Revealing social disparities under natural disasters using large-scale mobility data: A dynamic accessibility perspective

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ABSTRACT

Accessibility is an essential indicator for measuring the functions and equity of urban services, and could be harnessed to provide insights into the social disparities in urban residents' interaction with urban services. In this study, we attempt to measure urban residents' accessibility patterns to urban services during natural disasters using an improved gravity model method. Firstly, by analyzing human digital trace data in the Wilmington metropolitan area over three months, we assessed the residents' accessibility levels of grocery stores and restaurants before, during and after Hurricane Florence, and captured the diverse trends of residents' responses to the hurricane. Then, we identified and statistically tested the social disparities in residents' accessibility behaviors in response to the hurricane. The findings may provide new insights for city planners and policymakers in terms of equity evaluations of resource accessibility and resource allocations among different communities and improvement of their resilience against natural disasters.

Keywords

Mobility, natural disaster, social disparity, spatial accessibility.

INTRODUCTION

Cities face significant risks from natural disasters, such as floods, hurricanes, and winter storms, which can damage critical infrastructure (e.g., power, transportation, and systems) (Huck et al., 2020; Wang et al., 2023) and significantly impact human lives. While the perturbation of the growing frequency and devastation of extreme events is being disproportionately felt in vulnerable groups (i.e., those of lower income, ethnic minorities, etc.) (Zhang and Li, 2022), urban policymakers have few tools to understand dynamic behaviors of residents during natural disasters at high spatial and temporal resolutions. Such information, if made available, could be used to evaluate the disparities in residents' behaviors, which in turn could help policymakers to execute comprehensive planning strategies that can reduce the disparities among different communities and hence improve their overall disaster resilience (Mayaud et al., 2019).

There is an increasing body of research that aims to link social disparities to natural disasters through frameworks such social equity or environmental justice (Adeola and Picou, 2017), with particular focus on behavioral disparities across disaster phases (i.e., preparedness, response and recovery). For the preparedness phase, previous studies suggested that race and socioeconomic status (SES) significantly impact evacuation behaviors, with ethnic minority groups with low SES less likely to evacuate than wealthier white residents (Deng et al., 2021). Vulnerable groups with low SES also have constrained access to critical resources for mitigating disasters (Brody et al., 2017). For the response phase, it is suggested that ethnic minority groups with low SES are more likely to be affected by disasters (Bolin and Kurtz, 2018). For example, it was found that minority households experienced disproportionately greater unmet needs, such as power outage and lack of transportation, compared to white household during Hurricane Harvey (Flores et al., 2020). As for the recovery phase, previous studies generally reported that ethnic minority groups tend to experience longer post-disaster recovery times than high-SES households (Rivera, 2020). To this end, researchers have traditionally relied on data from surveys and interviews,

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presenting drawbacks in sample bias, expensive costs and low efficiency. Despite these critical findings, there is still a lack of large-scale quantitative research on the comprehensive examination of disaster response of the urban population and related disparities from a perspective of complex adaptive systems—characterized by the nonlinear interactions of residents, urban form, and physical facilities within cities.

Here we focus on an integrated socio-behavioral assessment of residents' response to natural disasters across temporal and spatial scales from a dynamic accessibility perspective — how the residents access and utilize urban facilities distributed within cities. Urban accessibility is defined as the ease of reaching goods, services, activities and destinations in cities (Páez et al., 2012). As a cross-cutting theme of the United Nations' Sustainable Development Goals (SDGs), better accessibility to essential services and opportunities for all citizens holds the promise of a more equitable, sustainable and economically viable future (Lee et al., 2016). The concept of accessibility has long been employed by policymakers who seek to provide citizens with improved access to employment, goods, services and other opportunities. In particular, accessibility to critical facilities, such as grocery store, pharmacy, hospital, shelter, and gas station, is pivotal in maintaining community resilience, as people require access to critical resources and services to resist and recover from the disaster-induces disruptions.

