Sustainable Cities and Society 62 (2020) 102366

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Assessment of household-level food-energy-water nexus vulnerability during disasters

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ARTICLE INFO

Keywords:
Food-energy-water nexus
Infrastructure resilience
Disaster risk
Social vulnerability

ABSTRACT

Water, energy, and food systems are highly interconnected, where disruptions in one system have direct or indirect impacts on others. Little has been studied regarding the nexus interactions at the household level, let alone in a disaster setting. Measuring household vulnerability to their disruptions is an important determinant of resilience and societal risk in the face of natural hazards. This study proposes a new framework based on disaster risk theory and Food-Energy-Water (FEW) Nexus systems thinking to analyze the collective influence of integrated infrastructure disruptions and socioeconomic factors on household vulnerability during disasters. ANOVA one-way tests are used to determine the disparity in disaster risk measures across non-vulnerable and highly vulnerable households. Structural Equation Modeling (SEM) is employed to test the proposed relationships between infrastructure disruptions, urban attributes, household preparation behaviors in the context of the 2017 Hurricane Harvey in Harris County, Texas. Overall, the pre-existing conditions of communities in terms of its physical attributes, preparation behaviors, and the coupled durations of FEW infrastructure disruptions were each found to have statistically significant associations with heightened household vulnerability to FEW service disruptions. Physical attributes ($\beta = 0.134$, $p = 0.001$) and prior experience with disasters ($\beta = -0.103$, $p = 0.000$) were found to be the most significant indicators of poor preparation behavior. households with children, racial minority status, and low income and educational attainment of households were associated with having lower levels of preparedness. The framework developed in this study can serve as a foundation to expand the transdisciplinary research of infrastructure and community resilience to better address the needs of the population in an emergency.

1. Introduction & background

Water, energy, and food infrastructure systems are essential for contributing towards and maintaining the wellbeing of households sheltering-in-place during disasters. The cross-sector interdependencies inherent to these systems make them highly susceptible to physical disruptions, and as a result, have the potential to transform a natural hazard, like a hurricane, into a disaster of cascading events. For example, the energy infrastructure systems provide essential power and fuels upon which most critical infrastructure sectors rely on to operate (FEMA - U.S. Department of Homeland Security, 2017). Damages to food, energy, and water infrastructure systems can lead to water scarcity or contamination, while lack of the quality provision of water, sanitation, health care, food, and transportation services affects the capacity of urban residents to recover and affect households' health and well-being (Dong, Esmalian, Farahmand, & Mostafavi, 2019; Dong, Wang, Mostafavi, & Gao, 2019; Najafi, Peiravi, & Guerrero, 2018; Baker, 2012; Dominianni et al., 2018; Rasoulkhani, Mostafavi, Sharvelle, & Cole, 2019; FEMA - U.S. Department of Homeland Security, 2017;). Similarly, poor solid waste management can cause blockages to stormwater and sewage networks which can lead to waterlogging and flooding (Naik, Kominers, Raskar, Glaeser, & Hidalgo, 2015).

In the aftermath of a disaster, the resiliency of a city relies on the functioning of complex and interdependent infrastructure systems, both soft and physical (Chang et al., 2014). Infrastructure systems must be designed to not only continue functioning under hazardous conditions (Chang, et al., 2014; Godschalk, 2011) but also to provide equitable services to the community (Batouli & Mostafavi, 2018; Davis, Mostafavi, & Wang, 2018). Resilience planning and emergency management require policymakers and agency leaders to make difficult decisions regarding which at-risk populations should be given priority

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https://doi.org/10.1016/j.scs.2020.102366
Received 5 December 2019; Received in revised form 25 May 2020; Accepted 29 June 2020
Available online 14 July 2020
2210-6707/

in the allocation of limited resources (Kontokosta and Malik, 2018). Neglecting to include people who rely on certain infrastructure services to support or sustain life and wellbeing, disproportionately places these segments of the population in a higher category of risk and increases their likelihood of requiring rescue and response requirements in the event of a disaster (FEMA - U.S. Department of Homeland Security, 2017). In certain communities, marginalized populations are more likely to depend on public transportation services for daily needs (Jiao, 2017). Inadequate transportation in general sets barriers to financial and job stability (Ewing et al., 2015), as well as healthcare services (Syed et al., 2013). Households living in urban areas known as "food deserts" could be more vulnerable to disruptions in FEW nexus resources in disasters (Alwitt and Donley, 1997). Also, disasters may lead to the emergence of new food deserts in urban areas (Walker et al., 2010; Cummins, 2002), all the while the impacts of FEW resource disruptions may be more severe on vulnerable populations such as older adults (Biehl et al., 2017). Kontokosta and Malik (2018) found that resilient neighborhoods were shown to better withstand disruptions to normal activity patterns and more quickly recover to pre-event functional capacity.

The literature on infrastructure interdependencies continues to focus on systems engineering approaches that aim for system optimization while neglecting the concept of resilience (Chang et al., 2014). Examples of these approaches include the use of computer-based simulation models of infrastructure systems and their linkages (Rasoulkhani & Mostafavi, 2018; Dueñas-Osario, 2007; Min et al., 2007) and analytical models that characterize interdependencies and identify key vulnerabilities, particularly from terrorism threats (Haime and Jiang, 2001, Apostolakis and Lemon, 2005). Haraguchi and Kim (2016) analyzed the impact of Hurricane Sandy from the perspective of interdependence among different sectors of critical infrastructure in New York City, finding that the electricity sector was the key sector to propagate risks to other sectors. Most initiatives to increase the resilience of critical infrastructures in New York City after Hurricane Sandy focused primarily on building hard infrastructures to decrease direct damages, disregarding social dimensions prevalent in the disaster frameworks. It is proposed that switching towards a decentralized scale of operation by decoupling infrastructure systems will help reduce the vulnerability of both the physical and social systems (Stringer et al., 2014) in day-to-day life and in face of disasters. The Food-Energy-Water (FEW) nexus is championed as an approach for attaining sustainable development agenda (Terrapon-Pfaff, Ortiz, Dienst, and Gröne (2018)), and countering the impacts of climate change Blumenfeld et al. (2017) and to reduce system interdependencies and increase system resilience (Daher & Mohtar, 2015). Cross-sector collaboration, as emphasized by the FEW nexus approaches can collectively build community resilience (Miller, 2015). In decentralizing infrastructure system services, essential services can continue to be provided while minimizing the demand for and reliance on emergency services (Miller, 2015). While there are various approaches to FEW nexus applications reviewed by Endo et al., 2015, these simulation models also tend to focus on physical aspects of the supply side of resources, leaving out the critical analysis of the social and behavioral elements of FEW resilience. Furthermore, studies involving the FEW nexus are centralized in historically water-scarce or arid regions, which do not capture the context of natural disasters that typically have sudden onsets like hurricanes, tornadoes, and earthquakes. One exception is a study carried out about Stringer et al. (2014), which combined the nexus approach with resilience thinking resulting in a multiscale framework aimed at understanding the factors that shape equitable and just outcomes. However, the existing framework was not developed in the context of disasters and natural hazards and does not empirically demonstrate or implement the model.

FEW Nexus and disaster resilience research have generally overlooked the disparities that exist in the experience and impact that disruptive events have on marginalized and vulnerable population groups (Stringer et al., 2014). Studies in both disaster and infrastructure interdependencies also tend to focus on broad-scale impacts as opposed to analyzing problems at the household-level, the unit at which infrastructure system services are consumed, and do not consider the bi-directional relationship of the built environment and social systems. Several recent approaches have been developed to quantify the resilience of physical infrastructure systems, namely water supply systems (Balaei et al., 2020), the interconnection between stormwater drainage systems and road transport systems (Yang, Thomas Ng, Zhou, Xu, & Li, 2020), and a resilience index for power distribution systems (Najafi et al. (2018). However, these methods do not directly account for factors and measures of social systems. Methods which did consider aspects of community resilience with the inclusion of social factors include a quantitative framework that models recovery patterns of economic activity in a natural disaster (Qiang et al., 2020), and a social network analysis (SNA) model for characterizing community resilience during different disaster stages, focusing primarily on the role of social capital in shaping resilience (Cui & Li, 2020). These studies do not consider the connections to infrastructure service disruptions experienced at the household level. Kontokosta and Malik (2018) assessed neighborhood resilience capacity during emergencies and disasters by developing an index based on a neighborhood's proximity to certain infrastructure services. While they considered both physical and social infrastructure systems in their study, they did not consider the interactions between systems. Cariolet et al. (2019) reviewed existing approaches for mapping urban resilience, finding that most approaches are analytical and not integrate systemic properties of resilience, and thus, highlighting the need for more systematic studies of resilience. It is suggested that the modeling and mapping of subcomponent and subsystems are sufficient for understanding urban resilience due to the great complexity in mapping urban resilience in its entirety (Cariolet et al., 2019).

From the discussion of existing methods and studies on infrastructure resilience modeling, and community and disaster resilience, the knowledge gaps in the pathway between external factors and household vulnerability (Ge et al., 2017) become evident. As a result, a system-level understanding of household processes related to demand and access to FEW resources during disasters concerning differential household experiences remains limited (Dargin and Mostafavi, 2020; Hussein et al., 2017). The interdependencies among not only critical infrastructure systems but the interdependencies with related institutions are poorly understood (NIST, 2016) as a result of this limitation. In-depth knowledge of the links between cities' characteristic features or urban attributes, related systems, and disasters is indispensable for addressing the root cause of physical and social vulnerabilities as well as for mainstreaming risk reduction into urban planning and management (Wamsler and Brink, 2016). Understanding the integrated relationship of these factors is important for the foundation of planning resilient cities.

Combining disaster risk theory and Food Energy Water (FEW) Nexus systems thinking, this paper presents a new framework for assessing the collective influence of integrated infrastructure disruptions and socio-economic factors on the vulnerability and resilience of households during a hurricane event. Using empirical data from a household survey on disaster experience and infrastructure disruption in Harris County, Texas during Hurricane Harvey in 2017, zip-code areas of high and low FEW infrastructure disruptions were determined. ANOVA one-way testing is used to determine the disparity in disaster risk measures in households across areas of differential infrastructure disruption impact. Structural Equation Modeling (SEM) is employed to test the proposed framework and its associative pathways between infrastructure disruptions, urban attributes, and household preparation behaviors based on the disaster risk measures most associated with households in FEW nexus disruption hotspots. The results of the model intend to build an empirical understanding of the interdependencies among urban FEW nexus systems and households in the context of disasters from the consumption perspective. This study and its findings have multiple novel scientific and practical contributions to both the fields of infrastructure and disaster resilience. In particular, the results of this study allow us to understand, (1) the urban attributes and disaster characteristics influence the sensitivity of vulnerable populations to FEW system disruptions, (2) nature and the extent to which interdependencies among urban food, energy, and water systems influence a households' demand and access to these critical resources during extreme weather events, (3) the cascading effects of disruptions in one system of FEW nexus on households' demand and access to resources from other systems, and (4) the behaviors that directly and indirectly influence the extent to which households are impacted by FEW disruptions.

This paper will continue with a review of existing approaches in infrastructure system interdependencies, disaster risk management, and recovery along with their shortcomings. A conceptual framework is introduced as a means for integrating these disciplines addressing the critical research gaps in our understanding of household vulnerabilities to infrastructure disruptions during disasters. The following sections discuss the methodological approach and implementation of the conceptual framework in the form of a structural equation model using empirical data collected from households in Houston, Texas on their experience with Hurricane Harvey in 2017. The paper is concluded with a summary of the results followed by a discussion of the key findings and conclusions.

2. Conceptual framework

A number of critical infrastructure dependencies contribute to the interconnectedness of risk to communities during disasters (Wamsler & Brink, 2016), such as Water, Energy, Food, and Transport. By definition, a critical dependency is "a dependency that is crucial for societal functions to work" (Wamsler & Brink, 2016). While it is common to see disasters as "causes", and the destruction of the built environment as "effects", the conceptual framework described here on out demonstrates that the nexus between cities, in terms of its physical infrastructure and social systems, and disasters have a bidirectional relationship, which constantly shapes, and is shaped by, both internal (social inequality) and external (climate change) processes. The Household FEW-Disaster Framework builds on prior frameworks of disaster risk and infrastructure nexus, discussed in the literature review to look at the interactions between infrastructure systems. It pays particular attention to the three fundamental components of disaster risk models: hazard, vulnerability, and exposure. Measures of that define physical attributes of urban areas and measure defining household preparation behaviors, and social characteristics and impact of infrastructure disruptions are used to examine the relationship between FEW vulnerabilities and social and physical vulnerability of households. Each subcomponent of the conceptual framework is depicted in Fig. 1 and is detailed accordingly in the subsequent sub-sections.

2.1. Disaster risk

Disaster risk is typically defined as a linear relationship (Alexander, 1991) and guides the development:

$$\text{hazard} \times \text{vulnerability} \; [\times \; \text{exposure}] = \text{risk} \rightarrow \text{disaster}$$

Modern definitions of disaster risk connect with the resilience and climate change adaptation agendas. It also responds to the imperative of sustainability (Alexander, 2012). Alexander proposes a new theory of disaster risk, where consequences or impacts of the disaster are influenced by human-vulnerability which is a factor of cultural, physical, and historical accounts. (Alexander, 2012; Zhu et al., 2017). The Pressure-and-Release (PAR) framework, the Hazards-of-Place (HOP) framework, the Exposure-Sensitivity-Resilience (ESR) framework, and the Bogardi-Birkmann-Cardona (BBC) framework are four of the most popular disaster-risk frameworks in the field and literature. The frameworks generally take into account the consequences of direct physical impacts (exposure and susceptibility) as well as indirect consequences (socio-economic fragility and lack of resilience) of a potentially hazardous event. Within each category, the vulnerability factors are described with sets of indicators or indices (Ciurean et al., 2013). Thomas et al. (2019) emphasize that vulnerability is multi-dimensional and differential. Hence, this study examined various factors influencing differential vulnerability among households while facing FEW nexus disruptions in disasters.

