Functionality, Access, and Implications: Assessing the Role of Organizations in Community Disaster Resilience

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Abstract

Communities are complex systems defined by the interaction of social, economic, environmental, and physical systems. Increasing rates and intensities of climatic natural hazards, coupled with rising urbanization and an increase in quality-of-life dependency on social and economic systems, underlines the importance of improving the resilience of buildings and infrastructure systems that play a key role in ensuring the functionality of the community's social and economic systems. Building codes are principal regulatory documents that aid in achieving this goal. However, building codes historically set their design-level performance goal with a primary focus on avoiding loss of life with limited considerations on how a building is actually used by its occupants or the broader community. To move towards resilience, the next generation of building codes should modify their design philosophy and extend their design goals to incorporate functionality-related performance goals into the design process, where functionality goals must include social, economic, and physical aspects of buildings and infrastructure.

This study posits that organizations are the key lynchpin connecting buildings and infrastructure systems to social and economic systems. Utilizing the Community Capitals framework, we propose a novel framework for assessing the implications of disruptions in the accessibility and functionality of organizations contributing to the resilience of a community's social and economic systems. The framework exemplifies the deliberate incorporation of organization-level functionality into community resilience and bridges the gap between the community's social and economic characteristics with conventional engineering-focused community resilience frameworks through including the concept of accessibility.

To identify components contributing to the functionality of an organization and define organizational functionality states, fault tree models were employed. In addition to conventional

physical components and utilities, staff and supply chain are introduced as critical non-physical components contributing to the availability, acceptability, and adequacy of products offered by organizations. Defining accessibility as the use of available products by community members with reasonable effort and cost to meet an essential need, two novel metrics for measuring accessibility are developed. The metrics consider access from the perspective of both service users and providers and reconcile accessibility with organizational functionality by incorporating proximity, availability, acceptability, and adequacy dimensions in measuring accessibility to both tangible products and intangible services.

To demonstrate the application of the framework the research used the Lumberton virtual community resilience testbed. Virtual testbeds are an effective tool to test, verify, and validate community resilience models and advance the state of knowledge on community resilience. The application of virtual testbeds is increasing as quantitative hazard research aims to move from component- and building-level modeling into the interdisciplinary space of community-level modeling for resilience. However, the characteristic of testbeds, their components, and development procedures was something embedded in published works, and somewhat ambiguous. Thus, we leveraged the current momentum on using virtual testbeds for community resilience analysis and performed a systematic literature review and an expert survey to dissect what testbeds are in practice. We, finally, defined testbeds as a virtual environment with enough supporting architecture and metadata to be representative of one or more systems such that the testbed can be used to (a) design experiments, (b) examine model or system integration, and (c) test theories. From the literature review, it was illuminated that the lack of a standardized and systematic approach for testbed development, testbed publication, or testbed reuse virtual testbeds is a significant issue that needs to be addressed. Thus, a systematic schema for testbed development is also proposed. The workflow facilitates testbed creations by introducing a generic structure defining minimum requirements for initiating a testbed and by defining a step-by-step development procedure. The application of the proposed workflow has been demonstrated by establishing a testbed based on Onslow County, NC using publicly available data in the United States. The testbed is shared using the DesignSafe-CI for reusing by other researchers.

The other significant challenge in developing virtual community resilience testbeds is incorporating social systems and phenomena into testbeds. Social vulnerability indices are a convenient way to account for differential experiences and starting conditions of the population in resilience assessments. This dissertation proposes a scalable index, termed Social Vulnerability Score (SVS), to serve the purpose of testbed development. The SVS overcomes two important limitations of existing indices: it is constructed using an approach that does not decrease in validity with changing spatial resolution, and it only needs to be calculated for the geographic area of interest, instead of for the entire county thereby significantly reducing computational effort for testbed developers and users. The proposed SVS aggregates the ratio of a set of demographics from U.S. Census datasets at the desired location against their national average values. The resulting scores are mapped into five levels, called zones, ranging from very low vulnerability (zone 1) to very high (zone 5). The SVS model is incorporated into the Interdependent Networked Community Resilience Modeling Environment (IN-CORE).

Lastly, to exemplify the application of social vulnerability in the proposed framework, inequities in accessibility to schools after 2016 Hurricane Matthew were assessed across the different socially vulnerable populations in the Lumberton Testbed.

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Chapter 1: Introduction

The increasing intensity and frequency of climatic hazards, such as hurricanes, floods, severe storms, freezes, droughts, and wildfires are the evident consequences of climate change (Bell et al., 2018; Trenberth, 2018). These hazards annually cause billions of dollars in losses and casualties all around the globe, but their impacts are not limited to such physical destruction and direct human losses. These physical damages coupled with the consequent disruptions in a community's social and economic systems are intensifying the impacts of such events on communities, changing the community's long-term recovery trajectories, particularly for socially vulnerable communities, causing billions of dollars in direct and indirect losses every year, and severely degrading quality of life for disaster victims. Thus, to lower disaster costs and preserve quality of life, local-, state-, and federal governments must take actions to improve the resilience of buildings and infrastructure systems that play a key role in ensuring the functionality of the social and economic systems of communities. Building codes are considered key regulatory documents supporting resilient communities. However, building codes historically set their design-level performance goals to only ensure occupant safety for the majority of buildings and thus do not provide resilience. The exception in performance is for a small group of buildings such as nuclear facilities, hospitals, police, and fire stations, that are considered vital and are designed to remain functional during and after disasters. Importantly, there are many other buildings vital for continued functionality of communities and preserving quality of life. To move towards resilience, the next generation of building codes should modify their current design philosophy and extend their design goals to incorporate functionality-related performance goals into the design process, where functionality goals must include more than the physical aspects of buildings and infrastructure.

Transforming resilience concepts into practice remains a work in progress and requires more research. This study contributes to this need by proposing a novel framework for assessing the implications of disruptions in the accessibility and functionality of organizations that provide community members with essential services, including sheltering, healthcare, education, and sustenance, among others. The framework exemplifies the deliberate incorporation of organization-level functionality into community resilience. The target audiences of the developed framework are community resilience researchers, structural engineering standards developers, and disaster management policy- and decision-makers. This dissertation, eventual journal papers, and conference presentations will be the primary method of communicating the findings of this research. Although continued research is required, outcomes of this dissertation can be used as the preliminary basis for developing a Risk Category-equivalent scale in a new community resilience standard for communities, where this new scale directly incorporates how organizations are connected and used in order to support a functioning community in the prioritization of design-level performance goals for buildings and other structures. In addition, this research provides novel contribution to Interdependent Networked Community Resilience Modeling Environment (IN-CORE), which is a platform for running resilience analyses, to measure the socio-technical impact of natural hazards on communities.

The remainder of the Introduction Chapter presents the necessary background on the well-established and adopted community capitals framework (section 1.1) which serves as the backbone to the overarching framework proposed for this research (introduced in section 1.2) with a clear accounting of which aspects are completed within the dissertation and which aspects are recommended as future work (section 1.3).

1.1 Community Capitals Framework

The Community Capitals (CC) framework was developed by social scientists to better articulate the various dimensions and components of a community (Flora et al., 2005). The CC framework assesses a community's functionality by its stock of seven capitals including natural, cultural, human, social, financial, political, and built capital. These seven capitals, as described below, are in fact a community's assets and dynamically interact with one another at different spatio-temporal scales to build, foster, and improve the community's response to any disruption (Emery & Flora, 2006).

(1) *Natural Capitals* are assets tied to the location: weather, wildlife, natural resources, and beauty; quality of air, land, water, level of biodiversity, and scenery are all examples (Emery & Flora, 2006; Flora, 2015).

(2) *Cultural Capitals* are the traditions, language, and social creativity that emerge in an area. This can include inherent social values, the way attitudes are nurtured, and what heritage(s) is recognized and celebrated in a community (Flora, 2015; Mattos, 2015).

(3) *Human Capital* is the skills and abilities of people in a given area and contributes to community building, knowledge sharing, and innovation. This can include educational attainment, technical skills, health and vitality, creativity, and diversity of the population (Flora, 2015). Human capital relates to leadership's ability to focus on assets, be proactive in the future, and access outside resources to improve practices (Mattos, 2015).

(4) *Social Capital* is the network of social connections amongst people that 1) build cohesion through bonding; 2) bridge together loose social ties; and 3) link community members to those in power. This can be measured through network structures, group membership, common goals, diversity, and trust in a community (Flora, 2015).

(5) *Political Capital* is the access to resources, including services, information, and power, such as officials to influence standards and rules; the level to which a community organizes to interact with the government or leverage a collective voice (Flora, 2015; Mattos, 2015).

(6) *Financial Capitals* are the resources to spur community development through business, civic, and social entrepreneurship (Mattos, 2015). This can include state and federal tax monies, investments, loans, grants, and poverty rates (Flora, 2015).

(7) *Built Capitals* are the infrastructure that supports many aforementioned activities, and often become a focus of community development. This can include the building stock, transportation infrastructure, utilities, technology, tools, and machinery (Flora, 2015).

Daniel et al. (2022) performed a concise yet comprehensive literature review on each of the community capitals, their intersections, and how they can be distinctively generated in each community. For example, financial capital in a community is partly dependent on knowledge and skills possessed by the population (human capital), the networks of people in and outside of the community (social capital), and their influence on the distribution of resources within and outside the community (political capital), and being influenced by natural resources (natural capital) in the community, such as beachfront property, mountain views, port access, or coal mines. As discussed by Daniel et al. (2022), these seven community capitals are not self-governing and oftentimes overlap. For example, built capital will be higher in communities with higher human, political, and financial capitals. Similarly, communities with greater social and human capitals tend to have more political capital through intentional resilience planning whereby stakeholders unite around common goals and risks with a sense of trust, they share ideas that can drive innovation and increase resilience (National Academies, 2019). From their literature review, Daniel et al. (2022) concluded that different building occupancy types, through their organizations, generate different community capitals. For example, religious organizations and museums generate cultural capital through the programming they offer. Additionally, religious organizations and physical fitness centers generate social capital through their membership functions and events. Schools and healthcare facilities generate human capital through increasing the knowledge and health of community members. Retail shops and restaurants facilitate financial capital through offering places of employment and providing a means for local commerce. These relationships, albeit proxy measures of the community capitals, were discussed for a selection of organization types and used to develop a framework for measuring community resilience. The framework used a counting mechanism to capture the number of ways a given organization promotes the different elements described in the definition of each community capital.

Daniel et al.'s framework focused on buildings, and how said portion of the built capital supports the other six capitals. Furthermore, different organizations can mobilize community capitals, particularly human and social capitals, in a community (Choi et al., 2019). For example, after Hurricane Katrina, the Mary Queen of Vietnam Catholic Church used its members' social networks to relay critical developing information during the disaster (human and cultural capital), provide shelter for those who could not evacuate (built capital), and build community morale and structure in recovery (financial, political, and human capital). In this case, a faith-based organization filled critical gaps in community recovery and contributed to the Versailles Parish coming back quickly and more robustly than nearly all of its neighboring parishes (Aldrich, 2012; Rivera & Nickels, 2014). Daniel et al. (2022) illustrated their quantitative framework using the Centerville testbed effectively demonstrating how damage to different building types, and thereby different organizations, can disproportionately decrease community capitals and thereby community resilience.

1.2 Problem Statement and Proposed Framework

Relating the seven community capitals to organizations enables community resilience researchers to extend their models beyond the community's physical infrastructure systems to include social, economic, and environmental dimensions. Therefore, we reframe the CC framework by Flora et al. (2005) by setting a unique role for the built capital in supporting the other six capitals, where all seven capitals are essential and their details are distinctive to each community. An overview of the proposed concept is illustrated in Figure 1.

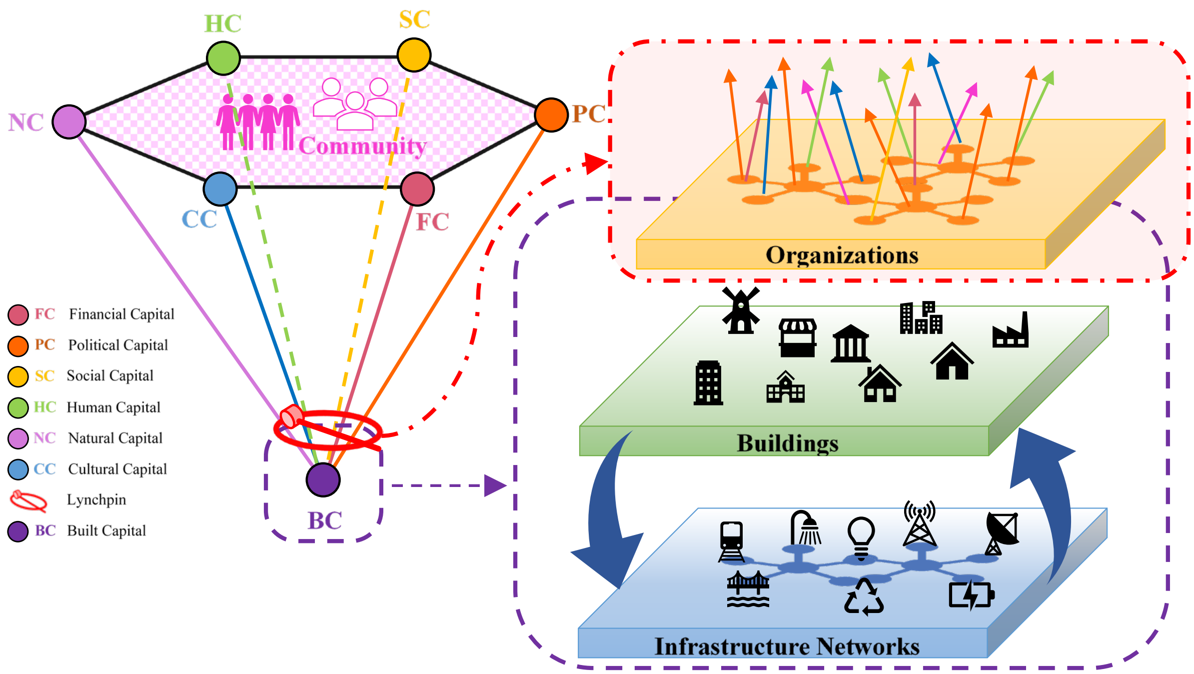

Figure 1. Dissecting the Community Capitals in terms of Community Functionality

Different components of the built capital work together to enable organizations through a complex network of interacting capitals. Organizations inherently rely on the built capital through either the building they occupy or the benefit they derive from infrastructure networks; organizations also contribute to a community's human, social, political, financial, natural, and cultural capitals through their services, users (including consumers and employees), and supply chains. Hence, as illustrated in Figure 1, organizations are the lynchpin connecting the built capital to the other capitals. Multi-colored arrows projecting out of the organization layer in Figure 1 depict how organizations (generally) support one or more of the community capitals, where the colors of the arrows correspond to the various capitals. Large arrows on the right side of Figure 1 capture the well-established dependencies within the built capital, specifically between buildings and infrastructure network layers.

With the relationships in Figure 1 in mind, the conceptual framework shown in Figure 2 is proposed for assessing the role of organizations in community disaster resilience. In the first step, the community should establish their desired resilience goals and determine the recovery objective for each community capital based on the established goals. These goals can be different for different neighborhoods with different levels of social vulnerability within the target community. Then, as shown in Figure 2, after assessing the built environment under the hazard(s) that the community is susceptible to, the post-disaster functionality of existing organizations will be estimated while considering the interdependency among organizations, buildings, and infrastructure. In the third step, the contribution of each organization to generating or mobilizing every community capital needs to be investigated to measure the capital levels at the intended times after the disaster and compare the results with the recovery objectives that are defined in step 1. In the last step, after implementing various resilience strategies based on different organizational recovery scenarios, steps 2 and 3 should be repeated to determine the most effective strategy. The organizational recovery scenario corresponding to the selected strategy will provide a preliminary basis for the prioritization of design-level performance goals for associated buildings and structures.

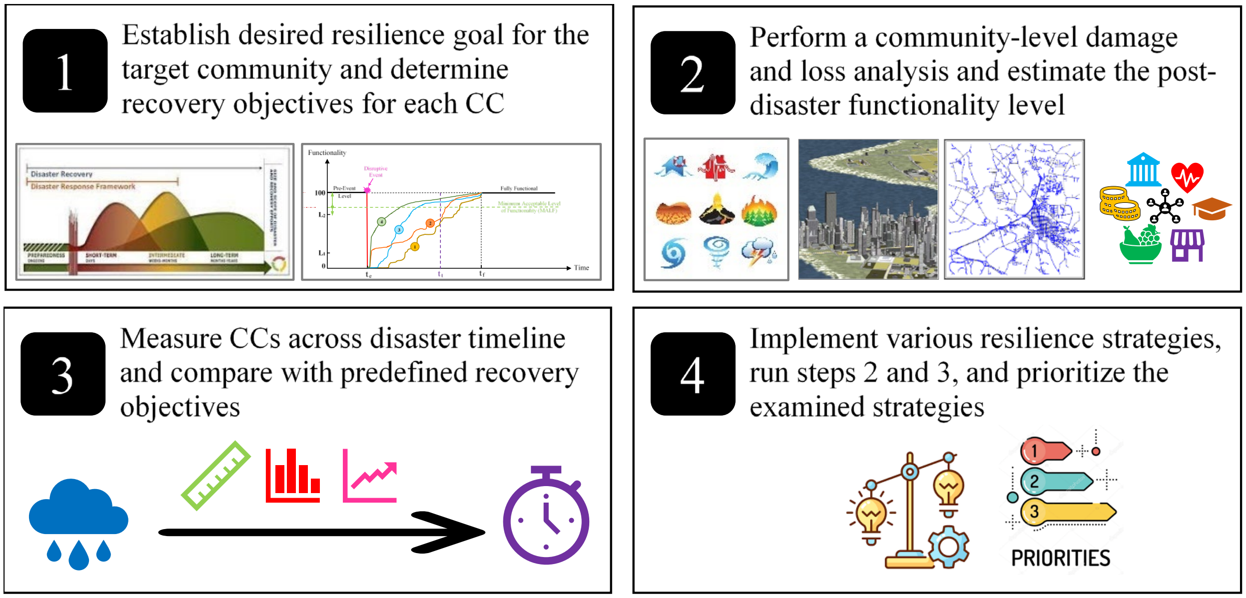

Figure 2. Proposed Conceptual Framework for Incorporating Organization Functionality into Community Resilience

1.3 Dissertation Scope and Outline

The purpose of the framework shown in Figure 2 is to implement the framework and organizational functionality into community resilience practice in a real community. The actual implementation is beyond the scope of this research. Steps on what must be done to be able to use the framework include:

Task 1 (a) Determine the recovery objective for each CC in the target community; (b) quantify interdependencies and relationships among existing organizations; (c) develop a set of quantifiable proxies to measure CCs; (d) identify and select the primary organizations that contribute to generating and mobilizing each CC based on the community's priorities and needs.

Task 2 (a) Develop a community-level model (e.g., testbed) of the target study area including the physical, social, and economic systems of the community as well as the natural hazards that the community is susceptible to; (b) establish a procedure for estimating the pre- and post-disaster functionality of the selected organization considering their primary and secondary products.

Task 3 (a) quantify the CCs considering the estimated post-disaster products of every identified organization generating each respective CC and aggregate across organizations; (b) measure each CC in the target community and compare the estimate with the predefined objective and resilience goals.

Task 4 (a) Verify and validate the proposed framework's components, including models, equations, and algorithms before and after being stitched together and integrated; (b) develop a cost-benefit algorithm based on the community preferences to aid with decision making.

All tasks are required for a community to implement the framework; however, task 1 parts a, b, and d, task 3 part b, and task 4 are out of the scope of this dissertation and remain for future research. The manner in which organizations contribute to a community's cultural character, built environment, social networks, human ability, and economic engine is complicated. A wealth of services is offered through organizations in a community, from basic goods such as clean water and food, to specialized services, such as healthcare and education. Each service creates a small, critical link to community functionality through its connection to the community capitals, creating an interdependency between community and organization, and from organization to organization. Given that communities consist of many organizations, task 1 parts a, b, and d, task 3 part b and task 4 require data collection and conducting a comprehensive survey in different parts of the country, go beyond this dissertation timeline, and remain for the author's future work.

In this dissertation, a small selection of organizations is investigated including *gas stations, banks, and schools*, in the organizational functionality definition paper (Chapter 2), and *schools and pharmacies* in the accessibility paper (Chapter 5). These organizations, although not an exhaustive list, are selected here because of their significant role in community functionality and contribution to a community's Human and Political Capitals, assigned risk category in ASCE 7-

16 (Risk Categories II and III), dependency relationship with a physical building for operation, and assigned post-disaster recovery priority (not critical infrastructure according to the United States Department of Homeland Security). Thus, for tasks 2 and 3, this dissertation focuses on the selected organizations although the developed approaches, models, and equations can be adapted for other organizations and CCs.

In addition to the Introduction, this dissertation is composed of five chapters consisting of five individual seminal journal articles (either published papers or submitted manuscripts) in chapters 2 through 5. With Enderami as the first author, each paper details different elements of the framework introduced in Chapter 1 according to the dissertation scope. Thus, the dissertation is organized as follows:

Chapter 2 investigates how different organizations contribute to community resilience and how to model and quantify functionality by introducing the concept of organizational functionality; **Chapter 3** dissects the major components and characteristics of virtual community resilience testbeds through a systematic literature review and proposes a schema for initiating community resilience testbeds; **Chapter 4** establishes the Social Vulnerability Score (SVS), a scalable index representing the social vulnerability of community members and serves the purpose of virtual testbed development; **Chapter 5** develops two novel accessibility metrics for measuring how access to different organizations changes across the disaster timeline, ties the concepts described in chapters 2, 3, and 4 together, and evaluates how accessibility metrics alter inequitably among community members, using the Lumberton virtual testbed; **Chapter 6** concludes the dissertation, summarizes the contributions of this thesis and makes recommendations for future continued research for using this framework.

Chapter 2[1]: Defining Organizational Functionality for Evaluation of Post-Disaster Community Resilience

Communities are complex systems defined by the interaction of social, economic, environmental, and physical systems. The dynamic response and recovery of a community to a disaster is often tied to the response and recovery of its organizations. This paper employs the Community Capitals framework to understand how organizations contribute to community resilience. The organization-level functionality is defined as the capability of an organization to be used for its intended purposes. Organizations are not solely physical objects, *staff* and *supply chain* are identified as critical non-physical components contributing to organizational functionality alongside conventional physical components. Fault trees and a probabilistic framework are developed to measure organizational functionality failure. A fault tree is presented in detail for three organizations, namely, *banks*, *gas stations*, and s*chools,* to illustrate the different components necessary for functionality of different organizations. Lastly, a framework for evaluation of community resilience based on organizational functionality is proposed.

2.1 Introduction

As the years of research on community disaster resilience continues, more is understood about what immediate disaster impacts are, how to prevent immediate impacts through mitigation and response, and what services and critical infrastructure need to be prioritized in the immediate aftermath. While long-term recovery has always been articulated as part of the disaster lifecycle, less attention has been spent on understanding how long-term recovery takes place, and what

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[1] This chapter is based on a published journal paper with this dissertation's author as the first author:

Enderami, S. A., Sutley, E. J., & Hofmeyer, S. L. (2021). Defining organizational functionality for evaluation of post-disaster community resilience. *Sustainable and Resilient Infrastructure*, 1-18. https://doi.org/10.1080/23789689.2021.1980300 factors or interventions increase or decrease recovery times and change recovery trajectories. This latter statement is true for communities, as well as the long-term recovery of community components, such as businesses, schools, housing, and households (Sutley & Hamideh, 2020). In addition to causing casualties and damage to physical infrastructure, disasters disrupt the availability of social services critical for a community's long-term recovery. As a result, different dimensions of community resilience (e.g., population, ecosystem, government services, etc.) are affected (Cimellaro et al., 2016).

Historically, building codes consider occupancy of the building during the design process but do not consider how the building is otherwise part of a larger system, i.e., a community. The building code design goals, for most buildings, are to provide functionality during routine events and to maintain occupant safety during disasters; the exception is for nuclear facilities and a small group of emergency buildings (e.g., hospitals, police stations, fire stations, etc.) that are considered vital during and after disasters. The significant decrease in the number of collapsed buildings and casualties caused by recent disasters, relative to other countries, proves that code-based designs have been largely successful in meeting their design objectives. For example, no shaking-related fatalities were reported during the July 4th and 5th, 2019 Ridgecrest California M 6.4 and M 7.1 earthquakes. Similarly, apart from very vulnerable building types, such as unreinforced masonry structures, very little structural damage was observed in San Bernardino County and the city of Ridgecrest, the most heavily impacted areas. However, nonstructural damage and discontinued services continue to be prevalent after disasters and very costly, causing an estimated $1 billion in losses after the 2019 earthquake (Osalam, 2019).

This continued disruption and billions of dollars in losses every year by disasters are not representative of resilience. To move towards resilience, next-generation building codes should extend their design goals to incorporate functionality goals into the design process (McAllister, 2016) where functionality goals must include more than the physical aspects of infrastructure. Designing with functionality goals in mind does not necessarily mean a significant increase in construction costs. Applying the FEMA P-58 methodology, Haselton (2018) demonstrated that it is possible to design new buildings with considerably improved performance and a significant drop in repair cost and time with very small additional initial investment. Even still, research is needed to understand how to incorporate functionality goals into codes and standards, including understanding which buildings should be prioritized. The present work begins to chip away at this latter need by examining how different organizations contribute to community resilience, and how to model functionality and functionality loss of organizations. Organizations create an important extension, given that it is the people who work and utilize buildings and infrastructure that will enable higher level resilience goals to be achieved, including innovation, adaptability, and transformation. This work distinguishes organizations from social institutions and businesses, although there is overlap, and both have been the focus of other research. *Social institutions* integrate the norms and values of a community to meet its members' social needs such as education, family, healthcare, and religion. However, they do not encapsulate other necessary products and services, offered by organizations such as grocery stores, needed for communities to function and recover after a disaster. The term *businesses* focuses on the commerce aspect of organizations, as opposed to the product or service offered, and how said service supports a community beyond economics. Thus, here we define organizations as any entity that is designed to provide products and services to a community in an effort to meet the community members' needs from various perspectives.

Over the past decade, several community resilience studies have begun to develop conceptual models of resilience in terms of functionality and assess the impacts of the functional built environment on community recovery following disasters. Lin and Wang (Lin & Wang, 2017a) developed a stochastic functionality restoration model for the physical recovery processes of buildings. The model predicts post-disaster functionality recovery time and trajectory for a community's building portfolio using two metrics: (1) the portfolio recovery index and (2) the portfolio recovery time. Cimellaro et al. (2010) developed a building-centric framework to quantitively evaluate the resilience of healthcare facilities subjected to earthquakes. The evaluation was based on the dimensionless analytical functions associated with variation in post-disaster functionality of system during the recovery period. Nevill and Lombardo (Nevill & Lombardo, 2020) distinguished structural functionality (defined as the ability to safely provide shelter) from total functionality of a building (which includes the functionality of nonstructural components, such as electric power, water, and transportation access), and proposed a scale to measure structural functionality of light-framed wood buildings. The scale was presented through: (1) a set of structural functionality indicators for windstorm damage, and (2) a set of guidelines to extend the indicators to other hazards. Burton et al. (2016) presented a framework for incorporating probabilistic building performance limit states in the assessment of community resilience to earthquakes. They proposed building-level recovery functions considering uncertainties in the recovery path to a limit state and employed a probabilistic approach to evaluate functionality restoration for buildings. The application of the proposed procedure to model post-earthquake community-level recovery functions was demonstrated using a case study. Davis (Davis, 2013; Davis, 2014) illustrated the relationship between community resilience and post-earthquake functionality of water systems using a case study of the Los Angeles Water System. After making a clear distinction between functionality and operability of water systems, the work demonstrated how functional water systems that are able to provide post-earthquake services to other lifelines and emergency operations, help to improve community resilience.

The previously reviewed works adopted adopted an infrastructure-centric (mostly buildings) definition for functionality and neglected the effects of non-physical components. However, there are a few studies that have recognized the role of buildings in supporting society and offered more holistic functionality models for community resilience assessment. For example, by assessment of the observational data on the performance of the hospitals in past earthquakes, Yavari et al. (2010) traced four interacting components (structural, non-structural, lifelines, and personnel) influencing a hospital's functionality and used them to develop a predictive model of hospital functionality in the event of an earthquake. Later, Jacques et al. (2014) studied the functionality of the Canterbury healthcare system after the 2011 Christchurch earthquake. Adopting a multidisciplinary approach, Jacques et al. (2014) identified that the functionality of crucial hospital services primarily depends on the availability of three factors: *structure*, *staff*, and *stuff*.

Then, Mieler and Mitrani-Reiser (2018) performed a comprehensive review of the state of the art in assessing earthquake-induced loss of functionality in buildings. The review commented on how functionality loss within individual buildings and infrastructure can affect a community at different spatio-temporal levels. After identifying incidents that commonly cause loss of functionality in a building, a fault tree model was applied to capture and relate these incidents to the building's functionality. Then, to demonstrate how the availability of such incidents affects post-earthquake building functionality recovery, the conceptual functionality-restoration curves were presented. It is concluded that existing analytical models for assessing loss of building functionality need to be refined to include all components that contribute to functionality, including non-physical components like staff availability. Finally, Choi et al. (2019) moved beyond healthcare systems and introduced an interdisciplinary platform for planning community post-disaster recovery within the framework of seven layers of critical infrastructures (i.e. civil, civic, financial, environmental, educational, and cyber). Their framework articulates interdependencies within and between functional physical infrastructure and structure-based systems (civil layer), and the other layers that are important to sustain the functionality of a community during post-disaster recovery.

Collectively, these studies provide a strong foundation necessary for advancing the state of knowledge on the concept of functional recovery for communities and their components. This paper advances these lines of inquiry by introducing and defining the concept of organizational functionality as it relates to community resilience. A conceptual framework for linking organizations to community functionality is proposed using the Community Capitals framework. The paper closes with a probabilistic approach to evaluate organizational functionality failure used to guide the development of a procedure for the practical assessment of a community's disaster resilience.

2.2 The Role of Organizations in Community Resilience

A community is a complex system of systems comprised of dynamically interacting non-homogeneous built, natural, and human infrastructure (Bozza et al., 2015). Resilience is also a multidimensional concept, particularly when applied at the community level; community resilience cuts across different stressors (natural, man-made, biological), scales (state, regional, local), and community dimensions (physical, natural, social, financial, political) (Koliou et al., 2018). Community disaster resilience is measured based on a community's ability to prepare and mitigate a hazard (natural and/or human-caused), respond dynamically to reduce consequences of any functionality loss when disasters do occur, and carry out recovery actions that minimize recovery time and future vulnerabilities in an equitable manner (S. L. Cutter et al., 2013; PPD-21, 2013; Risk Steering Committee, 2008; SDR, 2005; United Nations, 2011). Preventing functionality loss is the first part of assessing resilience, where functionality is a scale of how well a system operates to deliver its products or meets its intended purposes (Mieler & Mitrani-Reiser, 2018). Functionality, including community functionality, building functionality, and organizational functionality, varies across the disaster timeline. Figure 3, adapted from the NIST Community Resilience Planning Guide (CRPG) (NIST, 2016), illustrates the temporal variability of functionality following a disruptive event. The period between the time of the disruptive event (t_e) and the time of target functionality restoration (t_f) is defined as the Time to Recover Functionality (TRF). TRF is a measure of how long it takes before a system becomes functional after a disruption. In Figure 3, the pre-event functionality is normalized for deterioration or improvement effects during normal operation and the post-event target level is set as the pre-event level. However, true resilience must also incorporate building back better such that pre-event vulnerabilities are not re-established during recovery. This is referred to as service equilibrium shift by Davis (Davis, 2014), and is outside of the scope for this paper.

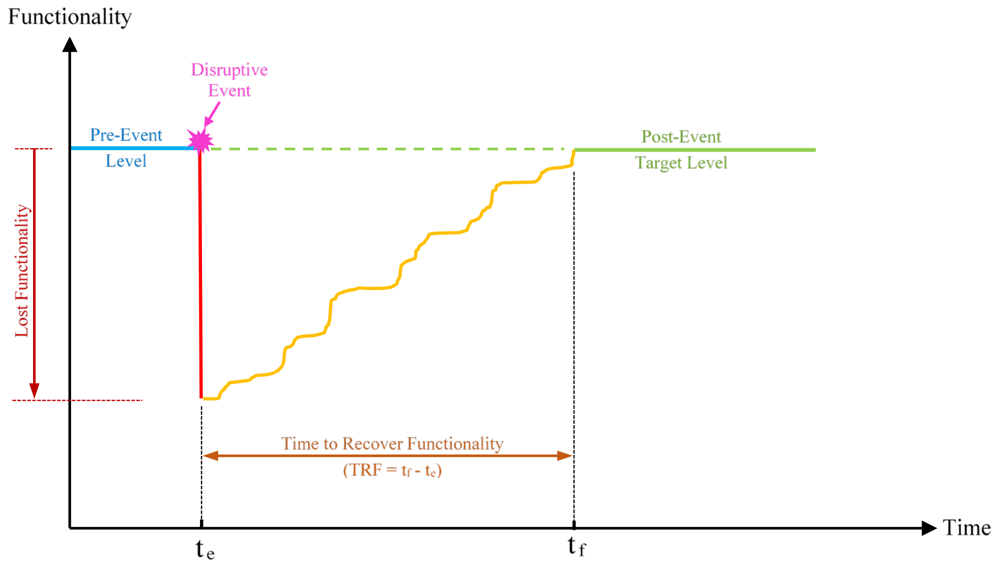

Figure 3. Resilience definition in terms of functionality and the time to recover functionality (adapted from (NIST, 2016))

The dynamic response and recovery of a community to a disaster is directly tied to the response and recovery of its organizations. Past research has illustrated the undeniable connection between community resilience and the functionality of its organizations (Dalziell & McManus, 2004; Lee et al., 2013); thus, understanding and modeling such relationships will provide critical insight into a community's resilience. Therefore, in line with the community definition, in seeking resilience, a community's primary objectives should be minimizing (1) the amount of lost functionality after a disruptive event, and (2) critical organizations' TRF to an acceptable level. Here, two important metrics are introduced towards these objectives: (1) the Minimum Acceptable Level of Functionality (MALF) which limits the value of lost functionality and provides a lower threshold for the system's post-event target functionality; and (2) the Maximum Tolerable Period of Disruption (MTPD) which represents the maximum allowable time that a system can be non-functional before its impact is deemed unacceptable. These metrics are revisited later for the evaluation of organizational functionality failure.

2.2.1 Organizations and the Community Capitals Framework

To better articulate different capacities and components in a community, social scientists have developed the Community Capitals (CC) Framework (Flora et al., 2005). The CC framework assesses the stock of seven capitals, the types of capital that are invested in a community, and the interaction of these capitals (Emery & Flora, 2006). Ultimately, these seven capitals, or community assets, interact and build upon one another at different spatio-temporal scales, creating and enhancing a collective (community) response toward disruptions. A community's functionality is defined by its stock of the following assets:

(1) Natural capital, or assets tied to the location: weather, wildlife, natural resources, and beauty; quality of air, land, water, level of biodiversity, and scenery are all examples (Emery & Flora, 2006; Flora, 2015).

(2) Cultural capital, or the traditions, language, and social creativity that emerge in an area. This can include inherent social values, the way attitudes are nurtured, and what heritage is recognized and celebrated in a community (Flora, 2015; Mattos, 2015).

(3) Human capital, or the skills and abilities of people in a given area, which contributes to community building, knowledge sharing, and innovation. This can include educational attainment, technical skills, health and vitality, creativity, and diversity of the population (Flora, 2015). Human capital relates to leadership's ability to focus on assets, be proactive to the future, and access outside resources to improve practices (Mattos, 2015).

(4) Social capital, or the network connections amongst people that 1) build cohesion through bonding; 2) bridge together loose social ties; and 3) link community members to those in power. This can be measured through network structures, group membership, common goals, diversity, and trust in a community (Flora, 2015).

(5) Political capital, or the access to resources and officials in order to influence standards and rules. The level to which a community organizes to interact with the government or leverage a collective voice is an important metric of this capital (Flora, 2015; Mattos, 2015).

(6) Financial capital, or the resources to spur community development through business, civic, and social entrepreneurship (Mattos, 2015). This can include state and federal tax monies, investments, loans, grants, and poverty rates (Flora, 2015).

(7) Built capital, or the infrastructure that supports many aforementioned activities, often becoming a focus of community development. This can include housing stock, transportation infrastructure, telecommunications, utilities, and hardware (Flora, 2015).

All seven capitals are essential, and their details are distinctive to each specific community; however, here it is proposed that built capital has a unique role in supporting the other six capitals. Different components of the built capital work together to enable organizations through a complex network of interacting capitals. An overview of this concept is illustrated in Figure 4. Disaster resilience is often studied as infrastructure resilience, where multi-layer network models connect the various physical infrastructure systems (lifelines). To study community resilience, the analysis must extend beyond physical infrastructure systems to social, economic, and environmental dimensions. Relating the seven community capitals to organizations enables this extension.

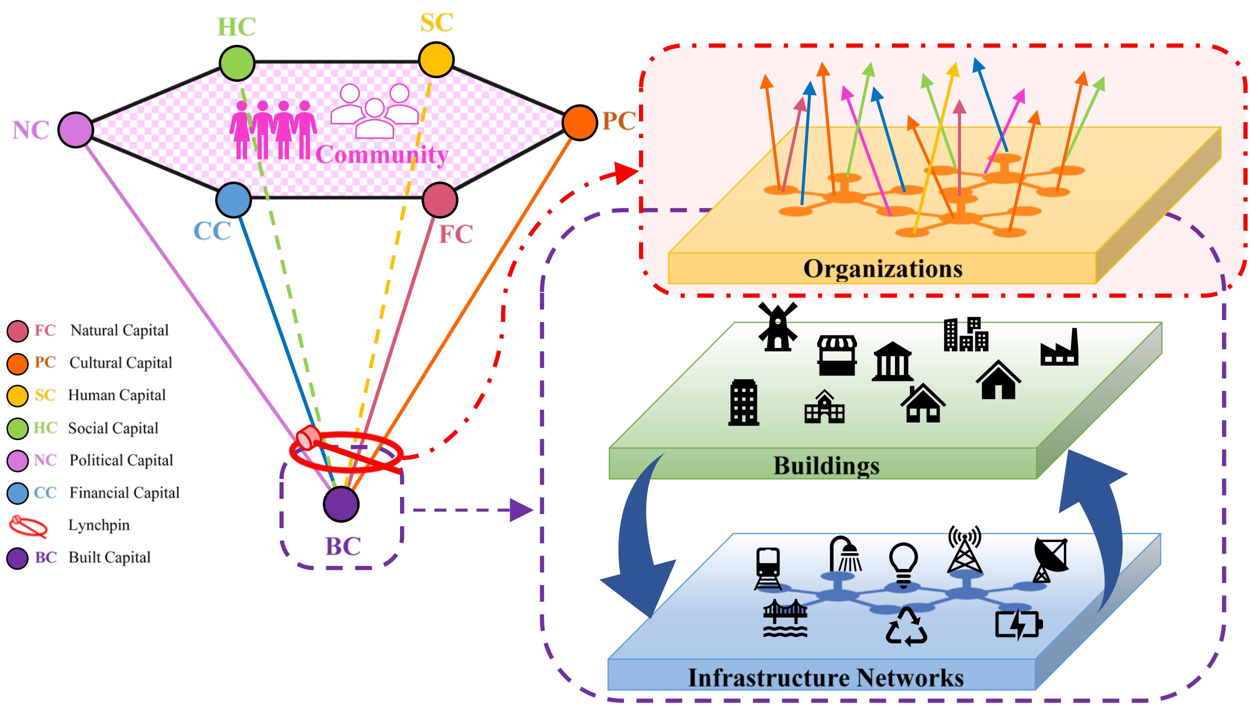

Figure 4. Dissecting the Community Capitals in terms of Community Functionality

Organizations inherently rely on the built capital through either the building they occupy or the benefit they derive from infrastructure networks; organizations also contribute to a community's human, social, political, financial, natural, and cultural capitals through their services, users (including consumers and employees), and supply chains. Hence, as illustrated in Figure 4, organizations are the lynchpin connecting the built capital to the other capitals. Multi-colored arrows projecting out of the organization layer in Figure 4 depict how organizations (generally) support one or more of the community capitals, where the colors of the arrows correspond to the various capitals. Large arrows on the right capture the well-established dependencies within the built capital, specifically between buildings and infrastructure network layers.

As discussed in Daniel et al. (2022), oftentimes community capitals will overlap. For example, communities with greater social and human capitals tend to have more intentional resilience planning whereby stakeholders unite around common goals and risks with a sense of trust, they share ideas which can drive innovation and increase resilience (National Academies, 2019). Different organizations can mobilize community capitals, particularly human and social capitals (Choi et al., 2019). For example, after Hurricane Katrina, the Mary Queen of Vietnam Catholic Church used its members' social networks to relay critical developing information during the disaster (human and cultural capital), provide shelter for those who could not evacuate (built capital), and build community morale and structure in recovery (financial, political, and human capital). In this case, a faith-based organization filled critical gaps in community recovery and contributed to the Versailles Parish coming back quickly and more robustly than nearly all of its neighboring parishes (Aldrich, 2012; Rivera & Nickels, 2014).

Organizations play an important role in community resilience before, during, and after the recovery phase. Community resilience requires a certain type and number of organizations to maintain a minimum acceptable level of functionality after disruptive events. Communities need to ensure that their organizations can be recovered within a specified period to support their short, intermediate, and long-term recovery goals. The manner in which organizations contribute to a community's cultural character, built environment, social and human ability, and economic engine is complicated. A wealth of services are offered through organizations in a community, from basic goods such as clean water and food, to specialized services, such as healthcare and education. Each service creates a small, critical link to community functionality through its connection to the community capitals, creating an interdependency between community and organization, and from organization to organization. Consequently, the functionality of the buildings these organizations occupy, as well as their inner organizational constraints, requires further investigation. For organizations to fully contribute to community functionality and resilience during a disaster, resilience scholars and planners must understand the inner mechanisms of how organizations function. This paper connects these internal organizational components in order to analyze the functionality of organizations.

2.2.2 Defining Organizational Functionality

This paper proposes the following definition of organizational functionality; *organizational functionality is the quality in performance of an organization and its ability to be used for its intended purposes*. Organizations provide various products for the community. Here, a product is any good or service, either tangible or intangible, that can be offered by an organization to satisfy a want or need. *Primary products* are the main objective and intended purpose of an organization; any other offered product(s) are denoted as *secondary products*. For example, a gas station is a facility that sells fuel and lubricants for motor vehicles (primary products). However, many gas stations have convenience stores or tunnel carwash (secondary products). To characterize organizational functionality, it is necessary to understand the type, quality, and quantity of primary and secondary products provided under normal operations, to then define organizational functionality states. Organizational functionality states are used for step-wise modeling of functional recovery trajectories. Here, considering several similar studies available in the literature on building functionality (NIST, 2016; Cimellaro et al., 2010; Davis, 2019; Lin & Wang, 2017a; McDaniels et al., 2008; Mieler & Mitrani-Reiser, 2018; Nevill & Lombardo, 2020), five discrete functionality states for an organization are defined:

Out of Service Organization: Either internal or both internal and external essential components of organizational functionality are disrupted; consequently, the organization <u>is NOT working</u>

Intrinsically Operable Organization: The essential internal components of organizational functionality are maintained, or restored; however, the organization is NOT working yet since at least one essential external component of organizational functionality has not been recovered.

Fully Operable Organization: Both internal and external essential components of organizational functionality are maintained, or restored so that the organization is working but NOT at an admissible level; some or more secondary products may be completely interrupted, however, primary products are available albeit at an *unacceptable* capacity or quality, or in an unsustainable fashion.

MALF Organization: The organization is working at an admissible level of functionality; some or more secondary products may be completely interrupted, but primary products are available albeit at an *acceptable* reduced capacity and quality, and potentially in an unsustainable fashion.

Fully Functional Organization: The organization is working properly and providing all primary and secondary products at the intended level of quality and quantity in a sustainable fashion.

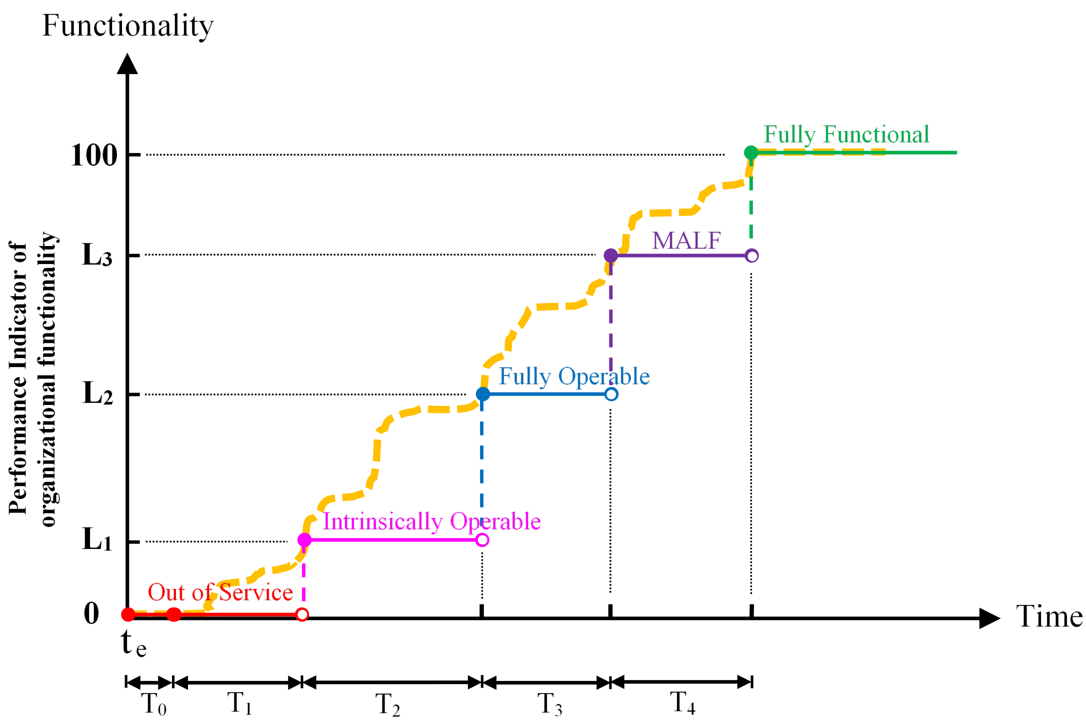

Figure 5. Post-disaster functionality states of an organization

Figure 5 transforms the functional recovery trajectory of an organization into an equivalent step function using the defined post-disaster functionality states. The percent of functionality is 100% for the Fully Functional state, measured relative to the pre-event level, and 0% for Out of Service State. The percent of functionality associated with Intrinsically Operable (L_1), Fully Operable (L_2), and MALF (L_3) states are organization-specific and can be determined empirically, through engineering judgment, or through input from the owner or manager of the organization being analyzed. However, a systematic approach to estimating the L_1 is proposed later in this paper. The key concept for the MALF state is that the admissible intended functions of an organization are often something less than a Fully Functional state. Various reasons can cause the MALF state; for example, using a temporary power supply instead of a permanent one in a hospital (e.g. a back-up generator being used because electricity is out) may increase the waiting time to receive a particular healthcare service but the service is available at a reduced capacity. The organization will work at the MALF state if the available reduced capacity is equal or greater than the admissible capacity, otherwise, the available capacity will be ignored and the organization will be considered at the Fully Operable state.

As shown in Figure 5, when a disruptive event occurs, an organization's functionality shifts to the Out of Service State for a period T_0. Similar to the time lapses for mobilizing resources and decision-making discussed in previous works (Comerio, 2006; Comerio & Blecher, 2010), T_0 represents a delay time that accounts for the amount of time where that organization must contact employees, survey and assess physical assets, such as the building, equipment, and inventory, and perform any other assessments before the organization can potentially move into a functionality state. T_3, and T_4 denote the time spent in the Out of Service, Intrinsically Operable, Fully Operable, and MALF states, respectively. The TRF is the sum of the time spent in each state previous to the MALF state, including T_0.

Although the organizational functionality states are shown sequentially in Figure 5, the organization can move directly into any of the other states after time T_0. Furthermore, since the Intrinsically Operable state is based on the outage of an external component, it and the Fully Operable state do not necessarily happen successively, although they can.

Organizational functionality can be related to a community's functionality through the networked relationship shown in Figure 6. Applying fundamental concepts from Graph Theory (Trudeau, 1993) to visualize the bi-directional relationship, wherein a node represents (a) a community, (b) an organization, (c) a building, or (d) an infrastructure network. The relationships between nodes are represented by edges, which can manifest as their communication, interaction, or supply chain connections (Li et al., 2019). Each infrastructure (blue) node (built capital, e.g., water network) is a set of interconnected components (e.g., storage tanks, pipe networks, valves, pumps, etc.) that work together to provide a service to the organizations (red nodes). Organization nodes interact to support the functionality of the community (green) nodes. Each community node consists of sub-clusters of the other six community capitals, as shown on the right side of Figure 6. Thus, as shown by the red-dashed outline marked (a), organizations are supported by infrastructure services, and as shown by the green-dashed outline marked (b), communities are supported by organizations.

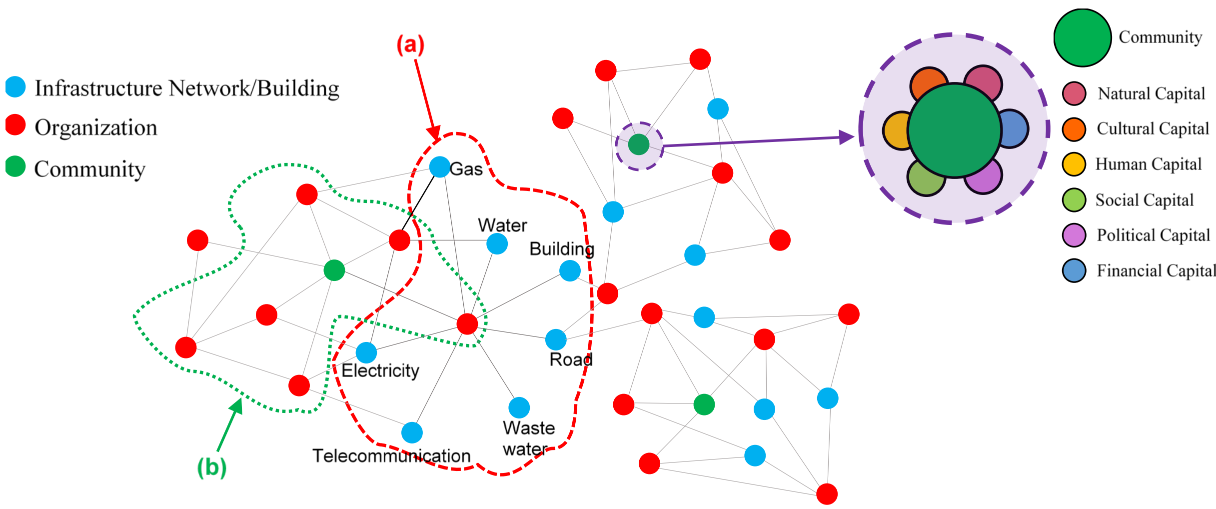

Figure 6. Relating organizations to the community capitals: a) organizations are supported by infrastructure services (built capital), b) communities are supported by organizations.

The following section describes the relationships, dependencies, and other internal components that cause organizational functionality loss in a quantitative framework.

2.3 Measuring Organizational Functionality

2.3.1 Defining Failure through Fault Tree Analysis

Fault tree analysis (FTA) is a simple analytical technique that has been widely used for quantitative reliability and safety analysis. FTA can be used for any system which is composed of discrete components with independent probabilities of failure. The fault tree (FT) itself is a qualitative and graphical model that combines a series of parallel and sequential failure events which will lead to the occurrence of a predefined undesired event in the system. This predefined undesired event is the top event of the FT. A FT applies logic gates to combine the basic events and connect them to intermediate events that lead to the top event (Ruijters & Stoelinga, 2015; Vesely et al., 1981). FTA is executed using two primary techniques: (1) qualitative vulnerability detection through a logical expression of the top event in terms of the basic events; (2) quantitative measurement of the probability of occurrence of the top event obtained through combining the failure probabilities of the basic events (Durga Rao et al., 2009).

In a quantitative FTA, logic gates, more specifically AND gates and OR gates, combine the probabilities of connected events using basic probability rules. In engineering risk assessment using FTA, the combined failure probability of a system (*S*) which consists of *n* components (s_1, s_2, …., s_n) that are connected with AND and OR gates, can be calculated as (Porter & Ramer, 2012):

$$P(S|AND)=\prod_{i=1}^{n} P(s_i) \tag{1}$$

$$P(S|OR)=1-\prod_{i=1}^{n}[1-P(s_i)] \tag{2}$$

where $P(S)$ is the failure probability of the system, $P(s_i)$ is the failure probability of the *i*th component connected to that gate, and Π denotes the product. The AND gate represents a parallel system in which a system will not fail unless all of its components fail, whereas the OR gate depicts a system in series in which the failure of any component leads to system failure.

2.3.2 Causes of Organizational Functionality Loss

Disasters, small and large, can damage buildings, cause lifeline service outages, disrupt supply chains, and displace people (employees and customers), all leading to organizational functionality loss. If the amount of the loss exceeds the predefined lower threshold (the MALF) and organizational functionality does not restore to the MALF before the MTDP, the organizational functionality will fail. Then, the availability of an organization's primary products is a key factor in modeling the organizational functionality failure. Building off of the work by Yavari et al. (2010) and Jacques et al. (2014) on healthcare facilities, Figure 7 presents a generic fault tree for organizations, setting organization functionally failure as the top event. Beneath the top event is the first tier of intermediate events: the organization's primary products being compromised, where three primary products are arbitrarily shown in Figure 7 and the tree is developed for the second product as an example. The Tier 1 events are connected to the top event through an OR gate, meaning that if any Tier 1 event occurs, the organization will lose some of its functionality. Tier 2 consists of five intermediate events that are similarly connected to the Tier 1 event through an OR gate, including physical space compromised, staff unavailable, physical access compromised, supporting external utilities compromised, and supply chain compromised. Tiers 3 and 4 further break down failure events into greater detail, where more tiers are possible but cannot be generalized; further detailed failure events will require input from the specific organization being modeled. The structure of the FT in Figure 7 is such that the occurrence of any of the events (basic or intermediate) in the first three tiers will cause some functionality loss and may lead to the top event, showing the wide range of events contributing to organizational functionality. Each event is associated with different recovery costs, recovery times, and consequences which lead to different values of TRF for the organization.

