economically disadvantaged people even more vulnerable to the risk of the disaster (Fatemi et al., 2017). Low-income individuals are more prone to residing in less expensive and environmentally vulnerable areas, which makes them more separated from accessing services and resources in the event of natural disasters (Benevolenza & DeRigne, 2019). On the contrary, people with higher socioeconomic status typically have a higher degree of accessibility and affordability of services, even though the location of those services is distant from their residential areas (Browning et al., 2017). Additionally, residents from high-income communities tend to have a high evacuation rate to the same type of neighborhoods, making the pre-existing segregation pattern even more separated (Deng et al., 2021; Yabe & Ukkusuri, 2020). Other studies provide a solid foundation for the existence of potential disparity in mobility activity patterns during the disaster (Fan, Jiang, Lee, & Mostafavi, 2022; Hong, Bonczak, Gupta, & Kontokosta, 2021; Wei & Mukherjee, 2022), but they do not quantitatively examine disaster-induced income segregation in people's activity space.

2.2. Activity space characterization

To better understand income segregation in activity spaces, it is of critical importance to accurately characterize the locations where people perform socioeconomic activities. However, it is quite challenging to fully capture the activity space, due to lack of detailed data to describe human activities across spatial and temporal scales (Sun et al., 2013). Traditionally, people often make use of travel survey data to capture the activity space of residents. For example, one study leverages the survey data to identify travel locations of people in Beijing, and suggests that residents from economically ordinary neighborhoods are more likely to visit public places such as parks, while economically advantaged residents often visit shopping malls and supermarkets (Wang et al., 2012). Another research conducts a longitudinal study using surveys to investigate the diversity of activity space, and concludes that high-income commuters tend to travel farther distances and visit more places during workdays compared with low-income commuters in Hong Kong (Tao, He, Kwan, & Luo, 2020). Such analyses that hinge on survey data are often constrained by a limited sample size and a high implementation cost, which may fall short of capturing high-resolution dynamics of mobility interactions on a finer scale (Farber et al., 2015). In addition, social media (e.g., Twitter, Meta) provides geographic and contextual information about where users move (Huang & Wong, 2015). In this view, activity space is described as individual movement patterns through a sequence of historical geo-tagged posts (Jurdak et al., 2015). By analyzing geo-coded Twitter data, one study reveals the existence of spatial segregation by race and income, as racial minorities and lower-income individuals are more confined to move within the same type of communities (Mirzaee & Wang, 2020). Although social media data are valuable in providing insights on segregation from both cyberspace and physical space aspects, such data often suffer from the selection bias, as about one-third of Twitter users fail to provide their real locations or content (Barbosa et al., 2018; Hecht et al., 2011).

Recently, the burgeoning of large-scale mobile phone data opens up unique opportunities to better characterize activity space of high granularity (Zhang, Duan, Wong, & Lu, 2021). By analyzing human mobility patterns from mobile phone data, a study reveals that local shops and grocery stores are more likely to be segregated by income in comparison to the public areas such as museums and art venues (Moro et al., 2021). Food outlets (e.g., restaurants, bakeries, bars, cafes) tend to attract customers with diverse backgrounds in race and income; while retail stores (e.g., supermarkets) typically have more homogeneous visitors (Lee, 2021).

2.3. Research gaps and our contribution

To summarize, a growing body of literature has focused on analyzing segregation behavior by income. However, these studies analyze income segregation of people either within their residential space (i.e., where people live) or in their activity space (i.e., where people move), which only partially reveals how people with diverging economic backgrounds interact with each other during their daily lives. Moreover, most of the previous studies examine income segregation under blue-sky conditions, which may not be sufficient to capture segregation behaviors in the context of a natural disaster. It is imperative to examine income segregation patterns during natural conditions, which could be beneficial for relief planning to potentially mitigate economic disparities. Therefore, this paper aims to fill these gaps by analyzing income segregation behaviors by integrating both the residential and activity spaces under natural disaster leveraging fine-grained human mobility network. The main contribution of this study can be summarized as follows.

1. This study provides a holistic view to systematically consider income segregation behavior by examining both residential and activity spaces of residents at fine-grained spatiotemporal resolution. This could enhance our understanding of the full spectrum of segregation that people experience in their daily lives.
2. We propose a generalized framework to construct dynamic human mobility networks that can characterize the movement of people from residential areas to various places within their activity spaces, leveraging large-scale mobile phone data. This mobility network is derived using a nonlinear optimization method that generates the most probable population flow from the data. Such a network contributes to a better understanding of high-granularity human mobility behaviors in the face of a natural disaster.
3. We explore income segregation behaviors in access to a wide range of critical facilities between low-income and high-income neighborhoods in the context of natural disaster. This could inform policy makers in the equitable allocation of resources to mitigate the socioeconomic disparities.

3. Methodological framework

This section provides the details of our proposed framework that leverages human mobility behaviors to analyze the income segregation patterns of people in their activity spaces in the face of a disaster. This framework consists of three parts: mobility network construction, income segregation assessment, and mobility behaviors characterization. In the first part, we present a time-dependent mobility network at a neighborhood level that integrates both the residential and the activity spaces. The mobility network is formulated as a nonlinear programming model, and solved through the Lagrangian relaxation technique and the numerical iterative method. In the second part, based on the network theory, we introduce the concept of assortativity coefficient to assess how people experience income segregation at different locations in their activity space. In the last part, human mobility behaviors, characterized by the proportion of visitors and their travel distances to the facilities within the activity spaces, are analyzed to better understand income segregation patterns.

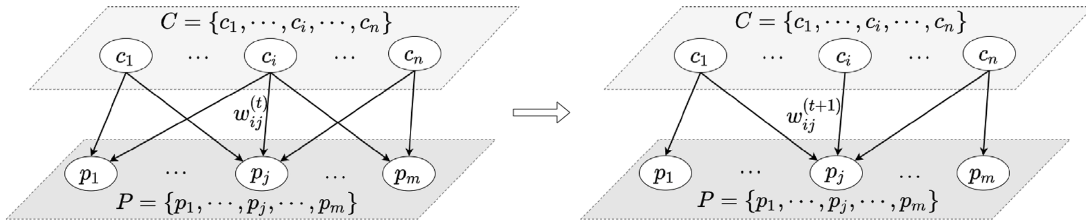


Fig. 1. Schematic illustration of the dynamic CBG-POI mobility network.

Table 1
Description of notations in the model.

Notation	Description
Sets	
C	Set of CBGs, $C = \{c_1, c_2, \dots, c_n\}$.
P	Set of POIs, $P = \{p_1, p_2, \dots, p_m\}$.
T	Set of time, $T = \{t_1, t_2, \dots, t_l\}$.
Parameters	
$Q_i^{(t)}$	The number of people left home situated in CBG c_i at time t.
$V_j^{(t)}$	The number of people visited POI p_j at time t.
U_{ij}	The total number of people from CBG c_i to POI p_j.
Variables	
$\boldsymbol{W} = \{w_{ij}^{(t)}\}$	The number of visitors from CBG c_i to POI p_j at time t.

3.1. Mobility network construction

We first describe some key terms before constructing the proposed human mobility network. A *census block group* (CBG) is a geographic area defined by the U.S. Census Bureau that usually contains between 600 to 3,000 residents (USCB, 2015). We use the CBG to represent where people live (i.e., residential/home area). A *point-of-interest* (POI) refers to a non-residential geographic location where people may find it useful or interesting to visit such as gas station, grocery store, and restaurant (Wiki, 2021). The POI denotes the place where people may conduct daily activities. The mobility patterns at different POIs establish an activity space in a region. In this paper, we aim to build a dynamic mobility network (namely, CBG-POI network) that characterizes the movement of residents from each CBG to any POI. This CBG-POI network allows us to comprehensively assess mobility interactions of people in their activity space across both spatial and temporal scales.

3.1.1. Notations and problem definition

The notations for characterizing the CBG-POI mobility network are described in Table 1. Let $C = \{c_1, c_2, \dots, c_n\}$ denote a set of CBGs, and $P = \{p_1, p_2, \dots, p_m\}$ denote a set of POIs. To be concise, this paper uses the index i to represent the CBG c_i, and the index j to indicate the POI p_j. The CBG-POI mobility network is modeled as a bipartite graph $G = \{C, P, E\}$, where all vertices can be divided into two disjoint and independent sets C and P. A set of edges is denoted by E, where an edge $e_{ij} \in E$ $(\forall i \in C, \forall j \in P)$ links from CBG c_i to POI p_j. A time-dependent weight $w_{ij}^{(t)}$ is associated with the edge e_{ij} representing the number of people visiting POI p_j from CBG c_i during the time t. Here we consider a discrete time indexed by t, where $t \in T = \{t_1, t_2, \dots, t_l\}$. With all these notations, the CBG-POI mobility network can be represented by $\boldsymbol{W} = \{w_{ij}^{(t)}, i \in C, j \in P, t \in T\}$. The schematic representation of this network is displayed in Fig. 1.

