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Susceptibility curves for humans: Empirical survival models for determining household-level disturbances from hazards-induced infrastructure service disruptions

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ABSTRACT

In natural hazard engineering, fragility curves are used to determine the likelihood of damage to an engineered system under different magnitudes of hazard intensity. Analogous to fragility curves for engineered systems, survival models developed in the present study determine the extent of disturbances for shelter-in-place households caused by infrastructure service disruptions during disasters. This study used empirical data from household surveys collected in the aftermath of Hurricane Harvey, Hurricane Florence, and Hurricane Michael to create empirical survival models for determining household-level disturbances related to eight infrastructure services: power, water, communication, sewer systems, transportation, solid waste collection, grocery stores, and healthcare facilities. The survival models considered various influencing factors, such as sociodemographic factors, previous experience, risk perception, and access to resources to determine what percentage of households in a community would experience considerable hardship under varying durations of service disruptions. The developed curves suggested that although the susceptibility patterns are similar for short durations of infrastructure service disruptions, prolonged service disruptions pose varying levels of disturbance in different communities based on the household characteristics and contextual factors. Susceptibility curves could be implemented with current tools for assessing the reliability and resilience of infrastructure systems to promote understanding of the societal impacts that disruptions in these services pose to the affected communities. The resulting empirical survival models provide necessary tools and insights for determining the susceptibility of communities to disruptions of various infrastructure services during disasters. Hence, the outcomes of this study provide new empirical insights and models enabling decision-makers to integrate human-centric dimensions into infrastructure retrofit and restoration processes to more equitably reduce societal impacts of service disruptions. Such human-centric approaches enable designing socially resilient cities and contribute to designing sustainable infrastructure systems.

1. Introduction

Assessment of the resilience and reliability of engineered systems has advanced in recent years due to the development of empirical and analytical models for investigating system performance. As shown in Fig. 1, the focus of reliability and resilience analysis studies has been to create empirical models and analytical methods to evaluate the extent of damage and disruptions in engineered systems given hazards of varying magnitudes. First, various prediction tools were developed to estimate different hazard scenarios posing threats of various magnitudes to communities (Komatitsch, Erlebacher, Göddeke, & Michéa, 2010; Vickery, Lin, Skerlj, Twisdale, & Huang, 2006). These assessment tools then employ fragility curves for determining the likelihood of damage to engineered systems under different hazard magnitudes (Dunn et al., 2018). The fragility curves assist in translating the impacts of hazards into the probability of failure in systems (U.S. Army Corps of Engineers 2010). Similarly, restoration curves have been created and used to estimate the restoration time of damaged engineered systems (Lei, Chen, Li, & Hou, 2019; Mensah & Dueñas-Osorio, 2016). With advancements in natural hazard engineering methods, such as reliability and resilience

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models, the impacts and failures of engineered infrastructure systems could be estimated, and mitigation and retrofit actions plans could be developed (Dehghani, Mohammadi Darestani, & Shafieezadeh, 2020; Hendricks et al., 2018). The impacts of natural hazards, however, are not limited to the failure of engineered physical systems, and there is a need for translating these impacts on the affected communities and considering societal impacts (Applied Technology Council, 2016). An important gap in the current literature is the absence of empirical and analytical models and tools to determine the societal impacts of infrastructure disruptions (Dong, Esmalian, Farahmand, & Mostafavi, 2020; Mostafavi, 2018). Determining the societal impacts helps to understand the inequities in the impact of natural hazard on the communities and promoting sustainable way to design and repair the infrastructure systems.

The inclusion of societal impacts in resilience and reliability analysis requires an understanding of the tolerance and susceptibility of households to the service losses (Coleman, Esmalian, & Mostafavi, 2020). The lack of empirical information about the underlying mechanisms and extent of households' susceptibility to infrastructure service disruption has led to the inadequate consideration of the human-centric aspect in assessing the societal risks of such hazards (Mostafavi & Ganapati, 2019). Prior studies have shown that the susceptibility to service disruptions is not equal among the households in an affected community (Coleman, Esmalian, & Mostafavi, 2019; Dargin & Mostafavi, 2020; Mitsova, Esnard, Sapat, & Lai, 2018). The determinants of the disparities in the susceptibility to the service disruptions have been attributed to the sociodemographic characteristics of the households, their capabilities, expectations and needs, protective actions and risks perceptions (Chakalian, Kurtz, & Hondula, 2019; Coleman et al., 2019; Coleman et al., 2020; Dargin, Berk, & Mostafavi, 2020; Esmalian, Dong, Coleman, & Mostafavi, 2019; Mitsova et al., 2018). While these studies have improved understanding of the factors influencing the susceptibility of households, empirical models for the determination of households' tolerance to service disruptions for determining the impacts of infrastructure service disruptions on the communities are lacking. In other words, analogous to fragility curves for engineered systems, there is a need for susceptibility curves for humans to determine the extent of disturbances caused by service outages

In this study, we developed empirical models to bridge the gap between the reliability and resilience assessment of the physical system and societal considerations (Fig. 1). We first developed models to determine susceptibility level for shelter-in-place households based on the duration of the service disruptions. To examine societal risks, the models integrate reliability assessment of the engineered system with susceptibility of households. We used the survey data collected in the aftermath of 2017 Hurricane Harvey in Texas, 2018 Hurricane Florence in the Carolinas, and 2018 Hurricane Michael in Florida to develop empirical survival models for each infrastructure service. Accordingly, empirical models were implemented to generate susceptibility curves. These curves provide a tool for translating the extent of service disruptions into societal impacts. Analogous to the use of fragility curves, one could use the susceptibility curves to identify the proportion of households for which a certain level of service disruptions exceeds their tolerance. The susceptibility curves could be integrated with available reliability and resilience models to estimate the proportion of the susceptible households in a community. The susceptibility curves help infrastructure owners and operators, emergency managers, and utility companies to better examine the societal risks of such service losses. These empirical curves provide a decision-making tool enabling stakeholders to plan service recovery strategies while considering the societal impacts on the affected residents. Enabling consideration of human-centric aspect into the resilience assessment is a key aspect of designing sustainable cities.

2. Factors affecting household-level disturbances

Multiple factors influence the extent of household-level susceptibility to infrastructure service disruption. Esmalian et al. (2019) developed a service gap model for assessing households' susceptibility to infrastructure service disruptions. Households' tolerance is a metric evaluating the susceptibility of the households to the service disruptions (Esmalian et al., 2019). This model captures disparities in societal risks due to such disruptions. The disparities in the societal impacts of infrastructure disruptions are due not solely to the higher exposure of certain households. Households intrinsically have different levels of tolerance to cope with disruptions. In this study, the measure of a household's tolerance is used to address this differential ability to cope with the threats posed by infrastructure service disruptions.

Susceptibility of households to the infrastructure systems disruptions is affected by various influencing factors. Previous research (e.g., Coleman et al., 2019) has shown that socially vulnerable populations, such as lower-income families, those with lower educational attainment, households with a young member, and racial minorities, have a significantly lower tolerance for infrastructure services. In this study, influencing variables (Fig. 2) were identified through an exploratory analysis of three hurricanes, Hurricane Harvey, Hurricane Florence, and Hurricane Michael. These variables were chosen through a systematic process. First, an extensive review of the literature was conducted to identify the potential factors which could influence tolerance level. Then survey data were collected from households who experienced one of the three hurricane events, yielding a large dataset for investigating importance of the variables. Finally, the significance of the variables was

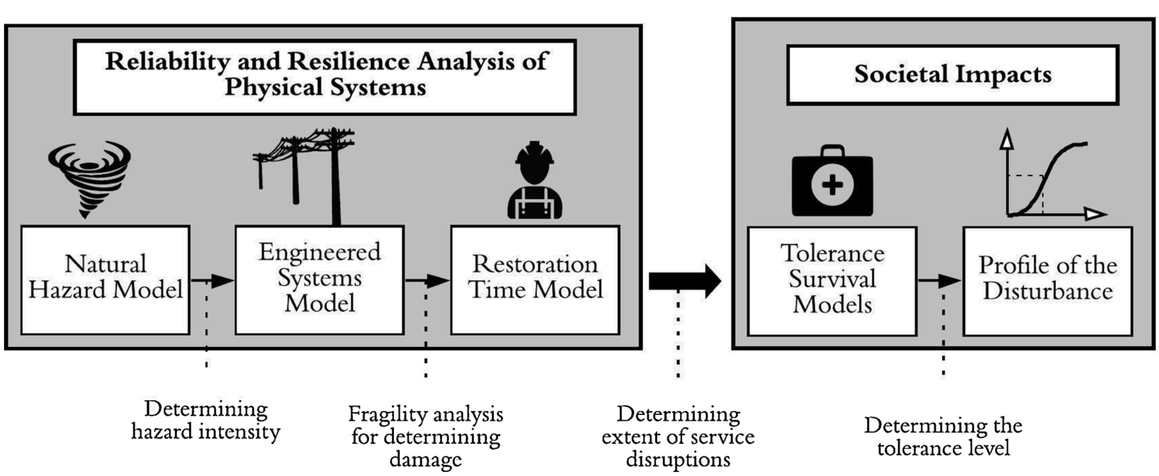

Fig. 1. Spectrum of analysis tools and models for assessing the physical disruptions and social disturbances in the nexus of hazards, built environment, and humans.