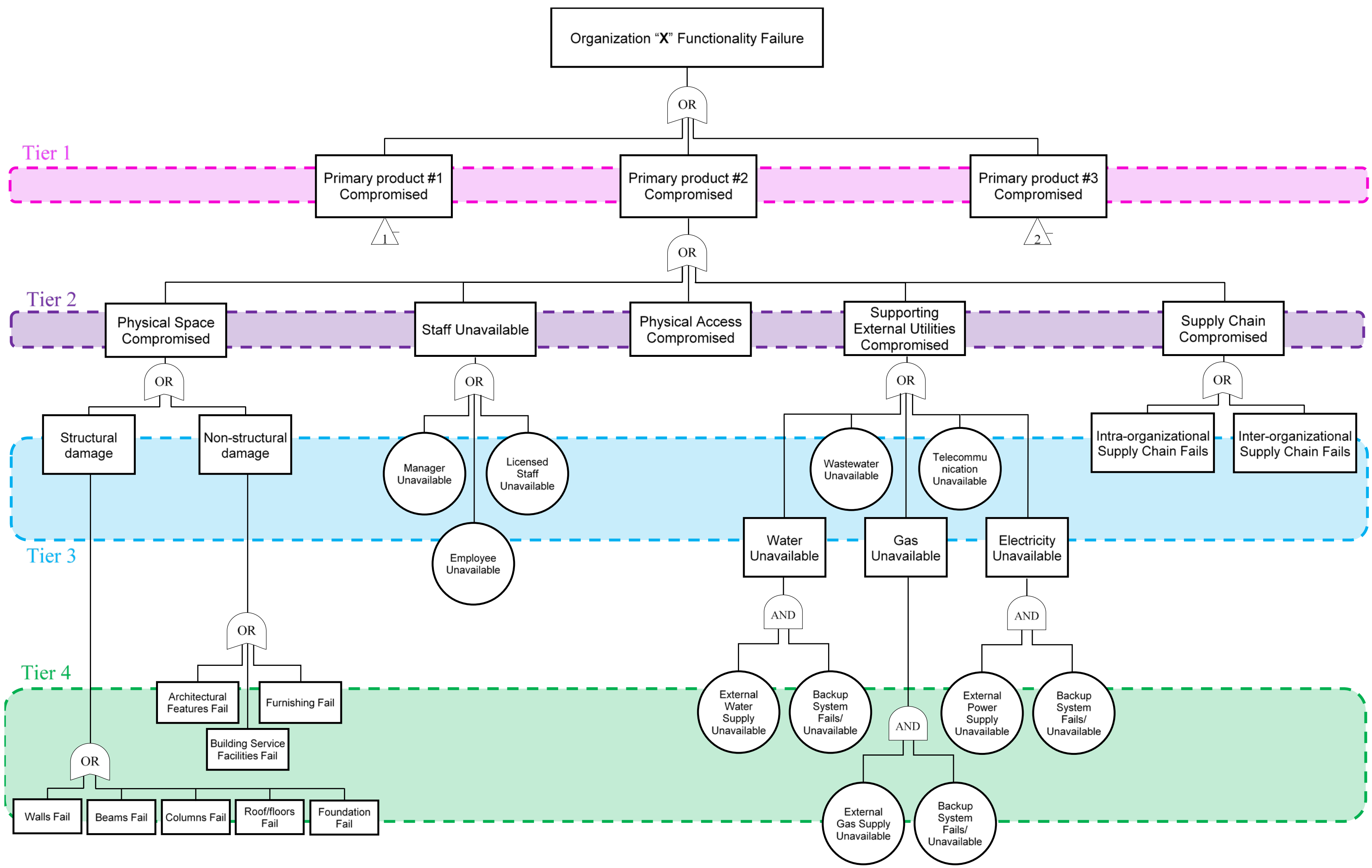

Figure 7. Fault tree for displaying the incidents that commonly cause organizational functionality loss in a hypothetical organization with three primary products

As shown in Figure 7, damage to both structural and non-structural components of a building can endanger the functionality of the organization; main non-structural components that may be available in organizations are classified into (1) architectural features (such as doors, windows, stairs, ceilings, partitions, etc.), (2) building service facilities (including HVAC, lighting systems, fire detection and suppression systems, elevators, etc.), and (3) furnishing equipment (e.g., shelving, desks, furniture, computer stuff, etc.). Even if the building is structurally sound, disruption to physical accessibility may also threaten the organization's functionality. The disruption can be due to temporary road closures, restricted site access, or the destruction of an adjacent building. If employees and customers cannot access the organization, then it cannot function as intended. Sometimes, rather than physical access, access through a loss of telecommunication network can cause functionality loss. Other lifeline service disruptions can similarly cause failure in organizational functionality. For example, restaurants cannot operate without a clean water supply. In general, damage to external lifeline systems, including water and wastewater, energy, and telecommunication, can cause organizational functionality loss.

Adapting the concept of defining rational and irrational components of downtime for buildings (Comerio, 2006) to this study, causes of organizational functionality loss are comprised of both rational and irrational situation-specific components. Substantial research has produced reliable measures of rational components, such as physical space, access, and external utilities being compromised; whereas less research has been spent quantifying the probability of occurrence and recovery times for irrational components. Measuring irrational component failures is complicated and highly variable given the dependence on social, political, and financial factors (Krawinkler & Miranda, 2004). The FT in Figure 7 highlights the irrational components associated with the functionality of an organization, including staff and supply chains. Failure of irrational components will result in some organizational functionality loss even if the rational components are functioning. For example, the COVID-19 pandemic has shown how many organizations can operate remotely without their traditional physical space, as long as their staff and telecommunication services are available. This example also showcases how it is ultimately the people (staff, suppliers, users) who differentiate an organization from a building, and the people who enable higher levels of resilience to be achieved, including innovations, adaptability, and transformation, like moving traditional in-person services to online. The required staff is organization-specific and may include managers, licensed or key personnel, and other employees. Supply chain disruptions are another type of irrational component which can occur in inter- or intra-organizational supply chain, or both. Inter-organizational supply chains are external or between two or more different organizations, such as the relationship between a grocery store and food supplier. Intra-organizational is within an organization and refers to any process within the organization, such as e-mail that connects different branches of the organization. While modeling irrational components is important for understanding and predicting organizational functionality loss, doing such complicates the modeling process, particularly given data limitations.

Furthermore, components contributing to organizational functionality can be classified as internal and external essential components. In the FT in Figure 7, physical space-related events are internal essential components; any other events including those related to physical access, staff, supporting utilities, and supply chain are external essential components. The ratio of the number of internal components to the total number of components on Tier 2 of an organization-specific FT (1:5 for generic FT in Figure 7) can be used as a rough estimate of the organizational functionality percentage associated with the Intrinsically Operable state (L_1) in Figure 5.

2.3.3 Quantifying Organizational Functionality Failure

This section provides a formulation for quantifying organizational functionality failure using FTA. Looking back to Figure 5, the probability of organizational functionality failure can be interpreted as the probability that the TRF exceeds the MTPD (*P[TRF>MTPD]*), where the value of the MTDP for each organization may be determined using predefined quantities (e.g., NITS CRPG (NIST, 2016)), modeling tools (e.g., Critical Path Method (Lavelle et al., 2020)), and/or through input from the organization owner/manager.

To estimate the probability of organizational functionality failure, (1) the probability of occurrence for each basic event must be known, and (2) the combination of all basic events must be estimated. The latter is done using Equations (1) and (2) based on the logic gates connecting each basic event across tiers. The former is estimated as *P(e,t)*, the probability of the basic component being in the non-functional state at time *t* subject to a demand parameter *e*. *P(e,t)* must be based on disruption levels for each component, which classify component disruption into increments. For rational components, such as structural damage, disruption levels are the same as conventional damage states (e.g., none, slight, moderate, extensive, and complete (FEMA, 2003)). Damage states are widely used by researchers in the development of fragility functions with criticality that their definitions are quantitative and not subjective. However, for irrational components, as well as for some non-structural components such as building service facilities and equipment, a consensus formal definition of disruption levels does not currently exist in the literature and requires further research.

As such, *P(e,t)* is determined based on (1) *G(e)*, the probability of that component, subject to demand parameter *e*, being disrupted, and (2) *Ŕ(t)*, the probability of the disrupted component being unrestored before time *t*. Since the component's disruption and restoration time are statistically dependent through disruption levels, the failure probability of the *i*th component in a FT model with *n* basic events can be estimated using

$$P^{(i)}(e,t) = 1 - \prod_{DL=1}^{n_{DL}} \left[1 - \left(G_{DL}^{(i)}(e) \right) \left(\acute{R}_{DL}^{(i)}(t) \right) \right] \tag{3}$$

where $P^{(i)}(e,t)$ is the probability of component *i* being in a non-functional state before time *t* subject to demand parameter *e*, Π denotes the product, *DL* represents disruption levels (assuming *n* levels of disruption for the component, n_{DL}), and $G_{DL}(e)$ and $\acute{R}_{DL}(t)$ are cumulative probabilities of disruption and restoration time, respectively, for a given disruption level. For rational components, *G(e)* and *Ŕ(t)* can be specified using existing (or new) fragility and restoration functions (Prabhu et al., 2020). However, functions for irrational components cannot (or should not) be modeled using similar fragility functions due to their more complex nature with dependencies extending externally.

Once the probability of occurrence of each basic event is estimated, a Monte Carlo simulation can be applied to determine the probability of occurrence of the FT top event, $F^{(top)}(t,e)$ for a range of values of *e* and *t*. $F^{(top)}(t,e)$ gives the probability that the organizational functionality is not recovered before time *t* subjected to demand *e*. Employing probability theory and setting *t* equal to MTPD, the failure probability of organizational functionality and the expected value of the TRF (mean TRF) for a given demand *e*, can be predicted as

$$P\left(TRF > MTPD \middle| e\right) = F^{(top)}(MTPD,\, e) \tag{4}$$

$$Q(t,e) = P\left(TRF \le t \middle| e\right) = 1 - F^{(top)}(t,\, e) \tag{5}$$

$$E\left(TRF \middle| e\right) = \int_0^\infty t \cdot q\left(t \middle| e\right) dt \tag{6}$$

where $P(TRF>MTPD\,|\,e)$ is the probability of organizational functionality failure, and $E(TRF\,|\,e)$ is the organization's mean TRF, given the demand *e*. *Q(t,e)* is the cumulative distribution function for the probability of non-exceedance of the TRF, and *q(t|e)* is its associated probability density function which provides the probability that the organization is functional at time *t* for demand *e*. Figure 8 shows a conceptual illustration of *Q(t,e)* and the organization's mean TRF for a range of hypothetical demand values sorted in ascending order by the intensity/magnitude value ($e_1, e_2, ..., e_n$).

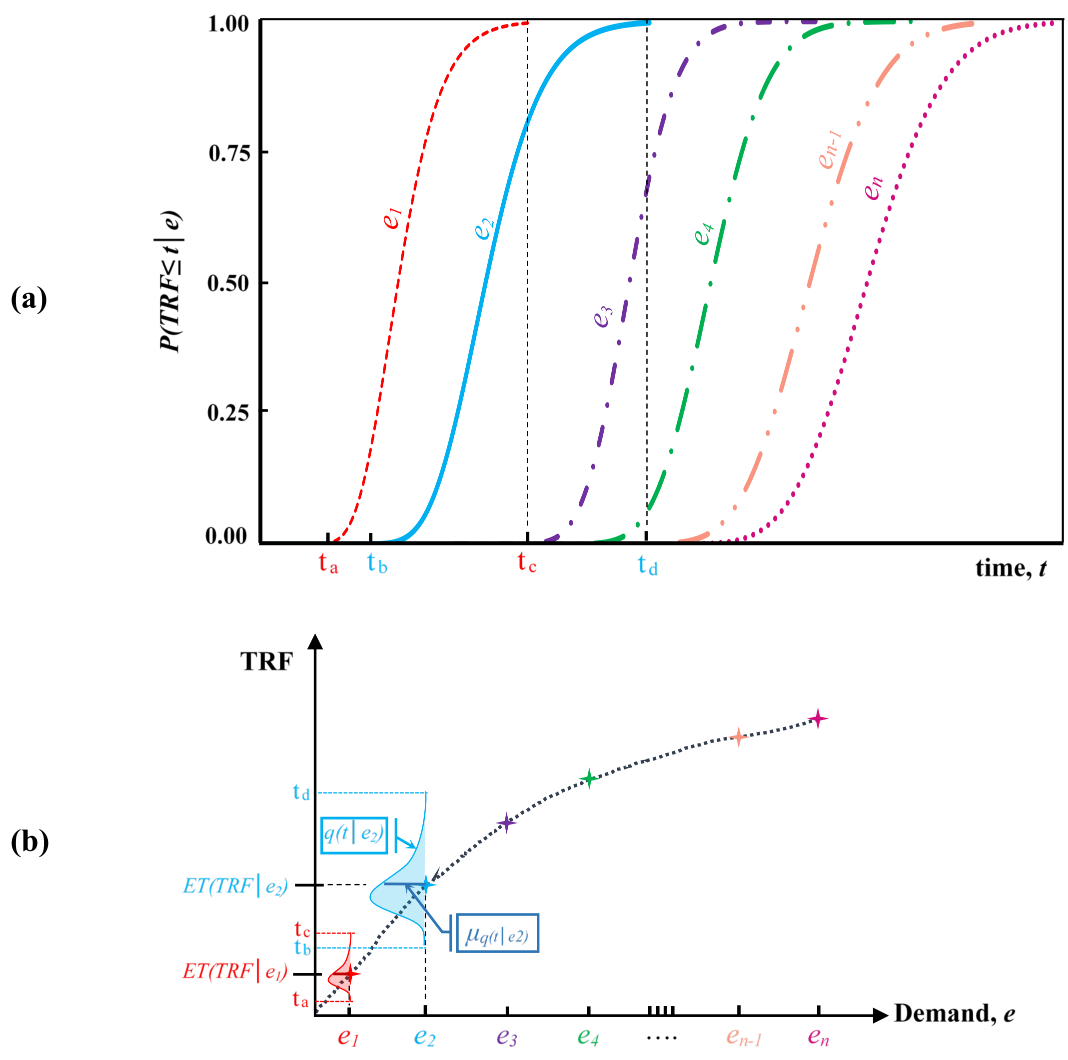

Figure 8. Conceptual illustration of: a) cumulative distribution function for probability of non-exceedance of TRF, Q(t,e); b) organization's mean TRF for a range of hypothetical demand intensity

The curves in Figure 8a illustrate the time required to restore organizational functionality to the MALF (horizontal axis), and the probability that the TRF takes a value less than or equal to that time (vertical axis). For instance, the probability that the organization's TRF is less than or equal to t_c for demand e_1 is 1.0, which means there is a 100% chance the organizational functionality restores to the MALF before this time. Figure 8b fits a curve to values calculated using Equation (6) with varying demand ($e_1, e_2, ..., e_n$) to illustrate the mean TRF. The colors and symbols in Figure 8a correspond to the same scenarios in Figure 8b.

The main goal of defining organizational functionality, modeling, and quantification of its failure probability in this paper, is to develop a framework for the assessment of a community's post-disaster resilience objectives through measuring the stock of community capitals. The purpose of this framework is to help community decision-makers to develop more informed disaster risk mitigation and long-term recovery plans. In the next sections, to clarify the framework previously formulated, first, fault tree models of organizational functionality for three specific organizations: *banks*, *gas stations*, and *schools* are developed and discussed. Then, a step-by-step procedure for evaluating community resilience using this concept is presented.

2.4 Application of the Proposed Fault Tree Model for Various Organizations

Although generalized in Figure 7, physical space, access, staff, supporting services, and supply chain differ significantly across organizations. These details must be known in order to prioritize components and begin to understand what is necessary for the minimum acceptable level of functionality (MALF) for a given organization. The application of the generalized fault tree in Figure 7 will differ amongst organization types, and even within a type, depending on size, structure, resource dependencies, and other larger contextual variables. Influential variables are extensive, so this tool must be used in conjunction with accurate data, relevant stakeholders, and simulations, where possible, for an organization (Jacques et al., 2014). Still, the proposed generic fault tree can be adapted to pinpoint vulnerabilities for a given organization, as is done here. To describe key differences across different types of organizations, this section develops fault trees for three specific organizations: *banks*, *gas stations*, and *schools*, where a specific model for healthcare facilities can be found in Jacques et al. (2014). The three organizations are selected here based on their different organizational structures, functionality dependencies, and product diversity with respect to each other; they also contribute differently to the community capitals. These organizations do not reach the highest risk category under the current approaches in ASCE7-16; thus, they are not required to be functional following a design-level hazard event though research has shown all three are important for maintaining and restoring community's functionality after a disruptive event (NIST, 2016). Banks, or financial institutions, primarily contribute to financial and social capitals and are less dependent on the physical space they occupy compared to their staff and supply chains. Gas stations, on the other hand, depend on their physical space, access, and supply chain more than their staff. Schools primarily generate social and human capitals, can substantially change their product during a disaster, and overall have a wider range of undesired events that threaten their functionality compared to banks and gas stations. Each is described in detail in the following subsections.

2.4.1 Banks

Banks vary in structure to include central banks, retail banks, commercial banks, investment banks, private banks, and credit unions. These organizations serve different consumer bases to include community members (individuals), businesses, and larger commercial entities. They also differ in the structure; members take ownership in a credit union, whereas larger banks rely on a top-down structure. This aside, primary products remain the same: (a) loan services (car, home mortgage, credit lines), (b) transactional accounts (checking and savings) and their maintenance through withdrawal services, and (c) debit, credit, and Certificate of Deposit (CD) services. Common supplemental services occurring often include investment consulting, wealth management, and safety deposit boxes as secondary products (Shekhar & Lekshmy, 2013). Taking the primary products into consideration, the generic fault tree from Figure 7 is adapted for banks in Figure 9. A functional bank is able to provide its primary products: transactional accounts services, loan services, and debit, credit, and CD services. For brevity, the branch corresponding to debit, credit, and CD services is not shown here, as it is essentially identical to the FT branch for loan services.

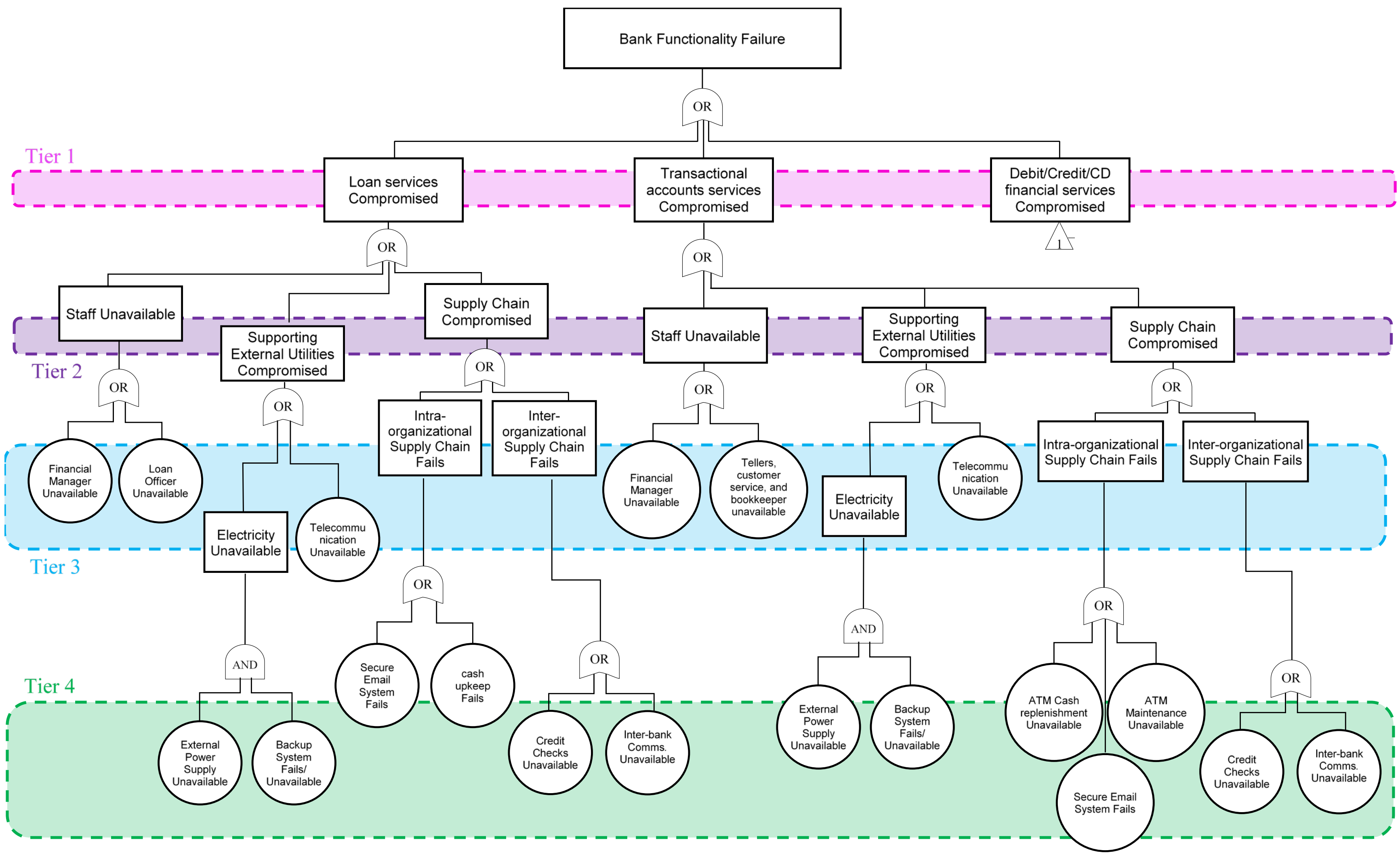

Figure 9. Fault tree of functionality loss of a bank

The FT in Figure 9 only specifies events that are critical for the bank's functionality in the aftermath of a disaster. The FT excludes events associated with the compromising of physical space and physical access as non-critical fault events. This is directly tied to the advent and extensive use of online banking services and the popularity of ATMs for withdrawals. In this respect, the value of L_1 would be zero which means the Intrinsically Operable state will be omitted from the post-disaster functionality states of a bank. The events beneath supporting external utilities are modified in Tier 3 and Tier 4; the events of water, wastewater, and gas unavailability are excluded since they are connected to the physical space and thus not critical for the bank's functionality. Electricity and telecommunications are still included for the use of the Electronic Payment Network. The Tier 2 event of staff unavailability remains unchanged, highlighting the significance of financial managers, customer service and tellers, and loan officers to the service delivery and functionality of banks. Also, both intra-organizational and inter-organizational supply chains are considered critical for a bank's functionality. Any disruption in the replenishment of ATM cash, ATM maintenance, or cash upkeep as the intra-organizational supply chain can compromise the availability of withdrawal services. Similarly, inter-organizational supply chains are required for credit checks or inter-bank communication. Nonetheless, it is important to note the physical structure and external utilities are still required for a typical bank to be fully functional. Staff needs a physical space for long-term work, and a neutral meeting point for in-person services such as wealth management, investment consulting, and safety deposit boxes is undeniable.

Banks can also temporarily change their primary products. For example, after a disaster, a bank might still service existing customers whilst shifting to disburse Small Business Administration loans for recovery needs. This change in primary products is important for understanding the role financial institutions play in community functionality in short and intermediate-term, dynamic financial capital.

2.4.2 Gas Stations

The products of a gas station include the provision of automotive fuels (such as gasoline, diesel, gasohol), motor vehicle parts (e.g., lubricants, filters, etc.), restroom services, and some groceries, oftentimes drinks and snacks (BLS, 2020). Although gas stations might be a primary grocery supplier in some communities, the primary products of gas stations are the retail sale of fuel and lubricant for motor vehicles. Gas stations are often small employee-based organizations that do not require staff with technical degrees and almost always offer self-service and a pay-at-the-pump system. On the other hand, gas stations' procurement and distribution of fuel ties them to a physical space, and make them a supply chain-reliant organization. Thus, physical space, access, supporting external utilities, and supply chain, due to their interdependence, are critical components of a functional gas station, as shown in Figure 10. In this example, 25% is an appropriate estimate of the organizational functionality percentage associated with the Intrinsically Operable state (L_1) of a gas station.

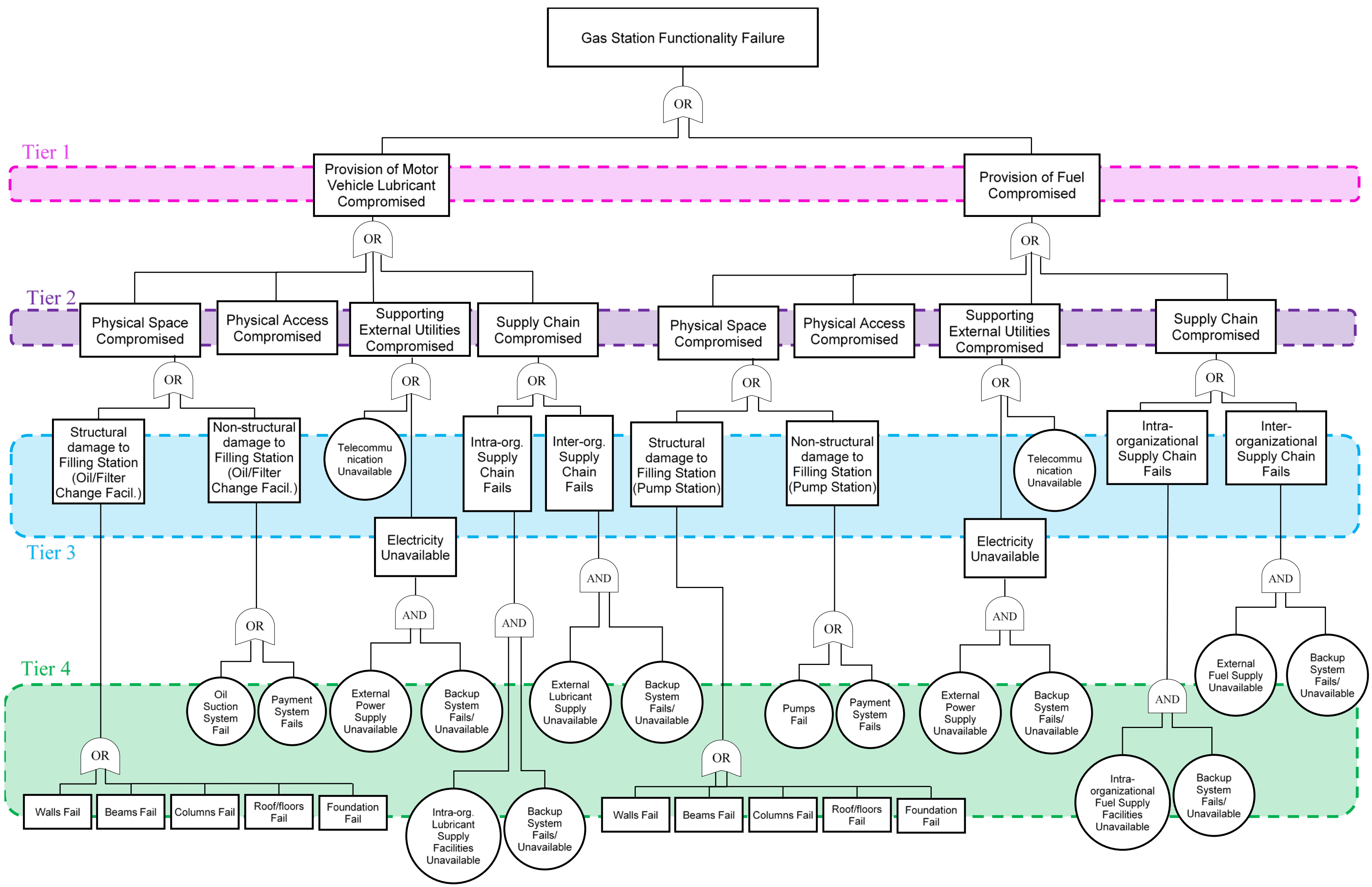

Figure 10. Fault tree of functionality loss of a gas station

The FT in Figure 10 solely considers the events that are essential for the delivery of the primary products of a functional gas station. The FT includes all events associated with the compromising of physical space, physical access, and supply chain as they are critical fault events. Any type of structural damage to filling stations or non-structural damage to self-service facilities (such as failure of payment systems, oil suction systems, and gas pumps) can seriously compromise the physical space. The supply chain can be disrupted through failure in either external supply resources of fuel and lubricants or intra-organizational distribution systems. The functioning of pumps and pay-at-the-pump systems also depend on supporting external utilities of electricity and telecommunications; these events are included in the FT in Figure 10.

2.4.3 Schools

Schools are considered as a third and final example organization. Schools (K-12 and higher education) contain the most intra-archetype variation of the three organizations covered here. Schools vary considerably in size, organizational structure, and physical space. For example, smaller elementary schools can sometimes exist in one building, while larger campuses contain several buildings and many levels of staff and faculty to coordinate hierarchy within (Ungar et al., 2019). Figure 11 provides the fault tree for the functionality loss of a mid-sized K-12 school.

Schools exist to provide students with products of education, food, and recreation. Schools are highly staff-reliant, with generalized and specialized teachers being the main implementer of the products. Specialized teachers refer to those that require additional training and licensure, such as teachers who assist in teaching students with learning disabilities or technical coursework. Principal and superintendent availability becomes crucial to decision-making, advancement for the district, and any disciplinary action. Supporting staff are also vital to student well-being through food delivery, health services, and administration. So, too, is the supply chain to keep education products, food, and health items in stock at the school's location. In this case, the FT gives an estimate of 20% for the value of L1 in schools.

While the physical space, physical access, and external utilities are essential for a school's functionality, the basic objective of education can occur online, as exemplified through the COVID-19 pandemic and subsequent online-based education. Still, the quality of educational product delivery and schools' (and students') capacity to move online become serious limitations. This underscores a school's reliance on physical space while recognizing the flexibility and importance of at-home back-up space when the school's physical space is compromised. Also, when planning for community resilience, it is important to consider how the products of an organization may change during a disaster. For example, in addition to providing educational services, school buildings serve another primary role after disasters: the role of emergency shelters (McArdle, 2014; Mutch, 2014). In this second case, the physical space is extremely important, as well as physical access and supporting utilities.

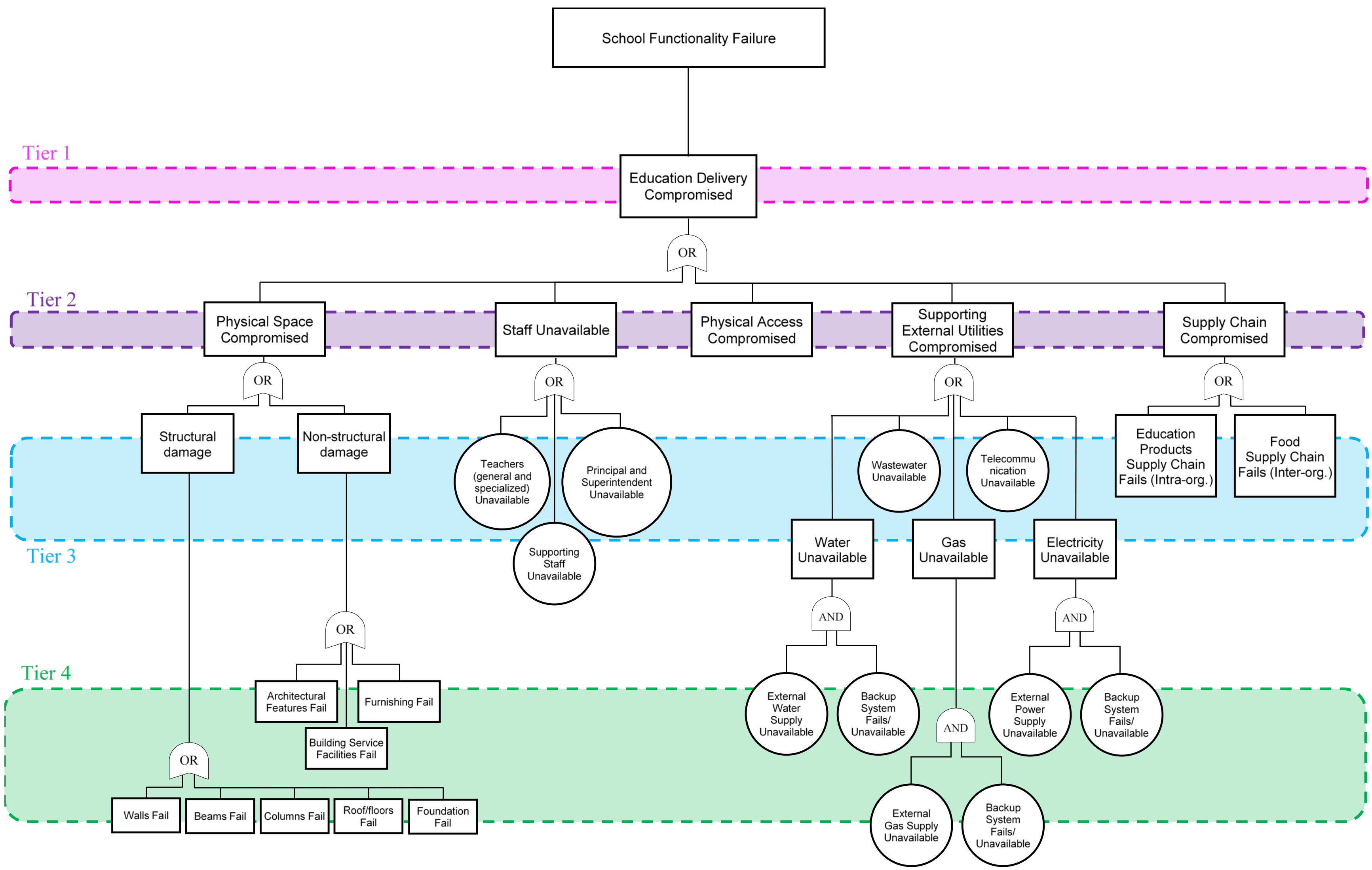

Figure 11. Fault tree of functionality loss of a mid-size K-12 school

2.5 Step-by-Step Procedure for Community Resilience Evaluation

Summarized below are the basic steps of a proposed practical framework to evaluate the post-disaster resilience of a community using the organizational functionality and community capitals concepts.

1. Define a set of quantifiable metrics for each community capital (except built capital) regarding the existing organizations' products. For example, one scale for measuring social capital, particularly when it comes to organizations, is the *community housing capacity* which can be offered by single and multi-family dwellings, shelters, and hotels following a disaster.
2. Calculate the expected capacity of individual organizations contributing to the desired community capitals at the time *t* after the event using the relevant metrics defined in step 1, as:

$$ET\left[c(t)\middle|e\right]=\left[Q(t,e)\right]\left[c(t)\middle|\bar{e}\right]\left[\frac{L_3-L_2}{100-L_2}\right] \tag{7}$$

(8) where $ET[c(t)|e]$ is the expected capacity of the individual organization concerning metric *k* at time *t* after given disruptive event with demand *e*; $[Q(t,e)]$ denotes the probability of that organization becomes functional before time *t* which can be calculated by Equation (5); $[c(t)|\bar{e}]$ is the capacity of the individual organization concerning metric *k* at time *t* if the disruptive event does not happen; L_2 and L_3 are the percentage of functionality determined for Fully Operable and MALF organizations, respectively.

3. Calculate the expected capacity of each metric at the community-level by aggregating the expected capacity of the individual organizations computed in step 2, as

$$C\left[c(t)\middle|e\right]=\sum_{j=1}^{n}\left(ET\left[c(t)\middle|e\right]\right)_j \qquad j=1, 2, \ldots, n \tag{8}$$

(9) where $C[c(t) \mid e]$ is the expected capacity at the community-level concerning metric k at time t for the given disruptive event with demand e and is aggregated for n organizations that contribute to that metric capacity; all other parameters were previously defined.

4. Compare the expected capacity at the community-level considering metric k with community resilience and recovery plans and use the results to make more informed decisions that minimize the long-term recovery time of the community. Several approaches exist in the literature for community resilience planning and risk-informed decision-making (e.g.,(United Nations, 2016)), but this is outside of the scope of this paper.

2.6 Conclusion

The need to rethink design goals in U.S. building codes to include functional recovery targets has gained significant traction in recent years. Designing for functional recovery should consider limit states for both safety and functional recovery time. Buildings are should not be considered as isolated structure, but as part of a community. As such, it is imperative to understand, measure, and evaluate how that building supports or otherwise contributes to various community functions and related capitals. This relationship can be understood through (1) the organization(s) residing in the building, and (2) how the products of the organization(s) support the community measured through the community capitals.

Organizations work as a lynchpin connecting the built capital to the other capitals. Communities need to ensure that their organizations will be recovered within an acceptable period to support short, intermediate, and long-term functional recovery goals. Therefore, the availability of a decision variable which links the community resilience objectives to the built environment functional recovery goals will result in more informed disaster risk mitigation and long-term recovery plans at the community level.

The concept advances research on community resilience planning and functional recovery design, and can be applied by researchers, practitioners, and policymakers. Importantly, organizations require physical and non-physical, or rational and irrational, components to function; the details of which are organization-specific. To validate organization-specific fault trees and quantify the contribution of organizations to the community, further research and data collection are required, which should include working directly with organizations. More research is needed to define explicit measures for the MALF and MDTP of an organization, and to develop a comprehensive library of fragility and restoration functions for the components of organization functionality.

Chapter 3[1]: Community Resilience Testbeds

3.1 Virtual Testbeds for Community Resilience Analysis: State of the Art Review, Consensus Study, and Recommendations

As the quantitative hazard research, particularly stemming from the engineering fields, aims to move from component- and building-level modeling into the interdisciplinary space of community-level modeling for resilience, the need to test, verify, and validate community resilience algorithms becomes a critical challenge; *virtual testbeds* are an effective tool for such purposes. We define a virtual testbed as an environment with enough supporting architecture and metadata to be representative of one or more systems such that the testbed can be used to design experiments, examine model or system integration, and test theories. Testbeds enable researchers to assess multidisciplinary integrated community resilience models thereby helping decision-makers to make better community hazard mitigation plans and recovery decisions. This paper leverages the current momentum on using virtual testbeds for community resilience analysis to dissect what testbeds are in practice. To obtain consensus on the above-presented definition of a testbed, the paper conducted a virtual survey with testbed experts. The survey primarily explored how testbeds have been used across different disciplines, how testbeds differ from case studies, and what are the minimum requirements for a testbed. The paper, then, presents findings from a systematic literature review on 22 identified existing community resilience testbeds and 103

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[1] This chapter is based on two journal papers, one published and one manuscript, in both this dissertation's author is the first author:

Enderami, S. A., Mazumder, R. K., Dumler, M., & Sutley, E. J. (2022). Virtual Testbeds for Community Resilience Analysis: State-of-the-Art Review, Consensus Study, and Recommendations. *Natural Hazards Review, 23*(4), 03122001. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000582 **© 2022 ASCE**.

Enderami, S. A., Sutley, E. J., Mazumder, R. K., & Dumler, M. (n.d). Virtual Testbeds for Community Resilience Analysis: Step-by-Step Development Procedure and Future Orientation. To be submitted to the Journal *Sustainable and Resilient Infrastructure* in January 2023.

associated publications. According to the literature review and survey results, community resilience testbeds should have both a hazard module and a community module which ideally includes physical, social, and economic systems. The literature review concludes with a discussion on the available tools for testbed development, typical challenges testbed developers encounter, and areas for future testbed research. The availability of existing testbeds for reuse by other researchers, standardization of development and publication process of new testbeds including obtaining, cleaning and validating the required data, and verification of numerical algorithms are the main detected issues that need to be addressed in future research.

3.1.1 Introduction

Virtual testbeds are being developed and used across the community resilience literature to serve the purpose of verification and validation (V&V) (Attary et al., 2019; Ellingwood, Cutler, et al., 2016; Fereshtehnejad et al., 2021; Loggins et al., 2019; Noori et al., 2017; Park et al., 2019; Shang et al., 2020). Testbeds were first termed in the Nuclear Power (NP) industry to be used as a means for NP plant process validation (OHara & Wachtel, 1995). However, the idea of developing virtual testbeds at the community level dates back to the 1980s when water distribution network designers were striving to optimally size water distribution pipes although those published works might have been imprecisely termed as a *test case* or *case study* (Walski et al., 1987). Testbeds are an essential part of the development and testing of community resilience algorithms and serve the needs of training and educational purposes as well. Testbeds enable multidisciplinary teams to design, test, integrate, verify, and validate community resilience algorithms and numerical models at different scales and resolutions, which is critical when interdependencies across systems are of interest. Verification and validation of numerical models is an important step in model development enabled by testbeds (Sargent, 2010). Validation is the process of determining if a mathematical or computational model of an event represents the actual event with sufficient accuracy. Whereas, verification is the process of determining that model's implementation accurately represents the developer's conceptual description and specifications of the model (CFDC, 1998). As discussed herein, the development and application of virtual testbeds: (1) enables researchers to test their models that predict the performance of interdependent physical, social, and economic systems and their immediate and long-term impacts in an integrated community resilience assessment; and (2) better support risk-informed decision-making by communities to optimize public and private investments.

This paper presents findings from a virtual survey administered to *testbed experts* and a systematic literature review on community resilience testbeds. The survey results provide insight on the minimum requirements for a testbed, how testbeds differ from case studies, and obtain consensus on the definition of a testbed. Findings from the literature review include metadata for how the identified testbeds have been developed and used. Of note, this paper does not intend to criticize existing testbeds, point out their shortcomings, or rate them, but rather synthesize their existence given that testbeds are almost always indirectly presented in papers. Finally, the available tools for testbed development, typical challenges testbed developers encounter, and areas of future testbed research are discussed. This review can be used to aid interdisciplinary teams of hazards and disasters researchers in working together on testbeds and in understanding where the state of knowledge is on testbed development.

3.1.2 Testbeds as Real and Imaginary Communities

Communities are defined as places, such as towns, cities, or counties, designated by geopolitical boundaries (NITS, 2016). As such, communities are complex systems comprised of interconnected social, economic, and physical systems and processes (S Amin Enderami et al., 2022; Enderami et al., 2021), and can be very difficult to accurately model. Testbeds can be designed to represent communities, including imaginary or real communities. Being real versus imaginary is different from being virtual or physical. Virtual and physical refer to whether the testbed itself is digitally simulated on a computer network or has a material existence, whereas real and imaginary are terms used to indicate whether the testbed is a representation of a real or hypothetical community. As physical testbeds for community resilience are neither feasible nor ethical, this paper only discusses virtual testbeds. Imaginary testbeds can be entirely fabricated, including all required data. For example, Gotham City was modeled after the fictitious city from the comic Batman to be used for verifying community resilience models (Mahmoud & Chulahwat, 2018). Imaginary testbeds may be based on some sort of reality whilst still not being a perfect representative and accurate model of an existing location. The Centerville testbed is an example of such an imaginary community, which models a typical mid-size community using average statistics of several communities in the Midwest United States (Ellingwood, Cutler, et al., 2016).

Imaginary testbeds are often used when there are significant data limitations, or when the research is intended to be highly generalizable for geographic areas with similar topology, population, and infrastructure (Ellingwood, Cutler, et al., 2016). Imaginary testbeds are also particularly useful when a team is attempting to understand how their algorithms fit together given that an imaginary testbed can be modified for convenience and simplicity. For example, instead of chaining numerical models for hundreds of thousands of nodes and links in a given network with hundreds of thousands of end-users, a simplified and smaller version of the models which use dozens of nodes, links, and end-users, can be tested and verified before scaling up. Imaginary testbeds enable simplified analysis and verification. Imaginary testbeds are helpful as well when security is of the utmost importance, such as identifying the location of key infrastructure, as well as when sensitivity of the results is important, such as simulating terrorist attacks so as not to scare people living in an actual community. Thus, security and sensitivity concerns could arise from the nature of the data or analytical results, as well as from the potential trauma and alarm that could be garnered from the publication of the simulation results.

Nonetheless, testbeds are not limited to imaginary communities but can model a real-world community too. How well the testbed models the real community (e.g., the level of detail captured in the testbed) varies depending on the availability and type of data, as well as the analytical needs. For the latter, a testbed may need to model a community on a building-level basis, or on a larger scale such as a census block basis. Some testbeds model real communities with high-resolution details. Take Harris County testbed for example, which was constructed using data from Harris County, Texas. The Harris County testbed modeled power, gas, healthcare, and transportation networks along with the regional topology to simulate and measure the risk of flood hazard scenarios (Dong, Yu, et al., 2020). This was done to mirror the real conditions of the county in the testbed as best as possible. Upkeep of data can be a pressing concern and is needed for testbeds modeling real communities. On the other hand, some testbeds, such as pseudo-Norman, roughly model an existing community using only a few of its attributes. The pseudo-Norman testbed is a coarse replica of the city of Norman, Oklahoma. Since the testbed includes only some aspects of Norman and is not an exact representation of Norman, the originating authors named it *pseudo*-Norman (Masoomi & van de Lindt, 2017).

As evident here, testbeds come in a variety of shapes and sizes. To understand what it means to be a testbed, we designed and virtually administered an expert survey, and coupled these findings with our synthesis from a systemic literature review.

3.1.3 Expert Survey

An expert survey was developed in Qualtrics, a powerful online survey tool, to obtain a consensus definition for the term testbed; the survey data and report are published on DesignSafe-CI (Enderami & Sutley, 2021; E. Sutley et al., 2021). A link to the survey was emailed to 267 experts, where 90 responses were received for a response rate of 34%. This human subject research was approved by the University of Kansas Institutional Review Board (STUDY00147164). Experts were identified through one of two ways. First, 153 experts were identified as an author on one or more of the testbed publications reviewed in the systematic literature review (inclusion/exclusion criteria for the literature review are described later). Although there are more authors than 153 on the papers included in the literature review, the email addresses could be obtained online for only 153. Second, based on our team's experience and professional network, we were aware of other ongoing projects that were developing or using testbeds; from that, we came up with a list of 114 additional experts. This totaled 267 experts; however, in the recruitment email, respondents were asked to share the link with any collaborators they considered as testbed experts. No personally identifiable information was collected from respondents, so we do not know how many people the survey was shared with outside of the 267 experts we directly emailed. We suspect this number is quite low, and that the overall response rate is very near the calculated response rate of 34%.

The survey consisted of a series of questions to categorize respondents, including position, disciplinary expertise, and whether the respondent had used a testbed before or not. If the respondent had used a testbed before, they were asked which testbed(s) they had experience with, which hazards and types of systems they had examined in their use of a testbed, where they obtained data or architecture for the testbed(s), and any validation performed by them or otherwise on the testbed(s). The remainder of the survey consisted of a series of questions intended to define what a testbed is with explicit differentiation from a case study. Results from selected questions are presented and discussed herein.

Figure 12 provides responses from the first two survey questions on the primary discipline and position of the 90 respondents. As shown in Figure 12(a), nearly two-thirds of respondents' primary discipline is the same as this paper's authors, civil engineering. However, the remaining one-third span diverse disciplines in engineering, social and physical sciences. Similarly, as shown in Figure 12(b) nearly 75% of respondents identified their position as academic-based, whether faculty, retired faculty, post-doc, or student. However, 15% of respondents work in government positions, and 7% in industry. Of the 90 completed surveys, 58 respondents indicated that they personally had used a testbed before. Although we are not sure the exact reasons behind the 32 identified experts who indicated they had not personally used a testbed, we are anecdotally aware of many cases where teams of people work together on a project and some team members work directly with computational algorithms and testbeds, and other team members provide feedback, discussion, idea generation, and the like. Thus, the latter category of team members is very familiar with testbeds even if they personally had not used one before.

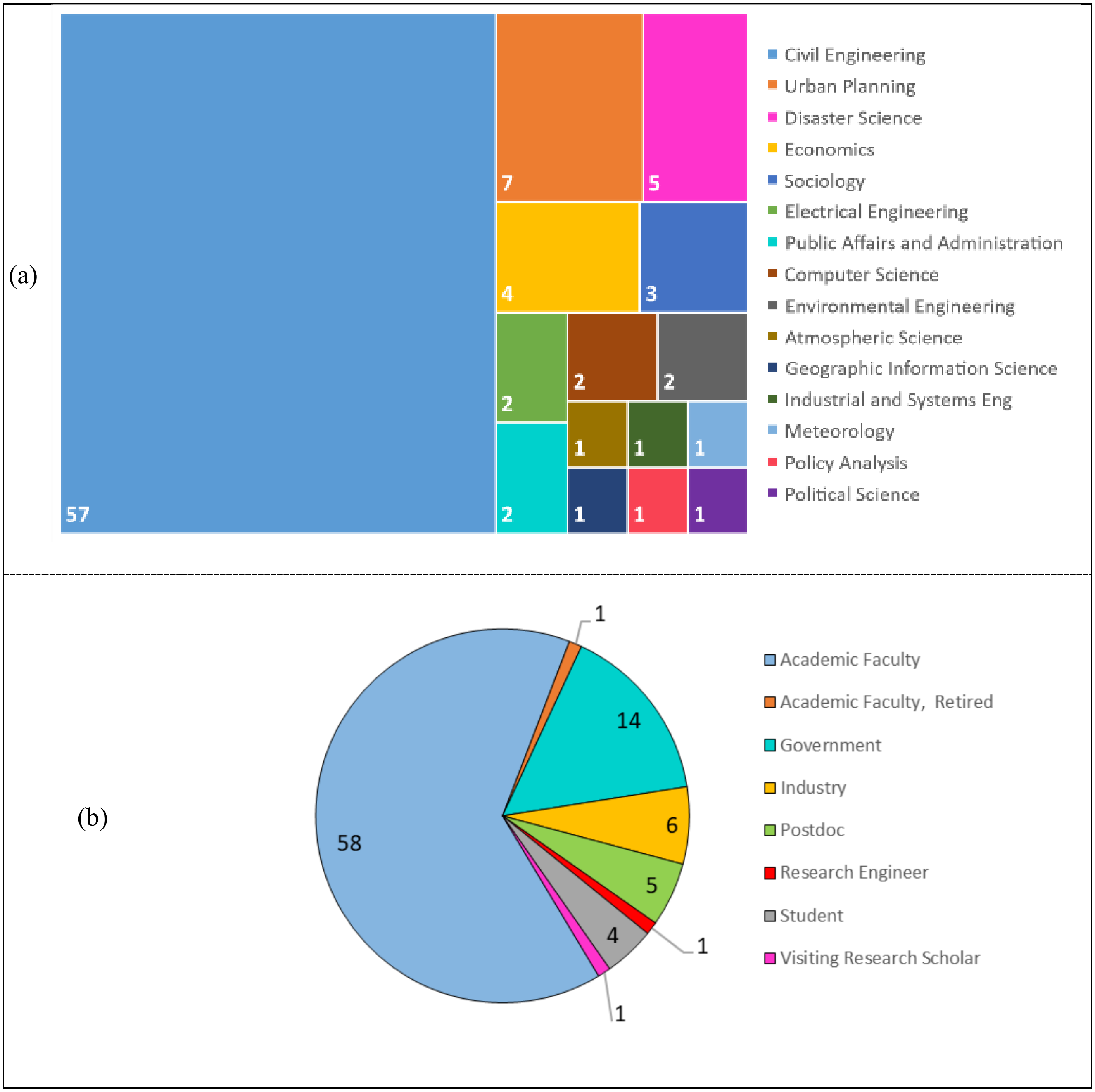

Figure 12. Primary (a) discipline and (b) position of survey respondents (n=90)

3.1.3.1 Defining a Testbed

The term testbed has been used across many disciplines to test scientific theories, computational tools, and new technologies. Meriam-Webster (https://www.merriam-webster.com/) defines the word "testbed" as "any device, facility, or means for testing something in development". This definition does not fully align with how testbeds have been applied in the literature and it is insufficient in capturing the specific needs for community resilience analysis. We believe a testbed is more than a device or facility; so, we included two open-ended questions in the survey to facilitate consensus on the definition of a testbed. The questions provided our proposed definitions of a testbed and a case study and requested the respondent for any comments to refine the definitions. Based on the 96 comments received from these two questions, along with comments recorded from other open-ended questions, we made the required revisions to form the following consensus definition for a testbed:

A testbed is an *environment* with enough supporting architecture and metadata to be representative of one or more systems such that the testbed can be used to (a) design experiments, (b) examine model or system integration, and (c) test theories.

The concept of virtual community resilience overlaps with some existing commercial catastrophe modeling software, publicly available tools for hazard mitigation and preparedness planning (e.g., HAZUS), or other modern high-tech simulation tools such as a Digital Twin. But these tools do not fit into the proposed definition of the testbeds although they might be effective tools in community resilience research. For example, existing risk assessment tools do not provide the required architecture for designing experiments, examining models that include social and economic aspects of a community, and integrating them into the other components. For example, a Digital Twin of a community is a virtual environment that represents the physical aspects of a community and does not simulate the other dimensions of a community. In the survey, a complementary open-ended question was also asked, "*What, if any, minimum requirements are necessary for something to be considered a testbed?*". Sixty-six responses were received. Qualitative analysis revealed three categories of comments: (a) applicability of the testbed to be applied to research questions; (b) requirements of what must be modeled (e.g., systems, hazards);

and (c) the accessibility and documentation of the testbed for the research community. The first category was coded into two themes. These two themes were that the testbed must (1) represent reality, and (2) be a real community. The second category was coded into three themes, that the testbed must include models of (1) multiple hazard options (e.g., type, level); (2) multiple systems; and (3) must have humans. The third category was coded into eight themes, including that the testbed must: (1) be developed and useable from a multi-disciplinary team or perspective; (2) have broad applicability for examining different community resilience algorithms to answer a broad range of research questions relevant for the community at hand; (3) have a defined purpose; (4) be accessible to other users outside the original developers; (5) well-documented; (6) replicable or reliable; (7) scalable; and (8) open-source or modifiable. Finally, there were two other themes that were not categorized: (1) that there are no minimum requirements for something to be defined as a testbed; and (2) other, which included comments not captured by the other 14 themes. The number of responses classified into each of the 15 themes is depicted in Figure 13. The most common response was that at a minimum, a testbed should represent reality (n=21). Three of the 21 comments distinguished that the testbed must indeed be real, as opposed to only a representation of reality. The second most common response was that a testbed should be broadly applicable (n=20); whereas 9 responses indicated a testbed must have a defined, specific purpose.

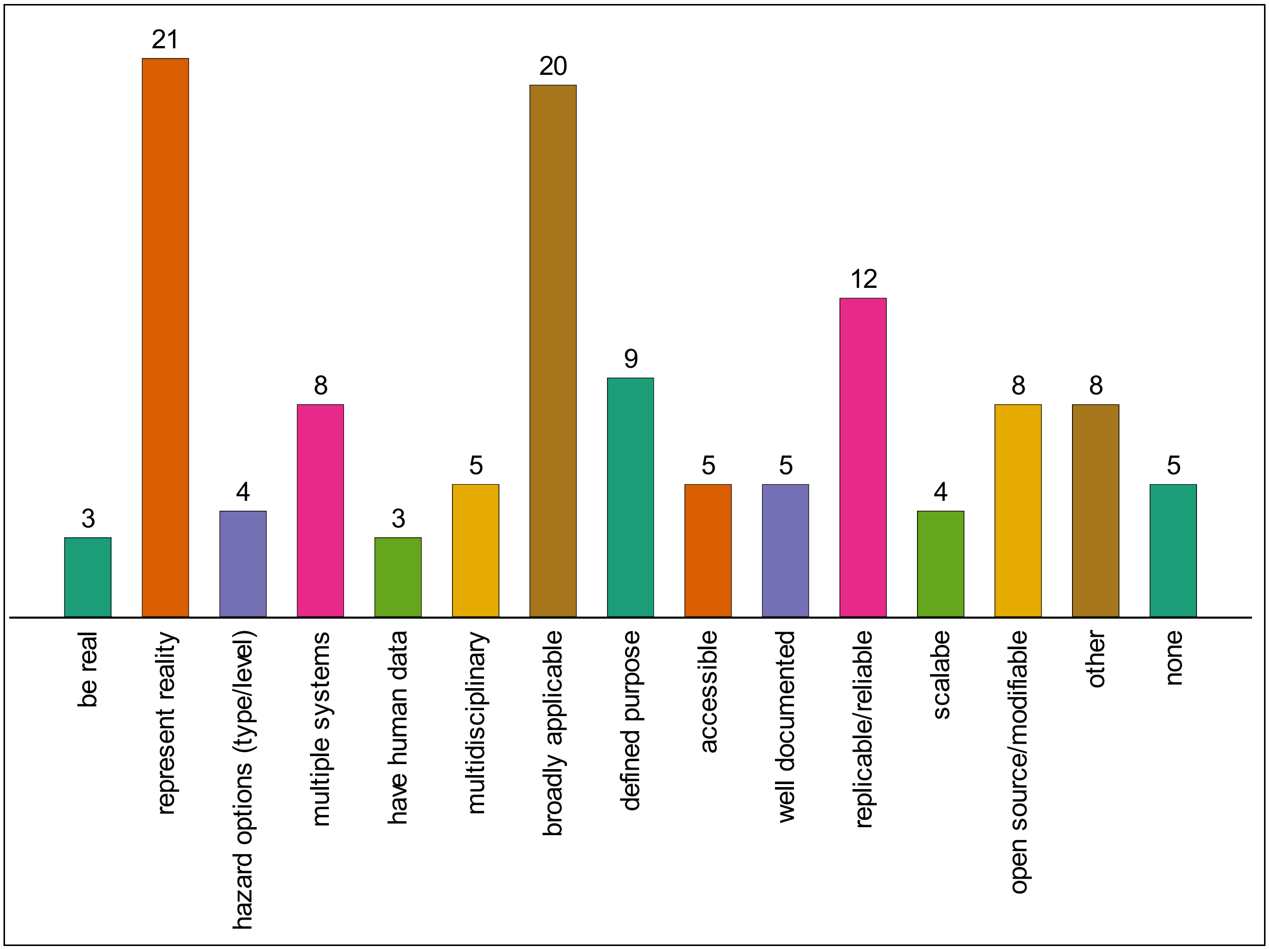

Figure 13. Expert-Identified Minimum Requirements for a Testbed

3.1.3.2 Distinguishing a Testbed from a Case Study

Although distinct concepts and not synonymous terms, the words *testbed* and *case study* are often used interchangeably (particularly in community resilience studies) which has the potential to be misleading. Both case studies and testbeds can be utilized at the community level, but testbed is not a term frequently used in conjunction with a study of a specific past event or single system. Here, we define a case study as research performed to glean new insight from the analysis of a specific situation or demonstrate analysis results. This definition received consensus from the expert survey. A distinguishing feature between a testbed and a case study is that in a testbed, the researchers have some level of control in the design of a testbed and can project a range of scenarios or events, whereas this is not true with a case study. To better illustrate ways to distinguish a testbed from a case study, two examples are provided from the literature.