2.2. Household vulnerability

Reported household-hardship experienced due to disruptions in the FEW infrastructure system services is used as a proxy for measuring vulnerability in the framework and the survey. Hardship is generally distinguished from vulnerability by a temporal difference, where hardship is often used to define an experience of the present, while vulnerability indicates a risk of experiencing future hardship (Adelman et al., 2015). Concerning the proposed conceptual framework, therefore, the authors assume that experienced hardship due to infrastructure service disruptions is indicative of being vulnerable to additional impacts. In theory, there should be indirect relationships between the disruptions and hardships for non-corresponding disruptions. For example, a household may face more food hardship if their power went out for a significant amount of time and the food inside their fridge spoiled. The next question the framework attempts to answer is the extent that certain preparation behavior affects the household's vulnerability, and to what extent access to infrastructure before the storm affected their ability to prepare. The proposed framework allows us to look at vulnerability from physical and social perspectives while highlighting which behaviors and characteristics might trigger individual and collective vulnerability of the FEW nexus systems. Vulnerability is a function of physical disruptions, urban attributes and characteristics, and household behavioral attributes, consistent with preexisting disaster risk models. The vulnerability for each sector of the FEW Nexus is defined by the presence of disruption, while overall nexus vulnerability is defined by the level of hardship a household faced.

2.3. Description of the pathways and links

The conceptual model presented here will ultimately be tested using empirical data from a household survey and through the development of a structural equation model (SEM). In the construction of this model, there are defined pathways that represent different causal relationships. These pathways are the following: Physical attributes and behavioral socio-cultural aspects are directly linked to the physical/spatial features of a city. For example, high population density, overpopulation, lack of affordable space, and the lack of green and recreational areas can influence family structures, social cohesion, and the sense of community (Wamsler & Brink, 2016). In overcrowded conditions, issues such as competition for space and poor infrastructure (e.g. lack of, or leaking wastewater pipes) can generate conflicts between neighbors. Likewise, the failure of infrastructure to provide adequate water, sanitation, drainage, roads, and footpaths increases the health problems, workload, and insecurity of residents, especially women (IFRC, 2010; Tacoli, 2012). Inadequate transportation infrastructure forces citizens to cross insecure areas (Amnesty International, 2010; Tacoli, 2012). Also, difficult access to urban areas, together with a lack of public leisure space, can isolate certain groups (such as the elderly and women with small children) and make them even more bound to their compact homes (Wamsler & Brink, 2016). Each group of attributes is explained in the following sub-sections.

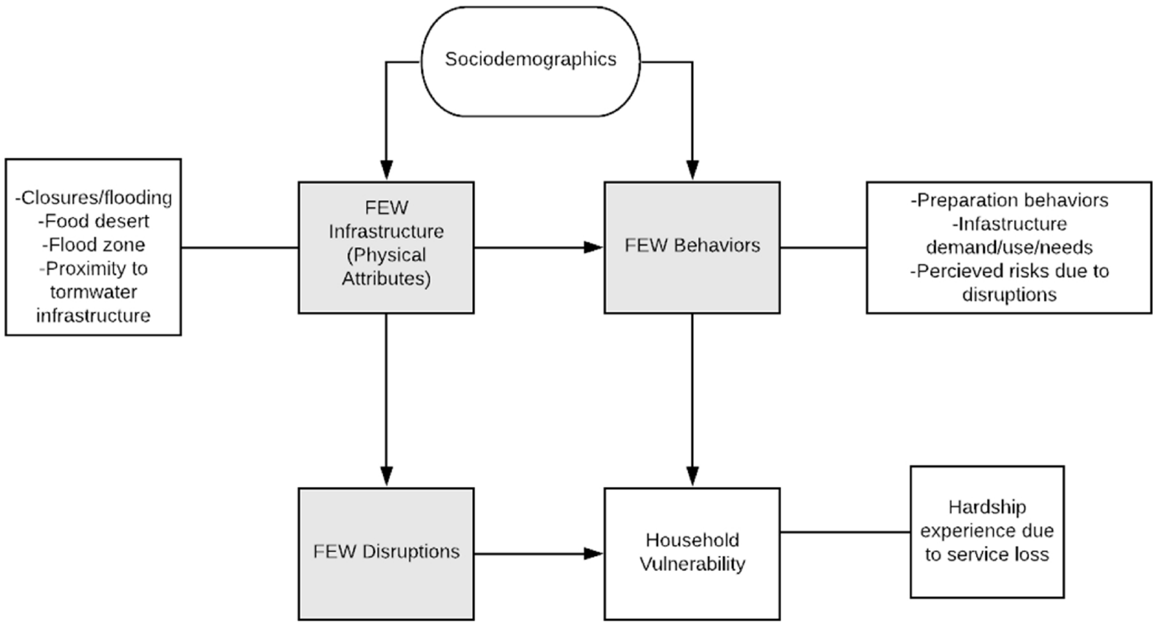

Fig. 1. FEW nexus-Disaster Framework: the grey-shaded boxes represent the factors contributing to the vulnerability of households during disasters. Measures of these factors are defined in their respective connected boxes. The lines with arrows signify the direction of the relationships between each factor.

2.4. Urban/physical attributes

Many social scientists argue that society determines the changes in the physical city (Naik et al., 2015). Physical space has the potential shape social characteristics, by documenting that neighborhoods contain fewer minorities when regulations prevent the construction of multi-family housing neighborhoods (Resseger, 2013; Naik et al., 2015). The most famous hypothesis connecting urban perception and human behavior is the Broken Windows Theory (BWT) of Wilson and Kelling (1982), now used to describe how urban disorder can trigger disorderly behavior (Naik et al., 2015). Other studies have linked socioeconomic characteristics to the built-environment, showing the demographic minorities and low-income households are more likely to reside in closer proximity to hazardous areas, such as toxic waste facilities and industrial facilities (Bullard et al., 2007). Lambert and Boerner (1995) find that housing values grew less rapidly in locations where there was at least one waste site, and percent minority increased more rapidly in these locations than it did in other neighborhoods. Hersh (1995) found evidence that both White and higher-income households tend to leave neighborhoods after industrial plants and waste facilities were constructed, while minorities were more likely to move into these more polluted areas (Gray and Shadbegian, 2010).

Community water systems serve approximately 96 % of the US population (EPA, 2013) however since water utility companies are not required to collect information on their customers, it is difficult to assess social inequities in service provision (EPA, 2013), as it the case with other infrastructure services. Despite the dearth of data in this realm, studies have drawn empirical evidence of social inequities related to water infrastructure services: studies have documented limited access to clean water in low-income communities of color (VanDerslice, 2011). Only 3 studies explicitly examined differences in water infrastructure by income or race in areas served by community water systems. In each of these studies, US Census demographic data for a geographic area (i.e., census block groups, zip code, county) were linked to aggregated water quality or violation data from the community water systems serving that area. The location and use of inferior quality construction materials for building homes are cited as variables that contribute to a vulnerable household's heightened vulnerability during disasters (Bergstrand et al., 2014; Baker, 2012). Another interesting phenomenon related to urban connectivity and system attributes and vulnerability is the design of water drainage infrastructure in systems: the development of drainage infrastructure in more affluent communities often diverts flooding problems downstream, usually less affluent communities (Parkinson, 2003)

Existing studies that look at the intersection of social vulnerability to natural hazards, particularly flooding events, do not include neighborhood or urban characteristics beyond population density and transportation. The physical attributes highlighted in this study are those relevant to FEW systems and their role in pre and post-disaster. Physical attributes include food deserts, flood zones, proximity to stormwater infrastructure, and environmental hazards. The physical attributes selected in this study are summarized in Table 1 in the next section. These attributes are selected because of their roles in social inequity landscapes and stormwater mitigation, which are significant in the face of hurricanes. In the framework, it is shown that physical attributes are influenced by socio-demographics, which influence the risk of FEW disruption impacts. Secondly, the physical attributes influence behaviors and consumption of FEW resources at the household level. There are numerous characteristics of current urban planning and development that drive vulnerability. Human processes such as urbanization and structural defenses (e.g., levees, dams, sea walls) have a large influence on the movement and severity of flooding, ameliorating impacts in some cases, but amplifying them in others (Rufat, Tate, Burton, & Maroof, 2015). Poorly planned and managed urban development has generated new hazards and extensive risk (UNISDR, 2013). The growing concentration of people and assets in high-hazard areas, along with the marginalization of the urban poor in particularly unsafe areas drives exposure to disaster impact. The most vulnerable groups tend to settle and build homes in unsafe locations that are without adequate provision of infrastructure and critical services (Mechanic and Tanner, 2007). It was theorized that households from historically underrepresented minorities would experience more inaccessibility to food infrastructure, making it more difficult to prepare and exacerbating hardship during the storm. For example, Najafi, Ardalan, Akbarisari, Noorbala, and Elmi (2017) showed that a household is less likely to prepare if they do not perceive that they have the means to; therefore, a high negative correlation between food insecurity was expected, especially in highly vulnerable populations.

Table 1
Survey measures.

		Indicator
	Food Desert	Distance to closest grocery store (miles)
		Binary Yes – 1, No - 0
		Binary Yes – 1, No - 0
	Perceived disruption risks	Likert Scale 1 – 5 (No risk at all – severe risk)
	Health and Social Services	The 2019 SocioNeeds Index - 1 – 5 (increasing values correspond to areas with higher disparity in health outcomes and services)
		Binary Yes – 1, No - 0
		Likert scale 1 – 5 (overprepared – not at all prepared)
		# of days
	% of households with Power backup	Binary Yes – 1, No - 0
	% of households reporting use of Power for food	Binary Yes – 1, No - 0
	% of households reporting use of Roads for food and water	Binary Yes – 1, No - 0
	% of households reporting use of Power for health	Binary Yes – 1, No - 0
	% of households reporting use of Roads for health	Binary Yes – 1, No - 0
	% of households reporting use of Water for food	Binary Yes – 1, No - 0
	% of households reporting use of Water for health	Binary Yes – 1, No - 0
		# of days of disruptions reported
		# of days of disruptions reported
		# of days of disruptions reported
	Days of food disruptions	# of days of disruptions reported
	Days of electricity outage	# of days of disruptions reported
		Likert scale 1 – 5 (None at all – A great deal)
		Likert scale 1 – 5 (None at all – A great deal)
		Likert scale 1 – 5 (None at all – A great deal)
		Likert scale 1 – 5 (None at all – A great deal)
Sociodemographic Characteristics	Minority – (White – non-White)	Binary Yes – 1, No - 0
	Income	Scale 1 – 7 (less than $25,000 – more than $125,000)
	Health – Chronic	Binary Yes – 1, No – 0 (any member in household with chronic health condition)
	Health – Disability	Binary Yes – 1, No – 0 (any member in household with a disability)
	College Educated	Binary Yes – 1, No – 0 (any member in household with a college degree or higher)
	Children Under 10 years	Binary Yes – 1, No – 0 (any member in household with children under 10)
	Elderly residents	Binary Yes – 1, No - 0 (any member in household with elderly resident(s))

2.5. *Household behaviors and characteristics*

There is recognition that the physical environment can influence human behavior and sociodemographic characteristics of a neighborhood (Raman, 2010; Handy, Boarnet, Ewing, & Killingsworth, 2002). Processes involving characteristics such as race, gender, age, and income are principal drivers of a population's ability to prepare for, respond to, and recover from damaging flood events (Rufat et al., 2015). Alexander, 2012Alexander (2012) argues that perception and culture are also significant factors of disaster vulnerability. Other important drivers that are not directly addressed in the framework include coping capacity, land tenure, and governance. While these studies focused on neighborhood levels, the household is the fulcrum and most simple unit of measure in which FEW resources are consumed and disruption in FEW systems affects household well-being. Households are the smallest decision-making units and likely to be exposed to external turmoil. This is why in the framework, household behaviors are influenced by the environment (physical attributes) and sociodemographic characteristics of the household. Waitt et al. (2012) produced “three core dimensions of sustainable household capability” which can be implemented to identify household resilience and are adapted in the framework: “household practices” (preparation actions taken to save or improve the household system); “household structure” (demographic, physical and economic features); “household sustainability judgments” (knowledge, awareness, concerns toward externalities). In this model, sustainability judgments are represented by the perceived risk of the disaster. The sociodemographic background was included in the framework as an overarching effect on vulnerability factors. The general population's experience with extreme weather and disasters is also an important component of both disaster resilience and FEW resilience. Most households do not prepare for disaster until it hits (Najafi et al., 2017), increasing their risk to FEW vulnerabilities.

2.6. *FEW infrastructure disruptions*

Disruptions are characterized by a direct and lasting impairment to a dependent activity (Wamsler & Brink, 2016). Disruptions are defined by the presence of a failure or interruption of a service and its duration. For the scope of this paper, food infrastructure is represented as food service and supplies at grocery stores. Water infrastructure refers to drinking water supply and stormwater infrastructure. The energy infrastructure is represented by electricity, fuel, and transportation (roads). Disruptions are triggered by external events, in this case a natural hazard (hurricane). The extent of disruption, however, is determined by physical attributes and household behavioral attributes.