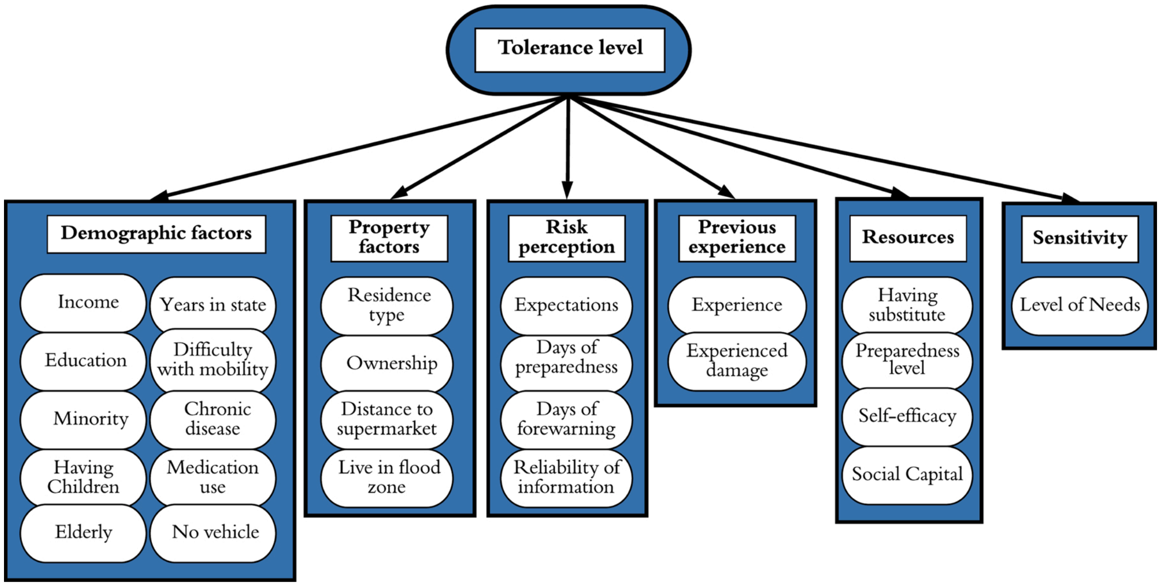

Fig. 2. Factors influencing susceptibility to infrastructure service disruption.

tested on tolerance to various infrastructure services to identify influencing factors. In this study, we built the models to determine the tolerance using these identified variables. Following is a brief description of each variable. (A detailed description of the influencing factors can be found in (Coleman et al., 2020).

2.1. Demographic factors

Demographic characteristics influence households' perceptions, resources, and vulnerability to a threat (Baker, 2011). In this study, we collected the demographic characteristics of the households responding to the survey; specific characteristics of individuals were not considered. Characteristics considered in the models for determining tolerance of loss of services were: household income (Fothergill & Peek, 2004), education level of the head of the household (Muttarak & Pothisiri, 2012), ethnicity (Marsh, Parnell, & Joyner, 2010), a member less than 10 years of age or older than 65 years of age (Flanagan, Gregory, Hallisey, Heitgerd, & Lewis, 2011), disabled individual (Stough, Sharp, Resch, Decker, & Wilker, 2015), an individual ill with chronic disease (Kessler, Wang, Kendrick, Lurie, & Springgate, 2007), and whether households have a vehicle. These variables have been shown to separately impact the tolerance level, but in this research, we investigate their importance in the presence of the other variables in the model.

2.2. Property factors

Four variables were considered for residences: (1) type of the residence, (2) if the residence is owned or rented, (3) distance from supermarkets, and (4) whether residences are located in a flood zone. These variables influence the preparation (Baker, 2011), adjustment (Lindell & Hwang, 2008), and exposure (Koks, Jongman, Husby, & Botzen, 2015) of households for the service disruptions.

2.3. Risk perception

(1) Forewarning (the length of time in advance of the event that households first learn of an impending event), (2) the time that households start taking preparation actions, (3) information they receive about the disruptions, and (4) the household's expectation of the duration of the disruptions. These variables can influence tolerance by affecting perception (Morss, Mulder, Lazo, & Demuth, 2016), protective actions (Lindell, Arlikatti, & Prater, 2009), and responses (Lindell & Hwang, 2008) of the households about the threats of the disruptions.

2.4. Resources

The household's (1) preparedness for the event, (2) if they have a substitute for the disrupted services, and (3) the social capital of the households were considered as households' resources for coping with the service disruptions. Households with better general preparedness for the disruptions would better tolerate the disruptions (Baker, 2011). Moreover, disruptions in some services, such as electricity, could be offset by the substitute, such as a generator, if available. Households with a higher level of self-efficacy are more likely to take protective actions (Douglas & David, 2001; McIvor & Paton, 2007). Finally, households having friends and family members on whom they can rely during the disaster can better cope with the disruptions (Esmalian et al., 2019).

2.5. Sensitivity

Households' sensitivity to service losses is determined by their need for the service. The need for the service influences susceptibility to infrastructure service disruption (Clark, Seager, & Chester, 2018). Households with a higher level of need for the service will have a lower tolerance for the service disruption. For example, the elderly have seen to have a high tolerance for the disruption in wireless networks (Coleman et al., 2019) due to less reliance on wireless networks in their day-to-day lives.

In this paper, we collected household surveys and created empirical models to determine the households' tolerance to the disruption of eight critical infrastructure services—electricity, transportation, water, communication, sewer, solid waste removal, supermarkets, and healthcare services—using the empirical data collected from the three hurricanes.

3. Data and method

Three household surveys were deployed in the aftermath of Hurricane Harvey, Hurricane Florence, and Hurricane Michael to collect relevant service disruption data. Hurricane Harvey was a category 4 hurricane (highest wind 130 mph), which made landfall on Harris County, Texas, in August 2017. Harvey caused catastrophic flooding in Houston and caused severe disruptions in infrastructure services.

Harvey was formed over the Atlantic Ocean on August 17, 2017, and made landfall August 25, 2017, a forewarning time of roughly 8 days. Hurricane Florence was a category 4 hurricane with highest wind speed of 150 mph. Hurricane Florence made landfall in the Carolinas in September 2018, causing severe damage. This event caused flooding and was the wettest tropical cyclone of record in the Carolinas. Hurricane Florence was formed on August 31, 2018, and made landfall at the Carolina coastal areas around September 13, a forewarning time of roughly 14 days. The third event considered in this study was Hurricane Michael, which was a category 5 hurricane (highest wind speed of 160 mph). Hurricane Michael affected the Florida Panhandle in October 2018, and was one of the most severe wind events occurring in the United States. Hurricane Michael was formed on October 7, 2018, and made landfall on October 10, 2018, in Florida, which due to its quick movement, had a short forewarning time of around 3 days. These events, with Hurricane Harvey as a major flooding hurricane, Michael as an event with severe winds, and Florence with a combination of the wind and flooding, were used to explore households' experience with infrastructure disruptions. Fig. 3 shows the study area of (a) Hurricane Harvey, (b) Hurricane Florence, and (c) Hurricane Michael.

3.1. Survey implementation

We collected survey data in the aftermath of Hurricane Harvey, Hurricane Florence, and Hurricane Michael using the Qualtrics survey platform. Qualtrics maintains online panels of responders who have agreed to take surveys. Qualtrics surveys have successfully collected data in surveys implemented by scholars and practitioners. As households who evacuate before the disaster may not experience infrastructure service disruptions, the survey focused mainly on shelter-in-place households which decided not to evacuate during the event.