The assessment of accessibility has been extensively studied since Hansen (1959). Numerous metrics have been developed by various academic communities to serve different purposes. Accessibility metrics can be analyzed through three dimensions (International Transport Forum, 2015), namely how transport costs are understood and assessed, how the spatial distribution of valued destinations is represented, and how the individual perception of transport costs and opportunities are represented. However, the existing metrics in the literature could be enhanced by addressing these limitations: (1) despite that accessibility is a wide-ranging multi-dimensional concept, a composite indicator of spatial accessibility encompassing multiple dimensions is still missing. Most of metrics are limited to simplified distance measures, thresholds and gravity-based estimations; (2) most existing metrics are defined as static expenditures rather than realized usages, and therefore are incapable of continuously monitoring residents' actual behaviors during disasters. An improved accessibility metric needs to be proposed from a dynamic perspective, to understand the holistic process of residents' response to extreme events.

The specific objectives of this study are to assess residents' accessibility to urban services by the proposed metric and reveal neighborhoods' disparities in their response patterns. The accessibility to services is measured and analyzed before, during, and after the hurricane, using a human trace dataset for the 2018 Hurricane Florence in the Wilmington metropolitan statistical area (MSA), North Carolina. To evaluate the impact of the hurricane, this study identifies two types of points of interest (POIs) for analysis: grocery stores (North American Industry Classification System (NAICS) code: 4451), and restaurants and other eating places (NAICS code: 7225). Findings of this study provide useful information that may be used to enhance practices in the allocation of urban resources under perturbations. The findings also provide new insights into the spatial equity of communities when facing large-scale disasters.

DATA AND METHODS

Overview of the dataset

This study used digital trace data of POI visits in Wilmington MSA in the context of Hurricane Florence in the year of 2018. Hurricane Florence made landfall on the south of Wrightsville Beach, North Carolina, on September 14, 2018. Hurricane Florence contributed to the wettest year in Wilmington's history, with annual rainfall totals eclipsing the previous record set in 1877 (National Weather Service, 2018). Wilmington area became entirely isolated during the hurricane, as all roads to the city were flooded and impassable. The impact of Hurricane Florence on Wilmington area dissipated after September 18, 2018.

The timeframe of the dataset used in this study includes five weeks before the landfall week, two weeks during the hurricane, and six weeks during the recovery period. Weekly POI visit data collected at the POI level are obtained from SafeGraph, Inc., which collects unique visit instances to physical locations from anonymized mobile devices (SafeGraph, 2020). The data are aggregated from about 10% of mobile devices (e.g., cellphones) in the U.S., and the sampling correlates highly with the actual U.S. Census populations, with a Pearson correlation coefficient of 0.97 at the county level (Squire, 2019).

An Improved Gravity-based Accessibility Metric

Table 1 provides a summary of the accessibility measures that have been commonly used in previous studies.

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Table 1 accessibility measure in previous studies

Measure	Formular	Description	Reference
Travel cost	T_{ij} or D_{ij}	Travel time or distance	(A. Li et al., 2020; Qin et al., 2020)
Cumulative opportunities	$A_i = \sum_t O_t$	$O(t)$ is an opportunity that can be reached within threshold t.	(Kelobonye et al., 2019)
Gravity	$A_i = \sum_j O_j f(C_{ij})$	O_j is number of opportunities in location j. $f(C_{ij})$ is the travel impedance function of travel cost between neighborhood i and location j.	(Benevenuto & Caulfield, 2020; Miller, 2005)
Two step floating catchment area (2SFCA)	$A_i = \sum_{j \in \{d_{ij} \leq d_0\}} R_j = \sum_{j \in \{d_{ij} \leq d_0\}} \left(\dfrac{C_j}{\sum_{k \in \{d_{kj} \leq d_0\}} P_k} \right)$	d_{kj} is the distance between location j and neighborhood k. C_j represents the service capability at location j. P_k is the size of population whose home location falls within the catchment area ($d_{kj} <= d_0$).	(Luo & Wang, 2003; Ye et al., 2018)

In response to the aforementioned research gaps, this study intends to improve the gravity model method, which offers a conceptual framework that has the flexibility to absorb future extensions, to propose a dynamic measure for accessibility of urban services at the neighborhood level (operationally at the census block group (CBG) level in this study). The improved dynamic accessibility metric developed in this study consists of three components – residents, travel cost, and interactions, which are considered as critical components of the accessibility concept (Järv et al., 2018).