3. Methodology

3.1. *Study context*

The study is centered around the FEW nexus infrastructure outages affecting Harris County residents during Hurricane Harvey (Fig. 1). Hurricane Harvey was a Category 4 storm that made landfall in Texas on August 25th, 2017. Harvey led to severe rainfall and mass flooding throughout the state, impacting all 4.7 million inhabitants of Harris County, the most populous county in Houston and Texas. Record-breaking rainfall wreaked havoc on Houston's infrastructure systems and households making it one of the costliest disasters in U.S. History, after Hurricane Katrina. All 22 of Houston metro's major freeways were flooded and impassable during the storm while nearly 300,000 households lost power (HCFCD, 2017). The proposed framework is used to draw on the causal pathways of risk disparity due to infrastructure service disruptions within a population. The survey design, data measures, and analytical approach are described. Moreover, we utilize empirical data from Hurricane Harvey to test the proposed framework in answering the proposed research questions in the context of critical infrastructure system disruptions due to disaster. The focus of this research is on households sheltering in place during a disaster; this discretion, therefore, excludes households that evacuated before Harvey's landfall. Harris County was selected particularly because mandatory evacuation orders were not issued to its residents. Within Harris County, only one city issued a voluntary evacuation order (WFFA, 2017). Several coastal counties along the Gulf Coast were ordered to evacuate which would have made these counties inadequate for our study. The rationale for this selection was that, for the people who evacuated and had to move to shelters or other places, the relevance of infrastructure service disruptions becomes of secondary importance since they have already lost their shelter (the primary place in which infrastructure services are utilized).

3.2. Survey

A web-based survey was deployed between April and May 2018 through Qualtrics, a survey company that matches respondent panels with demographic quotas. To represent the vulnerable population groups in the study area, the authors provided quotas created from U.S. Census Bureau data to draw a sample from Harris County based on age, race/ethnicity, income, and health status. All participants in the survey were required to be age 18 years or older. The survey focused on the households' experience of disruptions that may have inhibited their access to basic needs (food, energy, water resources). Questions about the occurrence and magnitude of these obstacles, preparation and response behaviors, and the impact that disruptions had on the household were addressed, as well as information about their sociodemographic background. The purpose of the data was to highlight the trends in vulnerable population group experiences with infrastructure disruptions during a disaster event. As suggested by Lindell (2008) the degree to which sample means and proportions are representative of the study area population is less important than having enough demographic diversity to provide an adequate test of the relationships in the presented correlation analysis. A total of 1081 household samples were collected from 140 of the 145 zip codes in Harris County. According to power analysis, this is a sufficient number of responses to conduct inferential statistics that systematically examine associations within the survey data. Those with incomplete responses and those that had evacuated their households before Hurricane Harvey landed were eliminated from the analysis, narrowing the analyzed sample to 884 households.

3.3. Research measures

Table 1 summarizes the variables used from the survey to measure each component of the framework. Food deserts were defined were households experienced food shortages. Food infrastructure is defined by the distance from the nearest grocery store and how many stores a household had to visit before obtaining sufficient supplies. The distance was specifically defined by a binary indicator representing whether a household lived in a food desert. The USDA defines a food desert as an area where the nearest grocery store is over a mile away and a majority of the population is low income and has little access to transportation (Ver Ploeg, Nulph, & Williams, 2011). The socio-demographic factors were drawn from themes commonly found in the social vulnerability literature identified by Rufat et al. (2015). Measures for the physical attributes, behaviors, and vulnerability were developed based on an in-depth literature review on disaster risks and vulnerabilities that are determined by the conceptual framework which informed the questions used in the survey. A 4-item Likert scale question captured households' perception of the risk of disruptions. Risk perception of infrastructure disruptions is included as an influencing attribute measure because it is driven by one's circumstances, surroundings, and past experiences (Lindell & Perry, 2012). From this explanation it is assumed that a household's perceived risk of infrastructure disruption is reflective of their trust and evaluation of their community's infrastructure systems and services. Another 4-item question dealt with residents' concern about potential consequences of the storm such as disruption of supplies, damage to public facilities, damage to houses or possessions, financial loss, psychological health, and inconvenience of the recovery process after the flood. Finally, a 4-item question dealt with how likely the respondents were to take preparation and protective measures to reduce the risk of flooding. The respondents used a 5-point Likert rating scale (0 = Not at all to 4 = extremely) to evaluate each question in the survey. Any answers that had selections that indicated a lack of behavior was omitted, or turned into a "0", to prevent contradiction. Outliers were removed from much of the remaining numerical data used, such as days spent preparing. Multiple-choice questions that consisted of levels, such as from "[no hardship] at all" to "a great deal [of hardship]", were assigned numbers from 0 to 4. This allowed the data to be used in an empirical analysis. The low-income group included residents who selected their income to be $0-$25,000 as well as $50,000; low education included anybody who did not complete higher education.

3.4. Statistical analysis

The data collected from the survey were analyzed using a combination of bivariate and multivariate analysis to understand the underlying characteristics of FEW vulnerable households. First, the nexus interactions were determined based on the response of households to the following question: "What were your primary needs for the following infrastructure services before and during the hurricane?" ANOVA testing and Structural equation models are formed to test the pathways proposed in the conceptual framework. The data and analysis focused on the differential preparation behaviors and FEW nexus disruptions' impacts on households in the context of a disaster event.

3.5. Bivariate analysis – ANOVA 1-way testing

To observe the relationship between the FEW vulnerabilities and the disaster risk measures in the conceptual framework, the interquartile range of the dataset was determined according to the aggregated sum of the FEW hardship measures. The disaster risk variables measuring physical attributes, sociodemographic characteristics, preparedness behaviors, and disruptions were evaluated and compared by categorizing households as either low, medium, or high vulnerability according to the percentile range of their combined FEW vulnerability scores (the aggregated sum of FEW hardship measures). ANOVA one-way tests were used to compare the mean values of the disaster risk measures among the non-vulnerable and vulnerable households and examine if differences are statistically significant.

In order to evaluate pair means, a Tukey HSD post hoc test was conducted. Accordingly, structural equation models were developed using the disaster risk measures which were found to be statistically significant in households demonstrating higher FEW vulnerabilities according to the post hoc test analysis.

3.6. Structural equation modeling

The framework is then analyzed via exploratory structural equation modeling (SEM), with the Lavaan Package (Rosseel Y (2012) on R Studio software. SEM is beneficial because it allows for the creation of latent variables from existing data, and then uses logistical regression to compare the correlation between the latent variables and identifies significant pathways. The resulting coefficients indicated the significance of the indices and allowed for further interpretation. Lavaan is particularly useful in that it provides fit data to determine how well the framework functions. SEM is selected as a statistical tool because it can estimate multiple and interrelated dependence relationships simultaneously. This allows us to assess the significance and strength of a particular relationship in the context of the complete model. We want to see if the model as proposed in the discussion of the conceptual framework is validated by the empirical survey data that has been gathered by households and their experience with Hurricane Harvey. The overall objective of structural equation modeling is to establish that a model derived from theory has a close fit to the sample data in terms of the difference between the sample and model-predicted covariance matrices. To test the proposed relationships among the study variables as shown in Table 1, structural equation modeling (SEM) was developed using Maximum likelihood (ML) as an estimation method. For model evaluation purposes the following fit indices are used, and their thresholds are as follows: The Root means square error of approximation (RMSEA < 0.07), the Comparative Fit Index (CFI > 0.95) and the Tucker Lewis Index (TLI > 0.95). The RMSEA also takes the model complexity into account as it reflects the degree of freedom. RMSEA value smaller than 0.05 can be said to indicate a convergence fit to the analyzed data of the model while also indicating a fit close to good when it produces a value between 0.05 and 0.08.

Being an exploratory analysis, multiple models were fitted to test for the effect of disaster risk measures and sociodemographic characteristics on the associative pathways in the proposed conceptual framework. The first model is run without testing for the sociodemographic effects while the subsequent models are fitted with the measures associated with zip code areas with high FEW vulnerabilities.

4. Results

4.1. FEW Nexus interactions during hurricane and flooding

Table 2 summarizes the key household-level nexus relationships based on the results from the household survey. For example, electricity was identified as a need for heating and preparing food and water, and maintaining the livability of homes. Water and food needs were unsurprisingly cited for health and livability needs. Mapping these households FEW nexus needs highlights another significant subcomponent of the nexus which is the health and well-being of households. Ultimately, these systems provide the means for and support health and well-being.

4.2. Bivariate analysis

Table 3 summarizes the underlying characteristics of FEW vulnerable households. The survey variable represents the measures used according to each of the four constructs of the proposed nexus-disasters framework. Columns LQ1, LQ2, LQ3 represents households by the FEW vulnerability interquartile range, where the highest quartile represents households with greater vulnerability. For example, the average number of households in a FEMA Flood-zone located in areas of less vulnerability is 25.20 %, whereas 45.50 % of households in FEW vulnerable areas responded that they are in a FEMA flood zone. For complete test statistics, refer to the appendix. These results helped to inform the variables used in the development of SEM models based on the High FEW-vulnerability being statistically significantly different from both medium and low vulnerability groups according to the ANOVA 1-way tests. Variables that were found to be statistically different from both groups have been marked with an asterisk. All variables were found to have different occurrences between at least one group. There were no statistically significant differences across the households concerning: having a power backup, using power for food, and using roads for food and water, and days preparing.

There was a statistically significant difference across households classified as low vulnerability, medium vulnerability, and high vulnerability as determined by one-way ANOVA concerning various disaster risk characteristics measured in the survey. A Tukey post hoc test revealed characteristics that were statistically significantly higher in High FEW vulnerable households compared to both low and medium vulnerability. Survey variables that were statistically significantly different between High FEW vulnerable households and Medium and Low vulnerability are indicated in the last column.

Households experiencing greater FEW-vulnerability were more likely to need FEW sources for health-related needs. This highlights another significant subcomponent of the nexus which is the health and well-being of households. Ultimately, these systems provide the means for and support health and well-being. The days spent preparing for the storm were not found to be statistically significantly different across highly vulnerable households and low vulnerable households. Similarly, there was no statistically significant difference among the engagement of households in preparedness actions. Households rating as more vulnerable to FEW disruptions on average, reported higher engagement in certain preparation activities where 12 % of the least vulnerable households did not engage in any preparation action at all, whereas only 5% of highly vulnerable households reported no engagement in preparation actions. An interesting finding from the ANOVA results was this discrepancy between extent or attempt to prepare and the household's perception of the importance of preparations. Households that were rated more vulnerable on average reported lower levels of importance towards preparation actions. Perhaps this represents the household's frustration with the effort and attempts to prepare but the lack of resources due to urban attributes. Vulnerable households do prepare, however, certain behaviors influenced by urban attributes inhibit the ability of the household to prepare sufficiently.

Most striking from the ANOVA analysis is the disparity in food and water supply at stores in the preparation phase of the disaster. 44 % of households rating as high vulnerability experienced supply shortages during their attempt to prepare, whereas only 1% of households rating very low in vulnerability experiencing shortages. FEW vulnerable households were much more likely to report high perceived risks to infrastructure disruptions, indicating there is not as much trust in the reliability and robustness of the infrastructure services and systems in the community of the household. Overall, vulnerable households were more likely to be close to hazardous areas such as in flood zones, close to drainage and stormwater infrastructure, and in areas of lower livability rating, as determined by the Houston SocioNeeds Index.

Table 2
Household Nexus Relationships Based on Household Survey Responses: "What were your primary needs for the following infrastructure services before and during the hurricane?

Infrastructure	Household-level nexus Interactions
Energy	Indirect via transportation: getting food and water
	Food storage and preparation, boiling or heating water
	Livability of household (A/C, lighting, health treatments)
Water	Food preparation
	Health & Hygiene
	Drinking water
Food	Health needs

4.3. Structural equation model results

SEM is selected as a statistical tool because it can estimate multiple and interrelated dependence relationships simultaneously. Results of the SEM model are presented and consistent with Journal Article Reporting Standards (JARS) (Hoyle & Isherwood, 2013) and (Schreiber

Table 3
Bivariate analysis - Underlying Characteristics of FEW Vulnerable Households.

	Survey Variable	*Low FEW Vulnerability n = 93*	*Medium FEW Vulnerability n = 530*	*High FEW Vulnerability n = 261*	*ANOVA 1-way test result*
Physical Attributesh	*% of households in a FEMA Flood-zone*	0.18	0.25	0.41	***
	% of households Neighborhood flooded	0.46	0.60	0.74	***
	Average Reported Flood duration	1.80	3.32	5.29	***
	Average Reported Road risk	2.07	2.44	2.83	***
	Average Reported Power risk	2.07	2.33	2.68	***
	Average Reported Water risk	1.48	1.90	2.48	***
	Average Reported Food risk	2.15	2.47	2.79	***
	Average Reported Fuel risk	2.03	2.28	2.77	***
	Average Reported Grocery store distance	2.35	3.04	3.47	***
	% of households experiencing Grocery store food/water shortage	0.01	0.09	0.44	***
	Flood proximity	0.42	0.50	0.57	**
	Index score	51.04	53.68	64.68	***
	Index rank	3.06	3.11	3.63	***
	Average Reported Food	0.97	2.58	5.20	***
	Average Reported Roads	3.26	6.04	7.57	***
Disruption Duration	*Average Reported Water*	0.19	0.37	1.27	***
	Average Reported Water boil notice	0.12	0.54	2.15	***
	Average Reported Power	0.27	0.59	2.04	***
	% of households with Power backup	0.18	0.16	0.18	
	% of households reporting use of Power for food	0.71	0.74	0.77	
Household Behaviors	*% of households reporting use of Roads for food and water*	0.80	0.84	0.84	
	% of households reporting use of Power for health	0.68	0.76	0.74	*
	% of households reporting use of Roads for health	0.18	0.20	0.35	***
	% of households reporting use of Water for food	0.68	0.76	0.76	*
	% of households reporting use of Water for health	0.84	0.88	0.94	*
	Average Days aware of hurricane	5.27	4.87	4.30	***
	Average Days of preparation	4.60	4.00	4.06	
	% of households reporting underestimating disruption impact	0.02	0.13	0.32	***
	% of households Did not prepare enough	0.11	0.51	0.86	***
	Average rating of Importance of preparation (out of 4)	3.02	2.74	2.65	***
	Took 3 or more preparation actions	0.62	0.67	0.63	
	Took no preparation action	0.12	0.07	0.05	
	Food prep	0.76	0.81	0.84	
	Water prep	0.78	0.83	0.87	
	Energy prep	0.83	0.86	0.87	
	% of households with Prior disaster experience	0.89	0.83	0.74	***
	Median Years lived in Harris County	30.68	24.06	24.26	***
Sociodemographic Characteristics	*% of households with children Age; Under 2 years*	0.25	0.43	0.57	**
	% of households with children Age; 11–17 years	0.18	0.30	0.43	***
	% of households with Age;65+	0.62	0.49	0.23	***
	Median Income (1 − 7)	3.57	3.59	2.84	***
	% of households Minority	0.34	0.41	0.56	***
	Black	0.19	0.18	0.28	*
	Latino	0.07	0.14	0.16	**
	Other	0.05	0.05	0.09	
	White	0.67	0.60	0.40	***
	% of households College degree	0.65	0.64	0.45	***
	% of households Disability	0.11	0.21	0.23	***
	% of households Chronic Illness	0.25	0.34	0.30	*

** Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1.

et al., 2010). Using the hypothesized framework (Fig. 1), the specified measures from the survey data (Table 1), and results from the above ANOVA testing, a base structural model consisting of 19 observed variables (Model 1, Fig. 2) associated with 4 latent variables was developed. Five additional models were developed controlling for various sociodemographic groups, with the final model taking into account all sociodemographic groups. The results obtained from the SEM analysis show that the factor loadings for each of the items were significantly larger than their standard errors, and the associated t-statistics (critical ratio (C.R) values) exceeded ± 1.96 (at $p < 0.05$). A complete summary of the fit statistics and comparison with acceptable values is presented in Table 4. The latent factor loadings, regression, and covariance results of each model can be found in Tables A1–A3 in Appendix A.