The focus of this study was to examine the impacts of infrastructure service disruptions on households; thus, coastal areas with evacuation orders were not included in the samples. The data for Hurricane Harvey were collected from Harris County, with a population of around 4.65 million. The number of responders for each focus area was designed to be proportional to the population of each ZIP code. Those who evacuated their homes and the flooded households were removed from the analysis. The Hurricane Harvey survey numbered 1,008 complete responses, from which 850 were used for creating the models after removing surveys of households which evacuated. Household data for Hurricane Florence were collected from affected counties in North Carolina, with a combined population of 1 million. A total sample of 573 responses was collected, with 401 used for analysis. The data for Hurricane Michael were collected from the residents of Florida, Georgia, and Alabama, with the largest portion of responses from Florida. The impacts of infrastructure service disruptions extended to residents of Georgia and Alabama; thus, we enlarged our sample to include those households as well. This survey contained 706 responses, from which 619 responses were drawn for developing the models.

3.2. Measures

The tolerance of households to service disruptions was measured by asking, *Considering an upcoming severe hurricane (like Harvey/Florence/Michael),* ***overall,*** *how many days could your household tolerate the (Service disruptions)?*. In this way, we measured the subjective capability of the households to tolerate the disruptions, which helps to understand the underlying causes and mechanisms leading to susceptibility. Examining a household's tolerance through the subjective measure takes into account that households recognize what factors influence their ability to anticipate, buffer, and adapt to the hazard. Therefore, these measures are related to the cognitive self-evaluation of a household's capabilities and capacities for responding to risks (Jones & Tanner, 2017). Households' tolerance to the disruptions in the eight infrastructure services was measured, and the models were developed using the identified significant influencing factors. The descriptive statistics of the variables used to develop the models is presented in Table 1. In addition, Table 2 presents the summary statistics for the level of tolerance under the three events. The survey questions regarding each question and the specific variable for each service are presented in the Supplementary information section.

3.3. Survival analysis

Accelerated failure time models (AFT) were used for modeling tolerance level. AFT models use a survival analysis approach for the time-to-event data. Survival analysis has been adopted in medical research, engineering, and economics to describe duration between events (Barker & Baroud, 2014) and proved to be an appropriate approach in modeling the restoration of failed engineering systems (Dale, 1985; Liu, Davidson, & Apanasovich, 2007). Survival data are triggered by an initial event, such as electrical system failure in power outages and followed by a subsequent event, such as the restoration of electricity in this example. The time between these two events is called survival time (Oakes, 2001). This situation could describe tolerance data, which are triggered by the initial service losses and are followed by the time when the duration of service disruptions exceeds what households could tolerate and thus cause them disturbance. In addition, survival data are generally positive and non-symmetrically distributed, often with a positive skew. Such characteristics make survival analysis a proper tool for determining the tolerance, which is the time span in which a household could cope with the service disruptions without experiencing significant hardship. Other types of modeling the tolerance

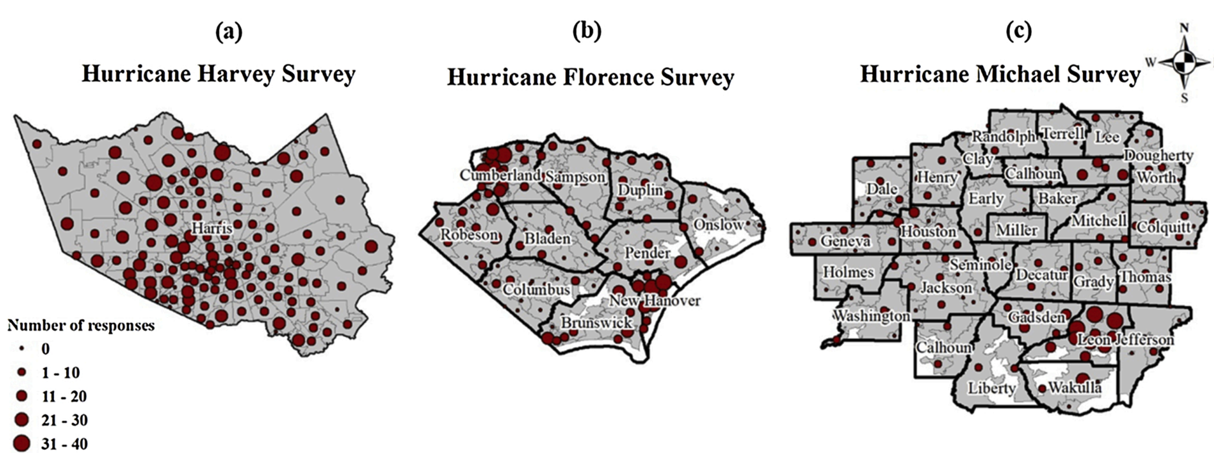

Fig. 3. Survey response distribution over the study areas: (a) Hurricane Harvey, (b) Hurricane Florence, (3) Hurricane Michael.

Table 1
Measures for the influencing factors of the susceptibility to infrastructure services.

	Coding scheme	H	F	M
Demographic characteristics				
Income	Less than $25,000 (=1)	13.6	20.7	25.6
	$25,000-$49,999 (=2)	21.9	26.8	26.2
	$50,000-$74,999 (=3)	22.8	24.6	20.4
	$75,000- $99,999 (=4)	12.7	13.0	13.0
	$100,000 -$124,999 (=5)	9.2	5.5	6.0
	$125,000-$149,999 (=6)	7.4	4.4	3.8
	More than $150,000 (=7)	12.4	5.0	5.0
Education	Less than High School (=1)	1.9	0.8	2.6
	High school graduate or GED (=2)	12.9	14.9	17.8
	Trade/ technical/ vocational training (=3)	4.5	3.9	6.2
	Some college (=4)	17.4	20.7	18.2
	2-year degree (=5)	8.5	16.0	13.4
	4-year degree (=6)	32.4	24.6	22.5
	Post Graduate Level (=7)	22.1	19.1	19.4
Racial/ Ethnic Minority	White (=0)	61.9	65.7	72.7
	Non-White (=1)	38.1	32.9	25.9
Having Children (younger than 10 years)	Yes (=1)	16.7	21.0	21.6
	No (=0)	83.1	79.0	78.4
Elderly (65 years or older)	Yes (=1)	34.9	25.7	25.9
	No (=0)	64.8	74.3	74.1
Years in State*	Number of years living in the respective state	27.41	25.83	29.66
Difficulty with Mobility	Yes (=1)	18.0	27.6	10.8
	No (=0)	82.0	72.4	89.2
Having Chronic Medical Condition	Yes (=1)	29.5	30.1	37.0
	No (=0)	70.5	69.9	63.0
Medication Use	Yes (=1)	48.0	37.6	42.5
	No (=0)	52.0	62.4	57.5
Having a Vehicle	Yes (=0)	97.2	92.5	92.8
	No (=1)	2.80	7.5	7.2
Property factors				
Residence Type	Apartment/ mobile home (=0)	74.7	75.1	67.9
	Single-family home (=1)	24.1	23.8	31.0
Homeownership	Rented the residence (=0)	70.4	70.2	66.4
	Full payment/ mortgage loan (=1)	28.0	28.5	31.6
Live in Flood Zone	Yes (=1)	17.1	14.4	9.8
	No (=0)	68.7	75.7	78.4
	I do not know (N/A)	14.2	9.9	11.8
Distance to Supermarkets*	Number in miles	2.97	4.16	6.10
Risk perception				
Expected Disruption **	Number in days	–	–	–
Days of Forewarning*	Number in days	5.82	8.24	6.26
Days of Preparation*	Number in days	4.19	4.49	3.23
Access to Reliable Information **	Did not search for information (N/A)	–	–	–
	Never (=1)	–	–	–
	Seldom (=2)	–	–	–
	Sometimes (=3)	–	–	–
	Often (=4)	–	–	–
	Almost Always (=5)	–	–	–
Previous Experience				
Experience	Yes (=1)	84.7	87.0	78.9
	No (=0)	15.3	13.0	21.1
Experienced Damage	Yes (=1)	52.8	48.3	48.0
	No (=0)	47.2	51.7	52.0
Resources				
Preparedness Level	Not at all Prepared (=1)	2.1	0.8	2.6
	Poorly Prepared (=2)	3.9	6.3	8.9
	Somewhat Prepared (=3)	40.1	32.3	36.5
	Well-prepared (=4)	49.0	54.0	46.0
	Over-prepared (=5)	4.9	6.6	6.0
Substitute-power	Yes (=1)	20.4	32.6	36.5
	No (=0)	79.6	67.4	63.5
Self-efficacy for protective actions related to infrastructure service disruptions	Strongly agree (=5)	26.0	28.5	25.7
	Somewhat agree (=4)	44.6	47.2	46.7
	Neither agree nor disagree (=3)	18.7	16.3	17.0
	Somewhat disagree (=2)	7.9	6.1	7.5
	Strongly disagree (=1)	2.8	1.9	3.1
Social Capital (Friends/Family)	Yes (=1)	54.5	55.0	57.5
	No (=0)	45.5	45.0	42.5
Social Capital (Emotional Well-being)	Yes (=1)	79.9	77.1	78.6
	No (=0)	20.1	22.9	21.4
Social Capital (Community Member)	Yes (=1)	42.9	44.2	43.9
	No (=0)	57.1	55.8	56.1
Sensitivity				
Level of Need for Service **	Not at all important (=1)	–	–	–
	Slightly important (=2)	–	–	–
	Moderately important (=3)	–	–	–
	Very important (=4)	–	–	–
	Extremely important (=5)	–	–	–