Galveston, TX is a community with a long history of hurricanes and has been studied by many hazards and disasters researchers. Hamideh and Rongerude (2018) studied the impacts of community members' social vulnerability in their participation in disaster recovery decisions using Galveston's public housing after Hurricane Ike as a case study. In another study, Fereshtehnejad et al. (2021) developed a Galveston testbed for studying the cumulative impact of hurricane-induced damages to civil infrastructure and evacuation decisions of the population. The former was a specific study documenting what happened to a specific group of people following Hurricane Ike. The latter consisted of multiple models chained together capable of simulating and assessing a range of hazard scenarios and subsequent impacts for Galveston.

Similarly, after Lumberton, NC was flooded following 2016 Hurricane Matthew, a team of researchers began a longitudinal field study to collect cross-disciplinary data on impact and recovery (van de Lindt et al., 2018). Many analyses use this data taking the form of case studies [see (Aghababaei et al., 2019)]. However, the larger research team is also building a virtual testbed of Lumberton for model validation purposes. Nofal and van de Lindt used the Lumberton testbed as both a case study to look at the specific one-time scenario of the 2016 flooding (Nofal & van de Lindt, 2020c) and a testbed to evaluate the vulnerability to flooding and the effectiveness of different mitigation strategies (Nofal & van de Lindt, 2020a, 2020b). This has become common to develop testbeds of communities that are rich in case studies.

The expert survey asked respondents one open-ended question to help distinguish a case study from a testbed. Sixty-nine responses were received to the question, "*How do you describe the differences between a testbed and a case study?*" Responses pointed to differences in the scale of the analysis, being able to simulate predictions and interventions with testbeds, and broader use of testbeds. Whereas case studies must be real, apply a pre-designed methodology by the researcher(s), and be limited to a particular study objective.

Five prompts followed which requested respondents to categorize each prompt as describing a testbed, a case study, both, or neither. The prompts were based on statements identified during the literature review describing testbeds or case studies, as well as through informal conversations with colleagues about testbeds and case studies. The five prompts read as follows:

i. A zipped folder containing geospatial data of building footprints, road networks, hazard probability, and population demographics all for a particular community.

ii. A zipped folder containing geospatial data of building footprints, road networks, hazard probability, population demographics all for a particular community, along with the algorithm script for simulating hazard occurrence, physical damage, and restoration processes.

iii. The script file and results from a regression analysis performed on damage and disruption data collected in the field using survey methods after a specific hurricane.

iv. A paper presenting a "proof of concept" test for risk assessment involving 1. Assessment of seismic hazard and ground motions for City-A; 2. Definition of the inventory for buildings, bridges, and utility lines in City-A; 3. Development of vulnerability curves for buildings and bridges in the area; 4. Evaluation of economic impact on property owners and businesses, disruption of social services, and factors influencing local decision making; 5. Recommendation of mitigation measures for improved seismic safety; 6. Creation of decision support tools for comparing solutions for seismic mitigation.

v. On-the-ground investigation into the failure sequence of a particular building damaged during a tornado.

Figure 14 provides the classifications from these five prompts, where each prompt was classified in multiple categories by different respondents. Prompt *ii* received 70 responses, whereas the other four prompts all received 71 responses. As evident in Figure 14, there was fair variability across the five prompts, where prompt *v* got the most consistent responses (86% categorizing as a case study). Of note, 18 of the 70 and 19 of the 71 were from respondents who indicated they had not used a testbed before, there was still proportional variability in classification from respondents who had used a testbed before. An open-ended question followed the five prompts requesting respondents to share any comments about the classification; 19 responses were recorded. Comments were mostly in line with our team's intention in the ill-defined prompts in that prompt *i* is considered data and would be classified as other, prompt *ii* is essentially a testbed, prompt *iii* describes the components of an analysis that is likely enabled because of a case study and would be classified as other, prompt *iv* is a paper presenting an analysis and would be classified as other, and prompt *v* is a field-based case study. As shown in Figure 14, the highest agreement between our team and the respondents were with classifying prompt *ii* as a testbed (63% of respondents), and prompt *v* as a case study (86% of respondents). Prompt *ii* is a good example of a real testbed (since it is for a particular community) that provides metadata (i.e.; geospatial data of building footprints, road networks, population demographics, hazard probability) and supporting architecture (i.e. algorithm script for simulating hazard occurrence, physical damage, and restoration processes). The testbed can be used to design and examine various community resilience models to answer a broad range of research questions such as assessing physical vulnerability, post-disaster accessibility, and social service disruptions.

Furthermore, despite many respondents also identifying prompt *iv* as a testbed, the open-ended responses following these prompts indicated that most respondents overlooked the fact that testbeds are inherently virtual *environments*, while prompt *iv* is limited to just a *paper*. A soft copy (e-version) of the script defined in prompt *iv* would be essentially a testbed, a virtual environment with enough supporting architecture and metadata that it can be applied to examine different community resilience algorithms to answer a broad range of research questions regarding City-A. This means despite the agreement between researchers on the definition of the testbed and case study, there are still some discrepancies in how these terms are distinguished and used in practice.

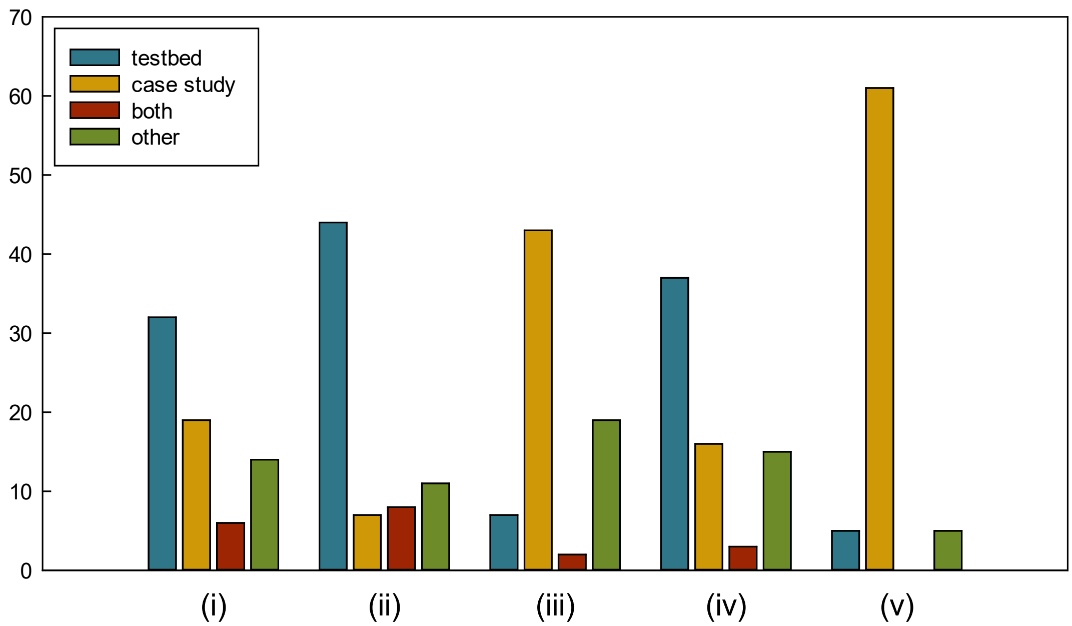

Figure 14. Classifying five descriptions as a testbed, case study, both, or other

3.1.4 Existing Virtual Testbeds

This section presents findings from a systematic literature review on testbeds used for community resilience analysis. Papers were identified using specific keywords, including "testbed", "test bed", "case study", "test case", "virtual city", and "benchmark city". Three inclusion/exclusion criteria were used for categorizing identified papers in the literature review.

First, the paper had to use the testbed for studying the impact of hazards on the community. Even though some of the testbeds included in our review were initiated for purposes other than community resilience research, they are included here if they otherwise fit the consensus definition of a testbed and have been extended later by incorporating a hazard module or social and economic systems into the testbed. As an example, Mazumder et al. (2020) added a hazard module to the Anytown testbed (Walski et al., 1987), which had not been used previously for community resilience analysis. Of note, the application of virtual testbeds for community-level analyses has been popularized among researchers from different disciplines such as environmental science, meteorology, engineering, sociology, urban planning, and disaster science. The NOAA Hydrometeorology Testbed (HMT) was developed by the Office of Oceanic and Atmospheric Research and National Weather Service to improve and advance extreme precipitation and hydrologic predictions (Schneider et al., 2010). Although HMT represents a novel and important testbed, associated publications were excluded from this review since HMT does not meet the first inclusion criteria for a community resilience testbed.

Second, the paper had to develop or use a testbed, as opposed to a case study; the criteria for this are fully described above in the expert survey sections of this paper. As a rule of thumb, in a case study, the researcher examines the impacts of the specific event(s) on the intended community. Whereas, the goal of developing a testbed is to provide an environment with the potential of being used for evaluating different community resilience algorithms and models under different events. Third, the paper had to otherwise align with the proposed definition of a testbed. Papers utilizing the ASCE Structural Control Benchmarks (Dyke et al., 2003), Virtual Supervisory Control and Data Acquisition (Dayal et al., 2015), and Southern California Planning Model

(Richardon & Davis, 1998) testbeds were excluded from this review given that they do not have enough components to be used for the specified purposes in the testbed definition.

Considering the aforementioned criteria, 22 testbeds including 12 imaginary and 10 real communities are identified and incorporated into this review. Table 1 provides a comprehensive list of the 22 testbeds reviewed, including a short description of their development timeline and identified publication inventory. Although the identified testbeds differ in terms of development level, all of them meet the designated inclusion/exclusion criteria. The testbeds in Table 1 are introduced through their hazard module, building and infrastructure inventory, and socioeconomic systems, if any. Also, Table 1 provides a summary of each testbed's V&V process (if any), introduces the testbed's data resources (if known), and explains how to access the testbed's data (if available). The sections that follow describe commonalities, gaps, and other observations on hazard modules and community modules across testbeds with comparisons to the expert survey responses where possible.

Table 1. Summary of existing virtual testbeds included in the review

Testbed	Description	Identified Publications
CLARC	The Customizable Artificial Community (CLARC) is a virtual imaginary testbed based on the scaled data inventory of New Hanover County, North Carolina. The CLARC testbed was initiated by Loggins and Wallace (2015) to demonstrate the benefits of modeling interdependencies among community's infrastructure assets when estimating disruptions arising from hurricanes. Later, Little et al. (2020) and Loggins et al. (2019) advanced the testbed to study the interdependencies between a community's civil and civic infrastructure and to validate their novel proposed model (CRISIS) for community recovery following a hurricane. The CLARC testbed represents a coastal community with a population of approximately 500,000 and an area of 1,065 square miles divided into 77 census blocks. The testbed community module consists of a set of datasets on residential building inventory (at the census block level), power, water, wastewater, transportation, communication networks, and a few civic infrastructures (such as public safety, healthcare, fuel, and banking) and demographic data. The CLARC dataset is developed as a GIS database that is housed in Microsoft Access and is available via https://doi.org/10.17603/DS2FX2D (Little et al., 2020). During the COVID-19 pandemic, Little et al. (2021) employed the CLARC testbed and CRISIS model to investigate the effects of a global pandemic on community recovery time following a hurricane.	Loggins and Wallace (2015); Loggins et al. (2019); Little et al. (2020); Little et al. (2021);
Centerville	The Centerville Virtual Community is an imaginary testbed initiated by Ellingwood, Cutler, et al. (2016) to be used for developing community-level resilience assessment approaches that consider cumulative impacts of natural hazards to the community's physical, social, and economic systems. The testbed represents a middle-class Midwestern State city in the US with a population of about 50,000 which is situated approximately 50 miles from the New Madrid Seismic Zone and close to tornado alley (Ellingwood, Cutler, et al., 2016). So far, the testbed has been mostly applied to study the consequences of earthquakes and tornados. However, the testbed has the potential to be used in other hazard scenarios. For instance, Zhang and Nicholson (2016) applied a hurricane hazard scenario on the Centerville testbed. The infrastructures considered in the testbed include the buildings (13 building occupancy types in 16 building archetypes), water, electrical power, and transportation networks (Ellingwood, Cutler, et al., 2016). The testbed's social system consists of hypothetical demographics (such as the number of households, households mean income, owner or renter status, population number, diversity, sex, and age range), population dislocation (Ellingwood, Cutler, et al., 2016), social vulnerability level assignment to households and housing recovery models (Sutley & Hamideh, 2020). Also, a dynamic spatial computable general equilibrium model is incorporated into the community module to establish the testbed's economic system. (Cutler et al., 2016). The testbed datasets have been fully incorporated into IN-CORE (Interdependent Networked COmmunity Resilience modeling Environment (Gardoni et al., 2018) and are accessible at https://identity.ncsa.illinois.edu.	Ellingwood, Cutler, et al. (2016); Ellingwood, van de Lindt, et al. (2016) Lin and Wang (2016); van de Lindt et al. (2016); Cutler et al. (2016); Zhang and Nicholson (2016); Guidotti et al. (2016); Lin and Wang (2017b); Sutley and Hamideh (2020); Zou and Chen (2020); Daniel et al. (2021);
Benchmark City (China)	A GIS-based virtual imaginary testbed named Benchmark City was created by Shang et al. (2020) based on a common mid-size city located in the southeastern coastal region of China. The testbed is used for evaluating existing resilience assessment frameworks for Chinese cities. The required information such as demographics, site condition, land use, potential hazard exposure (i.e.; earthquake hazard), infrastructure inventory (including power, transportation, water, drainage, and natural gas distribution networks) as well as the locations of	Shang et al. (2020); Jichao et al. (2021);

Testbed	Description	Identified Publications
	hospitals, emergency shelters, and schools are hypothetically considered by Shang et al. (2020). Jichao et al. (2021) applied the Benchmark City testbed to assess the seismic functionality of the water distribution network.	
Shelby County	Shinozuka et al. (1998) initiated the Shelby County, Tennessee testbed in 1998 for investigating the effects of seismic damages to the electrical power system on the local community's economy. Since then, the testbed's hazard module has been developed slightly by adding more earthquake scenarios, whereas its community module has been developed significantly by multiple research groups for different research purposes (Adachi & Ellingwood, 2009; Chang & Shinozuka, 2004; Dueñas-Osorio et al., 2007; Hwang et al., 2000; Johansen & Tien, 2018; Lin & El-Tawil, 2020; Roohi et al., 2021; Wu & Dueñas-Osorio, 2013; Zhang et al., 2018). So far, the community module's physical system includes data on the community's building inventory (Roohi et al., 2021; Zhang et al., 2018), water (Chang & Shinozuka, 2004), power (Shinozuka et al., 1998), gas (Adachi & Ellingwood, 2009; Dueñas-Osorio et al., 2007; Johansen & Tien, 2018; Wu & Dueñas-Osorio, 2013), and transportation networks (Hwang et al., 2000). Shinozuka et al. (Shinozuka et al., 1998) initially applied a classic input-output impact model to build the community module's economic system for regional impact analysis; afterward, Roohi et al. (2021) incorporated a Computable General Equilibrium (CGE) model into the testbed's economic system. A population dislocation model is also employed by Roohi et al. (2021) to establish the testbed's social system.	Shinozuka et al. (1998); Hwang et al. (2000); Chang and Shinozuka (2004); Adachi and Ellingwood (2009); Dueñas-Osorio et al. (2007); Wu and Dueñas-Osorio (2013); Johansen and Tien (2018); Zhang et al. (2018); Lin and El-Tawil (2020); Roohi et al. (2021);
Seaside	Seaside, OR is a small low-lying coastal city with a population of approximately 6,000 residents in the US Pacific Northwest. The city is susceptible to tsunamigenic earthquakes originating from the Cascadia Subduction Zone (CSZ) (González et al., 2009; Park & Cox, 2016). The testbed hazard module includes multi-hazards cascading seismic and tsunami scenarios. The testbed's community module has been developed in multiple phases; as yet, building inventory (Park et al., 2017; Wiebe & Cox, 2014), water (Rosenheim et al., 2019) and power (Kameshwar et al., 2019) networks, roads (Wang et al., 2016), and bridges (Priest et al., 2015) are the physical systems that have been incorporated into the testbed's community module. A multi-hazard damage analysis model that combines the earthquake- and tsunami-induced damages is also appended to the testbed's community model (Park et al., 2019). A set of demographic data such as population density (Wang et al., 2016) and a community evacuation model (Mostafizi et al., 2017) build the testbed's social system. The testbed datasets have been incorporated into IN-CORE (Gardoni et al., 2018) and its datasets are accessible for the researchers at https://identity.ncsa.illinois.edu.	González et al. (2009); Wiebe and Cox (2014); Priest et al. (2015); Wang et al. (2016); Park and Cox (2016); Mostafizi et al. (2017); Park et al. (2017); Rosenheim et al. (2019); Kameshwar et al. (2019); Park et al. (2019);
Galveston	The city of Galveston is a barrier island located off the coast of Texas in the Gulf of Mexico. The main motivation of creating the Galveston testbed was to use it for studying community resilience metrics of coastal communities under hurricane-induced hazards such as surge, wave, inundation, and wind. The Center for Risk-Based Community Resilience Planning released Galveston Testbed as a library in the IN-CORE (Gardoni et al., 2018). So far, the testbed's hazard module encompasses wind, riverine and storm-surge flooding models (Czajkowski et al., 2013; He & Cha, 2018). A residential building portfolio (Czajkowski et al., 2013), an electric power network (He & Cha, 2018), and transportation-related datasets (Gardoni et al., 2018) create the community module's physical systems. To estimate hurricane-induced damages, parametrized fragility models for buildings, coastal bridges, and coastal roadways are incorporated into the community module (Fereshtehnejad et al., 2021). The social system of the community module includes a population dislocation	Islam et al. (2010); Czajkowski et al. (2013); He and Cha (2018); Hamideh and Rongerude (2018); Fereshtehnejad et al. (2021);

Testbed	Description	Identified Publications
	and a housing unit allocation model that enables using U.S. Census household-level data for assessing the social impacts of the hurricane hazards (Gardoni et al., 2018).	
Gotham City	Gotham City is a virtual imaginary testbed created by Mahmoud et al. (2018) to be used for demonstrating and verifying community resilience models. The city is divided into four regions which are connected through bridges only. The testbed's community module consists of hypothetical social, economic, and physical systems. The physical system encompasses data on water, power, communication, transportation infrastructures as well as residential and health building inventories for each region (Mahmoud & Chulahwat, 2018). Mahmoud et al (2018) used the hypothetical attribute of social and economic systems to compute the social vulnerability index and infrastructure stability matrix for each region. The testbed's hazard module is capable of accommodating various types of hazards that cause physical disruptions, economic downtimes, and even social disorders (Mahmoud & Chulahwat, 2019).	Mahmoud and Chulahwat (2018); Mahmoud and Chulahwat (2019);
Harris County	Harris County, TX, is a hurricane-prone county located near the Gulf Coast in the United States. The testbed has been advanced in multiple phases for different research purposes. So far, the community module's physical system consists of models for the power and gas transmission infrastructure and their cascading failure effects (Ouyang & Duenas-Osorio, 2012, 2014; Ouyang & Dueñas-Osorio, 2011; Ouyang et al., 2012; Ouyang & Wang, 2015) as well as transportation networks (Dong, Esmalian, et al., 2020; Dong, Yu, et al., 2020; Fan et al., 2020). The traffic data of the transportation network are collected from INRIX (https://inrix.com), a private company providing location-based data and analytics, and so are not publicly available. The testbed's hazard module encompasses a series of pre-generated hurricane scenarios that can cause floods and inundation.	Ouyang and Dueñas-Osorio (2011); Ouyang and Duenas-Osorio (2012); Ouyang et al. (2012); Ouyang and Duenas-Osorio (2014); Ouyang and Wang (2015); Dong, Esmalian, et al. (2020); Dong, Yu, et al. (2020); Fan et al. (2020);
Gilroy	The Gilroy testbed is modeled after the real city Gilroy, CA; a moderate-size town located approximately 6 miles from the San Andreas Fault. The testbed was initially created by Nozhati et al. (2018) to study the relationship between specific community resilience metrics (e.g.; food security, post-earthquake recovery) and interdependent critical infrastructure (such as energy, transportation, and water systems) following a seismic event. A scenario earthquake with a magnitude of 6.9 (similar to the Loma Prieta Earthquake 1989) builds the testbed's hazard module (S Nozhati et al., 2018). The community module's physical system comprises data on electrical power networks, water systems, highway bridges, and food retailers. The community module's social system consists of a set of demographic data (such as population density) from the 2010 census database (S Nozhati et al., 2018; Nozhati, Ellingwood, et al., 2020; Nozhati, Ellingwood, et al., 2019; Saeed Nozhati, Bruce R Ellingwood, et al., 2018; Nozhati, Rosenheim, et al., 2019; Nozhati, Sarkale, et al., 2020; Nozhati, Sarkale, et al., 2019; Saeed Nozhati, Yugandhar Sarkale, et al., 2018; Sarkale et al., 2018).	S Nozhati et al. (2018); Saeed Nozhati, Bruce R Ellingwood, et al. (2018); Saeed Nozhati, Yugandhar Sarkale, et al. (2018); Sarkale et al. (2018); Nozhati, Ellingwood, et al. (2019); Nozhati, Rosenheim, et al. (2019); Nozhati, Sarkale, et al. (2019); Nozhati, Ellingwood, et al. (2020); Nozhati, Sarkale, et al. (2020);
pseudo-Norman	The pseudo-Norman testbed is a simplified coarse model after the real city Norman, OK. The testbed was initially created by Masoomi and van de Lindt (2017) to investigate the community-level risk and recovery modeling after a tornado. The testbed takes only a few attributes of the Norman community into accounts; therefore, it is called *pseudo-Norman*. The testbed's community module includes data on households and businesses, residential and school buildings, and water and electric power networks. A few aspects of demographics such as the population, the number of students, and employees are also appended to the community module (Masoomi & van de Lindt, 2017). The testbed datasets have not been published separately,	Masoomi and van de Lindt (2017); Masoomi et al. (2018);

Testbed	Description	Identified Publications
	but, the primary parameter that has been used for developing community and hazard modules can be found in the published works on the testbed (Masoomi et al., 2018; Masoomi & van de Lindt, 2017).	
Joplin	The Joplin testbed represents the city of Joplin located in the southwest of the Missouri State. The testbed was created following the EF5 Joplin tornado in 2011 to assess the disruptions due to hurricane-induced damages of interdependent infrastructures (particularly buildings and power networks) and socioeconomic impacts of such disruptions on community recovery (Attary et al., 2019). However, the testbed has been further used to verify and validate building inventory damage models and recovery trajectories (Aghababaei, Koliou, Pilkington, et al., 2020; Pilkington, Curtis, et al., 2020; Pilkington & Mahmoud, 2020). The building inventory and power network dataset are the only two components of the testbed's physical system (Attary et al., 2019; Pilkington, Curtis, et al., 2020). The testbed's economic system includes a model that can estimate the economic impacts of scenario tornado-induced disruptions. Also, a population dislocation model at the household level builds the community module's social system (Van De Lindt et al., 2019). The testbed's accuracy and validity of social and economic models were verified using results from several case studies on Joplin after the 2011 tornado (Kuligowski et al., 2014). The testbed has been incorporated into IN-CORE (Gardoni et al., 2018) and its datasets are accessible at https://identity.ncsa.illinois.edu/register/BSKC2UKQPU. Simulating the tornado event in IN-CORE (Gardoni et al., 2018)allows the researchers to model different tornado scenarios by generating random tornado paths across the community to get a full risk profile (Attary et al., 2019; Pilkington, Mahmoud, et al., 2020; Van De Lindt et al., 2019).	Attary et al. (2019); Van De Lindt et al. (2019); Pilkington, Curtis, et al. (2020); Pilkington, Mahmoud, et al. (2020); Aghababaei, Koliou, Pilkington, et al. (2020); Pilkington and Mahmoud (2020);
ASCE First Generation Testbed	ASCE First Generation Testbed is an imaginary testbed that has been initiated based on the ASCE Sub-Committee on Disaster Resilience of Structures and Infrastructures proposal. Cimellaro et al. (2014) applied the testbed to compare the pros and cons of different resilience-based design strategies available in the literature. The testbed consists of two critical structures (including Town Hall and Hospital), a University Campus, and the water distribution network of a small town.	Cimellaro et al. (2014);
Lumberton	Lumberton is a small city in North Carolina, hugely impacted by Lumber River flooding in 2016 after Hurricane Matthew. After the flooding, comprehensive longitudinal field studies and interdisciplinary technical investigations have collected cross-disciplinary data on impact and recovery (van de Lindt et al., 2018; van de Lindt et al., 2020). The Lumberton testbed was created to investigate the building- and community-level flood vulnerability, and V&V of different community resilience models (Nofal & van de Lindt, 2020d). The testbed's hazard module consists of a flood scenario based on a flooding event after hurricane Matthew in 2016. So far, a building inventory including 15 building archetypes and building damage analysis models using flood fragility functions are incorporated into the testbed's community module (Nofal & van de Lindt, 2020a, 2020b; Omar M Nofal & John W van de Lindt, 2021; Omar M. Nofal & John W. van de Lindt, 2021; Nofal et al., 2020; Nofal, van de Lindt, Do, et al., 2021; Nofal, van de Lindt, Yan, et al., 2021). Also, to assess the social impacts of the flood hazard, a housing unit allocation and a population dislocation model comparable to the Galveston testbed's social models (Gardoni et al., 2018) are appended to the testbed's community module (Rosenheim et al., 2021). The testbed has been incorporated into IN-CORE (Gardoni et al., 2018) and its datasets are accessible at https://identity.ncsa.illinois.edu/register/BSKC2UKQPU. Of note, multiple researchers are still working on case studies of business interruption and recovery models that can be	van de Lindt et al. (2018); van de Lindt et al. (2020); Nofal and van de Lindt (2020a, 2020b, 2020d); Nofal et al. (2020); Omar M Nofal and John W van de Lindt (2021); Omar M. Nofal and John W. van de Lindt (2021); Nofal, van de Lindt, Do, et al. (2021); Nofal, van de Lindt, Yan, et al. (2021); Rosenheim et al. (2021); Aghababaei, Koliou, Watson, et al. (2020); Watson et al. (2020); E. J. Sutley et al. (2021); Helgeson et al. (2021);

Testbed	Description	Identified Publications
	used for establishing the testbed's economic system later (Aghababaei, Koliou, Watson, et al., 2020; Watson et al., 2020).	
Atlantic County	Atlantic County, NJ is a county with three adjacent barrier islands that lie along the Atlantic Coastal Plain on the east coast of the U.S. The county is prone to hurricane-induced hazards, such as strong wind, riverine flooding, and storm surge on the ocean-facing coastline (NJOEM, 2019). The SimCenter, in collaboration with a team of researchers from different universities, developed the Atlantic County Testbed to be used for introducing the implementation of SimCenter's Hurricane Regional Loss Modeling Workflow (McKenna et al., 2021). However, the testbed can be used for other regional studies. Wind and storm surge models are incorporated into the testbed's hazard module (McKenna et al., 2021). The testbed's building inventory encompasses the required attributes of community buildings at the parcel level (McKenna et al., 2021). The Building Footprint Data obtained from the New Jersey Department of Environmental Protection, Microsoft Footprint Database (Microsoft, 2020), New Jersey Tax Assessor Database (NewJerseyOfficeofGIS, 2021), and computer vision methods (Chaofeng Wang et al., 2021) were utilized to create the testbed's building inventory. Although such attempts can partially validate the accuracy of the building inventory dataset, the quality of the data has not been guaranteed by the developers (McKenna et al., 2021). The testbed datasets can be downloaded from https://nheri-simcenter.github.io/R2D-Documentation/common/testbeds/atlantic_city/index.html.	McKenna et al. (2021);
San Francisco Bay Area	The San Francisco Bay Area is a region in Northern California with a population of more than 7.7 million and three large cities including San Francisco, Oakland, and San Jose. The Bay Area is located close to the San Andreas and Hayward faults which are capable of magnitude 8.0 and 7.0 earthquakes, respectively (Aagaard et al., 2016). The risk from such earthquakes to the built environment has always been of interest to researchers, practitioners, and policymakers working on the community resilience concept. From our research, Kiremidjian et al. (2007), for the first time, applied San Francisco Bay Area as a testbed to evaluate the risk of a magnitude 7.0 scenario event on the Hayward fault to the Bay's transportation network. Later, the San Francisco testbed was demonstrated in the guise of an example in SimCenter's regional Workflow for Hazard and Loss Estimation (rWHALE) for buildings (Elhaddad et al., 2019). The testbed's hazard module comprises a magnitude 7.0 Hayward earthquake scenario (Rodgers et al., 2019). The testbed's community module encompasses a building inventory of 1.8 M buildings located in the Bay Area (except Alameda County and San Francisco Tall Building) (Elhaddad et al., 2019). The accuracy and quality of the inventory were verified by cross-referencing the input datasets. A sample dataset of the San Francisco Testbed is available at DesignSafe-CI Data Depot (https://www.designsafe-ci.org/data) or by submitting a request to the Message Board (https://simcenter-messageboard.designsafe-ci.org/smf/index.php?board=8.0) on SimCenter Forum.	Kiremidjian et al. (2007); Elhaddad et al. (2019);
Micropolis	Micropolis is a small, virtual, imaginary city of approximately 5,000 residents initiated as a testbed for the development of infrastructure models, particularly water distribution systems. The testbed's community module has been supplemented by adding a power distribution network layout (Bagchi, 2009). To provide the required information for replicating the infrastructures of a real typical small city in a historical rural region, a timeline spanning 130 years is created. This hypothetical timeline was used for the design of infrastructure systems, mapping roads and buildings (Brumbelow et al., 2007). The data files describing Micropolis testbed, including basic GIS and EPANET model files, can be downloaded from https://ceprofs.civil.tamu.edu/	Brumbelow et al. (2007); Bagchi (2009); Torres et al. (2009);

Testbed	Description	Identified Publications
	kbrumbelow/Micropolis/index.htm. The testbed has been applied for man-made hazards such as water supply contamination and urban fire (Bagchi, 2009; Torres et al., 2009).	
Turin Virtual City	The Turin Virtual City was created after the city of Turin, Italy for predicting the physical impacts of a seismic hazard scenario on the building inventory of an urban area (Noori et al., 2017). The testbed's hazard module consists of a seismic hazard scenario recorded during the 2016 Central Italy earthquake. The testbed's community module encompasses a building inventory consisting of 30,122 buildings with different occupancy types and socioeconomic roles.	Noori et al. (2017);
Anytown	The Anytown virtual water distribution network is an imaginary testbed initiated by Walski et al. (1987). The testbed represents a water distribution network of a hypothetical U.S. community. The testbed has been developed assuming Anytown as an old town with real characteristics and problems of common real water distribution systems. The primary objective of developing testbed was determining an economically effective design approach for reinforcing the existing system to meet projected demands. Researchers further applied the testbed for water system design optimization and resilience analysis (Mazumder et al., 2020; Salehi et al., 2018).	Walski et al. (1987); Farmani et al. (2005); Prasad and Tanyimboh (2008); Herstein and Filion (2010); Atkinson et al. (2014); Salehi et al. (2018); Mazumder et al. (2020);
unnamed water network	The *unnamed water network* is a virtual simplified water distribution system that has been constructed to serve as a testbed for research on water distribution systems (Islam et al., 2011; Islam et al., 2014; Shuang et al., 2017; Shuang et al., 2014). The testbed has not been named although it has been applied in several studies by different researchers. The testbed did not have a hazard module until a scenario earthquake model was appended to it by Mazumder et al. (2021) to implement a post-earthquake analysis on the testbed.	Islam et al. (2011); Islam et al. (2014); Shuang et al. (2014); Shuang et al. (2017); Ram K. Mazumder et al. (2021);
UW Power Systems Test Case Archive	The UW Power System Test Case Archive is a website that provides required datasets for modeling common 1960s power systems in the Midwestern US. The website (https://labs.ece.uw.edu/pstca/) has been maintained voluntarily by the participation of multiple researchers and faculty since the 1990s. The testbed datasets have been used in multiple studies by Didier et al. (2018; 2017; 2015) to evaluate the application of various seismic resilience frameworks for electrical power networks.	Didier et al. (2015); Didier et al. (2017); Didier et al. (2018);
C-Town	The C-Town water distribution network is an imaginary testbed initially applied for the Battle of the Water Calibration Network (BWCN) competition and introduced in the 12th Water Distribution Systems Analysis Symposium in 2010. The testbed was also used for water network design optimization purposes (Creaco et al., 2014) and investigating the consequences of cyber-physical attacks on a water distribution system (Nikolopoulos et al., 2020; Taormina et al., 2016). The data files describing the C-Town water distribution network and its EPANET input files are available online in the ASCE Library at www.ascelibrary.org	Alvisi and Franchini (2011); Kim et al. (2011); Ostfeld et al. (2012); Creaco et al. (2014); Taormina et al. (2016); Nikolopoulos et al. (2020);
Mesopolis	Mesopolis is a mid-size virtual imaginary city with a population of 140,000 created for research in water distribution systems (Johnston, 2008). The city has a hot and humid Texas climate and a geography layout combining aspects of the East Coast, West Coast, and Gulf Coast geography. A hypothetical history is assumed for mapping roads, land-use distribution, and infrastructures design purposes. The testbed's community module includes the water, power, and communication network models and its hazard module consists of water	Johnston (2008); Shafiee and Zechman (2010); Shafiee and Zechman (2011); Shafiee and Berglund (2014);

Testbed	Description	Identified Publications
	contamination scenarios only. The testbed datasets, were published with open access to the testbed's latest version at https://ceprofs.civil.tamu.edu/kbrumbelow/Mesopolis/index.htm.	

3.1.4.1 Inclusion of Hazard Module in Community Resilience Testbeds

The hazard module in the majority of the reviewed testbeds comprises natural hazard scenarios such as earthquake, hurricane-induced flood and wind, tornado, and tsunami. However, man-made hazards including contamination, cyber-physical attack, and urban fire are modeled in Micropolis, Mesopolis, and C-Town testbeds. CLARC is the only testbed with a hazard module including both natural and man-made hazard models together. Little et al. (2021) employed the CLARC testbed to investigate the effects of a global pandemic on a community recovery time following a hurricane. A few of the reviewed testbeds such as Harris County, CLARC, Galveston, Centerville, Seaside, and Atlantic County employ a hazard module with multi-hazard models and provide the opportunity to assess the cumulative impacts of the cascading hazards. The hurricane models in CLARC, Galveston, and Atlantic County testbeds enable researchers to study the consequences of both flood- and wind-induced disruptions together. The hazard module of the Seaside testbed consists of a tsunamigenic earthquake model that considers both earthquake shakings and tsunami inundation (Fereshtehnejad et al., 2021; Little et al., 2020; McKenna et al., 2021; Park et al., 2019). Other than Galveston, Mesopolis, and Seaside testbeds that benefit from probabilistic approaches to simulate the future events and predict their impacts; the other reviewed testbeds employ scenario events (either one single event or a suite of synthetic scenarios that happened in the past) in their hazard modules (Fereshtehnejad et al., 2021; Park et al., 2019; Torres et al., 2009). Figure 15 compares the number of testbeds with a particular hazard module across different hazard types with the number of identified publications applying those hazard modules and the number of survey respondents who indicated they personally had examined such hazard type in a testbed. In Figure 15, the number of testbeds with earthquake hazard models is significantly higher than that of other hazard types. On the other hand, tsunami hazard is rarely included in testbeds. Of note, the Seaside testbed that models tsunami hazard has been used in nine different studies (González et al., 2009; Kameshwar et al., 2019; Mostafizi et al., 2017; Park et al., 2019; Park & Cox, 2016; Park et al., 2017; Priest et al., 2015; Wang et al., 2016; Wiebe & Cox, 2014). Anytown, C-Town, and unnamed water network were initiated without a hazard module; however, Anytown, unnamed water network, and C-Town were supplemented later by appending a hazard module (Ram K. Mazumder et al., 2021; Mazumder et al., 2020; Nikolopoulos et al., 2020; Taormina et al., 2016). As evident in Figure 15, there is a direct relationship between the number of existing testbeds and identified publications across every hazard type except hurricane-induced floods with the number of respondents who indicated they had examined that hazard type to a testbed. The greater number of respondents who have personal experience of applying flood hazards to a testbed compared to the other types of hazards may result in a slight bias in the survey results, however, there is still fair variability in the experience of the respondents.

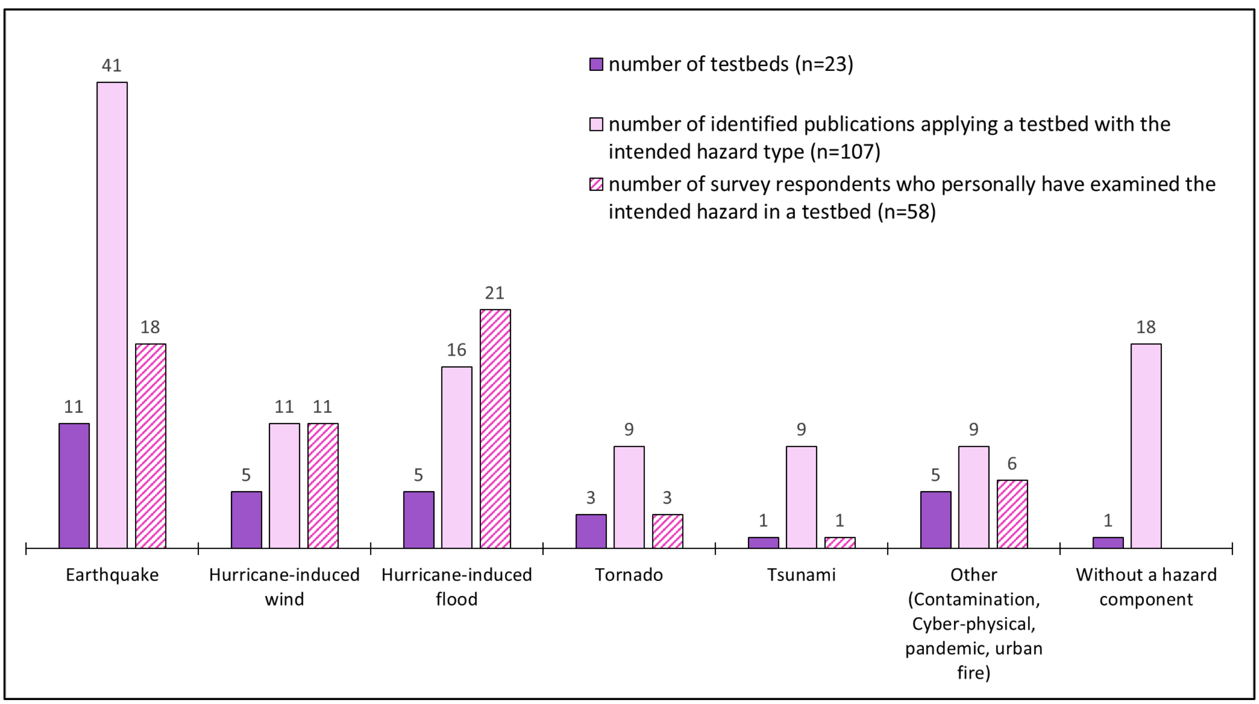

Figure 15. Dispersion of different hazard types in the reviewed testbeds

3.1.4.2 Inclusion of Community Module in Resilience Testbeds

The community module of a testbed is a geospatial model of one or preferably more interconnected physical, social and economic systems; however, including either of the three systems is adequate to initiate the community module of a testbed. As identified in the literature review, most papers to date have focused initially on modeling physical systems, whereas in a community resilience study it is important to also capture the community's social and economic systems and cascading effects of their failure. Also, in the existing testbeds, researchers have resorted to simplifying their physical system models to reduced order physical models (such as Turin Virtual City) or fragility-based statistical models. However, along with advances in computational science and technologies classical finite element models and data-driven machine learning models are likely to be applied in future testbeds.

Physical System: The physical system of the existing testbeds includes the community's building inventory and/or infrastructures-asset inventory such as water, electric power, gas, transportation, communication, wastewater, and drainage networks. Of note, all of these infrastructures are not modeled for every existing testbed; only 6 out of the 22 reviewed testbeds (namely Shelby County, Benchmark City, CLARC, Gotham City, Centerville, and Seaside) include more than three infrastructure types besides their building inventory. The physical system in four testbeds, including Anytown, C-Town, the unnamed water network, and Mesopolis consists of water networks only (Alvisi et al., 2012; Alvisi & Franchini, 2011; Islam et al., 2011; Johnston, 2008; Walski et al., 1987). Turin Virtual City, Atlantic County, and Lumberton solely included the community's building inventory to create their physical system (McKenna et al., 2021; Noori et al., 2017; van de Lindt et al., 2020). The physical systems in UW Power Systems Test Case Archive only consider electrical power networks (Didier et al., 2015). Of the testbeds that do incorporate more than one type of infrastructure, many remain uncoupled and are presented in independent analyses in separate publications since they are modeled by more than one team of researchers, as is the case for Shelby County (Adachi & Ellingwood, 2009; Chang & Shinozuka, 2004; Dueñas-Osorio et al., 2007; Hwang et al., 2000; Shinozuka et al., 1998), Harris County (Dong, Esmalian, et al., 2020; Fan et al., 2020; Ouyang & Duenas-Osorio, 2012, 2014; Ouyang & Dueñas-Osorio, 2011; Ouyang et al., 2012; Ouyang & Wang, 2015), Micropolis (Bagchi, 2009; Brumbelow et al., 2007), and San Francisco Bay Area (Elhaddad et al., 2019; Kiremidjian et al., 2007). Figure 16 compares the number of testbeds modeling a particular physical system component with the number of identified publications applying that component and the number of survey respondents who indicated they personally had examined such components in a testbed. As shown in Figure 16, the building inventory and water network are the most common components included in the modeling of the existing testbed's physical system, followed by power and transportation networks. The number of publications for testbeds with an incorporated water network is more than that of testbeds with building inventory. However, the number of expert survey respondents with personal experience of modeling a testbed's physical system using a building inventory is greater than the water network; which shows a slight chance of bias in the survey results. It is also remarkable that the Harris County testbed and UW Power Systems Test Case Archive are the only two testbeds that have not included either building portfolio or water networks in modeling the testbed's physical systems. On the other hand, the communication network is modeled in Gotham City only (Mahmoud & Chulahwat, 2018).

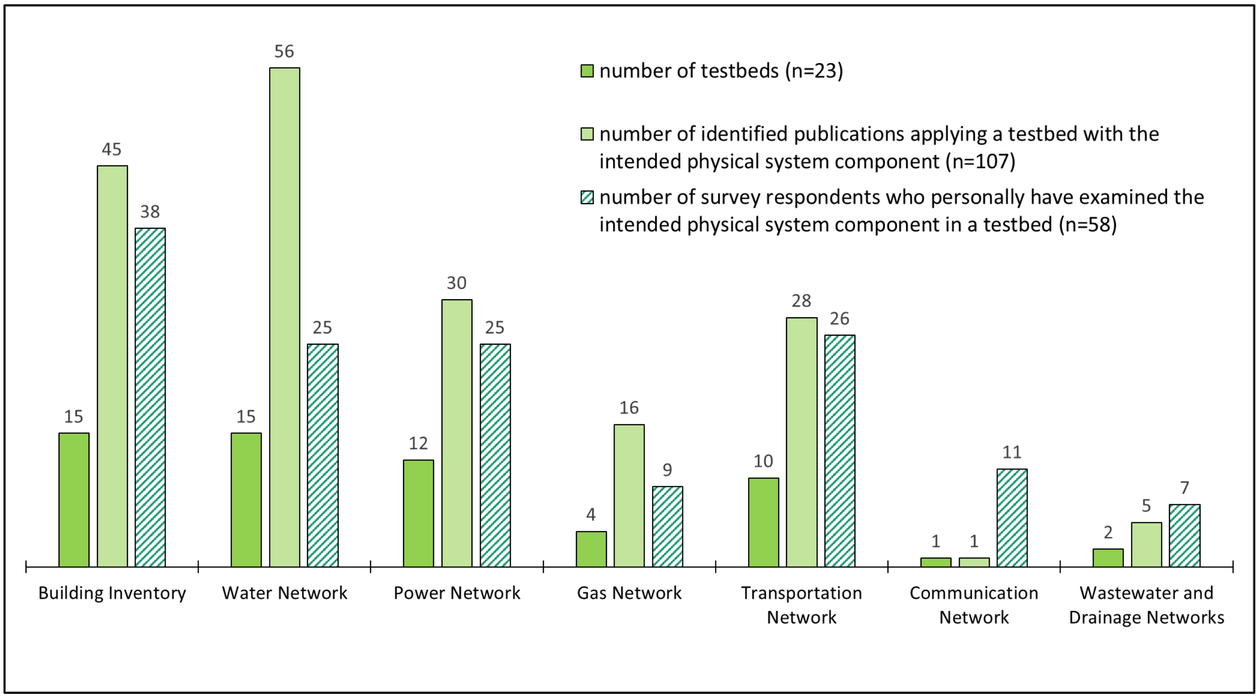

Figure 16. Dispersion of different physical systems in the reviewed testbeds

Social and Economic Systems: Physical systems are only useful if they serve people. Thus, it is critically important to include the social and economic systems in community resilience analyses. Few testbeds incorporate predictive simulation models for social and economic systems, as opposed to static estimates of demographics, social vulnerability, or post-disaster economic impacts. The *social system* captured in existing testbeds includes one or more social models such as population evacuation (Wang et al., 2016), population dislocation (Roohi et al., 2021; Van De Lindt et al., 2019), housing unit allocation (Gardoni et al., 2018), and housing recovery model (Sutley & Hamideh, 2020). The *economic system* of the reviewed testbeds comprises either classic input-output impact models (Shinozuka et al., 1998), Computable General Equilibrium (CGE) models (Chen & Rose, 2018; Cutler et al., 2016; Roohi et al., 2021), or business interruption and recovery models (Aghababaei, Koliou, Watson, et al., 2020; Attary et al., 2019; Watson et al., 2020; Yang et al., 2016). However, as identified in our review, most testbeds limit social and economic system consideration to socioeconomic indicators. The indicators are either a composite indicator such as the social vulnerability index (Little et al., 2020; Mahmoud & Chulahwat, 2018) or a set of census data including age, race, ethnicity, housing vacancy rates, population density, the number of households, household mean annual income, owner or renter status, and the number of students and employees (Masoomi & van de Lindt, 2017; S Nozhati et al., 2018; Shang et al., 2020). The degree of social and economic data and resolution of such models in a testbed, either imaginary or real, depends on the data available, and the skillset of the researchers involved with the testbed. The availability of high-resolution social and economic data is difficult to obtain, and cannot be made publicly available due to ethical and security-related issues in real testbeds.

3.1.5 Next Steps in Testbed Development

Based on our findings from the literature review, we have identified four aspects of community resilience testbeds that warrant additional research, including (1) data needs, data collections, and data security concerns; (2) testbed visualization; (3) testbed verification and validation; and (4) testbed availability and reuse; each is discussed herein.

3.1.5.1 Data Needs, Data Collections, and Data Security Concerns

In the development of virtual testbeds, a major limitation is access to data due to availability, security issues, and ethical considerations, particularly as it relates to accessing and publishing data for reuse. Researchers have often resorted to modeling major simplification of real communities as testbed communities, using aggregate data, a suite of archetypes to represent all buildings in a community, and limiting the scope of their analyses. For example, roof shape is an important building attribute for testbeds with wind hazard modules, but is often not provided in public data. In these cases, Artificial Intelligence (AI) and computer vision methods (Chaofeng Wang et al., 2021) can be employed to capture the required information from Google Street View and satellite images. For example, leveraging recent developments in AI (particularly in deep learning) and computer vision techniques, Microsoft Building Footprint Database created nationwide building footprint maps (Microsoft, 2020) that are very useful for community resilience testbeds. Similarly, Chaofeng Wang et al. (2021) developed a machine learning-based framework for generating building inventory of a community to support regional hazard analysis; the framework has been applied for the development of the Atlantic County testbed (McKenna et al., 2021).

Private data can fill these needs, sometimes, but can be too expensive for academic researchers, and again, cannot be published for reuse by the research community. For example, insurance data is not publicly available at a household level, and even OpenFEMA data is aggregated to the zip code level. Without access to high-resolution social and economic data, those types of systems will always lag behind physical models in testbed development.

The other challenge that testbed developers encounter is merging different datasets with different spatial and temporal units. For example, Building Footprint, Land Use, and Tax Parcels are the common public datasets that are used for compiling the building inventory of a testbed. However, each of these datasets uses different identifiers, including individual building, map block number, and parcel number, respectively. Additionally, different data sources generate their data differently and handle missing data differently. For example, McKenna et al. (2021) reported that Microsoft Footprint Database sometimes lumps the footprints of closely spaced buildings together.

3.1.5.2 Testbed Visualization

Any Geographic Information System (GIS) software can be used to visualize a testbed. The GIS provides the opportunity to integrate both the attribute and spatial data for all of the components in a testbed's community module to be stored in a single database. The community resilience analysis outcomes can also be mapped into GIS. The ESRI ArcGIS and Q-GIS are the most popular software for testbed visualization, but require other software to chain algorithms and simulate disasters. Open-source libraries, such as Leaflet and Folium, are also recently used widely to visualize testbed interactively in Python environments.

3.1.5.3 Testbed Verification and Validation

The process of verification and validation of testbeds is an important step to be able to apply results from a testbed analysis to the real world. This is a challenging process that is often considered but not fully discussed in publications. Such a complex computational environment must be validated with each component being verified as a single or integrated module or system. The accuracy of the data (particularly the public data) that are used for the testbed creation can initially be verified using online tools and comparing the mutual attributes between datasets from different resources. For example, in the San Francisco testbed, Elhaddad et al. (2019) verified the accuracy and quality of UrbanSim datasets by comparing its information on location and building geometry with the Microsoft Building Footprint database. After verifying the accuracy of integrated datasets, the testbed's numerical simulation models should be validated to ensure that it results in the desired outputs. There are various existing techniques to verify and validate a testbed. In the CLARC testbed, the verification and validation were performed by involving stakeholders and local experts in comparison between the analysis results and past storm events (Loggins & Wallace, 2015). Attary et al. (2019) and Van De Lindt et al. (2019) used the building damage assessment report of the Joplin 2011 tornado as well as power outage reports by the residents after the tornado to validate their testbed model. Even if an individual researcher validates their model contributions, as testbeds grow and expand, who performs validation and how will remain an important challenge.

The expert survey asked, “Are you aware of, or did you perform, any validation of the testbed(s) you used?” and gave additional guidance that “Validation could have consisted of testing accuracy of assets, locations, properties, matching information to prior events, etc.” It should be noted that besides the importance of a testbed's V&V itself, the documentation of the V&V process and making the documentation of the V&V process available to testbed's users are two essential steps in a testbed's development process to make the testbed functional for researchers other than the testbed's development team. 51 responses were recorded to this question, where 32 reported YES and 19 reported NO, which illuminates that almost 37% of respondents neglected this important step. Of the 32 respondents indicating they had performed or were otherwise aware of validation of the testbed(s), 28 provided comments. Through the comments, 15 validated results using post-disaster data; 5 used expert knowledge, 8 used other secondary data comparisons, such as census data and google maps; 2 performed sensitivity analysis, and 3 made a comparison with other published work. This provides a guide for how future testbed developers and users can verify and validate their work.

3.1.5.4 Testbed Availability and Reuse

After the creation of a testbed, most testbeds are reused by the researchers who created them. At this point in time, testbeds are not frequently reused by other researchers, but through the creation of recent platforms such as DesignSafe-CI and IN-CORE, datasets can be shared and used by others. Data collection and validation are extensive and time-consuming processes. The sharing and reuse of testbeds that have already been verified and validated, push forward the progress of community resilience research.

3.1.6 Conclusions

Virtual testbeds are being developed and used across the community resilience literature to serve the purpose of verification and validation. We identified 22 community resilience testbeds and 103 publications that use community resilience testbeds. There is no shortage of testbeds, however, their accessibility for use by the research community and availability of their development documents remains a major challenge. There is no apparent standardized process for testbed development, testbed publication, or testbed reuse. It is no trivial effort to develop a testbed, including obtaining and cleaning data, developing, validating, and chaining algorithms, and verifying simulation results. Such standardizations may help improve the accessibility of testbeds to the research community, which can have important implications towards advancing knowledge on community resilience analysis where every next researcher does not have to reinvent the wheel by developing a new testbed. A secondary outcome of this review is to aid interdisciplinary teams of hazards and disasters researchers in working together on testbeds and in understanding where the state of knowledge is on testbed development.

Community resilience testbeds should have both a hazard module and a community module. Ideally, the community module in a fully-developed testbed includes one or more interconnected models of the desired community's physical, social, and economic systems, however, only one of the three is required to *initiate* a testbed. The concept of virtual community resilience overlaps with some common classic risk assessment tools or modern high-tech simulation instruments such as a Digital Twin. However, these tools do not meet the proposed definition of the testbeds and do not provide the required architecture and ample metadata that testbeds are supposed to provide.

Aside from the fact that none of the existing testbeds are fully developed, the majority of them have been created with a focus on earthquake hazards and physical infrastructure systems. Even if a testbed intends to include social and economic systems, these models are primarily population-based and the other dimensions of the social and economic systems, such as social services and organizational preparedness, are consistently overlooked. This leads to ample opportunity to advance knowledge with other hazard types, and social and economic systems, which requires multi-, inter- and transdisciplinary collaborations.

Virtual Testbeds for Community Resilience Analysis: Step-by-Step Development Procedure and Future Orientation

Virtual community resilience testbeds enable verification and validation of emerging computational models and frameworks for quantitative assessment of the disaster impacts and recovery process of the communities and are important to advance the state of knowledge on community resilience. This paper illuminates the significance of establishing a standardized approach for developing virtual community resilience testbeds and proposes a systematic schema for this purpose. The workflow facilitates testbed development by defining a series of steps, starting with specifying the testbed simulation scope. Arguing that hazard and community modules are the principal components of a testbed, we present a generic structure for testbeds and introduce minimum requirements for initiating each module. In line with that, the workflow dissects different attributes of the components beneath these modules. In particular, the proposed steps outline relevant tools, techniques, and resources that exist for constructing a community's building inventory, power, water, and road networks, as well as its social and economic systems. The paper also discusses possible challenges testbed developers may encounter in procuring, cleaning, and merging required data and offers the initiatives and potential remedies, developed either by the authors or other researchers, to address these issues. The workflow concludes by describing how the testbed will be verified and validated, visualized, published, and reused. The paper demonstrates the application of the proposed workflow by establishing a testbed based on Onslow County, NC using publicly available data in the United States. To foster sharing and reusing of developed testbeds by other researchers, all supporting documents, metadata, template algorithms, computer codes, and datasets used for developing the different modules of Onslow Testbed are available at the DesignSafe-CI.

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3.2.1 Introduction

Climate change is becoming a worldwide crisis. The increasing intensity and frequency of natural climatic hazards, such as hurricanes, floods, severe storms, freezes, droughts, and wildfires are the apparent consequences of climate change (Bell et al., 2018; Trenberth, 2018). While the precise prediction of the time and location of occurrence of extreme natural hazards is still an issue, the overall hazard risk is evidently increasing. The effects of climate change, particularly coupled with urbanization growth, pose destructive impacts on human lives and the built environment across the world every year. However, the consequences are not limited to civilian casualties, physical damages, and direct financial losses only and are often intensified due to possible disruptions in the community's social and economic systems and result in a disaster. Thus, taking firm actions to tackle the intensive impacts of climate change and adopting a proactive approach to disasters is imperative. This issue, in some countries such as the United States, is even deemed a national security threat and has been put at the center of government policies (The White House, 2021).