For each dimension of the CBG-POI network, the parameter $Q_i^{(t)}$ describes the number of people who left their home CBG c_i at time t. Similarly, $V_j^{(t)}$ indicates the number of people visiting POI p_j at time t, and U_{ij} denotes aggregated number of people from CBG c_i to POI p_j throughout the entire time frame. Given $Q_i^{(t)}$, $V_j^{(t)}$, and U_{ij} as inputs, we aim to infer the unknown time-dependent mobility network $\boldsymbol{W}$ with the most probable population flows $w_{ij}^{(t)}$. It is worth noting that, the problem of estimating the CBG-POI network is analogous to traditional Origin–Destination (OD) estimation problem with an additional dimension of time. However, our problem is different in a way that it has a strict bipartite structure, while in the traditional OD problem, each node represents both the origin and destination station as in a transit network. There is only one paper that attempted to establish a similar mobility network for simulating the spread of COVID-19 virus (Chang et al., 2021), but their objective and method are different from our study. Specifically, their paper aims to get a possible mobility network, while our work focuses on inferring an optimal mobility network that describes the most probable population flow by making the most of the data. Additionally, they use a classic statistical method to proportionally adjust mobility distributions, while we directly formulate it as a nonlinear programming using optimization techniques to solve this problem. Thus, to the best of our knowledge, this is the first work focusing on developing and inferring the optimal mobility network from mobile phone data using optimization methods.

3.1.2. Mathematical formulation

To formulate the CBG-POI mobility network, we leverage the principle of entropy maximization (equivalent to information minimization) that provides an unbiased estimate on the mobility network by making full use of the information contained from the observed data (Xie, Kockelman, & Waller, 2010). The motivation of using the entropy approach can be summarized as follows. On the one hand, the most probable mobility network maximizes the total entropy in the system while satisfying certain constraints, accounting for the uncertainty that stemmed from the limited data (Kapur, 1989). On the another hand, entropy maximization model can produce an unbiased estimate by making the most of given information (Van Zuylen & Willumsen, 1980).

$$\underset{w_{ij}^{(t)}}{\text{minimize}} \quad f(\boldsymbol{W}) = \sum_{i \in C} \sum_{j \in P} \sum_{t \in T} \left(w_{ij}^{(t)} \log w_{ij}^{(t)} - w_{ij}^{(t)} \right) \tag{1a}$$

$$\text{subject to} \quad \sum_{j \in P} w_{ij}^{(t)} = Q_i^{(t)}, \quad \forall (i \in C, t \in T) \tag{1b}$$

$$\sum_{i \in C} w_{ij}^{(t)} = V_j^{(t)}, \quad \forall (j \in P, t \in T) \tag{1c}$$

$$\sum_{t \in T} w_{ij}^{(t)} = U_{ij}, \quad \forall (i \in C, j \in P) \tag{1d}$$

$$w_{ij}^{(t)} \geq 0, \quad \forall (i \in C, j \in P, t \in T) \tag{1e}$$

The mathematical formulation for the dynamic CBG-POI estimation problem is illustrated through (1a)–(1e). The maximum entropy function is denoted as $-f(\boldsymbol{W})$. For simplicity, instead of maximizing the total entropy (i.e., $-f(\boldsymbol{W})$), we equivalently minimize the total information (i.e., $f(\boldsymbol{W})$), while satisfying each CBG constraint (1b), POI constraint (1c), and time constraint (1d). Constraint (1e) indicates non-negative variables. We denote the above mathematical formulation as the primal problem.

3.1.3. Lagrangian relaxation

The primal problem is shown to be a convex minimization program with a nonlinear objective function and a set of linear constraints. It is often difficult to obtain a closed form for the nonlinear function and hard to solve for optimization problem with large instances. To address this issue, we utilize the Lagrangian relaxation technique, which is often used in solving large-scale optimization problem with coupling constraints (Fisher, 1981). First, we construct the Lagrangian function denoted as $\mathcal{L}$ that relaxes the model constraints by augmenting the objective function with a weighted sum of the constraint functions, which is given by

$$\mathcal{L}(\boldsymbol{W},\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\phi}) = \sum_{i,j,t}\left(w_{ij}^{(t)}\log w_{ij}^{(t)} - w_{ij}^{(t)}\right) + \sum_{i,t}\lambda_{it}\cdot\left(Q_i^{(t)} - \sum_j w_{ij}^{(t)}\right) + \sum_{j,t}\mu_{jt}\cdot\left(V_j^{(t)} - \sum_i w_{ij}^{(t)}\right) + \sum_{i,j}\phi_{ij}\cdot\left(U_{ij} - \sum_t w_{ij}^{(t)}\right). \tag{2}$$

The associated Lagrangian multipliers $\boldsymbol{\lambda} = \{\lambda_{it}, \forall(i,t)\}$, $\boldsymbol{\mu} = \{\mu_{jt}, \forall(j,t)\}$, $\boldsymbol{\phi} = \{\phi_{ij}, \forall(i,j)\}$ are orthants with respect to constraints (1b), (1c) and (1d).

Next, the Lagrange dual function $\mathcal{D}$ is defined as the minimum value of the Lagrangian function over $\boldsymbol{W}$, which can be formed as

$$\mathcal{D}(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\phi}) = \min_{\boldsymbol{W}\geq\boldsymbol{0}} \mathcal{L}(\boldsymbol{W},\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\phi}). \tag{3}$$

To explicitly write down the equation $\mathcal{D}$, we need to find the minimum value of $\mathcal{L}$. Based on the first and second order optimality conditions, we can obtain

$$\begin{cases} \frac{\partial\mathcal{L}(\boldsymbol{W},\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\phi})}{\partial w_{ij}^{(t)}} = 0 \Longrightarrow w_{ij}^{*(t)} = \exp\left(\lambda_{it} + \mu_{jt} + \phi_{ij}\right) \\ \frac{\partial^2\mathcal{L}(\boldsymbol{W},\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\phi})}{\partial w_{ij}^{(t)2}} = \frac{1}{w_{ij}^{(t)}} > 0. \end{cases} \tag{4}$$

Eq. (4) indicates that the optimal solution $w_{ij}^{*(t)}$ of $\mathcal{L}$ hinges on the Lagrangian multipliers λ_{it}, μ_{jt}, and ϕ_{ij}. Mathematically, the Lagrangian dual function $\mathcal{D}$ provides a lower bound on the optimal value of the primal problem due to relaxed constraints, and the value of lower bound is dependent upon Lagrange multipliers. In order to achieve the best (i.e., largest) lower bound, we further introduce the corresponding Lagrange dual problem as follows.

$$\underset{\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\phi}}{\text{maximize}} \quad \mathcal{D}(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\phi}) = -\sum_{i,j,t}\exp(\lambda_{it} + \mu_{jt} + \phi_{ij}) + \sum_{i,t}\lambda_{it}Q_i^{(t)} + \sum_{j,t}\mu_{jt}V_j^{(t)} + \sum_{i,j}\phi_{ij}U_{ij} \tag{5}$$

Throughout the procedures above, we convert the optimization with constraints to the unconstrained optimization. By applying the first order optimality condition for the Lagrange dual function $\mathcal{D}$ with the optimal value $w_{ij}^{*(t)}$, we have

$$\begin{cases} \frac{\partial\mathcal{D}(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\phi})}{\partial\lambda_{it}} = Q_i^{(t)} - \exp\left(\lambda_{it}^*\right)\cdot\sum_j\exp\left(\mu_{jt}^* + \phi_{ij}^*\right) = 0 \\ \frac{\partial\mathcal{D}(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\phi})}{\partial\mu_{jt}} = V_j^{(t)} - \exp\left(\mu_{jt}^*\right)\cdot\sum_i\exp\left(\lambda_{it}^* + \phi_{ij}^*\right) = 0 \\ \frac{\partial\mathcal{D}(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\phi})}{\partial\phi_{ij}} = U_{ij} - \exp\left(\phi_{ij}^*\right)\cdot\sum_t\exp\left(\lambda_{it}^* + \mu_{jt}^*\right) = 0 \end{cases}$$

$$\Longrightarrow \begin{cases} \lambda_{it}^* = \log\frac{Q_i^{(t)}}{\sum_j\exp\left(\mu_{jt}^*+\phi_{ij}^*\right)} \\ \mu_{jt}^* = \log\frac{V_j^{(t)}}{\sum_i\exp\left(\lambda_{it}^*+\phi_{ij}^*\right)} \\ \phi_{ij}^* = \log\frac{U_{ij}}{\sum_t\exp\left(\lambda_{it}^*+\mu_{jt}^*\right)}. \end{cases} \tag{6}$$