Integrating the three components into accessibility measurement allows the inspection of dynamic landscapes of residents' service accessibility at the CBG level. In mathematical terms, as shown in Equation (1), the measurement of dynamic accessibility can be defined as:

$$A_i = \sum_j \frac{v_{ij}}{P_i} f(d_{ij}) \tag{1}$$

where A_i is the accessibility levels of neighborhood i to a specific service, v_{ij} is the number of daily visits from neighborhood i to place j, which represents the "interactions" component, d_{ij} is the straight-line distance between i and j representing the "travel cost" component. $f(d_{ij})$ is an impedance function that measures the spatial separation between i and j, which commonly takes the form of inverse Power function: $f(d_{ij}) \sim d_{ij}^{-a}$, where parameter a is fitted based on the dataset (Wan et al., 2012). P_i is the population of the neighborhood i and represents the "population" component.

Two categories of services, including grocery stores and restaurants, are selected and assessed in this study. Grocery stores are selected for the reason that they provide essential food supplies, which are considered as priority needs for residents in response to the hurricane or other extreme events (Lee et al., 2022). By contrast, the access to restaurants is less necessary activities for residents during disasters that previous studies suggests that residents did not prioritize visiting restaurants before and during the disaster (Podesta et al., 2021). Thus, accessibility to the above two categories of services that have different priorities can be compared with each other to understand different aspects of residents' lifestyle and their different levels of disruptions during disasters.

Trend Classification in Residents' Responses to the Hurricane

To understand the disparities in disaster response patterns across neighborhoods, we cluster neighborhoods into different groups based on changes in their accessibility over time, using an unsupervised machine learning

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technique. Based on the dynamic accessibility measurement, a baseline was calculated using average accessibility levels in the period of pre-hurricane equilibrium. It is assumed that activity in the baseline period is not affected by perturbations caused by disasters so that the accessibility level of a given neighborhood is relatively stable. The percentile change was calculated from the weekly values of the service accessibility in a given neighborhood specified as:

$$D_{it} = \frac{A_{it} - A_N}{A_N} \qquad (2)$$

where D_{it} is the percentile change between the baseline value of the accessibility level to the accessibility level in a given week, A_{it} is the accessibility of neighborhood i to a certain service in a specific week t, and A_N is the baseline value of the accessibility of neighborhood i. The time series $\{D_{it}, t = 1,2,...,n\}$ represent the changing pattern of weekly service accessibility for neighborhood i for n weeks, which provides a measure of the variance in its accessibility before, during and after the hurricane.

To understand the disparities in disaster response patterns across neighborhoods, this study adopted the agglomerative hierarchical clustering algorithm to classify trends of CBGs in access behaviors. The advantage of applying this algorithm is that CBGs having similar dynamic trends can be discovered and grouped to understand the impact of hurricane on the service utilization. In order to identify disaster response patterns, the above time series values of every neighborhood in Wilmington MSA are decomposed on a three-week moving average to extract a trend. Then, a widely used bottom-up hierarchical clustering algorithm was implemented on the trends of all neighborhoods (Day & Edelsbrunner, 1984). The algorithm starts by treating each input vector as a separate cluster. An input variable is a vector of a neighborhood's changing pattern of weekly service utilization under the influence of the hurricane. Then, at each iteration, the algorithm repeatedly executes two steps: (1) identify the neighboring clusters that are closest together, and (2) merge the two closest clusters. The iteration continues until all clusters are merged into one cluster. The optimized number of clusters is then selected by the hierarchical clustering dendrogram based on similarities of input vectors, aiming to minimize the variance within the clusters and maximizing the variance between the different clusters. Ward's metric (Olson, 1995) is used to calculate the distance between clusters.

Selecting SES Variables in Revealing Disparities

Population subgroups can be characterized by their social class, ethnicity, and other SES characteristics. They may differ in terms of their needs for and accessibility to urban services. Based on previous research, this study considers the following variables in explaining disparities in service accessibility, all obtainable from the 2018 ACS (American community survey) data:

Table 2. Definitions of variables

Metric	Definition	Reference
White (%)	The proportion of white people	(Shi & Starfield, 2001)
Black (%)	The proportion of black people	(Dai, 2010)
No health insurance (%)	The proportion of households without health insurance	(Gibson et al., 2014)
No education attainment (%)	The proportion of no educational attainment	(Kaljee et al., 2013)
Median income	Median household income	(Lei et al., 2012; Omer, 2006)
No internet access (%)	The proportion of households with no internet access	(Lin et al., 2019)