The ability to estimate cascading impacts of natural hazards on a community's physical, social, and economic systems and improve community resilience through reducing such social and economic burdens that disasters can cause is an important evolving science. Community resilience researchers have been developing numerical models that can predict the performance of interdependent physical, social, and economic systems and assess their integrated impacts. Verification and validation (V&V) of the developed numerical models is an important step (Sargent, 2010) and remains a critical challenge. To perform V&V on community resilience algorithms, many researchers have turned to developing and using virtual testbeds (Attary et al., 2019; Ellingwood, Cutler, et al., 2016; Fereshtehnejad et al., 2021; Loggins et al., 2019; Ram K

Mazumder et al., 2021; Noori et al., 2017; Park et al., 2019; Shang et al., 2020). A virtual testbed is an *environment* with enough supporting architecture and metadata to be representative of one or more systems such that the testbed can be used to (a) design experiments, (b) examine model or system integration, and (c) test theories (S. Amin Enderami, Ram K. Mazumder, et al., 2022). Virtual community resilience testbeds enable researchers to test, verify, and validate their multidisciplinary community resilience algorithms at different scales and spatial resolutions. Virtual testbeds also are being used to serve the needs of training and educational purposes as well as provide better support for risk-informed decision-making by communities to optimize public and private investments.

Interest in the development and application of virtual community resilience testbeds has gained momentum along with rapid advances in computational science, tools, and technologies over the past few years. However, a systematic literature review of 22 identified existing community resilience testbeds and a total of 103 publications that have applied these testbeds revealed that there are several crucial gaps in testbed development knowledge (S. Amin Enderami, Ram K. Mazumder, et al., 2022). For example, there is no apparent standardized workflow for testbed development and publication in the literature which has caused major challenges in reusing testbeds. The availability of existing testbeds for use by the research community has profound implications for advancing community resilience knowledge since each next researcher will not have to develop a new testbed from scratch. Developing a community resilience testbed, even at a town or city scale, is too demanding and expensive for most research teams. In addition to collecting valid and verified data, building a community resilience testbed requires developing, validating, and chaining cross-disciplinary community resilience models and algorithms. This latter step is possible only if there are sufficient post-disaster longitudinal field studies on the impact and recovery in the desired community or if the community is rich in case studies. Of note, there are only a limited number of community resilience-focused longitudinal investigations that have documented the impacts and post-disaster recovery processes following an extreme event in communities (Helgeson et al., 2021; E. J. Sutley et al., 2021; van de Lindt et al., 2018; van de Lindt et al., 2020).

On the other hand, the lack of a standard testbed development guideline that provides consistent instructions for testbed creation, validation, and publication, resulted in an uneven distribution of testbeds with different hazard and system types. The vast majority of existing testbeds focus on seismic-related hazards and physical infrastructure systems exclusively and overlook modeling other hazard types and a community's social and economic systems. This paper develops a systematic schema for initiating community resilience testbeds. It begins by introducing a standard structure for community resilience testbeds and introducing the minimum components needed to initiate a testbed based on findings from a systematic literature review. The paper, then, proposes a workflow for developing virtual testbeds. The workflow begins with determining the testbed simulation scope and ends with testbed publication for reuse. Existing approaches and data sources for implementing the workflow and modeling testbed components are described alongside possible challenges developers may encounter. The application of this workflow is demonstrated by establishing a testbed based on Onslow County, NC using publicly available data in the United States. The paper concludes with a discussion of potential remedies for addressing challenges in establishing a virtual community resilience testbed and areas for future testbed research.

3.2.2 Generic Structure of Community Resilience Testbeds

In line with the testbed definition stated in Section 3.7, we proposed a generic structure for community resilience testbeds, illustrated in Figure 17. Logical gates are borrowed from event-tree modeling to demonstrate the minimum components and hierarchy required for developing a testbed. The “AND” gate is used to show that the output component exists only if all input components are available; conversely, the output of an “OR” gate develops even if only one input component exists. As evident in Figure 17, community resilience testbeds must have both a hazard module and a community module. Ideally, the community module includes physical, social, and economic systems, however, only one of the three is sufficient to initiate a testbed. The proposed structure in Figure 17 is such that the availability of either of the community’s infrastructure assets or building inventory is adequate to establish the physical system of the community module. The community's social and economic systems can be simulated using social and economic models or closely resembled by indices representing their capacity. A hazard module consists of one or more probabilistic or deterministic hazard numerical models. The details of the systems and subsystems beneath community and hazard modules depend on the testbed's purpose and the availability of needed data; such details are discussed in the next sections.

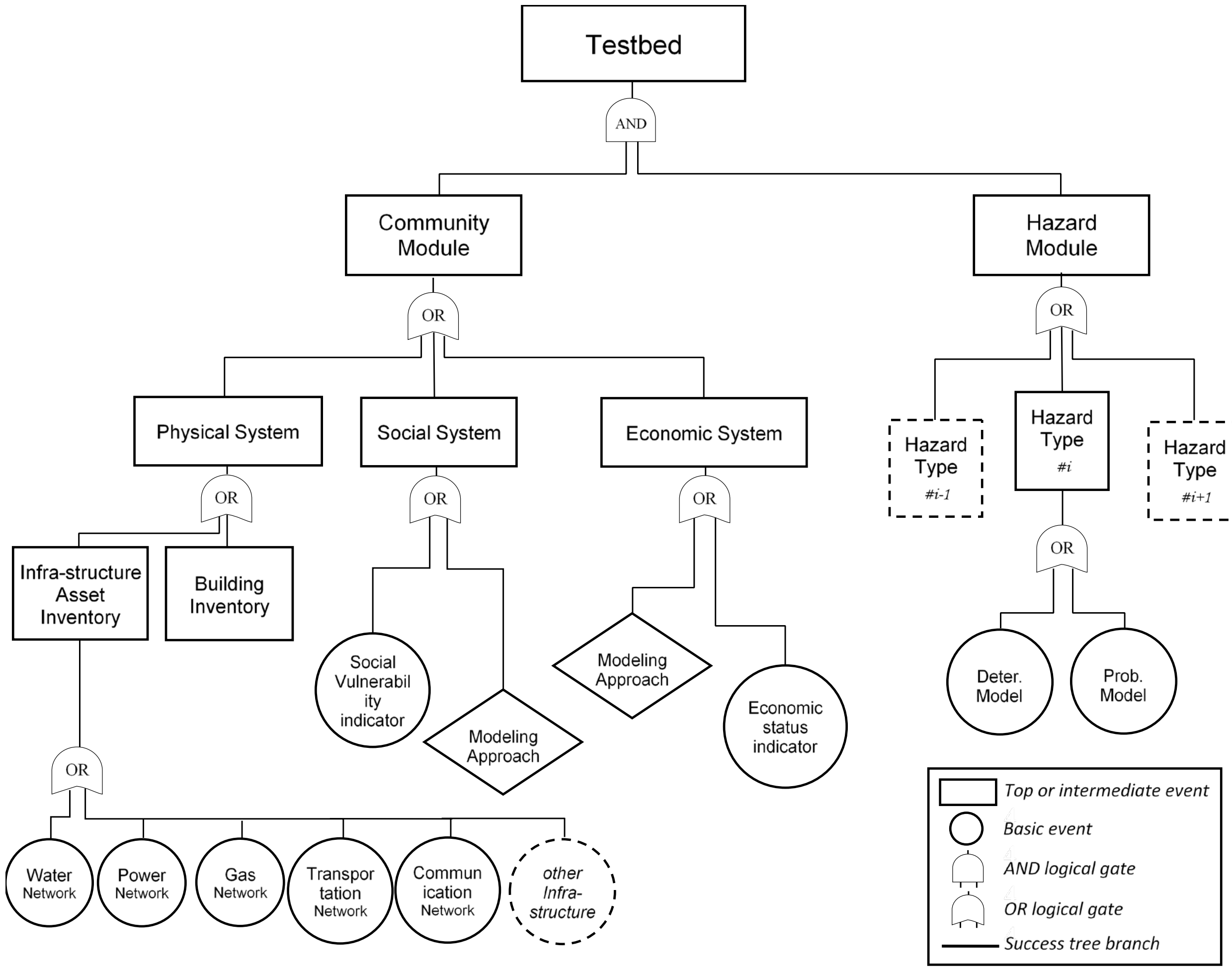

Figure 17. Generic structure of a community resilience testbed

The proposed generic structure was applied to the 22 community resilience testbeds identified by the authors in the review study (S. Amin Enderami, Ram K. Mazumder, et al., 2022) for validation. Table 2 presents a summary of the main features of the reviewed testbeds' systems and subsystems; the structure proposed in Figure 17 is completely compatible with the structure of the identified testbeds.

Table 2. Summary of main features and components of the existing testbeds

Testbed	Imaginary	Community Module									Hazard Module								
		Physical System							Social System	Economic System	Natural Hazard					Man-made Hazard			
		Building Inventory	Infrastructure Asset Inventory																
			Water	Power	Gas	Transportation	Communication	Wastewater and Drainage			Earthquake	Wind	Flood	Tornado	Tsunami	Urban Fire	Cyber-physical	Pandemic	Contamination
CLARC	●	●	●	●	●	●		●	●			●	●					●	
Centerville	●	●	●	●		●			●	●	●	●		●					
Benchmark City (China)	●	●	●	●	●	●		●			●								
Shelby County		●	●	●	●	●			●	●	●								
Seaside		●	●	●		●			●		●				●				
Galveston		●		●		●			●			●	●						
Gotham City	●	●	●	●		●	●		●	●									
Harris County				●	●	●						●	●						
Gilroy		●	●			●			●		●								
psuedo-Norman		●	●	●					●					●					
Joplin		●		●					●	●				●					
ASCE First Generation Testbed	●	●	●								●								
Lumberton		●							●				●						
Atlantic County		●										●	●						
San Francisco Bay Area		●				●					●								
Micropolis	●		●	●												●			●
Turin Virtual City		●									●								
Anytown	●		●								●								
The unnamed Water Network	●		●								●								
UW Power Systems Test Case Archive				●							●								
C-Town	●		●														●		
Mesopolis	●		●																●

3.2.3 Testbed Development Methodology

This section presents the methodology and workflow we established for developing a community resilience testbed. A community resilience testbed can represent either an imaginary or a real community (S. Amin Enderami, Ram K. Mazumder, et al., 2022). The methodology elaborated herein can be applied to both imaginary and real testbeds; however, there are certain details on data collection and processing that perhaps are only applicable to testbeds that represent real-world communities.

3.2.3.1 Testbed Simulation Scope

Defining the simulation and modeling scope is an overarching step in the development of a community resilience testbed. Ideally, a fully developed testbed consists of all components demonstrated in Figure 17; however, in practice, testbeds evolve gradually alongside the testbed users' needs. Thus, to establish a community resilience testbed, it is essential that developers determine the scope of their simulation at the outset. The simulation scope must be aligned with the model chaining and integration questions to be asked, and the theories to be tested. Defining the testbed simulation scope includes specifying components of the hazard and community modules, their types, modeling approaches, and spatial scale. Data availability and the skillset of the researchers involved in developing the testbed are the other determining factors that may govern the simulation scope. Thus, to determine the simulation scope, in addition to considering the testbed users' needs, it is also necessary to consider the simulation possibilities based on the available and accessible data.

3.2.3.2 Hazard Module

The hazard module of a testbed can include characteristics of either natural or man-made (e.g., contamination, cyber-physical attacks, urban fires, and disease pandemics) hazards or both.

Natural hazards are classified under two primary categories, 1) geologic hazards (which cover strong ground motions, liquefaction, tsunamis, landslides, and volcanic eruptions); and 2) climatic hazards (which include floods, hurricanes, storm surges, tornados, drought, and wildfire). The hazard module aims to quantify the hazard and provide an estimate of its severity at the location of interest. Several methods and multiple software programs and tools can be found in the literature regarding hazard intensity estimation and simulation (Beven, Almeida, et al., 2018; Beven, Aspinall, et al., 2018; Bulti & Abebe, 2020; Cui et al., 2021; Falcone et al., 2020; Marras & Mandli, 2021; Parisien et al., 2019; Pasquali, 2020; Soltanpour et al., 2021; Sugawara, 2021; Toja-Silva et al., 2018). The "State of the Art in Computational Simulation for Natural Hazards Engineering" report (Gregory G. Deierlein, 2021) comprehensively reviewed simulation methods, data sources, and software tools that are typically used in engineering disciplines to characterize earthquake, hurricane, and tsunami hazards. As hazard modeling is much further along in development than the community module of testbeds, it is outside the scope of this paper to discuss various hazard modeling techniques and tools. Instead, this section discusses the significant principles of hazard modeling methods and common challenges in building hazard modules and refers readers to other studies that have provided detailed reviews of the modeling processes.

To simulate a testbed's hazard module, both probabilistic and deterministic approaches are plausible and can be used based on the testbed's application. Probabilistic approaches consider all possible event scenarios with their likelihood of occurrence, whereas deterministic methods model a specific example of a scenario event, often the most adverse one, and do not have a probabilistic basis. The probabilistic approach typically applies ensemble modeling to account for uncertainties in event intensity, location, and time of occurrence. The output of a probabilistic approach is the exceedance probability of the hazard intensity that may be observed at the desired location in a given period. Natural hazards (particularly climatic hazards) are often complex adaptive phenomena and their characteristics change significantly with any variations in the current condition. This means with unavoidable errors in data measuring, it is impossible to precisely predict a future event using deterministic approaches (Patt & Dessai, 2005). Therefore, probabilistic methods can better estimate the characteristics of future natural events (especially climatic hazards), as climate change is concurrently happening. A major challenge with using probabilistic approaches is the presence of significant uncertainties in all components of the hazard model (Beven, Almeida, et al., 2018). Uncertainty is commonly divided into epistemic and aleatory uncertainty (Patt & Dessai, 2005). Epistemic uncertainty originates from incomplete knowledge of a phenomenon or process that influences the event. Aleatory uncertainty derives from the inherent variations in a random event and the chaotic nature of natural hazards. Aleatory uncertainty cannot be reduced with new knowledge (Hemmati et al., 2020). The aleatory uncertainty can be captured through multiple runs of the synthetic models with slight changes in initial and boundary conditions. Epistemic uncertainties are often quantified by employing statistical models (e.g., Monte Carlo simulation) and ensemble modeling, but ensemble models may not capture all possible future scenarios (Cremen et al., 2022).

Nevertheless, for the purpose of verification and validation of community resilience algorithms, testbed developers often use deterministic models of past events to develop the hazard module. The application of scenario-based analyses is relatively straightforward and their results, compared to probabilistic-based assessments, are easier to interpret for decision-makers (Adachi & Ellingwood, 2010; Adhikari et al., 2021; Krinitzsky, 1998). The National Institute of Standards and Technology (NIST) Community Resilience Planning Guide (National Institute of Standards and Technology (NIST), 2016) also recommends establishing scenario analyses for more general resilience plans or when the hazard levels are not defined by code.

3.2.3.3 Community Module

The community module of a fully-developed testbed is ideally a geospatial complex model of multiple interconnected social, economic, and physical systems, although developing only one of these three systems might suffice to start establishing the testbed. In general, it is very difficult to precisely model a community because of its complexity. On the other hand, developing either of the three systems requires substantial effort and resources for collecting, cleaning, and integrating data. The inherent complexity of community modeling and data restrictions, when coupled with other concerns such as security issues and ethical considerations, often persuade testbed developers to simplify their community models according to the specified simulation scope for the testbed. In this section, in addition to introducing the available data sources and modeling techniques, we discuss several common challenges in modeling each system of the community module and present conducive recommendations to address such challenges.

3.2.3.3.1 Physical System: Building Inventory

As evident in Figure 17, a testbed's physical system comprises the building and infrastructure inventories of the corresponding community. The building inventory typically consists of multiple datasets that include information about the main attributes of the existing buildings, along with corresponding damage functions and/or functionality models. Table 3 presents a set of the most common building characteristics that were used for building inventory development in the community resilience literature (Attary et al., 2019; Czajkowski et al., 2013; Ellingwood, Cutler, et al., 2016; Little et al., 2020; Loggins et al., 2019; McKenna et al., 2021; Nofal & van de Lindt, 2020a; Noori et al., 2017; Park et al., 2017; Pilkington, Curtis, et al., 2020;

Roohi et al., 2021; Wiebe & Cox, 2014; Zhang et al., 2018). The identified features are categorized into five overarching attributes, namely general, geotechnical, structural, architectural, and property-level, as shown in Table 3. Of note, to initiate developing a testbed, the building inventory's characteristics details and resolution level should be determined based on the defined simulation scope for the testbed.

Table 3. Most applicable characteristics of buildings in community resilience models

	Attribute	Characteristics	
1	General	• Location • Height • Year built	• Building boundary • Square footage • Land-use class
2	Geotechnical	• Soil type	• Foundation type
3	Structural	• Vertical load system • Lateral load system	• Structural Integrity • Vertical and lateral irregularity
4	Architectural	• Roof system • Floor system	• Exterior walls • External components (*chimney, parapets, roof overhang, etc.*)
5	Property-level	• Value *(building/content)* • Ownership structure *(private/public)*	• Occupancy • Tenure

It is becoming increasingly common for local and county governments to store a great deal of information about the buildings within their jurisdiction in digital repositories that are accessible to the public or that can be obtained upon reasonable request. This information typically includes the building's location, area, boundary, land-use class, year built, structural system material, building and contents value, occupancy, ownership, and tenure status. However, this data does not suffice for common community resilience models, and more building or property-level information is needed to estimate damage and loss at the community level. Private data may somewhat address such data needs, at least sometimes. ReferenceUSA (Data Axle, 2020), ATTOM (ATTOM Data Solutions, 2020), and Microsoft Building Footprint (Microsoft, 2020), to name only a few, are private databases that provide detailed building and property-level data in the United States.

Private data can be too expensive for academic researchers, and often cannot be published to be reused by the research community due to copyrights. More importantly, private data do not necessarily provide all essential information. For example, existing datasets often do not include information about a building's first-floor elevation and roof shape, whereas, both of which are important for estimating flood- and wind-induced damage, respectively. An alternative solution to fill this type of data gap is employing Artificial Intelligence (AI) techniques and computer vision algorithms to extract such visible attributes by processing the images. Chaofeng Wang et al. (2021) have developed an AI-enabled tool, termed BRAILS[1], for creating community-level building inventory. BRAILS is an open-source framework comprised of individual applications that are stitched together and use machine learning, particularly deep learning algorithms, to gather and process data from online resources such as Open Street Maps (OSM), Google Maps, Google satellite images, and street views. Although BRAILS was designed primarily for creating new building inventories in urban areas and has been used for this purpose since its inception (Deierlein et al., 2020; McKenna et al., 2021; McKenna et al., 2022), its modules can also be used individually to fill in gaps in an existing building inventory, as the authors did in Section 3.10.3.1 of the present paper. Although using private data and AI tools may fill some of the gaps in public data, there are still more details (e.g., lateral load system, foundation type, etc.) that should be included for community-level damage and loss analysis. In such cases, it is possible to simplify the building inventory based on some rational assumptions and use a suite of archetypes to represent all buildings in a community (Nofal & van de Lindt, 2020a).

[1] Building Recognition using Artificial Intelligence at Large Scale

Merging multiple datasets with different spatial and temporal resolutions is a common challenge in the testbed development process. Different datasets use dissimilar identifiers and diverse geographical reference units (e.g., individual building, map block number, parcel number, etc.), and deal with any missing data differently. For example, McKenna et al. (2021) reported that Microsoft Footprint Database sometimes lumps the footprints of closely spaced buildings together. Thus, it is required to verify the accuracy of data being used for the development of the testbed's components, particularly secondary data assembled by someone outside of the research team. A practical way to perform data verification is cross-referencing and comparing the mutual attributes across datasets from different resources. Due to using various sources for data procurement, various datasets may contain uneven or even contrary information. To address such probable conflicts, the testbed developer should apply a set of solid and transparent principles based on their judgment.

3.2.3.3.2 Physical System: Infrastructure Asset Inventory

Infrastructure inventories typically include information about water, electric power, transportation, gas and oil transmission, communication, wastewater, and drainage networks. As evident from Table 1, the first three types of aforementioned infrastructure have been of greater interest to testbed developers, whereas communication infrastructure has received the least attention from developers, despite being very common in reality. As the autonomous vehicle market is growing significantly and Internet of Things products (Madakam et al., 2015) are becoming common, the data transfer and communications infrastructure should be appended to the testbeds' infrastructure inventories in the future.

Security concerns often prevent detailed information about a community's infrastructure assets from being made public. Restricted access to infrastructure data is often a common worldwide challenge among testbed developers that have been reported by several researchers from other fields as well (Little et al., 2020; Nan & Eusgeld, 2011; Ouyang, 2014; Ouyang & Dueñas-Osorio, 2011; Svegrup & Johansson, 2015; Zhang & Peeta, 2011). This issue has been slightly resolved in the United States after establishing Homeland Infrastructure Foundation-Level Data (HIFLD) platform (DHS, 2022). The HIFLD data inventory comprised three categories of geospatial datasets, namely HIFLD Open, HIFLD Secure, and HIFLD Licensed Data. The HIFLD Open Data category contains national foundation-level geospatial critical infrastructure data within the public domain that are provided to support community preparedness, response, recovery, and resilience research. The HIFLD Secure data category, formerly known as Homeland Security Infrastructure Program (HSIP) Gold, is a for-official-use-only compilation of over 125 data layers characterizing domestic infrastructure and base map features. The HIFLD Licensed data is commodity data that is available upon a request in compliance with a set of predefined requirements (DHS, 2022). Even still, publishing that piece of the testbed for reuse by others may not be permitted. In these cases, testbed developers resort to publishing a coarse replica of the community's infrastructure network(s) containing only a few key aspects of the real system; e.g., pseudo-Norman testbed by Masoomi and van de Lindt (2017). We, herein, present our findings on a few existing resources that provide conducive data for simulating road, power, and water networks in testbed development.

Road networks are the backbone of a community's transportation network. Some road network attributes, such as route footprint, speed limit, and traffic direction, are often publicly accessible and can be procured from OpenSteetMaps (OSM, 2015) or the local government's Department of Transportation (DOT). Other attributes of road networks such as real-time traffic data might be obtainable from private companies that provide location-based data in the testbed's geographic scope such as Google Maps, INIRIX[1], Waze[2], Uber[3], etc. Additionally, Boeing (2022) developed a code for modeling road networks for every urban area in the world using OSMnx[4], an open-source Python tool. The code is available for public reuse at (https://github.com/gboeing/street-network-models).

An electric power network, in general, consists of three major components: (1) power stations to generate electricity, (2) a transmission system to carry the generated electricity to substations, and (3) a distribution system to provide end-users with power. The UW Power System Test Case Archive (https://labs.ece.uw.edu/pstca/) is a website that provides required datasets for modeling common 1960s power distribution systems in the Midwestern US. Also, the researchers at Texas A&M University have launched a repository named Texas A&M University Electric Grid Datasets (https://electricgrids.engr.tamu.edu/) that contains a collection of electric grid datasets. The S&P Global Commodity Insights, also known as Platts, is a private company that provides data on the global energy and commodities markets and offers spatial data on electric power, natural gas, and oil transmission network features in North America and Europe (https://www.spglobal.com/commodity-insights/en).

Water distribution systems typically consist of a water main, distribution pipelines, elevated water tanks, reservoirs, valves, pumps, and pumping stations. In the united states, Kentucky Water Resources Research Institute developed a database (http://www.uky.edu/WDST/database.html) that provides a collection of datasets for 40 different water distribution networks. The datasets consist of information on the networks' physical layout,

[1] https://inrix.com/
[2] https://www.waze.com
[3] https://www.uber.com/
[4] https://osmnx.readthedocs.org

geometry data, GIS maps, hydraulic models, and water demands (Kentucky Water Resources Research Institute, 2013).

3.2.3.3.3 Social and Economic Systems

Social and economic systems are more often discussed within case studies and theoretical works and incorporating such systems and phenomena into virtual community resilience testbeds is uncommon, as can be observed in Table 2. These two systems are, therefore, discussed together here, but not to symbolize any less importance relative to physical systems.

Ideally, social and economic systems in a community include multiple interconnected predictive models. However, in practice, it is pretty unlikely to simply obtain the high-resolution data needed for the validation of such interdependent models. For example, insurance data is not publicly available at a household level, and even publicly accessible OpenFEMA data is aggregated to the zip code level or higher. Thus, some testbed developers have resorted to using static indices to characterize a community's social and economic capacity. The ease of application and interpretation for non-experts is another benefit of making social and economic indices a popular tool among researchers and testbed developers with engineering backgrounds (Enderami & Sutley, n.d.). Gotham City and CLARC are two examples of testbeds from Table 2 using place-based social vulnerability indices to represent the social capacity of their target communities (Little et al., 2020; Mahmoud & Chulahwat, 2018).

Although most of the testbeds in Table 2 are created by developers mainly housed in engineering disciplines, a few include predictive social science and economic models. Population evacuation (Wang et al., 2016), population dislocation (Roohi et al., 2021; Van De Lindt et al., 2019), housing unit allocation (Gardoni et al., 2018), household housing recovery (Sutley & Hamideh, 2020) are a few examples of such social models, albeit they focus only on the population, ignoring other aspects of the social system, including social services, culture, education, and health. Computable General Equilibrium (CGE) modeling is, currently, the preferred tool for assessing the regional impact of natural hazards on a community's economy (Chen & Rose, 2018; Cutler et al., 2016; Roohi et al., 2021). The existing literature on testbed development also includes models for business interruption and recovery, which have been applied to community resilience analysis (Aghababaei, Koliou, Watson, et al., 2020; Attary et al., 2019; Watson et al., 2020; Yang et al., 2016). As interdisciplinary collaborations increase and more community resilience testbeds are being developed and reused, social and economic models are becoming more important. Thus, the next generation of testbeds should incorporate a more comprehensive simulation of a community's economic and social systems.

3.2.3.4 Testbed Verification and Validation

Testbeds are primarily used for verification and validation (V&V) of community resilience algorithms. Testbeds themselves must also go through V&V processes to be able to apply results from a testbed analysis to the real world. The process of testbed V&V is a crucial and challenging step that is accomplished in two phases. First, the accuracy of datasets used for testbed development must be verified. See section 3.9.3.1 for more information about how to do this first phase. Second, chained models, and integrated modules and systems must be validated after they are stitched together to ensure the reliability of the whole environment. To validate a complex computational environment of connected models and data, such as a community resilience testbed, post-disaster data collection and longitudinal studies are needed. As a result, it has become common to develop testbeds of communities that are rich in case studies and post-disaster data. Joplin and Lumberton are two examples of testbeds from Table 2 that are been validated using the post-disaster data. To validate the Joplin testbed, estimates obtained from the processing of collected data and reviewing existing government documentation, archived literature, and case studies on Joplin after the EF-5 tornado on May 22, 2011, were used (Attary et al., 2019). Lumberton Testbed was validated using post-event data from an ongoing longitudinal research study after the 2016 catastrophic flooding in the city of Lumberton, North Carolina due to Hurricane Matthew (van de Lindt et al., 2018).

A few years after a disaster, the population, demographic texture, built environment, and economy of the harmed community are likely to change significantly. Hence, for the V&V of a testbed, the datasets need to be modified to resemble the community at the time of the event. This modification will be very challenging if the event occurred before the digital age. If so, connecting results to existing theories, ground truthing, using expert panels, and comparing the results with other published research in the testbed scope are the alternative techniques for the second phase of testbed V&V (Sargent, 2010; Thacker et al., 2004). While no approach will provide a perfect validation check, the ones described here fairly verify the reliability of systems and modules, either separately or together.

3.2.3.5 Testbed Visualization, Publication, and Reuse

In addition to facilitating testbed reuse, testbed visualization can be remarkably effective when discussing analysis results with the decision- and policy-makers. Any geographic information system (GIS) software can be used for this purpose. The GIS environment not only provides the opportunity to integrate both the attribute and spatial data for all of the components in a testbed's community module to be stored in a single database but also can be applied to map the community resilience analysis results. ESRI ArcGIS and Q-GIS are conducive software for testbed visualization, however, require additional software to chain algorithms and simulate disasters. Open-source libraries, such as Leaflet and Folium, are also available to visualize testbed interactively in the Python environment.

Testbed publishing is another imperative step in the testbed development process that cannot be skipped. The creation and validation of testbeds require a great deal of time and effort. Thus, it is not trivial to share a verified and validated testbed to be reused by researchers other than those who created them. Publishing a testbed involves more than sharing the datasets and algorithms that form the testbed components. Documentation of data sources, data cleaning, and merging procedures, modeling assumptions, verification and validation process, and contact information for the developer (team) are also required to be published along with testbed components. Platforms such as DesignSafe-CI and IN-CORE are appropriate environments for publishing testbeds.

Figure 18 presents the step-by-step workflow of the methodology described in section 3.9.

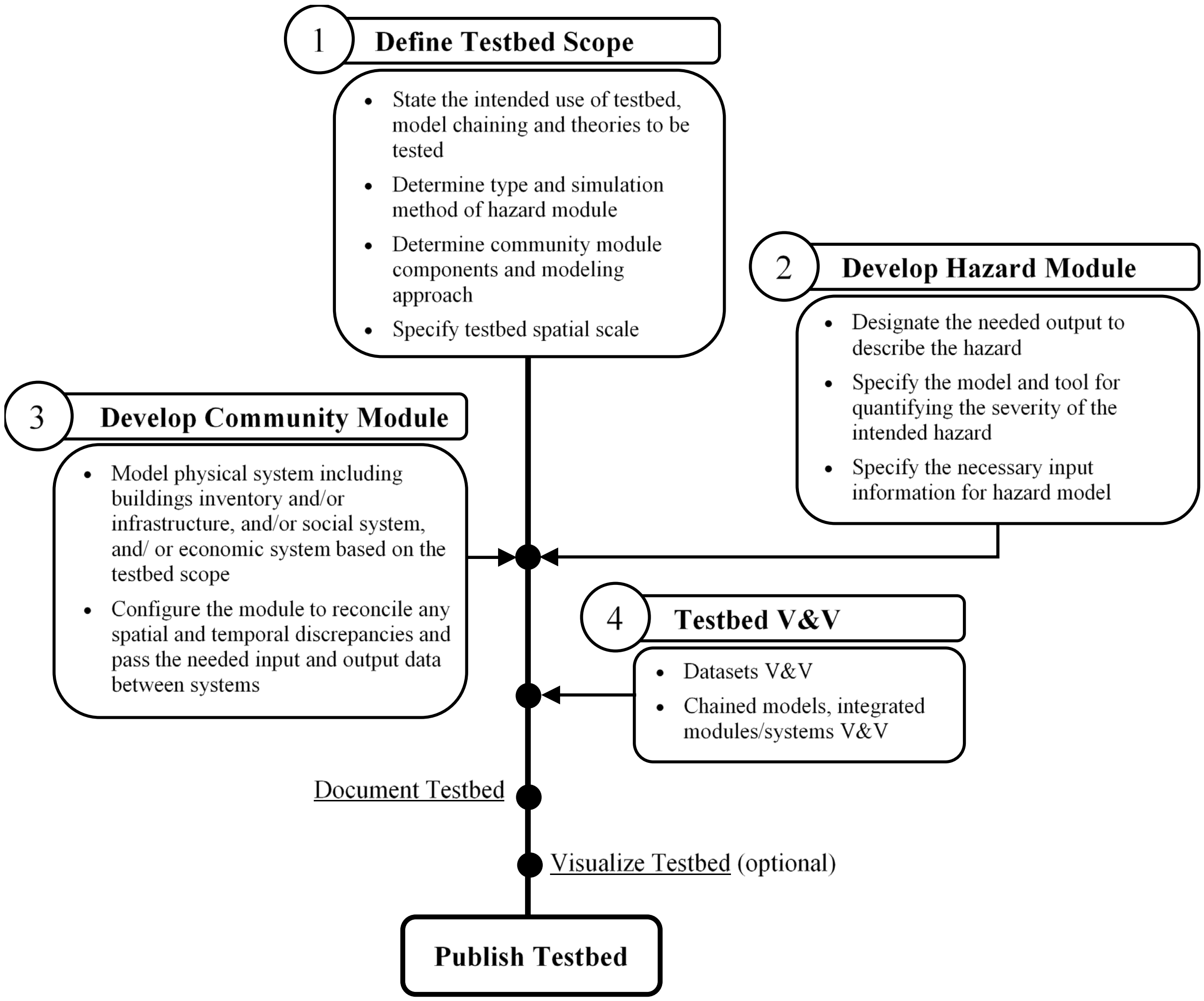

Figure 18. Testbed development workflow

3.2.4 Step-by-Step Example to Initiate a Testbed

To demonstrate the implementation of the workflow shown in Figure 18, the authors developed a testbed based on Onslow County, NC using publicly available data in the United States. All testbed documents, datasets, and algorithms (Python scripts and Jupyter notebooks) used for the creation of the testbed’s modules are open source and are available on DesignSafe-CI (S. Amin Enderami, Elaina Sutley, et al., 2022) to support an interdisciplinary collaboration for establishing a fully-developed testbed using the proposed workflow.

Onslow County is a coastal community in the State of North Carolina in the United States with a history of experiencing major hurricanes. The county comprises the City of Jacksonville, which is the County seat, and multiple towns. As of the American Community Survey (ACS) 2015-2020, 198,377 people including 66,131 households with a median income of $69,717 resided in the county. In terms of age, over two-thirds of the total population are between 18 and 65 years old. The racial composition of the county is 74.72% White, 13.99% African American, 0.55% Native American, 2.16% Asian, 0.15% Pacific Islander, 1.46% from other races, and 6.98% from two or more races. About 12.58% of the population is Hispanic or Latino of any race (U.S. Census, 2022). As a hurricane-prone area with a demographic similar to the national average, Onslow County is of interest to community resilience researchers. Onslow County has been used multiple times as a case study in the community resilience literature (Docekala et al., 2020; S Amin Enderami et al., 2022; Lyles, 2013, 2015; Mazumder et al., n.d; Ram K Mazumder et al., 2021; Mazumder et al., 2022; Monitz, 2011; Pamukçu et al., 2019) which makes it a proper community for developing a virtual testbed. The following subsections describe the testbed simulation scope and apply the proposed workflow step by step to develop its components.

3.2.4.1 Onslow Testbed Simulation Scope

To determine the simulation scope, we assumed that the Onslow Testbed is going to be used to generate community-level hurricane-induced wind risk maps for residential buildings. These maps are supposed to integrate the existing risk due to the social vulnerability of occupants into the physical vulnerability of residential buildings within the community of Onslow County. Additionally, the testbed will examine how households with different social vulnerability levels in Onslow experience changing access to the grocery after a 500-year flood. Thus, the simulation scope of the Onslow Testbed was defined as: (1) a hurricane-induced wind model and a 500-year flood map will be incorporated into the hazard module, (2) the community module consists of physical and social systems only, (3) residential buildings, grocery stores, and the County's road network will be included as the testbed's physical system, and (4) the community's social capacity will be represented using a place-based index. Figure 19 shows the Onslow Testbed structure, which is a modified revision of the generic testbed structure proposed in Figure 17.

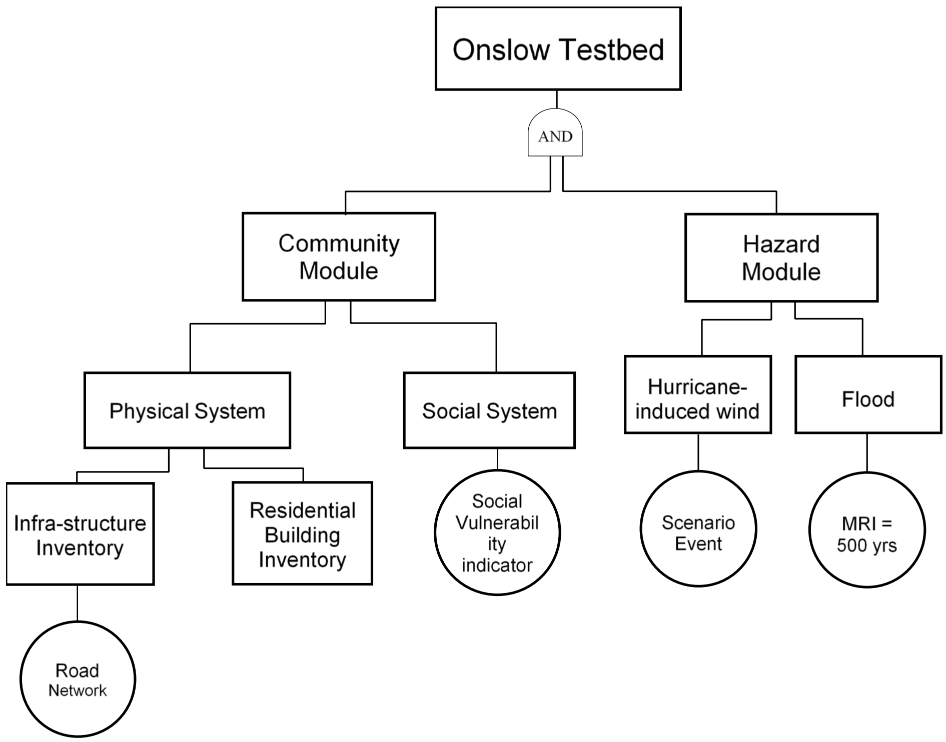

Figure 19. The structure of the Onslow Testbed

3.2.4.2 Onslow Testbed Hazard Module

According to the National Oceanic and Atmospheric Administration (NOAA, 2020) historical hurricane tracks database, Onslow County has never been hit by a Category 5 hurricane, but three Category 4 hurricanes, including Helene (1958), Diana (1984), and Hazel (1954), were recorded within 100 km of the county between 1857 and 2020. To simulate hurricane-induced winds, Hurricane Helene (1958), the most powerful one of those three Category 4 hurricanes, was chosen as the scenario event (Ram K Mazumder et al., 2021). The data needed for simulating the intended scenario event including information on its track, maximum wind speed, and the central pressure of the hurricane eye were retrieved from the Atlantic hurricane database (AOML 2020). The following wind field model, proposed by Holland (1980), was employed to estimate the maximum gradient wind speed at the location of interest. Despite its simple form, the model is highly efficient computationally and has been widely used in the literature for this purpose (e.g., Guo & Lindt, 2019; Salman & Li, 2018; Vickery et al., 2000; Vickery & Wadhera, 2008; Cao Wang et al., 2021):

$$\mathrm{V_G} = \left[\left(\frac{\mathrm{R_{max}}}{r}\right)^{B} \cdot \left(\frac{B \times \Delta\mathrm{p} \times \exp\left[-\left(\frac{\mathrm{R_{max}}}{r}\right)^{\mathrm{B}}\right]}{\rho}\right) + \frac{r^2 f^2}{4}\right]^{0.5} - \frac{r \times f}{2} \tag{1}$$

where $\mathrm{R_{max}}$ is the radius of the maximum wind, r indicates the distance from the hurricane eye to the desired location, B is the pressure profile parameter, f is the Coriolis parameter, Δ_p is the difference between the central pressure of the hurricane eye and atmospheric pressure, and ρ is the air density. The values of $\mathrm{R_{max}}$, B, and f were determined using Equations (2), (3), and (4), respectively.

$$\mathrm{R_{max}} = 2.556 - 0.000050255\,\Delta\mathrm{p}^2 + 0.042243032\,\psi \tag{2}$$ (FEMA, 2012)

$$B = 1.881 - 0.00557\mathrm{R_{max}} - 0.01097\psi \tag{3}$$ (Powell et al., 1998)

$$f = 2\Omega \cdot sin\varphi \tag{4}$$ (Xu & Brown, 2008)

where φ is the local latitude and Ω represents the average angular velocity of the earth. In the end, Gradient wind speed ($\mathrm{V_G}$) is converted into 3-s gust wind speed using conversion factors to yield the surface wind value at the location of interest (Salman & Li, 2018; Vickery et al., 2000; Xu & Brown, 2008). A Python script, executable on Jupyter Notebook and other computing platforms, is developed for simulating the wind field model and is publicly available on DesignSafe-CI (S. Amin Enderami, Elaina Sutley, et al., 2022).

The National Flood Insurance Program (NFIP) is a federal-level program managed by Federal Emergency Management Agency (FEMA), that enables homeowners, business owners, and renters in participating communities in the United States to purchase federally-backed flood insurance. NFIP publicly offers a wide range of digital resources for free download. The National Flood Hazard Layer (NFHL) database is one of those digital resources that provides geospatial data for floods with a 0.2% annual risk (FEMA, 2022b). For Onslow Testbed, NFHL data for Onslow County in a GIS file format and incorporated into the hazard module (FEMA, 2022a). Figure 20 shows a screenshot of the hazard maps included in the hazard module of Onslow Testbed.

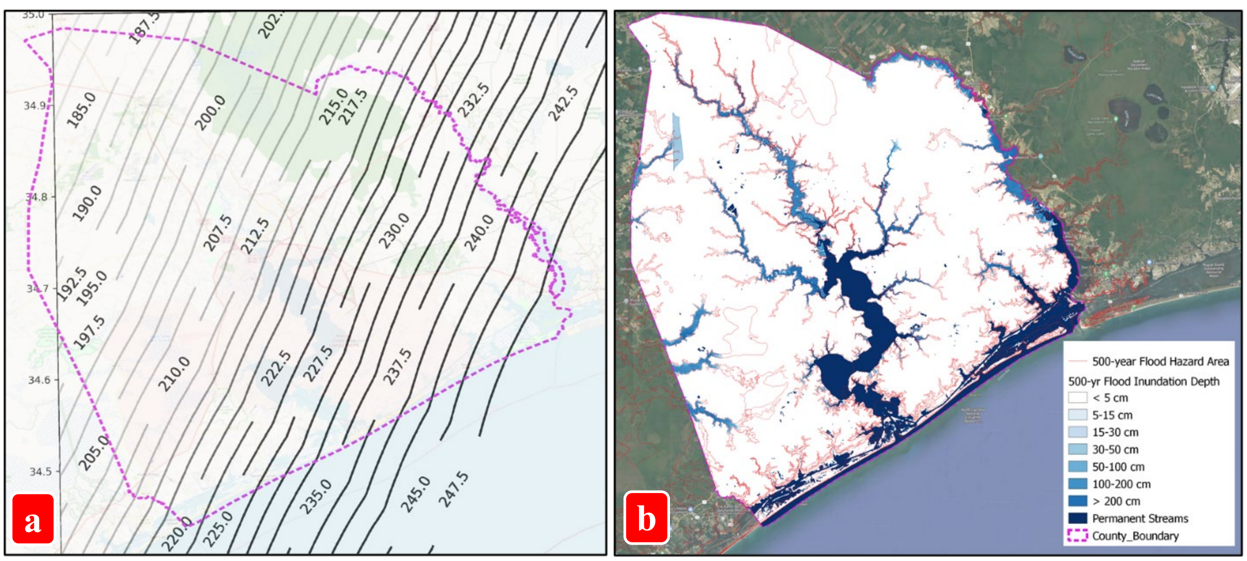

Figure 20. Onslow Testbed hazard module: a) Hurricane Helene (1958)-induced 3-s gust wind speeds (km/h); b)500-year flood map

3.2.4.3 Onslow Testbed Community Module

3.2.4.3.1 <u>Physical System: Building Inventory</u>

The building inventory in this example consists of geospatial data on physical characteristics, market values, and associated fragility-based vulnerability functions of intended buildings within the testbed area. This information was mostly obtained from the open-to-public datasets provided by Onslow County's government[1]. The tax records were used to identify each building's occupancy and dwelling type, the number of stories, exterior wall material, year built, square footage, and market value. The information retrieved from tax records is then spatially joined with the building footprint dataset to establish the testbed's base map. Microsoft Building Footprint data was used for cleaning and V&V of the building footprint dataset. The accuracy of the tax records data was verified through cross-referencing and comparing the mutual attributes with ReferenceUSA datasets. In addition to providing information on businesses in the United States, ReferenceUSA has a "U.S. New Movers/ Homeowners" dataset that includes proper data about single and multi-family dwellings. To determine the buildings' roof shapes, we used "RoofTypeClassifier" module of BRAILS (Charles Wang et al., 2021) and Google satellite images. Approximately one percent of the buildings in the testbed inventory were randomly selected, and the predicted shape for their roofs was visually validated using OSM and Google street views and images. Table 4 summarizes the features included in the building inventory of Onslow Testbed besides their data sources and verification procedures.

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[1] https://onslowcountync.gov/

Table 4. Onslow Testbed building inventory features

Building Attribute	Data Source
Location and footprint info	The building's location and footprint information were obtained from the building footprint dataset of the local government and were verified using the Microsoft Building Footprint data. This geospatial data was used to create the testbed's base map.
Occupancy and Dwelling type	The building occupancy and dwelling type was obtained from the local government's tax records and validated using the U.S. Homeowners and U.S. Business datasets, publicly available on ReferenceUSA.
Number of stories	The number of stories for each building was achieved from the local government's tax record database and was visually validated for a group of randomly selected buildings.
Exterior wall type	The information on the exterior walls of the buildings was obtained from the local government's tax record database.
Roof shape	The building roof shapes were determined using the BRAILS RoofTypeClassifier module and Google satellite images and were visually validated for a group of randomly selected buildings.
Market value	The market value of the buildings was fetched from the local government's tax records and was verified using the U.S. Homeowners and U.S. Business datasets, publicly available on ReferenceUSA.

To lower computation costs, we would rather use reduced-order vulnerability functions for developing the testbed's building inventory. An appropriate Hazus hurricane fragility model (FEMA, 2012) was assigned to each building in the inventory using the concept of the building portfolio. A building portfolio is a collection of building archetypes with different attributes that represent a community's building stock (Nofal & van de Lindt, 2020a). The building inventory was simplified to 22 archetypes, including one commercial archetype and 21 residential.

An F.16 Hazus damage model was assigned to all grocery stores within the testbed area. Residential buildings were mapped using the algorithm shown in Table 5. The mapping algorithm, first, categorizes residential buildings based on their dwelling type into four groups as defined in Table 5. Next, the algorithm determines the corresponding archetype for each building based on the (1) type of external wall, the number of stories, and roof shape for buildings in groups I and II; or (2) construction year for buildings in group III; or (3) number of stories for buildings in group

IV. Then, the algorithm maps associated Hazus fragility functions to the buildings. As can be seen in Table 5, more than one fragility function can be assigned to most of the residential archetypes. This is due to the fact that to assign the exact corresponding Hazus fragility function more data is needed, including information on the buildings' roof cover, sheathing, roof-wall connection type, window shutters, glazing coverage, missile environment, and terrain surface roughness. Procuring such types of data is almost impossible, even for a mid-size community such as Onslow County. In this example, a "0.35 m" terrain surface roughness and "A" missile environment are assumed according to Onslow County's topography. For roof cover, window shutters, and glazing coverage, the mapping algorithm randomly assigns possible options with equal likelihood to each building. For example, it is presumably as likely for an Archetype-1 building to have window shutters or not. To allocate roof-wall connection and sheathing type, the mapping algorithm applies the binomial probability rule, illustrated in Figure 21. The criteria in Figure 21 were selected due to the significant evolution in building codes in those periods such that more recent building codes comply with more strict requirements. For instance, the probability of using a strap for connecting the building's roof and wall increases from 20% to 50%, and 80% as the year built changes from periods before, between, and after 1950 and 2000. The Python script developed for executing the applied mapping algorithm is available on DesignSafe-CI (S. Amin Enderami, Elaina Sutley, et al., 2022).

Table 5. Mapping testbed's residential building inventory to Hazus damage functions

Archetype Group	Dwelling Type	Archetype †		Mapped Hazus Damage Functions *
I	Beach House, Single-Family	1	URM wall, 1-STY, Gable roof	A.2; A.10; A.50; A.58; A.66; A.74; A.82; A.90; A.98; A.106
		2	URM wall, 1-STY, Hip roof	A.6; A.14; A.54; A.62; A.70; A.78; A.86; A.94; A.102; A.110
		3	URM wall, 2-STY, Gable roof	A.34; A.42
		4	URM wall, 2-STY, Hip roof	A.38; A.46
		5	WFR wall, 2-STY, Gable roof	A.18; A.26
		6	WFR wall, 2-STY, Hip roof	A.22; A.30
II	Beach Townhome, Beach Duplex, Beach Condo, Town Home, Duplex, Condominium, Multi-Family, Apartment	7	URM wall, 1-STY, Gable roof	C.22; A.2; A.10; A.50; A.58; A.66; A.74; A.82; A.90; A.98; A.106
		8	URM wall, 1-STY, Hip roof	A.6; A.14; A.54; A.62; A.70; A.78; A.86; A.94; A.102; A.110
		9	URM wall, 2-STY, Gable roof	A.34; A.42
		10	URM wall, 2-STY, Hip roof	A.38; A.46
		11	WFR wall, 1-STY, Gable roof	C.14; C.20; C.21
		12	WFR wall, 1-STY, Hip roof	C.15
		13	WFR wall, 2-STY, Gable roof	C.24; A.18; A.26
		14	WFR wall, 2-STY, Hip roof	A.22; A.30
		15	WFR wall, 3-STY, Gable roof	C.25
		16	WFR wall, 4-STY, Gable roof	C.26
III	Multi-Section MH, Singlewide M/H	17	YB < 1976	B.3 (pre-HUD, Tied Down); B.3 (pre-HUD, NOT Tied Down)
		18	1976 < YB < 1994	B.3 (HUD, Tied Down); B.3 (HUD, NOT Tied Down)
		19	YB > 1994	B.3 (1994 HUD - Wind Zone II, Tied Down)
IV	Mixed-Use Res/Com	20	≤ 2-STY	F.9; F.10; F.11; F.12
		21	2 ~ 5-STY	F.27, F.28; F.29; F.30
		22	≥ 5-STY	F.45; F.46; F.47; F.48

† *URM = unreinforced masonry; WFR = wood frame; STY = story; YB = year built*

* *The notations used to introduce the damage functions match the notations in Hazus Technical Manual (FEMA, 2012)*

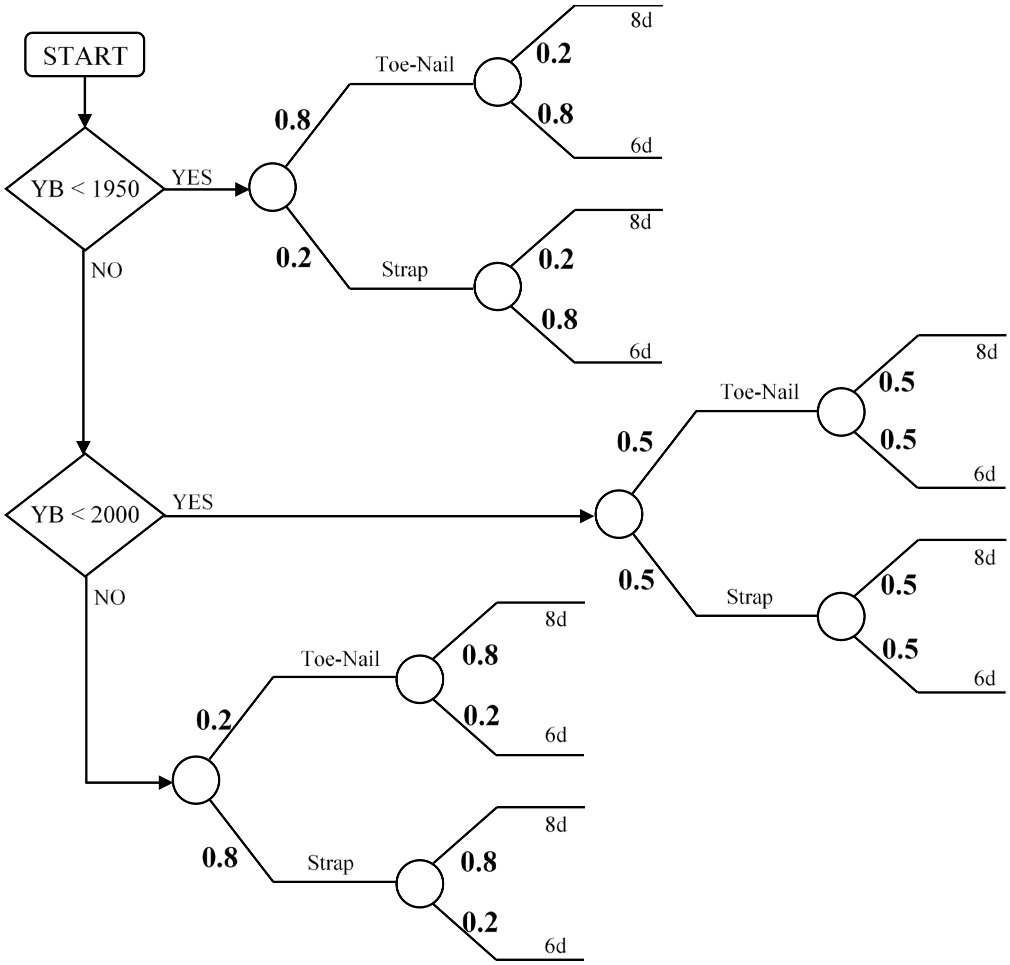
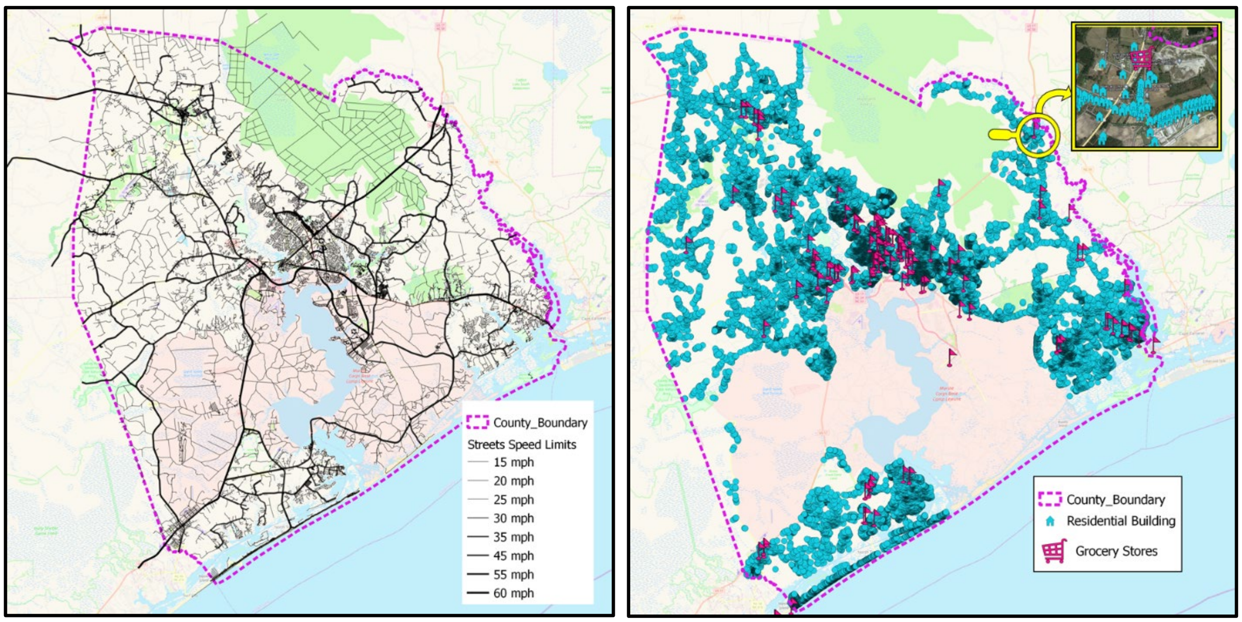


Figure 21. Algorithm for assigning roof-wall connection and sheathing type in Onslow Testbed

3.2.4.3.2 <u>Physical System: Road Network</u>

The Onslow road network model includes geospatial data about the speed limit, traffic direction, and routes footprint within the testbed area. These data were taken from OSM and the North Carolina Department of Transportation (NCDOT) open data. We used Graph theory for the mathematical simulation of the road network (Trudeau, 1993). Graphs are collections of nodes connected by edges. The nodes represent the locations where route footprints intersect, while the edges depict the routes that connect these intersections. Other attributes of the road network including streets' name, type, speed, and traffic data were assigned to the edges. The free-flow speed was estimated for streets located in urban areas by using Google Maps data and added to the road network dataset. Free-flow speed is the term used to describe the average speed that a motorist would travel if there were no congestion or other adverse conditions (such as bad weather). Finally, the developed datasets based on the road network were spatially merged and incorporated into the testbed's base map. Figure 22 illustrates the main physical components incorporated into the community module of Onslow Testbed.