3.1.4. Numerical solutions

To solve the system of nonlinear equations (6) above, we apply the fixed point iteration method for providing good approximate solutions to the dual variables. The basic idea of the fixed point iteration method is to generate a sequence of points to recursively estimate the solution of the equations given initial values, until the stopping criterion is met (Judd, 1998; Nocedal & Wright, 1999). The major advantageous feature of using the iterative method is the computational efficiency, as it is suitable for solving very large systems (Nocedal & Wright, 1999). The recursive process for each dual variable is defined as below.

$$\begin{cases} \lambda_{it}(k) := \log Q_i^{(t)} - \log\left(\sum_j\exp\left(\mu_{jt}(k-1) + \phi_{ij}(k-1)\right)\right), \forall(i\in C, t\in T) \\ \mu_{jt}(k) := \log V_j^{(t)} - \log\left(\sum_i\exp\left(\lambda_{it}(k-1) + \phi_{ij}(k-1)\right)\right), \forall(j\in P, t\in T), \\ \phi_{ij}(k) := \log U_{ij} - \log\left(\sum_t\exp\left(\lambda_{it}(k-1) + \mu_{jt}(k-1)\right)\right), \forall(i\in C, j\in P) \end{cases}$$
$$k = 1, 2, \ldots \tag{7}$$

The values $\lambda_{it}(k)$, $\mu_{jt}(k)$, and $\phi_{ij}(k)$ are the numerical results at the kth iteration. To measure the performance of each iteration, we also define the iteration error r_k at the kth iteration as the sum of mean absolute error across each set of dual variables. Mathematically, it is defined as below:

$$r_k := E\left(\left|\boldsymbol{\lambda}(k) - \boldsymbol{\lambda}(k-1)\right|\right) + E\left(\left|\boldsymbol{\mu}(k) - \boldsymbol{\mu}(k-1)\right|\right) + E\left(\left|\boldsymbol{\phi}(k) - \boldsymbol{\phi}(k-1)\right|\right), \tag{8}$$

where $E\left(\left|\boldsymbol{\lambda}(k) - \boldsymbol{\lambda}(k-1)\right|\right) = \frac{1}{|C||T|}\sum_{i,t}\left|\lambda_{it}(k) - \lambda_{it}(k-1)\right|$, $E\left(\left|\boldsymbol{\mu}(k) - \boldsymbol{\mu}(k-1)\right|\right) = \frac{1}{|P||T|}\sum_{j,t}\left|\mu_{j,t}(k) - \mu_{j,t}(k-1)\right|$, and $E\left(\left|\boldsymbol{\phi}(k) - \boldsymbol{\phi}(k-1)\right|\right) = \frac{1}{|C||P|}\sum_{i,j}\left|\phi_{ij}(k) - \phi_{ij}(k-1)\right|$. Next, we introduce the stopping criterion of the iterative method as the iteration error is smaller than a given tolerance ϵ. We also present another stopping criterion as the pre-determined maximum iteration K is reached to balance between computational expense and model accuracy. The iterative method is terminated as long as one of the above conditions is satisfied. The details of the algorithm are explained in Algorithm 1.

Algorithm 1 Iterative Method for Dynamic CBG-POI Estimation Problem

1: **Input:** $k = 1, K = 20, \epsilon = 0.01, Q_i^{(t)}, V_j^{(t)}, U_{ij}$
2: **Output:** $\boldsymbol{W} = \{w_{ij}^{(t)}\}$
3: Initialization: $\boldsymbol{\lambda}(0), \boldsymbol{\mu}(0), \boldsymbol{\phi}(0)$
4: **do**
5: Update $\boldsymbol{\lambda}(k)$, $\boldsymbol{\mu}(k)$, $\boldsymbol{\phi}(k)$ at the k-th iteration using Eq. (7)
6: Calculate the iteration error r_k using Eq. (8)
7: $k \leftarrow k + 1$.
8: **while** $r_k \geq \epsilon$ and $k \leq K$
9: $w_{ij}^{(t)} \leftarrow \exp\left(\lambda_{it}(k-1) + \mu_{jt}(k-1) + \phi_{ij}(k-1)\right)$

3.2. Income segregation assessment

In this research, we use an income quintile to represent a neighborhood economic status, where the neighborhoods are classified into five income groups with approximately 20% of the neighborhoods in each group. Here we assume that the neighborhood economic status represents the income level of its residents. Specifically, each CBG is assigned an income quintile based on the median household income of the CBG. Each POI is also associated with an income quintile based on the median household income level of the neighborhood where the POI is located. All income quintiles are labeled in order as Q1 (first quintile, lowest income groups), Q2 (second quintile), Q3 (third quintile), Q4 (fourth quintile), and Q5 (fifth quintile, highest income groups).

To describe the segregation behaviors in an activity space, we introduce the concept of assortativity (a.k.a., assortative mixing) based on the network theory, to quantify the tendency of people to visit POIs within the neighborhood that shares the same economic characteristics as their home neighborhood. To be specific, we construct a mobility assortativity matrix $M = \left\{m_{pq}, p, q = 1, 2, \ldots, 5\right\}$ to describe the percentage of visitors m_{pq} from CBG income quintile Q_p to POI income quintile Q_q, where m_{pq} is given by

$$m_{pq} = \frac{\sum_{i\in Q_p, j\in Q_q} w_{ij}^{(t)}}{\sum_{i\in Q_p} Q_i^{(t)}}. \tag{9}$$

To quantify the degree of income segregation, we further present the assortativity coefficient $\rho(M)$ with respect to the matrix M. Mathematically, $\rho(M)$ can be written as

$$\rho(M)=\frac{\left|\sum_{p,q} pq\cdot\overline{m}_{pq}-(\sum_{p,q} p\cdot\overline{m}_{pq})(\sum_{p,q} q\cdot\overline{m}_{pq})\right|}{\sqrt{\sum_{p,q} p^2\cdot\overline{m}_{pq}-(\sum_{p,q} p\cdot\overline{m}_{pq})^2}\sqrt{\sum_{p,q} q^2\cdot\overline{m}_{pq}-(\sum_{p,q} q\cdot\overline{m}_{pq})^2}}. \tag{10}$$

The construction of $\rho(M)$ is based on the Pearson correlation coefficient, but with normalized matrix entries (i.e., $\overline{m}_{pq} = {}^{m_{pq}}/\sum_{p,q} m_{pq}$) (Bokányi, Juhász, Karsai, & Lengyel, 2021). Note that, the assortativity coefficient $\rho(M)$ is bounded between 0 and 1. The larger value of $\rho(M)$ is associated with a higher level of segregation. Specifically, $\rho(M)=0$ indicates people do not exhibit any preference to visit POIs based on their neighborhood income level. When $\rho(M)=1$, it suggests mobility patterns to visit POIs are completely segregated by their income level in the neighborhood. Additionally, the mobility assortativity matrix M is dependent on the time t, suggesting that the assortativity coefficient $\rho(M)$ is a time-dependent value. This feature allows us to measure a dynamic pattern of income segregation of any given time.

3.3. Mobility behaviors characterization

The dynamics in human mobility behaviors, i.e., the proportion of visitors observed at each POI, signal the local perturbation in human movement patterns (Li et al., 2021). Increased proportion of visitors at POIs typically reflect the elevated demand of residents in access to these facilities. We examine the proportion of visitors to the POIs according to the economic conditions of their residential neighborhoods. Specifically, the proportion of visitors from CBG c_i to visiting POI p_j at time t is calculated by ${}^{w_{ij}^{(t)}}/Q_i^{(t)}$, which can be directly derived from our CBG-POI mobility network.

