International Journal of Disaster Risk Reduction 50 (2020) 101875

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: http://www.elsevier.com/locate/ijdrr

Anatomy of susceptibility for shelter-in-place households facing infrastructure service disruptions caused by natural hazards

Natalie Coleman, Amir Esmalian *, Ali Mostafavi

Urban Resilience.AI Lab, Zachry Department of Civil and Environmental Engineering, Texas A&M University, College Station, USA

ARTICLE INFO

Keywords:
Risk disparity
Protective actions
Shelter-in-place.
Natural hazards
Infrastructure
Service disruption
Social susceptibility

ABSTRACT

This paper provides empirical information for understanding the susceptibility of households to the infrastructure service disruptions caused by natural hazards. Understanding household-level susceptibility is critical to determine the risks associated with staying shelter-in-place during disasters. This information is essential for various stakeholders such as community leaders, emergency planners, and utility managers to prioritize and restore infrastructure services for the public. However, there is limited empirical information regarding the susceptibility of shelter-in-place households to the disruptions of different services. Hence, this study presents an exploratory analysis of empirical data collected from affected communities to identify the influencing factors of the households' susceptibility. We utilized survey data collected from Hurricane Harvey (850 respondents), Hurricane Florence (362 respondents), and Hurricane Michael (583 respondents) to study the anatomy of susceptibility to eight infrastructure service disruptions. The descriptive analysis compared the similarities, such as rating the sewer and water systems as most important services, and differences, such as the varying levels of expectation for the service disruptions, of the three regions impacted by the disasters. Correlation analysis considered which underlying factors, including sociodemographic characteristics, protective actions and adjustments, previous experience and previous damage, social capital, and need for service of individual households along with the contextual and communal factors of the community, such as urbanization and previous disaster declarations, were associated with the ability of residents to respond to and withstand service disruptions. Although there were consistencies in the relationship of influencing factors to the level of susceptibility, the findings highlight that some variation in the influence of these factors was event-specific or service-specific. Finally, the contextual and communal factors of a community can bring unique insights to the anatomy of susceptibility to the service disruptions, as each location has inherent characteristics that would, directly and indirectly, influence households' susceptibility to service disruptions. These findings provide the necessary empirical information to inform infrastructure prioritization decisions and emergency response actions to reduce the societal impacts of infrastructure service disruptions on vulnerable populations.

1. Introduction

Natural hazards such as Hurricane Harvey (2017), Hurricane Florence (2018), and Hurricane Michael (2018) cause inevitable infrastructure service disruptions such as flooded roadways, contaminated water sources, fallen power lines, and shortages in the food supply. Many residents choose to shelter-in-place during disaster events, and thus, greatly rely on infrastructure services to manage the impacts of natural hazards. If community residents are unable to access these critical infrastructure services, the state of the community during and the recovery process following the disaster are greatly affected [1]. Communities often have a limited understanding of the societal impacts associated with disaster-induced service disruptions, which can lead to mismanagement of resources and a lack of risk mitigation strategies for future disruption events. Resilience, or specifically the "disaster-resilient community," has been a popular topic of conversation in the disaster research field [2], and the concept of resilience has been used to properly invest, protect, and restore the functionality of infrastructure services [3,4]. To do so, both the physical and social characteristics of a community should be consolidated into an equitable infrastructure resilience model. Such a model would view the disaster from a holistic perspective, including the different dimensions of social systems within

* Corresponding author.
E-mail addresses: ncoleman@tamu.edu (N. Coleman), amiresmalian@tamu.edu (A. Esmalian), amostafavi@civil.tamu.edu (A. Mostafavi).

https://doi.org/10.1016/j.ijdrr.2020.101875
Received 14 April 2020; Received in revised form 10 July 2020; Accepted 8 September 2020
Available online 15 September 2020

a community, to better understand the complexities and nuances associated with service disruptions [5,6]. Hence, the human dimension should be integrated into the engineering perspective of protecting and sustaining infrastructure services [7].

Recent studies have highlighted the importance of considering social inequality and sub-populations' vulnerability in the planning and decision making for the development of disaster-resilient infrastructure services [8–10]. Since community residents do not experience service losses in the same way, resilient communities should distribute the benefits and costs of infrastructure systems by setting up equity standards and assisting vulnerable populations [11], a standard which should be emphasized in disaster settings. Several studies [12–14] conclude that there is an insufficient amount of empirical information addressing the societal risks and disparities (e.g. the most vulnerable populations and areas) associated with service disruptions caused by disasters. Thus, more empirical studies are needed to understand the human dimension associated with infrastructure service disruptions [15].

Disaster research, over the previous decades, have clearly shown that natural hazards are discriminate and do not impact all segments of the community equally [16–18]. Socially vulnerable groups (such as those with low-income, minorities, young children, and medical conditions) are more exposed to natural hazards [19–21] and less prepared for upcoming disasters [22,23]. Recent studies have demonstrated that disparities in societal risks of disaster-induced service disruptions exist among different sub-populations for shelter-in-place households [8,9,24]. These disparities include greater exposure to the service disruption or a lower ability to tolerate such service disruptions, which will be referred to in this paper as the *level of susceptibility*. While the previous research informs about the unequal disparity to various segments of the community, there is a need to identify the underlying factors influencing the level of susceptibility for different infrastructure services [25]. Thus, the focus of the study presented in this paper is to empirically identify the influencing factors which lead to a disproportionate level of susceptibility among individual households sheltering-in-place during disasters.

The research will study the anatomy of susceptibility to infrastructure services for shelter-in-place households, as such anatomy leads to the unequal societal impacts of the service disruptions. In particular, this research attempts to answer the following questions: (1) What are the influencing factors affecting the level of susceptibility of a household to disruptions in various infrastructure services?; and (2) To what extent do the influencing factors of susceptibility vary across different subpopulations, infrastructure services, and disaster contexts? To answer these questions, this study analyzes empirical data from Hurricane Harvey (850 respondents), Hurricane Florence, (362 respondents) and Hurricane Michael (583 respondents) to examine the following influencing factors across the three disaster events: (1) sociodemographic characteristics, (2) protective actions and adjustments, (3) previous experience and previous damage, (4) social capital, (5) need for service, and (6) contextual and communal factors (urbanization and previous disaster declarations) of the affected community.

2. Influencing factors of household susceptibility

In a recent study, Esmalian et al. (2019a) investigated disproportionate levels of tolerance and its correlation to the disparity in the experienced hardship from service disruptions for shelter-in-place households**.** *The level of tolerance* refers to the number of days a household can withstand a service disruption without experiencing significant hardship and well-being impacts. This study utilizes the level of tolerance as a way to measure the *level of susceptibility* of each household. As the level of tolerance decreases, the level of susceptibility increases. Households with a higher level of susceptibility are more vulnerable to the negative impacts associated with longer infrastructure service disruptions, while households with a lower level of susceptibility would experience less significant well-being impacts and hardship. Accordingly, the current study focuses on revealing the underlying factors influencing the level of susceptibility. By using empirical data from eight infrastructure service disruptions and three natural hazards events, the research will begin to develop the anatomy of susceptibility for shelter-in-place households. The study involved an exploratory analysis to determine whether and to which extent various sociodemographic characteristics, protective actions and adjustments, previous experience and previous damage, social capital, need for the service, and contextual and communal factors influence the level of susceptibility (Fig. 1). Table 1 displays the influencing factors found from the review of the existing literature and briefly summarizes their potential significance to the level of susceptibility. The existing literature examined the effects of these influencing factors on household's susceptibility to the general impacts associated with a disaster; however, the literature does not focus on household-level susceptibility to disruptions in various infrastructure services (such as power, water, transportation, and health care services).

3. Methodology

The study analyzed empirical data from three separate surveys, which consisted of the household experiences related to eight infrastructure service disruptions caused by Hurricane Harvey (2017), Hurricane Florence (2018), and Hurricane Michael (2018). The surveys were created and distributed through the online platform, Qualtrics. Qualtrics is a private company in the U.S. which specializes in online data collection and has been cited in numerous professional and academic journals [52,53]. In this case, the company used a stratified sampling strategy from a census-representative panel to distribute the respective surveys. The target subjects were residents above 18 years old who had directly experienced the service disruptions, meaning these households did not evacuate before the storm arrived and decided to or were forced to shelter-in-place. Meeting this criterion, 850 survey respondents were analyzed for Hurricane Harvey; 362 survey respondents were analyzed for Hurricane Florence, and 583 survey respondents were analyzed for Hurricane Michael. The sample size was collected from various locations and included different subpopulations of the community to provide a diverse sample population for testing the relationships among the variables. Survey data were analyzed using descriptive statistics to provide context for the communities and using Spearman's rank-order correlation to understand the relationship between the level of susceptibility and influencing factors.

3.1. Influencing factors

Survey respondents were asked questions related to their general experiences with disruptions in the eight infrastructure services and their level of tolerance. The level of tolerance is a proxy measure for the capability of the household to withstand service disruptions and is used to determine the level of susceptibility. In the survey, the households were asked: "if another disastrous event like what they experienced happened again, for how many days could they tolerate the disruptions in each infrastructure service?" Survey coding is summarized in Table 2, and the phrasing for each of the survey questions is included in the supplementary information (Section A). In addition to the survey analysis, contextual and communal factors of the affected communities were gathered based on reliable online sources and databases and the coding is also shown in Table 2.