* The responses for the mean values are reported.
** The responses for each service is provided in the supplementary information.

such as generalized linear models (Poisson family and negative binomial regression) and ensemble learning methods (random forests and boosting) were examined by the authors for developing the models; however, the AFT models were found to have the lowest prediction error and provided explanatory power. More details can be found in (Esmalian, Dong, & Mostafavi, 2020).

Using AFT models, we can relate the tolerance directly to the predictors with a linear relationship, as shown in Eq. (1).

$$\log\mu_i = x_i^T\beta + \varepsilon_i \tag{1}$$

where μ_i represents the mean tolerance, x_i^T denotes the vector of predictor, β is the vector of parameters, and ε_i is an error term that is assumed to be independently distributed.

We used the Kaplan-Meier estimator of residuals to determine which distribution for the survival time would best fit the data (Hosmer and Lemeshow 1999). We compared the Kaplan-Meier estimators of the residuals with the log-logistic distribution to check the fit. Close examination of the residuals (Supplementary information, Figs. A1–A8) revealed that the log-logistic distributions for error terms ε_i leads to an appropriate fit of the models.

AFT is especially useful for descriptive purposes, such as identifying the importance of factors influencing tolerance. In this study, we first included all factors identified to influence the tolerance for each service

Table 2
Level of Tolerance for Disruptions in Infrastructure Services.

		P	C	W	S	T	SW	SM	H
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	7.28	10.47	6.28	5.50	11.82	11.85	9.53	16.34
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	6.80	10.56	4.91	4.11	4.94	12.39	7.45	17.76

Note: Power (P), communication (C), water (W), sewer (S), transportation (T), solid waste collection (SW), supermarkets (SM), and healthcare facilities (H).

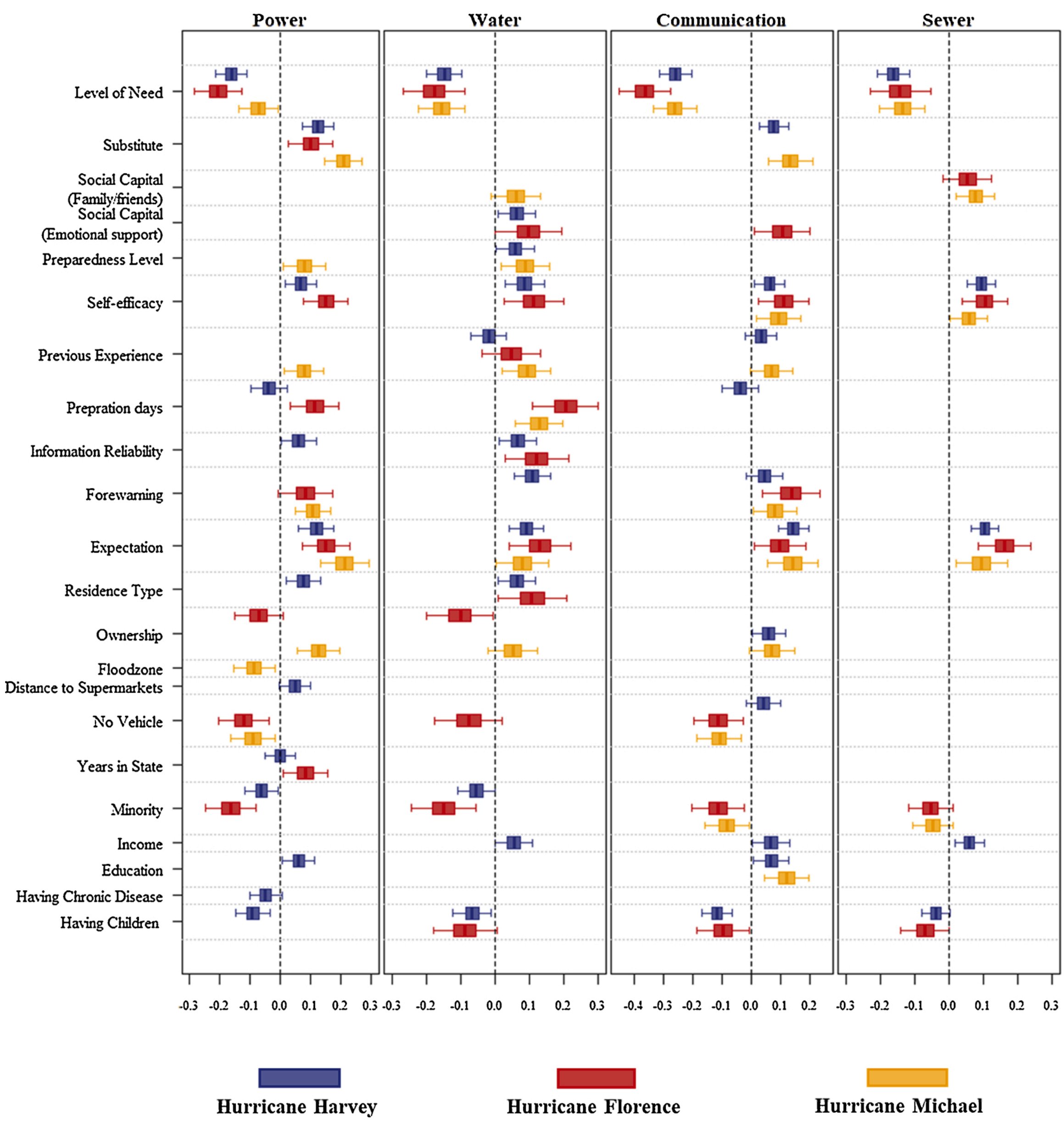

Fig. 4. Summary of the influencing factors of survival models for power, water, communication, and sewer systems under Hurricane Harvey, Hurricane Florence, and Hurricane Michael. Coefficients in this plot are normalized with the mean equal to zero and the variance equal to one. The whiskers show the 95 % confidence interval. Thus, the variables which do not cross the $x = 0$ line are significant at a 5 % level of confidence. The tables of these results are available in the supplementary information section (Table A2–5).

in the models. Then, Akaike Information Criterion (AIC), Eq. (2), was used in a stepwise model selection to choose the best subset of the variables determining the level of tolerance to disruption of various infrastructure services.

$$AIC = -2 \times \ln(L) + 2 \times (p) \qquad (2)$$

4. Household-level survival models for developing susceptibility curves

We developed models based on empirical survey data to determine the tolerance of households to the eight infrastructure services (power, transportation, water, communication, sewer, solid waste, supermarkets, and healthcare facilities). In this section, we provide a brief overview of the factors influencing household-level susceptibility based on the survival models developed for the three events (Hurricane Harvey, Florence, and Michael). These models enable determining the tolerance level for the disruption in each infrastructure service. A household's tolerance for the service outages is an indicator of their susceptibility to service losses. The greater a household's tolerance for the outages, the lower its susceptibility would be. The influencing factors for susceptibility regarding each service are identified; the rest of this section provides a short discussion regarding the influencing factors in the models for each infrastructure service. Interested readers are referred to the Supplementary Information for details about the factors and their associated parameters in the model. We first discuss the services which households need inside their homes, namely power, water, communication, and sewer (Fig. 4). Then, Fig. 5 presents the results for transportation, solid waste, supermarket, and healthcare services. These figures show the summarized results for the developed models for the household-level susceptibility to the service losses. In these figures, the whiskers show the 95 % confidence interval of the normalized coefficients. In addition, the $x = 0$ line is depicted to show the statistical significance of the variables in the models developed for each service.