Travel distance is another critical feature of human mobility behaviors, as it reflects the willingness of people to visit different facilities (Wang & Taylor, 2016). As people may travel by road or by air, it is often difficult to track the actual movement trajectories of individuals due to the privacy issue. In this study, we estimate the travel distance, denoted by $d(i,j)$, from mobile phone user's home location c_i (determined by the centroid of the CBG) to a POI p_j using the Haversine formula, which takes into account the curvature of the Earth. Haversine distance is widely adopted by previous studies related to human mobility, and has demonstrated a better performance than the Euclidean distance (Ghaderi, Tsai, Zhang, & Moayedikia, 2022; Roy, Cebrian, & Hasan, 2019). The travel distance $d(i,j)$ is given by

$$d(i,j)=2R\cdot\sin^{-1}\left(\sqrt{\sin^2\left(\frac{1}{2}(\omega_j^{\text{lat}}-\omega_i^{\text{lat}})\right)+\cos(\omega_i^{\text{lat}})\cdot\cos(\omega_j^{\text{lat}})\cdot\sin^2\left(\frac{1}{2}(\omega_j^{\text{lon}}-\omega_i^{\text{lon}})\right)}\right), \tag{11}$$

where $(\omega_i^{\text{lat}},\omega_i^{\text{lon}})$ and $(\omega_j^{\text{lat}},\omega_j^{\text{lon}})$ are the geographic coordinates (latitude and longitude) of the location i and j respectively, and R is radius of the Earth. To capture the temporal movement patterns of people in visiting each facility, the travel distance per capita at POI p_j is calculated as a weighted distance by considering the number of travelers, which is given by

$$\overline{D}_j^{(t)}=\frac{\sum_{i\in C} w_{ij}^{(t)}\cdot d(i,j)}{V_j^{(t)}}, \tag{12}$$

where $V_j^{(t)}$ is defined as the number of visitors at POI p_j at time t in Table 1. These mobility behaviors characterized by the proportion of visitors and travel distance could further provide insights on how people react to a disaster across different time stages.

4. Case study description

To establish the applicability of our proposed framework for analyzing income segregation in activity spaces in the context of a natural disaster, we implement the framework to a case study described in this section. Fig. 2 represents the overview of our case study analysis that consists of three parts. The first part (demonstrated in this section) consists of data collection and pre-processing, where we describe the disaster-stricken study area, integration of multiple data sources, and data discrepancy correction. The second part describes the proposed methodological framework for building human mobility networks and evaluating income segregation and mobility behaviors, which is explained in Section 3. Finally, the third part (presented in Section 5) illustrates our findings about how people experience income segregation at various critical facilities under a natural disaster, which is revealed by the mobility network.

4.1. Study area

In this paper, we select the Harris County in state of Texas as the study region, and the Winter Storm Uri that occurred during February 13–17, 2021, as the disaster event. Winter Storm Uri was a catastrophic weather event where more than two out of three Texans lost electricity for an average of 42 h and the community witnessed at least a hundred fatalities during the freeze. Overall, an estimated \$295 billion economic loss in damage was reported (Stipes, 2021). Particularly, Harris County suffered the worst effects of the storm with approximately 91% of the residents experiencing power outages, which was significantly higher than the average of 64% as reported by other counties in Texas (University of Houston, 2021). In addition, Houston, the most populous city in Texas and the fourth-most populous city in the United States, is located in Harris County, providing more diverse socioeconomic backgrounds among residents.

The mobility patterns in our study area before and during the storm are demonstrated in Fig. 3. A significant reduction in mobility can be observed during the winter storm Uri, indicating that human mobility behaviors are severely impacted by the winter storm Uri as expected.

4.2. Data collection

The mobile phone data are provided by SafeGraph—a company that collects geographic location data from mobile phone applications through GPS pings (SafeGraph, 2020a). The GPS pings capture geographic coordinates (longitude and latitude) and timestamp, which enable high spatial and temporal resolutions for each data point. Those data are anonymous and aggregated at the population level to ensure the privacy issue. Specifically, three datasets from SafeGraph are extracted. The *Weekly Patterns* (WP) dataset contains the foot traffics of POIs and aggregated weekly visitor flow patterns (SafeGraph, 2020d). The *Social Distancing Metrics (v2)* (SDM) dataset provides the home locations of mobile phone users at each CBG, where the home location of sampled mobile phone user is determined by where the user has spent most night times (between 6 pm and 7 am) over the previous six weeks (SafeGraph, 2020c). The *Places* dataset records the business type of each POI according to the North American Industry Classification System (NAICS) code that is useful for down-selecting POI groups (SafeGraph, 2020b). In addition, sociodemographic information (e.g., total population, household incomes) for each CBG in our study region is obtained from the American Community Survey (ACS) 5-year estimates (2016–2020) of the U.S. Census Bureau (US Census Bureau, 2020). To address the unavailability of income data of individual mobile phone users due to privacy issues, we use the median household income of the CBG where the mobile phone user's residence is located, as the surrogate variable to estimate the income level of users. This is a well-established technique that has been adopted in related previous studies

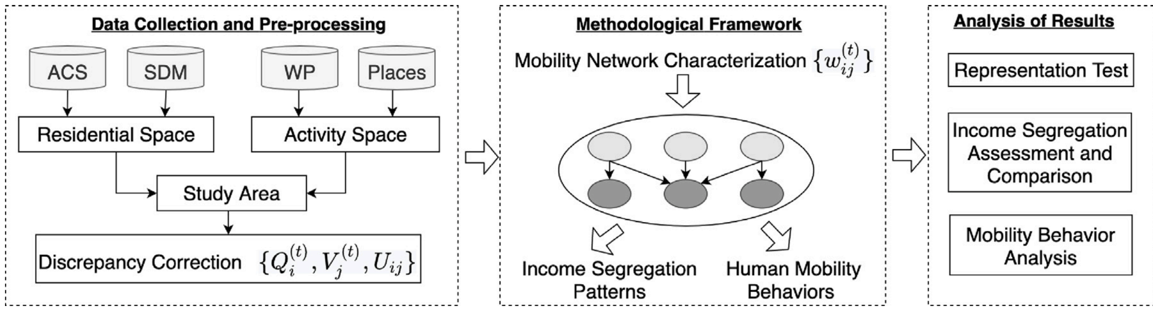
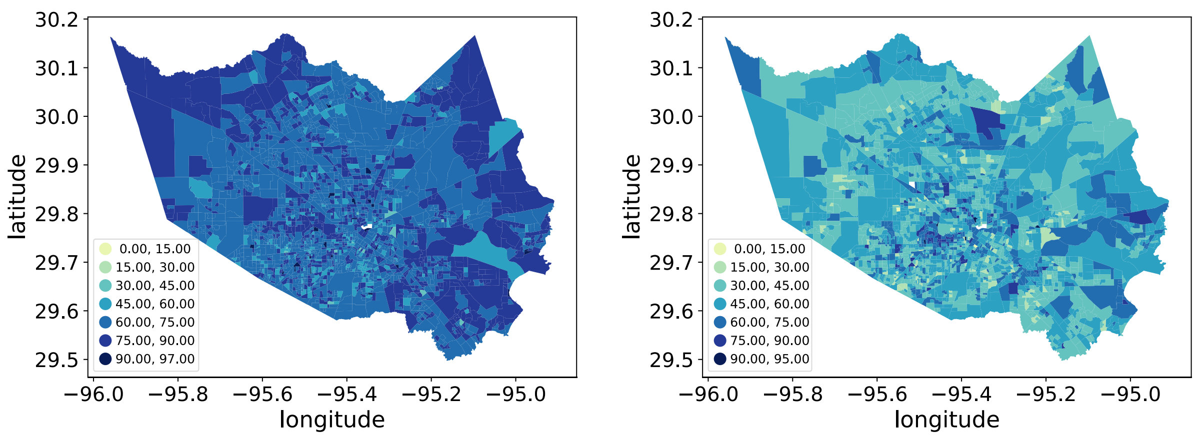


Fig. 2. Overview of the case study analysis.



(a) Before the storm (February 8) (b) During the storm (February 15)

Fig. 3. Mobility patterns in our study area (i.e., Harris County) before the storm (a) and during the storm (b). The colored polygons correspond to the CBGs where the percentage of people who left home is recorded. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Description of variables from the data.

Variable	Description	Spatial	Temporal	Source
`device_count`	Daily number of devices seen in each CBG.	CBG	Daily	SDM
`completely_home_device_count`	Daily number of devices that did not leave home in each CBG.	CBG	Daily	SDM
`raw_visit_counts`[a]	Weekly number of visits in each POI.	CBG	Weekly	WP
`raw_visitor_counts`[a]	Weekly number of unique visitors in each POI.	CBG	Weekly	WP
`visitor_home_cbgs`	Weekly number of visitors to POI from each CBG.	CBG	Weekly	WP
`visits_by_day`	Daily number of visits in each POI.	CBG	Daily	WP
`B01001e1`	Census population.	CBG	5-year	ACS
`B19001*`	Median household income.	CBG	5-year	ACS

[a]Typically, `raw_visit_counts` ≥ `raw_visitor_counts` as a visitor could visit the same POI more than once.

(Jay et al., 2020). The description of variables in details is presented in Table 2.

In summary, the study region contains 0.32 million sampled mobile phone users which account for approximately 7% of that census population across 2,142 CBGs and 53,457 POIs. The mobility network is constructed to describe the daily movement of residents in our study region moving between CBGs and POIs from February 8 to February 26, 2021, which covers one week before and one week after the winter storm. This allows us to better understand the human mobility behaviors and associated income segregation patterns within their activity spaces before, during, and after the natural disaster event.