3.2. Contextual and communal factors

The geographic makeup of the survey respondents is summarized in Table 3 by the disaster event, state, and then counties. These areas were selected based on (1) the occurrence and severity of the infrastructure service disruptions gathered from reliable online sources and (2) whether the residents received mandatory evacuation notices, as those

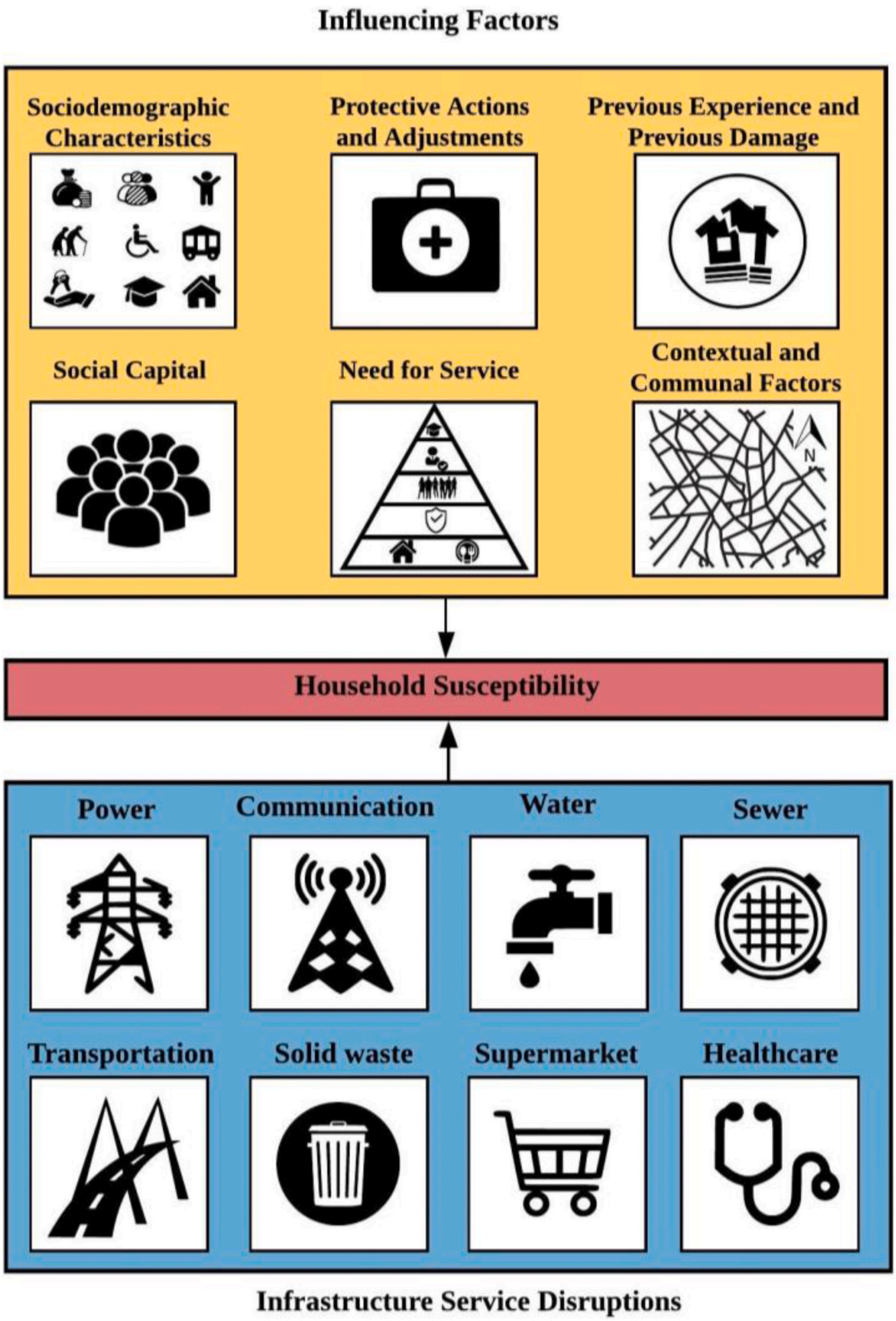


Fig. 1. Determinants of susceptibility to infrastructure service disruptions for shelter-in-place households.

with a mandatory evacuation would not provide much information about the experiences of shelter-in-place households.

Figs. 2–3 display the (1) urbanization of the areas [69] and (2) number of previous disaster declarations [68]. Fig. 2 presents the averaged values of each state based on the counties selected from the geographic makeup. The urbanization of the areas represents the population density of the counties divided into the metro and non-metro areas. This brings important context to the results related to the influencing factors as metropolitan areas typically have an abundance of community resources, while rural areas are known to have closer neighborhood ties (Table 1). The number and type of previous disaster declarations support the discussion surrounding the previous experience of the affected residents and helps to recognize the common hazard types of the study areas. Other contextual factors, including

Table 1
Literature review of influencing factors and the significance to the level of susceptibility.

Influencing Factors	Literature	Significance	Influence on Susceptibility
I. Sociodemographic Characteristics			
Socially Vulnerable Populations	[22]	Lower levels of preparedness	↑
	[26]	Influence various stages of the disaster impact while depending on the contextual characteristics	↑
Low Income and Low Education	[17]	Lower levels of preparedness	↑
	[27]	Less familiarity with the local environment and issues with the English language	↑
	[28]	Less likely to negotiate with bureaucratic entities for resources	↑
Renters and Non-detached Homes	[17]	Low structural integrity to withstand physical damage from natural hazards	↑
	[29]	Limited control over household repairs	↑
	[29]	Legal and space restrictions to carry supplies	↑
	[18]	Exposed to more damage and recovered more slowly following a disaster	↑
Closer Proximity to Hazards	[21]	More prone to physical damages from natural hazards	↑
Minority Groups	[30]	Correlation with low-socioeconomic status which leads to additional societal and economic barriers	↑
	[31]	Systematic inequalities established by political geographies	↑
	[16]	Lower levels of preparedness and language barriers	↑
Children	[32]	High levels of physical and emotional vulnerability due to dependence on guardians	↑
Elderly	[33]	Higher proportion of fatalities due to increased physical vulnerabilities	↑
Difficulty with Mobility	[34]	Challenges associated with mobility issues are increased by disruptions in the transportation services	↑
Not Owning a Vehicle	[33]	Reliance on public forms of transportation	↑
II. Protective Actions and Adjustments			
Higher Levels of Preparedness	[35]	Acquisition of supplies, developing emergency plans, making modifications to properties	↓
	[12]	Importance of having generators for power disruptions	↓
Longer Length of Forewarning	[36]	Early warning implementation system to allow communities to adequately respond	↓
	[37]	Information must be reliable and timely to maintain community trust and effectiveness	↓
High Level of Expectation	[38]	Risk perception enhances the likelihood of taking risk mitigation actions	↓
Information Seeking	[39]	Proper interpretation of reliable and available information	↓
	[40]	Social media attention for rescue and donation efforts	↓
	[41]	Advice from government officials	↓
III. Previous Experience and Previous Damage			
Previous Experience	[23]	Increased levels of preparedness and familiarity with the incoming disaster	↓
	[42]	Previous experience leads to increased levels of preparedness (timing of previous disaster may influence the benefits of previous experience)	↓
IV. Social Capital			
Integration into Community Networks	[41]	More likely to prepare for disaster	↓
	[43]	Greater access to critical resources	↓
V. Need for Service			
High Levels of Need	[44]	Vulnerability associated with infrastructure is rooted in a household's relative dependence for the service	↑
	[45]	Relative need affects the ability to tolerate service disruptions	↑
VI. Contextual and Communal Factors			
Greater Number of Previous Disaster Declarations	[46]	Improvement in the culture of preparedness and risk mitigation strategies	↓
	[47]	Development of risk mitigation strategies	↓
Increased Levels of Urbanization	[48]	Social inequality is more prevalent in metropolitan areas due to extreme division in income brackets	↑
	[48]	Greater access to advanced technological resources and services	↓
	[49]	Urbanization may have exacerbated the rainfall and flooding caused by Hurricane Harvey	↑
Rural Areas	[50,51]	Establishment of closer community networks for support and emergency assistance	↓
	[51]	Lower levels of community wealth for resources and infrastructure	↑

socioeconomic status, were not considered because these factors were addressed in the survey on an individual household level.

Hurricane Harvey made landfall on the southeastern Texas coastline on August 25, 2017. The storm dropped more than 60 inches of rainfall in the area, triggering immense flooding and causing several infrastructure service disruptions [54,55]. Since Harris County is more inland in Texas, it has a fewer number of previous disaster declarations about hurricanes but a greater number about flooding events (Fig. 3). Thus, the area could be frequently impacted by service disruptions caused by flooding events such as transportation disruptions. Indeed, Hurricane Harvey severely impacted transportation services, and the catastrophic effects could be felt for weeks following the storm. Harris County is also classified as a metropolitan area (Fig. 2). This classification brings advantages in the form of resource availability and disadvantages in the form of interconnectedness between the infrastructure

Table 2
Coding of the influencing factors.

Influencing Factors	Input
I. Sociodemographic Characteristics	
Income	Less than $25,000 (=1), $25,000-$49,999 (=2), $50,000-$74,999 (=3), $75,000- $99,999 (=4), $100,000 -$124,999 (=5), $125,000-$149,999 (=6), and More than $150,000 (=7)
Education	Less than high school (=1), High school graduate or GED (=2), Trade/technical/vocational training (=3), Some college (=4), 2-year degree (=5), and 4-year degree (=6), and Post-graduate level (=7)
Renters	No (=1), Yes (=2)
Non-detached Home (Apartment/Mobile Home)	No (=1), Yes (=2)
Live in a Flood Zone	No (=1), Yes (=2)
Minority	No (=1), Yes (=2)
Having Children (<10 years)	No (=1), Yes (=2)
Elderly (>64 years)	No (=1), Yes (=2)
Difficulty with Mobility	Yes (=1), No (=2)
Not Owning a Vehicle	No (=1), Yes (=2)
Distance to Supermarket	Number of miles to the nearest supermarket
Years in State	Number of years living in the respective state
II. Protective Actions and Adjustments	
Power Substitute	No (=1), Yes (=2)
Perception of Preparedness	Not at all prepared (=1), Poorly prepared (=2), Somewhat prepared (=3), Well-prepared (=2), Over-prepared (=5)
Infrastructure Capability	Strongly disagree (=1), Somewhat disagree (=2), Neither agree or disagree (=3), Somewhat agree (=4), Strongly agree (=5)
Days of Preparedness	Time to prepare for the approaching storm (# of days)
Days of Forewarning	Time of awareness before the approaching storm made landfall (# of days)
Expectation	Number of days the household expected for an infrastructure service to be disrupted (per service disruption)
Reliability of Information	Not at all reliable (=1), Somewhat unreliable (=2), Neutral (=3), Somewhat reliable (=4), Very reliable (=5) (per service disruption)
III. Previous Experience and Previous Damage	
Previous Experience	No (=1), Yes (=2)
Previous Damage	No (=1), Yes (=2)
IV. Social Capital	
Rely for Emergency Assistance	No (=1), Yes (=2)
Rely for Emotional Well-Being	No (=1), Yes (=2)
Member of a Community Organization	No (=1), Yes (=2)
V. Need for Service	
Need for Service	Not at all important (=1), Slightly important (=2), Moderately important (=3), Very important (=4), Extremely important (=5)
VI. Contextual and Communal Factors	
Urbanization	Metro counties (=1), Non-metro counties (=2)
Previous Disaster Declarations	Number of previous disaster declarations of floods and hurricanes

Table 3
Geographic makeup of the survey respondents.