All the fit statistics were within the accepted fit ranges for all models tested (Table 4). It is apparent that the model performance is sacrificed

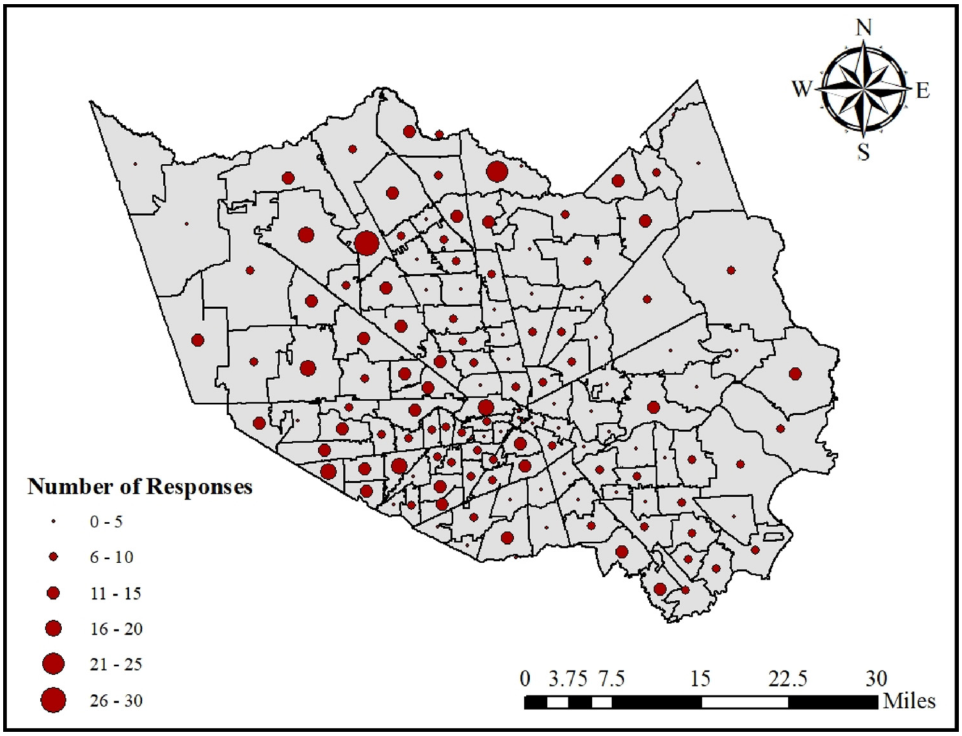

Fig. 2. Model 1 pathway diagram; weighted lines indicate strong relationships, while shaded lines indicate weaker relationships. Dashed lines represent the factor loadings of the first indicators in each latent variable construct. The numerical values indicate the β values and factor loadings. FEM = FEMA flood zone; IR = Infrastructure failure risk; IP = Industrial plant proximity; Fl = Flood control infrastructure proximity; GR = distance to grocery store; fh = Food hardship; wh = water hardship; ph = power hardship; th = transportation hardship; ss = storage space; sc = supply costs; st = storage space; ud = underestimated disruptions; lt = lack transportation; us = underestimated storm impact; td = transportation duration; fd = food duration; pd = power duration; wd = water duration.

Table 4
Summary of Model Performance Indices.

Fit index	Model 1 (without vulnerable populations)	Model 2 (Control for Income, Education, Race)	Model 3 (Control for Disability)	Model 4 (Control for households with children)	Model 5 (Control for prior experience)	Model 6 (All variables)	Recommended Value*
RMSEA	0.000	0.020	0.000	0.001	0.007	0.020	< = 0.05
TLI	1.009	0.967	1.004	1.000	0.996	0.950	Approaches 1
CFI	1.000	0.973	1.000	1.000	0.997	0.960	> = 0.95
P-value (Chi-square)	0.800	0.000	0.639	0.482	0.332	0.000	> 0.00

* Byrne (2001).

slightly when accounting for vulnerable populations in the SEM. Most of the pathways between the exogenous variables and the endogenous variables are statistically significant at the 0.001 and 0.01 level of significance. A good fit indicates that the variance in the variance-covariance matrix is well represented by the models. A complete summary of the test results for each model, including the latent factor loadings, variances, covariances is included in *Appendix Section A*.

4.4. Model 1: base model without social factors

The physical attributes of a household's community is a moderately strong indicator of its ability to sufficiently prepare for a disaster (β = 0.317, p = 0.000). Similarly, the physical attributes of a household's community are strongly indicative of the extent of disruptions experienced (β = 0.500, p = 0.000). These findings alone highlight the strong intersection of the pre-existing conditions of a community and its vulnerability at both a social and physical perspective. Ultimately, disruptions are more significant in determining FEW-vulnerability (β = 1.458, p = 0.000) compared to preparation behaviors (β = 0.717, p = 0.000), though it is still strongly associated and statistically significant; for every one-unit increase in a household's FEW-vulnerability, the likelihood that a household will not have proper access to resources, whether through knowledge, supply, and or money, will increase by 0.72.

4.5. Model 2 - control for income, education, and racial minorities

Being of a racial minority is positively associated with lower levels of preparation behaviors (β = 0.220, p = 0.000). Income and education have a negative correlation (β = -0.02, p = 0.018; β = -0.02, p = 0.045), which signifies that decreasing household income and lower attainment of education are associated with poorer preparation behaviors. When adjusted for these variables, the behavior is still a significant indicator of FEW vulnerabilities, but compared to Model 1, the coefficient is reduced (β = 0.490, p = 0.025). The association between FEW vulnerability and preparation behaviors is smaller after adjusting for income, race, and education level. The behavior remains statistically significantly associated with FEW-vulnerability, but the magnitude of the association is lower after the adjustment. The regression coefficient decreases by nearly 46 %. It can be concluded that the model supports the constructs and pathways proposed in the conceptual framework. The association between disruptions and FEW-vulnerability (β = 1.55, p = 0.025) also appears to have been impacted by the inclusion of these sociodemographic variables. The magnitude of association increased by 8.30 %, meaning that part of the association between FEW - vulnerability and Infrastructure Disruptions is explained by low income, low education attainment, and minority racial status.

4.6. Model 3 - control for age (Households with young children)

From the ANOVA testing, it was found that less vulnerable households were more likely to have elderly residents while more vulnerable households were more likely to have children. Therefore, this model introduces households with children under 10 years old as a measure of a vulnerable population group during disasters. Households with children had a statistically significant yet mild association with preparedness (β = 0.09, p = 0.000). The association between physical attributes and preparedness remains statistically significant and the magnitude of the relationship is reduced only slightly. There is therefore a slight indication that the relationship between the two constructs is explained by households with children. The association between FEW vulnerability and preparedness behaviors is also explained by households with children.

4.7. Model 4 - control for disability

Model 4 tests for the effect of a household having a resident with a disability. Disability was selected based on the results of the ANOVA testing. When controlling for households with a disabled resident, all measures remain statistically significant. However, it appears that having a disability has a minor impact on the level of preparation (β = 0.09, p = 0.001), while its association with the outcome variable, FEW-vulnerability, is slightly greater (β = 0.170, p = 0.11).

4.8. Model 5 - control for prior disaster experience

Lastly, the prior experience was introduced to a fifth model to determine its role in a household's vulnerability to a FEW disruptions (Appendix A, Table 5). Overall, households having prior experience with a disaster were more likely to not face issues with preparing for a storm (β=-0.23, p = 0.001). Having prior experience in disaster situations was similarly associated with greater preparedness, as indicated by its inverse relationship (β = -0.12, p = 0.000).

4.9. Model 6 – controlling for all social attributes

Table 5 presents a decomposition of the standardized direct, indirect, and total effects of each model construct and social attributes on household FEW-vulnerability, as well as the particular indirect effects modeled through various pathways and the total effects of each of the model's mediating variables. A sixth model was constructed and fitted with all of the social variables to determine the total relative weight each variable has in influencing a household's vulnerability to food, energy, and water infrastructure disruptions during a hurricane event. In the 6th model (Table 5), urban attributes, household preparation behaviors, and infrastructure disruptions had a significant direct (1.634) effect on household FEW-vulnerability, while indirect effects were minimal (0.011). From Model 6, it can be inferred that the probability of a household experiencing greater vulnerability to the combined effects of food, energy, and water infrastructure disruptions increased by 162.4 % of a standard deviation for every one standard deviation increase in the duration of infrastructure disruptions and increase in poor preparation behavior. Of the mediating variables tested in the model, the duration of infrastructure disruption experienced (1.622) had the largest total effect on household vulnerability, followed by preparation behaviors (0.404), Race/Ethnicity (0.245), and prior disaster experience (-0.230). Income and educational attainment level of a household appears to have a negative but minimal effect on a household's vulnerability to food, energy, and water infrastructure disruptions (-0.039; -0.049).

5. Discussion

The empirical data and statistical analysis applied in this study reveal that physical attributes, the extent of disruptions, household preparation behaviors, and sociodemographic characteristics each contribute to a household's vulnerability to FEW disruptions. This relays the notion that pre-existing conditions of communities in which households live have a significant role in determining their risk and vulnerability to disaster impacts. Consequently, heightened vulnerability corresponds to low levels of resilience: households will face more challenges in recovering from impacts and withstanding future hazardous events.

The use of ANOVA one-way testing allowed for the identification of disaster risk measures that are significantly different across different thresholds of household vulnerability, in other words, which disaster

Table 5
Total, direct, and indirect standardized effects of urban attributes, preparation behaviors, infrastructure disruptions, and social factors on FEW Vulnerability.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Total (All attributes to FEW)	1.535	1.557	1.570	1.606	1.549	1.634
Total Indirect (All attributes to FEW)	0.012	0.011	0.012	0.012	0.012	0.011
Total Direct (All attributes to FEW)	1.547	1.568	1.582	1.618	1.561	1.645
Specific Indirect Effects						
Urban to disruption to FEW	0.213	0.216	0.215	0.222	0.215	0.227
Urban to behavior to FEW	0.057	0.040	0.055	0.050	0.051	0.032
Prior to behavior to FEW	–	–	–	–	−0.075	−0.030
Race to behavior to FEW	–	0.043	–	–	–	0.024
Income behavior to FEW	–	−0.008	–	–	–	−0.006
Education behavior to FEW	–	−0.007	–	–	–	−0.004
Age behavior to FEW	–	–	–	0.051	–	0.026
Disability behavior to FEW	–	–	0.062	–	–	0.030
Total Effects						
Urban Attributes	0.224	0.221	0.222	0.223	0.686	0.220
Disruptions	1.524	1.546	1.558	1.595	1.537	1.622
Behavior	0.671	0.488	0.655	0.596	0.601	0.404
Experience	–	–	–	–	−0.354	−0.230
Race/Ethnicity	–	0.303	–	–	–	0.245
Income	–	−0.042	–	–	–	−0.039
Education	–	−0.061	–	–	–	−0.049
Age	–	–	–	0.214	–	0.143
Disability	–	–	0.260	–	–	0.206

*All values significant at $p < 0.05$.

Table A1
Model 1 (No Social Controls) & Model 2 (Control for Race, Income, & Education.