4.3. Data pre-processing

We notice that there are two main issues in the collected data. The first problem is the varying unit of measure (e.g., visits vs. visitors). To unify the measure, we first calculate the ratio between the number of visitors and the number of visits at each POI on a weekly basis (i.e., `raw_visitor_counts/raw_visit_counts`). This ratio is typically less than one as a visitor could visit a POI several times. Then, we use this ratio to convert the daily raw visits (i.e., `visits_by_day`) into the daily visitors $\widetilde{V}_j^{(t)}$ at each POI, which can be expressed in Eq. (13). On the other hand, to obtain the raw daily number of people who left their home CBG i (i.e., $\widetilde{Q}_i^{(t)}$), we subtract the number of people who did not leave their home from the total observed people from the panel data. We further assume that each mobile phone user has one mobile device. With that, $\widetilde{Q}_i^{(t)}$ and $\widetilde{V}_j^{(t)}$ can be calculated using our collected variables described in Table 2, which are given by:

$$\begin{aligned} \widetilde{Q}_i^{(t)} &= \texttt{device\_count} - \texttt{completely\_home\_device\_count} \\ \widetilde{V}_j^{(t)} &= \texttt{visits\_by\_day} \cdot \frac{\texttt{raw\_visitor\_counts}}{\texttt{raw\_visit\_counts}}. \end{aligned} \tag{13}$$

The second problem of the data is the existence of discrepancy, suggesting that the total number of people who are not at home (i.e., $\sum_{i,t} \widetilde{Q}_i^{(t)}$) is not equal to the number of people who visit any POI

Table 3
Description of selected essential POI categories.

Essential roles	POI categories	NAICS	Example	Functionality
Emergency preparedness	Grocery stores	445110	Food Lion	Provide basic foods and supplies
	Gas station	447110	Exxon Mobil	Provide fuel and power generators
	Pharmacies and drug stores	446110	Rite Aid	Provide health products
Emergency response	Offices of mental health	621330	Trauma Center	Offer treatment for emotional trauma/stress
	Offices of physicians	621111	Northwell Health	Provide general or specialized medicine
	General medical & surgical hospitals	622110	Mercy Health	Offer diagnostic and medical treatment (both surgical and nonsurgical)
Emergency recovery	Religious organizations	813110	Church	Provide spaces for long-term healing
	Hardware stores	444130	Home Depot	Provide equipment for debris clearance
	Commercial banking	522110	Wells Fargo	Help customers go through financial crisis

(i.e., $\sum_{j,t} \widetilde{V}_j^{(t)}$), resulting in some residents who remain unclassified (i.e., neither at home nor in their activity space). This can also be problematic in constructing the CBG-POI mobility network. The observed discrepancy can be due to several reasons such as SafeGraph may not correctly determine the home of POI visitors, or it is unable to track all the mobile phone users. To correct for such discrepancy, we introduce the scaling of parameters to proportionally adjust the marginal distribution of people at each CBG and POI. We adopted this idea from a previous study that assumes the relative proportions of POI visitors coming from each CBG follows the relative proportions of people who left their home from each CBG (Chang et al., 2021). Here, we use $\widetilde{Q}_i^{(t)}$ and $\widetilde{V}_j^{(t)}$ to represent the raw data (before correction), $Q_i^{(t)}$ and $V_j^{(t)}$ to indicate the processed data (after correction) that served as model inputs. Based on the baseline value U_{ij}, $Q_i^{(t)}$ and $V_j^{(t)}$ are estimated leveraging the following equations:

$$Q_i^{(t)} = \alpha_i \cdot \widetilde{Q}_i^{(t)} = \frac{\sum_j U_{ij}}{\sum_t \widetilde{Q}_i^{(t)}} \cdot \widetilde{Q}_i^{(t)}$$
$$V_j^{(t)} = \beta_j \cdot \widetilde{V}_j^{(t)} = \frac{\sum_i U_{ij}}{\sum_t \widetilde{V}_j^{(t)}} \cdot \widetilde{V}_j^{(t)}, \tag{14}$$

where α_i and β_j are the scaling parameters for CBG i and POI j respectively. Based on Eq. (14), we can show $\sum_{i,t} Q_i^{(t)} = \sum_{i,j} U_{ij}$, and $\sum_{j,t} V_j^{(t)} = \sum_{i,j} U_{i,j}$, which indicates $\sum_{i,t} Q_i^{(t)} = \sum_{j,t} V_j^{(t)}$. Thus, the issue of data discrepancy is resolved, where the total number of people who left their home is equal to the total number of people who visited any POI in our study region.

4.4. POI selection

To examine the income segregation in people's activity space during the storm Uri, we select a group of POIs according to the NAICS code. Table 3 displays the selected nine POI groups as well as the major functionality played by these POIs in the emergency management cycle (preparedness, response and recovery). The selection of POI groups is based on the importance of the facilities in providing essential services to satisfy people's needs in times of natural disaster, which has been justified in a previous study (Podesta, Coleman, Esmalian, Yuan, & Mostafavi, 2021). More specifically, grocery stores, gas stations and drug stores are considered essential for providing necessities of basic human needs in preparing for the crisis. Health-related POI groups (e.g., offices of mental health and physicians, medical and surgical hospitals) are relevant to disaster response in saving the lives, and reducing the suffering of injured individuals. Religious organizations, hardware stores and commercial banking are crucial to help people recover from the disaster. Overall, the selected nine POI groups cover 10,333 individual POIs, accounting for 19% of all POIs in the network.

5. Results

In this section, we first perform the representation test to demonstrate the reliability of the sampled data. Second, based on the constructed mobility network, the magnitude of income segregation at different POI groups is examined in the various phases of the disaster (e.g., before, during, and after). Lastly, we illustrate the heterogeneity in human mobility behaviors associated with income segregation, which further highlights the existing disparity in access to critical facilities between low-income and high-income neighborhoods.

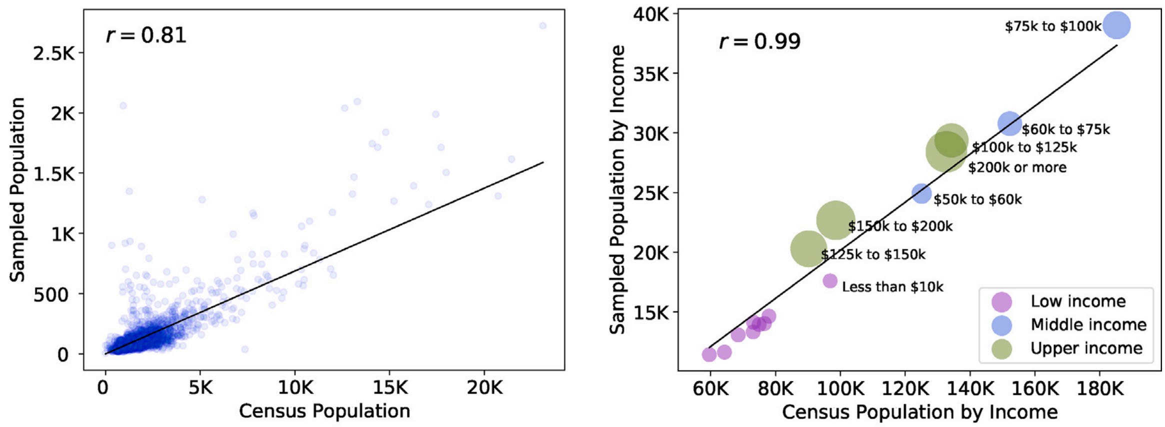
5.1. Representation test

Selection bias of sample data is a critical issue that could potentially result in an overestimation or underestimation of mobility patterns in the population. To analyze the potential selection bias, we checked if the mobile phone users and the income distribution of our sample data represent the true population and income distribution of the study region, which is referred to as "representation test" in this study. Specifically, we calculated the Pearson correlation coefficient (denoted as r) between sample data and census population data in terms of population coverage and income distribution. Fig. 4(a) displays the correlation between the sampled mobility data and census population, where each dot represents a unique CBG that corresponds to the number of sampled mobile phone population (on y-axis) and census population (on x-axis). Note that, the data points above (or below) the regression line indicate the over-sampling (or under-sampling). Overall, we found that sampled data are highly correlated with census data ($r = 0.81$, $p < 0.05$) in terms of population coverage across all CBGs. Fig. 4(b) depicts the relationship of income distribution between sampled and census data, where each data point denotes one income group. This relationship is also statistically significant ($r = 0.99$, $p < 0.05$). We observed that low income groups (median household income < $\$54,000$) are slightly under-sampled (below the regression line), while the upper income populations (median household income > $\$100,000$) are over-sampled (above the regression line). This may be because that low income groups have relatively less mobile phone usage in comparison to high income groups (Kraemer et al., 2020).