4.1. Power

Racial minority households had a significant negative coefficient in both Hurricane Harvey and Hurricane Michael, showing that these groups have a lower tolerance for power outages even when other variables are taken into account in the models. The metropolitan areas with densely interconnected roads provide better accessibility for the residents to obtain their supplies in the case of road closures. Households in more metropolitan areas could provide essential supplies, such as canned food and flashlights, to better withstand the potential prolonged power outages. Thus, in the less urban areas of the Carolinas and Florida, not having a vehicle was a significant negative factor in influencing the tolerance in Hurricane Michael and Hurricane Florence. In urban Harris County, this variable was not significant in the model developed for Hurricane Harvey. Responders affected by Hurricane Harvey live in

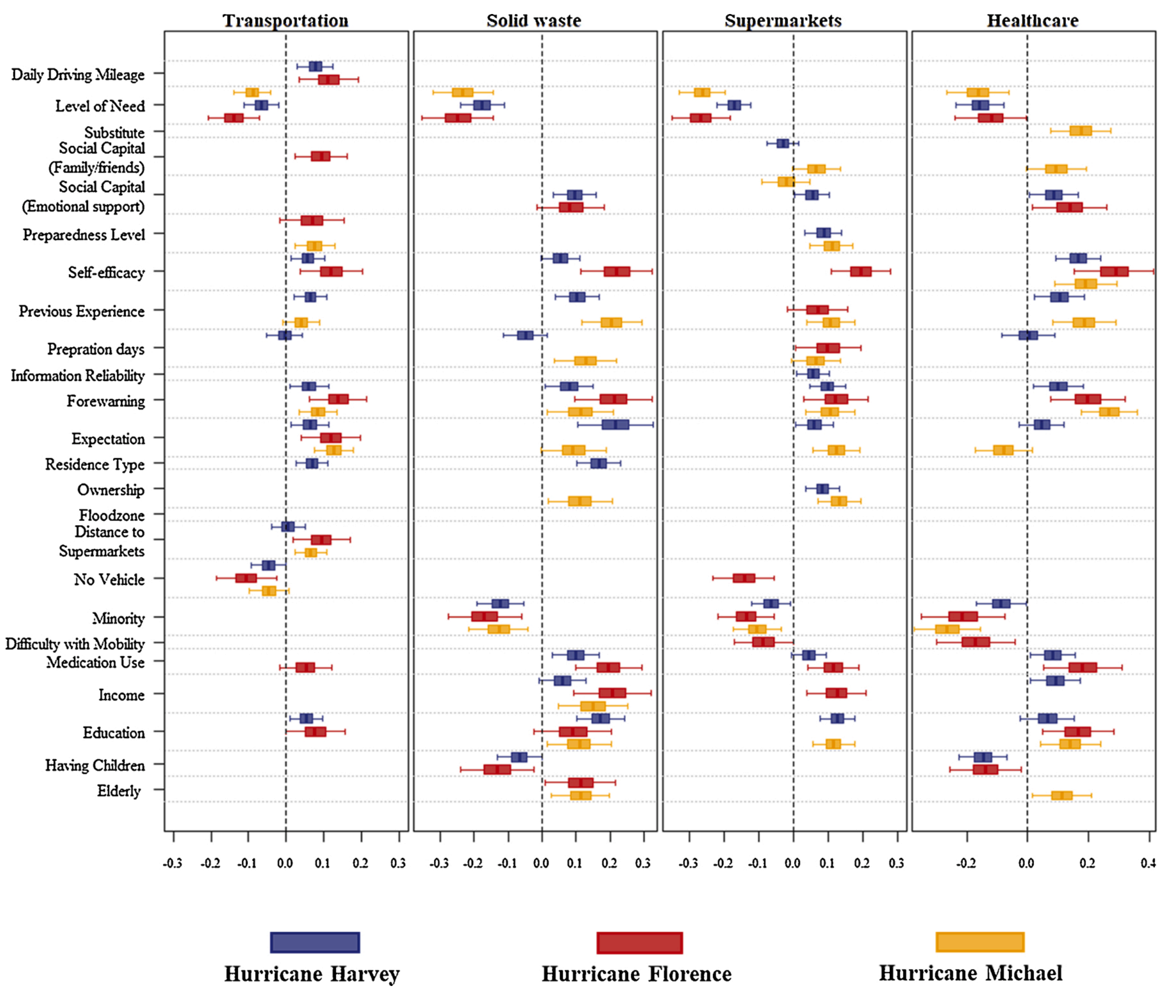

Fig. 5. Summary of the influencing factors of survival models for transportation, solid waste, supermarkets, and healthcare systems under Hurricane Harvey, Hurricane Florence, and Hurricane Michael. Note: Coefficients in this plot are normalized with the mean equal to zero and the variance equal to one. The whiskers show the 95 % confidence interval. Thus, the variables which do not cross the $x = 0$ line are significant at a 5 % level of confidence. The tables of these results are available in the supplementary information section (Table A6-9).

more urban areas compared to those who were affected by Hurricane Florence and Hurricane Michael. Home ownership and the type of resident had a significant positive association with the tolerance level; however, when including other variables, such as having power back up, these variables became partly significant. This is due to the fact that homeowners and those living in single-unit houses are more likely to take protective actions and buy generators, and the impact of these property factors is mediated in the models.

Having a generator, self-efficacy, and preparedness of the households play an important role in the susceptibility of the households to disruptions. These protective actions would increase a household's tolerance to power outages. For households to take proper protective actions, it is important to have advanced warning about the event and to expect disruptions. Forewarning and preparation duration had a significant positive association with the tolerance level in Hurricane Florence and Hurricane Michael. Affected households in these events had a higher incidence of previous hurricane encounter with wind-related power outages. On the other hand, having reliable information about the disruptions after the outages occur was a significant positive factor in Hurricane Harvey with fewer wind-related extreme event encounters. Although correlation analyses (Coleman et al., 2020) revealed that those with previous experience have a greater tolerance for power outages, this variable was only significant in Hurricane Michael when other factors are included. Finally, household's need for power had a significant negative influence on the tolerance level, which shows that, in addition to the protective actions, it is important to consider the specific needs of the households in determining their tolerance for the service disruptions.

4.2. Water

Residence type, racial minority households, and having a child were significant sociodemographic factors in the developed models. Similar to power outages, the negative coefficient of being a racial minority showed that these households reported having a lower tolerance for the water outages. Those who live in detached housing have more space for storage of the supplies and potentially more space for storing water which could afford them a higher tolerance. The direct well-being impact of water disruption on the children and protecting them from the potential threats give these households a lower tolerance for the disruptions.

Storing food and water before the event could help households prepare for water disruptions. As a result, the significant positive role of accessing reliable information, the expectations regarding the disruption, general preparedness level, the duration of forewarning, the preparation level of the households, and self-efficacy becomes clear. If proper information about the potential disruption is communicated to households, preparations such as supplying food and water could significantly help a household to cope with the water disruptions. Having social capital in different forms was a significant positive factor in increasing households' tolerance for water outages. These households could rely on assistance from their social ties in coping with water disruptions. Households with a higher need for water were found to have a lower tolerance for water disruptions. Therefore, the specific needs of the household, such as larger households or those with children, largely influence their tolerance.

4.3. Communication

Although correlation analysis (Coleman et al., 2020) suggested that factors such as ownership, type of residence, and income are significant factors influencing tolerance, the developed models showed a decrease in the influence of such variables when other influencing factors were included in the models. For example, a lower proportion of the socially vulnerable households own generators, and including this factor in the models could mediate the effect of the sociodemographic factors considering the cost and space requirement of the generators. On the other hand, the significance of race, education, having a child, and having a vehicle in different regions was not mediated by the other variables included in the models. This could be related to the inherent needs of these groups in the affected regions or to the influence of other factors, outside the boundary of the considered variable in the models, that could affect the tolerance for the communication service disruptions.