(a) (b)

Figure 22. Physical components of Onslow Testbed: a) road network; b) residential buildings and grocery stores spatial distribution

In summary, to replicate a similar physical system for another testbed, the testbed developer should go through the following procedure step-by-step:

<u>Step 1</u> Fetch the most updated geospatial data of building footprints from the local government and Microsoft Building Footprint databases; clean and cross-check the retrieved data.

<u>Step 2</u> Download the tax record information from the local government's website; clean the data, keep the required attributes including occupancy, dwelling type, number of stories, exterior wall material, year built, and square footage, and delete the extra information; verify the

information using the U.S. Homeowners and U.S. Business datasets, publicly available on ReferenceUSA.

Step 3 Merge the datasets resulting from Steps 1 and 2; keep an eye out for differences between the spatial units of the building footprint and the tax record dataset. For example, a condominium that often contains multiple individually owned apartments is represented by one single footprint record that is associated with multiple tax parcels. In such cases, aggregate the information of tax parcels into a single record.

Step 4 Determine the building roof shape using the "RoofTypeClassifier" module of BRAILS and Google satellite images and add it to the building attribute dataset. BRAILS is an open-source Python package that has multiple modules with different capabilities and was developed by SimCenter to populate the building inventory of a community (Charles Wang et al., 2021). In this example, we modified BRAILS to fetch the footprint data locally, from the clean and verified dataset created in step 1. By default, BRAILS read the footprint data from OSM and Microsoft Building Footprint databases.

Step 5 Use expert knowledge and engineering judgment to develop a proper mapping algorithm for assigning Hazus fragility functions to their corresponding buildings in the inventory.

Step 6 Obtain data on the speed limit, traffic direction, and routes footprint from OSM and the State DOT; estimate the free-flow speed of urban streets using Google Maps data; create a graph model of the road network; assign the attributes of each street to the corresponding edge;

Step 7 Spatially join the road network model with the base map from Step 3.

3.2.4.3.3 Social System

The community's social capacity in Onslow Testbed is represented using the Social Vulnerability Score (SVS) developed by S. A. Enderami and E. J. Sutley (2022) to serve the purpose of testbed development. The SVS is a scalable composite index that overcomes two important limitations of existing place-based social vulnerability indices: it is constructed using an approach that does not decrease in validity with changing spatial resolution, and it only needs to be calculated for the geographic area of interest, instead of for the entire county thereby significantly reducing computational effort for testbed developers and users. The SVS synthesizes a set of demographics from the U.S. Census database at the desired location and yields a number, called a score, that represents the relative social vulnerability with respect to its national average. The resulting scores are mapped into five zones, ranging from very low vulnerability (zone 1) to very high (zone 5). Details on SVS development and verification can be found at (S. A. Enderami & E. J. Sutley, 2022). The open-source code published by S. A. Enderami and E. Sutley (2022), was used to map the social vulnerability of census block groups in the testbed area using ACS 2015-2020 data (U.S. Census, 2022), as its results are shown in Figure 23. As a point of note, the households are evenly distributed among census blocks, and a larger census block does not necessarily indicate a larger population.

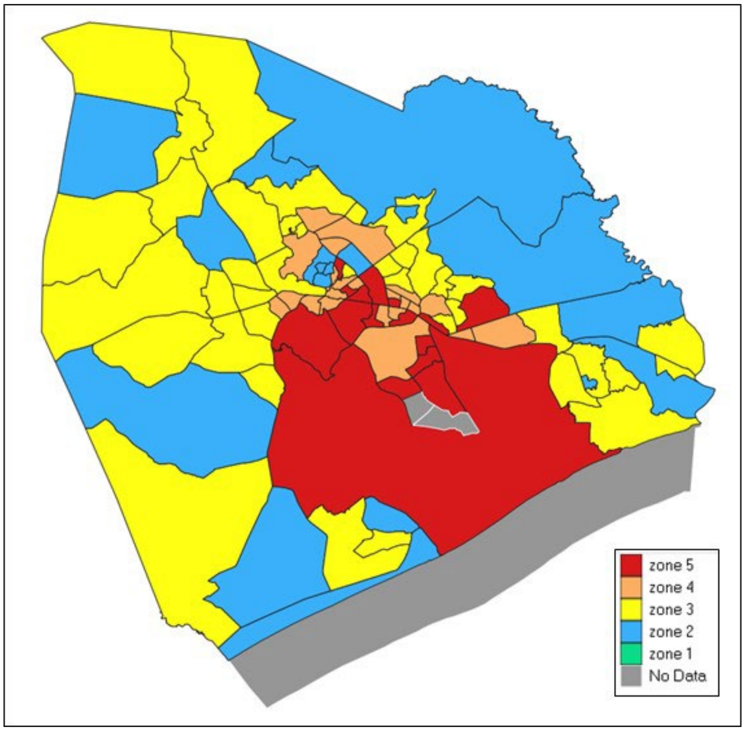


Figure 23. Mapped SVS zones at the census block group level in Onslow Testbed

3.2.4.4 Onslow Testbed Verification and Validation

The wind model in the hazard module was validated by comparing the estimated peak gust wind speed with data recorded during Hurricane Helene. For example, the peak gust wind speed recorded during Hurricane Helen was identical to the value estimated by the incorporated wind model, almost 240 km/h. No further V&V for using the FEMA flood hazard map is needed since we only use the simulation results of a validated flood model in the hazard module. The validity of data used for developing the testbed's physical system was verified, as explained in Section 3.10.3.1. Similar to the FEMA flood hazard maps, using the SVS to represent the testbed's social capacity does not need any additional V&V. A detailed description of evaluating the external validity and internal robustness of the SVS can be found in S. A. Enderami and E. J. Sutley (2022).

To V&V the testbed as an integrated system, we require damage survey results after Hurricane Helene, which we were not able to find. Importantly, the building inventory and population data used in testbed development are modern, while hurricane Helen is 70 years old. Thus, even if this historical data were available, it could not validate damage analysis outcomes since the population and building inventory are totally different now than then. Thus, In this example, the reliability of each testbed's components was independently verified by comparing the outcomes to published similar research results and relying on the authors' engineering judgment.

3.2.4.5 Onslow Testbed Visualization and Publication

In the end, all testbed components, including the Python scripts, Jupyter Notebooks, GIS files, hazard models, inventory datasets, and geographical data files were integrated into a package to constitute the Onslow Testbed. The package and the testbed's supporting documents (e.g. data cleaning process) are available on DesignSafe-CI for re-use and further development.

Figure 24 illustrates an overview of how the proposed testbed development workflow was implemented to establish the Onslow Testbed.

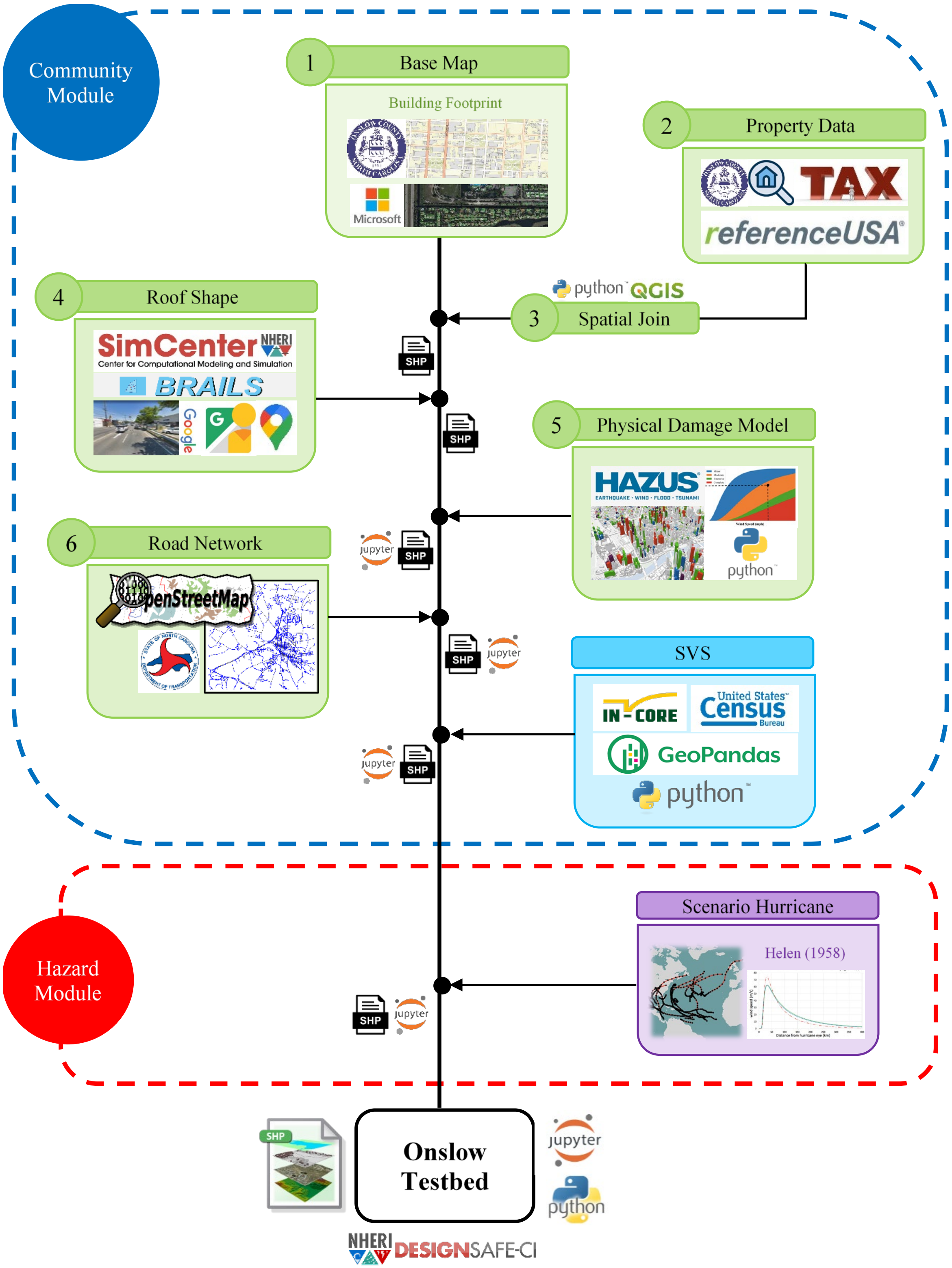


Figure 24. Onslow Testbed development workflow

3.2.5 Conclusions

Virtual testbeds are being developed and used across the community resilience literature to serve the purpose of V&V. As computational technologies advance, the interest in developing and using virtual community resilience testbeds is rapidly growing among researchers, however, there is no apparent standardized procedure for establishing virtual community resilience testbeds. The guideline proposed in this paper systematizes the development of virtual testbeds and facilitates the reuse of a testbed by researchers other than those who primarily established it. It is critical that the research community reuses existing testbeds in their research to advance the state of the knowledge on community resilience. To resue a testbed, only access to the testbed's datasets and chaining algorithms is not enough. The testbed users should also be aware of data procurement and processing procedures, modeling assumptions in testbed creation, approaches applied for testbed verification and validation, and the results of this phase. The testbed development procedure introduced in this paper fairly addresses this issue as well.

Community resilience cuts across different stressors (natural, man-made), scales (national, state, local), and community dimensions (physical, natural, cultural, human, social, financial, political), and a community resilience testbed should be aligned with all these considerations. Our proposed testbed development practice only discusses civil infrastructure networks and population-focused social and economic systems, leaving out other critical systems such as education, public safety, and healthcare. However, the introduced approach boosts multi-, inter-, and transdisciplinary collaborations on community resilience research and provides ample opportunity to incorporate more fitting social and economic phenomena and theories into testbeds. This contribution leads to developing more balanced testbeds with more evenly-evolved community modules which are needed to accommodate next-generation numerical models of community resilience.

Aside from introducing the current data resources to testbed developers, a secondary outcome of this study is to aid researchers in understanding the existing shortages of high-resolution data on social, economic, and infrastructure systems and identifying research needs and future direction in this field. As is showcased in the paper, developing machine learning-based predictive models to fill in the data gaps in the testbed development process is an evolving research area. In addition, more longitudinal studies are needed to establish diverse testbeds representing a variety of communities under different circumstances and hazards. This also leads to the opportunity of developing a uniform community-level taxonomy for data collection for post-disaster reconnaissance and advances current practices.

Chapter 4[1]: Social Vulnerability Score: a Scalable Index for Representing Social Vulnerability in Virtual Community Resilience Testbeds

Incorporating social systems and phenomena into virtual community resilience testbeds is uncommon but becoming increasingly important. Social vulnerability indices are a convenient way to account for differential experiences and starting conditions of the population in resilience assessments. This paper proposes a scalable index, termed Social Vulnerability Score (SVS), to serve the purpose of testbed development. The SVS overcomes two important limitations of existing indices: it is constructed using an approach that does not decrease in validity with changing spatial resolution, and it only needs to be calculated for the geographic area of interest, instead of for the entire county thereby significantly reducing computational effort for testbed developers and users. The proposed SVS aggregates the ratio of a set of demographics from U.S. Census datasets at the desired location against their national average values. The resulting scores are mapped into five levels, called zones, ranging from very low vulnerability (zone 1) to very high (zone 5). The validity of the SVS was investigated through a regression analysis of flood outcomes in Lumberton, North Carolina caused by Hurricane Matthew in 2016. The resulting correlations between the SVS zones and post-disaster outcomes of household dislocation and home repair times match the social vulnerability theory. The paper concludes with a comparison between the SVS and two existing social vulnerability indices at the census tract level for the State of Kansas.

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[1] This chapter is based on a manuscript in review with this dissertation's author as the first author:

Enderami, S. A., & Sutley, E. J. (2022). Social Vulnerability Score: a Scalable Index for Representing Social Vulnerability in Virtual Community Resilience Testbeds. *Natural Hazards, PREPRINT (Version 1) available at Research Square*. https://doi.org/10.21203/rs.3.rs-2113725/v1

4.1 Introduction

Disasters occur at the intersection of hazard exposure and vulnerability, where that vulnerability can be physical or social, but is the product of society (Mileti, 1999; Tierney, 2014). A well-documented and fundamental canon to disaster research is that there is no such thing as a *natural* disaster (Squires & Hartman, 2006). Rather, disasters are the direct result of society-made vulnerabilities, such as poor structural design and poor land-use planning, as well as a long history of policies distilling social inequalities, such as systemic racism. Social vulnerability is defined as "the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impacts of a natural hazard" (Blaikie et al., 2003). Social vulnerability thus implies an increased susceptibility to harm or negative outcomes which is based on pre-existing social characteristics stemming from race, ethnicity, income, education, disability, tenure, and their intersection.

Decades of disaster research have demonstrated that disasters do not affect all members of society equally (Fothergill & Peek, 2004; Sutley & Hamideh, 2020). Important social, physical, economic, cultural, and political factors drive people, households, and communities to be more or less vulnerable (Cutter, 1996). Fothergill and Peek (2004) illustrate how people with different socioeconomic status (1) perceive, prepare for, and respond to natural hazard risks, (2) have been differentially impacted physically and psychologically, and (3) are differentially affected by the social class during different stages along the disaster timeline. The vulnerability of poor people in the U.S. is exacerbated by the place and type of residence, building construction, and social exclusion, providing important implications for social equity and policy. Existing disaster recovery policies have further exacerbated social inequalities after disasters by setting qualifying criteria that exclude socially vulnerable people, including renters, the poor, and some cultures, from accessing recovery resources (Kamel & Loukaitou-Sideris, 2004; Sutley & Hamideh, 2018; Van Zandt, 2019). As Peacock et al. (2005) point out, women and ethnic minorities and individuals of low income and little education have higher perceptions of risk from natural hazards. A common theme explaining the increased risk perception is attributed to the lack of power and resources often available to people within these groups. A lack of power and resources leads to less ability to make one's own choices, less trust in institutions, and reduced likelihood to be in positions of relative power and control, altogether attributing to a higher social vulnerability. Hamideh and Rongerude (2018) point out how these very dynamics make public housing residents some of the most socially vulnerable members of communities given their lack of social and political capital. For a recent review of disaster and policy impacts on socially vulnerable populations, see Van Zandt (2019).

Historically, the focus of most hazard research resilience studies, particularly those stemming from engineering fields, has been on the built environment and reducing physical vulnerabilities; however, when communities set their resilience goals, it is imperative to consider community-specific social, human, and cultural systems, and assess social vulnerabilities along with physical vulnerability in striving for resilience. For social vulnerability and its influence on resistance and recovery to be incorporated into community resilience analysis, there must be robust tools for quantitatively measuring social vulnerability. There is a long history of the social sciences documenting and measuring which factors, and to what extent those factors contribute to social vulnerability. Place-based social vulnerability indices are simplified powerful tools for measuring social vulnerability and are often presented via mapping. This simplification has been commonly adopted in the literature to progress the state of knowledge on social vulnerability in some ways while waiting for more robust studies on the intersectionality of social vulnerability to develop.

These indices serve as proxies for a community's social vulnerability status and their mapping is sufficient for identifying geographic areas that are quite different in abilities to respond to a natural hazard and bounce back from its impacts. The basic logic of social vulnerability mapping is to identify concentrations of populations with particular social vulnerability characteristics to identify areas within a community that will likely require special attention, planning efforts, and external support in responding to and recovering from hazards and disasters. The strength of social vulnerability indices to properly capture a community's social status, combined with their ease of application and interpretation for non-experts, have made them a popular tool among researchers from engineering disciplines.

The tendency to use place-based social vulnerability indices increased as the development and application of virtual testbeds for community resilience studies gained momentum. A community resilience testbed is a virtual "environment with enough supporting architecture and metadata to be representative of one or more systems such that the testbed can be used to (a) design experiments, (b) examine model or system integration, and (c) test theories" (S. Amin Enderami, Ram K. Mazumder, et al., 2022, p. 031220013). As natural hazards engineering research is shifting from component- and building-level modeling into the interdisciplinary space of community-level, the application of virtual community resilience testbed is growing. Virtual testbeds enable researchers to test, verify, and validate their community resilience algorithms at different scales and spatial resolutions. For this purpose, a community's physical, social, and economic systems should be properly modeled and embedded in the associated testbed. Testbeds, however, lag behind in their ability to precisely model social and economic systems and have mainly focused on modeling buildings and physical infrastructure within a community (S. Amin Enderami, Ram K. Mazumder, et al., 2022). The community's social and economic systems can be represented using either a predictive model or a static indicator such as a place-based social vulnerability index. However, due to the complexities in modeling social systems, the use of place-based social vulnerability indices for characterizing a community's social capacity is more common among testbed developers, particularly those with engineering backgrounds. For instance, the Gotham City (Mahmoud & Chulahwat, 2018) and CLARC (Little et al., 2020) testbeds use place-based social vulnerability indices to represent the social capacity of their target communities.

Despite the advantages of existing social vulnerability indices, there are limitations regarding their application with changes in spatial resolution and geographic territory, which are common needs for testbed development and use. Testbeds must be capable of being scaled into different levels (such as counties, census tracts, census block groups, etc.) and jurisdictions (for example towns, cities, and metropolitan areas) to meet the requirements of the desired resilience assessment. Often, the higher the spatial resolution, the more meaningful the results can be to inform decision-makers. The current most widely used social vulnerability indices use scale-sensitive algorithms and were initially established at a county or census tract level (S. Cutter et al., 2013; Cutter et al., 2003; Flanagan et al., 2011). Most testbeds are developed at a county or city-scale, and thus only being able to evaluate social vulnerability once for the entire study area does not enable investigations of how differences in social vulnerability across the geographic area of interest may influence disaster impacts and outcomes. Downscaling existing social vulnerability indices to a geographic unit finer than their original scale, regardless of challenges in obtaining high-resolution data, may lead to results that are inconsistent with their original-scale estimates (Rufat et al., 2019, 2021; Spielman et al., 2020; Tate, 2012). Furthermore, any change in spatial scale, geographic domain, or temporal change often requires a full national-level analysis of the social vulnerability index (Spielman et al., 2020) creating extending the computational effort required to use the index. To serve the purpose of testbed development purposes, a social vulnerability index that is not scale-sensitive and is capable of applying to other geographic territories and spatial resolutions (particularly finer than a county) is needed.

The objective of this paper is to address this gap, by developing a scalable social vulnerability index to serve the purpose of community resilience testbed development. The paper begins with reviewing the state of knowledge in social vulnerability drivers and measuring social vulnerability to disasters through assessing a selection of key studies in the literature grounded on the household and housing experience. The paper continues by introducing the Social Vulnerability Score (SVS), a scalable social vulnerability index, and describing its construction methodology and validation process. The validity of the SVS is investigated using the disaster outcomes measured following the 2016 catastrophic flooding in the city of Lumberton, North Carolina due to Hurricane Matthew. The paper concludes with a discussion on the SVS estimates and comparing them with two well-known existing social vulnerability indices.

4.2 Background on Social Vulnerability

Over the past two decades, social science studies have identified social and institutional norms that contribute to social vulnerability. These studies altogether have provided a solid foundation for developing social vulnerability assessment tools and methods. In this section, a brief review of the current state of knowledge regarding social vulnerability drivers and quantitative models for measuring social vulnerability are presented.

4.2.1 Social Vulnerability Drivers

Previous studies have shown community members with certain social characteristics are more likely to experience more severe consequences of exposure to natural hazards (Bergstrand et al., 2015; Birkmann, 2013; Burton et al., 2018; Burton, 2010; Cutter et al., 2003; Daniel et al., 2022; Dintwa et al., 2019; Drakes et al., 2021; Dunning & Durden, 2011; Flanagan et al., 2011; Guillard-Gonçalves & Zêzere, 2018; Laska & Morrow, 2006; Liu & Li, 2015; Myers et al., 2008; National Research Council, 2006; Oliver-Smith, 2009; Van Zandt et al., 2012; Zahran et al., 2008). A summary of the most common social vulnerability drivers, namely households' race, ethnicity, tenure status, income, size, educational attainment, age, and disability, and the rationale for each driver are discussed herein.

Race and ethnicity have often been considered social vulnerability drivers due to long-standing systemic discrimination and racism leading to limited access to resources of all kinds, as well as lower income, and cultural and language barriers. Minority groups are more likely to occupy houses that are located in hazardous locations, and less likely to have connections to decision-makers and political capital (Cutter et al., 2003; Dunning & Durden, 2011; Flanagan et al., 2011; Laska & Morrow, 2006; Myers et al., 2008; National Research Council, 2006). However, different racial and ethnic identities among minority populations may even differently experience exposure to disasters. For example, African Americans and Hispanics are more likely to live in areas at high risk of flooding from natural disasters than Asian people (Bakkensen & Ma, 2020).

Renters tend to be more socially vulnerable than those who own their homes. Commonly referenced causes for greater social vulnerability for renters include having trouble finding shelter after a disaster, accessing or knowing about recovery financial aid programs, and having limited control over property-level hazard mitigation actions. Renters are also more likely to dislocate after a disaster with limited control over if, when, and for how long they dislocate, making them more susceptible to permanent dislocation. (S. Cutter et al., 2013; Cutter et al., 2003; Dunning & Durden, 2011)

Household income is directly associated with the number of financial resources that are available for households' risk mitigation and disaster recovery actions. Poor people are less likely to have savings, insurance, or social capital networks with strong financial capital to help them absorb losses and recover or political capital to lobby on their behalf for assistance. Low and very low income households have historically been excluded from accessing federal recovery resources as a result of overlooking policies that require them to demonstrate that damage is in no part due to deferred maintenance (Daniel et al., 2022; Hamideh & Rongerude, 2018). Low and very low income households are also more likely to live in substandard housing in a higher-risk location and may lack resources such as having a vehicle to evacuate in an emergency (Cutter et al., 2003; Dunning & Durden, 2011; Flanagan et al., 2011). In addition, the risk of post-disaster unemployment is greater for lower-wage workers (Laska & Morrow, 2006).

Household size has been attributed to social vulnerability due to imposing a financial burden. Also, larger households are less likely to evacuate in an emergency because of difficulty in coordination, often being multigenerational with young children and elderly members, and difficulty in finding adequate shelter (Dintwa et al., 2019; Liu & Li, 2015).

Educational Attainment is associated with the household's social, financial, human, and political capitals (Daniel et al., 2022). Higher education is associated with higher salaries, easier access to public resources for hazard preparation and recovery, and more powerful networks with local authorities. On the contrary, for low-educated people, besides lower incomes, practical and bureaucratic obstacles can make it difficult for low-educated individuals to cope with and recover from disasters (Cutter et al., 2003; Flanagan et al., 2011).

The elderly and very young are very likely to pose evacuation challenges, this is true for those with special medical needs and who live in nursing homes or hospitals, as well as for those who live in their own homes (Dunning & Durden, 2011; Myers et al., 2008). Elderly people are more often on fixed incomes and may lack access to financial resources to help them prepare for and recover from a disaster. Elderly homeowners are more likely to have paid off any mortgage on their home and thus are less likely to opt into purchasing flood insurance. On the other hand, children also present important challenges with disasters, including evacuation decisions, and post-disaster childcare (Dunning & Durden, 2011; Laska & Morrow, 2006)

Disabled people face important challenges surrounding disasters, including evacuation challenges depending on the nature of their disability, as well as having access to information, potentially needing a dependent to assist in decision-making around preparedness, evacuation, and recovery, and also more likely being on a fixed income with limited resources at their disposal (Dunning & Durden, 2011; Laska & Morrow, 2006). Literature has also shown that disabled people are more likely to live in manufactured housing. Manufactured housing has its own set of limitations that contribute to the resident's vulnerability, including being physically vulnerable to natural hazards, less likely that the resident carries insurance, and often complicated tenancy situations where the resident may own the home but rent the land and thus not be in control over dislocation and return decisions (Al-Rousan et al., 2015).

The factors reviewed in this section are the ones adopted into the proposed SVS, and are described from the U.S. perspective. Importantly, there are many other factors that contribute to a household's social vulnerability in the U.S., such as being a non-native English speaker, household size, and being a female-headed household, among others. Outside of the U.S., many of these factors still contribute to social vulnerability but potentially in different ways alongside other factors. Only considering the above six factors has three other important limitations. First, within the six factors described above are other factors that contribute to social vulnerability, such as not owning a vehicle when someone is also low income. Second, these six factors are not necessarily independent in their influence on social vulnerability. For example, renters, those with limited education, and with disabilities are more likely to be lower income. Third, people have more than one characteristic that defines them; the influence of the intersectionality of factors on social vulnerability is poorly understood. Even when a specific factor, like income, is well-covered in the literature, quantifying its influence on social vulnerability and disaster impacts and outcomes, has important limitations. Social vulnerability itself is a qualitative concept. This paper takes the perspective that quantifying social vulnerability is important for its inclusion in community resilience analysis, but that it must be done with a thorough understanding of the limitations in doing such. The next section reviews the quantitative research on social vulnerability.

4.2.2 Social Vulnerability Measurement

Models serve an important role in understanding the intersection of humans, disasters, and the built environment. Social vulnerability is an important dynamic at this intersection that is difficult to model and validate given its multidimensional nature and inability to be directly observed and measured (Tate, 2012). Although social vulnerability is complex, situational, and dynamic, past research has made incredible strides forward in measuring social vulnerability during and after disasters. Qualitative disaster studies have widely recognized that multiple dimensions of diversity can have a profound effect on pre-disaster vulnerability and preparation measures, disaster impacts, and post-disaster recovery experiences (Tierney & Oliver-Smith, 2012). However, the intersection of these dimensions is poorly understood, and has not been systematically and quantitatively measured in the past. From our literature review, we found there are three types of quantitative studies on social vulnerability, those that quantify *indicators*, *indices*, and *influencers*. Indicators are quantitative variables intended to represent a characteristic of a system of interest, e.g., the percent of African Americans in a community. Indicators can be composed of single or multiple variables, e.g., the percentage of minorities in a community. Alternatively, multiple indicators can be combined to construct composite indices, which attempt to distill the complexity of an entire system to a single measure. Lastly, influencer studies measure or model the influence that various social vulnerability indicators or composite indices have on specific dependent variables or outcomes. Different studies use different types of data to model social vulnerability, including (a) publicly accessible data, such as census data and tax assessment data; (b) primary data collected in the field before, during, or after a disaster; and (c) social media data. The data may be collected at different spatial scales and resolutions (e.g., state-, county-, census tract-, block group-, neighborhood-, and individual-levels). Given the focus of the present article, only examples of social vulnerability indices that use various types of data at different scales and resolutions are reviewed here.

The social vulnerability index (SoVI) developed by Cutter et al. (2003) is perhaps the most frequently cited place-based social vulnerability index. The effort started with 250 variables and was reduced to 85 variables after testing for multicollinearity, but finally, 42 independent variables were used in the factor analysis. Through their principal component factor analysis, the 42 indicators were reduced to 11 independent factors accounting for 76.4% of the variance in social vulnerability across all counties examined. The 11 independent factors included per capita income, median age, number of commercial establishments per square mile, the percent of the population employed in extractive industries, percent of housing units that are mobile homes, percent of the population that is African American, percent of the population that is Hispanic, percent of the population that is Native American, percent of the population that is Asian, percent of the population employed in service occupations, and percent of the population employed in transportation, communication, and public utilities. The factor scores were incorporated into an additive model producing the social vulnerability index. The SoVI formulation has evolved over time in response to changes in the knowledge of vulnerability assessment and data collection methods. The SoVI was initiated using the U.S. 1990 decennial Census data, however, its most recent version (SoVI 2010–14) synthesizes data on 29 variables from the American Community Survey (ACS) 5-year survey (Cutter & Morath, 2013). The SoVI 2010-14 was computed and mapped for all 3,141 counties and its value ranges from 9.6 (lowest) to 49.51 (highest) across the counties. The values were classified into five qualitative categories, from "Very Low" to "Very High," using a mean and standard deviation.

The SVI/CDC is another common place-based social vulnerability index and is developed by the U.S. Center for Disease Control and Prevention (Flanagan et al., 2011). Public health officials use the SVI/CDC to identify and map community members most likely to need support before, during, and after hazardous events. The index is composed of 15 equally weighted variables at the census tract that are classified into four overarching themes with the same level of importance. The 15 variables include below poverty, unemployed, income, no high school diploma, aged 65 or older, aged 17 or younger, civilian with a disability, single-parent households, minority, aged 5 or older who speaks English less than well, multi-unit structures, mobile homes, crowding, no vehicle, and group quarters. The four themes include (1) socioeconomic status, (2) household composition and disability, (3) minority status and language, and (4) housing type and transportation, where each theme represents an underlying dimension of social vulnerability. A percentile rank is calculated for each census tract over each of 15 variables. The percentile rank of variables is summed into each theme to produce a theme score. In the next step, the scores are summed, then the census tracts are ordered based on their summed scores to calculate the overall percentile ranking. Lastly, a quartile classification system is used to classify the ranked census tracts, where the highest and lowest quartiles represent the highest and lowest socially vulnerable tracts, respectively. The CDC published social vulnerability maps and index values for the entire United States for the years 2000, 2010, 2014, 2016, and 2018.

There are examples of using other social vulnerability indices in the literature. For example, Van Zandt et al. (2012) built a place-based social vulnerability index on the basis of the SoVI to be used for census block-level community-based planning. At this smaller scale, only 17 out of 29 SoVI variables were available from public data sources. Through an unarticulated weighting system, each variable value was normalized to range from 0 to 1. These normalized indicators were then split into groups to form several composite indices of second-order social vulnerability measures (e.g., child care needs, transportation needs), and finally, all 17 normalized indicators were combined into a third-order hotspot index and mapped across Galveston, TX.

In another study, Collins et al. (2009) developed a social vulnerability index to combine with physical vulnerability and map the risk of natural hazards in a metropolis that straddles the Mexico-United States border. The model measures social vulnerability by assessing four related elements including population, access to resources, socioeconomic status, and institutional capacity. Each of these elements is represented by a set of sociodemographic and economic variables with a value ranging from 0 to 1. Once all variables are computed, their average is calculated to create the index. The index values are then divided into quintiles and mapped.

Wu et al. (2002) employed a modified version of the methodology adopted by Cutter et al. (2000) and calculated a vulnerability index using only 9 demographic variables taken from the 1990 US Census block statistics. The list of variables includes total population, housing units; the number of females, non-white residents, people under 18, people over 60, female-headed single-parent households, renter-occupied housing units, and median house value. The model calculates the ratio of each variable's value in each census block against the maximum value for the variable in the county. The ratios range from 0 to 1; higher index values represent higher vulnerability. The arithmetic mean of these 9 variables for each census block was defined as the social vulnerability index. Then, the values were divided into quartiles, labeled respectively as low, moderate, high, and very high social vulnerability regions.

Montz and Evans (2001) developed a new means of measuring social vulnerability based on the existing indices. According to Montz and Evans (2001), social vulnerability can be measured sufficiently by using only five socioeconomic characteristics, namely population under 15, population over 65, a single female head of household, median household income, and population density. These variables were estimated for each census block in the study area and then aggregated by three different models to produce the index. The first model assumes that each variable contributes equally to differentiating vulnerability. The second model, inversely, was built on the assumption that different variables contribute differently to determining social vulnerability, and weights are assigned to each variable, based on their relative contribution. The third model includes a scaling scheme in addition to weighting the variables. The social vulnerability maps were created individually based on each model. Montz and Evans (2001) concluded that their first two models map social vulnerability similarly, but they may overestimate vulnerability in flood plains compared to the third model.

Of the indices reviewed above, the SoVI and SVI/CDC are the most widely applied, however, they are not easily executable for testbed development purposes because (1) both the SoVI and SVI/CDC synthesize needed data from the ACS five-year surveys, which do not provide reliable data finer than the census tract level for the demographic variables they use (Coggins &

Jarmin, 2021); (2) multiple SoVI-based measurements of the vulnerability of the same place can yield significantly different results using the same data (Spielman et al., 2020); (3) SoVI and SVI/CDC are sensitive to their initial model's spatial scale and any changes in their spatial resolution may result in estimates that are inconsistent with their original-scale estimates (Rufat et al., 2019). Similar limitations exist for other available social vulnerability indices which constrain their usage for testbed development purposes. Tate (2012) examined the configurations of available social vulnerability indices to determine how each stage of the index construction process contributes to its overall reliability and internal validation. The present study leverages Tate's (2012) findings and recommendations about improving the stability of the social vulnerability indices to fill an important niche in the literature: to develop an internally robust scalable social vulnerability index for the purpose of adoption in community resilience testbeds.

4.3 Social Vulnerability Score Development

This section introduces our methodology for developing the Social Vulnerability Score (SVS) and describes our rationale for its configuration. Although there is no standard procedure for developing social vulnerability indices, previous indices mostly have employed a similar multi-stage process. The process typically starts with determining the index construction method, followed by specifying the intended social vulnerability indicators, their measurement units, weights, and aggregation approach. Each of these stages involves choices between multiple plausible alternatives whose differences distinguish various social vulnerability indices. In this study, the choices have been made based on Tate's (2012) research results to produce an internally robust index.

4.3.1 Construction Method

The index construction method is an overarching stage in building social vulnerability indices that determines the index configuration (Tate, 2012). There are three common approaches in the literature for the construction of a composite social vulnerability index, namely *deductive*, *hierarchical*, and *inductive* approaches (Collins et al., 2009; Cutter et al., 2003; Cutter et al., 2000; Flanagan et al., 2011; Montz & Evans, 2001; Wu et al., 2002).

Deductive approaches linearly combine designated indicators (often less than ten) to build the composite indicator. The *hierarchical approach* consists of dividing the designated indicators into subsets that share a common dimension of vulnerability and assigning a specific normalized weight for each indicator and subset based on the experts' knowledge. After the weighted indicators are aggregated in each subset, the subset scores are then combined to create the desired index. The SVI/CDC is the most renowned social vulnerability index with a hierarchical structure. However, the index technically follows the deductive approach since the themes are mathematically ignored in the aggregation phase by considering equal weight for all subsets and indicators (Rufat et al., 2019). The *inductive approach* typically starts with a set of more than twenty indicators; these indicators are then reduced to a smaller set of latent factors by the means of statistical methods such as Factor Analysis or Principal Component Analysis. The intended indicator is constructed by combining these factors. The SoVI is perhaps the most common index that is constructed based on the inductive approach.

Tate (2012), Rufat et al. (2019), and Burton et al. (2018) studies illuminate that each construction approach has its specific pros and cons and none of them can be argued to be inherently better or worse than the others. Evaluating the strength of the index depends on the specific situation in which it is being used. For example, the inductive approach is highly dependent on its model spatial resolution (Tate, 2012), which makes it an inappropriate method for constructing a testbed-specific social vulnerability index. The deductive and hierarchical approaches are most sensitive to selected indicators' measurement units and weights, respectively (Tate, 2012). Thus, the deductive approach is used for constructing the SVS as it is more feasible to define an appropriate measuring unit for selected indicators than to determine each indicator's contribution to social vulnerability and assign weights accordingly.

4.3.2 Indicators and their measurement units

The indicators are generally selected based on the factors such as identified social vulnerability drivers and data availability. The primary motivation for introducing the SVS is to use it for developing community resilience testbeds. Given that testbeds are intended to be used for years or decades' worth of research (S. Amin Enderami, Ram K. Mazumder, et al., 2022), the SVS will be grounded on the ACS five-year demographic estimates. On the other hand, ACS five-year surveys do not provide reliable data at scales finer than the census block group (Coggins & Jarmin, 2021). Thus, according to common social vulnerability drivers, and constrained by the information that is available in the ACS five-year datasets, the SVS employs the set of social vulnerability indicators in Table 6.

Table 6. Social vulnerability indicators used for SVS development

Social Characteristic	Social Vulnerability Indicator	Notation
Race and Ethnicity	Ratio of the percentage of white alone (not Hispanic or Latino) population at the intended location against its national average percentage	R_1
Housing Tenure	Ratio of owner-occupied housing unit rate at the intended location against its national average percentage	R_2
Poverty Level	Ratio of the percentage of population earning greater than official poverty threshold at the intended location against its national average percentage	R_3
Education Level	Ratio of the percentage of persons over age 25 with a high school diploma or higher education at the intended location against its national average percentage	R_4
Age Disability Status	Ratio of the percentage of the population between 18 and 65 years old without disability at the intended location against its national average percentage	R_5

The indicators defined in Table 6 encapsulate all common social vulnerability drivers reviewed in Section 4.2.1 but capture them by five inverse compound variables such that a higher value indicates a lower level of social vulnerability. For example, the consequences of race and ethnicity were mixed so that all races and ethnicities, except those who identify themselves as white (non-Hispanic or Latino), are considered as a minority; then, the proportion of non-minorities, who are indeed less vulnerable members, in the intended location is computed. As a result of using compound variables, a fewer number of variables are included in the SVS model, which reduces the possibility of data collection errors and uncertainty of the mean value, particularly for smaller sample sizes (Tate, 2012). The use of compound variables, however, may lead to undesirable implicit assumptions. For instance, by taking the compound variable 'non-Hispanic White', the SVS inherently assumes that all minority races and ethnicities, such as Black, Native American, Asian, Hispanic, Latinx, etc, have the same influence on social vulnerability, which is not true. However, the specific differences are only partially understood, and quantifying each racial and ethnic identity individually also has its limitations by inherently assuming more is understood than what is actually known. Furthermore, the SVS uses the poverty level that takes both household size and income into account together. Less than high school education, for those 25 and older, is taken as the cut-off for educational attainment in the SVS model since many jobs require at least a diploma or GED to qualify. The very young was defined as age 18 and younger according to the United Nations Convention on the Rights of the Child (Peek, 2008).

The measuring unit characterizes how each indicator is represented in the model. The most common data presentation formats are numbers, percentages, and densities. Given that vulnerability is inherently a relative concept, SVS calculates each indicator as the ratio between the non-vulnerable population percentage at the desired location and the corresponding national average percentage. The percentage of the non-vulnerable population ranges from 0 to 100, with 0 representing complete vulnerability and 100 indicating no vulnerability. Measuring a social characteristic at the desired location with respect to its national average enables analysis of relative vulnerability across the U.S.

4.3.3 Weighting and aggregation

The indicators are in terms of unitless ratios, so there is no need to normalize before the weighting and aggregation stages; regardless, deductive models are insensitive to weighting and aggregation approaches (Tate, 2012). Thus, the indicators are aggregated while equally weighted, which implies that their relative importance is the same. The SVS calculates the arithmetic mean of the indicator values at the location of interest, expressed as

$$\mathrm{SVS} = \frac{1}{5}\sum_{i=1}^{5} \mathrm{R_i} \tag{1}$$

The resulting values can be used directly to compare the relative social vulnerability of different communities. Of note, a higher value of SVS indicates a lower level of vulnerability given that the indicators used in the SVS development process are inversely related to social vulnerability.

For ease of interpretation, the SVS was mapped to five discrete vulnerability categories, named zones using a standard deviation classification. The zones range from very low vulnerability (zone 1) to very high vulnerability (zone 5). The zones and the criteria used to define them are shown in Table 7.

Table 7. Social vulnerability zones

	Vulnerability Description	Criteria
zone 1	Low	SVS > 1+ 1.5*(std.)*
zone 2	Medium to Low	1+ 0.5*(std.)* < SVS < 1+ 1.5*(std.)*
zone 3	Medium	1- 0.5*(std.)* < SVS < 1+ 0.5*(std.)*
zone 4	Medium to High	1- 1.5*(std.)* < SVS < 1- 0.5*(std.)*
zone 5	High	SVS < 1- 1.5*(std.)*

In Table 7, *(std.)* represents the standard deviation of the SVS values for the entire country. Since 99.7% of values following a normal distribution lie within 3 standard deviations of the mean (Ang & Tang, 2007), *(std.)* value can be estimated as:

$$std. = \frac{(SVS)_{max} - 1}{3} \tag{2}$$

where $(SVS)_{max}$ is the maximum possible, and one represents the mean of SVS values for the entire country. Equation (1) gives the maximum of the SVS if the percentage of the non-vulnerable population at the desired location equals 100 for all indicators in Table 6. Therefore, only the average of the reciprocal values of national average percentages of indicators in Table 6 is required for calculating the *(std)* values.

For the convenience of testbed developers, the SVS calculation is automated using a Python script. The code is open source and published on DesignSafe-CI (S. A. Enderami & E. Sutley, 2022) for being used by other researchers to facilitate advances in current practice. The code takes the name of the intended state and county, desired spatial resolution (census tract or block group), and year as the input data. The output includes a geospatial data file (.csv) containing the SVS values and a choropleth map (.png) of the predicted social vulnerability zones. The code is only written for the spatial scales of census tract and block group given the lack of reliability in census data at higher resolutions. The SVS is capable of being applied to testbeds that require higher resolutions than the block group, including the block- and household-level, as will be demonstrated in Section 4.4.2.

4.4 Validation of Social Vulnerability Score

Validation is a major challenge with community resilience analysis given that simulations cannot be performed in real life, having the appropriate data is nearly impossible, and many of the concepts (e.g., social vulnerability) are immeasurable. Social vulnerability is a multidimensional qualitative concept that is not directly observable or measurable. Researchers have resorted to the use of outcome, socio-economic and demographic data collected from post-disaster household surveys as proxies to validate their social vulnerability models (Schneiderbauer & Ehrlich, 2006). These proxies range from physical damage and economic loss to population impacts such as mortality, dislocation, and mail delivery (Burton, 2010; Finch et al., 2010; Flanagan et al., 2011; Gall, 2007; Myers et al., 2008; Schmidtlein et al., 2011). In addition to such external validation efforts, which have been fairly successful, Tate (2012) explored the internal validity of common social vulnerability indices.

To externally validate how well the proposed SVS represents the social vulnerability of community members, we employed post-disaster household-level survey results on household dislocation, physical damage, and repair time of residential dwellings. The field data used in this paper are from the second wave of an ongoing longitudinal research project following the 2016 hurricane-induced riverine flooding in the city of Lumberton, NC (E. J. Sutley et al., 2021). To internally validate the SVS, Tate's (2012) findings were integrated into the SVS development to ensure internal robustness and stability, as described in Section 4.3.

4.4.1 Background on Lumberton Longitudinal Field Study

Lumberton is an inland city holding the county seat in predominantly rural Robeson County, North Carolina. Lumberton was one of the communities most impacted by Hurricanes Matthew (2016) and Florence (2018) due to the historic flooding of the Lumber River. The impacts of Hurricanes Matthew and Florence were exacerbated in the areas that were deprived in terms of health, wealth, and infrastructure. The community has significant racial diversity of black/African-American, Native American, and white populations, with a median annual income well below the national average, and a poverty rate nearly 2.5 times as high as the national poverty rate (see Table 8 for Lumberton demographics). To illustrate the community's socio-demographic makeup prior to the Hurricane Matthew flooding in comparison to the national averages, the U.S. Census 2016 ACS 5-year estimates were used, as presented in Table 8.

Table 8. Comparison of demographics between Lumberton and U.S. based on 2016 ACS 5-year census data

Demographics		**Lumberton**	**United States**
Population (count)		21,646	318,558,162
Race	White (%)	38.4	73.4
	Black/African American (%)	37.5	12.6
	Native American/ American Indian (%)	12.8	0.8
	Two or more races (%)	8.8	10.1
	Other (%)	2.5	3.1
Ethnicity	Not Hispanic or Latino (%)	90.6	82.7
	Hispanic or Latino (%)	9.4	17.3
Tenure	Owner occupied (%)	63.6	45.5
	Renter occupied (%)	36.4	54.5
Education	Less than high school (%)	23.0	13.0
	High school (%)	30.9	27.5
	Some college (%)	20.1	21.0
	Associate's (%)	8.4	8.2
	Bachelor's (%)	11.1	18.8
	Master's or higher (%)	6.5	11.5
Income	Median annual (USD)	31,126	55,322
	Below poverty (%)	15.1	35.1
	Above poverty (%)	84.8	64.9
Age	Under 18 years (%)	26.2	23.1
	18 to 64 years (%)	59.6	62.4
	64 years and over (%)	14.2	14.5
Disability	With at least one type of disability	15.1	12.5
	No disability	84.9	87.5

In October 2016, Lumberton was catastrophically flooded due to an intensive period of seasonal rain followed by rains by Hurricane Matthew. Many areas of Lumberton were inundated for several days, which resulted in disruption in businesses, power, communication, water, and transportation networks as well as significant building damage and lasting social impacts (van de Lindt et al., 2020).

In November 2016, a team of researchers from the Center of Excellence for Risk-Based Community Resilience Planning, alongside researchers at the National Institute of Standards and Technology’s Community Resilience Group, launched a longitudinal study on the impacts and recovery of Lumberton. At the time of this writing, five waves of systematic data collection have been completed in Lumberton, each with its own goals and objectives, and the study continues. The first field study, denoted as Wave 1, was performed in November 2016, and collected household and housing data on initial damage and dislocation. The household and housing data were collected through door-to-door surveys across a random sample of 568 housing units (van de Lindt et al., 2018). A probability proportion-to-size random sampling procedure selected census blocks located in high probability flooding areas over those in low probability flooding areas at a 3-to-1 weight. Eight housing units were then randomly selected from each census block, along with two alternate housing units per block in case a unit needed replacing; ultimately, 568 housing units were visited to implement the survey.

The second field study, denoted as Wave 2 and performed in January 2018, conducted systematic surveys of the same housing units as in Wave 1 with the overall intention to document recovery progress (E. J. Sutley et al., 2021). This paper uses post-disaster outcome data collected from household surveys during Wave 2. The data collection has continued, including a systematic survey immediately after Hurricane Florence in September 2018, a recovery follow-up in April 2019 (Helgeson et al., 2021), a virtual data collection during the COVID-19 pandemic in Spring 2021 (Watson et al., forthcoming), and recovery follow-up in June 2022.

4.4.2 Measurement of Social Vulnerability Score

The SVS values were calculated for each census block group within the city of Lumberton using 2016 ACS 5-year census data to correspond to the timing of Hurricane Matthew. Corresponding social vulnerability zones were then assigned, as shown in Figure 25(a). No block group was assigned a low vulnerability level. There are likely individual households who fall into the lowest vulnerability level; however, at the block group level, these households did not represent a majority in a given neighborhood and thus this outcome is consistent with field study findings.

As shown Figure 25(b) the inundated area caused by the 2016 Lumber River flooding primarily overlaps with block groups with high social vulnerability, as is expected due to social vulnerability theory (Fothergill & Peek, 2004).

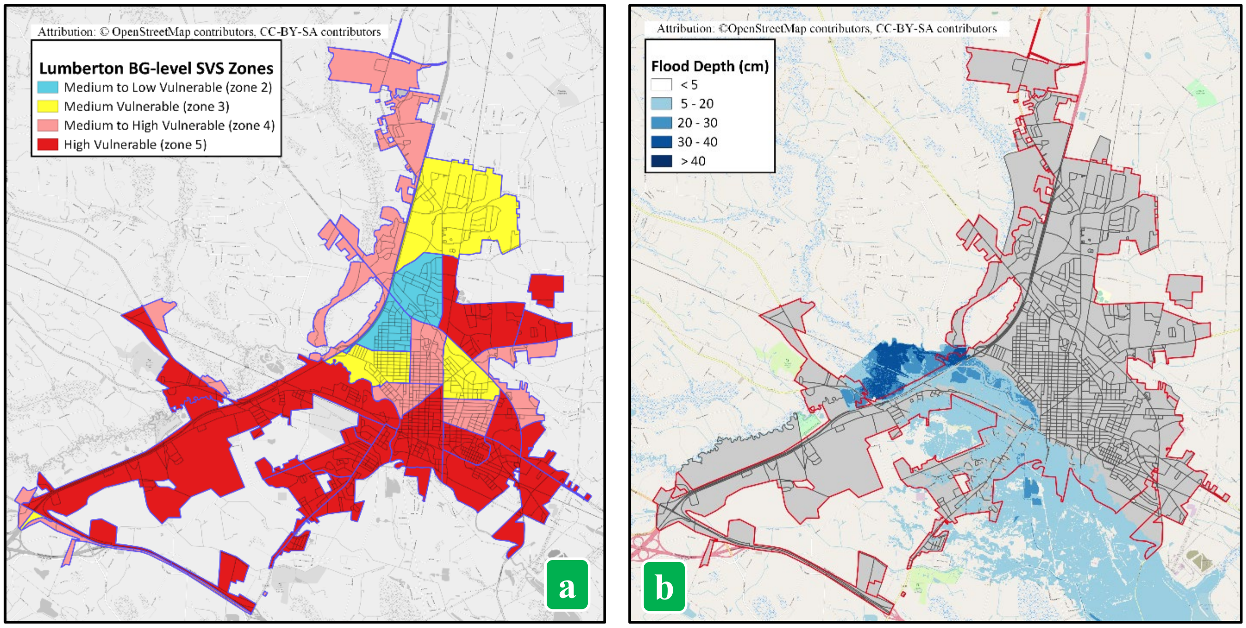

Figure 25. a) Mapped SVS zones at the block group level; b) flood inundation map after 2016 Hurricane Matthew in Lumberton

To utilize the Lumberton survey results for validation, a household-level estimate of social vulnerability is required. Thus, every household within the study area was randomly assigned a value based on their corresponding SVS zone and the ranges described in Table 9. To address the consequences of spatial clustering of sociodemographic characteristics in real-world communities, each zone is assumed to have a small percentage of households with higher or lower social vulnerability. For example, in zone 2, the likelihood of households with values ranging between (0.2 to 0.4), (0 to 0.2), and (0.4 to 1.0) are 85%, 5%, and 10%, respectively. These ranges were established based on the authors' judgment and can be revised based on a given testbed developer's judgment as needed. In Table 9, the footnote describes the defined social vulnerability levels for households based on quantitative values.

Table 9. Household Social Vulnerability Values based on SVS Zone

SVS Zone	Range 1*	Likelihood of Range 1	Range 2	Likelihood of Range 2	Range 3	Likelihood of Range 3
zone 1	0.0 - 0.2	95%	0.2 - 1.0	5%	-	-
zone 2	0.2 - 0.4	85%	0.0 - 0.2	5%	0.4 - 1.0	10%
zone 3	0.4 - 0.6	80%	0.0 - 0.4	10%	0.6 - 1.0	10%
zone 4	0.6 - 0.8	85%	0.0 - 0.6	10%	0.8 - 1.0	5%
zone 5	0.8 - 1.0	95%	0.0 - 0.8	5%	-	-

**value < 0.2 → low;*
0.2 ≤ value< 0.4 → medium to low;
0.4 ≤ value <0.6 → medium;
0.6 ≤ value <0.8 → medium to high;
0.8≤ value → high;

Figure 26 displays the social vulnerability level assigned to the households occupying the 568 housing units in the study area. As can be seen, some households have been assigned a low social vulnerability level despite the block groups not being assigned zone 1.

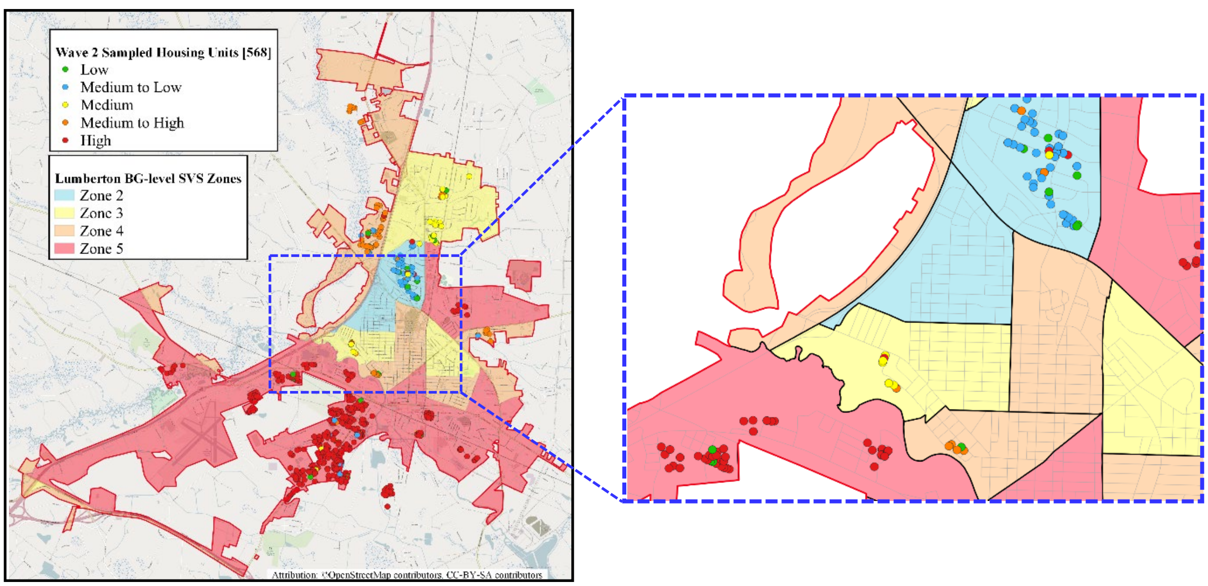

Figure 26. Household social vulnerability levels for sampled housing units in corresponding block group-level SVS zones

4.4.3 Household Dislocation

In Wave 2, 166 (of 568) households reported information on dislocation and confirmed they were living in their current home at the time of Hurricane Matthew. Approximately 28% of these respondents indicated they did not dislocate, and 60% reported that their household dislocated for at least one day. The households' self-reported dislocation time due to Hurricane Matthew was used to validate the SVS. Figure 27(a) illustrates household dislocation time versus SVS-based social vulnerability level for the 166 households that reported their dislocation experience. The average dislocation time for the households in each social vulnerability category is also shown in Figure 27(a). In total, the average dislocation time increases as social vulnerability increases. For instance, the average dislocation time for households with low, medium, and high social vulnerability is 2, 15, and 102 days, respectively.

Figure 27(b) provides the percentage of dislocated households in each social vulnerability level who have been dislocated for more than one week, more than one month, and more than three months. A similar trend can be observed in Figure 27(b) as in Figure 27(a), where the direct correlation between households' average dislocation time and social vulnerability becomes more significant as the dislocation time increases. As can be seen in Figure 27(b), the percentage of high socially vulnerable households who were dislocated for more than one week (66%) is nearly three times more than that of medium to low vulnerable households (24%). For households who have dislocated for more than one month, the corresponding percentage consistently increases from 12% for medium to low to 15% for medium, 19% for medium to high, and 39% for high social vulnerability. In addition, only high and medium to high socially vulnerable households experienced dislocation for more than three months, at 26% and 10%, respectively. These findings are indicative of households who have different social and political capital, and thus different dislocation experiences across social vulnerability levels (Sutley & Hamideh, 2020). The findings also confirm the trend detected in Figure 27(a) that households with higher social vulnerability are more likely to dislocate for longer periods, thereby validating the reliability of the SVS-based estimates.