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RESULTS

Dynamic accessibility assessment and trend classification

Based on the above dataset and methods, we assessed residents' response to the hurricane in terms of their accessibility to two types of services, namely grocery stores and restaurants. Figure 1 illustrates the clustering results for neighborhoods' accessibility to grocery stores and restaurants. For both categories, neighborhoods are classified into three groups based on changes in their dynamic accessibility over time. Each group's response patterns can be observed via its empirical dynamic accessibility curve. The curves clearly demonstrate three phases of disaster response, including pre-event equilibrium, event impact, and recovery.
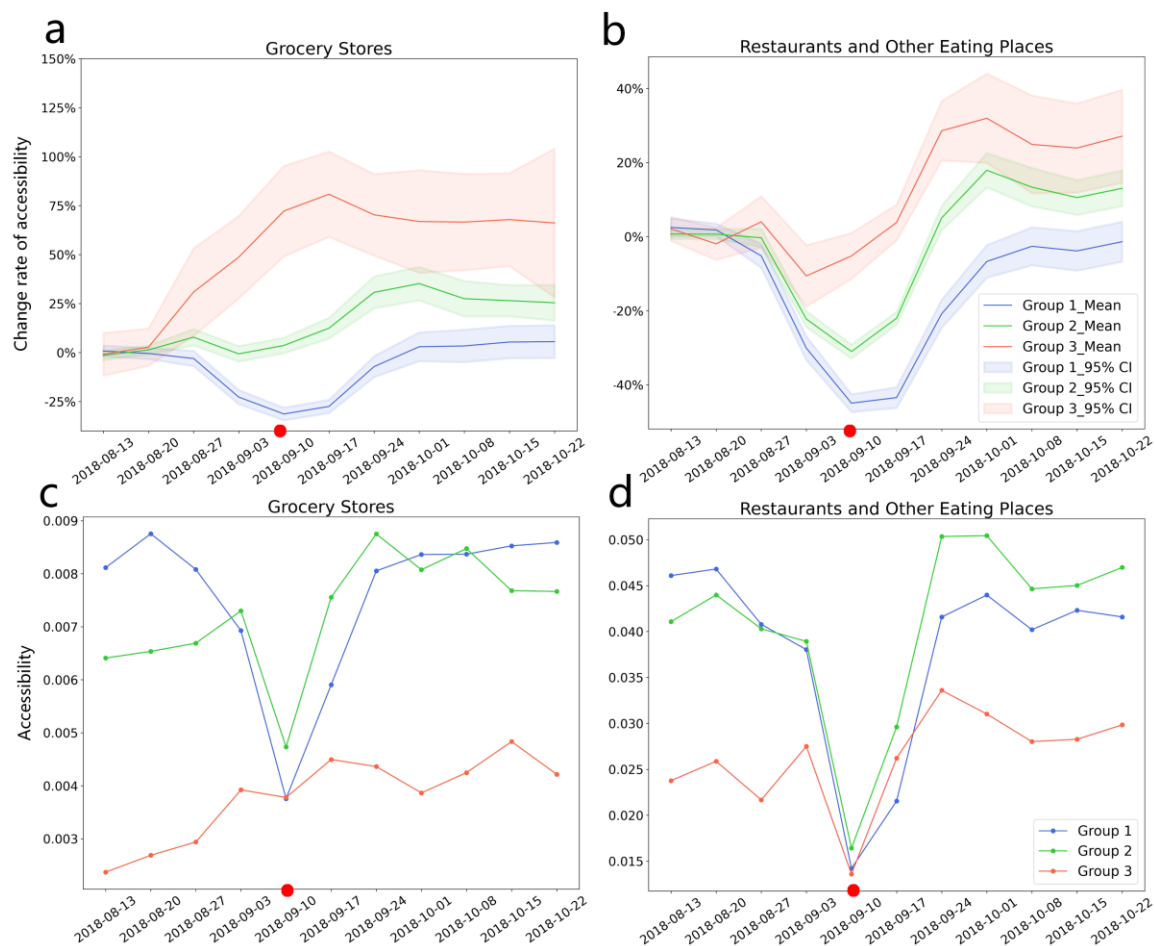

Figure 1. Distinct neighborhood groups based on disaster response patterns as identified by agglomerative clustering. a-b show the change rates of accessibility with 95% confidence intervals, and c-d show the mean values of accessibility. The red point in the x-axis indicates the landfall week of the hurricane. (The changes before the landfall week in a-b result from the moving average transformation).