Model 1

	Estimate	Std. Err.	z	p
	Factor Loadings			
Infra.disruption				
days.water	1.00 +			
days.power	1.68	0.28	6.07	0
days.food	3.27	0.59	5.5	0
days.transport	3.04	0.6	5.08	0
Urban_attributes				
grocery.dist	1.00 +			
proxim.flood.infra	0.1	0.03	3.12	0.002
proxim.industrial.plant	0.12	0.03	4.37	0
Infra.Fail.Risk	3.45	0.69	5.03	0
FEMA.Floodzone	0.07	0.03	2.64	0.008
Behavior				
underestimate.storm	1.00 +			
lack.transport	0.11	0.02	6.05	0
underestimate.disruptions	0.49	0.05	10.24	0
supply.costs	0.33	0.04	8.49	0
storage.space	0.19	0.03	6.5	0
supply.shortage	0.67	0.06	10.81	0
FEW_Vulnerability				
road.hardship	1.00 +			
power.hardship	0.75	0.08	9.08	0
water.hardship	0.7	0.07	9.76	0
food.hardship	1.22	0.09	12.93	0
Regression Slopes				
FEW_Vulnerability				
Infra.disruption	1.52	0.33	4.56	0
Behavior	0.67	0.2	3.32	0.001
Behavior				
Urban.attributes	0.29	0.07	4.28	0
Infra.disruption				
Urban.attributes	0.48	0.12	3.88	0
	Residual Variances			
days.water	1.56	0.29	5.39	0
days.power	2.63	0.54	4.87	0
days.food	12.9	1.35	9.56	0
days.transport	21.52	2.62	8.22	0
grocery.dist	11.85	4.12	2.88	0.004
proxim.flood.infra	0.25	0	115.06	0
proxim.industrial.plant	0.07	0.01	8.94	0
Infra.Fail.Risk	10.81	1.07	10.14	0
FEMA.Floodzone	0.16	0.01	18.64	0
underestimate.storm	0.1	0.01	7.51	0
lack.transport	0.02	0	3.57	0
underestimate.disruptions	0.07	0.01	7.78	0
supply.costs	0.07	0.01	8.12	0
storage.space	0.05	0.01	7.2	0
supply.shortage	0.1	0.01	9.76	0
road.hardship	0.69	0.11	6.5	0
power.hardship	0.92	0.08	10.98	0
water.hardship	0.72	0.09	8.42	0
food.hardship	0.35	0.13	2.67	0.008
num.grocery	0.32	0.06	5.73	0
	Residual Covariances			
days.water w/days.power	0.46	0.17	2.8	0.005
days.food w/days.transport	2.83	0.9	3.16	0.002
days.transport w/road.hardship	1.24	0.26	4.74	0
days.water w/water.hardship	0.34	0.08	4.57	0
days.power w/power.hardship	0.74	0.13	5.77	0
days.food w/food.hardship	0.93	0.2	4.58	0
power.hardship w/water.hardship	0.29	0.07	4.27	0
road.hardship w/food.hardship	−0.34	0.1	−3.46	0.001
days.water w/power.hardship	0.2	0.08	2.71	0.007
days.power w/water.hardship	0.32	0.12	2.72	0.007
days.food w/underestimate.storm	0.26	0.07	3.53	0
proxim.flood.infra w/FEMA.Floodzone	0.04	0.01	5.92	0
FEMA.Floodzone w/road.hardship	0.07	0.02	3.82	0
days.transport w/proxim.flood.infra	0.21	0.08	2.54	0.011
days.transport w/underestimate.storm	0.24	0.08	2.92	0.003
supply.shortage w/num.grocery	−0.01	0.01	−1.86	0.062
days.food w/supply.shortage	0.25	0.06	3.89	0
road.hardship w/water.hardship	−0.14	0.07	−2.06	0.039
proxim.flood.infra w/road.hardship	0.06	0.02	2.86	0.004

(continued on next page)

Table A1 (*continued*)

Model 1				
proxim.industrial.plant w/FEMA.Floodzone	0.01	0	2.55	0.011
Latent Variances				
Infra.disruption	0.07	0.03	2.39	0.017
Urban.attributes	0.3	0.11	2.66	0.008
Behavior	0.06	0.01	6.4	0
FEW.Vulnerability	0.19	0.08	2.28	0.023
	Fit Indices			
$\chi 2$	132.41(147)			0.8
CFI	1			
TLI	1.01			
RMSEA	0			
$^{+}$Fixed parameter				
Model 2	Estimate	Std. Err.	z	p
	Factor Loadings			
Infra.disruption				
days.water	1.00^{+}			
days.power	1.71	0.28	6.06	0
days.food	3.1	0.57	5.41	0
days.transport	2.92	0.58	4.99	0
Behavior				
underestimate.storm	1.00^{+}			
lack.transport	0.13	0.02	6.91	0
underestimate.disruptions	0.5	0.05	10.71	0
supply.costs	0.37	0.04	9.45	0
storage.space	0.19	0.03	6.63	0
supply.shortage	0.66	0.06	11.24	0
FEW_Vulnerability				
road.hardship	1.00^{+}			
power.hardship	0.82	0.08	10.13	0
water.hardship	0.77	0.07	10.96	0
food.hardship	1.22	0.09	13.65	0
Urban_attributes				
Infra.Fail.Risk	1.00^{+}			
FEMA.Floodzone	0.02	0.01	2.97	0.003
grocery.dist	0.29	0.06	5	0
proxim.flood.infra	0.03	0.01	3.6	0
proxim.industrial.plant	0.03	0.01	6.2	0
Regression Slopes				
Behavior				
Urban.attributes	0.08	0.02	3.62	0
Minority	0.09	0.02	4.1	0
Education	−0.02	0.01	−2	0.045
Income	−0.02	0.01	−2.37	0.018
Infra.disruption				
Urban.attributes	0.13	0.04	3.15	0.002
FEW_Vulnerability				
Urban.attributes	0.27	0.07	3.77	0
Minority	0.26	0.05	5.36	0
Education	−0.05	0.02	−3.16	0.002
Income	−0.03	0.01	−2.3	0.021
	Residual Variances			
days.water	1.54	0.29	5.28	0
days.power	2.54	0.55	4.65	0
days.food	12.81	1.37	9.36	0
days.transport	21.41	2.63	8.14	0
underestimate.storm	0.1	0.01	8.12	0
lack.transport	0.02	0	3.5	0
underestimate.disruptions	0.07	0.01	7.89	0
supply.costs	0.06	0.01	7.84	0
storage.space	0.05	0.01	7.23	0
supply.shortage	0.1	0.01	10.24	0
road.hardship	0.75	0.1	7.84	0
power.hardship	0.89	0.08	10.59	0
water.hardship	0.68	0.09	7.94	0
food.hardship	0.43	0.11	3.83	0
Infra.Fail.Risk	10.81	1.25	8.65	0
FEMA.Floodzone	0.16	0.01	18.62	0
grocery.dist	11.86	4.12	2.88	0.004
proxim.flood.infra	0.25	0	114.29	0
proxim.industrial.plant	0.07	0.01	8.89	0
num.grocery	0.32	0.06	5.73	0
Minority	0.24	0	68.01	0
Education	3.07	0.12	26.06	0
Income	3.63	0.13	27.29	0
	Residual Covariances			

(*continued on next page*)

Table A1 (*continued*)

Model 1				
days.water w/days.power	0.42	0.17	2.43	0.015
days.food w/days.transport	2.73	0.92	2.96	0.003
days.transport w/road.hardship	1.28	0.26	4.96	0
days.water w/water.hardship	0.33	0.08	4.36	0
days.power w/power.hardship	0.71	0.13	5.56	0
days.food w/food.hardship	1.01	0.2	5.08	0
power.hardship w/water.hardship	0.26	0.07	3.75	0
road.hardship w/food.hardship	−0.27	0.09	−3.1	0.002
days.water w/power.hardship	0.19	0.08	2.54	0.011
days.power w/water.hardship	0.3	0.12	2.48	0.013
days.food w/underestimate.storm	0.27	0.07	3.62	0
FEMA.Floodzone w/proxim.flood.infra	0.04	0.01	5.91	0
road.hardship w/FEMA.Floodzone	0.07	0.02	3.79	0
days.transport w/proxim.flood.infra	0.22	0.08	2.6	0.009
days.transport w/underestimate.storm	0.25	0.08	2.98	0.003
supply.shortage w/num.grocery	−0.01	0.01	−1.86	0.062
days.food w/supply.shortage	0.25	0.06	3.98	0
road.hardship w/water.hardship	−0.14	0.07	−2.19	0.028
road.hardship w/proxim.flood.infra	0.06	0.02	2.87	0.004
FEMA.Floodzone w/proxim.industrial.plant	0.01	0	2.52	0.012
Minority w/Education	−0.17	0.03	−5.85	0
Minority w/Income	−0.21	0.03	−6.97	0
Education w/Income	1.5	0.11	14.27	0
	Latent Variances			
Infra.disruption	0.1	0.05	2.16	0.031
Behavior	0.06	0.01	5.28	0
FEW.Vulnerability	0.28	0.09	3.07	0.002
Urban.attributes	3.52	0.94	3.76	0
Latent Covariances				
Infra.disruption w/Behavior	0	0.01	0.27	0.787
Infra.disruption w/FEW.Vulnerability	0.1	0.04	2.39	0.017
Behavior w/FEW.Vulnerability	0.02	0.02	1.12	0.262
Constructed				
indirect.effect	0.01	0.01	1.83	0.068
Total.effect	0.28	0.08	3.66	0
	Fit Indices			
χ2	267.75(199)			0.001
CFI	0.97			
TLI	0.97			
RMSEA	0.02			

+ Fixed parameter.

risk measures are more prevalent in households experiencing greater FEW-vulnerability? Structural equation models were used to measure the magnitude of the proposed pathways of the Nexus-Disaster framework based on the feedback of the ANOVA results. In summary, certain measures of disaster risk were found to be more prevalent in households experiencing significant levels of FEW vulnerability, whereas the structural equation models supported the theorized pathways between the disaster risk and infrastructure nexus constructs of the proposed conceptual model guiding this research study. The following discussion highlights significant findings and their implications with respect to the existing disaster literature.

5.1. Pre-disaster conditions influence household vulnerability to FEW disruptions

Urban attributes influence household vulnerability by increasing the duration of disruptions and diminishing the ability for disaster preparations of each household. Based on the results, preparation behaviors, duration of infrastructure disruptions, and the urban attributes of communities collectively contribute to the FEW- vulnerability of households during a hurricane.

Vulnerable households were more likely to reside in close proximity to flood control infrastructures such as bayous or dams, FEMA designated flood zones and areas of low social, health, and community services as defined by the Houston SocioNeeds Index. Interestingly, vulnerable households were more likely to report higher perceived risk to infrastructure system failures. This may indicate their experience of disruptions in FEW infrastructure systems overall. They also lived further from the grocery stores and experienced supply shortages at grocery stores during storm preparation.

The bivariate analysis conducted using ANOVA one-way tests confirms that preparation behaviors are significant indicators of household vulnerability to FEW disruptions during disasters. The duration of preparation and extent of preparedness actions taken by households varied only slightly across the FEW infrastructure vulnerability thresholds and did not appear to be significant indicators of household vulnerability to infrastructure disruptions. On the other hand, preparation behaviors appear to play a significant role in determining the vulnerability of households to food, energy, and water disruptions, however, the duration of preparation and the number of preparation actions households took do not appear to be strong indicators of vulnerability. According to the ANOVA one-way tests, the average preparation days are not statistically significantly different across households scoring low in vulnerability and high. Similarly, households regardless of vulnerability status appear to have similar behavior and demand with regards to the need for water, energy, and food resources immediately before, during, and after the storm. However, it did appear that households scoring higher in vulnerability were more likely to report needing power, transportation, and water for health purposes compared to low vulnerability households. Fothergill and Peek (2004) noted similar findings in their research investigating preparedness behaviors before Hurricane Andrew in 1992. They found the type of preparedness activities and their timing were consistent across different income groups.

Table A2
Model 3 (Control for Children) & Model 4 (Control for Health – Disability).

Model 3	Estimate	Std. Err.	z	p
	Factor Loadings			
Infra.disruption				
days.water	1.00+			
days.power	1.68	0.28	6.07	0
days.food	3.28	0.59	5.51	0
days.transport	3.07	0.6	5.09	0
Urban_attributes				
grocery.dist	1.00+			
proxim.flood.infra	0.1	0.03	3.12	0.002
proxim.industrial.plant	0.12	0.03	4.38	0
Infra.Fail.Risk	3.44	0.68	5.04	0
FEMA.Floodzone	0.07	0.03	2.64	0.008
Behavior				
underestimate.storm	1.00+			
lack.transport	0.11	0.02	6.15	0
underestimate.disruptions	0.49	0.05	10.36	0
supply.costs	0.34	0.04	8.76	0
storage.space	0.19	0.03	6.61	0
supply.shortage	0.68	0.06	11.04	0
FEW_Vulnerability				
road.hardship	1.00+			
power.hardship	0.73	0.08	9.22	0
water.hardship	0.68	0.07	9.95	0
food.hardship	1.2	0.09	13.18	0
	Regression Slopes			
FEW_Vulnerability				
Infra.disruption	1.59	0.35	4.54	0
Behavior	0.6	0.22	2.68	0.007
Kids	0.13	0.04	2.89	0.004
Behavior				
Urban.attributes	0.29	0.07	4.28	0
Kids	0.09	0.02	4.53	0
Infra.disruption				
Urban.attributes	0.48	0.12	3.88	0
	Residual Variances			
days.water	1.56	0.29	5.4	0
days.power	2.63	0.54	4.89	0
days.food	12.91	1.35	9.58	0
days.transport	21.52	2.62	8.22	0
grocery.dist	11.85	4.12	2.88	0.004
proxim.flood.infra	0.25	0	114.63	0
proxim.industrial.plant	0.07	0.01	8.94	0
Infra.Fail.Risk	10.81	1.07	10.13	0
FEMA.Floodzone	0.16	0.01	18.63	0
underestimate.storm	0.1	0.01	7.77	0
lack.transport	0.02	0	3.57	0
underestimate.disruptions	0.07	0.01	7.89	0
supply.costs	0.07	0.01	8.03	0
storage.space	0.05	0.01	7.2	0
supply.shortage	0.1	0.01	9.69	0
road.hardship	0.67	0.11	6.18	0
power.hardship	0.92	0.08	11.14	0
water.hardship	0.72	0.09	8.48	0
food.hardship	0.34	0.13	2.67	0.008
num.grocery	0.32	0.06	5.73	0
Kids	0.58	0.07	7.96	0
	Residual Covariances			
days.water w/days.power	0.47	0.16	2.83	0.005
days.food w/days.transport	2.84	0.9	3.16	0.002
days.transport w/ road.hardship	1.22	0.26	4.66	0
days.water w/ water.hardship	0.34	0.07	4.6	0
days.power w/ power.hardship	0.74	0.13	5.83	0
days.food w/food.hardship	0.94	0.2	4.61	0
power.hardship w/ water.hardship	0.3	0.07	4.35	0
road.hardship w/ food.hardship	−0.35	0.1	−3.59	0
days.water w/ power.hardship	0.21	0.07	2.75	0.006
days.power w/ water.hardship	0.33	0.12	2.75	0.006