Disasters	State	County
Hurricane Harvey	Texas	Harris
Hurricane Florence	North Carolina	Bladen, Brunswick, Columbus, Cumberland, Duplin, New Hanover, Pender, Robeson, Sampson
	Florida	Leon, Gadsden, Holmes, Jefferson, Jackson, Calhoun, Wakulla, Washington, Liberty
Hurricane Michael	Alabama	Houston, Dale, Geneva, Henry
	Georgia	Colquitt, Thomas, Grady, Decatur, Worth, Dougherty, Terrell, Early, Lee, Clay, Mitchell, Seminole, Miller, Randolph

systems, which may result in a cascade of service failures from one initial system failure [56].

Hurricane Florence made landfall on September 14, 2018. The slow-moving storm flooded several counties in the Carolinas, with some areas receiving a record-breaking 30 inches of rainfall [57]. Severe infrastructure service disruptions occurred in several areas, including Wilmington, New Hanover County, a city that was isolated from the mainland for several days because of flooded roads [57]. With the combination of powerful winds and heavy rainfall, both the power and transportation services were greatly impacted. When compared to the other regions, the impacted counties of North Carolina had the highest average number of previous disaster declarations with hurricanes (Fig. 3). Coastal counties identified as being more urban while inland counties identified as being more rural (Fig. 2).

Hurricane Michael was a sudden event. The storm was classified as a tropical depression on October 7, 2018, and landed as a Category 5 hurricane on October 10, 2018. Top wind-speeds of 160 mph reached both coastline and inland houses and caused extensive power outages across the affected regions [58]. Survey data were collected from Florida, Alabama, and Georgia. Among these states, Florida has the greatest number of previous disaster declarations involving hurricanes and floods, and in comparison, Alabama and Georgia have relatively the same level of previous disaster declarations against each other (Fig. 3).

4. Results of descriptive analysis

The descriptive analysis compared the level of tolerance of the survey respondents for eight different infrastructure services (Table 4). The level of tolerance was determined based on the number of days a household could withstand service disruptions without experiencing a significant negative impact. There is an inverse relationship between the level of tolerance and level of susceptibility, meaning as the level of tolerance increases, the level of susceptibility decreases.

First, there were certain distinctions in the level of tolerance relative to the infrastructure services (Table 4). Across the three disasters, survey respondents reported the lowest level of tolerance for disruptions in the sewer system with an average between 1.34 and 1.69 days and a median value of 0 days. This indicates that residents had little to no ability to withstand potential sewer disruptions. In contrast, respondents reported the highest level of tolerance for disruption in healthcare facilities with an average between9.25 and13.20 days; however, the service also had the highest standard deviation.

Second, there were certain differences in the level of tolerance relative to the impacted region. Respondents reported a relatively higher level of tolerance for the transportation disruptions caused by Hurricane Harvey and Hurricane Florence when compared to those impacted by Hurricane Michael. This implies that residents impacted by Hurricane Michael could comparatively be more susceptible to transportation disruptions. In the same manner, respondents reported a higher level of tolerance for the power disruptions caused by Hurricane Florence and Hurricane Michael when compared to those impacted by Hurricane Harvey. Thus, residents affected by Hurricane Harvey were comparatively more susceptible to power disruptions.

The analysis also examined the descriptive statistics of the influencing factors. Tables 5a–d summarizes the frequency (F#) and percentages (P%) of the categorical influencing factors. In addition, the mean values of the numerical and ordinal responses are presented in Fig. 4a-d.

4.1. Sociodemographic characteristics

Table 5a displays the frequency and percentage values of sociodemographic characteristics of the regions impacted by the three hurricanes. The greatest difference between the regions was the distribution of income as survey respondents impacted by Hurricane Harvey had higher income levels compared to those impacted by Hurricane Florence

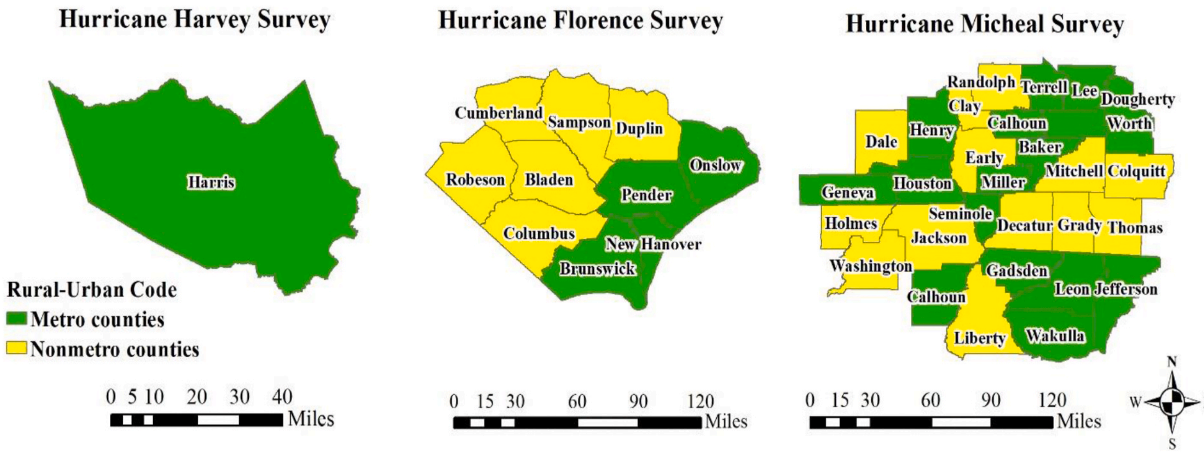


Fig. 2. Urbanization of three study area.

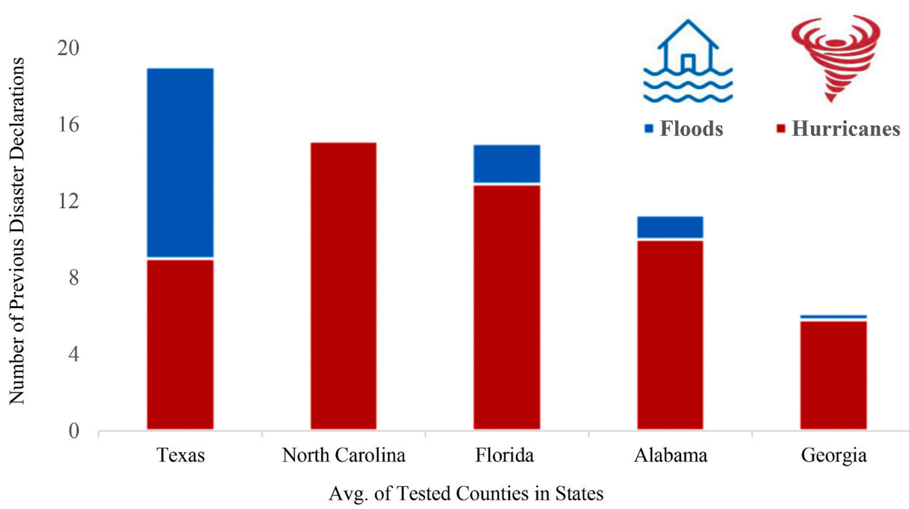


Fig. 3. Previous disaster declarations of the affected states.

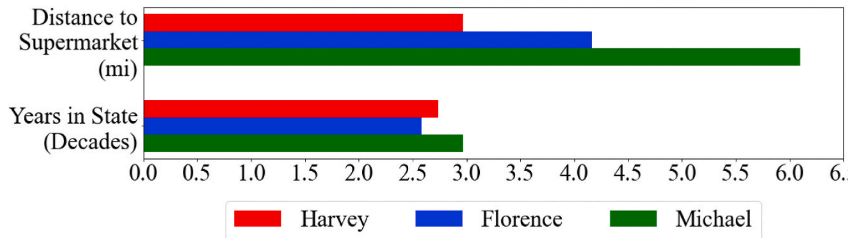
Table 4
Level of tolerance for disruptions in infrastructure services.