A range of neighborhood response profiles can be determined from the clustering results. As Figure 1 shows, during normal weeks, the restaurant accessibility is higher than accessibility to grocery stores because the neighborhoods' access to restaurants is more frequent compared to grocery stores (Lee et al., 2022; Mahajan et al., 2021). However, despite of the high accessibility to restaurants in normal states, Figure 1a-b reveals that restaurant accessibility experienced a sharper decline than grocery store accessibility. It might be caused by residents' decreased priority in accessing non-essential services during the hurricane (Podesta et al., 2021)

As illustrated in Figure 1a, for grocery stores, which are essential needs of residents' lives, changes in accessibility of Group 1 ("decreasing") and Group 2 ("slight decreasing") form U-shape curves, representing a decrease in accessibility levels during the hurricane. Variations in grocery store accessibility of neighborhoods in Group 3 ("increasing") form a positive bell-shaped curve, representing an increase in neighborhood accessibility to grocery stores above pre-event equilibrium. Moreover, Figure 1c suggests the regular accessibility levels of Group 1 and Group 2 before the hurricane are higher than the regular accessibility level of Group 3.

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By contrast, for restaurants, as illustrated in Fig. 1b, which are not essential needs for residents, accessibility levels in Group 1 ("large decreasing"), Group 2 ("medium decreasing") and Group 3 ("slight decreasing") all form U-shape curves, sharing a similar decreasing trend and only differing in the magnitude of the impact, from the most impacted class to the least impacted class, respectively. The accessibility levels of Group 1 and Group 2 before the hurricane are higher than that of Group 3.

The next section implements statistical analysis on the neighborhoods' SES variables, with the aim to better explore and explain the formation of the above diverse patterns in both grocery store accessibility and restaurant accessibility among different groups.

Effects of social disparities on service accessibility

Neighborhood cluster characteristics are presented in Figures 2-3, which show clear disparities in the dynamic accessibility assessment. Statistical test results for the significance of the differences are summarized in Tables 3 and 4.

For grocery stores, which are essential needs of residents' lives, neighborhoods in Group 1 ("decreasing") had high accessibility levels before the hurricane, and adjusted their access to grocery stores into a relative low level during the hurricane. These neighborhoods had the lowest proportion of black people and people without health insurance, the highest median income, and the lowest proportion of people without education attainment. Group 2 ("slight decreasing") neighborhoods maintained relatively stable accessibility levels of services and they slightly adjusted their access to grocery stores during the hurricane. These neighborhoods are characterized by relatively higher household incomes (lower than Group 1) and a smaller share of minority population compared with the Group 3 (larger than Group 1). In contrast, for neighborhoods in Group 3, their access had an increasing trend during the hurricane. This group represents socio-economically vulnerable neighborhoods characterized by lower household incomes, higher unemployment rates, and a larger share of minority population. In addition, the one-way ANOVA reveals that median income, the proportion of population without health insurance and no internet access are the three most significant variables in explaining social disparities found in grocery store accessibility ($p < 0.05$). It suggests that financial ability, along with awareness of risk mitigation and disaster preparedness partly reflected by health insurance coverage (Brody et al., 2017), are determinants in residents' access behaviors to grocery stores across phases of the hurricane event.

In sum, the above results suggest that Group 1 and Group 2 with advantaged characteristics such as high median income and low proportion of minorities have relatively higher accessibility to grocery stores under normal conditions. As essential POIs for emergency preparedness, the higher accessibility to grocery stores has ensured general disaster preparedness actions such as food stockpile for residents in these two groups before the hurricane (Brody et al., 2017). As a result, the sufficient preparedness and risk awareness allowed them to reduce their access behaviors during the hurricane to mitigate disaster risks. By contrast, residents in Group 3 were less likely to take general disaster preparedness actions under the low accessibility to grocery stores before the hurricane. Thus, those residents were inclined to continue their access to grocery stores for essential goods even under the influence of the hurricane. Furthermore, post-hurricane activity levels of residents in Group 3 did not fully return to pre-hurricane levels at the end of the study period (6 weeks after the landfall). One possible reason could be that these vulnerable neighborhoods were more sensitive to the impact caused by the hurricane, resulting in extended recovery periods beyond the study period.

Table 3. Neighborhood cluster characteristics for three groups formed based on grocery store accessibility.
Statistically significant differences between groups are tested using one-way ANOVA (analysis of variance). Mean values with standard deviation in parentheses. The Turkey test is employed to identify which two groups exhibit significant differences from each other.