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Table A2 (*continued*)

Model 3	Estimate	Std. Err.	z	p
days.food w/ underestimate.storm	0.26	0.07	3.55	0
proxim.flood.infra w/ FEMA.Floodzone	0.04	0.01	5.92	0
FEMA.Floodzone w/ road.hardship	0.07	0.02	3.79	0
days.transport w/ proxim.flood.infra	0.21	0.08	2.53	0.011
days.transport w/ underestimate.storm	0.24	0.08	2.93	0.003
supply.shortage w/ num.grocery	−0.01	0.01	−1.86	0.062
days.food w/ supply.shortage	0.25	0.06	3.87	0
road.hardship w/ water.hardship	−0.14	0.07	−2.16	0.031
proxim.flood.infra w/ road.hardship	0.06	0.02	2.83	0.005
proxim.industrial.plant w/ FEMA.Floodzone	0.01	0	2.54	0.011
	Latent Variances			
Infra.disruption	0.06	0.03	2.38	0.017
Urban.attributes	0.3	0.11	2.67	0.008
Behavior	0.06	0.01	6.11	0
FEW.Vulnerability	0.19	0.09	2.16	0.031
	Fit Indices			
χ^2	165.15(165)			0.482
CFI	1			
TLI	1			
RMSEA	0			

+Fixed parameter

Model 4

	Estimate	Std. Err.	z	p
	Factor Loadings			
Infra.disruption				
days.water	1.00+			
days.power	1.68	0.28	6.07	0
days.food	3.29	0.6	5.51	0
days.transport	3.08	0.6	5.09	0
Urban_attributes				
grocery.dist	1.00+			
proxim.flood.infra	0.1	0.03	3.11	0.002
proxim.industrial.plant	0.12	0.03	4.37	0
Infra.Fail.Risk	3.44	0.68	5.03	0
FEMA.Floodzone	0.07	0.03	2.64	0.008
Behavior				
underestimate.storm	1.00+			
lack.transport	0.11	0.02	6.18	0
underestimate.disruptions	0.49	0.05	10.27	0
supply.costs	0.33	0.04	8.6	0
storage.space	0.19	0.03	6.54	0
supply.shortage	0.67	0.06	10.9	0
FEW_Vulnerability				
road.hardship	1.00+			
power.hardship	0.73	0.08	9.15	0
water.hardship	0.67	0.07	9.77	0
food.hardship	1.22	0.09	13.11	0
	Regression Slopes			
FEW_Vulnerability				
Infra.disruption	1.56	0.34	4.56	0
Behavior	0.65	0.21	3.13	0.002
disability.health	0.17	0.07	2.53	0.011
Behavior				
Urban.attributes	0.29	0.07	4.28	0
disability.health	0.09	0.03	3.37	0.001
Infra.disruption				
Urban.attributes	0.48	0.12	3.88	0
Residual Variances				
days.water	1.56	0.29	5.4	0
days.power	2.63	0.54	4.88	0
days.food	12.89	1.35	9.55	0
days.transport	21.5	2.62	8.21	0
grocery.dist	11.85	4.12	2.88	0.004
proxim.flood.infra	0.25	0	114.73	0
proxim.industrial.plant	0.07	0.01	8.94	0

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Table A2 (*continued*)

Model 3	Estimate	Std. Err.	z	p
Infra.Fail.Risk	10.81	1.07	10.14	0
FEMA.Floodzone	0.16	0.01	18.63	0
underestimate.storm	0.1	0.01	7.64	0
lack.transport	0.02	0	3.56	0
underestimate.disruptions	0.07	0.01	7.85	0
supply.costs	0.07	0.01	8.08	0
storage.space	0.05	0.01	7.2	0
supply.shortage	0.1	0.01	9.73	0
road.hardship	0.67	0.11	6.23	0
power.hardship	0.92	0.08	11.07	0
water.hardship	0.73	0.08	8.67	0
food.hardship	0.33	0.13	2.52	0.012
num.grocery	0.32	0.06	5.73	0
disability.health	0.14	0.01	16.59	0
	Residual Covariances			
days.water w/days.power	0.46	0.17	2.82	0.005
days.food w/days.transport	2.82	0.9	3.14	0.002
days.transport w/ road.hardship	1.22	0.26	4.68	0
days.water w/ water.hardship	0.35	0.07	4.65	0
days.power w/ power.hardship	0.74	0.13	5.81	0
days.food w/food.hardship	0.93	0.2	4.54	0
power.hardship w/ water.hardship	0.3	0.07	4.42	0
road.hardship w/ food.hardship	−0.36	0.1	−3.59	0
days.water w/ power.hardship	0.21	0.07	2.74	0.006
days.power w/ water.hardship	0.33	0.12	2.8	0.005
days.food w/ underestimate.storm	0.26	0.07	3.54	0
proxim.flood.infra w/ FEMA.Floodzone	0.04	0.01	5.92	0
FEMA.Floodzone w/ road.hardship	0.07	0.02	3.8	0
days.transport w/ proxim.flood.infra	0.21	0.08	2.53	0.011
days.transport w/ underestimate.storm	0.24	0.08	2.92	0.003
supply.shortage w/ num.grocery	−0.01	0.01	−1.86	0.062
days.food w/ supply.shortage	0.25	0.06	3.88	0
road.hardship w/ water.hardship	−0.13	0.07	−2.02	0.044
proxim.flood.infra w/ road.hardship	0.06	0.02	2.84	0.004
proxim.industrial.plant w/ FEMA.Floodzone	0.01	0	2.54	0.011
	Latent Variances			
Infra.disruption	0.06	0.03	2.4	0.016
Urban.attributes	0.3	0.11	2.66	0.008
Behavior	0.06	0.01	6.33	0
FEW.Vulnerability	0.2	0.09	2.27	0.023
	Fit Indices			
χ2	157.95(165)			0.639
CFI	1			
TLI	1			
RMSEA	0			

[+] Fixed parameter.

This finding demonstrates the need for infrastructure systems to address the needs of vulnerable population communities to ensure better livability before and after disruptive events like hurricanes. In terms of policy development, this translates to building and redesigning city infrastructure (such as grocery stores) in ways that cater to population needs (i.e. human-centric planning) and for city planners to address and social inequities that already exist in communities.

5.2. Prior disaster experience is a significant indicator of preparation behaviors and vulnerability

Not being able to prepare enough due to shortages of supplies at grocery stores was positively correlated to the reported duration of food infrastructure disruptions. Physical attributes (β = 0.290, p = 0.000) and prior experience (β = -0.120, p = 0.000) with disasters were found to be the most significant indicators of poor preparation behavior. While sociodemographic characteristics of households were shown to

Table A3
Model 5 (Control for Children) & Model 6 (Control for Health – Disability).

Model 5	Estimate	Std. Err.	z	p
	Factor Loadings			
Infra.disruption				
days.water	1.00+			
days.power	1.68	0.28	6.07	0
days.food	3.25	0.59	5.5	0
days.transport	3.02	0.59	5.08	0
Urban_attributes				
grocery.dist	1.00+			
proxim.flood.infra	0.1	0.03	3.12	0.002
proxim.industrial.plant	0.12	0.03	4.37	0
Infra.Fail.Risk	3.46	0.69	5.03	0
FEMA.Floodzone	0.07	0.03	2.64	0.008
Behavior				
underestimate.storm	1.00+			
lack.transport	0.11	0.02	5.97	0
underestimate.disruptions	0.49	0.05	10.33	0
supply.costs	0.32	0.04	8.55	0
storage.space	0.19	0.03	6.54	0
supply.shortage	0.67	0.06	10.96	0
FEW_Vulnerability				
road.hardship	1.00+			
power.hardship	0.76	0.08	9.23	0
water.hardship	0.72	0.07	9.98	0
food.hardship	1.23	0.09	13.02	0
Regression Slopes				
FEW_Vulnerability				
Infra.disruption	1.54	0.34	4.55	0
Behavior	0.6	0.21	2.91	0.004
prior.experience	−0.23	0.07	−3.19	0.001
Behavior				
Urban.attributes	0.29	0.07	4.28	0
prior.experience	−0.12	0.03	−4.09	0
Infra.disruption				
Urban.attributes	0.48	0.12	3.88	0
	Residual Variances			
days.water	1.56	0.29	5.39	0
days.power	2.63	0.54	4.87	0
days.food	12.92	1.35	9.58	0
days.transport	21.54	2.62	8.23	0
grocery.dist	11.85	4.12	2.88	0.004
proxim.flood.infra	0.25	0	115.32	0
proxim.industrial.plant	0.07	0.01	8.94	0
Infra.Fail.Risk	10.81	1.07	10.13	0
FEMA.Floodzone	0.16	0.01	18.64	0
underestimate.storm	0.1	0.01	7.42	0
lack.transport	0.02	0	3.59	0
underestimate.disruptions	0.07	0.01	7.82	0
supply.costs	0.07	0.01	8.15	0
storage.space	0.05	0.01	7.21	0
supply.shortage	0.1	0.01	9.7	0
road.hardship	0.71	0.1	6.81	0
power.hardship	0.92	0.08	10.97	0
water.hardship	0.71	0.09	8.25	0
food.hardship	0.36	0.13	2.83	0.005
num.grocery	0.32	0.06	5.73	0
prior.experience	0.13	0.01	15.24	0
	Residual Covariances			
days.water w/days.power	0.46	0.17	2.8	0.005
days.food w/days.transport	2.85	0.9	3.18	0.001
days.transport w/ road.hardship	1.25	0.26	4.79	0
days.water w/ water.hardship	0.34	0.08	4.5	0
days.power w/ power.hardship	0.73	0.13	5.75	0
days.food w/food.hardship	0.94	0.2	4.62	0
power.hardship w/ water.hardship	0.29	0.07	4.16	0
road.hardship w/ food.hardship	−0.32	0.1	−3.39	0.001
days.water w/ power.hardship	0.2	0.08	2.68	0.007

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Table A3 (*continued*)

Model 5				
	Estimate	Std. Err.	z	p
days.power w/ water.hardship	0.32	0.12	2.65	0.008
days.food w/ underestimate.storm	0.26	0.07	3.52	0
proxim.flood.infra w/ FEMA.Floodzone	0.04	0.01	5.92	0
FEMA.Floodzone w/ road.hardship	0.07	0.02	3.83	0
days.transport w/ proxim.flood.infra	0.21	0.08	2.54	0.011
days.transport w/ underestimate.storm	0.24	0.08	2.92	0.004
supply.shortage w/ num.grocery	−0.01	0.01	−1.86	0.062
days.food w/ supply.shortage	0.25	0.06	3.87	0
road.hardship w/ water.hardship	−0.14	0.07	−2.11	0.035
proxim.flood.infra w/ road.hardship	0.06	0.02	2.88	0.004
proxim.industrial.plant w/ FEMA.Floodzone	0.01	0	2.55	0.011
	Latent Variances			
Infra.disruption	0.06	0.03	2.37	0.018
Urban.attributes	0.29	0.11	2.66	0.008
Behavior	0.06	0.01	6.3	0
FEW.Vulnerability	0.17	0.08	2.12	0.034
	Fit Indices			
χ2	172.31(165)			0.332
CFI	1			
TLI	1			
RMSEA	0.01			
+Fixed parameter				

Model 6				
	Estimate	Std. Err.	z	p
	Factor Loadings			
Infra.disruption				
days.water	1.00+			
days.power	1.68	0.28	6.06	0
days.food	3.12	0.56	5.53	0
days.transport	2.94	0.58	5.09	0
Urban_attributes				
grocery.dist	1.00+			
proxim.flood.infra	0.1	0.03	3.14	0.002
proxim.industrial.plant	0.12	0.03	4.4	0
Infra.Fail.Risk	3.46	0.68	5.06	0
FEMA.Floodzone	0.07	0.03	2.64	0.008
Behavior				
underestimate.storm	1.00+			
lack.transport	0.13	0.02	7.04	0
underestimate.disruptions	0.49	0.04	10.93	0
supply.costs	0.38	0.04	9.89	0
storage.space	0.19	0.03	6.81	0
supply.shortage	0.67	0.06	11.7	0
FEW_Vulnerability				
road.hardship	1.00+			
power.hardship	0.79	0.08	10.46	0
water.hardship	0.75	0.07	11.31	0
food.hardship	1.2	0.09	14.15	0
	Regression Slopes			
FEW_Vulnerability				
Infra.disruption	1.62	0.36	4.55	0
Behavior	0.4	0.24	1.67	0.095
disability.health	0.13	0.07	1.97	0.049
prior.experience	−0.16	0.07	−2.11	0.035
Minority	0.19	0.06	3.32	0.001
Education	−0.04	0.02	−2.18	0.029
Income	−0.02	0.02	−1.55	0.12
Kids	0.08	0.04	1.88	0.06
Behavior				
Urban.attributes	0.28	0.06	4.31	0
disability.health	0.07	0.03	2.51	0.012
prior.experience	−0.08	0.03	−2.33	0.02

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Table A3 (*continued*)