These representation tests demonstrate that our dataset does not have significant biases in terms of population coverage and income distribution in the study region, as $p < 0.05$. This is in line with the previous examination that SafeGraph data are statistically representative to the census data (Squire, 2019).

5.2. Analyzing income segregation within activity space

We first examined the income segregation behaviors at the essential POI groups during the storm. Fig. 5 shows the mobility assortativity matrix for each selected POI group during the storm, from where we can observe the income segregation patterns from the principal diagonal elements with darker colors in the matrix. Specifically, a higher value of the cell along the principal diagonal indicates that people are more likely to visit POIs that are located in the same income quintile of neighborhoods as their residential areas. On the other hand, people are less likely to visit POIs in the area that has a larger income discrepancy from their own neighborhoods, indicated by the lighter colors in the matrix plots. For example, in the first subplot (top left corner), 59.5% of people who live in the highest income-level



(a) CBG population representativeness (b) Income representativeness

Fig. 4. Comparison between sampled mobile phone users and census population in terms of (a) population coverage, and (b) income distribution.

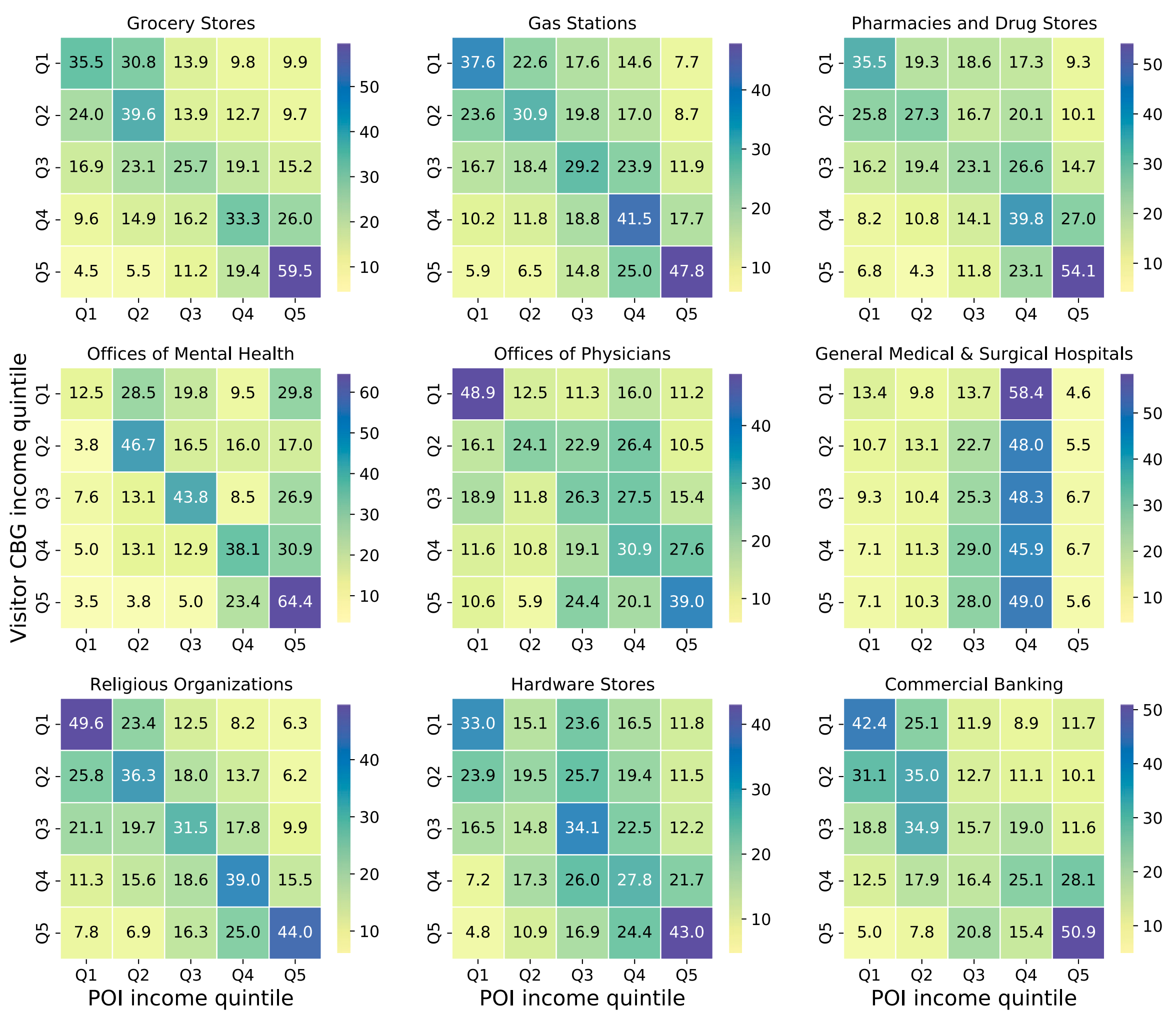


Fig. 5. The percentage of visitors from CBG income quintiles (y-axis) to POI income quintiles (x-axis) aggregated by days during the Winter Storm Uri. Each numerical value represents the proportion of visitors, and all rows sum to 100%. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

neighborhoods (i.e., Q5) visited grocery stores that are also located within the Q5 neighborhoods, while only 4.5% of them visited grocery stores in the Q1 low-income neighborhoods. These phenomena can be observed from all selected POI groups except general medical & surgical hospitals, where people tend to visit hospitals within the Q4 neighborhoods, regardless of where they live. This could be attributed

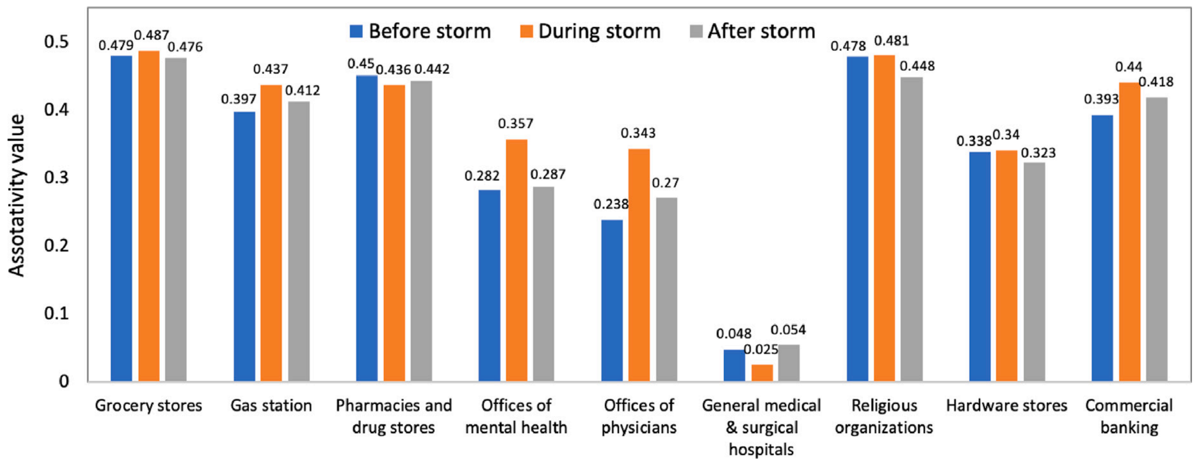


Fig. 6. The assortativity value (y-axis) for each POI group (x-axis) before, during and after the winter storm Uri.

to the uneven geographical distribution of hospitals, as majority of the hospitals (~45%) are located in the Q4 regions in our study area.

We then quantified the magnitude of income segregation at each POI group using the assortativity coefficient ρ described in Section 3.2. We found that, during the storm, grocery stores have the largest assortativity value (ρ = 0.487), followed by religious organizations (ρ = 0.481), gas stations (ρ = 0.437), pharmacies and drug stores (ρ = 0.436), commercial banking (ρ = 0.44), offices providing mental health services (ρ = 0.357), offices of physicians (ρ = 0.343), hardware stores (ρ = 0.34), and general medical and surgical hospitals (ρ = 0.025). The grocery stores and religious organizations exhibit the highest level of segregation by the income level of visitors, which is in line with the previous study (Moro et al., 2021). This may be attributed to the fact that grocery stores and religious organizations primarily serve the local communities, especially in the context of natural disaster. On the contrary, general medical and surgical hospitals acting as public service are found to be less segregated, as it serves a wide range of population.