		Power	Comm.	Water	Sewer	Transpo.	Solid Waste	Super-Market	Healthcare Facilities
Hurricane Harvey	Mean	3.84	3.94	3.33	1.34	8.28	9.17	6.98	9.25
	Median	3.00	2.00	2.00	0.00	7.00	7.00	5.00	5.00
	Std. Dev	4.91	4.76	3.83	3.07	7.32	10.77	6.54	13.95
Hurricane Florence	Mean	6.31	5.73	4.33	1.69	8.94	8.06	7.64	12.65
	Median	5.00	3.00	3.00	0.00	7.00	5.00	6.00	7.00
	Std. Dev	7.27	10.46	6.27	5.49	11.81	11.84	9.52	16.32
Hurricane Michael	Mean	6.97	6.25	4.12	1.66	5.59	8.38	6.50	13.20
	Median	5.00	3.00	3.00	0.00	5.00	5.00	5.00	7.00
	Std. Dev	6.79	10.55	4.91	4.11	4.94	12.38	7.44	17.75

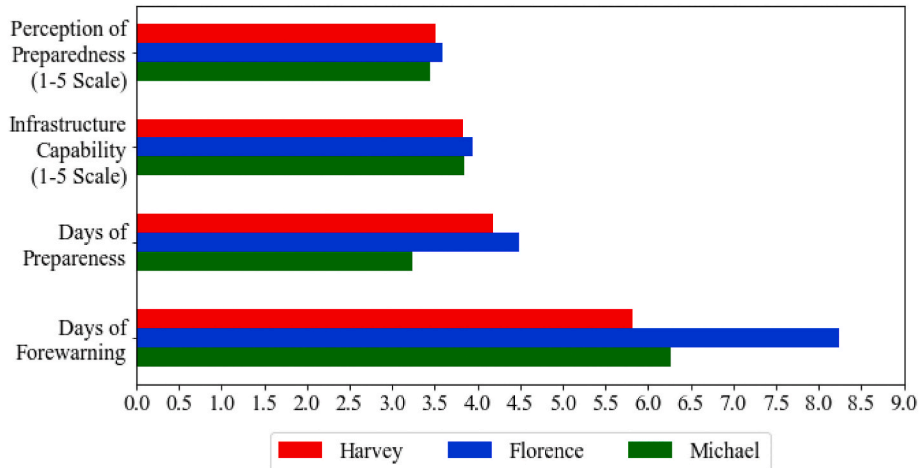
and Hurricane Michael. Approximately 47.5% of respondents affected by Hurricane Florence and 51.8% of respondents affected by Hurricane Michael reported an income below $50,000 when compared to the 35.5% of respondents affected by Hurricane Harvey. In Fig. 4a, Hurricane Michael respondents reported the longest distance to supermarkets (6.10 miles), followed by Hurricane Florence (4.16 miles) and Hurricane Harvey (2.97 miles).

4.2. Protective actions and adjustments

In Fig. 4b, households in all regions reported being somewhat to well prepared (scores around 3.5 out of 5), which means that households in the different areas had a similar perception of their preparedness for the disasters. However, respondents impacted by Hurricane Michael reported having the shortest duration of preparedness days while respondents impacted by Hurricane Harvey had the shortest duration of forewarning to the storm. Meanwhile, respondents impacted by Hurricane Florence had the highest duration of preparedness days and longest duration of forewarning. Additionally, Table 5b demonstrates that impacted by Hurricane Michael had the highest percentage of households with a power substitute/backup (36.5%), followed by those of Hurricane Florence (32.6%) and then Hurricane Harvey (20.4%). Although residents impacted by Hurricane Michael had a relatively short time of preparedness and forewarning, the overall households



a



b

Fig. 4. a: Sociodemographic Characteristics Mean Values, b: Protective Actions and Adjustment Mean Values, c: Expectations and Reliable Information Mean Values, d: Need for Service Mean Values.

could be less susceptible to power disruptions because of a greater percentage of households owning a power substitute/backup.

In regards to the expectations of the service disruptions shown in Fig. 4c, households reported the lowest average level of expectation for disruption in the sewer system (0.95–1.3 days) and the health facilities (1.38–1.63 days). Households reported the highest level of expectation for disruption in access to supermarkets (3.81–4.10 days) and solid waste collection (3.00–4.71 days). Respondents expected a lower duration of disruption in the power service caused by Hurricane Harvey (2.17 days) compared to respondents who expected a higher duration of disruption in the power service caused by Hurricane Florence (3.78 days) and Hurricane Michael (4.85 days). In regards to information-seeking behavior, respondents across all three events reported having similar levels of access to reliable information for each of the infrastructure services (Figure 4c).

4.3. Previous experience and previous damage

As shown in Table 5c, a high percentage of survey respondents had previous experience with disasters (78.9%- Hurricane Michael, 84.7%- Hurricane Harvey, 87.0%- Hurricane Florence). The percentages of the households who experienced damages from the disasters were also similar. Although these numbers were consistent across the three events, the results from the previous disaster declarations imply that the type of disaster event experience and type of damage could be different (Fig. 3).

4.4. Social capital

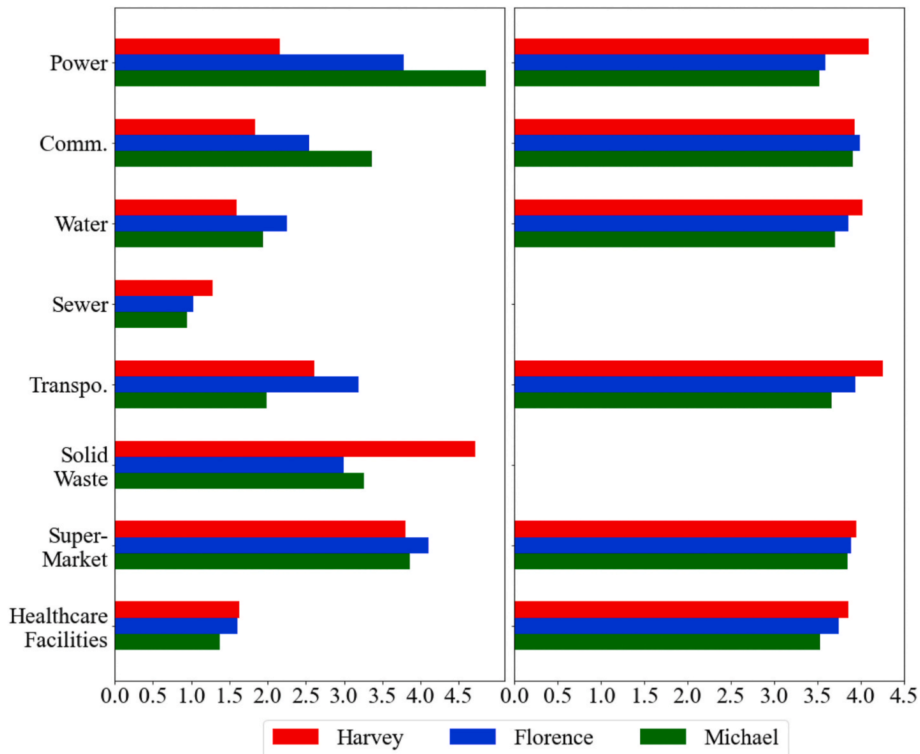
The survey respondents affected by the three events reported approximately similar percentages for each element of social capital; thus, no significant difference was found (Table 5d). Social capital was measured through three parameters (1) reliance for emotional well-being, (2) reliance for emergency assistance, and (3) being a member of a community organization. Among these social capital measures, the highest percentage of respondents reported the reliance on family and close friends for emotional well-being (~77–80%), having family and close friends in the area for emergency assistance (~54–58%), and being a member of a community organization (~43–45%).

4.5. Need for service

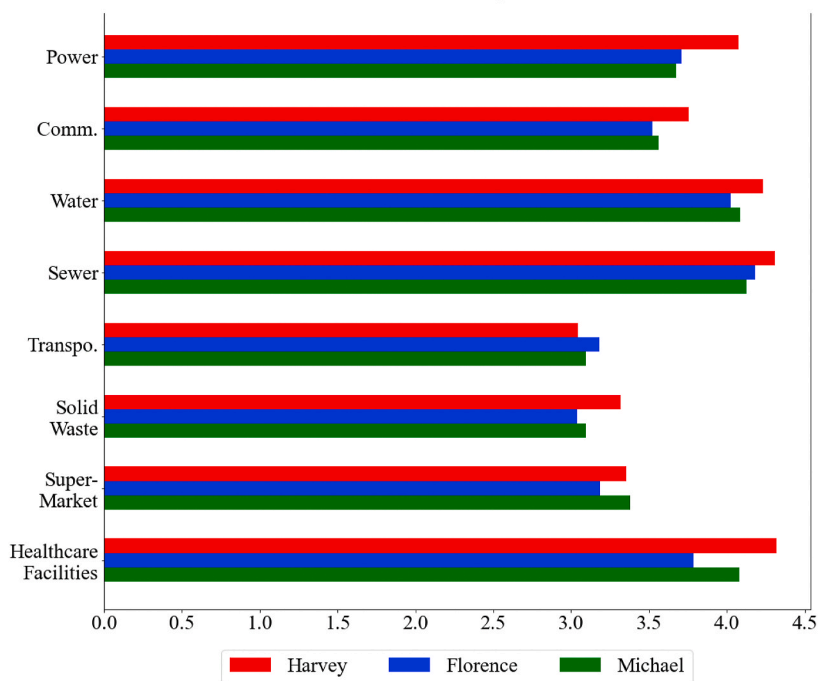
Fig. 4d summarizes the statistical values for need for service, which was measured based on the relative need that the households reported. The ranking of the results was consistent across the three events. Water and sewer systems were rated as extremely important services; healthcare facilities, power, and communication had mean values between extremely important to very important services; transportation, supermarkets, and solid waste had mean values between very important to moderately important.

5. Correlation analysis

Spearman correlation analysis was conducted to determine the influencing factors related to the level of susceptibility. These correlation relationships were calculated for each influencing factor and the level of tolerance for each service disruption across three different disasters (Fig. 5a-e). The level of tolerance indicates the ability of a household to withstand a particular service disruption and is inversely related to the level of susceptibility. Thus, if an influencing factor has a positive correlation with the level of tolerance, it would have a negative correlation with the level of susceptibility. The correlation graphs in Fig. 5a-e presents the 95% confidence interval of the Spearman correlation coefficients and the mean values (points). The $x = 0$ line is depicted to identify the significant correlations; confidence intervals



c



d

Fig. 4. (*continued*).

which cross the $x = 0$line are not significant at 5% level of confidence. The table format of the correlation analyses is available in the Supplementary Information (Section B).

5.1. Sociodemographic characteristics

Examining the three independent disaster events, households with low-income, low-education, minority groups, and renters had statistically significant ($p < 0.05$) correlations with higher levels of susceptibility for the majority of service disruptions. In contrast, elderly residents had statistically significant correlations with lower levels of susceptibility for several of the service disruptions. Specific to Hurricane Harvey, residents having young children and those living in non-detached households were frequently correlated with higher levels of susceptibility at a statistically significant level. Specific to Hurricane Florence and Hurricane Michael, not owning a vehicle had statistically significant correlations with higher levels of susceptibility for the majority of service disruptions. For the three events, these were statistically

Table 5a
Frequency and Percentage of Sociodemographic Factors.