(a)

(b)

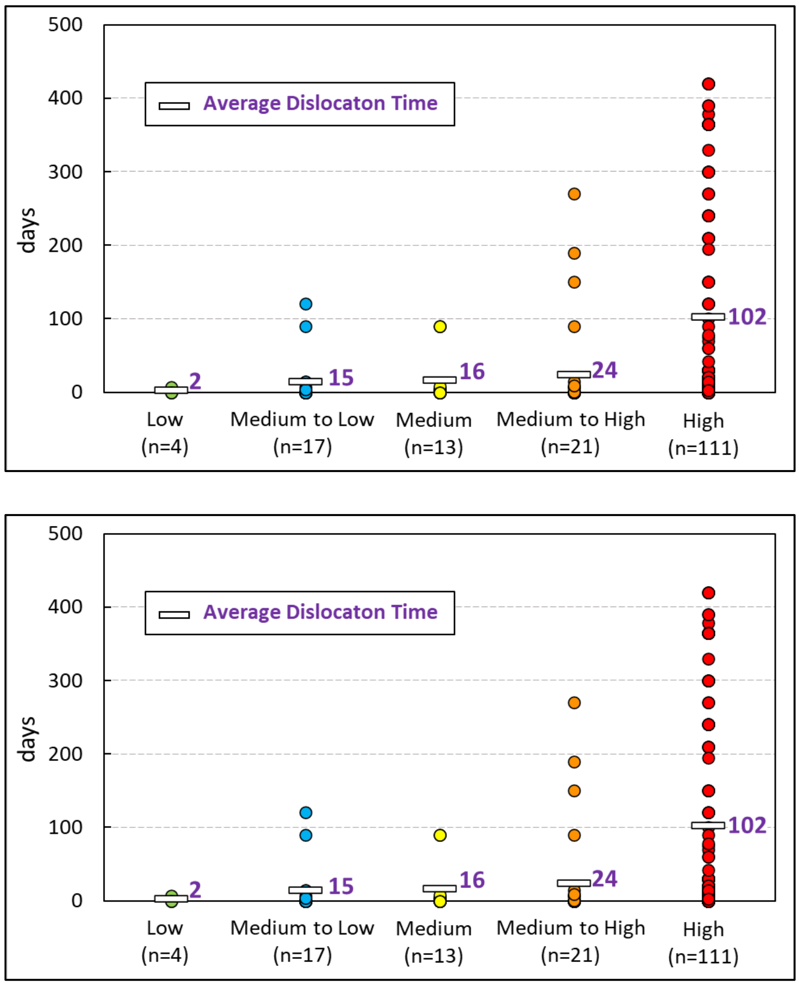

Figure 27. a) Household dislocation time versus social vulnerability level; b) Percentage of households dislocated for selected durations at each social vulnerability level

4.4.4 Physical Damage and Repair Time of Residential Dwellings

A total of 107 households reported some initial physical damage to their homes during Wave 2; of these, 61 respondents indicated that their homes had been completely repaired at the time of Wave 2. One of the 61 households reported the highest level of damage to their home; this record has been deemed an outlier and thus removed from the present analysis. We also excluded households assigned low, medium to low, and medium levels of social vulnerability as they totaled six records only. This finally resulted in a dataset including 54 records.

The least-square linear regression model was applied to resident-reported repair time, damage level, and social vulnerability data. The number of days to repair completion was the dependent variable while damage and social vulnerability levels were used as binary independent variables. A summary of the regression analysis results is presented in Table 10.

Table 10. Ordinary Least Square Regression Results

R-squared:	0.336		**F-statistic:**	8.449	
Adj. R-squared:	0.297		**Significance (F-statistics):**	0.000121	
Independent Variables †	Medium to High Social Vul.	High Social Vul.	Minor Damage	Moderate Damage	Severe Damage
Coefficient	86.31 *	90.97 **	-23.68	42.63 *	158.33 **

† *dependent variable: repair time (days)*
* *p-value < 0.05*
** *p-value < 0.001*

The top two rows of Table 10 report how well the overall regression model fits the dataset by measuring the R-squared and the significance of the F-statistic. Almost 34% of the variance in repair time is accounted for by the dependent variables included in the model (R^2=33.6%), which fairly explains the relationship between independent and dependent variables. Of note, there are several other rational and irrational factors that affect repair time, such as decision-making time, time to hire a contractor or repair crew, and time to obtain a permit, for example (Comerio, 2006; Comerio & Blecher, 2010). The p-value associated with the F-statistic (i.e. 0.000121) is far less than common significance levels (e.g., 0.01 and 0.05), meaning the independent variables in the model improve the fit of the model, and the regression model as a whole is statistically significant. The bottom row of Table 10 provides the regression coefficients and their statistical significance. On average it took 91 days longer to complete repairs for households with high social vulnerability.

Moderately and severely damaged homes took 43 and 158 days longer, respectively, to be completely repaired compared to homes with minor damage net of other factors. This demonstrates how social vulnerability alongside physical damage strongly affects repair time. These findings, overall, confirm the reliability of the social vulnerability index developed in this paper, at least for medium to highly vulnerable households. For further investigation of the SVS's capability to consistently interpret disaster outcomes under different circumstances, more empirical research and longitudinal post-disaster studies are required, considering a variety of places, hazard types, and temporal and spatial scales.

4.5 Comparison of SVS with Two Well-known Social Vulnerability Indices

The validity of the SVS was examined empirically using outcomes from a previous disaster in the previous section. This section discusses the performance of the SVS by comparing its estimated zones with those of two well-known and widely-adopted social vulnerability indices, namely the SoVI and SVI/CDC. For comparison sake, it is important to note that the SVI/CDC divides the estimated social vulnerability values into four quartiles, where the SVS and SoVI use the standard deviation and map vulnerability values into five zones. Thus, because of the different categorization criteria across indices, SVS and SoVI zones overlap with more than one vulnerability category defined by SVI/CDC, as illustrated in Figure 28. The SVI/CDC quartile-based categorizing criterion imposes identical numbers of census tracts to each social vulnerability level, which is mathematically sound but does not necessarily align with social vulnerability theory. With these caveats in mind, in this section, we discuss SVS, SoVI, and SVI/CDC estimates through a pairwise comparison between their estimated social vulnerability zones at the census tract level. The National Risk Index dataset, designed and built by FEMA, provides SoVI estimates at the census tract level for all 50 states in the United States (Zuzak et al., 2021). The census tract-level estimate SVI/CDC are also publicly available (Centers for Disease Control and Prevention et al., 2018). The results are shown in Figure 29 for each census tract within the State of Kansas, where the authors are located.

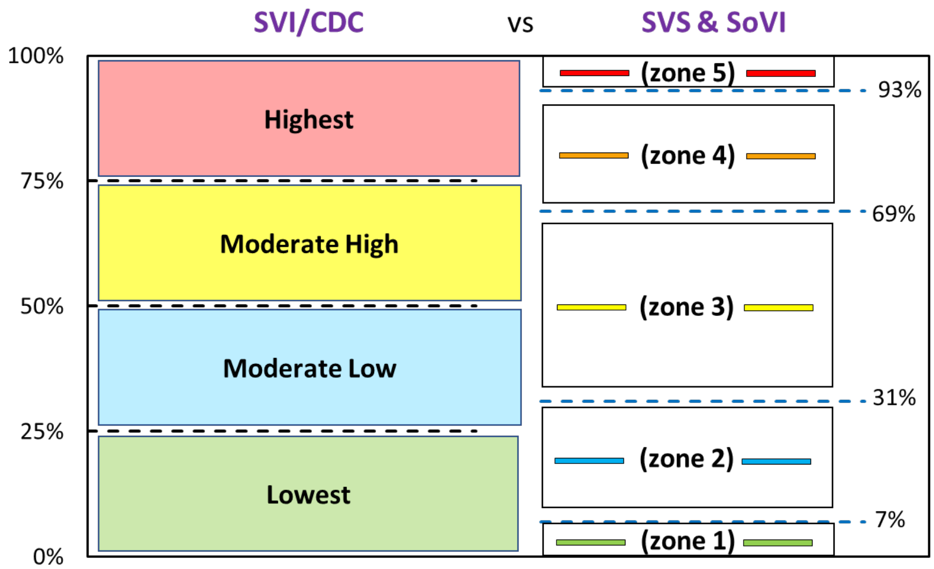

Figure 28. Social Vulnerability Categories

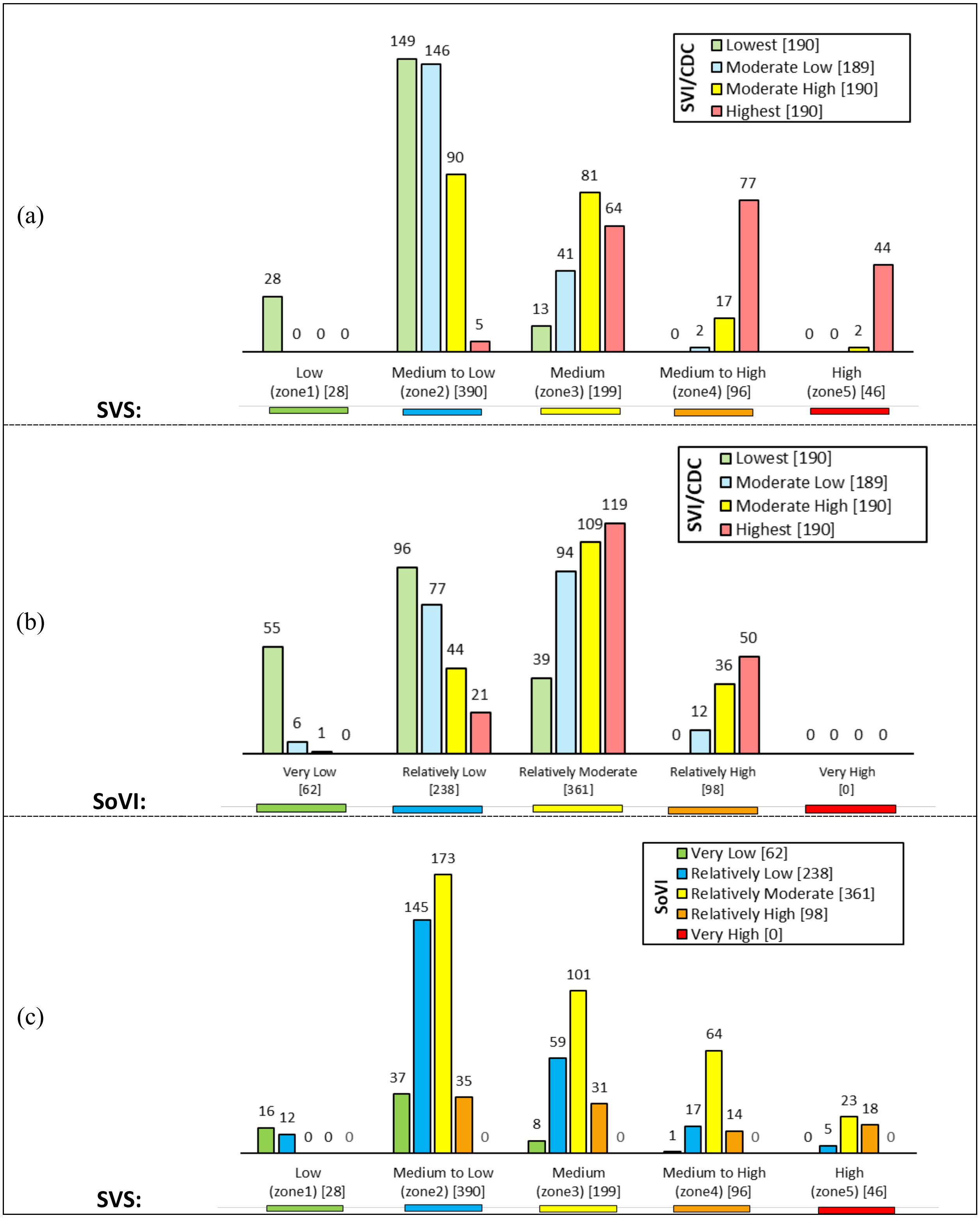

Figure 29. Paired comparison between (a) SVS to SVI/CDC, (b) CoVI to SVI/DCD, and (c) SVS to SoVI, in measuring social vulnerability in terms of the estimated number of census tracts in each social vulnerability zone in the State of Kansas

The SVS, SoVI, and SVI/CDC estimates are all fairly aligned in Figure 29 although they do not exactly match. Figure 29(a) shows the dispersion of social vulnerability estimated using SVI/CDC in each SVS zone in terms of the number of census tracts at different vulnerability levels. For zones 1, 4, and 5, the vulnerability levels estimated by SVI/CDC are aligned with the SVS zones. For zones 2 and 3, about 24% and 40% of the census tracts, respectively, mismatch due to the different categorization criteria across indices. Similar discrepancies can be seen for zones 2 and 3 in Figure 29(b), where the dispersion of social vulnerability levels estimated using SVI/CDC in each SoVI zone is demonstrated. As shown in Figure 29(a) and Figure 29(b), due to the quartile-based categorization criterion, SVI/CDC estimated exactly the same number of low, moderate to low, moderate to high, and high socially vulnerable census tracts for Kansas, whereas the SoVI and SVS capture different proportions across zones. Figure 29(c) displays the distribution of SoVI categories in terms of the number of census tracts in each SVS zone. None of the 46 census tracts in the SVS zone 5 are estimated to be in the SoVI very high category, which is inconsistent with the authors' lived experience in the study area and SVI/CDC estimates. For example, the five SoVI relatively low vulnerable census tracts in SVS Zone 5 in Figure 29(c) are estimated to be in high or medium to high vulnerability categories by SVI/CDC. This mismatch is aligned with Tate's findings (2013) that SoVI does not provide accurate estimates of social vulnerability in census tracts where social vulnerability is high.

4.6 Conclusions

The concept of measuring social vulnerability using a single numeric index is a bold simplifying assumption. However, social vulnerability indices are conducive tools to advance the state of knowledge in community-related studies, while waiting for emerging more robust approaches to measure social vulnerability. Public health officials, hazard mitigation planners, community resilience researchers, and testbed developers use such indices to identify differences in social vulnerability across a population to help understand where resources may be needed to better prepare for and respond to a natural hazard and bounce back from its impact. However, the literature review presented in this paper illuminated that experts and policy-makers should be cautious in the application of these indices in some circumstances particularly based on limitations in index construction (see Tate (2012) for more detail), and in the extreme simplification of capturing social vulnerability using factors conveniently found in census data.

While the proposed SVS is still subject to some of the same limitations in simplifying a measurement of social vulnerability, it offers important advantages to existing indices. The SVS (a) does not decrease in reliability as a function of geographic scale, so long as the data is reliable; (b) only requires calculation for the specific area of interest; (c) measures social vulnerability as a relative quantity to the national context; (d) does not yield different estimates of social vulnerability of the same place, using the same data, with changes in the geographic scope of the study area; and (e) uses fewer variables which reduces uncertainty in the influence of different factors on social vulnerability and reduces uncertainty transferred through the data itself in the final estimate. Thus the SVS presented here addresses the need for a social vulnerability index that more consistently explains disaster outcomes, can be used at various spatial scales, and requires minimal data inputs and computational efforts making it particularly suitable for use in virtual community resilience testbeds.

The SVS prediction was validated here using household-level disaster outcomes measured following the 2016 flooding in Lumberton, NC. Even still, more research is needed to understand how the SVS holds up to pre-disaster and other post-disaster outcomes beyond those evaluated here because of the dynamic nature of social vulnerability which can emerge differently depending on the context and situation. Finally, comparing the SVS and SoVI measurements with SVI/CDC demonstrated general agreement with some discrepancies based on limitations associated with each index. This paper does not dwell on the question of whether the SVS estimates compared to other widely used social vulnerability indices provides more accurate results. Instead, the paper seeks to open up the discussion on the need for the construction of a scalable social vulnerability index and proposes the SVS as a conceptually based, yet practically useful, social vulnerability index to serve the purpose of community resilience testbed development.

In addition to being scalable, the next generation of social vulnerability indices should account for the intersectionality of factors and explore variables outside of census data to truly understand what contributes to social vulnerability.

Chapter 5: [1] Conceptualizing and Measuring Accessibility to Essential Services for Community Resilience

Accessibility is an abstract phenomenon that can be influenced by the characteristics of both service users and service providers. For years, quick restoration of access to essential services has been referred to be of paramount importance in community resilience and recovery. Yet, there is no consensus on how access should be defined, measured, or employed. Distance-based metrics, although common, cannot fully proxy accessibility dimensions for community resilience purposes. Using the term product for any type of goods and services, this paper defines accessibility as the actual use of available products with a reasonable amount of effort and cost. In compliance with this definition, accessibility should be addressed from six different aspects, namely, *proximity*, *availability*, *adequacy*, *acceptability*, *affordability*, and *awareness*. We argue, among these six dimensions of accessibility, *availability*, *adequacy*, and *acceptability* are dependent on the functionality of the product provider. Utilizing concepts from organizational functionality, we propose quantitative, temporally-based metrics for accessibility. The metrics calculate the ratio of post-disaster access time to the intended product against its pre-disaster time and yield a unitless ratio between zero and one, with zero expressing a complete accessibility loss and one proxying no loss of accessibility. The metrics are illustrated using data collected following the 2016 flood in Lumberton, North Carolina after Hurricane Matthew. The metrics are also applied to demonstrate how accessibility to schools and education recovery alter inequitably across the

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[1] This chapter is based on manuscript of a journal paper with this dissertation's author as the first author:

Enderami, S. A., Sutley, E. J., & Helgeson, J. (n.d). Conceptualizing and Measuring Accessibility to Essential Services for Community Resilience. To be submitted to the Journal *Computers, Environment and Urban Systems* in February 2023.

Lumberton community. The paper concludes by discussing issues and barriers related to developing and validating accessibility metrics, and areas for future research.

5.1 Introduction

Conceptualizing and measuring community members' access to addressing their needs is a classic but still ongoing field of research that has been approached from multiple perspectives (e.g., urban planning, social justice, equity, and equality), in different contexts (e.g., education, public health, community resilience), and various scales (e.g., federal, state, and local) (Dempsey et al., 2011; Docekala et al., 2020; Dong, Esmalian, et al., 2020; Logan & Guikema, 2020; Logan et al., 2019; Loreti et al., 2022; Paschall et al., 2022; Penchansky & Thomas, 1981; Saurman, 2016; Talen, 2003; Talen & Anselin, 1998; Thomson et al., 2020; Vaughan et al., 2013; Y. Wang et al., 2021; Williams et al., 2020). These studies, altogether, have provided the foundation necessary for advancing the state of knowledge on quantifying and measuring access. Even still, in the context of community resilience, more research is needed to advance the measurement of access beyond simply physical access. There is no doubt that access to goods and services such as sustenance, education, healthcare, and recreation, in addition to shelter and typical critical infrastructure, is crucial for communities to function (Dempsey et al., 2011). Lack of access to such essential services disrupts quality of life and may lead to permanent relocation (Contreras et al., 2017). To improve resilience, communities need to ensure that organizations providing essential products will be functional within an acceptable period after a disaster, while also ensuring that people have access to (i.e., are actually using) the offered products (Enderami et al., 2021). Here, the term product captures both goods and services, either tangible or intangible, offered by the organizations to community members.

The concept of access has not been precisely defined and is somewhat ambiguous in community resilience literature. Access has most often been employed as the presence of physical access to a functional organization and characterized from the potential product perspective, without including the users' characteristics (Logan & Guikema, 2020). This perception of access results in a bias in the frequency of functionality-focused frameworks for community resilience assessment in scholarly works. Additionally, distance-based indicators have been predominantly used to quantify accessibility. Proximity, which considers both physical access and distance, is the most widely applied distance-based proxy for measuring access in community resilience literature (Saxon, 2020). Proximity operates as a simple proxy for quantifying the ease of use in a non-remote environment (Khan & Bhardwaj, 1994), but does not at all proxy accessibility in remote environments. Although proximity implicates the spatial distribution of access across the population, it does not capture whether the product is actually being used or the quality of that use. Physical access and organizational functionality are necessary components of access and represent the potential of use, but do not guarantee the actual use or real access (Khan & Bhardwaj, 1994) which is critically important for being able to evaluate and ensure equity. Real access, referred to herein as "accessibility", occurs when products offered by functional organizations are being used by community members.

In the context of community resilience, Logan and Guikema (2020) conducted a literature review on accessibility measurement methods across many disciplines and came up with six dimensions that have to be included for measuring accessibility to essential services in a community. These six dimensions are based on the five dimensions of access identified by Penchansky and Thomas (1981), including *proximity*, *availability*, *adequacy*, *acceptability*, and *affordability*, as well as *awareness* that was later appended to those five by Saurman (2016). In a community resilience assessment, all six dimensions are crucial to ensure accessibility, and together these dimensions capture both user characteristics and intended product features. In practice, including these dimensions in measuring accessibility also requires a minimum suitable level for each dimension (Logan & Guikema, 2020). This minimum suitable level should be determined based on the community's social, cultural, and financial characteristics and considering the intended product features. For example, vehicle ownership can affect the way the proximity threshold will be defined (Constas et al., 2014).

Beyond proximity, the essence and scope of the other five dimensions depend on the context in which accessibility is applied. Taking Early Care and Education (ECE) as an example, ECE Access Guidebook (Friese et al., 2017) states that improving the quality of ECE, in addition to the availability of affordable ECE options near children's residences or parents' workplaces, requires considering two other dimensions ECE accessibility: (1) sufficient quality to meet the children's age-appropriate needs, and (2) enough capacity to satisfy parents' needs and preferences (e.g., providing care at non-traditional hours). Dimensions of accessibility may also change over time, before, during and after disasters, and as urbanization and technology advance. For example, in the case of ECE, researchers have recently added equity as another dimension for measuring accessibility to address disparities in the availability, affordability, and quality of ECE (Paschall et al., 2022; Thomson et al., 2020).

Proximity, acceptability, adequacy, and awareness dimensions ensure that only a reasonable level of effort is needed for using the available product while affordability certifies that the product is available for use at a reasonable cost. Thus, we define accessibility to essential services as *use of available products by community members with reasonable effort and cost to meet an essential need*. The proposed definition bridges the gap between the community's social, cultural, and economic characteristics with conventional functionality-focused community resilience frameworks. The goal of this paper is to provide a means to operate aligned with our proposed definition of accessibility that captures the proximity, availability, acceptability, and adequacy dimensions of accessibility for the purpose of advancing community disaster resilience. As such, the remainder of this paper first elaborates on the concept of organizational functionality reconciling it with the dimensions of accessibility. Next, two quantitative metrics are developed for measuring temporally-varying, multi-dimensional accessibility. The metrics are illustrated considering accessibility to pharmacy and education services using the results of a longitudinal field study following the 2016 catastrophic flooding in the city of Lumberton, North Carolina after Hurricane Matthew. The paper concludes with a discussion of our findings during the development of accessibility metrics, potential remedies for addressing the challenges we faced, and areas for future research on incorporating accessibility in community resilience frameworks.

5.2 Organizational Functionality, Accessibility, and Community Resilience

5.2.1 Organizational Functionality

Here, an organization is any entity in the community intended to provide products to the community to meet the needs of community members (Enderami et al., 2021). Social institutions (e.g., schools and healthcare facilities) and businesses are perhaps the most common examples of organizations within a community, although organization are not limited to these two categories. In this paper, we use the term organization for referring to social institutions and businesses within the community to set the focus on their users and products rather than the social and commercial aspects.

Enderami et al. (2021) defined organizational functionality as “the quality of the performance of an organization and its ability to be used for its intended purposes”. Most, if not all, organizations provide multiple products to their customers. To characterize organizational functionality, and its restoration after a disaster, Enderami et al. (2021) distinguished primary products from secondary products. Primary products are the main objective and intended purpose of an organization; any other offered product(s) are denoted as secondary products. For example, fuel may be the primary product of a gas station whereas snacks and a carwash may serve as secondary products of a gas station. A gas station without gas is not functional while a gas station, whose carwash is out of service only, is still serving its intended purpose of providing fuel. Thus, the availability of primary products is crucial, although not sufficient, for the functionality of the organization. For an organization to be considered functional, it must also operate at an acceptable level and provide adequate primary products even if some or all of the secondary products are still unavailable.

Using a Fault Tree model, Enderami et al. (2021) identified essential components that contribute to the availability, acceptability, and adequacy of primary products in an organization. Physical space components (structural or non-structural), physical access, utilities, staff, and supply chain are generally crucial components for organizational functionality in non-remote environments. However, the COVID-19 pandemic has shown that many organizations can operate remotely. In a remote environment, the essential components evolve, and organizational functionality may no longer depend on the original physical space and physical access, yet accessibility is still very important. These concepts were used to define five post-disaster organizational functionality states, namely, Out of Service, Intrinsically Operable, Fully Operable, MALF, and Fully Functional, where a comprehensive description of post-disaster functionality states can be found in Enderami et al. (2021). By introducing the minimum acceptable level of functionality and maximum tolerable period of disruption time, Enderami et al. (2021) developed the required equations for estimating the probability of an organization becoming functional before a particular time after a disaster. The expected capacity of an organization at a given time after the event can be calculated as

$$C^{a}(t) = Q(t) \times C^{b} \times \left[\frac{L_3 - L_2}{100 - L_2} \right] \tag{1}$$

where $C^a(t)$ is the expected capacity of the intended organization at time t after the disaster, and C^b is the pre-event capacity of the organization. The other parameters in equation (1), including $Q(t)$, L_2, and L_3 denote the probability of the organization becoming functional before the intended time, functionality level corresponding to a Fully Operable, and a MALF organization, respectively. The details for calculating $Q(t)$, $L2$, and $L3$ can be found in Enderami et al. (2021).

5.2.2 Reconciling Accessibility and Organizational Functionality for Community Resilience

Three dimensions of accessibility, including *availability*, *adequacy*, and *acceptability*, directly relate to an organization's functionality; a fourth, proximity, is indirectly related as follows. As the concept of organizational functionality and post-disaster functionality states were defined, a functional organization ensures the primary products offered by that organization are available at an adequate and acceptable level. So, the post-disaster functionality of an organization implies that the adequacy and acceptability dimensions of accessibility have already been satisfied from the available product perspective. Finally, availability and physical access go hand-in-hand, where physical access is needed to measure *proximity*.

Therefore, we propose to employ equation (1) which was originally developed for estimating the probability of post-disaster organizational functionality to evaluate the availability, adequacy, and acceptability dimensions of accessibility. Given that organizational functionality varies across the disaster timeline, changes in these three dimensions, and consequently, a community's accessibility to essential services, can be calculated before and any time after a disaster. As discussed earlier, to move towards resilience, community members must have access to essential services within the time frame specified in the community's recovery plan. This opens up the ability to use accessibility metrics as a means for assessing the resilience of that community.

5.3 Quantitative Metrics to Measure Accessibility to Essential Services

This section presents two novel metrics for evaluating accessibility to tangible and intangible products as a function of time. The metrics operate at the household level and are intended to be measured within and across a given community. The metrics measure the ratio of access time to the product at a specific time post-disaster against its pre-disaster time. This means we presume the pre-disaster accessibility level of every household to the desired product as the standard acceptable level of accessibility, and then measure post-disaster accessibility against this standard. To develop the metrics, we normalized the pre-disaster accessibility for any variations before the disruption and ignored any post-disaster service equilibrium shift (Davis, 2014), as both are outside of the scope of this paper. Thus, the developed metrics yield a unitless ratio between zero and one, with zero representing a complete accessibility loss and one indicating no loss of accessibility. The developed metrics are aligned with the definition of accessibility provided in the literature and summarize multiple dimensions of access, as far as data limitation allows.

5.3.1 Accessibility to Tangible Products

The first metric introduced calculates accessibility to tangible products, which include organizations such as gas stations which provide fuel, and grocery stores which provide groceries. The access time to tangible products provided by an organization is comprised of the *travel time* to where the organization is located, and the time required to receive the desired product. This latter time is referred to herein as *response time*. For each community member, accessibility to tangible products at the time t after the disaster can be estimated as

$$\Delta A_T(t)=\frac{AT^{max}-AT_T^a(t)}{AT^{max}-AT_T^b}\geq 0 \tag{2}$$

where AT^{max} is the maximum acceptable threshold for access time to receive the intended product, $AT_T^a(t)$ represents the access time to the tangible product at time *t* after the disaster, and AT_T^b points out the access time to that tangible product during the normal period before the disaster. The proposed metric captures how accessibility to the intended tangible product changes across the disaster timeline within a community.

The value of AT^{max} may vary based on the characteristics of a community. For instance, the usual travel time to a grocery store in a rural community may be longer than its maximum acceptable threshold in an urban area. Assuming that the maximum acceptable threshold for travel times is equal to the average of travel time to all organizations providing the intended product in the study area before the disaster, AT^{max} can be estimated using

$$AT^{\max}=T_{tr}^{ave}+RT^b \tag{3}$$

where T_{tr}^{ave} represents the average drive time to all organizations providing the intended product in the study area before the disaster and RT^b is the usual response time in the target community before the disaster.

To estimate the access time to the intended product during normal times and in the aftermath of the disaster, the travel time to the nearest MALF organization providing that product is used, thus, AT_T^b and $AT_T^a(t)$ can be calculated as

$$AT_T^b=T_{tr}^b+RT^b \tag{4}$$

$$AT_T^a(t)=T_{tr}^a(t)+RT^a(t) \tag{5}$$

where T_{tr}^b and $T_{tr}^a(t)$ represent the travel time to the nearest MALF organization providing the desired product before the disaster and at time *t* after the disaster, respectively, RT^b indicates the usual pre-disaster response time in the target community, and $RT^a(t)$ is the response time at the nearest MALF organization at time t after the disaster. A conceptual illustration of the parameters that are used to develop the metric for evaluating accessibility to tangible products within a community is shown in Figure 30.

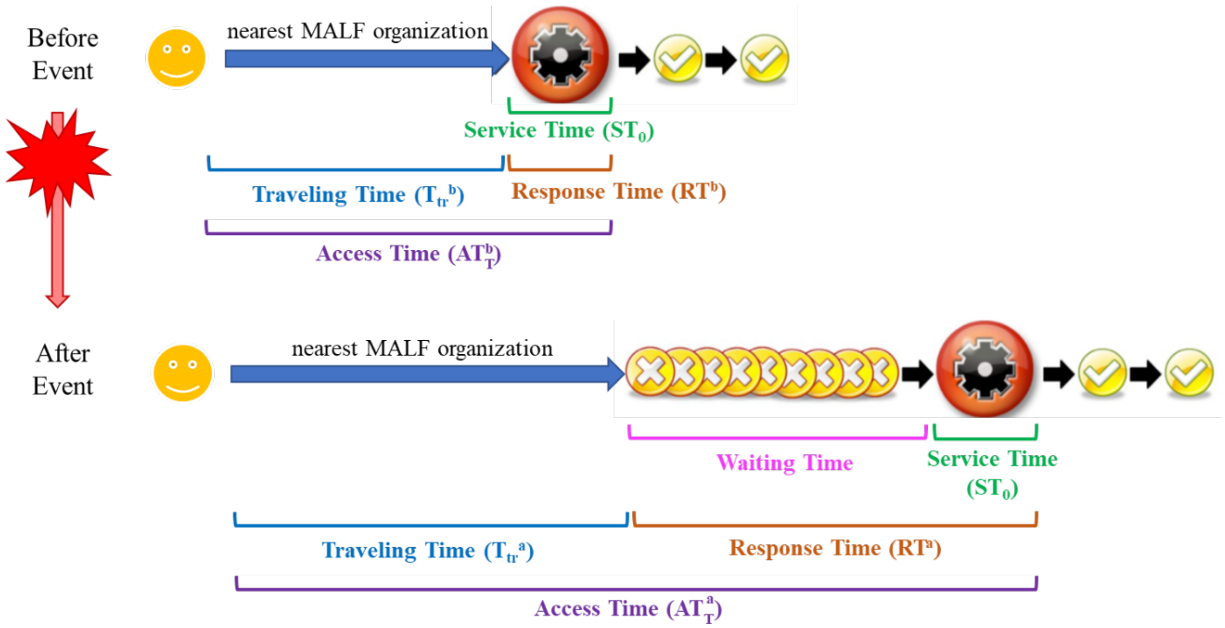


Figure 30. Conceptual illustration of quantifying accessibility to tangible products

Both travel time and response time may vary across the disaster timeline and be different from their corresponding pre-disaster values. As the disaster occurs, the travel time to the nearest MALF organization providing the intended product is likely to increase due to disaster-induced disruption in the community road network, among other disaster-prompted supply and demand issues. Inside the MALF organization, the response time, $RT^{a}(t)$, might also be prolonged due to a loss of functionality (e.g., staff shortage) and/or an increase in the product demand (e.g., customers). As shown in Figure 30, after a disaster, it becomes very likely that newly arriving customers will have to wait in line. In light of the Queuing Theory (Allen, 1978), the response time is associated with the usual time needed for the desired product to be provided by the intended organization at the normal time, termed service time (ST_0) in Figure 30. Thus, using the fundamentals of Queuing Theory, we estimated the $RT^{a}(t)$ as

$$RT^{a}\left(t\right)=ST_{0}\left[\exp(2.5\times\frac{C^{b}-C^{a}(t)}{C^{b}})\times\left(2.55\times\frac{D^{a}(t)}{D^{b}}-1.55\right)\right] \tag{6}$$

where ST_0 represents the service time, $C^a(t)$ and $D^a(t)$ are, respectively, the expected capacity of the intended organization and product demand at time t after the disaster, C^b is the pre-disaster capacity, and D^b represents the pre-disaster product demand for that organization.

The amount of $C^a(t)$ depends on the intended organization's functionality level and can be estimated using Equation (1). Then, by combining Equations (1) and (6) and plugging ST_0 into the developed formulas, Equations (3), (4), and (6) can be rewritten as

$$AT^{\max}=T_{tr}^{ave}+ST_{0} \tag{7}$$

$$AT_{T}^{b}=T_{tr}^{b}+ST_{0} \tag{8}$$

$$AT_{T}^{a}(t)=T_{tr}^{a}(t)+ST_{0}\left[\exp(2.5\times(1-\left\{Q(t)\times\frac{L_{3}-L_{2}}{100-L_{2}}\right\}))\times\left(2.55\times\frac{D^{a}(t)}{D^{b}}-1.55\right)\right] \tag{9}$$

All parameters are defined earlier. The metric developed in this section combines 4 (out of 6) dimensions of accessibility including proximity, acceptability, adequacy, and availability. Including the travel time to the MALF organization in estimating the access time before and after the disaster indicates that proximity and availability dimensions are considered in assessing accessibility. Post-disaster response time, on the other hand, takes the probable adverse effects of loss of organizational functionality level (product perspective) and increases in the product demand (customer perspective) on adequacy and acceptability dimension into account. The metric can be applied to evaluate the accessibility to any tangible product at any time after the disaster.

5.3.2 Accessibility to Intangible Products

The second metric introduced calculates accessibility to intangible products, which include organizations such as hospitals which provide inpatient services, and schools which provide education services. The access time to intangible products provided by an organization can be calculated by subtracting the travel time to where the organization is located from the time devoted exclusively to the recipient of the intangible product by that organization. The latter is termed *individual attention time* (*IAT*). For example, doctor-to-patient and bed-to-patient ratios are often major factors affecting *IAT* for inpatient care in healthcare facilities, whereas teacher-to-student and desk-to-student ratios are the primary factors governing *IAT* for education services in schools. For each community member, accessibility to intangible products at the time *t* after the disaster can be estimated as

$$\Delta A_I(t)=\frac{AT_I^a(t)-AT^{min}}{AT_I^b-AT^{min}}\geq 0 \tag{10}$$

where $AT_I^a(t)$ is the access time to the intangible product at time *t* after the disaster, AT_I^b points out the access time to that intangible product during the normal period before the disaster, and AT^{min} represents the minimum acceptable threshold for access time to receive the intended product.

The values of AT_I^b and $AT_I^a(t)$ are calculated as

$$AT_I^b=IAT^b-T_{tr}^b \tag{11}$$

$$AT_I^a(t)=IAT^a(t)-T_{tr}^a(t) \tag{12}$$

where T_{tr}^b and $T_{tr}^a(t)$ represent the travel time to the nearest MALF organization providing the desired product before the disaster and at time *t* after the disaster, respectively, IAT^b is pre-disaster individual attention time estimated for the organization providing the intended intangible product before the disaster, and $IAT^a(t)$ points out post-disaster individual attention time estimated for the organization providing the intended intangible product at the time *t* after the disaster.

Due to the same rationale outlined in developing the accessibility metric for tangible products, travel time to the nearest MALF organization providing the intended intangible product is likely to increase as a result of the disaster. On other hand, the post-disaster individual attention time of that MALF organization, $IAT^a(t)$, might be shortened due to similar reasons that prolong response time for tangible products. Thus, the individual attention time needs to be updated across the disaster timeline to address the effects of a probable increase in product demand and a likely reduction in the organization's functionality.

To estimate the minimum acceptable threshold for access time to the intended intangible product, AT^{min}, the average of travel time to all organizations providing that product in the study area before the disaster is subtracted from the minimum acceptable individual attention time as follows

$$AT^{min} = IAT^{min} - T_{tr}^{ave} \tag{13}$$

where T_{tr}^{ave} is the average of pre-disaster travel time to all organizations providing the intended intangible product in the study area before the disaster, and IAT^{min} represents the minimum acceptable individual attention.

The metric developed in this section enables the evaluation of the accessibility to intangible products within the community across the disaster timeline. The metric also combines 4 (out of 6) dimensions of accessibility. It includes the travel time to the MALF organization in estimating the access time, reflecting proximity and availability dimensions. Furthermore, the metric integrates adequacy and acceptability dimensions through post-disaster ITA that considers the adverse effects of loss of organizational functionality level and increases in the product demand.

5.4 Illustrative Example using the Lumberton, North Carolina Testbed

To highlight the application of the metrics developed in section 5.3, the metrics were used to evaluate the accessibility to the products offered by pharmacies and schools within the Lumberton Testbed following a catastrophic flooding scenario. Pharmacies and schools were selected here given that they exemplify two critically important types of products offered in a community. As a business, pharmacies provide tangible goods, including prescription and nonprescription medicines, and often groceries and basic household items. Schools, on the other hand, are a social institution satisfying intangible human and social needs through educational services and social development for children, and employment for staff.

Lumberton is a small inland city in Robeson County, North Carolina, hugely impacted by flooding of the Lumber River following Hurricanes Matthew (2016) and Florence (2018). In October 2016, Lumberton was catastrophically flooded due to an intensive period of seasonal rain followed by rains by Hurricane Matthew. Many areas of Lumberton were inundated for several days, which resulted in disruption in businesses, power, communication, water, and transportation networks as well as significant building damage and lasting social impacts (van de Lindt et al., 2020). The Lumberton Testbed is a virtual community resilience testbed that has been developed based on the results of a longitudinal field study on the impacts and recovery process of the community (Helgeson et al., 2021; E. J. Sutley et al., 2021; van de Lindt et al., 2018; van de Lindt et al., 2020). A community resilience testbed is a virtual "environment with enough supporting architecture and metadata to be representative of one or more systems such that the testbed can be used to (a) design experiments, (b) examine model or system integration, and (c) test theories" (S. Amin Enderami, Ram K. Mazumder, et al., 2022, p. 031220013). The field study also captured data on school and business functionality at different points in time, including operational status and customer loss, which provides information needed for calculating the accessibility metrics. Thus, here, we use the Lumberton Testbed to demonstrate the proposed accessibility metrics.

5.4.1 Lumberton Post-disaster Field Studies

In November 2016, a team of researchers from the Center of Excellence for Risk-Based Community Resilience Planning, alongside researchers at the National Institute of Standards and Technology's Community Resilience Group, launched a longitudinal study on the impacts and recovery of Lumberton. Five waves of systematic data collection, each with its own goals and objectives, have been completed in Lumberton by the time of drafting this manuscript, and the study continues. The first field study, denoted as Wave 1, was performed in November 2016 and documented the initial physical and socio-economic impacts of the flooding on the community, including for housing, households, schools, and a few public sectors. The information on the response of the public sectors, schools, and businesses to the flood event was collected through a series of 22 qualitative interviews with corresponding stakeholders including the Robson County school district's representatives, infrastructure managers, and Local, State, and Federal officials (van de Lindt et al., 2018).

The second field study, denoted as Wave 2 and performed in January 2018, included systematic surveys of the same housing units and schools as in Wave 1, a new sample of businesses, as well as interviews with select public officials, with the overall intention to document recovery progress (E. J. Sutley et al., 2021). To sample the businesses for the survey, a total of 350 businesses out of the 2,017 records of for-profit organizations with a valid Lumberton address existing in the ReferenceUSA (Infogroup, 2016) database were drawn. This sample size of 350 includes all businesses located inside a 100-meter buffer around the Hurricane Matthew inundated area (i.e., 218 records) and 132 additional randomly selected businesses that fell out of the inundated area but still were within the FEMA 100-year floodplain for Lumberton (E. J. Sutley et al., 2021).

The third round of field study, denoted as Wave 3 began immediately after Hurricane Florence in September 2018, followed by a complementary assessment in April 2019 to document the recovery from Hurricanes Matthew and Florence. In Wave 3 data collection, in addition to the initial damage investigation, two systematic surveys on the impact and recovery process of the most heavily-affected housing and businesses as well as interviews and meetings with the same schools and public officials as in Wave 2, were conducted (Helgeson et al., 2021). The data collection has continued, including a virtual data collection during the COVID-19 pandemic in Spring 2021 (Watson et al., forthcoming), and an in-person recovery follow-up in June 2022.

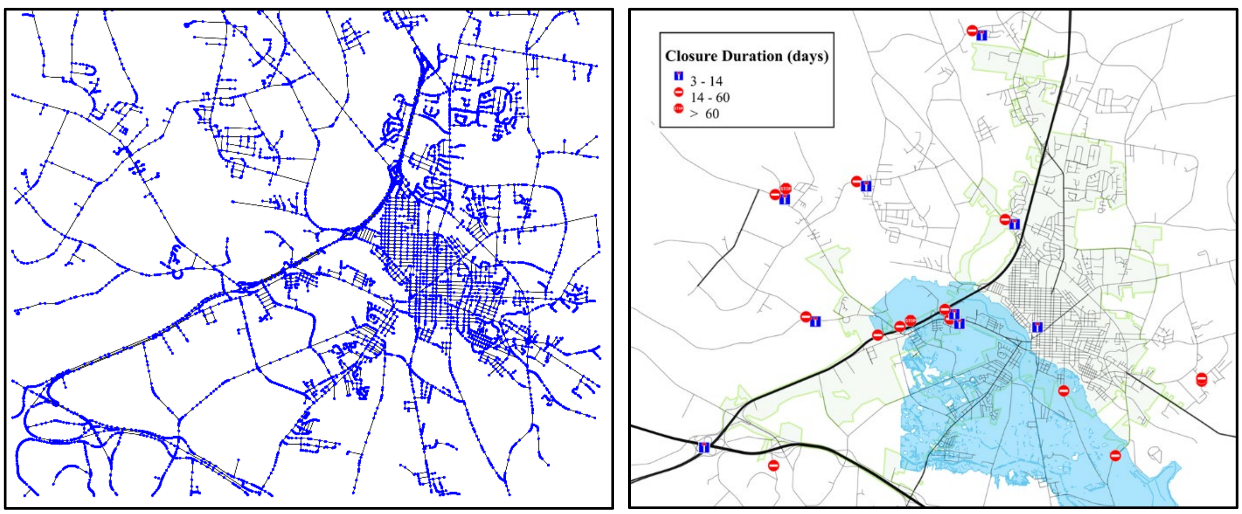
This paper uses findings on flood impacts and recovery of businesses during Wave 2 and 3, as well as reported findings from interviews with school stakeholders during Waves 1 and 2. The Wave 2 survey asked businesses (1) if their organization is dependent on its physical location, (2) whether they experienced any access problem such as street or sidewalk closure after Hurricane Matthew, (3) how much their property was physically damaged due to Hurricane Matthew, (4) whether their business experienced any utility loss, and, if yes, how long it took to fully recover, (5) if they completely ceased operating at their location immediately after the flood, (6) how long it took for them to resume normal operation, and (7) how much they estimate their percentage capacity, at the time of the survey compared to the pre-flood time (E. J. Sutley et al., 2021). During the Wave 3 survey, businesses responded to similar questions about the kind and severity of the physical damage caused by Hurricane Matthew, as well as, how much they estimate their percentage capacity, immediately before hurricane Florence compared to the pre-flood time (Helgeson et al., 2021). The responses to these questions were used to estimate the post-disaster capacity of pharmacies in Lumberton. In addition, we applied the summary of findings from qualitative interviews, as presented in the Wave 1 and 2 reports, to estimate the post-disaster functionality of schools within Lumberton.

5.4.2 Lumberton Testbed Preparation

In parallel with the field studies, an expanded research team from the Center of Excellence for Risk-Based Community Resilience Planning, alongside a team of experts from the National

Center for Supercomputing Applications (NCSA) have been developing the Lumberton virtual testbed using the field study data and other secondary, and incorporating the testbed into IN-CORE (Gardoni et al., 2018). More information about the testbed as well as details of the algorithms, models, and datasets that have been already appended to it can be found here. (Nofal & van de Lindt, 2020a, 2020b, 2020c; Omar M. Nofal & John W. van de Lindt, 2021; Nofal et al., 2020; Rosenheim, 2020; Rosenheim et al., 2021). This paper applies the testbed's building inventory, detailed household and housing unit characteristics, and student datasets developed by Rosenheim (2020) to estimate the accessibility metric for pharmacy and education services.

Furthermore, to calculate the travel time between different locations within the testbed, a mathematical simulation of the testbed road network is needed. This component of the Lumberton Testbed has not yet been incorporated into IN-CORE. Thus, here, we developed the Lumberton roads network model including geospatial data about the routes' footprint, speed limit, and traffic direction. These data were procured from OpenSteetMaps (OSM, 2015) using the OSMnx Python package (Boeing, 2017) and the North Carolina Department of Transportation (NCDOT) open data. OSMnx applies the concept of Graph Theory (Trudeau, 1993) to the geospatial data downloaded from OSM and yields a mathematical simulation of real-world street networks for the desired region, as shown in Figure 31(a). Graphs are collections of nodes connected by edges. The nodes represent the locations where route footprints intersect, while the edges depict the routes that connect these intersections. Although the study area in this research is restricted to the geographical scope of the city of Lumberton, the testbed's road network goes beyond the city's geographical boundaries and spans some other regions of Robeson County in the vicinity of the study area. This larger extent of the road network is necessary as commuters' shortest driving routes do not always lie within the city limits only. The free-flow speed was also estimated for streets located in urban areas using Google Maps data and added to the road network dataset. Free-flow speed is the term used to describe the average speed that a motorist would travel if there were no congestion or other adverse conditions (such as bad weather). As documented in the Wave 1 report, the flood washed out some access roads in the study area and damaged transport infrastructure, resulting in long-term road closures. Using NCDOT's Traffic Incident Management System records, we determined the location and duration of such road closures within the testbed area. Figure 31(b) shows the spatio-temporal distribution of the long-term road closure incidents in Lumberton's roads after Hurricane Matthew.



(a) (b)

Figure 31. Lumberton roads network a) mathematical model; b) long-term closures following 2016 Hurricane Matthew

In addition to physical damage to transportation infrastructure, flood events may disrupt traffic flow in urban areas as well (Brown & Dawson, 2016). Such disruptions do not necessarily result in fully blocked and impassable streets and may only slow the running traffic speed for a while. In fact, observations from flooding events in the past have shown that inundated roads do not necessarily preclude people from driving along them, and to assess the disruptive impacts of flooding on roads, the relationship between flood depth, vehicle size, and speed should be taken into account (Pregnolato et al., 2017). Thus, to assess the flood impact on the Lumberton road network, the flood hazard maps, including flood depth and duration, were overlaid on the developed road network and the routes' traffic speeds were modified across the disaster timeline based on a set of rules, including (a) no changes in traffic speed if the inundation depth is not more than 10 cm, (b) the traffic speed will be limited to 10 km/h if the inundation depth is between 10 and 20 cm, and (c) roads with over 20 cm of inundation depth will be assumed to be closed to traffic. The bounds incorporated in the applied rules are based on the safe-driving thresholds found for a typical average-size vehicle in the research conducted by Pregnolato et al. (2017) on the relationship between flood depth and vehicle speed.

5.4.3 Quantifying accessibility to pharmacies after the 2016 Lumberton flood

In 2016, the city of Lumberton had 29 active pharmacies with the spatial distribution shown in Figure 32. According to the sampling procedure used in the Lumberton field study described earlier, three pharmacies, including one that was located inside the inundated area and two other pharmacies sampled from outside the flooded area, were surveyed during Wave 2 and 3 data collection.

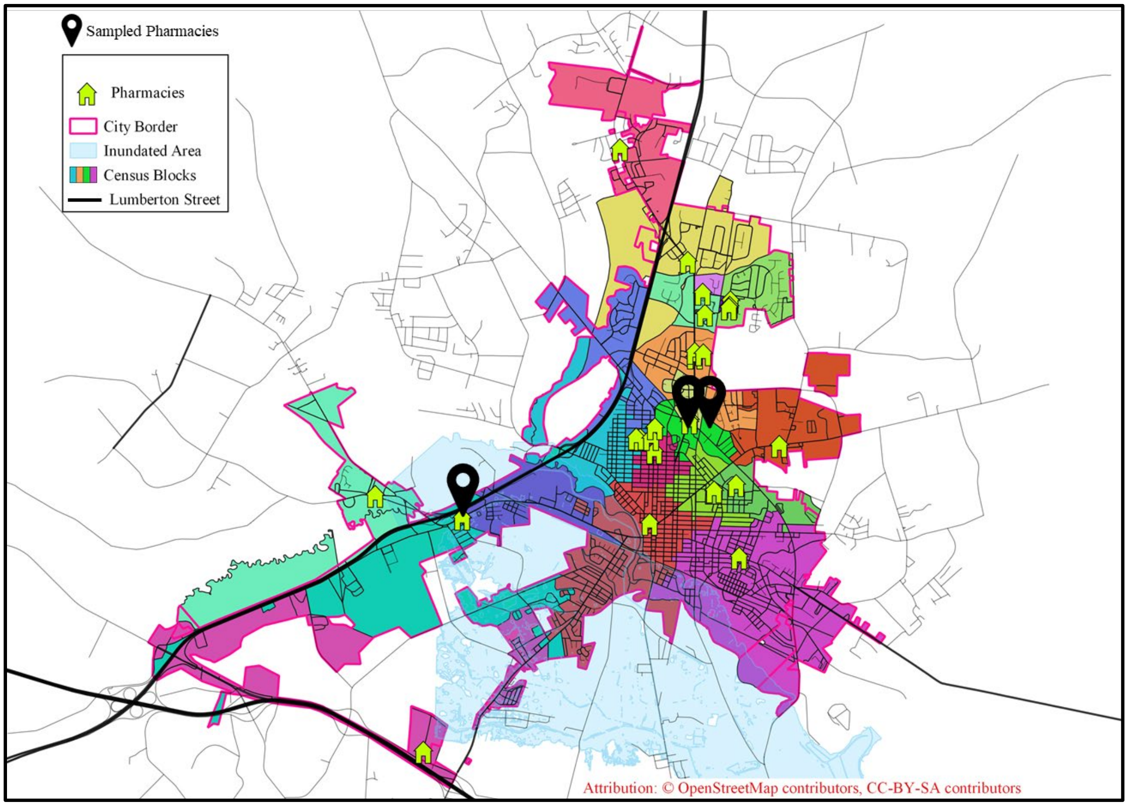


Figure 32. Spatial distribution of pharmacies in Lumberton and their nearby census blocks

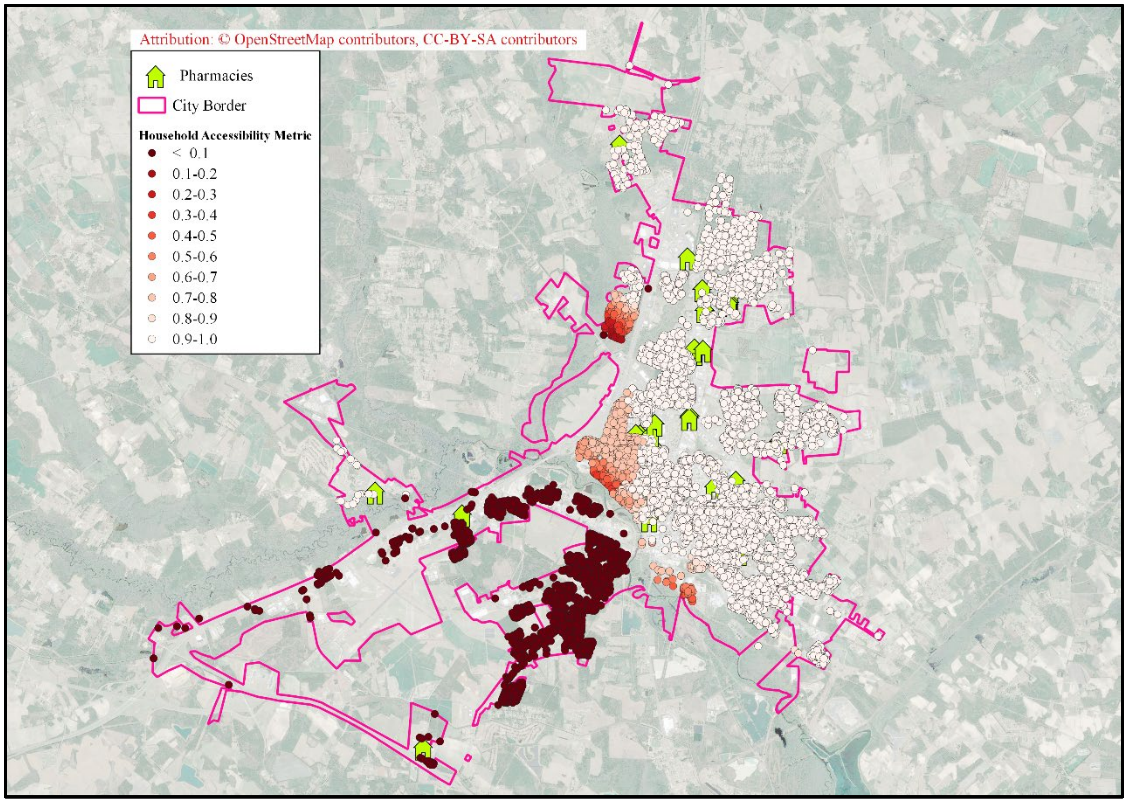
Although none of the surveyed pharmacies experienced significant physical damage, all three completely ceased operation for a few days immediately after Hurricane Matthew. Both pharmacies sampled from outside of the inundated area reported taking 3 days to resume their normal operations, while the one from within the inundated area remained closed for 6 days and operated at reduced capacity upon reopening. In addition to the loss of power and water that were reported by all three pharmacies, the pharmacy from within the inundated area reported physical access interruptions for six days. At the time of Wave 2 data collection, all three pharmacies were open but operating at different functionality levels; the pharmacy from within the inundated area declared that it was operating at 75% capacity compared to before Matthew, while the other two announced that they were almost fully recovered. These findings were used to infer information about the post-disaster functionality of the pharmacy population in the Lumberton community, as shown in Table 11.

Table 11. Post-disaster functionality level of pharmacies in Lumberton

Location (# of pharmacies)	Operation Capacity (percentage)	
	4 days after Matthew	15 months after Matthew
inside the inundated area (1)	0%	75%
out of the inundated area (28)	100%	100%

The accessibility metric for pharmacy services was calculated for every housing unit at two different points in time following the procedure described in Section 5.3.1, including at four days after floodwaters from Hurricane Matthew peaked in Lumberton, and 15 months later, as shown in Figure 33 Of note, a metric value of less than 0.1 is assumed to indicate a complete loss in accessibility to pharmacy services while one represents no loss of accessibility.