We further investigated how the income segregation at each POI group changes before, during, and after the storm. As shown in Fig. 6, the changes of assortativity values in most POI groups are subtle across different periods of the storm. This suggests that the degree of income segregation is less sensitive to the storm in the short term, as people may still prefer going to the places where they frequently visited before. But, we also noticed that people experience a relative higher degree of income segregation at offices of mental health and physicians (revealed by larger assortativity values) during the storm compared to other time periods. This indicates that health-related services tend to be more segregated during the disaster, as low-income residents may have limited access to essential services that are situated in higher-income neighborhoods.

5.3. Mobility behaviors associated with income segregation

5.3.1. Proportion of visitors

Besides the income segregation patterns observed in each POI group, we also found that the human mobility behaviors in response to the storm are heterogeneous between high-income and low-income neighborhoods. As shown in Fig. 7, each subplot is corresponding to a POI group, where y-axis represents the proportion of daily visitors and x-axis indicates the date. Note that we only demonstrated the mobility patterns from the lowest income neighborhoods (Q1) and the highest income neighborhoods (Q5), as those two groups have the largest discrepancy in terms of income.

Overall, we can observe that a significant reduction in mobility occurs during the storm across all the POI groups. Notably, the extent of mobility decline is quite different between high-income and low-income neighborhoods, indicating the existence of mobility disparity in access to critical facilities in face of a natural disaster. Generally speaking, a higher proportion of people from disadvantaged income groups (Q1) visited POIs such as grocery stores, gas stations, offices of physicians, religious organizations and commercial banking, compared to people living in the higher-income areas. Irrespective of the disaster impact, a higher proportion of low-income people going to these stores may be attributed to necessities rather than choice to sustain their daily demands. These findings are consistent with previous study highlighting that economically disadvantaged people are more likely to experience an inadequate physiological need (e.g., foods) and a lack of access to critical facilities (e.g., grocery stores) during disasters (Hallegatte, Vogt-Schilb, Rozenberg, Bangalore, & Beaudet, 2020). People from low-income neighborhoods are more likely to visit religious organizations (e.g., churches) during the storm. This may be because religious organizations often provide social services such as food banks for low-income households (Jay et al., 2020). Mobility differences are less substantial between low- and high-income groups for visiting locations such as pharmacies and drug stores, offices of mental health, general medical and surgical hospitals and hardware stores.

Just before the storm, an increased proportion of people in grocery stores, gas stations and drug stores can be observed in both Q1 and Q5 neighborhoods. This suggests that people tend to stockpile before the disaster event, which could be captured by their mobility activities. Followed by a significant reduction in mobility during the storm, a slowly growing number of visitors can be observed in POI groups in the post-disaster period, indicating the recovery patterns of neighborhoods. For instance, a higher proportion of low-income individuals visited commercial banks after the storm, as banks could help them manage funds and loans for post-disaster reconstruction.

5.3.2. Travel distance

We also depict the travel distance between low-income and high-income neighborhoods in visiting each POI group before, during, and after the storm. Fig. 8 demonstrates the time-dependent travel distance for low-income and high-income neighborhoods to visit each selected POI group. It is noticeable that heterogeneous behaviors in travel distance vary differently across POIs as well as income level of neighborhoods. People living in the low-income areas tend to exhibit longer travel distances to grocery stores, gas stations, pharmacies and drug stores, offices of mental health, and hardware stores, compared to individuals from high-income neighborhoods. On the contrary, people living in the high-income areas have long-distance trips to offices of physicians, general medical and surgical hospitals, religious organizations and commercial banking. The discrepancy in people's travel distance between poor and rich neighborhoods is consistent before,

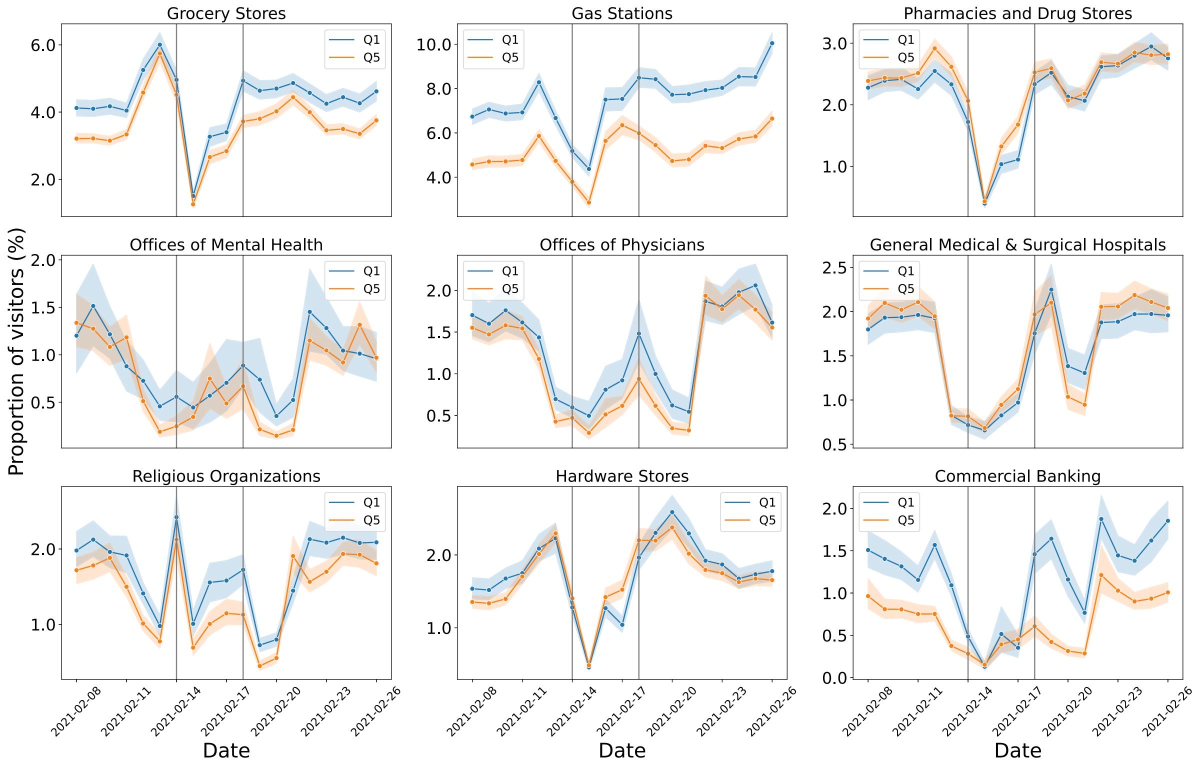


Fig. 7. Proportion of daily visitors in each POI group between low-income (Q1) and high-income (Q5) neighborhoods. The shaded area shows 95% confidence interval of the mean value of daily proportion of visitors. Two gray vertical lines denote the period of the Winter Storm Uri during February 13–17, 2021.

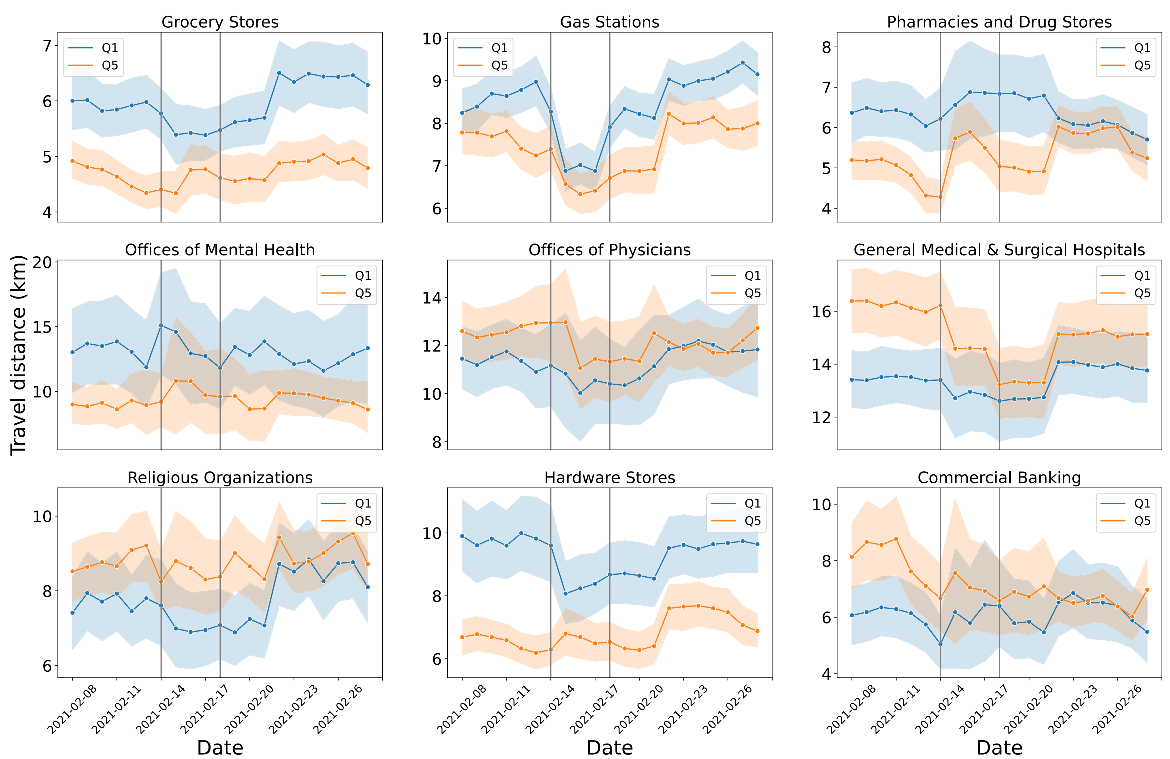


Fig. 8. Travel distance per capita (in kilometers) in each POI group between low-income (Q1) and high-income (Q5) neighborhoods. The gray vertical lines indicate the period of the winter storm Uri.

during and after the storm, reinforcing the mobility disparity in access to different essential POIs.