Model 5	Estimate	Std. Err.	z	p
Minority	0.06	0.02	2.46	0.014
Education	−0.01	0.01	−1.22	0.224
Income	−0.01	0.01	−2.03	0.042
Kids	0.06	0.02	3.35	0.001
Infra.disruption				
Urban.attributes	0.48	0.12	3.9	0
	Residual Variances			
days.water	1.56	0.29	5.39	0
days.power	2.63	0.54	4.87	0
days.food	13.02	1.34	9.71	0
days.transport	21.6	2.62	8.26	0
grocery.dist	11.85	4.12	2.88	0.004
proxim.flood.infra	0.25	0	114.27	0
proxim.industrial.plant	0.07	0.01	8.92	0
Infra.Fail.Risk	10.74	1.08	9.98	0
FEMA.Floodzone	0.16	0.01	18.64	0
underestimate.storm	0.1	0.01	8.41	0
lack.transport	0.02	0	3.52	0
underestimate.disruptions	0.07	0.01	8.08	0
supply.costs	0.06	0.01	7.74	0
storage.space	0.05	0.01	7.23	0
supply.shortage	0.1	0.01	10.11	0
road.hardship	0.73	0.1	7.56	0
power.hardship	0.89	0.08	10.82	0
water.hardship	0.69	0.08	8.12	0
food.hardship	0.42	0.11	3.74	0
num.grocery	0.32	0.06	5.73	0
disability.health	0.14	0.01	16.58	0
prior.experience	0.13	0.01	15.24	0
Minority	0.24	0	68.01	0
Education	3.07	0.12	26.06	0
Income	3.63	0.13	27.29	0
Kids	0.58	0.07	7.95	0
	Residual Covariances			
days.water w/days.power	0.46	0.17	2.8	0.005
days.food w/days.transport	2.93	0.89	3.29	0.001
days.transport w/ road.hardship	1.25	0.26	4.83	0
days.water w/ water.hardship	0.33	0.08	4.36	0
days.power w/ power.hardship	0.72	0.13	5.61	0
days.food w/food.hardship	0.98	0.2	4.95	0
power.hardship w/ water.hardship	0.27	0.07	3.91	0
road.hardship w/ food.hardship	−0.29	0.09	−3.31	0.001
days.water w/ power.hardship	0.19	0.08	2.53	0.011
days.power w/ water.hardship	0.3	0.12	2.52	0.012
days.food w/ underestimate.storm	0.27	0.07	3.69	0
proxim.flood.infra w/ FEMA.Floodzone	0.04	0.01	5.92	0
FEMA.Floodzone w/ road.hardship	0.07	0.02	3.85	0
days.transport w/ proxim.flood.infra	0.21	0.08	2.54	0.011
days.transport w/ underestimate.storm	0.25	0.08	3.03	0.002
supply.shortage w/ num.grocery	−0.01	0.01	−1.86	0.062
days.food w/ supply.shortage	0.25	0.06	3.99	0
road.hardship w/ water.hardship	−0.15	0.06	−2.26	0.024
proxim.flood.infra w/ road.hardship	0.06	0.02	2.89	0.004
proxim.industrial.plant w/ FEMA.Floodzone	0.01	0	2.54	0.011
disability.health w/ prior.experience	0.01	0	2.43	0.015

(*continued on next page*)

Table A3 (*continued*)

Model 5

	Estimate	Std. Err.	z	p
disability.health w/ Minority	0	0.01	0.07	0.947
disability.health w/ Education	−0.1	0.02	−4.03	0
disability.health w/Income	−0.12	0.02	−4.96	0
disability.health w/Kids	0.02	0.01	1.5	0.132
prior.experience w/ Minority	−0.03	0.01	−5.27	0
prior.experience w/ Education	0.09	0.02	3.88	0
prior.experience w/Income	0.07	0.02	2.89	0.004
prior.experience w/Kids	−0.04	0.01	−3.56	0
Minority w/Education	−0.17	0.03	−5.85	0
Minority w/Income	−0.21	0.03	−6.97	0
Minority w/Kids	0.09	0.01	6.21	0
Education w/Income	1.5	0.11	14.27	0
Education w/Kids	−0.17	0.05	−3.55	0
Income w/Kids	−0.12	0.05	−2.32	0.021
	Latent Variances			
Infra.disruption	0.06	0.03	2.39	0.017
Urban.attributes	0.3	0.11	2.68	0.007
Behavior	0.05	0.01	5.96	0
FEW.Vulnerability	0.12	0.08	1.44	0.149
	Fit Indices			
χ^2	367.20(255)			0
CFI	0.96			
TLI	0.95			
RMSEA	0.02			

[+] Fixed parameter.

have a statistically significant association in the pathways leading to FEW-vulnerability and with FEW-vulnerability itself, prior disaster experience was found to be a stronger indicator of FEW-vulnerability and preparation behaviors overall. This means that holding socio-demographic characteristics constant, households with prior disaster experience are less likely to be vulnerable to FEW disruptions. This finding is in agreement with past research which has shown that direct experience of a disaster can be a strong motivator of preparedness (Becker, Paton, Johnston, Ronan, & McClure, 2017). Several preparedness theories and approaches suggest that prior experience of earthquakes and other disasters influences the preparedness process (Rogers, 1983; Mulilis et al., 2003; Lindell & Perry, 2012).

5.3. Social vulnerability explains the extent of preparedness actions and influences FEW vulnerability

Through the bivariate and multivariate analysis, household FEW vulnerabilities were found to be statistically significantly associated with vulnerable population groups, namely: less-educated, racial minorities, lower-income households, households with young children, and households with disabled and limited mobility members. In terms of preparation behaviors, vulnerable households were less likely to have power backups and had greater dependencies on FEW resources for health-related purposes. Related to preparation behaviors, vulnerable households also had a greater tendency to underestimate the impact of the disaster and expressed having more barriers to storm preparation. They were more likely to report “not being prepared enough,” due to either cost of supplies at stores, supply shortages at the stores, underestimating storm impact, lack of transportation to stores, or a combination of these factors. This finding provides a critical perspective to previous research findings which have concluded that vulnerable populations are less likely to prepare for disasters (Ballen, 2009). Some research has found residents of low social and economic status to be less prepared than other residents for disasters. This study shows that level of preparation has more to do with the existing services and access to services and supplies (urban attributes) before the storm. Being less prepared has less to do with the duration of preparation. Preparation depends on costs, availability of supplies at stores, access to reliable transportation, access to adequate storage. This is also supported by research conducted by Gladwin and Peacock (1997), in which the time between beginning preparation and the onset of the hurricane did not vary significantly by socioeconomic status, in this case, measured by income.

The findings are aligned with the outcomes of other research showing that certain demographic characteristics determine necessities to prepare and associated with an increase in the likelihood of preparednessfor an example, having dependent members in the home (Ablah et al., 2009; Hoffmann and Muttarak, 2017) and having children (Basolo et al., 2009; Eisenman et al., 2009). The outcomes of prior studies provide context to the finding that vulnerable households were more likely to report needing or using FEW resources for health-related purposes.

5.4. Infrastructure disruptions and hardship experienced are interconnected

Of all of the nexus system interactions, water and power appear to have the strongest interdependency. The duration of water disruption experienced by households and power outages were statistically significant ($\beta = 0.460$, $p = 0.005$), as were the hardships experienced for both: the reported hardship experienced due power outages was positively correlated to experiencing water hardships ($\beta = 0.290$, $p = 0.000$). These positive and statistically significant correlations provide empirical evidence related to the strong linkage of water and power in the context of hurricanes and flooding disasters. Similarly, we observe that increasing the duration of water outages leads to an increase in power hardship ($\beta = 0.200$, $p = 0.007$), whereas the relationship between power outage duration and water hardship is slightly stronger ($\beta = 0.320$, $p = 0.008$). Interestingly, there is a negative relationship between transportation hardship and food hardship (β = -0.320 $p = 0.001$). It appears that food hardship was greatly determined by pre-disaster conditions of grocery stores: stores already facing shortages prior to the storm were perhaps less likely to have supplies during and immediately after the storm, therefore increasing the extent of hardship and duration faced by households (supply shortage ∼∼ food duration, $\beta = .250$, $p = 0.000$). Transportation hardship appears to be independent of FEW infrastructure systems considered in this study.

Households who had water shutoffs were especially vulnerable to hardship in all areas. The deficiency of clean water may have made food preparation more difficult: some food needs to be washed before consumption or needs to be boiled. One cause of water hardship could be water facilities relying on the output from power sources; a power outage may have affected water utilities nearby and caused dual disruption. Most pumps and wastewater treatment plants rely on the power grid to function and may not all have a backup generator (Miles et al., 2015). A power outage could have also made it difficult to heat water in a household that uses only electric appliances. This made hygiene, laundry, and food preparation and sanitation much more difficult. Plus, if a household was unable to boil their water when they have a boil notice, their access to clean water was limited.

Households that experienced greater FEW vulnerability experienced longer disruptions across all infrastructure services compared to households that reported none to minimal hardship due to the respective service. For example, Table 3 shows that on average, households in the upper percentile range of FEW vulnerability experienced 7.57 days of disruptions to transportation services, while households in the lower percentile range of FEW vulnerability experienced on average of 3.26 days of disrupted services. This relationship is also apparent in the results of the structural equation models, where the latent variable, infrastructure disruptions, is positively associated with the latent variable, FEW vulnerability. The structural equation model also justifies the proposed relationship between urban attributes and disruptions. The assumption was that urban attributes measure the quality of services and the living environment of the households. The model proposed that the infrastructure disruptions along with the duration of the disruption are influenced by the urban or physical attributes of a household's community or surrounding environment. Across each model analyzed, this proposed pathway was supported, being positively correlated.

5.5. Study limitations

To the best of the authors' knowledge, this study was the first attempt to assess FEW system interactions and impact at the household level in the context of a natural disaster. The analysis can be improved upon by integrating other data types into the modeling and analysis, such as measures for physical attributes of cities that might not be accurately depicted by households due to lack of knowledge or concern. Despite the limitations presented, this study was able to successfully identify the foundation of a causal model using SEM. The results show that there are additional variables that may influence vulnerability. There are other factors of disaster risk which were not explored in this paper, particularly social capital and information distribution, which may be significant indicators of FEW vulnerability. It is apparent that there are additional factors that influence a household's resilience to infrastructure disruptions and impact brought on by disasters. The results hint at the idea that vulnerability is not a factor of disruptions alone, but a result of complex interactions between a household and its access to certain services, proximity to hazardous areas, and access to food and water services. While the bivariate analysis shows that more vulnerable households are more likely to display more vulnerable characteristics, in the presented SEM model, sociodemographic characteristics do not appear to have as significant of a role as anticipated. Preparation actions were found to have a significant direct role in determining FEW-vulnerability. Further investigation is needed to understand which factors determined why certain households were not able to prepare sufficiently for the hurricane event.

6. Conclusion

The results of the model specified the effects of infrastructure disruptions on households' access and use of FEW resources and informed about the household-level attributes and behaviors that shape demand and access to FEW resources in the context of natural hazards. As a result, the following gaps in our understanding of FEW nexus system interactions and vulnerabilities at the household level were addressed: (1) urban attributes and disaster characteristics influence the sensitivity of vulnerable populations to FEW system disruptions, (2) the nature and extent interdependencies among urban food, energy, and water systems influencing households' demand and access to these critical resources during extreme weather events, (3) the cascading effects of disruptions in one system of FEW nexus on households' demand and access to resources from other systems, (4) the preparation behaviors that influence the extent of impact experience by FEW disruptions.

Resiliency and disaster recovery planning for natural hazards entails navigating the complex interactions among the social and infrastructure systems that support our cities. Many overlapping factors are at play that collectively contribute to household vulnerability during disasters, as evident from the results and findings of the structural equation models. Most of these challenges can be mitigated by addressing inequities in infrastructure systems and social inequities. Given the future projections of more intense and frequent storms tied to climate change (Risser & Wehner, 2017), it is becoming more necessary to recognize infrastructure and system interdependencies as a component of disaster preparedness and resiliency. This study is part of an overall effort to better understand the effects that disasters have on people and communities as they relate to the built environment and social fabric of cities. Through the descriptive analysis and the development of SEM models based on the proposed FEW-Disaster framework, our empirical understanding of the nexus between F—E—W infrastructure systems and households during disasters has been refined. The urban attributes of communities play a significant role in the preparedness of households before the storm, which has significant implications on the overall vulnerability of households to FEW disruptions. Consequently, vulnerable population groups, particularly racial minorities, low-income households, households with young children, and households with a disabled resident(s) are at greater risk of disaster impacts due to FEW disruptions. The extent of preparation measured by the reported days of disruption and extent of preparation actions taken by households do not appear to mitigate vulnerabilities.

Findings from this research may be used to create a model for stakeholders and government leaders to simulate the effects of future disasters. By making disasters more predictable, funds can be allocated more efficiently, and policies can better prioritize protection for communities most affected by disasters. Fourth, the information collected in this study will provide a basis for developing a defensible empirical agent-based model (in future studies) in order to provide a robust analytical tool for decision-making and planning. This information is essential in identifying vulnerabilities and devising resilience- enhancing strategies to better cope with FEW nexus disruptions in disasters. This understanding will inform decision-makers and FEW resource providers to better prepare and respond to disruptions to minimize the impacts on households. This information is expected to inform plans that guide urban developments as well as resilience improvement investments to minimize the impacts caused by FEW disruptions on vulnerable populations.

Declaration of Competing Interest

The authors declare that there are no known conflicts of interest associated with this publication.

Acknowledgements

The authors would like to acknowledge the funding support from the National Science Foundation under grant number 1846069, NSF Sustainability Research Network (SRN) Cooperative Agreement1444758, and an Institutional Grant (NA18OAR4170088) of 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, conclusion, or recommendations expressed in this research are those of the authors and do not necessarily reflect the view of the funding agencies.

Appendix A

References

Ablah, E., Konda, K., & Kelley, C. L. (2009). Factors predicting individual emergency preparedness: a multi-state analysis of the 2006 BRFSS data. *Biosecur Bioterror, 7*, 317–330.