Availability of power back-up supports operation of communication devices and, therefore is a significant variable in increasing tolerance for communication disruptions. The general preparedness and the duration of preparation, on the other hand, may not be relevant to the tolerance of households to the disruptions in communication services, as suggested by the models. The major ways that households use communication services are related to communicating with friends and family and receiving and sharing information about the event, followed by entertainment, work, and education. Therefore, although general preparedness might help in attaining a higher state of preparedness for those who decide to shelter in place, it may not directly affect their tolerance for loss of communication services. Those with a greater self-efficacy and those who received a longer forewarning were found to have a higher tolerance for the disruptions. Households with lower levels of need and higher expectations of the disruptions had higher levels of tolerance in all the events.

4.4. Sewer

Those with a child are more concerned about the well-being of their household members and reported having a significantly lower tolerance for disruptions in sewer service. In general, we found no significant differences in the manner in which different sociodemographic characteristics influence tolerance level for the disruptions in sewer systems. In addition, the protective actions for the sewer systems are limited and are mostly effected after the event. Therefore, variables such as preparedness, forewarning, and preparation duration were found not to influence tolerance for sewer systems disruptions. Households with social capital can rely on the help of their social ties in coping with these disruptions or evacuating their homes, as suggested by the significant positive coefficient of this variable. Those with a lower need, heightened anticipation of disruptions, and a higher level of self-efficacy seem to have the highest tolerance for the sewer disruptions.

4.5. Transportation

Sociodemographic characteristics of households are mainly mediated by other variables in the models. One exception is related to the influence of not having a vehicle on the tolerance for transportation disruptions, which has a significant negative association with the level of tolerance. The effect of this variable on the tolerance level could not be explained by other variables in the models. Households without a car generally rely on public transportation for commutes and are highly susceptible to the impact of road closures on public services.

Forewarning is a critical factor in determining tolerance level to transportation disruptions; this variable has a positive association with the level of tolerance. Households need to be aware of disaster conditions to decide whether to evacuate or to shelter in place. Preparedness and self-efficacy help households to meet their needs for travel to obtain supplies, which make them less susceptible to transportation disruptions. Households who live farther away from the supermarkets have a higher tolerance for the prolonged road closures. This could be because these households may store more supplies in their homes to prevent multiple trips to the supermarkets, which satisfies households' high need for supplies during the disaster. The premise of this finding is dependent on other variables, such as having a vehicle in the models. If a vulnerable household does not have a vehicle and enough space for storing supplies and also lives farther away from the supermarkets, their tolerance for road closures may get severely affected. Another interesting pattern related to road closures is the higher tolerance of those who have a higher daily travel mileage. These households may either have more travel choices or have a better knowledge about the road conditions, which helps them have a better capability to cope with the closures.

In Hurricane Harvey, in which residents have more history of flooding, the previous experience with disasters was a significant factor influencing the households' tolerance. This marks the importance of how educating households on the potential threats of a disaster could help them in finding ways to mitigate the impacts. Having a higher expectation of the disruptions and a lower need for using the transportation infrastructure were highly significant in increasing households' tolerance for road closures.

4.6. Solid waste

Various sociodemographic characteristics, such as income, education, race, having a child, being elderly, and using medication, were found to be significant in affecting the households' tolerance for disruptions in solid water removal. Income, education, being elderly, and using medication had a positive association with the tolerance level while being minority and having children were negatively related to the households' tolerance. The significance of these sociodemographic characteristics in the presence of other variables in the models suggests that, compared to other services, the disparity in susceptibility to service disruptions, in this case, could not be explained by other variables considered in the model. The removal of solid waste is not typically done by individual households, and households' protective actions, such as obtaining supplies, usually do not include the preparedness for the disruptions in solid wastes; therefore, other variables could not mediate the effect of the sociodemographic characteristics.

Having social capital increases households' tolerance to disruptions in solid waste removal. Social ties of the households could help with debris removal. Having previous experience with a disaster, higher expectations of the disruptions, and longer duration forewarning increase the tolerance of the household for the service disruptions. The influence of these variables on the tolerance, however, is lower compared to other infrastructure services, especially considering that there are lower protective actions for mitigating impacts. The effect of these variables in the developed models shows that households with a better perception of upcoming disruptions generally have a higher tolerance for service disruption. This result highlights the importance of proper risk communication and education about the potential threats of the service disruptions. The need for the services remains the most significant factor in explaining the tolerance of the households for disruptions in solid waste removal.

4.7. Supermarket

Storing enough supplies for shelter-in-place condition could afford households with a higher tolerance for prolonged disruptions of supermarkets. Prior knowledge of the need for storing supplies, the capability of obtaining supplies, and the ability to store supplies play a significant role in the increase of tolerance. Socially vulnerable groups, such as renters, racial minority households, and households with lower education attainment reported a lower tolerance for these types of disruptions. These populations might have a lower capability to obtain and store the supplies or a lower perception of the need for storing supplies.

Having a long forewarning and higher expectation of disruptions could lead to greater household preparedness and could further increase the household tolerance for disruptions. Those households with strong social capital could rely on assistance from their social ties when the disruptions occur and consequently have a higher tolerance for the service disruptions. The need for the services highly influences the tolerance for the prolonged disruptions in supermarkets. Interestingly, the expectation and the preparedness level were not significant in Hurricane Florence (with a long forewarning duration); however, self-efficacy and the sociodemographic characteristics of households became significant in the Hurricane Florence model. One explanation for this pattern could be the longer forewarning of affected households in Hurricane Florence. The long forewarning gave affected households a longer lead time for obtaining the required supplies for the upcoming event to take protective actions.

4.8. Healthcare

Multiple sociodemographic characteristics affect the tolerance level of the households to the disruptions in healthcare facilities. Racial minority groups, households with lower education attainment, and those with a child indicated a lower tolerance for these service outages. Those households with an elderly member and those who take medication reported a high tolerance. This could be due to the fact that these households are in need of the service and consequently have stored medical supplies and are prepared for the potential disruptions.

The need for the healthcare service similar to most other infrastructure services affected tolerance level. There is a negative association between the level of need and households' tolerance for service disruptions. Forewarning, having previous experience, and self-efficacy are indicators that households will better prepare for potential disruptions in the healthcare services. These factors help households to provide items, such as commonly used medicine and first aid kits, to be prepared for the threats to well-being.; however, the expectation for potential disruptions in the healthcare services was not significant in influencing tolerance. In this case, it is worth mentioning that among all services, responders reported the lowest expectation of disruptions in healthcare services. Moreover, not many households have a regular need for the service before the event; this lower expectation could not explain the variability in the tolerance for healthcare services. Having social capital could help households obtain physical and mental support during the event; therefore, this variable was a significant factor in increasing tolerance. Having a power back-up was found to increase the tolerance for healthcare services in Hurricane Michael. Some medical devices require power and storage of some medication requires refrigeration; thus power back-up could be of high importance in such instances. An example like this shows how the increase in the tolerance for one service (electricity) affects the tolerance for another service (healthcare). Thus, the need for these services is interdependent.

5. Susceptibility curves for determining household-level disturbances due to infrastructure service disruptions

Survival curves were developed to determine the proportion of susceptible households that experience disturbance (i.e., service disturbance exceeding tolerance level) under different durations of service outages. These curves could be developed for various regions to answer the question: "What proportions of households will not tolerate a certain duration of service disruption?" In the curves, Kaplan-Meier estimates were implemented in determining survival probabilities. Survival probability (P_s) of T days is defined as surviving (not experiencing disturbance) the Tth day having already survived the previous T-1 days (Oakes, 2001). The overall probability of surviving T days of disruptions would be then calculated by the following equation:

$$S(T) = P_1 \times P_2 \times \ldots \times P_T \tag{3}$$

In this equation, each survival probability (P_T) is calculated by dividing the number of households that did not experience disturbance for T-1 days and survived day Tth by the number of households that did not experience disturbance by the end of day T-1. Figs. 6 and 7 depict the proportion of susceptible households for which the duration of disruption has exceeded their tolerance. This value is calculated as 1- ($S(T)$).

These curves could be used by utility providers and decision-makers to obtain an undemanding of the households' susceptibility to the potential service disruptions.