Feature	Group 1	Group 2	Group 3	p-value	Tukey test
White (%)	0.82 (0.15)	0.81 (0.21)	0.73 (0.16)	0.45	
Black (%)	0.11 (0.14)	0.14 (0.20)	0.19 (0.17)	0.43	
No health insurance (%)	**0.11 (0.06)**	**0.097 (0.07)**	**0.15 (0.06)**	**0.049**	2 versus 3
No education attainment (%)	0.009 (0.010)	0.005 (0.015)	0.013 (0.018)	0.19	
median income	**58660(21499)**	**64817 (29126)**	**38156(14866)**	**0.02**	2 versus.3
No internet access (%)	**0.13 (0.1)**	**0.14 (0.11)**	**0.24 (0.12)**	**0.02**	1 versus 3; 2 versus 3

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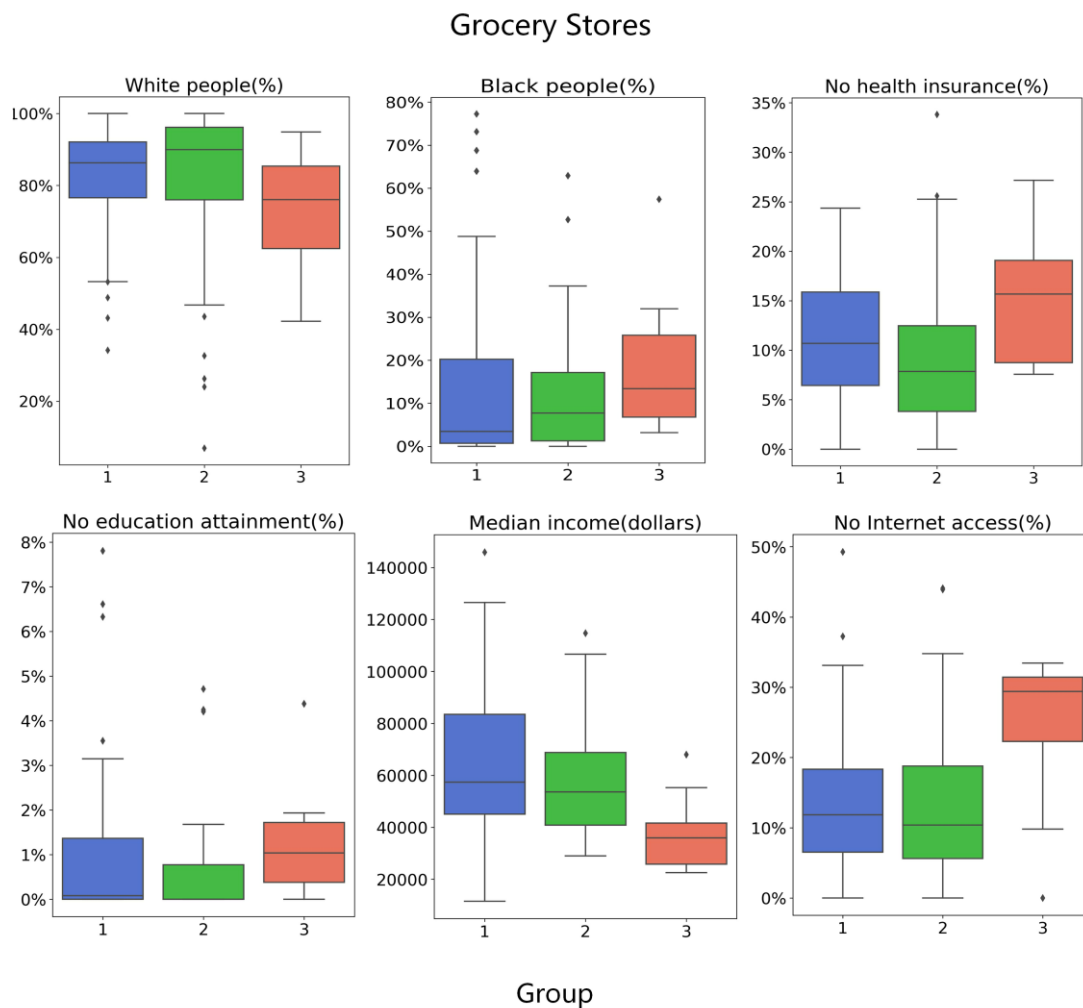
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Figure 2. Neighborhood cluster characteristic of cluster groups for the accessibility of grocery stores. X-axis represents the label of groups.