(a)



(b)

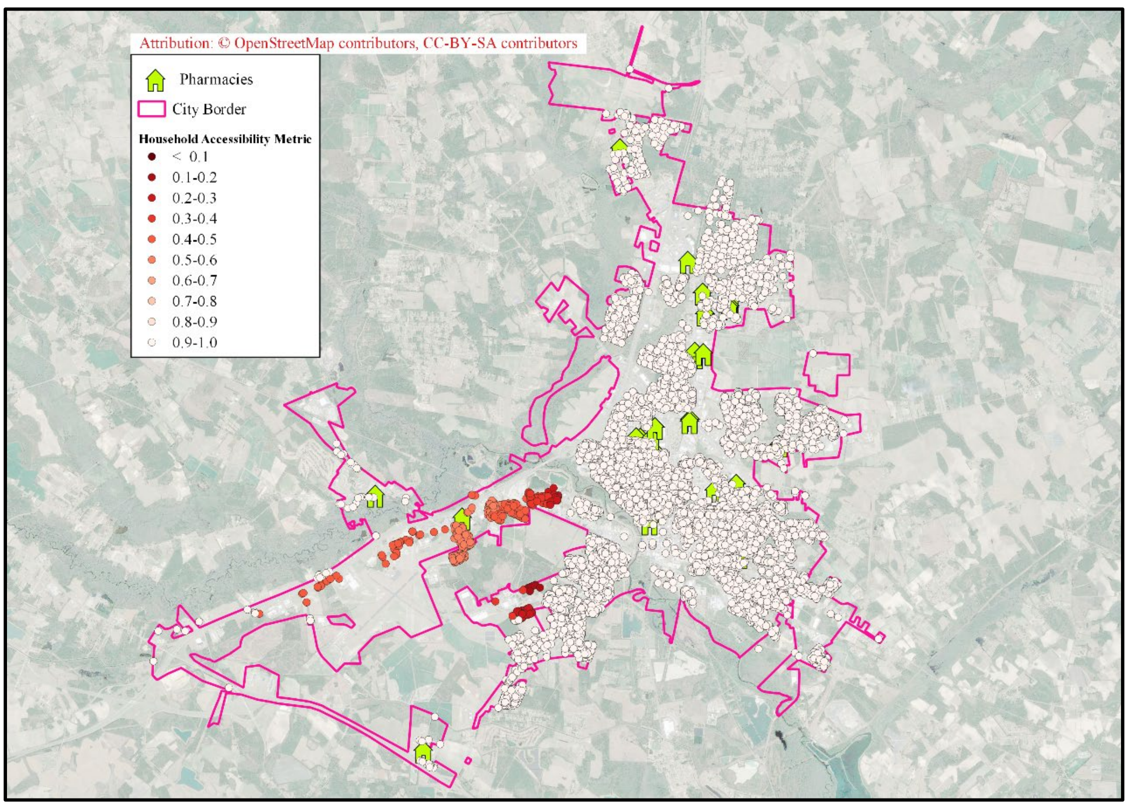


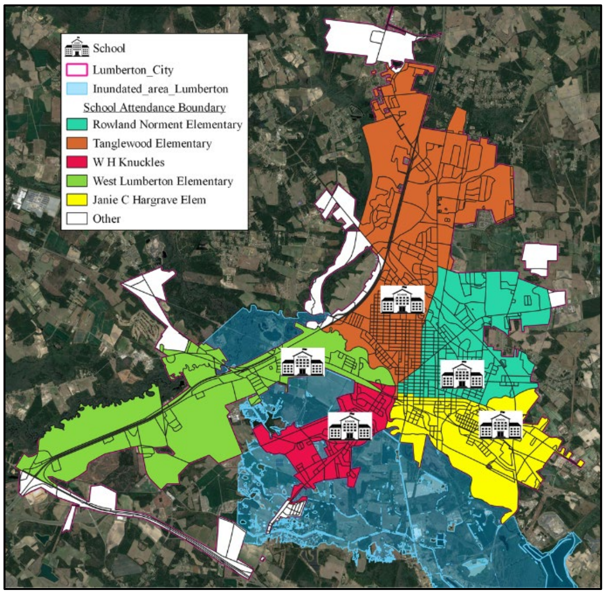
Figure 33. Household accessibility to pharmacy services in Lumberton at time of a) four days and, b) fifteen months after the 2016 flooding following Hurricane Matthew

As can be seen in the Figure 33(b) tangible accessibility metric estimates household access to pharmacy services will be severely impacted regarding housing units inside and around the inundated area. Although 28 out of 29 pharmacies in Lumberton are assumed to be fully functional on day 4 after the disaster, almost all housing units inside the inundated area will lose their access to pharmacy services for at least 4 days. This is not a surprising result since flood inundation maps simulated by Nofal and van de Lindt (2020a; Omar M. Nofal & John W. van de Lindt, 2021) shows that the streets in those census blocks will mostly remain inundated for more than 4 days. It also proves the importance of approaching the concept of accessibility from both product provider and user perspectives. In the case of Lumberton and Hurricane Matthew, the Wave 1 report (van de Lindt et al., 2018) also discusses the widespread, long-lasting, and disproportionate dislocation that occurred for Lumberton households. As such, access to pharmacy services was not needed within four days post-flood for most households whose home was located in the inundated area. However, as can be seen in Figure 33(b) the accessibility metric to pharmacy services for some households is still less than one. Thus, even 15 months after the flooding event, some households still did not have the same level of accessibility to pharmacy services as they did before the flooding.

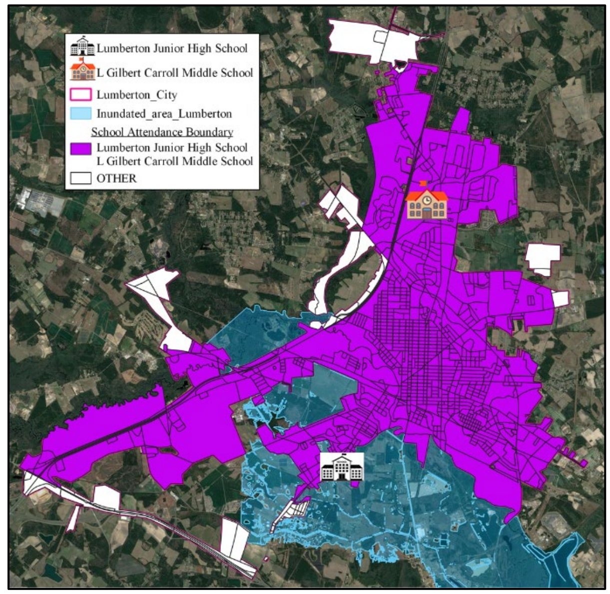
5.4.4 Quantifying accessibility to education services after the 2016 Lumberton flood

As is explained in section 5.3.2, individual attention time, *IAT,* is an organization-specific parameter and should be determined based on the characteristics of the product and organization. In this paper, by considering the publicly available data about schools, we propose using the student-teacher ratio for determining *IAT* in schools. According to the Glossary of Education Reform, “a student-teacher ratio expresses the relationship between the number of students enrolled in a school, district, or education system and the number of full-time equivalent teachers employed by the school, district, or system" (Great Schools Partnership et al., 2014). This ratio indicates the amount of individual attention any single student is likely to receive during a typical school day, assuming that all class sizes are the same. Thus, the *IAT*, here, is calculated by dividing the total number of hours in a typical school day (including lunch, recess, and study periods) by the student-teacher ratio; subsequently, the access time to educational services is calculated by subtracting the home-to-school *travel time* from individual attention time.

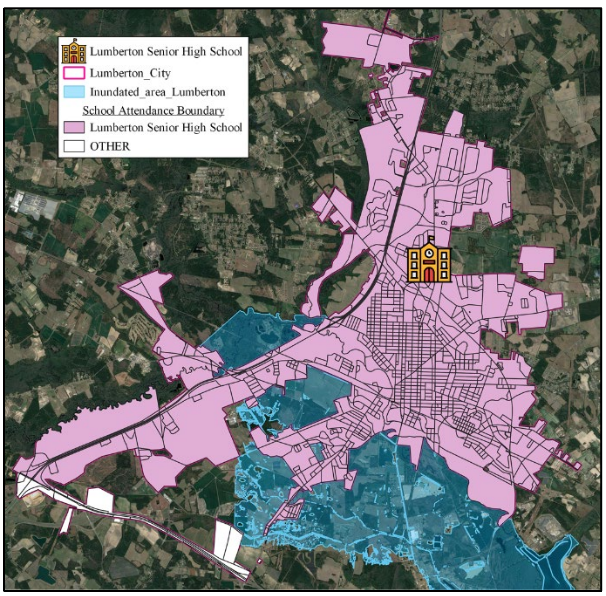
The Public School of Robeson County is the school district designated for Lumberton students to attend. In 2016, the district had 17 public schools to serve students of Lumberton, including 11 elementary, 3 middle, and 3 high schools.(van de Lindt et al., 2018). According to National Center for Education Statistics (NCES, 2016), the attendance boundary for 8 public schools lies within the city limits of Lumberton. In this paper, to illustrate the application of accessibility metric to education, only these eight schools were used.



(a)



(b)



(c)

School Name	Grade	Students (count)	Student-Teacher Ratio	Post-Disaster School Functionality (%)	
				3 weeks	*15 months*
Janie C Hargrave Elementary	Elementary	208	11.6	90%	100%
Rowland Norment Elementary	Elementary	442	13.8	90%	100%
Tanglewood Elementary	Elementary	422	13.8	90%	100%
W H Knuckles	Elementary	274	15.2	85%	100%
West Lumberton Elementary	Elementary	151	10.8	0%	0%
L Gilbert Carroll	Middle	577	14.5	90%	100%
Lumberton Junior High School	Middle	588	14.0	90%	100%
Lumberton Senior High School	High	1380	12.5	90%	100%

(d)

Figure 34. Location and attendance boundary of public a) elementary schools, b) middle schools, c) high schools in Lumberton, and d) and their characteristics and functionality levels after 2016 Hurricane Matthew

As can be seen in Figure 34(a) to (c), the elementary schools in Lumberton have discrete attendance boundaries, whereas the attendance boundaries of the middle schools and the high school fully overlap the boundaries of the five elementary schools. Based on the school locations, the flood directly and severely impacted two elementary schools, W.H. Knuckles and West

Lumberton Elementary, and one middle school, Lumberton Junior High School (van de Lindt et al., 2018, p. 25). The report also asserts that all schools, regardless of damage, were closed for at least three weeks due to incidents such as road closures, loss of power, and water outages, with many schools still needing bottled water for a while after reopening (van de Lindt et al., 2018, p. 64). As documented in Wave 1 and 2, the W.H. Knuckles Elementary school partially reopened after three weeks while there were ongoing repairs during the first year. The West Lumberton Elementary school was closed permanently after the flood. According to these findings, we estimated each school's post-disaster functionality level at three weeks and fifteen months post-flooding, depicted in Figure 34(d). The number of students and the student-teacher ratios in Figure 34(d) were obtained from NCES (2016) database. There were approximately 4,402 students enrolled in those eight schools before Hurricane Matthew in 2016, including 37% at the primary school level, 29% at the middle school level, and 34% at the high school level.

To estimate the post-disaster access time to education services for students whose pre-disaster schools do not function after the disaster, each of the students must be reassigned to a new school. Figure 35 presents a hypothetical algorithm for student admission and transfer. The algorithm takes the student's grade level, home address (or coordinates), and pre-disaster school as input and attempts to find a new school admission at the same grade level for every student in need. If the attempt succeeds, a new post-disaster school will be assigned to the student; otherwise, the student will not be able to attend school in Lumberton. The algorithm shown in Figure 35 simplifies the student transfer and enrollment process by making four assumptions; 1) admission to a new school is solely based on the grade level of the student and the school's capacity, 2) prioritization of transfers is based on proximity, 3) only public schools are taken into account, so affordability is not a concern, and 4) free and safe transportation is always secured for all students.

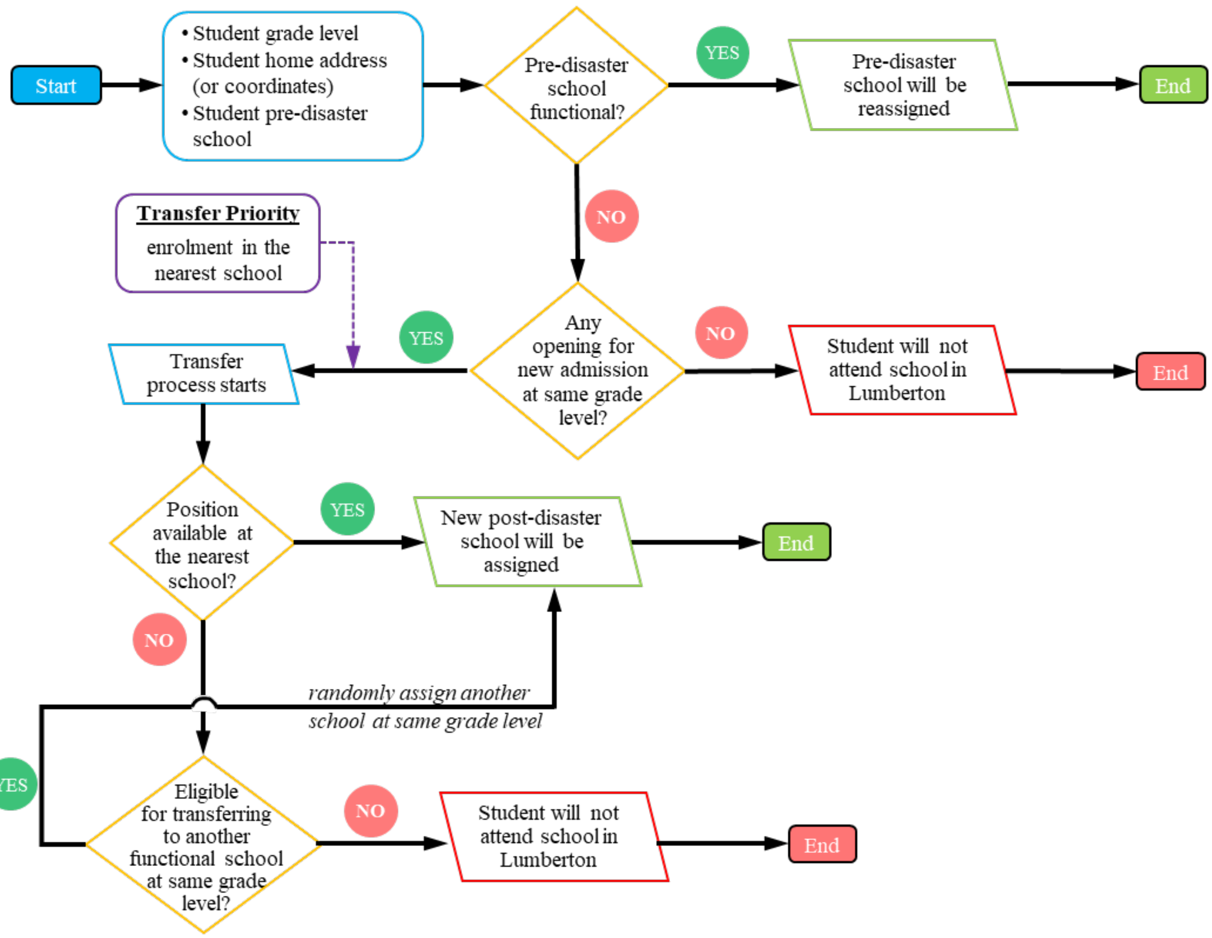


Figure 35. Hypothetical student enrollment and transfer processing algorithm

Transferring students involves estimating the maximum expected enrollment capacity of post-disaster functional schools within the school district using

$$SC^{a}_{\max}(t) = Q(t) \times SC^{b}_{\max} \times \left[\frac{L_3 - L_2}{100 - L_2} \right] \tag{14}$$

where $SC^{a}_{max}(t)$ is the maximum possible number of available student desks in a school at the time t after a disaster; $Q(t)$ denotes the probability of that school becoming functional before time t; L_2 and L_3 are corresponding functionality percentages for a Fully Operable and MALF school, respectively; and SC^{b}_{max} represents the maximum possible number of enrollments in the intended school before the disaster. The SC^{b}_{max} can be approximated using the maximum student-teacher ratio for the district's public schools and presuming the number of teachers working at every school remains constant.

As such, the accessibility metric to education services was calculated for all 4,042 students at two different points in time, 3 weeks after the flood from Hurricane Matthew in Lumberton, and 15 months later, as shown in Figure 36. Recall, as the metric value decreases from one to zero, the accessibility to education services declines from full access to a complete loss.

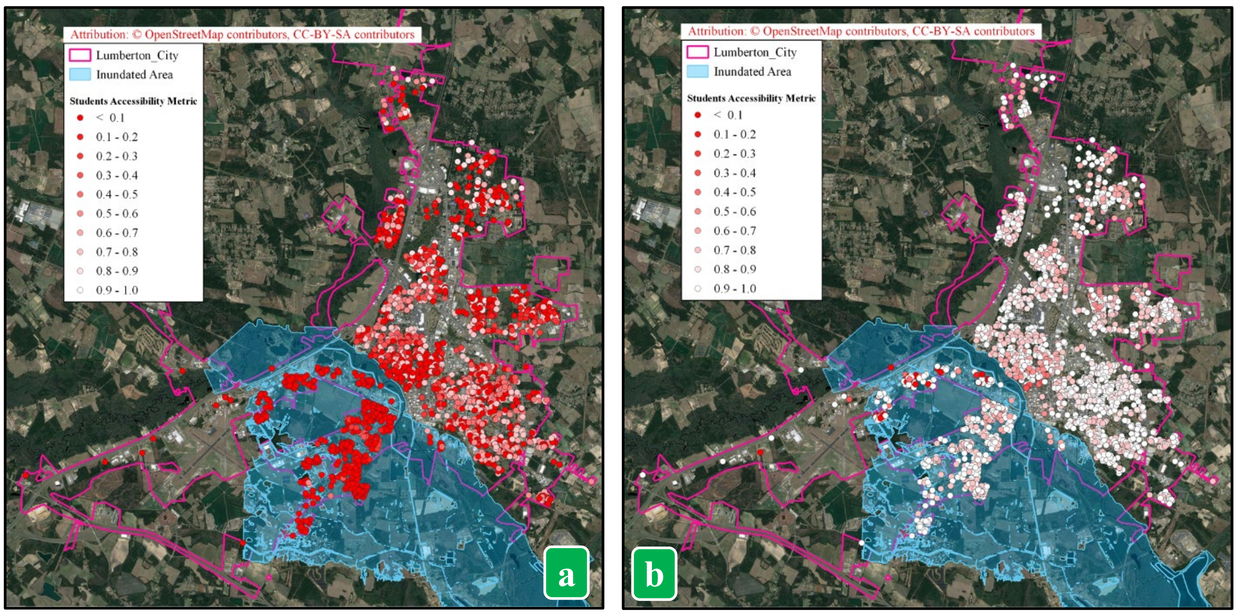


Figure 36. Household accessibility to education services in Lumberton at a) three weeks and, b) fifteen months after the 2016 flooding following Hurricane Matthew

As can be seen in Figure 36(a), it is estimated that almost all students experience reduced access to education even after schools reopened. This accessibility loss is primarily due to the increase in students' home-to-school travel time. The Wave 1 report, on the other hand, asserted that the schools' transportation systems, after reopening of schools (three weeks post-disaster), were on a two-hour delay since they had to accommodate new and longer routes (van de Lindt et al., 2018, p. 64). The accessibility to education will improve significantly after 15 months, as shown in Figure 36(b) however, even then some students are still experiencing school accessibility issues.

5.5 Measuring Inequities in Accessibility to Schools Across the Community

As explained in Chapter 4, disasters affect different populations within communities unevenly and the social impacts of natural hazards are associated with the population's social vulnerability level. Community members with higher social vulnerability levels are often more severely impacted by natural hazards due to pre-existing socioeconomic conditions resulting from a long history of inequitable and race-based policies (Hendricks & Van Zandt, 2021; Rivera, 2022). As a result of these policies, socially vulnerable populations were forced to endure disparities in infrastructure maintenance, access to recreational areas, and other public goods such as hospitals and quality schools during normal times. On the other hand, there is ample research showing that current disaster recovery policies have further exacerbated social inequalities after disasters by setting qualifying criteria that exclude socially vulnerable populations (Kamel & Loukaitou-Sideris, 2004; Sutley & Hamideh, 2018; Van Zandt, 2019).

The next generation of community resilience analysis tools and approaches should be able to estimate how these pre-existing inequities will be exacerbated across the community and address them in the community's risk reduction and recovery plans to ensure the post-disaster social, economic, and environmental well-being of all community members equitably. We argue that accessibility metrics proposed in this research, along with a place-based social vulnerability score, are a proper tool to serve this purpose. To demonstrate the application of the accessibility metric in this regard, this section employs the household-level social vulnerability estimated in Chapter 4 and presented Figure 26, and combines it with the calculated metric in section 5.4.4 and findings in Figure 36 to assess inequities in school access and educational recovery across Lumberton after Hurricane Matthew.

Figure 37 presents how access to schools was restored inequitably across Lumberton students with households from different social vulnerability groups after the 2016 flooding following Hurricane Matthew. As can be seen, almost all community members, regardless of their social vulnerability, lost their access to schools, either partially or completely, three weeks after the flooding event, whereas after fifteen months, the accessibility was restored unevenly across the community. The percentage of students who completely regained their access to school, fifteen months post-disaster, is considerably higher for students from low socially vulnerable households, i.e., 85%. The percentage decreases as the social vulnerability of the student's household increases. Also, still, fifteen months after the event, 10% of students from high social vulnerability households have completely lost their access to school, which is much higher than the percentage of students from households with other levels of social vulnerability.

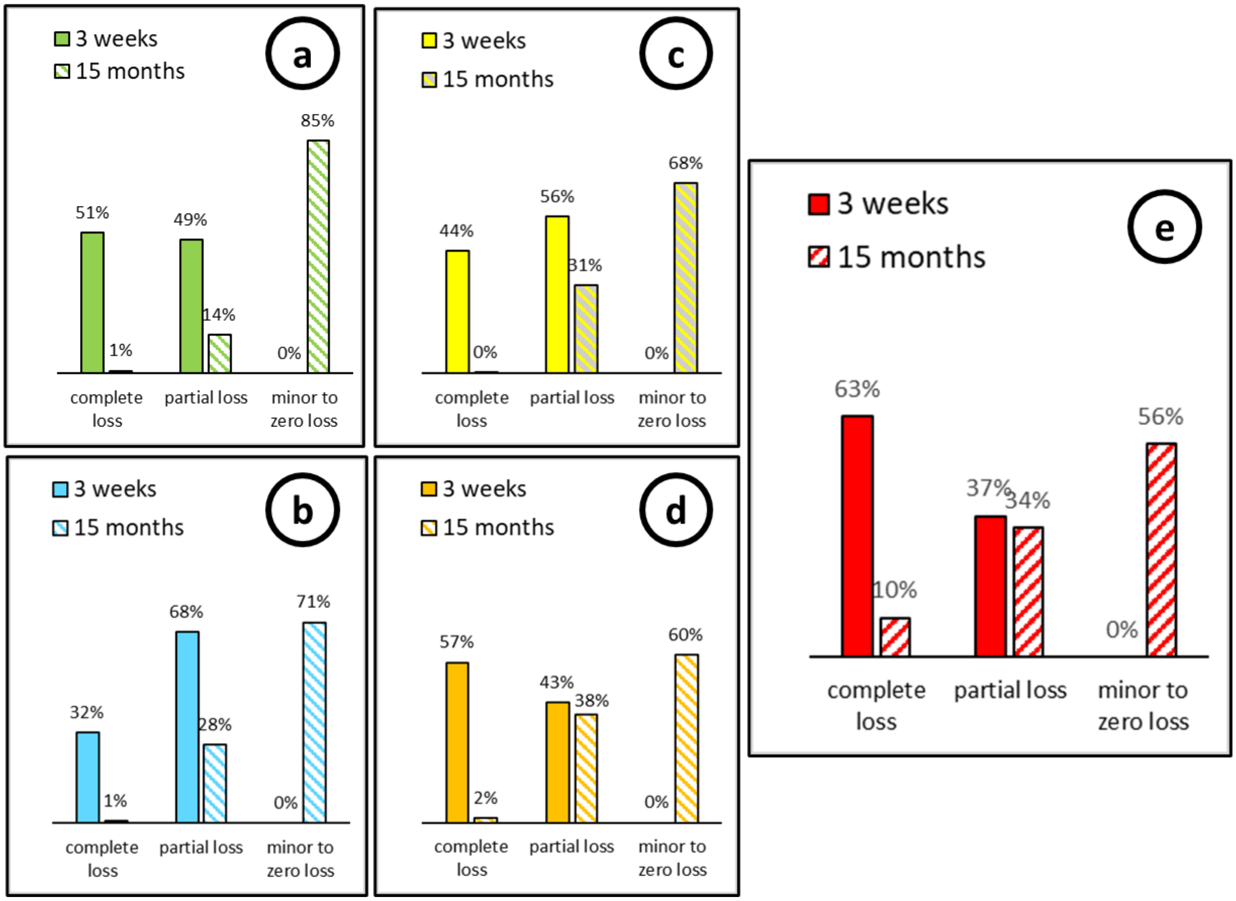


Figure 37. Percentage of Lumberton students with a) low, b) medium to low, c) medium, d) medium to high, and e) high social vulnerability levels based on their access-to-school status at 3 weeks and 15 months after 2016 flooding following Hurricane Matthew

5.6 Discussion and Conclusions

Accessibility of community members to essential services is an important proxy for assessing the resilience of a community. To measure accessibility in the context of community resilience, frameworks should employ metrics that (1) include dimensions other than just physical access and proximity, and (2) concurrently consider factors influencing the characteristics of both product users and product providers. Accessibility metrics developed in this paper combine proximity, acceptability, adequacy, and availability dimensions of accessibility. The developed metrics are also a function of time, which makes them suitable for evaluating a multi-dimensional temporally-varying concept such as accessibility. The metrics, on the other hand, employ the organizational functionality of the product providers in measuring accessibility. In addition to these advantages, metrics operate at the household level and yield a unitless ratio between zero and one, which can be aggregated for that household across multiple products, if necessary. For instance, outpatient and impatient are two common types of patient care that can be classified under the healthcare product category. Accessibility to outpatient care should be measured using the accessibility metric for tangible products, whereas the metric developed for intangible products is required to measure accessibility to inpatient care. However, a household's accessibility to patient care can be calculated by adding together the results of each metric.

Household displacement is a common outcome following disasters, which happened after the 2016 flooding event in Lumberton as well. In this paper, household displacement, and consequently, student and staff displacements, were overlooked due to a lack of data. As accessibility dimensions such as awareness, acceptability, and adequacy are not directly observable or measurable, validating the performance of the proposed accessibility metrics requires particular data to be collected during future post-disaster field studies.

Affordability and awareness are two accessibility dimensions that were not included in developing the accessibility metrics proposed in this paper and can be an area for future research. These two dimensions may not be applicable to measuring accessibility in the example illustrated in this paper, but they may participate more in defining accessibility to other products. Importantly, affordability and awareness of service users are getting more important as new visions for improving the resilience of communities emerge. For instance, the COVID-19 pandemic proved that there is a crucial need for community resilience frameworks to go beyond “resistance and returning to normal” to include adaptability and transformation along with mitigation, preparedness, robustness, and recovery. Communities can mobilize their adaptive capacity and reorganize to cope with their new situation after a disruption. Many organizations demonstrated such traits during the COVID-19 pandemic by transforming in-person services online. This adaptive capacity and transformation altered components contributing to organizational functionality, and consequently, reduced the risk of organizational functionality failure, which is a step toward resilience. However, this step will be taken only if the organization still remains accessible and its services are being used by community members. A reliable internet connection may be difficult to afford for the socially vulnerable population, for example. In that case, awareness and affordability are two accessibility dimensions that are more likely to be compromised which may lead to exacerbating the existing inequity in access to resources in the communities if ignored in measuring accessibility.

Chapter 6: Conclusions

The Community Capitals (CC) framework is a conducive tool for assessing the disaster resilience of communities as it examines the community through seven different lenses, termed capitals, including natural, cultural, human, social, financial, political, and built capital. The stock of these seven capitals and their interaction provides a holistic means to evaluate the state of a community at a given point in time and governs a community's ability to respond to disruption. This opens up the ability to employ temporal variations of the stock of community capitals as a means for assessing the functionality of the community across the disaster timeline.

While all seven capitals are essential and their details are distinctive to each community, this dissertation posits that the built capital, including buildings and infrastructures, plays a unique role in supporting the other six capitals. Importantly, buildings should not be designed as isolated structures but as part of a community. As such, it is imperative to understand, measure, and evaluate how buildings support or otherwise contribute to various community functions and related capitals. This relationship can be understood through (1) the organization(s) residing in the building, and (2) how the products of the organization(s) support the community measured through the community capitals. Organizations work as a lynchpin connecting the built capital to the other capitals. Communities need to ensure that their organizations will be recovered within an acceptable timeframe after a disaster to contribute to restoring the community capitals to support the community's short, intermediate, and long-term functional recovery goals.

This dissertation offers a novel definition of organizational functionality, and a means for quantifying organizational functionality through time. Importantly, organizations require physical (including space, access, and external utilities) and non-physical (including staff and supply chain) components to function; the details of which are organization-specific. These non-physical components, in fact, connect the organizations to each other and the community.

For community capitals to be generated or mobilized, and consequently for communities to achieve their recovery goals, the products offered by such functional organizations must be accessible to community members. This dissertation offers two novel metrics that combine proximity, acceptability, adequacy, and availability dimensions of accessibility to evaluate household-level access to tangible products and intangible services. The developed metrics are also a function of time, which makes them suitable for evaluating a multi-dimensional temporally-varying concept such as accessibility. The metrics operate at the household level and are intended to be measured within and across a given community. The metrics, also, consider the post-disaster functionality level of the organization offering a product and yield unitless ratios. This unitless essence enables accessibility to be aggregated across different organizations that are contributing to generating or mobilizing each community capital.

Based on the proposed framework, to evaluate a community's post-disaster functionality at a particular point in time, every household's accessibility to the products offered by organizations contributing to each community capital should be measured individually using the proper metric, then, aggregated across the different organizations. The resulting value for each community capital is the household's accessibility to that community capital and its cumulation across the households within the community represents the stock of that community capital. The ratio of each community capital at a specific time post-disaster against its pre-disaster time can be used as a proxy for the community's post-disaster functionality level . By incorporating household-level social vulnerability, equity can be evaluated in access to essential products and services through time.

Beyond the overarching framework presented here, an approach for testbed development was introduced which may boost multi-, inter-, and transdisciplinary collaborations on community resilience. This contribution will hopefully lead to more balanced testbeds with evolved community modules that have strong representations of social and economic systems. The SVS presented in Chapter 4 can be used to identify differences in social vulnerability across a population which may aid in resource allocation. Social vulnerability indices are starting to be used by public health officials, hazard mitigation planners, community resilience researchers, and testbed developers. While the proposed SVS is still subject to limitations in simplifying a measurement of social vulnerability, it addresses the need for a social vulnerability index that more consistently explains disaster outcomes, can be used at various spatial scales, and requires minimal data inputs and computational efforts making it particularly suitable for use in virtual community resilience testbeds.

This dissertation has illuminated (a) shortages of high-resolution data on social, economic, and infrastructure systems, (b) research needs and future orientations for pre-, and post-disaster data collection, (c) the necessity of more longitudinal studies to validate organization-specific fault trees, (d) the need for more social and economic models in community resilience testbeds, (e) the need for capturing dependencies and connections across organizations to further define community functionality, and (f) a need for developing a comprehensive library of fragility and restoration functions for the components of organization functionality, to name only a few.

The proposed framework for measuring accessibility to essential services can operate as a decision tool that links community resilience objectives to functional recovery goals, and can be applied by researchers, practitioners, and policymakers to develop more risk-informed disaster mitigation and long-term recovery plans at the community level. This research provides a foundation for future research to address the limitations that restrict its application in practice.

References

Aagaard, B. T., Blair, J. L., Boatwright, J., Garcia, S. H., Harris, R. A., Michael, A. J., Schwartz, D. P., & DiLeo, J. S. (2016). *Earthquake outlook for the San Francisco Bay region 2014–2043* (2327-6932).

Adachi, T., & Ellingwood, B. R. (2009). Serviceability Assessment of a Municipal Water System Under Spatially Correlated Seismic Intensities. *Computer-aided Civil and Infrastructure Engineering, 24*(4), 237-248. https://doi.org/https://doi.org/10.1111/j.1467-8667.2008.00583.x

Adachi, T., & Ellingwood, B. R. (2010). Comparative Assessment of Civil Infrastructure Network Performance under Probabilistic and Scenario Earthquakes. *Journal of Infrastructure Systems, 16*(1), 1-10. https://doi.org/doi:10.1061/(ASCE)1076-0342(2010)16:1(1)

Adhikari, P., Abdelhafez, M. A., Dong, Y., Guo, Y., Mahmoud, H. N., & Ellingwood, B. R. (2021, 2021-February-22). Achieving Residential Coastal Communities Resilient to Tropical Cyclones and Climate Change [Original Research]. *Frontiers in Built Environment, 6*. https://doi.org/10.3389/fbuil.2020.576403

Aghababaei, M., Koliou, M., Pilkington, S., Mahmoud, H., Lindt, J. W. v. d., Curtis, A., Smith, S., Ajayakumar, J., & Watson, M. (2020). Validation of Time-Dependent Repair Recovery of the Building Stock Following the 2011 Joplin Tornado. *Natural Hazards Review, 21*(4), 04020038. https://doi.org/doi:10.1061/(ASCE)NH.1527-6996.0000408

Aghababaei, M., Koliou, M., Watson, M., & Xiao, Y. (2019). Modeling business recovery after natural disasters: The case study of Lumberton, NC following Hurricane Matthew. 2nd Int. Conf. on Natural Hazards and Infrastructure (ICONHIC 2019). Athens, Greece: Innovation Center for Natural Hazards and Infrastructure,

Aghababaei, M., Koliou, M., Watson, M., & Xiao, Y. (2020). Quantifying post-disaster business recovery through Bayesian methods. *Structure and Infrastructure Engineering*, 1-19. https://doi.org/10.1080/15732479.2020.1777569

Al-Rousan, T. M., Rubenstein, L. M., & Wallace, R. B. (2015, Jul). Disability levels and correlates among older mobile home dwellers, an NHATS analysis. *Disabil Health J, 8*(3), 363-371. https://doi.org/10.1016/j.dhjo.2015.01.002

Aldrich, D. (2012). *Building Resilience: Social Capital in Post-Disaster Recovery*. University of Chicago Press.

Allen, A. O. (1978). Chapter Five - QUEUEING THEORY. In A. O. Allen (Ed.), *Probability, Statistics, and Queueing Theory* (pp. 149-233). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-051050-4.50011-3

Alvisi, S., Creaco, E., & Franchini, M. (2012). A multi-step approach for optimal design of the d-town pipe network model. In (pp. 103–112). Engineers Australia. https://doi.org/10.3316/informit.944289959162408

Alvisi, S., & Franchini, M. (2011). Calibration and Sensitivity Analysis of the C-Town Pipe Network Model. In *Water Distribution Systems Analysis 2010* (pp. 1573-1584). https://doi.org/doi:10.1061/41203(425)140

Ang, A. H.-S., & Tang, W. H. (2007). *Probability concepts in Engineering: Emphasis on applications in Civil & Environmental Engineering* (2 ed., Vol. 1). John Wiley and Sons.

Atkinson, S., Farmani, R., Memon, F. A., & Butler, D. (2014). Reliability Indicators for Water Distribution System Design: Comparison. *Journal of Water Resources Planning and Management, 140*(2), 160-168. https://doi.org/doi:10.1061/(ASCE)WR.1943-5452.0000304

Atlantic Oceanographic & Meteorological Laboratory (AOML). (2020). *Atlantic Hurricane Database (HURDAT2) 1851-2021*. Retrieved January from https://coast.noaa.gov/hurricanes/#map=4/32/-80

Attary, N., Lindt, J. W. v. d., Mahmoud, H., & Smith, S. (2019). Hindcasting Community-Level Damage to the Interdependent Buildings and Electric Power Network after the 2011 Joplin, Missouri, Tornado. *Natural Hazards Review, 20*(1), 04018027. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000317

ATTOM Data Solutions. (2020). *Premium Real Estate Data*. https://www.attomdata.com/

Bagchi, A. (2009). *Modeling the power distribution network of a virtual city and studying the impact of fire on the electrical infrastructure*

Bakkensen, L. A., & Ma, L. (2020, 2020/11/01/). Sorting over flood risk and implications for policy reform. *Journal of Environmental Economics and Management, 104*, 102362. https://doi.org/https://doi.org/10.1016/j.jeem.2020.102362

Bell, J. E., Brown, C. L., Conlon, K., Herring, S., Kunkel, K. E., Lawrimore, J., Luber, G., Schreck, C., Smith, A., & Uejio, C. (2018, 2018/04/03). Changes in extreme events and the potential impacts on human health. *Journal of the Air & Waste Management Association, 68*(4), 265-287. https://doi.org/10.1080/10962247.2017.1401017

Bergstrand, K., Mayer, B., Brumback, B., & Zhang, Y. (2015). Assessing the Relationship Between Social Vulnerability and Community Resilience to Hazards. *Social indicators research, 122*(2), 391-409. https://doi.org/10.1007/s11205-014-0698-3

Beven, K. J., Almeida, S., Aspinall, W. P., Bates, P. D., Blazkova, S., Borgomeo, E., Freer, J., Goda, K., Hall, J. W., Phillips, J. C., Simpson, M., Smith, P. J., Stephenson, D. B., Wagener, T., Watson, M., & Wilkins, K. L. (2018). Epistemic uncertainties and natural hazard risk assessment – Part 1: A review of different natural hazard areas. *Nat. Hazards Earth Syst. Sci., 18*(10), 2741-2768. https://doi.org/10.5194/nhess-18-2741-2018

Beven, K. J., Aspinall, W. P., Bates, P. D., Borgomeo, E., Goda, K., Hall, J. W., Page, T., Phillips, J. C., Simpson, M., Smith, P. J., Wagener, T., & Watson, M. (2018). Epistemic uncertainties and natural hazard risk assessment – Part 2: What should constitute good practice? *Nat. Hazards Earth Syst. Sci., 18*(10), 2769-2783. https://doi.org/10.5194/nhess-18-2769-2018

Birkmann, J. (2013). *Measuring vulnerability to natural hazards: towards disaster resilient societies (second edition)*. United Nations University.

Blaikie, P., Cannon, T., & Ian Davis, B. W. (2003). *At Risk Natural Hazards, People's Vulnerability and Disasters*. Routledge.

BLS. (2020). *Industries at a Glance: Gasoline Stations*. Bureau of Labor Statistics. Retrieved July 2 from https://www.bls.gov/iag/tgs/iag447.htm

Boeing, G. (2017). OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Computers, Environment and Urban Systems, 65*, 126-139.

Boeing, G. (2022). Street Network Models and Indicators for Every Urban Area in the World. *Geographical Analysis, 54*(3), 519-535. https://doi.org/https://doi.org/10.1111/gean.12281

Bozza, A., Asprone, D., & Manfredi, G. (2015). Developing an integrated framework to quantify resilience of urban systems against disasters. *Natural Hazards, 78*(3), 1729-1748.

Brown, S., & Dawson, R. (2016). Building network-level resilience to resource disruption from flooding: Case studies from the Shetland Islands and Hurricane Sandy. *E3S Web Conf., 7*, 04008. https://doi.org/10.1051/e3sconf/20160704008

Brumbelow, K., Torres, J., Guikema, S., Bristow, E., & Kanta, L. (2007). Virtual cities for water distribution and infrastructure system research. World environmental and water resources congress 2007: Restoring our natural habitat,

Bulti, D. T., & Abebe, B. G. (2020, 2020/09/01). A review of flood modeling methods for urban pluvial flood application. *Modeling Earth Systems and Environment, 6*(3), 1293-1302. https://doi.org/10.1007/s40808-020-00803-z

Burton, C., Rufat, S., & Tate, E. (2018). Social Vulnerability: Conceptual Foundations and Geospatial Modeling.

Burton, C. G. (2010). Social Vulnerability and Hurricane Impact Modeling. *Natural Hazards Review, 11*(2), 58-68. https://doi.org/doi:10.1061/(ASCE)1527-6988(2010)11:2(58)

Burton, H. V., Deierlein, G., Lallemant, D., & Lin, T. (2016). Framework for Incorporating Probabilistic Building Performance in the Assessment of Community Seismic Resilience. *Journal of Structural Engineering, 142*(8), C4015007. https://doi.org/doi:10.1061/(ASCE)ST.1943-541X.0001321

Centers for Disease Control and Prevention, Agency for Toxic Substances and Disease Registry, & Geospatial Research Analysis and Services Program. (2018). *CDC/ATSDR Social Vulnerability Index 2018 Database U.S.* https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html

Chang, S. E., & Shinozuka, M. (2004). Measuring Improvements in the Disaster Resilience of Communities. *Earthquake Spectra, 20*(3), 739-755. https://doi.org/10.1193/1.1775796

Chen, Z., & Rose, A. (2018, 2018/07/01). Economic resilience to transportation failure: a computable general equilibrium analysis. *Transportation, 45*(4), 1009-1027. https://doi.org/10.1007/s11116-017-9819-6

Choi, J., Deshmukh, A., & Hastak, M. (2019). Seven-Layer Classification of Infrastructure to Improve Community Resilience to Disasters. *Journal of Infrastructure Systems, 25*(2), 04019012. https://doi.org/doi:10.1061/(ASCE)IS.1943-555X.0000486

Cimellaro, G. P., Moretti, S., Piqué, M., Trozzo, A. C., Renschler, C. S., & Reinhorn, A. M. (2014). ASCE First Generation Testbed for Evaluating Resilience of Structures. In *Structures Congress 2014* (pp. 2292-2303). https://doi.org/doi:10.1061/9780784413357.201

Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010, 2010/11/01/). Framework for analytical quantification of disaster resilience. *Engineering Structures, 32*(11), 3639-3649. https://doi.org/https://doi.org/10.1016/j.engstruct.2010.08.008

Cimellaro, G. P., Renschler, C., Reinhorn, A. M., & Arendt, L. (2016). PEOPLES: A Framework for Evaluating Resilience. *Journal of Structural Engineering, 142*(10), 04016063. https://doi.org/doi:10.1061/(ASCE)ST.1943-541X.0001514

Coggins, W., & Jarmin, R. (2021). *Understanding and Using the American Community Survey Public Use Microdata Sample Files, What Data Users Need to Know*. U.S. Department of Census; CENSUS BUREAU. Retrieved March from https://www.census.gov/content/dam/Census/library/publications/2021/acs/acs_pums_handbook_2021.pdf

Collins, T. W., Grineski, S. E., & de Lourdes Romo Aguilar, M. (2009, 2009/07/01/). Vulnerability to environmental hazards in the Ciudad Juárez (Mexico)–El Paso (USA) metropolis: A model for spatial risk assessment in transnational context. *Applied Geography, 29*(3), 448-461. https://doi.org/https://doi.org/10.1016/j.apgeog.2008.10.005

Comerio, M. C. (2006). Estimating Downtime in Loss Modeling. *Earthquake Spectra, 22*(2), 349-365. https://doi.org/10.1193/1.2191017

Comerio, M. C., & Blecher, H. E. (2010). Estimating Downtime from Data on Residential Buildings after the Northridge and Loma Prieta Earthquakes. *Earthquake Spectra, 26*(4), 951-965. https://doi.org/10.1193/1.3477993

Computational Fluid Dynamics Committee. (1998). *Guide: Guide for the Verification and Validation of Computational Fluid Dynamics Simulations (AIAA G-077-1998 (2002))*. American Institute of Aeronautics and Astronautics, Inc.

Constas, M., Frankenberger, T., & Hoddinott, J. (2014). Resilience measurement principles: Toward an agenda for measurement design. *Food Security Information Network, Resilience Measurement Technical Working Group, Technical Series, 1*. https://www.fsnnetwork.org/sites/default/files/FSINRMTS1final.pdf

Contreras, D., Blaschke, T., & Hodgson, M. E. (2017, 2017/08/01/). Lack of spatial resilience in a recovery process: Case L'Aquila, Italy. *Technological Forecasting and Social Change, 121*, 76-88. https://doi.org/https://doi.org/10.1016/j.techfore.2016.12.010

Creaco, E., Alvisi, S., & Franchini, M. (2014, 2014/01/01/). A Multi-step Approach for Optimal Design and Management of the C-Town Pipe Network Model. *Procedia Engineering, 89*, 37-44. https://doi.org/https://doi.org/10.1016/j.proeng.2014.11.157

Cremen, G., Galasso, C., & McCloskey, J. (2022, 2022/04/15/). Modelling and quantifying tomorrow's risks from natural hazards. *Science of The Total Environment, 817*, 152552. https://doi.org/https://doi.org/10.1016/j.scitotenv.2021.152552

Cui, P., Peng, J., Shi, P., Tang, H., Ouyang, C., Zou, Q., Liu, L., Li, C., & Lei, Y. (2021, 2021/09/01/). Scientific challenges of research on natural hazards and disaster risk. *Geography and Sustainability, 2*(3), 216-223. https://doi.org/https://doi.org/10.1016/j.geosus.2021.09.001

Cutler, H., Shields, M., Tavani, D., & Zahran, S. (2016, 2016/11/28). Integrating engineering outputs from natural disaster models into a dynamic spatial computable general equilibrium model of Centerville. *Sustainable and Resilient Infrastructure, 1*(3-4), 169-187. https://doi.org/10.1080/23789689.2016.1254996

Cutter, S., CT; Emrich, Morath, D., & Dunning, C. (2013). Integrating social vulnerability into federal flood risk management planning. *Journal of Flood Risk Management, 6*(4), 332-344. https://doi.org/https://doi.org/10.1111/jfr3.12018

Cutter, S. L. (1996). Vulnerability to environmental hazards. *Progress in Human Geography, 20*(4), 529-539. https://doi.org/10.1177/030913259602000407

Cutter, S. L., Ahearn, J. A., Amadei, B., Crawford, P., Eide, E. A., Galloway, G. E., Goodchild, M. F., Kunreuther, H. C., Li-Vollmer, M., Schoch-Spana, M., Scrimshaw, S. C., Stanley, E. M., Whitney, G., & Zoback, M. L. (2013, 2013/03/01). Disaster Resilience: A National Imperative. *Environment: Science and Policy for Sustainable Development, 55*(2), 25-29. https://doi.org/10.1080/00139157.2013.768076

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social Vulnerability to Environmental Hazards*. *Social Science Quarterly, 84*(2), 242-261. https://doi.org/https://doi.org/10.1111/1540-6237.8402002

Cutter, S. L., Mitchell, J. T., & Scott, M. S. (2000). Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina. *Annals of the Association of American Geographers, 90*(4), 713-737. https://doi.org/https://doi.org/10.1111/0004-5608.00219

Cutter, S. L., & Morath, D. P. (2013). The evolution of the Social Vulnerability Index (SoVI). In J. Birkmann (Ed.), *Measuring Vulnerability to Natural Hazards: Towards Disaster Resilient Societies Second Edition* (Second ed., pp. 720). United Nations University Press.

Czajkowski, J., Kunreuther, H., & Michel-Kerjan, E. (2013, Dec). Quantifying riverine and storm-surge flood risk by single-family residence: application to Texas. *Risk Anal, 33*(12), 2092-2110. https://doi.org/10.1111/risa.12068

Dalziell, E. P., & McManus, S. T. (2004). Resilience, vulnerability, and adaptive capacity: implications for system performance.

Daniel, L., Mazumder, R., Enderami, S. A., Sutley, E. J., & Lequesne, R. (2021). A Community Capitals Framework for Linking Buildings and Organizations for Enhancing Community Resilience through the Built Environment. *Journal of Infrastructure Systems, Forthcoming*. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000668

Daniel, L., Mazumder, R. K., Enderami, S. A., Sutley, E. J., & Lequesne, R. D. (2022). Community Capitals Framework for Linking Buildings and Organizations for Enhancing Community Resilience through the Built Environment. *Journal of Infrastructure Systems, 28*(1), 04021053. https://doi.org/doi:10.1061/(ASCE)IS.1943-555X.0000668

Data Axle. (2020). *ReferenceUSA database*. https://www.data-axle.com/what-we-do/reference-solutions/

Davis, C. A. (2013). Quantifying Post-Earthquake Water System Functionality. In *International Efforts in Lifeline Earthquake Engineering* (pp. 19-26). https://doi.org/doi:10.1061/9780784413234.003

Davis, C. A. (2014). Water System Service Categories, Post-Earthquake Interaction, and Restoration Strategies. *Earthquake Spectra, 30*(4), 1487-1509. https://doi.org/10.1193/022912eqs058m

Davis, C. A. (2019). *Infrastructure System Resilience: Functionality and Operability* 2nd International Conference on Natural Hazards & Infrastructure, Chania, Greece.

Dayal, A., Yi, D., Tbaileh, A., & Shukla, S. (2015, 26-30 July 2015). VSCADA: A reconfigurable virtual SCADA test-bed for simulating power utility control center operations. 2015 IEEE Power & Energy Society General Meeting,

Deierlein, G. G., McKenna, F., Zsarnóczay, A., Kijewski-Correa, T., Kareem, A., Elhaddad, W., Lowes, L., Schoettler, M. J., & Govindjee, S. (2020, 2020-November-25). A Cloud-Enabled Application Framework for Simulating Regional-Scale Impacts of Natural Hazards on the Built Environment [Methods]. *Frontiers in Built Environment, 6*(196). https://doi.org/10.3389/fbuil.2020.558706

Dempsey, N., Bramley, G., Power, S., & Brown, C. (2011). The social dimension of sustainable development: Defining urban social sustainability. *Sustainable development, 19*(5), 289-300.

Department of Homeland Security. (2022). *Homeland Infrastructure Foundation-Level Data (HIFLD)*. Retrieved March, 3 from https://hifld-geoplatform.hub.arcgis.com/

Didier, M., Broccardo, M., Esposito, S., & Stojadinovic, B. (2018, 2018/04/03). A compositional demand/supply framework to quantify the resilience of civil infrastructure systems (Re-CoDeS). *Sustainable and Resilient Infrastructure, 3*(2), 86-102. https://doi.org/10.1080/23789689.2017.1364560

Didier, M., Esposito, S., & Stojadinovic, B. (2017). Probabilistic seismic resilience analysis of an electric power supply system using the Re-CoDeS resilience quantification framework. 12th International Conference on Structural Safety & Reliability, ICOSSAR,

Didier, M., Sun, L., Ghosh, S., & Stojadinovic, B. (2015). Post-earthquake recovery of a community and its electrical power supply system. Proceedings of the 5th ECCOMAS Thematic Conference on Computational Methods in Structural Dynamics and Earthquake Engineering (COMPDYN2015),

Dintwa, K. F., Letamo, G., & Navaneetham, K. (2019). Quantifying social vulnerability to natural hazards in Botswana: an application of cutter model. *International Journal of Disaster Risk Reduction, 37*, 101189.

Docekala, G., Tanga, W., Eastina, M., Lana, Y., & Delmelle, E. (2020). *Space-time variation in shelter accessibility in Eastern North Carolina, following Hurricane Florence (2018)* AutoCarto 2020, the

23rd International Research Symposium on Cartography and GIScience, Redlands, California. https://cartogis.org/autocarto/autocarto-2020/program/presentations/

Dong, S., Esmalian, A., Farahmand, H., & Mostafavi, A. (2020, 2020/03/01/). An integrated physical-social analysis of disrupted access to critical facilities and community service-loss tolerance in urban flooding. *Computers, Environment and Urban Systems, 80*, 101443. https://doi.org/https://doi.org/10.1016/j.compenvurbsys.2019.101443

Dong, S., Yu, T., Farahmand, H., & Mostafavi, A. (2020, 2020/11/01/). Probabilistic modeling of cascading failure risk in interdependent channel and road networks in urban flooding. *Sustainable Cities and Society, 62*, 102398. https://doi.org/https://doi.org/10.1016/j.scs.2020.102398

Drakes, O., Tate, E., Rainey, J., & Brody, S. (2021, 2021/02/01/). Social vulnerability and short-term disaster assistance in the United States. *International Journal of Disaster Risk Reduction, 53*, 102010. https://doi.org/https://doi.org/10.1016/j.ijdrr.2020.102010

Dueñas-Osorio, L., Craig, J. I., Goodno, B. J., & Bostrom, A. (2007). Interdependent Response of Networked Systems. *Journal of Infrastructure Systems, 13*(3), 185-194. https://doi.org/doi:10.1061/(ASCE)1076-0342(2007)13:3(185)

Dunning, M., & Durden, S. (2011). *Social Vulnerability Analysis Methods for Corps Planning*. https://www.iwr.usace.army.mil/Portals/70/docs/iwrreports/2011-R-07.pdf

Durga Rao, K., Gopika, V., Sanyasi Rao, V. V. S., Kushwaha, H. S., Verma, A. K., & Srividya, A. (2009, 2009/04/01/). Dynamic fault tree analysis using Monte Carlo simulation in probabilistic safety assessment. *Reliability Engineering & System Safety, 94*(4), 872-883. https://doi.org/https://doi.org/10.1016/j.ress.2008.09.007

Dyke, S. J., Bernal, D., Beck, J., & Ventura, C. (2003). Experimental phase II of the structural health monitoring benchmark problem. Proceedings of the 16th ASCE engineering mechanics conference,

Elhaddad, W., McKenna, F., Rynge, M., Lowe, J., Wang, C., & Zsarnoczay, A. (2019). *NHERI-SimCenter/WorkflowRegionalEarthquake: RWHALE (Version v1. 1.0)*. Zenodo.

Ellingwood, B. R., Cutler, H., Gardoni, P., Peacock, W. G., van de Lindt, J. W., & Wang, N. (2016, 2016/11/28). The Centerville Virtual Community: a fully integrated decision model of interacting physical and social infrastructure systems. *Sustainable and Resilient Infrastructure, 1*(3-4), 95-107. https://doi.org/10.1080/23789689.2016.1255000

Ellingwood, B. R., van de Lindt, J. W., & McAllister, T. P. (2016, 2016/11/28). Developing measurement science for community resilience assessment. *Sustainable and Resilient Infrastructure, 1*(3-4), 93-94. https://doi.org/10.1080/23789689.2016.1255001

Emery, M., & Flora, C. (2006). Spiraling-up: Mapping community transformation with community capitals framework. *Community development, 37*(1), 19-35.

Enderami, S. A., Mazumder, R. K., Dumler, M., & Sutley, E. J. (2022). Virtual Testbeds for Community Resilience Analysis: State-of-the-Art Review, Consensus Study, and Recommendations. *Natural Hazards Review, 23*(4), 03122001. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000582

Enderami, S. A., Mazumder, R. K., & Sutley, E. J. (2022). *Framework for Incorporating Community Social Vulnerability in the Assessment of Hurricane-Induced Wind Risk to Residential Buildings* 14th Americas Conference on Wind Engineering, Lubbock, TX.

Enderami, S. A., & Sutley, E. (2021). *Testbed Experts Survey Report* (PRJ-3333. https://doi.org/10.17603/ds2-91jj-fh94

Enderami, S. A., & Sutley, E. (2022). *Social Vulnerability Analysis in Virtual Community Resilience Testbeds*. DesignSafe-CI. Retrieved November from https://doi.org/10.17603/ds2-j95s-sp06

Enderami, S. A., Sutley, E., & Mazumder, R. K. (2022). *Onslow Community Resilience Testbed*. DesignSafe-CI. Retrieved November from https://doi.org/10.17603/ds2-8h8f-xe60

Enderami, S. A., & Sutley, E. J. (2022). Social Vulnerability Score: a Scalable Index for Representing Social Vulnerability in Virtual Community Resilience Testbeds. *Natural Hazards, PREPRINT (Version 1) available at Research Square*. https://doi.org/10.21203/rs.3.rs-2113725/v1

Enderami, S. A., Sutley, E. J., & Helgeson, J. (n.d). Conceptualizing and Measuring Accessibility to Essential Services for Community Resilience.