Fig. 6 shows susceptibility curves for power, water, communication, and sewer services. The results show that households in the three study regions have a higher susceptibility for disruptions in sewer systems, followed by water, communication, and power. One explanation for the higher susceptibility to water and sewer is the inability to provide a substitute for these services and theses services being related to the basic functioning of households. The susceptibility curves for these services are consistent across the three hurricanes. The similarities between the susceptibility curves for the same service decrease as the duration of the disruptions increases. This result shows that most communities would have a similar tolerance for short service disruptions; however, their disturbance from the prolonged service outages vary among communities. The duration of disruption which leads to the disturbance of 50 % of the households in the community is similar in most locations. As the duration of disruptions increases, however, there are some outlier households which could tolerate more days of disruptions. The susceptibility patterns for these outliers do not quite match in different regions and for various services (except for sewer system). The results unveil the contextual difference in the susceptibility patterns to the disruption to services. These differences could be related to the specific characteristics of the regions (e.g., urban versus suburban versus rural), historical and cultural backgrounds, and the sociodemographic characteristics of the areas. These factors should be considered while assessing the susceptibility of different regions. The largest deviation in susceptibility curves is apparent in the susceptibility to power disruptions in the context of Hurricane Harvey. Residents of Harris County who were affected by Hurricane Harvey have less experience with the prolonged power outages and also had a lower rate of having a substitute; therefore, they seem to have a higher proportion of not surviving the outages. The graphs containing the various service for each area are presented in the supplementary information section (Fig. A.9) to help with comparing susceptibility patterns among different services.

Fig. 7 displays susceptibility curves for susceptibility to transportation, solid waste, supermarkets, and healthcare services outages. The results show that shelter-in-place households are less susceptible to these services compared to services needed inside their households. In addition, the estimated susceptibility curves for these services have less agreement for the three regions. In general, households have a higher tolerance for disruptions in these services, and there is a higher uncertainty in estimating these curves. Unlike the susceptibility for power system disruption, residents affected by Hurricane Michael had a significantly lower tolerance to road closures compared to the residents affected by Hurricane Harvey and Hurricane Florence. The difference

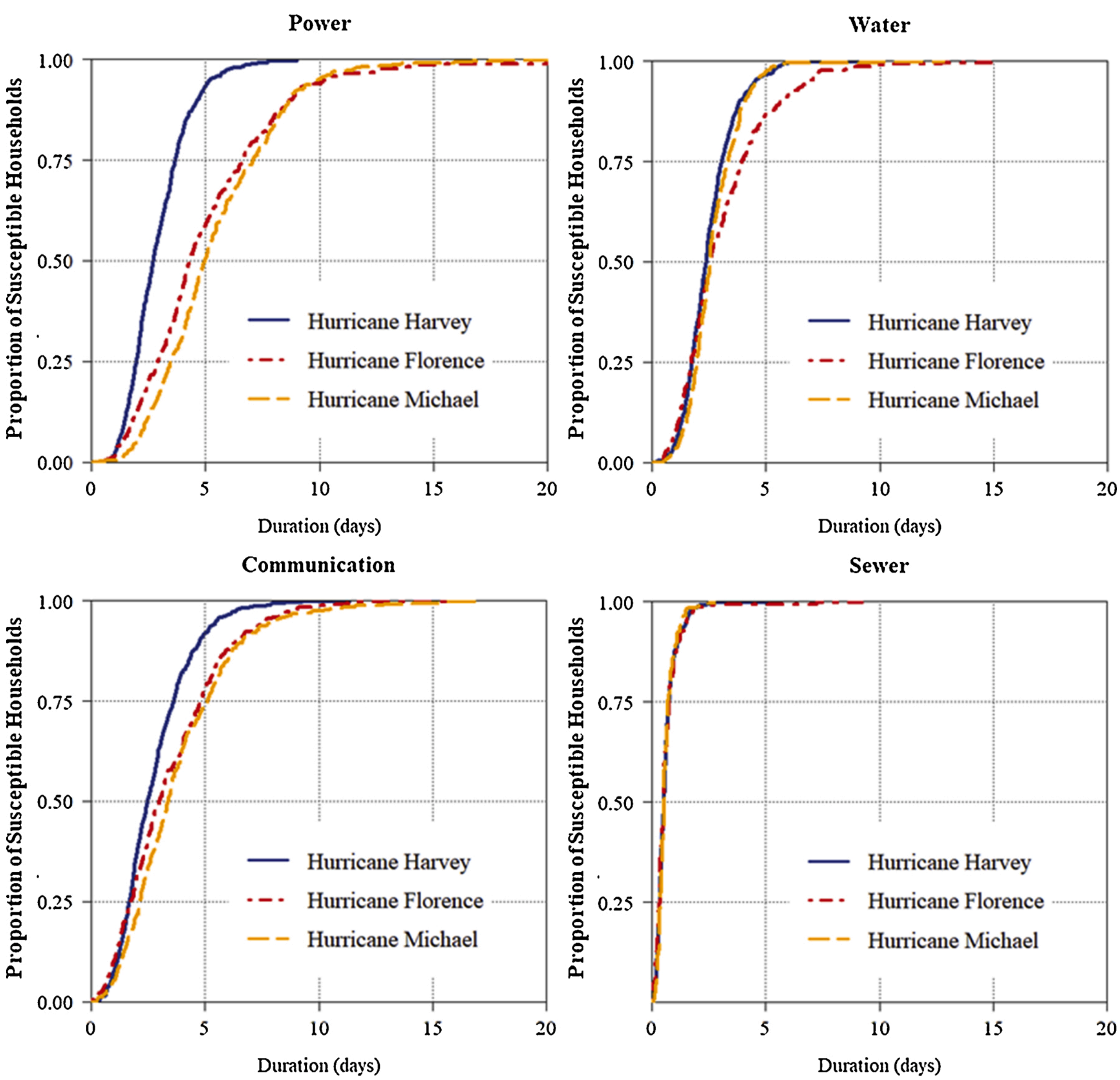

Fig. 6. Susceptibility curves for disruptions in power, water, communication, and sewer services.

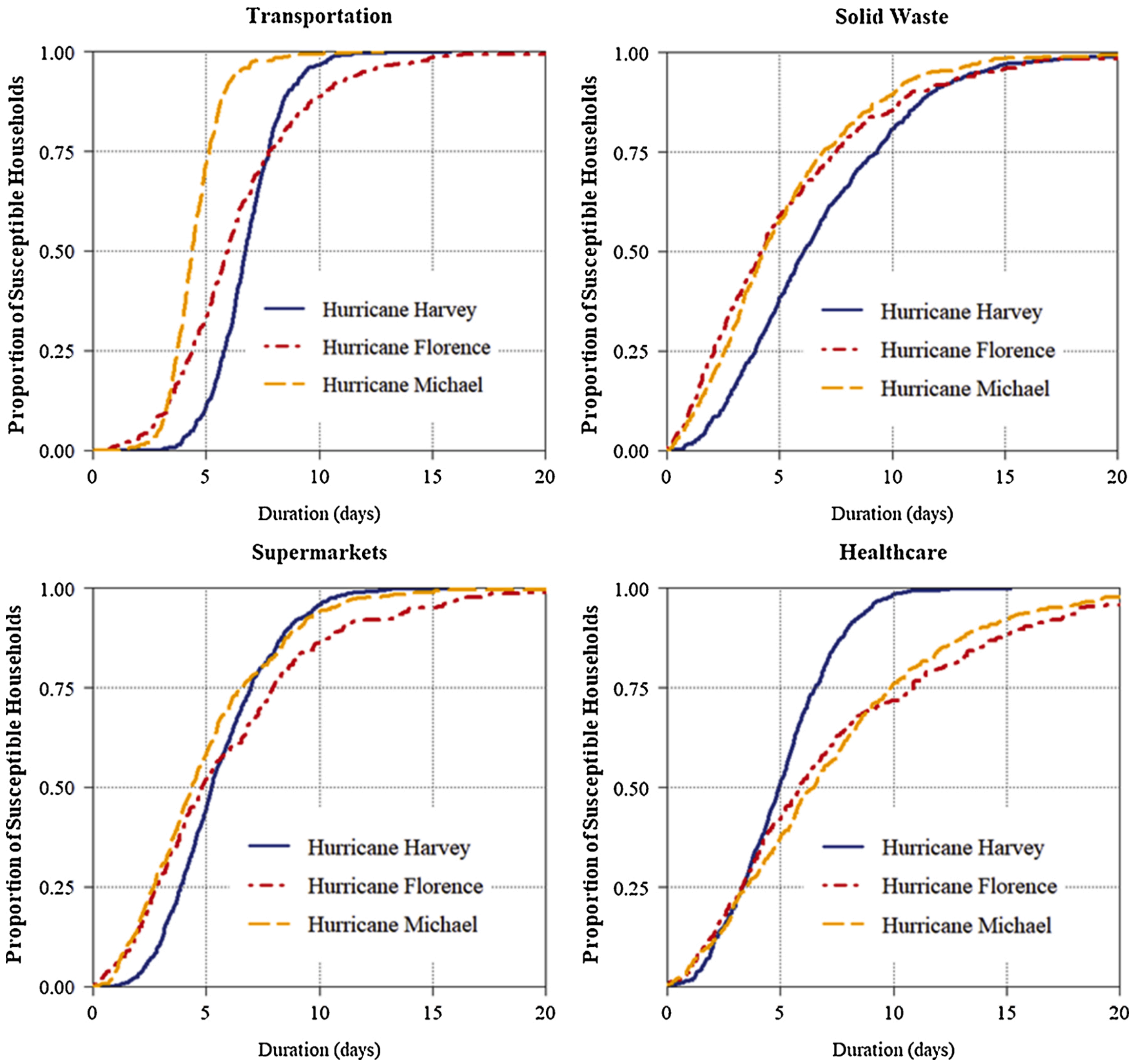

Fig. 7. Susceptibility curves for disruptions in transportation, solid waste collection, supermarkets, and healthcare services.