For restaurants, which are considered as non-essential needs for residents, neighborhoods in Group 1 ("large decreasing") and in Group 2 ("medium decreasing") had high accessibility levels before the hurricane. These neighborhoods are characterized by relatively higher household incomes, lower unemployment rates, higher education levels and a smaller share of minority population among three groups. Neighborhoods in Group 3 ("slight decreasing") had low accessibility to restaurants under normal conditions and represent socio-economically vulnerable neighborhoods with relatively lower SES and larger ethnic minority proportion. For the access to restaurants during the hurricane, a significant reduction was observed among neighborhoods in Group 1 and Group 2, possibly for the purpose to mitigate the risk of hurricane. By contrast, neighborhoods in Group 3 almost remained the same accessibility level to restaurants during the hurricane. Insufficient resource preparedness and low risk awareness are possible reasons why residents in these neighborhoods did not reduce non-necessary travels even under the influence of the hurricane. In addition, their low accessibility to restaurants under normal conditions suggests that they might need to travel long distance to reach the restaurants, thus exposing them to higher risks during the hurricane.

For the statistical test between clusters in their disparities, the one-way ANOVA test reveals that race, median income, health insurance coverage and the proportion of population without Internet access are the three most significant variables in explaining social disparities found in restaurant accessibility ($p < 0.05$). Previous studies have observed SES-based or ethnic disparities in the use of social media or Internet to obtain information in the disaster response phase (Zou et al., 2019), which could leave socio-economically marginalized residents without access to necessary information (Li et al., 2019). Low SES groups and ethnic minorities face challenges in participation in disaster preparedness planning because of their limited financial ability, along with difficulties in accessing preparedness information, altogether resulting in their low awareness and behavioral trend in reducing non-necessary travels to restaurants for risk mitigation.

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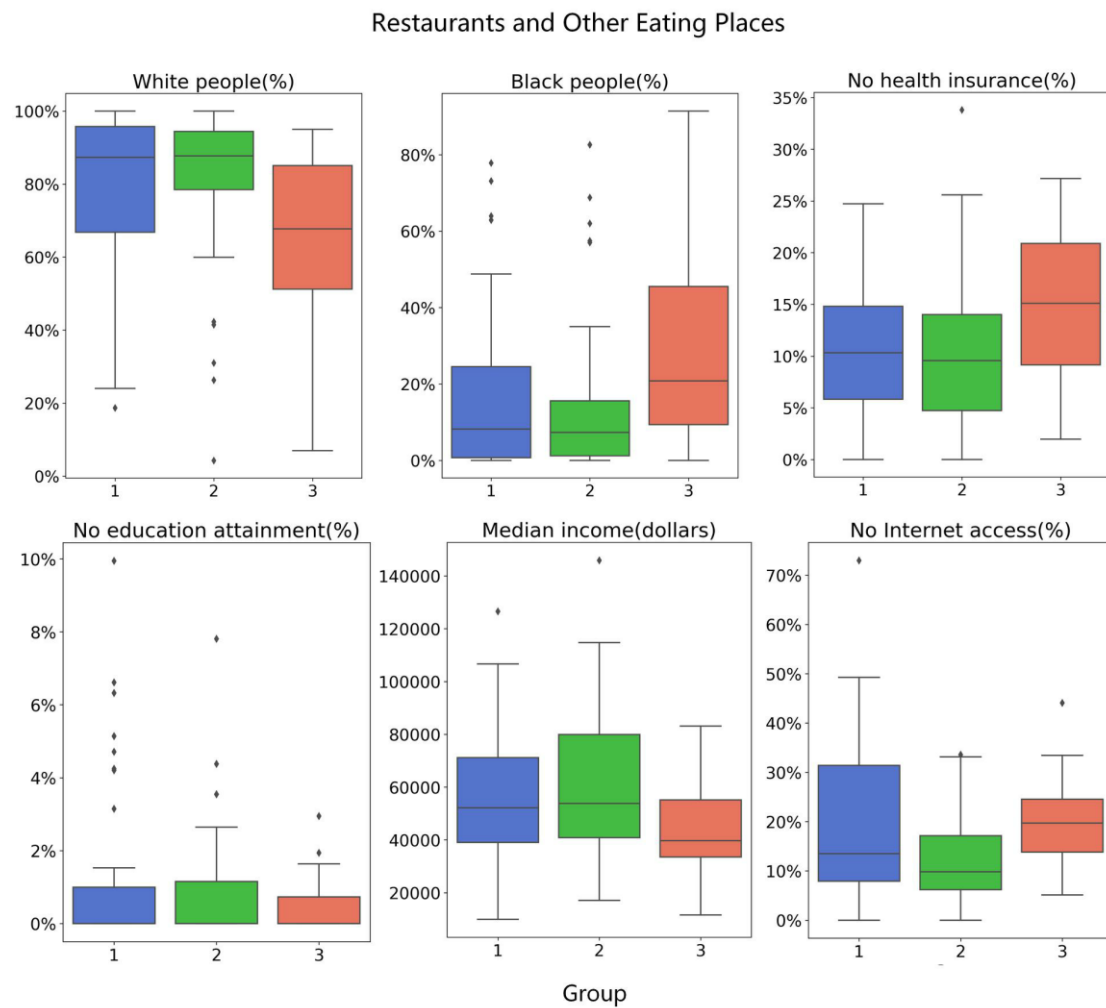
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Figure 3. Neighborhood cluster characteristic of cluster groups for the accessibility of restaurants and other eating places. X-axis represents the label of groups.