		Hurricane Harvey		Hurricane Florence		Hurricane Michael	
		F#	P%	F#	P%	F#	P%
Income	Less than $25,000	116	13.6	75	20.7	149	25.6
	$25,000-$49,999	186	21.9	97	26.8	153	26.2
	$50,000-$74,999	194	22.8	89	24.6	119	20.4
	$75,000-$99,999	108	12.7	47	13.0	76	13.0
	$100,000-$124,999	78	9.2	20	5.5	35	6.0
	$125,000-$149,999	63	7.4	16	4.4	22	3.8
	More than $150,000	105	12.4	18	5.0	29	5.0
Education	Less than high school	16	1.9	3	0.8	15	2.6
	High school/GED	110	13.0	54	14.9	104	17.8
	Trade/technical/vocational	38	4.5	14	3.9	36	6.2
	Some college	148	17.5	75	20.7	106	18.2
	2 Year Degree	72	8.5	58	16.0	78	13.4
	4 Year Degree	275	32.5	89	24.6	131	22.5
	Post Graduate Level	188	22.2	69	19.1	113	19.4
Renters	No	598	71.5	254	71.1	387	67.8
	Yes	238	28.5	103	28.9	184	32.2
Non-detached Home	No	635	75.6	272	76.0	396	68.6
	Yes	205	24.4	86	24.0	181	31.4
Live in Flood Zone	No	584	80.1	274	84.0	457	88.9
	Yes	145	19.9	52	16.0	57	11.1
Minority	No	526	65.0	238	70.4	424	75.3
	Yes	283	35.0	100	29.6	139	24.7
Children	No	706	83.3	286	79.0	457	78.4
	Yes	142	16.7	76	21.0	126	21.6
Elderly	No	551	65.0	269	74.3	432	74.1
	Yes	297	35.0	93	25.7	151	25.9
Difficulty with Mobility	No	697	82.0	262	72.4	520	89.2
	Yes	153	18.0	100	27.6	63	10.8
Not Owning a Vehicle	No	826	97.2	335	92.5	541	92.8
	Yes	24	2.8	27	7.5	42	7.2

Table 5b
Frequency and Percentage of Power Backup.

		Hurricane Harvey		Hurricane Florence		Hurricane Michael	
		F#	P%	F#	P%	F#	P%
Power Backup	Yes	173	20.4	118	32.6	213	36.5
	No	677	79.6	244	67.4	370	63.5

Table 5c
Frequency and Percentage of Previous Experience and Previous Damage.

		Hurricane Harvey		Hurricane Florence		Hurricane Michael	
		F#	P%	F#	P%	F#	P%
Previous Experience	Yes	720	84.7	315	87.0	460	78.9
	No	130	15.3	47	13.0	123	21.1
Previous Damage	Yes	380	52.8	152	48.3	221	48.0
	No	340	47.2	163	51.7	239	52.0

significant for transportation, solid waste, and supermarket, which are services outside of the households. Little to none of the sociodemographic characteristics had a significant correlation with the sewer disruption; thus, sewer system disruptions displayed a non-discriminate impact on different sociodemographic groups.

Table 5d
Frequency and Percentage of Social Capital.

		Hurricane Harvey		Hurricane Florence		Hurricane Michael	
		F#	P%	F#	P%	F#	P%
Rely for Emergency	Yes	463	54.5	199	55.0	335	57.5
	No	387	45.5	163	45.0	248	42.5
Rely for Emotional Well-being	Yes	679	79.9	279	77.1	458	78.6
	No	171	20.1	83	22.9	125	21.4
Community Member	Yes	365	42.9	160	44.2	256	43.9
	No	485	57.1	202	55.8	327	56.1

5.2. Protective actions and adjustments

The implementation of protective actions and adjustments was statistically significant with a lower level of susceptibility for the majority of the service disruptions across the three events. As the perception of preparedness, belief in infrastructure capability, days of preparedness, and days of forewarning increases, the level susceptibility to the service disruptions decreased for the majority of service disruptions expect for the sewer system. As households had greater time and ability to prepare, the level of susceptibility to the services decreased. Higher levels of expectation for the potential disruptions were correlated with lower levels of susceptibility for the majority of the service disruptions expect for the supermarkets and healthcare facilities. On the other hand, the reliability of information was significantly correlated with lower levels of susceptibility for the water disruptions caused by Hurricane Harvey and Hurricane Florence, but had little to no significance for the susceptibility of the remaining service disruptions.

5.3. Previous experience and previous damage

Previous experience was statistically significant with a lower level of susceptibility for the majority of the service disruptions across the three disasters except for the sewer system, but previous damage was not a significant factor.

5.4. Social capital

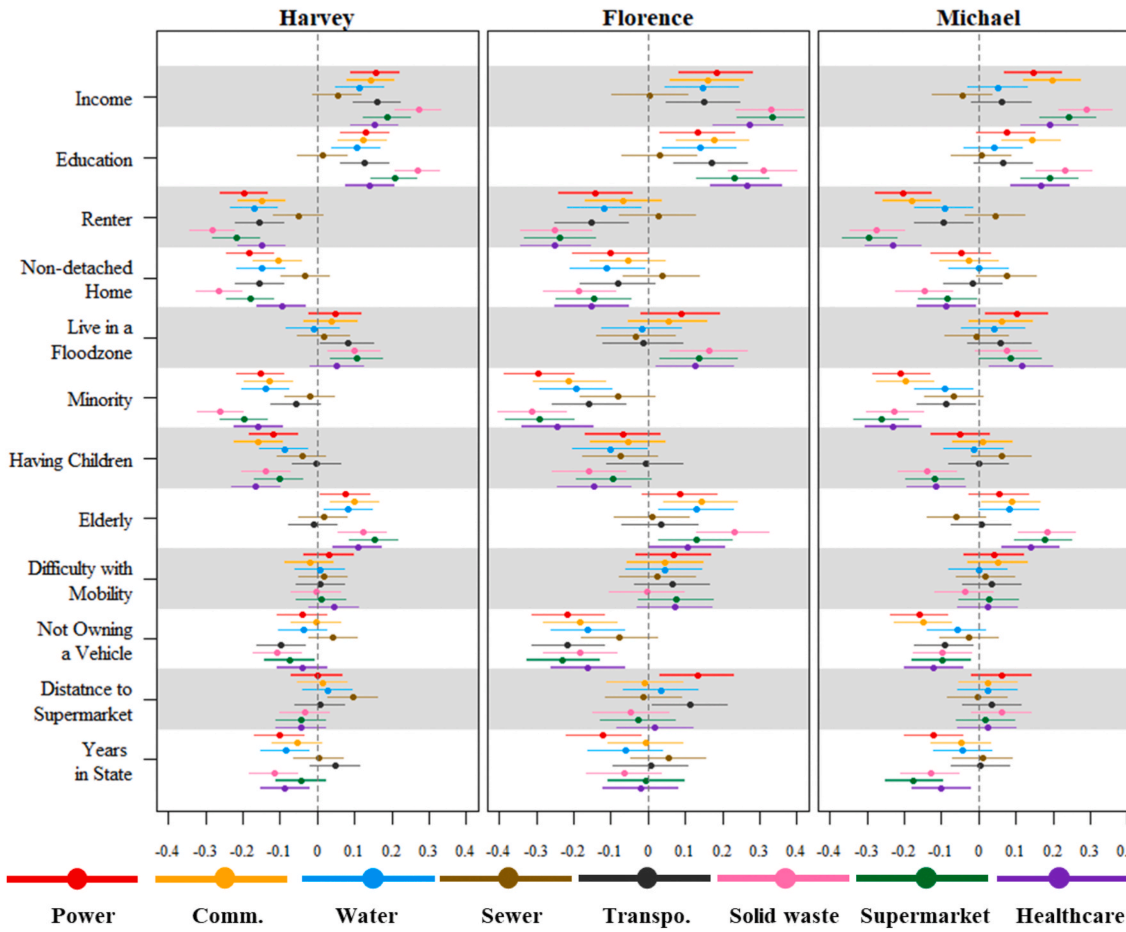
Having some form of social capital was correlated with lower levels of susceptibility at a statistically significant level. Reliance on emotional well-being was frequently correlated with a lower level of susceptibility for the majority of services across the three disasters. Specific to Hurricane Michael, reliance on friends and family for emergency assistance was correlated with a lower level of susceptibility for the majority of service disruptions.