Generally speaking, POI groups with longer travel distance on average (e.g., offices of mental heath and physicians, medical and surgical hospitals) are less likely to be segregated. The rationale can be attributed to the fact that those POIs that have larger catchment areas tend to attract people from more diverse neighborhoods, and create more opportunities for people to interact with each other. This can also be reflected by the associated assortativity coefficient, where health facilities have the lower assortativity values. On the other hand, some

POIs with shorter average travel distance include grocery stores, pharmacies and drug stores, and commercial banking are found to be more segregated, as those POIs primarily serve the local people from more homogeneous neighborhoods.

6. Discussion

6.1. Income segregation and mobility behaviors

Income segregation creates adverse conditions inimical to health in the social and physical environment, preventing low-income households from accessing educational and employment opportunities (Reardon & Bischoff, 2011). In this paper, we examined how residents living in neighborhoods with varying economic backgrounds experience income segregation in their activity space (i.e., places where they perform daily activities) under natural disaster. A novel framework is first proposed to build a human mobility network that describes the footprint of people in their residential neighborhoods and activity spaces. Then, to demonstrate its applicability, the proposed framework is applied to a case study where we analyzed the income segregation behaviors obtained from the developed mobility network. The case study focuses on the residents in Harris County in the state of Texas in the face of the severe winter storm Uri. We found that the income segregation patterns measured at different critical facilities are heterogeneous, as people are prone to going to places located in the neighborhoods that are similar in economic characteristics to their residential areas neighborhoods. In addition, our analyses indicate that places such as grocery stores, religious organizations and gas stations have a higher degree of income segregation, compared to the health-related facilities such as general medical and surgical hospitals. This is because the locations like the grocery stores mostly serve the local communities so that people from nearby neighborhoods are attracted, while medical centers and hospitals typically serve a wide range of populations with varying socioeconomic backgrounds. Our findings also suggest that income segregation is less sensitive to natural disasters in the short term, since people are likely to go to frequently-visited areas during and immediately after the disaster. The income segregation that people experienced at different facilities in activity spaces can be further understood by their mobility behaviors such as the travel distance, and the proportion of visitors in the activity spaces. We observe that the places with longer travel distances (e.g., health facilities) tend to be less segregated, as those locations have larger catchment area to draw residents with diverse economic backgrounds. The proportion of visitors to the different critical facilities reflects the demands of residents. For instance, we notice a higher proportion of people from low-income neighborhoods, compared to the high-income neighborhoods, visiting the critical facilities such as grocery stores and gas stations during the disaster. These mobility behaviors obtained from our developed mobility network could further provide the evidence to underpin the disparity in access to critical facilities among residents with varying economic characteristics.

6.2. Policy implications

The insights presented in this paper could advance our understanding of income segregation behavior in access to a wide range of critical facilities in the face of a natural disaster, which could help build more sustainable and resilient communities by providing equitable access to services and resources. Importantly, our analyses reveal that human mobility behaviors in response to a natural disaster are heterogeneous between the low-income and high-income neighborhoods, indicating the existing disparities in access to critical facilities among different economic groups. For example, the longer travel distance of low-income populations to critical facilities (e.g., gas station) could signal the limited access and/or uneven distribution of facilities in a community. Emergency responders could utilize this information to better design resource allocation strategies to make sure that all residents have equitable access to high-quality services during disaster conditions, especially for the socially vulnerable groups. Previous studies find that low-income households are often at a greater risk of disaster impacts, both in terms of having limited access to essential services as well as receiving unequal aid and care (Brouwer, Akter, Brander, & Haque, 2007; Deng et al., 2021). Thus, providing equitable access to essential services is crucial for developing a sustainable community, which consequently enhances the resilience of the community to prepare for and respond to evolving threats exacerbated by climate change (Logan & Guikema, 2020). In addition, the proportion of visitors in critical facilities may also reflect the demand of services provided by the specific facilities. Decision makers could capitalize on the proposed human mobility networks to better forecast people's demand ahead of a disaster, such that the resources can be pre-positioned in advance to potentially mitigate the disaster-induced risk across vulnerable regions.

By and large, this study provides a new venue to better understand how people experience income segregation at fine spatiotemporal resolution. Income segregation is a strong predictor of social, economic, political, and physical outcomes (Reardon & Bischoff, 2011). To this end, communities should be more integrated and economically diverse by opening more dialogues between different groups and supporting stable integration at all levels of social class. Our proposed framework could help decision makers identify socio-economically divergent regions and understand residents' daily interactions at a variety of places of interest. Moreover, this framework could be applied to analyze various kinds of segregation (e.g., by race, education) under different disaster scenarios.

6.3. Limitations and future work

We acknowledge some limitations in this study that could be addressed in the future work. Due to the nature of location data that are passively collected from mobile phones, we are not able to fully distinguish the mobile phone users in terms of who are the visitors or the workers at the POIs, nor correctly determine their true individual income level. This is because mobile phone data provided by the SafeGraph does not provide the sociodemographic information of individual users for the sake of privacy issues. We overcome this issue by using a proxy variable that is obtained from CBG median household income to estimate the income status of mobile phone users. Clearly, this method may contain estimation errors and bring some potential bias. Furthermore, if more accurate input data (e.g., mobile phone data, socioeconomic variables) can be obtained with the help of digital twin technology, the results of our analysis would be more convincing. Another limitation is that this paper only investigates the short-term income segregation patterns across the selected essential POI groups under disaster, as the short-term analysis is more appealing for emergency responders to understand the crisis. One of the future research directions is to understand how natural disaster affects human segregation behaviors in the long run, once the society reaches a steady state after the disaster. Similarly, the other types of critical facilities such as shopping malls which are of interest to the decision makers but not included in this paper, can also be investigated. Besides income segregation, it is also important to understand how the various types of other segregation, such as the racial segregation, educational segregation, evolve in a community in the aftermath of a disaster. Our proposed methodological framework can be further applied to understand such human behaviors using the dynamic mobility networks established in this study.

7. Conclusions

A marked increase in segregation by income has been a pressing issue in the U.S., and metropolitan areas have become more segregated over the last few years (Mijs & Roe, 2021). The growing frequency and intensity of natural disasters can aggravate this economic segregation and inequality to a greater extent. The income segregation coupled with natural disaster poses challenges for developing sustainable and resilient cities. The way people experience income segregation is often affected by both the economic characteristics of residential neighborhood (i.e., where people live) and the places they conduct daily activities (i.e., where people visit). This paper studies income segregation behaviors by connecting people's residential and activity spaces, and investigates how people experience income segregation in access to a variety of critical facilities under natural disaster. We first propose a generalized framework that integrates optimization techniques and the fixed point iteration algorithm to derive fine-grained neighborhood-level mobility networks from large-scale mobile phone data. Then, we present a case study to demonstrate the applicability of proposed framework, where we analyzed 0.32 million mobile phone users in Harris County (Texas) in the face of 2021 winter storm Uri. Our results suggest that segregation pattern in activity space is bound by neighborhood socioeconomic conditions and the places they visit. The segregation behavior in access to essential points of interest is different under natural disaster in the short term.

This paper highlights that human mobility plays a fundamental role in providing evidence on how different places play a role in affecting existing income segregation. Dynamic mobility networks characterize human activity patterns at the neighborhood level by connecting residential areas and activity spaces. Future research may apply this mobility network to a wide range application areas such as disaster management, regional planning, and demand forecasting. The methodological framework proposed in this paper could be easily extended to other regions and to different types of natural disasters of interest, given the availability of census data and mobility information.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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