Table 4. Neighborhood cluster characteristics for three groups formed based on restaurant accessibility.
Statistically significant differences between groups are tested using one-way ANOVA (analysis of variance). Mean values with standard deviation in parentheses. The Turkey test is employed to identify which two groups exhibit significant differences from each other.

Feature	Group 1	Group 2	Group 3	p-value	Tukey test
White (%)	**0.78 (0.22)**	**0.83 (0.17)**	**0.63 (0.25)**	**0.0013**	1 versus 3; 2 versus 3
Black (%)	**0.16 (0.21)**	**0.12 (0.16)**	**0.28 (0.24)**	**0.0060**	2 versus 3
No health insurance (%)	**0.11 (0.06)**	**0.10 (0.07)**	**0.14 (0.07)**	**0.038**	2 versus 3
No education attainment (%)	0.010 (0.02)	0.006 (0.01)	0.007 (0.01)	0.30	
median income	**57549 (25305)**	**61772 (26948)**	**43720 (18159)**	**0.02**	2 versus 3
No internet access (%)	**0.18 (0.15)**	**0.12 (0.08)**	**0.20 (0.09)**	**0.002**	1 versus 1 2 versus 3

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CONCLUSIONS

A dynamic accessibility metric is designed in this study. It can be used to capture the changes of residents' access behaviors to services affected by extreme events. In a case study in Willington MSA, we studied Hurricane Florence's influence on residents' access behaviors to grocery stores and restaurants, and revealed social disparities in residents' response to the hurricane. Then, the associations between SES variables and diverse change patterns were investigated and statistically tested. The findings suggest that large-scale mobility data can be used to help policymakers develop and implement emergency planning strategies that account for variations in accessibility of urban services. The findings can also help communities make data-driven strategies to improve their resilience to natural hazards, enhance social equity and foster economic growth. Specifically, our research has the potential to support urban decision-makers in developing and implementing resilience and emergency planning strategies that are data-driven and account for localized variations in service accessibility. By utilizing large-scale mobility data, our approach allows for near-real-time evaluation of the impact caused by the hurricane on different neighborhoods. The ability to rapidly assess the impact of the disaster based on observed accessibility provides local governments with valuable tools to prioritize the equitable allocation of resources and provide assistance to more vulnerable neighborhoods.

The results of our study should be interpreted in light of its limitations. Regarding the limitations of the mobility data, although the data has been used in multiple studies to understand human movements at various spatiotemporal scales in the U.S. (Chang et al., 2021; Kang et al., 2020; Li et al., 2021), more efforts are needed to evaluate the reliability of our findings at different geographic regions by comparing with other data sources. Regarding the study case, one type of natural disasters and two selected services are considered in this study. The methods and approaches may be applied to other types of services, such as gasoline stations, banks, and parks, and other types of extreme events, such pandemics, flooding and so on. In addition, the SES variables are selected based on previous studies and not all-inclusive. Future study could include more variables by exploring data available in the American Community Survey to deepen the understanding of the diverse response patterns in residents' service accessibility.

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