Alexander, D. (2012). Models of social vulnerability to disasters. *RCCS Annual Review*. https://doi.org/10.4000/rccsar.412.

Adelman, M., Ivaschenko, O., Packard, T. G., & Suri, V. (2015). Hardship and vulnerability in the Pacific island countries (English). *Washington, D.C*http://documents.worldbank.org/curated/en/649891468098658407/Hardship-and-vulnerability-in-the-Pacific-island-countries.

Apostolakis, G. E., & Lemon, D. M. (2005). A screening methodology for the identification and ranking of infrastructure vulnerabilities due to terrorism. *Risk Analysis, 25*(2), 361–376.

Baker, J. L. (2012). *Climate change, disaster risk, and the urban poor.* The World Bank.

Balaei, B., Wilkinson, S., Potangaroa, R., & McFarlane, P. (2020). Investigating the technical dimension of water supply resilience to disasters. *Sustainable Cities and Society.56.*. https://doi.org/10.1016/j.scs.2020.102077.

Basolo, V., Steinberg, L. J., Burby, R. J., Levine, J., Cruz, A. M., & Huang, C. (2009). The effects of confidence in government and information on perceived and actual preparedness for disasters. *Environment and Behavior, 41*(3), 338–364. https://doi.org/10.1177/0013916508317222.

Batouli, M., & Mostafavi, A. (2018). Multi-agent simulation for complex adaptive modeling of roadway infrastructure resilience to sea-level rise. *Journal of Computer-Aided Civil and Infrastructure Engineering, 33*(5), 17.

Becker, J. S., Paton, D., Johnston, D. M., Ronan, K. R., & McClure, J. (2017). The role of prior experience in informing and motivating earthquake preparedness. *International Journal of Disaster Risk Reduction, 22*, 179–193. https://doi.org/10.1016/j.ijdrr.2017.03.006.

Bergstrand, K., Mayer, B., Brumback, & Zhang, B. (2014). Assessing the Relationship Between Social Vulnerability and Community Resilience to Hazards. *Social Indicators Research, 122*. https://doi.org/10.1007/s11205-014-0698-3.

Blumenfeld, L., Hall, T., Henderson, H., Bressler, L., Moskos, C., Bhatia, U., & Ganguly, A. R. (2017). Climate and human stresses on the Water-energy-food nexus. In S. Shekhar, H. Xiong, & X. Zhou (Eds.). *Encyclopedia of GIS* (pp. 179–188). Cham: Springer International Publishing.

Cariolet, J. M., Vuillet, M., & Diab, Y. (2019). Mapping urban resilience to disasters – A review. *Sustainable Cities and Society, 51*, Article 101746. https://doi.org/10.1016/j.scs.2019.101746 ISSN 2210-6707.

Chang, S. E., McDaniels, T., Fox, J., Dhariwal, R., & Longstaff, H. (2014). Toward disaster-resilient cities: Characterizing resilience of infrastructure systems with expert judgments. *Risk Analysis, 34*, 416–434. https://doi.org/10.1111/risa.12133.

Ciurean, R. L., Schroter, D., & Glade, T. (2013). Conceptual Frameworks of Vulnerability Assessments for Natural Disasters Reduction. In J. Tiefenbacher (Ed.). *Approaches to Disaster Management—Examining the Implications of Hazards*. InTech: Emergencies and Disasters.

Cui, P., & Li, D. (2020). A SNA-based methodology for measuring the community resilience from the perspective of social capitals: Take Nanjing, China as an example. *Sustainable Cities and Society, 53*. https://doi.org/10.1016/j.scs.2019.101880.

Daher, B. T., & Mohtar, R. H. (2015). Water–Energy–Food (WEF) Nexus tool 2.0: Guiding integrative resource planning and decision-making. *Water International, 40*(5-6), 748–771. https://doi.org/10.1080/02508060.2015.1074148.

Dargin, J. S., & Mostafavi, A. (2020). Human-centric infrastructure resilience: Uncovering well-being risk disparity due to infrastructure disruptions in disasters. *PLOS ONE, 15*(6), https://doi.org/10.1371/journal.pone.0234381 e0234381.

Davis, C., Mostafavi, A., & Wang, H. (2018). Establishing characteristics to operationalize resilience for lifeline systems. *ASCE Natural Hazards Review, 19*(4).

Dong, S., Esmalian, A., Farahmand, H., & Mostafavi, A. (2019). An integrated physical-social analysis of disrupted access to critical facilities and community service-loss tolerance in urban flooding. *Computers, Environment and Urban Systems Journal*.

Dong, S., Wang, H., Mostafavi, A., & Gao, J. (2019). Impact of post-disaster network access to critical facilities on network robustness. *Journal of the Royal Society, Interface*. https://doi.org/10.1098/rsif.2019.0149.

Eisenman, D. P., Zhou, Q., Ong, M., Asch, S., Glik, D., & Long, A. (2009). Variations in disaster preparedness by mental health, perceived general health, and disability status. *Disaster Medicine and Public Health Preparedness, 3*(1), 33–41. https://doi.org/10.1097/DMP.0b013e318193be89.

Endo, A., Burnett, K., Orencio, P., Kumazawa, T., Wada, C., Ishii, A., ... Tsurita, I., et al. (2015). Methods of the water-energy-Food Nexus. *Water, 7*(10), 24. https://doi.org/10.3390/w7105806.

Ewing, R., Tian, G., Goates, J. P., Zhang, M., Greenwald, M. J., Joyce, A., & Greene, W. (2015). Varying influences of the built environment on household travel in 15 diverse regions of the United States. *Urban Studies, 52*(13), 2330–2348.

(EPA), E. P. A. (2013). *Providing Safe Drinking Water in America: 2013 National Public Water Systems Compliance Report*Office of Enforcement and Compliance Assurance EPA DOCUMENT 305R15001.

FEMA - U.S. Department of Homeland Security (2017). *Power outage incident annex to the response and recovery federal interagency operational plans: Managing the cascading impacts from a long-term power outage.* June. Power Outage Incident Annex. Access:https://www.fema.gov/media-library-data/1512398599047-7565406438d0820111177a9a2d4ee3c6/POIA_Final_7-2017v2_(Compliant_pda)_508.pdf.

Gray, W., and R. Shadbegian. 2010. When Do Firms Shift Production Across States to Avoid Environmental Regulation? U.S E.P.A. National Center for Environmental Economics mimeo.

Haime, Y. Y., & Jiang, P. (2001). Leontief-based model of risk in complex interconnected infrastructure. *Journal of Infrastructure Sys- tem, 7*(1), 1–12.

Handy, S. L., Boarnet, M. G., Ewing, R., & Killingsworth, R. E. (2002). How the built environment affects physical activity: Views from urban planning. *American Journal of Preventive Medicine, 23*(2, Supplement 1), 64–73. https://doi.org/10.1016/S0749-3797(02)00475-0.

Haraguchi, M., & Kim, S. (2016). Critical infrastructure interdependence in New York City during hurricane sandy. *International Journal of Disaster Resilience in the Built Environment, 7*(2), 10. https://doi.org/10.1108/IJDRBE-03-2015-0015.

Hersh, R. (1995). *Race and Industrial Hazards: A Historical Geography of the Pittsburgh Region, 1900-.* Discussion Paper 95-18. RFF.

Hoffmann, R., & Muttarak, R. (2017). Learn from the past, prepare for the future: Impacts of education and experience on disaster preparedness in the Philippines and Thailand. *World Development, 96*, 32–51. https://doi.org/10.1016/j.worlddev.2017.02.016.

Hussein, W. A., Memon, F. A., & Savic, D. A. (2017). An integrated model to evaluate water-energy-food nexus at a household scale. *Environmental Modelling & Software, 93*, 366–380. https://doi.org/10.1016/j.envsoft.2017.03.034.

Kontokosta, C., & Malik, A. (2018). The Resilience to Emergencies and Disasters Index: Applying big data to benchmark and validate neighborhood resilience capacity. *Sustainable Cities and Society, 36*, 272–285. https://doi.org/10.1016/j.scs.2017.10.025.

Lindell, M. K., & Perry, R. W. (2012). The protective action decision model: Theoretical modifications and additional evidence. *Risk Analysis, 32*(4), 616–632. https://doi.org/10.1111/j.1539-6924.2011.01647.x.

Naik, N. K., Kominers, S. D., Raskar, R., Glaeser, E. L., & Hidalgo, C. A. (2015). *Do people shape cities, or do cities shape people? The Co- evolution of physical, social, and economic change in five major U.S. Cities.* Harvard Kennedy School Faculty Research Working Paper Series, RWP15-061. Retrieved fromhttps://pdfs.semanticscholar.org/cd0d/fd293c6e3b8db9ec2c294212ef108c79c2f5.pdf.

Najafi, M., Ardalan, A., Akbarisari, A., Noorbala, A. A., & Elmi, H. (2017). The theory of planned behavior and disaster preparedness. *PLoS Currents, 9*. https://doi.org/10.1371/currents.dis.4da18e0f1479bf6c0a94b29e0dbf4a72 ecurrents.dis.4da18e10f1479bf1476c1470a1494b1429e1470dbf1474a1472.

Najafi, J., Peiravi, P., & Guerrero, J. P. (2018). Power distribution system improvement planning under hurricanes based on a new resilience index. *Sustainable Cities and Society, 39*, 592–604. https://doi.org/10.1016/j.scs.2018.03.022.

NIST (2016). *Community resilience planning guide for buildings and infrastructure systems.* Retrieved from Gaithersburg, MD.

Raman, S. (2010). Designing a liveable compact city: Physical forms of city and social life in urban neighbourhoods. *Built Environment (1978), 36*(1), 63–80. Retrieved from http://www.jstor.org/stable/23289984.

Rasoulkhani, K., & Mostafavi, A. (2018). 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*(11), Article e0207674. https://doi.org/10.1371/journal.pone.0207674.

Rasoulkhani, K., Mostafavi, A., Sharvelle, S., & Cole, J. (2019). Resilience-based infrastructure planning and asset management: Study of dual and singular water distribution infrastructure performance using a simulation approach. *Sustainable Cities and Society, 48*. https://doi.org/10.1016/j.scs.2019.101577.

Resseger, M. (2013). *The impact of land use regulation on racial segregation: Evidence from Massachusetts zoning borders. Harvard University Working Paper*.

Risser, M. D., & Wehner, M. F. (2017). Attributable human-induced changes in the likelihood and magnitude of the observed extreme precipitation during Hurricane

Harvey. *Geophysical Research Letters, 44*, 7. https://doi.org/10.1002/2017GL075888.
Rogers, R. W. (1983). *Cognitive and physiological processes in fear appeals and attitude change: A revised theory of protection motivation.* New York, New York: Guildford Press.
Rufat, S., Tate, E., Burton, C. G., & Maroof, A. S. (2015). Social vulnerability to floods: Review of case studies and implications for measurement. *International Journal of Disaster Risk Reduction, 14*, 470–486. https://doi.org/10.1016/j.ijdrr.2015.09.013.
Stringer, L., Quinn, C., Berman, R., Le, H., Msuya, F., Orchard, S., ... Pezzuti, J. (2014). *Combining nexus and resilience thinking in a novel framework to enable more equitable and just outcomes. Sustainability research institute, centre for climate change economics and policy working paper No. 193*.
Syed, S. T., Gerber, B. S., & Sharp, L. K. (2013). Traveling towards disease: transportation barriers to health care access. *Journal of Community Health, 38*(5), 976–993. https://doi.org/10.1007/s10900-013-9681-1.
Terrapon-Pfaff, J., Ortiz, W., Dienst, C., & Gröne, M.-C. (2018). Energising the WEF nexus to enhance sustainable development at local level. *Journal of Environmental Management, 223*, 409–416. https://doi.org/10.1016/j.jenvman.2018.06.037.
Thomas, K., Hardy, R. D., Lazrus, H., Mendez, M., Orlove, B., Rivera-Collazo, I., Roberts, J. T., Rockman, M., Warner, B. P., & Winthrop, R. (2019). Explaining differential vulnerability to climate change: A social science review. *Wiley interdisciplinary reviews Climate change, 10*(2), https://doi.org/10.1002/wcc.565 e565.
UNISDR (2013). Disaster Risk Reduction in the United Nations: Roles, Mandates, and results of key UN entities. Retrieved from: https://www.unisdr.org/files/32918_drrintheun2013.pdf .
VanDerslice, J. (2011). Drinking water infrastructure and environmental disparities: Evidence and methodological considerations. *American Journal of Public Health, 101 Suppl 1*(Suppl 1), S109–S114. https://doi.org/10.2105/AJPH.2011.300189.
Ver Ploeg, M., Nulph, D., & Williams, R. B. (2011). *Mapping food deserts in the U.S. Amber waves:The economics of food, farming, natural resources, and Rural America.* 120966. Retrieved fromhttps://EconPapers.repec.org/RePEc:ags:uersaw:120966.
Wamsler, C., & Brink, E. (2016). The urban domino effect: A conceptualization of cities' interconnectedness of risk. *International Journal of Disaster Resilience in the Built Environment, 7*(2), 33. https://doi.org/10.1108/IJDRBE-01-2015-0001.
Yang, Y., Thomas Ng, S., Zhou, S., Xu, F. J., & Li, H. (2020). Physics-based resilience assessment of interdependent civil infrastructure systems with condition-varying components: A case with stormwater drainage system and road transport system. *Sustainable Cities and Society,* 54. https://doi.org/10.1016/j.scs.2019.101886.
Zhu, j., Manandhar, J., Truong, J., Ganapati, E., Pradhananga, N., Davidson, R., ... Mostafavi, A. (2017). Assessment of infrastructure resilience in the 2015 gorkha earthquake. *Earthquake Spectra, 33*(S1), 18.