5.5. Need for service

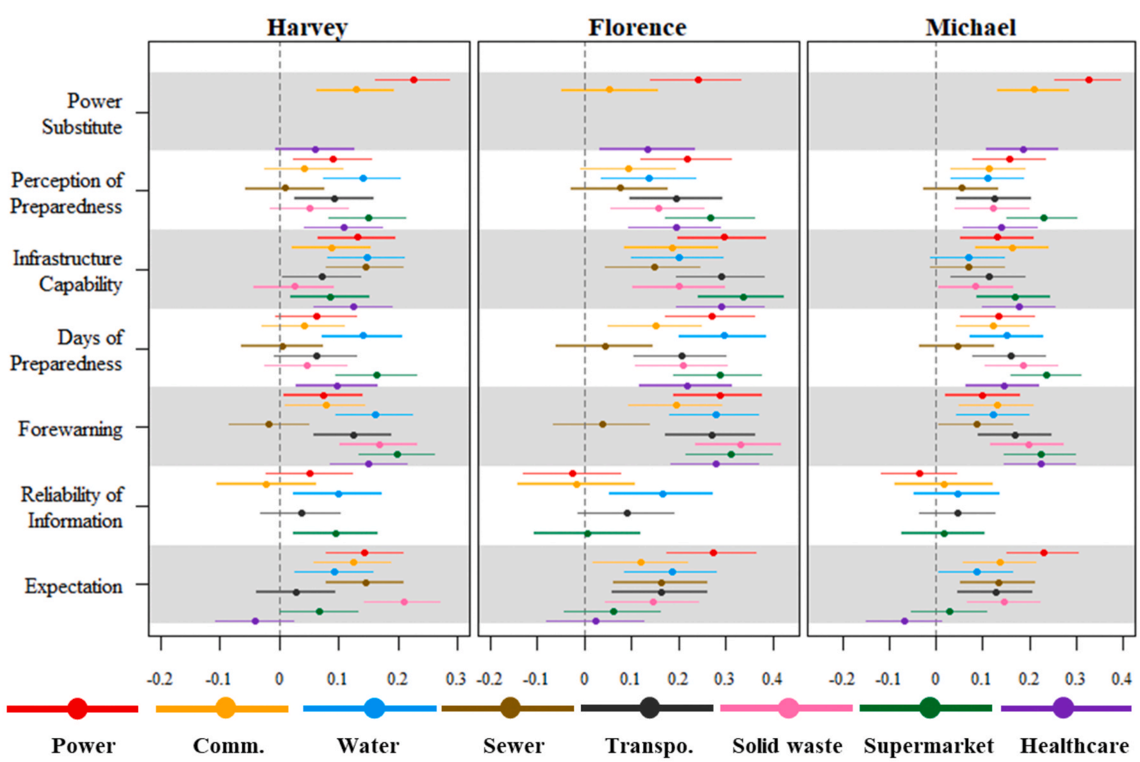
Higher need for the services had a higher level of susceptibility for the majority of the infrastructure services. This indicates that as households increasingly depend on a particular service disruption, the level of susceptibility also increases.

6. Discussion

The research study aims to bring a much needed human-centered approach to infrastructure planning and resilience strategies [10,59]. Examination of the influential factors provides unique insight into the anatomy of susceptibility of households against service disruptions caused by natural hazards. It should be noted that due to the large sample size and the examination of the human subjects, the correlation



a



b

Fig. 5. a: Sociodemographic Characteristics Spearman Correlation Values, b: Protective Actions and Adjustment Spearman Correlation Values, c: Previous Experience and Previous Damage Spearman Correlation Values, d: Social Capital Spearman Correlation Values, e: Need for Service Spearman Correlation Values.

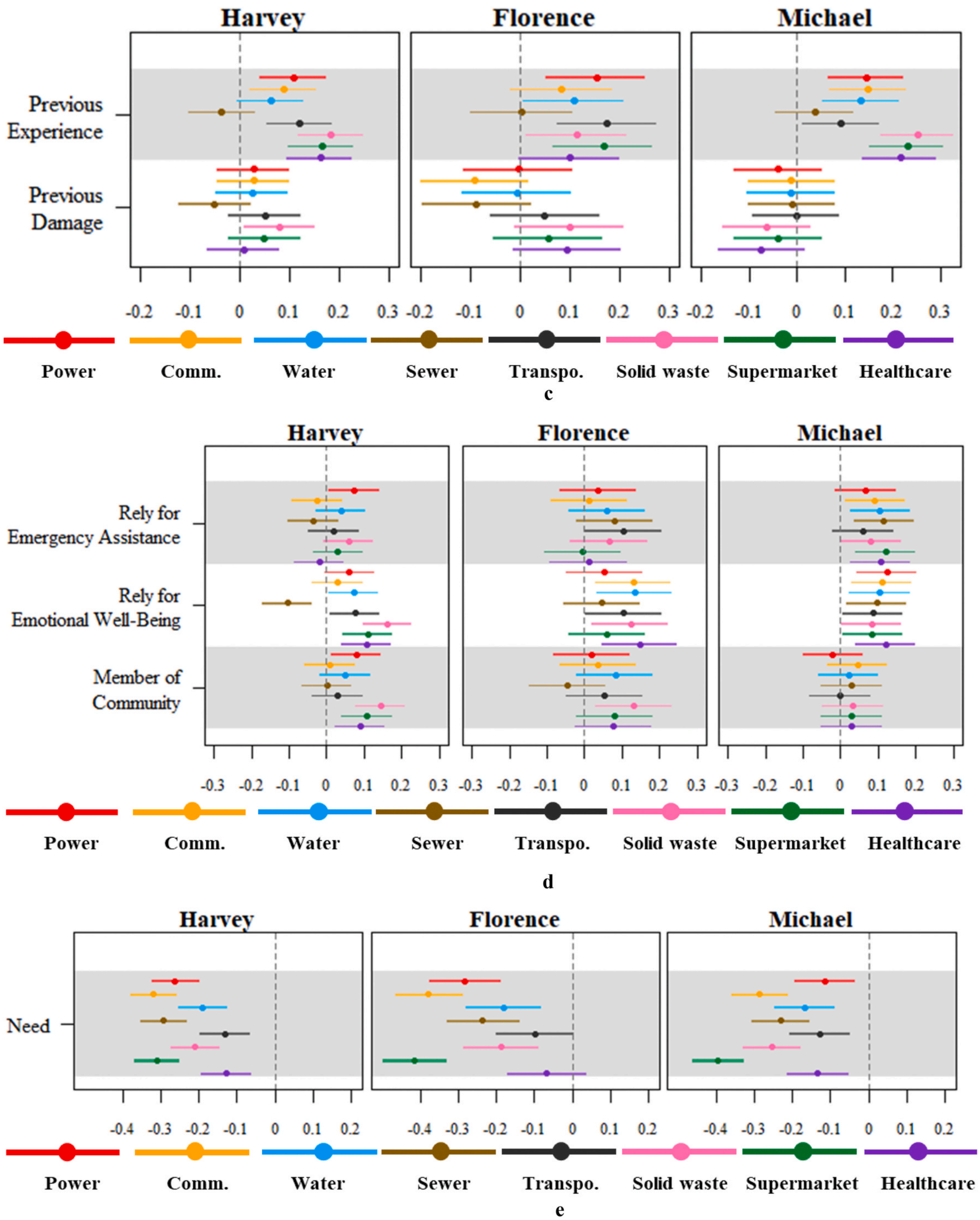


Fig. 5. (*continued*).

levels in this study were small. This means that while the association has not occurred by chance (significant p-values), the one-by-one identified correlation coefficients could explain a small portion of the variability in the susceptibility of the household. However, the statistical power provided by the large sample sizes enabled us to study the anatomy of susceptibility for shelter-in-place households across three major disaster events and eight infrastructure services. The findings highlight the extent which social disparities, protective actions and adjustments, and communal and contextual factors relate to the level of susceptibility.

6.1. Recognizing universal and situational social disparities

The results from the sociodemographic characteristics emphasize the need for recognizing social inequalities and risk disparities for disruptions in infrastructure services. In particular, households with low-income, low-education, minorities, and renters had statistically significant ($p < 0.05$) correlations with higher levels of susceptibility. Though the strength of the correlation is relatively low, the consistency across several service disruptions across three independent disasters shows that disparity in susceptibility may be inherent to differences in socio-demographic characteristics. Though previous research has demonstrated that socially vulnerable households were disproportionately impacted by service disruptions caused by Hurricane Harvey [8,9,24], this study illustrates that certain sociodemographic factors can be universally related to higher levels of susceptibility regardless of the service type or disaster event. For instance, low-income households could be more susceptible to the service disruptions because of an inability to afford expensive service alternatives such as power generators. Minority households would also have a higher level of susceptibility because of a struggle to communicate through language barriers or to negotiate with bureaucratic entities for access to necessary resources.

Furthermore, there is some event-specific or service-specific influence of the sociodemographic characteristics on the level of susceptibility. Not owning a vehicle had higher levels of susceptibility for the majority of service disruptions caused by Hurricane Michael and Hurricane Florence at a statistically significant level. Metropolitan areas, such as the region impacted by Hurricane Harvey, typically have a greater number of resources within a shorter distance of the households. This could explain why the ownership of a vehicle was not as statistically significant for respondents impacted by Hurricane Harvey. On the other hand, not owning a vehicle was correlated with higher levels of susceptibility for services outside of the household, including transportation, solid waste collection, and access to the supermarket, across all three disasters. Being outside of the household, residents without a vehicle could have difficulty utilizing or substituting these services without a vehicle regardless of the disaster events.

Sociodemographic groups may have distinct needs for the different infrastructure services, which would imply a discriminate impact from a service disruption. Indeed, increased need for the services was consistently correlated with higher levels of susceptibility for the majority of service disruptions. Thus, community leaders, emergency planners, and utility companies should prioritize infrastructure services and tailor risk mitigation plans which consider the distinct needs and issues related to the sociodemographic characteristics.

6.2. Incorporating protective actions and adjustments for service disruptions

Though previous research studies such as Paton et al. [39] and Kapucu [60] have discussed how protective actions and adjustments can mitigate the disaster impact, few studies have investigated how these actions could be specific to infrastructure service disruptions. Thus, the research aimed to examine these influences on the level of susceptibility for different services. Having a greater number of days to prepare, increased perception of preparedness, increased belief in the households' capabilities, and longer length of forewarning, correlated with lower levels of susceptibility for the majority of service disruptions at a statistically significant level ($p < 0.05$). This demonstrates that shelter-in-place households with lower perception of their preparedness capabilities, shorter number of days of preparedness, and a shorter length of forewarning are most susceptible to the service disruptions. In these cases, prioritization and restoration of the services should be focused on communities who had little warning of the impending disaster; and thus, little time to adequately prepare for the potential service disruptions. It has been discussed that the success of such early-warning systems is dependent on the trust of the community residents, and thus, the information about service disruptions should be consistently reliable and clear [37].

In addition, various studies have already discussed the importance of quantifying the risk associated with infrastructure and communicating this information to involved stakeholders through methodologies [61, 62] and grading systems [63]. Such efforts should ensure that households are aware of the potential service disruptions as quickly as possible for timely preparation. In the same manner, the research study highlights the importance of raising the risk perception by increasing the level of expectation households have for service disruptions. Higher levels of expectation were correlated with lower levels of susceptibility for the majority of service disruptions at a statistically significant level. Increased levels of expectation can impact the protective actions taken by households [64] and enhance the preparedness of these households [60]. For instance, the region impacted by Hurricane Michael reported the highest expectation for power outages and the greatest percentage of households with a power substitute. Households also impacted by Hurricane Michael reported a comparatively higher level of tolerance to the power disruption, although the community experienced a sudden event and reported a short time of preparation. Because these households expected a longer period of disruption, they would be more likely to preemptively prepare for possible disruptions.