could be due to the less experience with flooding of those affected households in Hurricane Michael than in Harvey and Florence. The curves in Fig. 7, indicate that while the residents affected by Hurricane Harvey seem to have a higher tolerance for transportation disruptions than those affected by Hurricane Florence, the residents of Hurricane Florence show a higher tolerance for road closures of more than a week (75 % proportion). There are some outliers among residents affected by Hurricane Florence who could better tolerate road closures due to their different characteristics and needs from the service.

The proportion of susceptible households for transportation and supermarket closures in Hurricane Harvey and the transportation disruption in Hurricane Florence could be zero for a short period of time. These patterns suggest that the residents of an affected community have a capacity to tolerate a short duration of outages without experiencing great disturbance. The susceptibility curves for the healthcare services for the three hurricanes are close for disruptions less than four days. As the duration of service disruptions increases, however, the susceptibility curves obtained from different hurricanes deviate significantly (Fig. 7). Residents affected by Hurricane Harvey had a higher susceptibility to the longer-duration disruptions in healthcare services. A larger proportion of Harris County households experienced disturbance from the long healthcare access disruptions compared to residents affected by Hurricane Florence and Hurricane Michael. It should be noted, however, that the curve is generated considering the responses from all households and not merely those who needed the healthcare services. Thus, some households might have reported a large tolerance for service disruptions due to their lesser need for the service.

6. Discussion and concluding remarks

Susceptibility curves for susceptibility to infrastructure service disruption were developed to bridge the gap in the reliability and resilience analysis of physical infrastructure systems and the impacts disruptions pose to communities. Susceptibility curves enable translating the service disruptions to the probability of the household-level disturbance in the affected communities. Advances in the resilience analysis of physical infrastructure systems have enabled the assessment of system performance under various hazard-induced disruptions. While these models for assessing the system resilience inform about the physical impacts of natural hazards, they provide no insights regarding the societal impacts on affected communities. Achieving sustainability goals such as designing human-centered resilient cities calls for human-centric approaches to enable inclusion of needs of the community in the performance assessment of infrastructure systems. In this research, we developed empirical models to determine households' tolerance for service disruptions. The empirical susceptibility curves were created accordingly to enable inclusion of social considerations in the assessment of the impacts of infrastructure service disruptions on communities. Researchers could therefore implement the curves to link the findings related to resilience of infrastructure systems to how a community could be impacted due to service disruptions. The integration of the outcomes of physical infrastructure models with susceptibility curves enables a more holistic assessment of infrastructure resilience through the considerations of societal impacts.

This study introduced the use of survival analysis and susceptibility curves for considering the societal impacts of disruptions in infrastructure services. The empirical survival models and curves created in this study offer a significant advancement in improving infrastructure resilience assessment through consideration of household-level disturbances. Advancement in reliability and resilience assessment of infrastructure systems have provided researchers and practitioners with models and tools (such as fragility curves) to estimate physical failures, loss of performance, and service disruptions on engineered systems during natural hazards. Little of the existing work, however, has considered societal impacts due to infrastructure service disruptions. This limitation was due mainly to the absence of empirical data and models to determine household-level disturbances caused by disruptions in various infrastructure services. This study addresses this important gap by creating empirical survival models and curves that could be effectively integrated with resilience and reliability models of infrastructure. For example, the existing infrastructure resilience models (Batouli & Mostafavi, 2018; Guikema & Nateghi, 2018; Ouyang & Dueñas-Osorio, 2014; Rasoulkhani, Mostafavi, Presa, & Batouli, 2020) could be used to estimate the extent of disruptions in power (Liu et al., 2007; Mensah & Dueñas-Osorio, 2016), transportation (Dong, Yu, Farahmand, & Mostafavi, 2020; Fan, Jiang, & Mostafavi, 2020), and water (Adachi & Ellingwood, 2008; Guidotti, Gardoni, & Rosenheim, 2019) infrastructure under different hazard scenarios. Then the estimated duration of disruptions could be used in the empirical susceptibility curves to estimate the portion of households experiencing disturbance under a particular duration of disruptions. Accordingly, additional societal considerations could be devised in the formulation of service restoration and resource allocation prioritization in the infrastructure models. Through this process, more convergent models of infrastructure resilience assessment could be obtained for disaster risk reduction (Mostafavi & Ganapati, 2019; Peek, Tobin, Adams, Wu, & Mathews, 2020).

The susceptibility curves provide emergency management and infrastructure/utility companies with a tool to determine susceptibility of the service users to disruptions and to proactively plan for mitigating the risks to households. These curves could be used to generate a profile of susceptibility for a specific infrastructure service in different locations. Thus, the curves could inform resource allocation and prioritization of the restoration of the services. Taking power outages as an example, the curves in Fig. 6 suggest that a utility company in Harris County should expect that a power outage lasting more than 2.5 days would cause disturbance to around 50 % of service users. In contrast, the same proportion of residents affected by Hurricane Michael and Hurricane Florence would tolerate the disruptions for up to around 5 days. This information could help the decision-makers in: 1) identifying the susceptibility of the communities to the disruptions in infrastructure services; 2) enhancing resource allocation to the improvement of infrastructure services which are critical for the functioning of the community; and 3) prioritizing the restoration of infrastructure systems based on the susceptibility of households to reduce the societal impacts of service disruption.

Susceptibility curves developed for different infrastructure services in this study suggest that community susceptibility patterns to service outages vary across services and regions. Households show greater susceptibility to disruptions in sewer systems, water, and power compared to the services provided outside their homes, such as transportation, supermarkets, solid waste collection, and healthcare facilities. The curves also show that, while the susceptibility patterns of different locations are similar below a certain duration of outage, prolonged outages might pose different levels of disturbance to a community. The difference observed in the susceptibility patterns of different areas could be related to specific sociodemographic, urban, and historical characteristics of the affected community. The historical hazard experience of a community influences its susceptibility to infrastructure service disruptions. Areas with more experience with flooding have a higher tolerance for flooding-related disruptions, such as road closures, and areas with more experience with hurricanes have a higher tolerance for wind-related disruptions, such as power outages. Thus, the inherent characteristics of different regions influence the susceptibility of the communities.

Survey data collected from the three major hurricane events enabled the development of the empirical survival models. These empirical models considered a range of variables affecting tolerance for service disruptions. Households have distinct needs and capabilities and, therefore, different tolerance for service outages. Susceptibility curves are based on the wide range of influencing factors and the specific characteristics of communities. Similar curves could be developed by implementing empirical models in different regions to examine the societal impacts of disruptions in various infrastructure services to inform infrastructure resilience, hazard mitigation, and emergency response plans.

While this research examined a wide range of identified influencing factors affecting households' susceptibility to infrastructure service disruptions, additional variables could influence the susceptibility of the households to the service disruptions. The examination of additional variables, such as disparities in political power and urban history, could be pursued in future research. In addition, as supported by the findings of this research, the susceptibility to one service could affect the susceptibility to other services. In other words, the susceptibility to infrastructure service disruptions is interdependent. Future investigations can focus on understanding the interconnected impacts of service disruptions on the households' disturbances.

Declaration of Competing Interest

The authors report no declarations of interest

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.scs.2020.102694.

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