The statistically significant relationships between high levels of expectation and lower levels of susceptibility for the majority of service disruptions hold true except for the supermarket and healthcare facilities. The results demonstrated that households already had a high level of expectation for supermarket closures, or within the top two services for the three disasters, and thus, the majority of people would acquire supplies from supermarkets early on. This almost universal expectation for these disruptions could explain the non-significant effect of the level of expectation on the susceptibility to the supermarket closures. In contrast, few people would directly depend on healthcare facilities, and thus, the level of expectation for disruptions would not greatly influence the susceptibility. Despite these exceptions, communities would benefit from raising the risk perception associated with service disruptions and communicating the relevant information to invested stakeholders [62].

Taking these protective actions were statistically significant with lower levels of susceptibility for the majority of service disruptions except for the sewer system. Sewer system disruptions did not discriminate based on typical protective actions or sociodemographic groups. Still, it is important to determine an approach for reducing the level of susceptibility for the sewer disruption because households not only ranked the sewer system as the most important service but were also unable to withstand this disruption for an average longer than one to two days.

6.3. Understanding communal and contextual factors for service disruption mitigation

Differences in the contextual and communal background of the regions may affect the influencing factors for the anatomy of susceptibility to service disruptions. One example is how previous experience of specific disasters varies across communities. According to Horney [23]; previous experience will increase the culture of preparedness as people become more familiar with the consequences of the disaster. Compared to other regions, respondents impacted by Hurricane Harvey could be more familiar with inland flooding events leading to a relatively lower level of susceptibility for transportation disruptions. Similarly, respondents impacted by Hurricane Michael would be more familiar with strong hurricane winds leading to a relatively lower level of susceptibility for power outages. Though different regions may be able to tolerate the impacts of hazards of greater familiarity to them, the impacts of certain service disruptions may be unclear to these communities and leave them vulnerable to unanticipated risks. Thus, there is a need to create comprehensive plans, which account for the background and resources of the communities, specific to the impacts of different disaster types, including which shelter-in-place households would be most and least susceptible to the negative impacts of service disruptions.

In addition, social capital may be influenced by the communal and contextual factors of the community. Active community participation has been shown to potentially increase the resilience and response to social problems [65], and the same could be applied to social networks responding to disaster-induced infrastructure service disruptions. In this research study, a household having some form of social capital was associated with lower levels of susceptibility, and the "rely for emergency well-being" variable was frequently correlated with lower levels of susceptibility for the majority of service disruptions across the three disasters at a statistically significant level. This variable may be correlated with lower levels of susceptibility because affected residents were able to vocalize their issues. However, having a social network in the area does not necessarily mean these people are able to provide assistance specific to the infrastructure service disruption. It is important to consider the different forms of social capital prevalent in a community as well as the various levels of coordination between community organizations which influence their effectiveness in a disaster setting [66, 67]. While respondents of Hurricane Michael reported lower levels of susceptibility for the majority of service disruptions for the "rely for emergency assistance" variable, this was not observed for the other two disasters. Instead, more metropolitan areas may have an abundance of established community organizations to provide resources after the disaster while less metropolitan areas may rely on neighborhood connection.

7. Conclusion

The contribution of the research paper is to provide empirical information about the anatomy of susceptibility regarding infrastructure service disruptions. The findings help to better incorporate the human dimension into the design and planning of infrastructure systems against the disaster impact. The exploratory analysis demonstrated that influencing factors have consistent statistically significant ($p < 0.05$) correlations with discriminating levels of susceptibility for eight infrastructure service disruptions across three independent disasters. This understanding is necessary for developing risk mitigation plans which effectively prioritize the investment and restoration of infrastructure services for shelter-in-place households.

The findings reveal that certain influencing characteristics have a universal impact on the level of susceptibility for shelter-in-place households. For instance, households with low-socioeconomic status, minority residents, and renters often reported a discriminate level of susceptibility at a statistically significant level. This consistency demonstrates these households are highly susceptible regardless of the specific service disruption or disaster event. As such, decision-makers should establish infrastructure resilience policies that address and prioritize the specific needs of these groups for having access to infrastructure services.

The study also demonstrated the importance of developing strategies that mitigate the impact of service disruptions, such as increasing the days of preparation, length of forewarning, and level of expectation. To ensure these households have ample time to prepare, it is critical to provide information as quickly as possible using reliable early-warning systems of the impending disaster and risk assessment tools about the potential service disruptions. Raising the risk-perception of the communities by increasing the level of expectation would mean communities are already aware of the potential service disruptions, and thus, would take the appropriate protective actions.

Decision-makers should incorporate the communal and contextual factors of the communities because different locations have distinct resources to mitigate potential service disruptions and inherent characteristics which influence the level of susceptibility across different disasters. For instance, the previous experience was statistically significant with lower the levels of susceptibility for the majority of service disruptions, but communities can experience different service disruption impacts across disaster events. A community may be familiar with one type of service disruption but unfamiliar with the impacts of other service disruptions. As such, risk mitigation plans should consider possible service disruptions with which a certain community is least familiar.

The current research establishes a fundamental empirical basis for understanding the anatomy of susceptibility to infrastructure service disruptions by identifying influencing factors. Future studies could develop models based on the identified influencing factors to determine susceptibility levels. These models would also consider the interplay between the identified influencing factors. Such approaches would provide invested stakeholders with tools that are more specialized in defining the anatomy of susceptibility. This understanding will help shed light on the mechanisms through which these factors influence the susceptibility of shelter-in-place households.

Data availability statement

Some or all data, models, or code generated or used during the study are proprietary or confidential in nature and may only be provided with restrictions. The household survey data used in this research received Institutional Review Board (IRB) for the human subject. As a part of the IRB data protection requirement, only the research team have access to the data, and the data cannot be shared with others.

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.

Acknowledgement

The authors would like to acknowledge the funding support from the National Science Foundation under grant number 1846069 and National Academies' Gulf Research Program Early-Career Research Fellowship. The research is supported in part by an Institutional Grant (NA18OAR4170088) to the Texas Sea Grant College Program from the National Sea Grant Office, National Oceanic and Atmospheric Administration, U.S. Department of Commerce. Any opinions, findings, conclusions, or recommendations expressed in this research are those of the authors and do not necessarily reflect the view of the funding agencies.

Appendix. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2020.101875.

References

[1] S. Chang, Socioeconomic impacts of infrastructure disruptions, Oxford Res. Encycl. Nat. Hazard Sci. (2016).
[2] Y.-S. Su, Urban flood resilience in New York city, London, Randstad, Tokyo, Shanghai, and Taipei, J. Manag. Sustain., Canadian Center Sci. Educ. 6 (1) (2016) 92.
[3] M. Batouli, A. Mostafavi, Multiagent Simulation for Complex Adaptive Modeling of Road Infrastructure Resilience to Sea-Level Rise, Computer-Aided Civil and Infrastructure Engineering, 2018.
[4] S. Dong, T. Yu, H. Farahmand, A. Mostafavi, Bayesian Modeling of Flood Control Networks for Failure Cascade Characterization and Vulnerability Assessment, Computer-Aided Civil and Infrastructure Engineering, 2020.
[5] M. Koliou, J.W. van de Lindt, T.P. McAllister, B.R. Ellingwood, M. Dillard, H. Cutler, "State of the Research in Community Resilience: Progress and challenges." *Sustainable and Resilient Infrastructure*, 2018.
[6] A. Mostafavi, N.E. Ganapati, H. Nazarnia, N. Pradhananga, R. Khanal, Adaptive capacity under chronic stressors: assessment of water infrastructure resilience in 2015 Nepalese earthquake using a system Approach, Nat. Hazards Rev. (2018).
[7] K. Rasoulkhani, A. Mostafavi, Resilience as an emergent property of human-infrastructure dynamics: a multi-agent simulation model for characterizing regime shifts and tipping point behaviors in infrastructure systems, PloS One 13 (2018), e0207674.
[8] N. Coleman, A. Esmalian, A. Mostafavi, Equitable resilience in infrastructure systems: empirical assessment of disparities in hardship experiences of vulnerable populations during service disruptions, Nat. Hazards Rev. (2019).
[9] J. Dargin, A. Mostafavi, Human-centric infrastructure resilience: uncovering well-being risk disparity due to infrastructure disruptions in disasters, PloS One (2020).
[10] S. Dong, A. Esmalian, H. Farahmand, A. Mostafavi, An integrated physical-social analysis of disrupted access to critical facilities and community service-loss tolerance in urban flooding, Comput. Environ. Urban Syst. Elsevier 80 (November 2019) (2020), 101443.
[11] D.R. Godschalk, Urban hazard mitigation: creating resilient cities, Nat. Hazards Rev. (2003).
[12] Applied Technology Council, Critical Assessment of Lifeline System Performance: Understanding Societal Needs in Disaster Recovery, 2016.
[13] A.R. Berkeley III, M. Wallace, A Framework for Establishing Critical Infrastructure Resilience Goals, National Infrastructure Advisory Council, 2010.

[14] S.L. Cutter, J.A. Ahearn, B. Amadei, P. Crawford, E.A. Eide, G.E. Galloway, M. F. Goodchild, H.C. Kunreuther, M. Li-Vollmer, M. Schoch-Spana, S.C. Scrimshaw, E.M. Stanley, G. Whitney, M. Lou Zoback, Disaster Resilience: A National Imperative, *Environment*, 2013.

[15] T. Welle, J. Birkmann, Measuring the unmeasurable: comparative assessment of urban vulnerability for coastal megacities — New York, London, Tokyo, Kolkata and Lagos, J. Extrem. Events 3 (3) (2017), 1650018. World Scientific Pub Co Pte Lt.

[16] A. Fothergill, J.A. DeRouen Darlington, E.G.M. Maestas, Race, Ethnicity and Disasters in the United States: A Review of the Literature, *Disasters*, 1999.

[17] A. Fothergill, L.A. Peek, Poverty and disasters in the United States: a review of recent sociological findings, Nat. Hazards (2004).

[18] W.G. Peacock, S. Van Zandt, Y. Zhang, W.E. Highfield, Inequities in long-term housing recovery after disasters, J. Am. Plann. Assoc. (2014).

[19] J. Chakraborty, T.W. Collins, M.C. Montgomery, S.E. Grineski, Social and spatial inequities in exposure to flood risk in Miami, Florida, Nat. Hazards Rev. (2014).

[20] J.W. Faber, Superstorm Sandy and the demographics of flood risk in New York City, Hum. Ecol. (2015).

[21] W.E. Highfield, W.G. Peacock, S. Van Zandt, Mitigation planning: why hazard exposure, structural vulnerability, and social vulnerability matter, J. Plann. Educ. Res. (2014).

[22] E.J. Baker, Household preparedness for the Aftermath of hurricanes in Florida, Appl. Geogr. (2011).

[23] J. Horney, Factors associated with hurricane preparedness: results of a pre-hurricane assessment, J. Disaster Res. 3 (2) (2008).

[24] A. Esmalian, S. Dong, N. Coleman, A. Mostafavi, Determinants of risk disparity due to infrastructure service losses in disasters: a household service gap model, Risk Anal. (2019).

[25] A. Esmalian, K. Dong, A. Mostafavi, Empirical assessment of household susceptibility to hazards-induced prolonged power outages, Construct. Res. Congress (2020).

[26] S. Rufat, E. Tate, C.G. Burton, A.S. Maroof, Social vulnerability to floods: review of case studies and implications for measurement, Int. J. Disaster Risk Reduct. (2015).

[27] M. Teo, A. Goonetilleke, A. Ahankoob, K. Deilami, M. Lawie, Disaster awareness and information seeking behaviour among residents from low socio-economic backgrounds, Int. J. Disaster Risk Reduct. (2018).

[28] M. Masozera, M. Bailey, C. Kerchner, Distribution of impacts of natural disasters across income groups: a case study of New Orleans, Ecol. Econ. (2007).

[29] R.J. Burby, Hurricane Katrina and the paradoxes of government disaster policy: bringing about wise governmental decisions for hazardous areas, Ann. Am. Acad. Polit. Soc. Sci. (2006).

[30] Y.T. Maru, M. Stafford Smith, A. Sparrow, P.F. Pinho, O.P. Dube, A linked vulnerability and resilience framework for adaptation pathways in remote disadvantaged communities, Global Environ. Change (2014).

[31] B. Marsh, A.M. Parnell, A.M. Joyner, Institutionalization of Racial Inequality in Local Political Geographies, *Urban Geography*, 2010.

[32] L. Aptekar, J. Boore, The emotional effects of disaster on children: a review of literature, Int. J. Ment. Health 19 (1990) 77–90.

[33] B.E. Flanagan, E.W. Gregory, E.J. Hallisey, J.L. Heitgerd, B. Lewis, A social vulnerability index for disaster management, J. Homel. Secur. Emerg. Manag. (2011).

[34] L.M. Stough, A.N. Sharp, A.J. Resch, C. Decker, N. Wilker, Barriers to the Long-Term Recovery of Individuals with Disabilities Following a Disaster, *Disasters*, 2015.

[35] J.N. Sutton, K. Tierney, Disaster Preparedness: Concepts, Guidance, and Research, *Boulder, University of Colorado Natural Hazards Center, Institute of Behavioral Science*, 2006.

[36] G. Lizarralde, A. Valladares, A. Olivera, L. Bornstein, K. Gould, J.D. Barenstein, A Systems Approach to Resilience in the Built Environment: the Case of Cuba, *Disasters*, 2015.

[37] C. Roy, S.K. Sarkar, J. Åberg, R. Kovordanyi, "The current cyclone early warning system in Bangladesh: providers' and receivers' views, Int. J. Disaster Risk Reduct. (2015).

[38] S.U. Khan, M.I. Qureshi, I.A. Rana, A. Maqsoom, An empirical relationship between seismic risk perception and physical vulnerability: a case study of Malakand, Pakistan, Int. J. Disaster Risk Reduct. (2019).

[39] D. Paton, J. McClure, P.T. Bürgelt, P. Burgelt, P.T. Bürgelt, Natural Hazard Resilience: the Role of Individual and Household Preparedness, Disaster resilience: An integrated approach, 2006.

[40] C. Fan, M. Esparza, J. Dargin, F. Wu, B. Oztekin, A. Mostafavi, Spatial biases in crowdsourced data: social media content attention concentrates on populous areas in disasters, Comput. Environ. Urban Syst. (2020).

[41] V.N. Martins, J. Nigg, H.M. Louis-Charles, J.M. Kendra, Household preparedness in an imminent disaster threat scenario: the case of superstorm sandy in New York City, Int. J. Disaster Risk Reduct. (2019).

[42] D.N. Sattler, C.F. Kaiser, J.B. Hittner, Disaster preparedness: relationships among prior experience, personal characteristics, and distress, J. Appl. Soc. Psychol. (2000).

[43] D.P. Aldrich, "The power of people: social capital's role in recovery from the 1995 Kobe earthquake, Nat. Hazards (2011).

[44] I.S. Holand, Lifeline issue in social vulnerability indexing: a review of indicators and discussion of indicator application, Nat. Hazards Rev. (2015).

[45] S.S. Clark, T.P. Seager, M.V. Chester, A capabilities approach to the prioritization of critical infrastructure, Environ. Syst. Decis., Springer US (2018), 0(0), 0.

[46] National Research Council, Facing Hazards and Disasters: Understanding Human Dimensions, The National Academies Press, *Washington, DC*, 2006.

[47] J.C. Schwab, Hazard Mitigation: Integrating Best Practices into Planning, vol. 560, 2010, p. 156.

[48] W. Donner, H. Rodriguez, Population Composition, Migration and Inequality: the Influence of Demographic Changes on Disaster Risk and Vulnerability, Social Forces, 2008.

[49] W. Zhang, G. Villarini, G.A. Vecchi, J.A. Smith, Urbanization exacerbated the rainfall and flooding caused by hurricane Harvey in Houston, Nature (2018).

[50] M.A. Brennan, C.G. Flint, Uncovering the hidden dimensions OF rural disaster mitigation: capacity building through community emergency response teams, South. Rural Sociol. (2007).

[51] M. Jurjonas, E. Seekamp, Rural Coastal Community Resilience: Assessing a Framework in Eastern North Carolina, *Ocean and Coastal Management*, 2018.

[52] H. Rosoff, R.S. John, F. Prager, "Flu, Risks, and Videotape: Escalating Fear and Avoidance." *Risk Analysis*, 2012.

[53] D.B. Wright, E.M. Skagerberg, Measuring empathizing and systemizing with a large US sample, PloS One (2012).

[54] E.S. Blake, D.A. Zelinsky, National Hurricane Center Tropical Cyclone Report, Hurricane Harvey, 2017.

[55] Federal Communications Commission, Communication Status Report for Areas Impacted by Hurricane Harvey, 2017.

[56] S.M. Rinaldi, J.P. Peerenboom, T.K. Kelly, Identifying, Understanding, and Analyzing Critical Infrastructure Interdependencies, *IEEE Control Systems Magazine*, 2001.

[57] S. Stewart, R. Berg, National Hurricane Center Tropical Cyclone Report: Hurricane Florence, 2019.

[58] J.L. Beven II, R. Berg, A. Hagen, National Hurricane Center Tropical Cyclone Report: Hurricane Michael, 2019.

[59] K. Rasoulkhani, A. Mostafavi, J. Cole, S. Sharvelle, Resilience-based Infrastructure Planning and Asset Management: Study of Dual and Singular Water Distribution Infrastructure Performance Using a Simulation Approach, *Sustainable Cities and Society*, 2019.

[60] N. Kapucu, "Culture of preparedness: household disaster preparedness, Disaster Prevent. Manag.: Int. J. (2008).

[61] J. Clarke, E. Obrien, A Multi-Hazard Risk Assessment Methodology, Stress Test Framework and Decision Support Tool for Transport Infrastructure Networks, *Transportation Research Procedia*, 2016.

[62] S. Esposito, B. Stojadinović, A. Babič, M. Dolšek, S. Iqbal, J. Selva, M. Broccardo, A. Mignan, D. Giardini, Risk-based multilevel methodology to stress test critical infrastructure systems, J. Infrastruct. Syst. (2020).

[63] A. Babič, M. Dolšek, A Five-Grade Grading System for the Evaluation and Communication of Short-Term and Long-Term Risk Posed by Natural Hazards, *Structural Safety*, 2019.

[64] M.K. Lindell, S.N. Hwang, "Households' Perceived Personal Risk and Responses in a Multihazard environment." *Risk Analysis*, 2008.

[65] J. Donatuto, E.E. Grossman, J. Konovsky, S. Grossman, L.W. Campbell, Indigenous Community Health and Climate Change: Integrating Biophysical and Social Science Indicators, *Coastal Management*, 2014.

[66] H. Farahmand, S. Dong, A. Mostafavi, P.R. Berke, S.C. Woodruff, B. Hannibal, A. Vedlitz, Institutional congruence for resilience management in interdependent infrastructure systems, Int. J. Disaster Risk Reduct. (2020).

[67] Q. Li, S. Dong, A. Mostafavi, Modeling of inter-organizational coordination dynamics in resilience planning of infrastructure systems: a multilayer network simulation framework, PloS One (2019).

[68] FEMA, Data visualization: disaster declarations for states and counties."≤https://www.fema.gov/data-visualization-disaster-declarations-states-and-counties> 19 (2019 Jun).

[69] USDA. "Rural-urban continuum codes."≤https://www.ers.usda.gov/data-products/rural-urban-continuum-codes.aspx> (Jun. 20, 2019).