Enderami, S. A., Sutley, E. J., & Hofmeyer, S. L. (2021). Defining organizational functionality for evaluation of post-disaster community resilience. *Sustainable and Resilient Infrastructure*, 1-18. https://doi.org/10.1080/23789689.2021.1980300

Falcone, R., Lima, C., & Martinelli, E. (2020, 2020/03/15/). Soft computing techniques in structural and earthquake engineering: a literature review. *Engineering Structures, 207*, 110269. https://doi.org/https://doi.org/10.1016/j.engstruct.2020.110269

Fan, C., Jiang, X., & Mostafavi, A. (2020, 2020/08/10). A network percolation-based contagion model of flood propagation and recession in urban road networks. *Scientific Reports, 10*(1), 13481. https://doi.org/10.1038/s41598-020-70524-x

Farmani, R., Walters, G. A., & Savic, D. A. (2005). Trade-off between Total Cost and Reliability for Anytown Water Distribution Network. *Journal of Water Resources Planning and Management, 131*(3), 161-171. https://doi.org/doi:10.1061/(ASCE)0733-9496(2005)131:3(161)

Federal Emergency Management Agency (FEMA). (2003). *Multi-hazard loss estimation methodology: Earthquake model Hazus-MH 2.1 technical manual*. Federal Emergency Management Agency Washington DC.

Federal Emergency Management Agency (FEMA). (2012). *Multi-hazard loss estimation methodology: Hurricane model Hazus-MH 2.1 technical manual*. Federal Emergency Management Agency Washington DC. Retrieved 2021 from

Federal Emergency Management Agency (FEMA). (2022a). *FEMA Flood Map Service Center*. Retrieved August from https://msc.fema.gov/portal/home

Federal Emergency Management Agency (FEMA). (2022b). *The National Flood Insurance Program*. Retrieved August from https://www.fema.gov/national-food-insurance-program

Fereshtehnejad, E., Gidaris, I., Rosenheim, N., Tomiczek, T., Padgett, J. E., Cox, D. T., Zandt, S. V., & Peacock, W. G. (2021). Probabilistic Risk Assessment of Coupled Natural-Physical-Social Systems: Cascading Impact of Hurricane-Induced Damages to Civil Infrastructure in Galveston, Texas. *Natural Hazards Review, 22*(3), 04021013. https://doi.org/doi:10.1061/(ASCE)NH.1527-6996.0000459

Finch, C., Emrich, C. T., & Cutter, S. L. (2010, 2010/03/01). Disaster disparities and differential recovery in New Orleans. *Population and Environment, 31*(4), 179-202. https://doi.org/10.1007/s11111-009-0099-8

Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., & Lewis, B. (2011). A social vulnerability index for disaster management. *Journal of homeland security and emergency management, 8*(1).

Flora, C. B. (2015). Community, climate change, and sustainable intensification: why gender is important. In *Sustainable Intensification to Advance Food Security and Enhance Climate Resilience in Africa* (pp. 515-531). Springer, Cham. https://doi.org/https://doi.org/10.1007/978-3-319-09360-4_27

Flora, C. B., Emery, M., Fey, S., & Bregendahl, C. (2005). Community capitals: A tool for evaluating strategic interventions and projects. *Ames, IA: North Central Regional Center for Rural Development. Retrieved on February, 27*, 2007.

Fothergill, A., & Peek, L. A. (2004, 2004/05/01). Poverty and Disasters in the United States: A Review of Recent Sociological Findings. *Natural Hazards, 32*(1), 89-110. https://doi.org/10.1023/B:NHAZ.0000026792.76181.d9

Friese, S., Lin, V.-K., Forry, N., & Tout, K. (2017). *Defining and Measuring Access to High-Quality Early Care and Education (ECE): A Guidebook for Policymakers and Researchers. Research Brief. OPRE #2017-08*. Office of Planning, Research and Evaluation, Administration for Children and Families, U.S. Department of Health and Human Services. https://www.acf.hhs.gov/opre/report/defining-and-measuring-access-high-quality-early-care-and-education-ece-guidebook

Gall, M. (2007). *Indices of Social Vulnerability to Natural Hazards: A Comparative Evaluatio* University of South Carolina]. Columbia, South Carolina.

Gardoni, P., van de Lindt, J., Ellingwood, B., McAllister, T., Lee, J. S., Cutler, H., Peacock, W., & Cox, D. (2018). The interdependent networked community resilience modeling environment (IN-CORE). Proceedings of the 16th European Conference on Earthquake Engineering, Thessaloniki, Greece,

González, F. I., Geist, E. L., Jaffe, B., Kânoğlu, U., Mofjeld, H., Synolakis, C. E., Titov, V. V., Arcas, D., Bellomo, D., Carlton, D., Horning, T., Johnson, J., Newman, J., Parsons, T., Peters, R., Peterson, C., Priest, G., Venturato, A., Weber, J., Wong, F., & Yalciner, A. (2009). Probabilistic tsunami hazard assessment at Seaside, Oregon, for near- and far-field seismic sources. *Journal of Geophysical Research: Oceans, 114*(C11). https://doi.org/https://doi.org/10.1029/2008JC005132

Great Schools Partnership, Education Writers Association, & Nellie Mae Education Foundationcite. (2014). *Glossary of Education Reform*. Retrieved October from https://www.edglossary.org/

Gregory G. Deierlein, A. Z., eds. (2021). *State of the Art in Computational Simulation for Natural Hazards Engineering (Version v2)* (2021-01). Zenodo.

Guidotti, R., Chmielewski, H., Unnikrishnan, V., Gardoni, P., McAllister, T., & van de Lindt, J. (2016). Modeling the resilience of critical infrastructure: The role of network dependencies. *Sustainable and Resilient Infrastructure, 1*(3-4), 153-168.

Guillard-Gonçalves, C., & Zêzere, J. L. (2018). Combining Social Vulnerability and Physical Vulnerability to Analyse Landslide Risk at the Municipal Scale. *Geosciences, 8*(8), 294. https://www.mdpi.com/2076-3263/8/8/294

Guo, Y., & Lindt, J. v. d. (2019). Simulation of Hurricane Wind Fields for Community Resilience Applications: A Data-Driven Approach Using Integrated Asymmetric Holland Models for Inner and Outer Core Regions. *Journal of Structural Engineering, 145*(9), 04019089. https://doi.org/doi:10.1061/(ASCE)ST.1943-541X.0002366

Hamideh, S., & Rongerude, J. (2018, 2018/09/01). Social vulnerability and participation in disaster recovery decisions: public housing in Galveston after Hurricane Ike. *Natural Hazards, 93*(3), 1629-1648. https://doi.org/10.1007/s11069-018-3371-3

Haselton, C. B., R.O. Hamburger, and J.W. Baker. (2018). Resilient Design and Risk Assessment using FEMA P-58 Analysis. *Structure Magazine*, *March 2018*, 12-15.

He, X., & Cha, E. J. (2018, 2018/09/01/). Modeling the damage and recovery of interdependent critical infrastructure systems from natural hazards. *Reliability Engineering & System Safety, 177*, 162-175. https://doi.org/https://doi.org/10.1016/j.ress.2018.04.029

Helgeson, J., Hamidah, S., & Sutley, E. (2021). The Lumberton, North Carolina Flood of 2016, Wave 3: A Community Impact and Recovery-Focused Technical Investigation Following Successive Flood Events. *NIST Special Publication, 1230*(3). https://doi.org/https://doi.org/10.6028/NIST.SP.1230-3

Hemmati, M., Ellingwood, B. R., & Mahmoud, H. N. (2020). The role of urban growth in resilience of communities under flood risk. *Earth's Future, 8*(3), e2019EF001382.

Hendricks, M. D., & Van Zandt, S. (2021). Unequal Protection Revisited: Planning for Environmental Justice, Hazard Vulnerability, and Critical Infrastructure in Communities of Color. *Environmental Justice, 14*(2), 87-97. https://doi.org/10.1089/env.2020.0054

Herstein, L., & Filion, Y. (2010). Life-Cycle Analysis of Water Main Materials in the Optimal Design of the "Anytown" Water Network. Water Distribution Systems Analysis 2010, Tucson, Arizona.

Holland, G. J. (1980, 01 Aug. 1980). An Analytic Model of the Wind and Pressure Profiles in Hurricanes. *Monthly Weather Review, 108*(8), 1212-1218. https://doi.org/10.1175/1520-0493(1980)108<1212:Aamotw>2.0.Co;2

Hwang, H., Jernigan, J. B., & Lin, Y.-W. (2000). Evaluation of Seismic Damage to Memphis Bridges and Highway Systems. *Journal of Bridge Engineering, 5*(4), 322-330. https://doi.org/doi:10.1061/(ASCE)1084-0702(2000)5:4(322)

Infogroup, I. (2016). *ReferenceUSA database*. https://www.data-axle.com/what-we-do/reference-solutions/

Islam, M. S., Sadiq, R., Rodriguez, M. J., Francisque, A., Najjaran, H., & Hoorfar, M. (2011, 2011/12/01). Leakage detection and location in water distribution systems using a fuzzy-based methodology. *Urban Water Journal, 8*(6), 351-365. https://doi.org/10.1080/1573062X.2011.617829

Islam, M. S., Sadiq, R., Rodriguez, M. J., Najjaran, H., & Hoorfar, M. (2014). Reliability Assessment for Water Supply Systems under Uncertainties. *Journal of Water Resources Planning and Management, 140*(4), 468-479. https://doi.org/doi:10.1061/(ASCE)WR.1943-5452.0000349

Islam, T., Merrell, W., & Seitz, W. (2010). Galveston Futures: Developing a disaster resilient community. *Journal of Geography and Regional Planning, 3*(1), 001-007.

Jacques, C. C., McIntosh, J., Giovinazzi, S., Kirsch, T. D., Wilson, T., & Mitrani-Reiser, J. (2014). Resilience of the Canterbury Hospital System to the 2011 Christchurch Earthquake. *Earthquake Spectra, 30*(1), 533-554. https://doi.org/10.1193/032013eqs074m

Jichao, L., Qingxue, S., Guanjie, H., Quanwang, L., & Tao, W. (2021, 2021/04/01). Functionality analysis of an urban water supply network after strong earthquakes. *Earthquake Engineering and Engineering Vibration, 20*(2), 291-302. https://doi.org/10.1007/s11803-021-2020-0

Johansen, C., & Tien, I. (2018). Probabilistic multi-scale modeling of interdependencies between critical infrastructure systems for resilience. *Sustainable and Resilient Infrastructure, 3*(1), 1-15.

Johnston, G. (2008). Developing Mesopolis: A 'virtual city'for research in water distribution systems and interdependent infrastructures. *Useful for Exploration Diversity*, 1-8.

Kamel, N. M. O., & Loukaitou-Sideris, A. (2004). Residential Assistance and Recovery Following the Northridge Earthquake. *Urban Studies, 41*(3), 533-562. http://www.jstor.org/stable/43197095

Kameshwar, S., Cox, D. T., Barbosa, A. R., Farokhnia, K., Park, H., Alam, M. S., & van de Lindt, J. W. (2019, 2019/11/01/). Probabilistic decision-support framework for community resilience: Incorporating multi-hazards, infrastructure interdependencies, and resilience goals in a Bayesian network. *Reliability Engineering & System Safety, 191*, 106568. https://doi.org/https://doi.org/10.1016/j.ress.2019.106568

Kentucky Water Resources Research Institute. (2013). *Water Distribution System Research Database*. Retrieved March from http://www.uky.edu/WDST/database.html

Khan, A. A., & Bhardwaj, S. M. (1994). Access to Health Care:A Conceptual Framework and its Relevance to Health Care Planning. *Evaluation & the Health Professions, 17*(1), 60-76. https://doi.org/10.1177/016327879401700104

Kim, J. H., Chung, G., & Yoo, D. G. (2011). Calibration of C-Town Network Using Harmony Search Algorithm. In *Water Distribution Systems Analysis 2010* (pp. 1610-1628). https://doi.org/doi:10.1061/41203(425)143

Kiremidjian, A., Moore, J., Fan, Y. Y., Yazlali, O., Basoz, N., & Williams, M. (2007, 2007/05/21). Seismic Risk Assessment of Transportation Network Systems. *Journal of Earthquake Engineering, 11*(3), 371-382. https://doi.org/10.1080/13632460701285277

Koliou, M., van de Lindt, J. W., McAllister, T. P., Ellingwood, B. R., Dillard, M., & Cutler, H. (2018). State of the research in community resilience: progress and challenges. *Sustainable and Resilient Infrastructure*. https://doi.org/10.1080/23789689.2017.1418547

Krawinkler, H., & Miranda, E. (2004). Performance-Based Earthquake Engineering. In Y. Bozorgnia & V. V. Bertero (Eds.), *Earthquake engineering: from engineering seismology to performance-based engineering* (pp. 560-636). CRC press.

Krinitzsky, E. L. (1998). Deterministic versus Probabilistic Seismic Hazard Analysis for Engineering. First US-Japan Workshop on Advanced Research on Earthquake Engineering for Dams. 12-14 November 1996,

Kuligowski, E. D., Lombardo, F. T., Phan, L. T., Levitan, M. L., & Jorgensen, D. P. (2014). *Final report, National Institute of Standards and Technology (NIST) technical investigation of the May 22, 2011, tornado in Joplin, Missouri*.

Laska, S., & Morrow, B. H. (2006). Social vulnerabilities and Hurricane Katrina: an unnatural disaster in New Orleans. *Marine technology society journal, 40*(4).

Lavelle, F. M., Goodhue, C., & Lyons, D. (2020). *Critical path method assessment of community recovery* (NIST GCR 20-023).

Lee, A. V., Vargo, J., & Seville, E. (2013). Developing a Tool to Measure and Compare Organizations’ Resilience. *Natural Hazards Review, 14*(1), 29-41. https://doi.org/doi:10.1061/(ASCE)NH.1527-6996.0000075

Li, Q., Dong, S., & Mostafavi, A. (2019). Modeling of inter-organizational coordination dynamics in resilience planning of infrastructure systems: A multilayer network simulation framework. *PLOS ONE, 14*(11), e0224522. https://doi.org/10.1371/journal.pone.0224522

Lin, P., & Wang, N. (2016, 2016/11/28). Building portfolio fragility functions to support scalable community resilience assessment. *Sustainable and Resilient Infrastructure, 1*(3-4), 108-122. https://doi.org/10.1080/23789689.2016.1254997

Lin, P., & Wang, N. (2017a, 2017/11/01/). Stochastic post-disaster functionality recovery of community building portfolios I: Modeling. *Structural Safety, 69*, 96-105. https://doi.org/https://doi.org/10.1016/j.strusafe.2017.05.002

Lin, P., & Wang, N. (2017b, 2017/11/01/). Stochastic post-disaster functionality recovery of community building portfolios II: Application. *Structural Safety, 69*, 106-117. https://doi.org/https://doi.org/10.1016/j.strusafe.2017.05.004

Lin, S.-Y., & El-Tawil, S. (2020). Time-dependent resilience assessment of seismic damage and restoration of interdependent lifeline systems. *Journal of Infrastructure Systems, 26*(1), 04019040.

Little, R., Roberts, M., & Wallace, W. (2021). Observations on the Effects of a Global Pandemic on the Time to Recovery (TTR) from Natural Disasters. Proceedings of the 54th Hawaii International Conference on System Sciences, Little, R. G., Loggins, R. A., Mitchell, J. E., Ni, N., Sharkey, T. C., & Wallace, W. A. (2020). CLARC: An Artificial Community for Modeling the Effects of Extreme Hazard Events on Interdependent Civil and Social Infrastructure Systems. *Journal of Infrastructure Systems, 26*(1), 04019041. https://doi.org/doi:10.1061/(ASCE)IS.1943-555X.0000519

Liu, D., & Li, Y. (2015). Social vulnerability of rural households to flood hazards in western mountainous regions of Henan province, China. *Nat. Hazards Earth Syst. Sci. Discuss, 3*, 6727-6744.

Logan, T. M., & Guikema, S. D. (2020). Reframing Resilience: Equitable Access to Essential Services. *Risk Analysis, 40*(8), 1538-1553. https://doi.org/https://doi.org/10.1111/risa.13492

Logan, T. M., Williams, T., Nisbet, A., Liberman, K., Zuo, C., & Guikema, S. (2019). Evaluating urban accessibility: leveraging open-source data and analytics to overcome existing limitations. *Environment and Planning B: Urban Analytics and City Science, 46*(5), 897-913.

Loggins, R., Little, R. G., Mitchell, J., Sharkey, T., & Wallace, W. A. (2019). CRISIS: Modeling the Restoration of Interdependent Civil and Social Infrastructure Systems Following an Extreme Event. *Natural Hazards Review, 20*(3), 04019004. https://doi.org/doi:10.1061/(ASCE)NH.1527-6996.0000326

Loggins, R. A., & Wallace, W. A. (2015). Rapid Assessment of Hurricane Damage and Disruption to Interdependent Civil Infrastructure Systems. *Journal of Infrastructure Systems, 21*(4), 04015005. https://doi.org/doi:10.1061/(ASCE)IS.1943-555X.0000249

Loreti, S., Ser-Giacomi, E., Zischg, A., Keiler, M., & Barthelemy, M. (2022, 2022/01/28). Local impacts on road networks and access to critical locations during extreme floods. *Scientific Reports, 12*(1), 1552. https://doi.org/10.1038/s41598-022-04927-3

Lyles, W. (2013). Social Network Analysis of Incorporation of Land Use Approaches in Hazard Mitigation Planning: Four Local Case Studies.

Lyles, W. (2015, 2015/11/02). Using social network analysis to examine planner involvement in environmentally oriented planning processes led by non-planning professions. *Journal of Environmental Planning and Management, 58*(11), 1961-1987. https://doi.org/10.1080/09640568.2014.973478

Madakam, S., Ramaswamy, R., & Tripathi, S. (2015). Internet of Things (IoT): A Literature Review. *Journal of Computer and Communications, Vol.03No.05*, 10, Article 56616. https://doi.org/10.4236/jcc.2015.35021

Mahmoud, H., & Chulahwat, A. (2018). Spatial and Temporal Quantification of Community Resilience: Gotham City under Attack. *Computer-aided Civil and Infrastructure Engineering, 33*(5), 353-372. https://doi.org/https://doi.org/10.1111/mice.12318

Mahmoud, H., & Chulahwat, A. (2019). A New Hazard-Agnostic Finite Element Model for Community Resilience Assessment. https://doi.org/https://doi.org/10.22725/ICASP13.157

Marras, S., & Mandli, K. T. (2021). Modeling and Simulation of Tsunami Impact: A Short Review of Recent Advances and Future Challenges. *Geosciences, 11*(1), 5. https://www.mdpi.com/2076-3263/11/1/5

Masoomi, H., Lindt, J. W. v. d., & Peek, L. (2018). Quantifying Socioeconomic Impact of a Tornado by Estimating Population Outmigration as a Resilience Metric at the Community Level. *Journal of Structural Engineering, 144*(5), 04018034. https://doi.org/doi:10.1061/(ASCE)ST.1943-541X.0002019

Masoomi, H., & van de Lindt, J. W. (2017, 2017). Restoration and functionality assessment of a community subjected to tornado hazard. *Structure and Infrastructure Engineering, 14*(3), 275-291. https://doi.org/10.1080/15732479.2017.1354030

Mattos, D. (2015). Community Capitals Framework As a measure of community development.

Mazumder, R., Enderami, S. A., & Sutley, E. (n.d). A Novel Framework to Study Community-Level Social and Physical Impacts of Hurricane-induced Winds Through Synthetic Scenario Analysis. *Frontiers in Built Environment, forthcoming*.

Mazumder, R. K., Dumler, M., Enderami, S. A., & Sutley, E. J. (2021). *A Scenario-based Hurricane Analysis Framework for Community-level Building Damage Estimation* 6th American Association for Wind Engineering Workshop, Clemson University, Clemson, SC, USA.

Mazumder, R. K., Enderami, S. A., & Sutley, E. J. (2022). *A Scenario-based Approach for Hurricane-Induced Wind Risk Analysis in Urban Areas* 14th Americas Conference on Wind Engineering, Lubbock, TX.

Mazumder, R. K., Salman, A. M., & Li, Y. (2021). Post-disaster sequential recovery planning for water distribution systems using topological and hydraulic metrics. *Structure and Infrastructure Engineering*, 1-16. https://doi.org/10.1080/15732479.2020.1864415

Mazumder, R. K., Salman, A. M., Li, Y., & Yu, X. (2020). Seismic Functionality and Resilience Analysis of Water Distribution Systems. *Journal of Pipeline Systems Engineering and Practice, 11*(1), 04019045. https://doi.org/doi:10.1061/(ASCE)PS.1949-1204.0000418

McAllister, T. (2016). Research Needs for Developing a Risk-Informed Methodology for Community Resilience. *Journal of Structural Engineering, 142*(8), C4015008. https://doi.org/doi:10.1061/(ASCE)ST.1943-541X.0001379

McArdle, A. (2014). Storm surges, disaster planning, and vulnerable populations at the urban periphery: Imagining a resilient New York after superstorm Sandy. *Idaho L. Rev., 50*, 19.

McDaniels, T., Chang, S., Cole, D., Mikawoz, J., & Longstaff, H. (2008). Fostering resilience to extreme events within infrastructure systems: Characterizing decision contexts for mitigation and adaptation. *Global Environmental Change, 18*(2), 310-318.

McKenna, F., Gavrilovic, S., Zsarnoczay, A., Zhong, K., & Elhaddad, W. (2021). *NHERI-SimCenter/R2DTool: Version 1.1.0 (Version v1.1.0)*. Zenodo.

McKenna, F., Gavrilovic, S., Zsarnoczay, A., Zhong, K., Elhaddad, W., & Arduino, P. (2022). *NHERI-SimCenter/R2DTool: Version 2.1.0 (Version v2.1.0)*. Zenodo.

Microsoft. (2020). *Microsoft Building Footprint Database for the United States*. https://www.microsoft.com/en-us/maps/building-footprints

Mieler, M. W., & Mitrani-Reiser, J. (2018). Review of the State of the Art in Assessing Earthquake-Induced Loss of Functionality in Buildings. *Journal of Structural Engineering, 144*(3), 04017218. https://doi.org/doi:10.1061/(ASCE)ST.1943-541X.0001959

Mileti, D. (1999). *Disasters by Design: A Reassessment of Natural Hazards in the United States*. The National Academies Press. https://doi.org/doi:10.17226/5782

Monitz, G. I. (2011). *Using vulnerability and planning data to measure resilience in coastal North Carolina*. East Carolina University.

Montz, B. E., & Evans, T. A. (2001). Gis and Social Vulnerability Analysis. In E. Gruntfest & J. Handmer (Eds.), *Coping With Flash Floods* (pp. 37-48). Springer Netherlands. https://doi.org/10.1007/978-94-010-0918-8_5

Mostafizi, A., Wang, H., Cox, D., Cramer, L. A., & Dong, S. (2017, 2017/09/01). Agent-based tsunami evacuation modeling of unplanned network disruptions for evidence-driven resource allocation and retrofitting strategies. *Natural Hazards, 88*(3), 1347-1372. https://doi.org/10.1007/s11069-017-2927-y

Mutch, C. (2014, 2014/01/02). The role of schools in disaster preparedness, response and recovery: what can we learn from the literature? *Pastoral Care in Education, 32*(1), 5-22. https://doi.org/10.1080/02643944.2014.880123

Myers, C. A., Slack, T., & Singelmann, J. (2008, 2008/07/01). Social vulnerability and migration in the wake of disaster: the case of Hurricanes Katrina and Rita. *Population and Environment, 29*(6), 271-291. https://doi.org/10.1007/s11111-008-0072-y

Nan, C., & Eusgeld, I. (2011). Adopting HLA standard for interdependency study. *Reliability Engineering & System Safety, 96*(1), 149-159.

National Academies of Sciences Engineering and Medicine. (2019). *Building and Measuring Community Resilience: Actions for Communities and the Gulf Research Program*. National Academies Press. https://doi.org/https://doi.org/10.17226/25383

National Center for Education Statistics (NCES). (2016). *School Attendance Boundary Survey (SABS)*. Institute of Education Science. Retrieved October from https://nces.ed.gov/programs/edge/SABS

National Institute of Standards and Technology (NIST). (2016). *Community resilience planning guide for buildings and infrastructure systems* (NIST Special Publication 1190). N. I. o. S. a. Technology. http://dx.doi.org/10.6028/NIST.SP.1190v1

National Oceanic and Atmospheric Administration (NOAA). (2020). *Historical Hurricane Tracks*. Retrieved December from https://coast.noaa.gov/hurricanes/#map=4/32/-80

National Research Council. (2006). *Facing Hazards and Disasters: Understanding Human Dimensions*. The National Academies Press. https://doi.org/doi:10.17226/11671

Nevill, J. B., & Lombardo, F. T. (2020). Structural Functionality Scale for Light-Framed Wood Buildings with Indicators for Windstorm Damage. *Journal of Structural Engineering, 146*(4), 04020033. https://doi.org/doi:10.1061/(ASCE)ST.1943-541X.0002551

NewJerseyOfficeofGIS. (2021). *Parcels and MOD-IV of Atlantic County, NJ*. https://njogis-newjersey.opendata.arcgis.com/documents/newjersey::parcels-and-mod-iv-of-atlantic-county-nj-shp-download/about

Nikolopoulos, D., Moraitis, G., Bouziotas, D., Lykou, A., Karavokiros, G., & Makropoulos, C. (2020). Cyber-Physical Stress-Testing Platform for Water Distribution Networks. *Journal of Environmental Engineering, 146*(7), 04020061. https://doi.org/doi:10.1061/(ASCE)EE.1943-7870.0001722

NJOEM. (2019). *State of New Jersey Hazard Mitigation Plan*. Retrieved December from http://ready.nj.gov/mitigation/2019-mitigation-plan.shtml

Nofal, O. M., & van de Lindt, J. W. (2020a, 2020/12/01/). High-resolution approach to quantify the impact of building-level flood risk mitigation and adaptation measures on flood losses at the community-level. *International Journal of Disaster Risk Reduction, 51*, 101903. https://doi.org/https://doi.org/10.1016/j.ijdrr.2020.101903

Nofal, O. M., & van de Lindt, J. W. (2020b). Minimal Building Flood Fragility and Loss Function Portfolio for Resilience Analysis at the Community Level. *Water, 12*(8), 2277. https://www.mdpi.com/2073-4441/12/8/2277

Nofal, O. M., & van de Lindt, J. W. (2020c). Probabilistic Flood Loss Assessment at the Community Scale: Case Study of 2016 Flooding in Lumberton, North Carolina. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 6*(2), 05020001. https://doi.org/doi:10.1061/AJRUA6.0001060

Nofal, O. M., & van de Lindt, J. W. (2020d). Understanding flood risk in the context of community resilience modeling for the built environment: research needs and trends. *Sustainable and Resilient Infrastructure*, 1-17. https://doi.org/10.1080/23789689.2020.1722546

Nofal, O. M., & van de Lindt, J. W. (2021). Fragility-Based Flood Risk Modeling to Quantify the Effect of Policy Change on Losses at the Community Level. *Civil Engineering Research Journal, 11*(5). https://doi.org/DOI: 10.19080/CERJ.2021.11.555822

Nofal, O. M., & van de Lindt, J. W. (2021, 2021/08/01/). High-resolution flood risk approach to quantify the impact of policy change on flood losses at community-level. *International Journal of Disaster Risk Reduction, 62*, 102429. https://doi.org/https://doi.org/10.1016/j.ijdrr.2021.102429

Nofal, O. M., van de Lindt, J. W., & Do, T. Q. (2020, 2020/10/01/). Multi-variate and single-variable flood fragility and loss approaches for buildings. *Reliability Engineering & System Safety, 202*, 106971. https://doi.org/https://doi.org/10.1016/j.ress.2020.106971

Nofal, O. M., van de Lindt, J. W., Do, T. Q., Yan, G., Hamideh, S., Cox, D. T., & Dietrich, J. C. (2021). Methodology for Regional Multihazard Hurricane Damage and Risk Assessment. *Journal of Structural Engineering, 147*(11), 04021185.

Nofal, O. M., van de Lindt, J. W., Yan, G., Hamideh, S., & Dietrich, C. (2021). MULTI-HAZARD HURRICANE VULNERABILITY MODEL TO ENABLE RESILIENCE-INFORMED DECISION. International Structural Engineering and Construction, Cairo, Egypt.

Noori, A. Z., Marasco, S., Kammouh, O., Domaneschi, M., & Cimellaro, G. (2017). Smart cities to improve resilience of communities. 8th International Conference on Structural Health Monitoring of Intelligent Infrastructure,

Nozhati, S., Ellingwood, B., Mahmoud, H., & van de Lindt, J. (2018). Identifying and analyzing interdependent critical infrastructure in post-earthquake urban reconstruction. 11th US National Conference on Earthquake Engineering: Integrating Science Engineering and Policy,

Nozhati, S., Ellingwood, B. R., & Chong, E. K. (2020). Stochastic optimal control methodologies in risk-informed community resilience planning. *Structural Safety, 84*, 101920.

Nozhati, S., Ellingwood, B. R., & Mahmoud, H. (2019). Understanding Community Resilience from a PRA Perspective Using Binary Decision Diagrams. *Risk Analysis, 39*(10), 2127-2142. https://doi.org/https://doi.org/10.1111/risa.13321

Nozhati, S., Ellingwood, B. R., Mahmoud, H., Sarkale, Y., Chong, E. K., & Rosenheim, N. (2018). An approximate dynamic programming approach to community recovery management. *arXiv preprint arXiv:1806.08492*.

Nozhati, S., Rosenheim, N., Ellingwood, B. R., Mahmoud, H., & Perez, M. (2019, 2019/08/03). Probabilistic framework for evaluating food security of households in the aftermath of a disaster. *Structure and Infrastructure Engineering, 15*(8), 1060-1074. https://doi.org/10.1080/15732479.2019.1584824

Nozhati, S., Sarkale, Y., Chong, E. K., & Ellingwood, B. R. (2020). Optimal stochastic dynamic scheduling for managing community recovery from natural hazards. *Reliability Engineering & System Safety, 193*, 106627.

Nozhati, S., Sarkale, Y., Ellingwood, B., K.P. Chong, E., & Mahmoud, H. (2019, 2019/01/01/). Near-optimal planning using approximate dynamic programming to enhance post-hazard community resilience management. *Reliability Engineering & System Safety, 181*, 116-126. https://doi.org/https://doi.org/10.1016/j.ress.2018.09.011

Nozhati, S., Sarkale, Y., Ellingwood, B. R., Chong, E. K., & Mahmoud, H. (2018). A modified approximate dynamic programming algorithm for community-level food security following disasters. *arXiv preprint arXiv:1804.00250*.

OHara, J., & Wachtel, J. (1995). *Validating cognitive support for operators of complex human-machine systems*.

Oliver-Smith, A. (2009). *Nature, society, and population displacement: towards understanding of environmental migration and social vulnerability*. UNU-EHS.

OpenStreetMap contributors. (2015). *Planet dump*. Retrieved April from https://planet.openstreetmap.org

Osalam, K. A., Veronica; Archbold, Jorge; Arteta, Carlos; Fischer, Erica; Gunay, Selim; Hakhamaneshi, Manouchehr; Hassan, Wael; Micheli, Laura; Muin, Sifat; Pajaro Miranda, Cesar; Pretell Ductram, Anthony Renmin; Peng, Han; Robertson, Ian; Roueche, David; Ziotopoulou, Katerina. (2019). *StEER - M6.4 and M7.1 Ridgecrest, CA Earthquakes on July 4-5, 2019: Preliminary Virtual Reconnaissance Report (PVRR).* DesignSafe-CI.

Ostfeld, A., Salomons, E., Ormsbee, L., Uber, J. G., Bros, C. M., Kalungi, P., Burd, R., Zazula-Coetzee, B., Belrain, T., Kang, D., Lansey, K., Shen, H., McBean, E., Wu, Z. Y., Walski, T., Alvisi, S., Franchini, M., Johnson, J. P., Ghimire, S. R., Barkdoll, B. D., Koppel, T., Vassiljev, A., Kim, J. H., Chung, G., Yoo, D. G., Diao, K., Zhou, Y., Li, J., Liu, Z., Chang, K., Gao, J., Qu, S., Yuan, Y., Prasad, T. D., Laucelli, D., Lyroudia, L. S. V., Kapelan, Z., Savic, D., Berardi, L., Barbaro, G., Giustolisi, O., Asadzadeh, M., Tolson, B. A., & McKillop, R. (2012). Battle of the Water Calibration Networks. *Journal of Water Resources Planning and Management, 138*(5), 523-532. https://doi.org/doi:10.1061/(ASCE)WR.1943-5452.0000191

Ouyang, M. (2014, 2014/01/01/). Review on modeling and simulation of interdependent critical infrastructure systems. *Reliability Engineering & System Safety, 121*, 43-60. https://doi.org/https://doi.org/10.1016/j.ress.2013.06.040

Ouyang, M., & Duenas-Osorio, L. (2012). Time-dependent resilience assessment and improvement of urban infrastructure systems. *Chaos: An Interdisciplinary Journal of Nonlinear Science, 22*(3), 033122.

Ouyang, M., & Duenas-Osorio, L. (2014). Multi-dimensional hurricane resilience assessment of electric power systems. *Structural Safety, 48*, 15-24.

Ouyang, M., & Dueñas-Osorio, L. (2011). An approach to design interface topologies across interdependent urban infrastructure systems. *Reliability Engineering & System Safety, 96*(11), 1462-1473.

Ouyang, M., Dueñas-Osorio, L., & Min, X. (2012). A three-stage resilience analysis framework for urban infrastructure systems. *Structural Safety, 36*, 23-31.

Ouyang, M., & Wang, Z. (2015). Resilience assessment of interdependent infrastructure systems: With a focus on joint restoration modeling and analysis. *Reliability Engineering & System Safety, 141*, 74-82.

Pamukçu, D., Zobel, C. W., & Arnette, A. (2019). A New Data-Driven Approach to Measuring Hurricane Risk. Proceedings of the 16th ISCRAM Conference,

Parisien, M.-A., Dawe, D. A., Miller, C., Stockdale, C. A., & Armitage, O. B. (2019). Applications of simulation-based burn probability modelling: a review. *International Journal of Wildland Fire, 28*(12), 913-926. https://doi.org/https://doi.org/10.1071/WF19069

Park, H., Alam, M. S., Cox, D. T., Barbosa, A. R., & van de Lindt, J. W. (2019, 2019/04/01/). Probabilistic seismic and tsunami damage analysis (PSTDA) of the Cascadia Subduction Zone applied to Seaside, Oregon. *International Journal of Disaster Risk Reduction, 35*, 101076. https://doi.org/https://doi.org/10.1016/j.ijdrr.2019.101076

Park, H., & Cox, D. T. (2016, 2016/11/01/). Probabilistic assessment of near-field tsunami hazards: Inundation depth, velocity, momentum flux, arrival time, and duration applied to Seaside, Oregon. *Coastal Engineering, 117*, 79-96. https://doi.org/https://doi.org/10.1016/j.coastaleng.2016.07.011

Park, H., Cox, D. T., & Barbosa, A. R. (2017, 2017/04/01/). Comparison of inundation depth and momentum flux based fragilities for probabilistic tsunami damage assessment and uncertainty analysis. *Coastal Engineering, 122*, 10-26. https://doi.org/https://doi.org/10.1016/j.coastaleng.2017.01.008

Paschall, K., Tout, K., & Fojut, J. (2022). *Measuring Access to Early Care and Education with the 2019 NSECE. OPRE Report #2022-234*. Office of Planning, Research and Evaluation, Administration for Children and Families, U.S. Department of Health and Human Services. https://www.acf.hhs.gov/sites/default/files/documents/opre/measuring_access_2019_nsece_oct2022.pdf

Pasquali, D. (2020). Simplified Methods for Storm Surge Forecast and Hindcast in Semi-Enclosed Basins: A Review. *Geophysics and Ocean Waves Studies*.

Patt, A., & Dessai, S. (2005, 2005/03/01/). Communicating uncertainty: lessons learned and suggestions for climate change assessment. *Comptes Rendus Geoscience, 337*(4), 425-441. https://doi.org/https://doi.org/10.1016/j.crte.2004.10.004

Peacock, W. G., Brody, S. D., & Highfield, W. (2005, 2005/10/15/). Hurricane risk perceptions among Florida's single family homeowners. *Landscape and Urban Planning, 73*(2), 120-135. https://doi.org/https://doi.org/10.1016/j.landurbplan.2004.11.004

Peek, L. (2008). Children and disasters: Understanding vulnerability, developing capacities, and promoting resilience—An introduction. *Children Youth and Environments, 18*(1), 1-29.

Penchansky, R., & Thomas, J. W. (1981). The concept of access: definition and relationship to consumer satisfaction. *Medical care*, 127-140.

Pilkington, S. F., Curtis, A., Mahmoud, H., Lindt, J. v. d., Smith, S., & Ajayakumar, J. (2020). Preliminary Documented Recovery Patterns and Observations from Video Cataloged Data of the 2011 Joplin, Missouri, Tornado. *Natural Hazards Review, 22*(1), 05020015. https://doi.org/doi:10.1061/(ASCE)NH.1527-6996.0000425

Pilkington, S. F., Mahmoud, H., van de Lindt, J. W., Koliou, M., & Smith, S. (2020). Hindcasting Loss and Evaluating Implications of Track Location for the 2011 Joplin, Missouri Tornado. *ASCE-ASME J Risk and Uncert in Engrg Sys Part B Mech Engrg, 6*(2). https://doi.org/10.1115/1.4046326

Pilkington, S. F., & Mahmoud, H. N. (2020). Interpreting the socio-technical interactions within a wind damage–artificial neural network model for community resilience. *Royal Society Open Science, 7*(11), 200922. https://doi.org/doi:10.1098/rsos.200922

Porter, K., & Ramer, K. (2012). Estimating earthquake-induced failure probability and downtime of critical facilities. *Journal of business continuity & emergency planning, 5*(4), 352-364.

Powell, M. D., Houston, S. H., Amat, L. R., & Morisseau-Leroy, N. (1998, 1998/09/01/). The HRD real-time hurricane wind analysis system. *Journal of Wind Engineering and Industrial Aerodynamics, 77-78*, 53-64. https://doi.org/https://doi.org/10.1016/S0167-6105(98)00131-7

Prabhu, S., Ehrett, C., Javanbarg, M., Brown, D. A., Lehmann, M., & Atamturktur, S. (2020). Uncertainty Quantification in Fault Tree Analysis: Estimating Business Interruption due to Seismic Hazard. *Natural Hazards Review, 21*(2), 04020015. https://doi.org/doi:10.1061/(ASCE)NH.1527-6996.0000360

Prasad, T. D., & Tanyimboh, T. T. (2008). Entropy based design of"anytown"water distribution network. In *Water Distribution Systems Analysis 2008* (pp. 1-12). https://doi.org/doi:10.1061/41024(340)39

Pregnolato, M., Ford, A., Wilkinson, S. M., & Dawson, R. J. (2017, 2017/08/01/). The impact of flooding on road transport: A depth-disruption function. *Transportation Research Part D: Transport and Environment, 55*, 67-81. https://doi.org/https://doi.org/10.1016/j.trd.2017.06.020

Presidential Policy Directive. (2013). *Critical Infrastructure Security and Resilience*. https://obamawhitehouse.archives.gov/the-press-office/2013/02/12/presidential-policy-directive-critical-infrastructure-security-and-resil

Priest, G. R., Stimely, L. L., Wood, N. J., Madin, I. P., & Watzig, R. J. (2015, 2016/01/01). Beat-the-wave evacuation mapping for tsunami hazards in Seaside, Oregon, USA. *Natural Hazards, 80*(2), 1031-1056. https://doi.org/10.1007/s11069-015-2011-4

Richardon, H. W., & Davis, B. (1998). Transport related impacts of the Northridge earthquake. *Journal of Transportation and Statistics, 1*(2), 21-36.

Risk Steering Committee. (2008). *DHS Risk Lexicon*. Department of Homeland Security. https://www.dhs.gov/xlibrary/assets/dhs_risk_lexicon.pdf

Rivera, D. Z. (2022). Disaster Colonialism: A Commentary on Disasters beyond Singular Events to Structural Violence. *International Journal of Urban and Regional Research, 46*(1), 126-135. https://doi.org/https://doi.org/10.1111/1468-2427.12950

Rivera, J. D., & Nickels, A. E. (2014). Social Capital, Community Resilience, and Faith-Based Organizations in Disaster Recovery: A Case Study of Mary Queen of Vietnam Catholic Church. *Risk, Hazards & Crisis in Public Policy, 5*(2), 178-211. https://doi.org/10.1002/rhc3.12050

Rodgers, A. J., Petersson, N. A., Pitarka, A., McCallen, D. B., Sjogreen, B., & Abrahamson, N. (2019). Broadband (0–5 Hz) fully deterministic 3D ground-motion simulations of a magnitude 7.0 Hayward fault earthquake: Comparison with empirical ground-motion models and 3D path and site effects from source normalized intensities. *Seismological Research Letters, 90*(3), 1268-1284.

Roohi, M., van de Lindt, J. W., Rosenheim, N., Hu, Y., & Cutler, H. (2021, 2021/04/03). Implication of building inventory accuracy on physical and socio-economic resilience metrics for informed decision-making in natural hazards. *Structure and Infrastructure Engineering, 17*(4), 534-554. https://doi.org/10.1080/15732479.2020.1845753

Rosenheim, N. (2020). Detailed Household and Housing Unit Characteristics: Alpha Release of Housing Unit Inventories.

Rosenheim, N., Guidotti, R., Gardoni, P., & Peacock, W. G. (2019). Integration of detailed household and housing unit characteristic data with critical infrastructure for post-hazard resilience modeling. *Sustainable and resilient infrastructure*, 1-17. https://doi.org/10.1080/23789689.2019.1681821

Rosenheim, N., Guidotti, R., Gardoni, P., & Peacock, W. G. (2021, 2021/11/02). Integration of detailed household and housing unit characteristic data with critical infrastructure for post-hazard resilience modeling. *Sustainable and Resilient Infrastructure, 6*(6), 385-401. https://doi.org/10.1080/23789689.2019.1681821

Rufat, S., Tate, E., Emrich, C. T., & Antolini, F. (2019, 2019/07/04). How Valid Are Social Vulnerability Models? *Annals of the American Association of Geographers, 109*(4), 1131-1153. https://doi.org/10.1080/24694452.2018.1535887

Rufat, S., Tate, E., Emrich, C. T., & Antolini, F. (2021, 2021/06/07). Answer to the CDC: Validation Must Precede Promotion. *Annals of the American Association of Geographers, 111*(4), em-vii-em-viii. https://doi.org/10.1080/24694452.2020.1857221

Ruijters, E., & Stoelinga, M. (2015, 2015/02/01/). Fault tree analysis: A survey of the state-of-the-art in modeling, analysis and tools. *Computer Science Review, 15-16*, 29-62. https://doi.org/https://doi.org/10.1016/j.cosrev.2015.03.001

Salehi, S., Jalili Ghazizadeh, M., & Tabesh, M. (2018, 2018/06/03). A comprehensive criteria-based multi-attribute decision-making model for rehabilitation of water distribution systems. *Structure and Infrastructure Engineering, 14*(6), 743-765. https://doi.org/10.1080/15732479.2017.1359633

Salman, A. M., & Li, Y. (2018, 2018/11/02). A probabilistic framework for multi-hazard risk mitigation for electric power transmission systems subjected to seismic and hurricane hazards. *Structure and Infrastructure Engineering, 14*(11), 1499-1519. https://doi.org/10.1080/15732479.2018.1459741

Sargent, R. G. (2010, 5-8 Dec. 2010). Verification and validation of simulation models. Proceedings of the 2010 Winter Simulation Conference,

Sarkale, Y., Nozhati, S., Chong, E. K., Ellingwood, B. R., & Mahmoud, H. (2018). Solving Markov decision processes for network-level post-hazard recovery via simulation optimization and rollout. 2018 IEEE 14th International Conference on Automation Science and Engineering (CASE),

Saurman, E. (2016). Improving access: modifying Penchansky and Thomas's theory of access. *Journal of health services research & policy, 21*(1), 36-39.

Saxon, J. (2020). Empirical Measures of Park Use in American Cities, and the Demographic Biases of Spatial Models. *Geographical Analysis, n/a*(n/a). https://doi.org/https://doi.org/10.1111/gean.12265

Schmidtlein, M. C., Shafer, J. M., Berry, M., & Cutter, S. L. (2011, 2011/01/01/). Modeled earthquake losses and social vulnerability in Charleston, South Carolina. *Applied Geography, 31*(1), 269-281. https://doi.org/https://doi.org/10.1016/j.apgeog.2010.06.001

Schneider, T., Cifelli, R., & Hmt, N. (2010). The NOAA-Hydrometeorology Testbed (HMT): A Vehicle for Collaborative Efforts on Hydrometeorological Research and Ground Validation in the GPM Era. AGU Fall Meeting Abstracts,

Schneiderbauer, S., & Ehrlich, D. (2006). Social levels and hazard (in)dependence in determining vulnerability. In J. Birkmann (Ed.), *Measuring Vulnerability to Natural Hazards: Towards Disaster Resilient Societies* (pp. 78-102). United Nations University Press.

Shafiee, M., & Zechman, E. M. (2010). An Agent-Based Modeling Approach for Simulating Contamination Events Applied to the Mesopolis Water Distribution System. In *World Environmental and Water Resources Congress 2010* (pp. 4339-4346). https://doi.org/doi:10.1061/41114(371)441

Shafiee, M. E., & Berglund, E. Z. (2014). Decision-Making Frameworks For Using Sensor Data And Evolutionary Algorithms To Flush A Contaminated Water Distribution System.

Shafiee, M. E., & Zechman, E. M. (2011). Sociotechnical simulation and evolutionary algorithm optimization for routing siren vehicles in a water distribution contamination event. Proceedings of the 13th annual conference companion on Genetic and evolutionary computation,

Shang, Q., Guo, X., Li, Q., Xu, Z., Xie, L., Liu, C., Li, J., & Wang, T. (2020, 2020/10/01). A benchmark city for seismic resilience assessment. *Earthquake Engineering and Engineering Vibration, 19*(4), 811-826. https://doi.org/10.1007/s11803-020-0597-3

Shekhar, K., & Lekshmy, S. (2013). *Banking theory and practice, 21 Edition*. Vikas Publishing House.

Shinozuka, M., Rose, A., & Eguchi, R. (1998). Engineering and socioeconomic impacts of earthquakes. *Buffalo: MCEER*.

Shuang, Q., Liu, Y., Tang, Y., Liu, J., & Shuang, K. (2017). System Reliability Evaluation in Water Distribution Networks with the Impact of Valves Experiencing Cascading Failures. *Water, 9*(6), 413. https://www.mdpi.com/2073-4441/9/6/413

Shuang, Q., Zhang, M., & Yuan, Y. (2014). Performance and reliability analysis of water distribution systems under cascading failures and the identification of crucial pipes. *PLOS ONE, 9*(2), e88445.

Soltanpour, M., Ranji, Z., Shibayama, T., & Ghader, S. (2021, 2021/08/01). Tropical Cyclones in the Arabian Sea: overview and simulation of winds and storm-induced waves. *Natural Hazards, 108*(1), 711-732. https://doi.org/10.1007/s11069-021-04702-z

Spielman, S. E., Tuccillo, J., Folch, D. C., Schweikert, A., Davies, R., Wood, N., & Tate, E. (2020, 2020/01/01). Evaluating social vulnerability indicators: criteria and their application to the Social Vulnerability Index. *Natural Hazards, 100*(1), 417-436. https://doi.org/10.1007/s11069-019-03820-z

Squires, G., & Hartman, C. (2006). *There is No Such Thing as a Natural Disaster: Race, Class, and Hurricane Katrina*. Routledge.

Subcommittee on Disaster Reduction (SDR). (2005). *Grand Challenges for Disaster Reduction*. National Science and Technology Council. https://www.sdr.gov/grandchallenges.html

Sugawara, D. (2021, 2021/03/01/). Numerical modeling of tsunami: advances and future challenges after the 2011 Tohoku earthquake and tsunami. *Earth-Science Reviews, 214*, 103498. https://doi.org/https://doi.org/10.1016/j.earscirev.2020.103498

Sutley, E., Enderami, S. A., Mazumder, R., & Dumler, M. (2021). *Testbed Experts Survey Responses* (PRJ-3333. https://doi.org/10.17603/ds2-9w9v-my55

Sutley, E. J., Dillard, M. K., & van de Lindt, J. W. (2021). Community Resilience-Focused Technical Investigation of the 2016 Lumberton, North Carolina Flood: Community Recovery One Year Later. *NIST Special Publication, 1230*(2). https://doi.org/https://doi.org/10.6028/NIST.SP.1230-2

Sutley, E. J., & Hamideh, S. (2018, 2018/07/03). An interdisciplinary system dynamics model for post-disaster housing recovery. *Sustainable and Resilient Infrastructure, 3*(3), 109-127. https://doi.org/10.1080/23789689.2017.1364561

Sutley, E. J., & Hamideh, S. (2020, 2020/08/06). Postdisaster Housing Stages: A Markov Chain Approach to Model Sequences and Duration Based on Social Vulnerability. *Risk Analysis*(40), 2675-2695. https://doi.org/https://doi.org/10.1111/risa.13576

Svegrup, L., & Johansson, J. (2015). Vulnerability analyses of interdependent critical infrastructures: Case study of the Swedish national power transmission and railway system. European Safety and Reliability Conference (ESREL2015),

Talen, E. (2003). Neighborhoods as Service Providers: A Methodology for Evaluating Pedestrian Access. *Environment and Planning B: Planning and Design, 30*(2), 181-200. https://doi.org/10.1068/b12977

Talen, E., & Anselin, L. (1998). Assessing spatial equity: an evaluation of measures of accessibility to public playgrounds. *Environment and planning A, 30*(4), 595-613.

Taormina, R., Galelli, S., Tippenhauer, N. O., Ostfeld, A., & Salomons, E. (2016). Assessing the Effect of Cyber-Physical Attacks on Water Distribution Systems. In *World Environmental and Water Resources Congress 2016* (pp. 436-442). https://doi.org/doi:10.1061/9780784479865.046

Tate, E. (2012). Social vulnerability indices: a comparative assessment using uncertainty and sensitivity analysis. *Natural Hazards, 63*(2), 325-347.

Tate, E. (2013, 2013/05/01). Uncertainty Analysis for a Social Vulnerability Index. *Annals of the Association of American Geographers, 103*(3), 526-543. https://doi.org/10.1080/00045608.2012.700616

Thacker, B. H., Doebling, S. W., Hemez, F. M., Anderson, M. C., Pepin, J. E., & Rodriguez, E. A. (2004). Concepts of model verification and validation.

The White House. (2021). *Executive order on tackling the climate crisis at home and abroad*.

Thomson, D., Cantrell, E., Guerra, G., Gooze, R., & Tout, K. (2020). Conceptualizing and measuring access to early care and education.

Tierney, K. (2014). The social roots of risk. In *The Social Roots of Risk*. Stanford University Press.

Tierney, K. J., & Oliver-Smith, A. (2012). Social Dimensions of Disaster Recovery. *International Journal of Mass Emergencies and Disasters, 30*(2), 123-146.

Toja-Silva, F., Kono, T., Peralta, C., Lopez-Garcia, O., & Chen, J. (2018, 2018/09/01/). A review of computational fluid dynamics (CFD) simulations of the wind flow around buildings for urban wind energy exploitation. *Journal of Wind Engineering and Industrial Aerodynamics, 180*, 66-87. https://doi.org/https://doi.org/10.1016/j.jweia.2018.07.010

Torres, J. M., Brumbelow, K., & Guikema, S. D. (2009). Risk classification and uncertainty propagation for virtual water distribution systems. *Reliability Engineering & System Safety, 94*(8), 1259-1273.

Trenberth, K. E. (2018, 2018/10/02). Climate change caused by human activities is happening and it already has major consequences. *Journal of Energy & Natural Resources Law, 36*(4), 463-481. https://doi.org/10.1080/02646811.2018.1450895

Trudeau, R. J. (1993). *Introduction to graph theory*. Dover Pub.

Ungar, M., Connelly, G., Liebenberg, L., & Theron, L. (2019, 2019/09/01). How Schools Enhance the Development of Young People's Resilience. *Social indicators research, 145*(2), 615-627. https://doi.org/10.1007/s11205-017-1728-8

United Nations. (2011). *United Nations International Strategy for Disaster Risk Reduction Secretariat (UNISDR)*. Retrieved May from https://www.undrr.org/

United Nations. (2016). *United Nations plan of action on disaster risk reduction for resilience*. United Nations System-Chief Executives Board New York. Retrieved May from https://www.preventionweb.net/publications/view/49076

United States Census Bureau. (2022). *American Community Survey (ACS) 2015-2020*. Retrieved March from https://www.census.gov/programs-surveys/acs

van de Lindt, J., Peacock, W., Mitrani-Reiser, J., Rosenheim, N., Deniz, D., Dillard, M., & Fung, J. (2018). The Lumberton, North Carolina Flood of 2016: A community resilience focused technical investigation. *NIST Special Publication, 1230*(1). https://doi.org/https://doi.org/10.6028/NIST.SP.1230

van de Lindt, J. W., Ellingwood, C. B. R., Wang, C. N., Mahmoud, H., & Koliou, C. M. (2016). The Role of Structural Robustness in Risk-Informed Community Resilience Planning.

Van De Lindt, J. W., Mahmoud, H., Pilkington, S., Koliou, M., Attary, N., Cutler, H., Smith, S., Rosenheim, N., Navarro, C. M., & Kim, Y. W. (2019). Validating Interdependent Community Resilience Modeling using Hindcasting. 13th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP13), Seoul, South Korea.

van de Lindt, J. W., Peacock, W. G., Mitrani-Reiser, J., Rosenheim, N., Deniz, D., Dillard, M., Tomiczek, T., Koliou, M., Graettinger, A., Crawford, P. S., Harrison, K., Barbosa, A., Tobin, J., Helgeson, J., Peek, L., Memari, M., Sutley, E. J., Hamideh, S., Gu, D., Cauffman, S., & Fung, J. (2020). Community Resilience-Focused Technical Investigation of the 2016 Lumberton, North Carolina, Flood: An Interdisciplinary Approach. *Natural Hazards Review, 21*(3), 04020029. https://doi.org/doi:10.1061/(ASCE)NH.1527-6996.0000387

Van Zandt, S. (2019). Impacts on Socially Vulnerable Populations. In M. Lindell (Ed.), *The Routledge Handbook of Urban Disaster Resilience Integrating Mitigation, Preparedness, and Recovery Planning* (pp. 440). Routledge.

Van Zandt, S., Peacock, W. G., Henry, D. W., Grover, H., Highfield, W. E., & Brody, S. D. (2012, 2012/01/01). Mapping social vulnerability to enhance housing and neighborhood resilience. *Housing Policy Debate, 22*(1), 29-55. https://doi.org/10.1080/10511482.2011.624528

Vaughan, K. B., Kaczynski, A. T., Wilhelm Stanis, S. A., Besenyi, G. M., Bergstrom, R., & Heinrich, K. M. (2013, Feb). Exploring the distribution of park availability, features, and quality across Kansas City, Missouri by income and race/ethnicity: an environmental justice investigation. *Ann Behav Med, 45 Suppl 1*, S28-38. https://doi.org/10.1007/s12160-012-9425-y

Vesely, W. E., Goldberg, F. F., Roberts, N. H., & Haasl, D. F. (1981). *Fault tree handbook*. U.S. Nuclear Regulatory Commission.

Vickery, P. J., Skerlj, P. F., Steckley, A. C., & Twisdale, L. A. (2000). Hurricane Wind Field Model for Use in Hurricane Simulations. *Journal of Structural Engineering, 126*(10), 1203-1221. https://doi.org/doi:10.1061/(ASCE)0733-9445(2000)126:10(1203)

Vickery, P. J., & Wadhera, D. (2008). Statistical Models of Holland Pressure Profile Parameter and Radius to Maximum Winds of Hurricanes from Flight-Level Pressure and H*Wind Data. *Journal of applied meteorology and climatology, 47*, 2497-2517.

Walski, T. M., Brill, E. D., Gessler, J., Goulter, I. C., Jeppson, R. M., Lansey, K., Lee, H. L., Liebman, J. C., Mays, L., Morgan, D. R., & Ormsbee, L. (1987). Battle of the Network Models: Epilogue. *Journal of Water Resources Planning and Management, 113*(2), 191-203. https://doi.org/doi:10.1061/(ASCE)0733-9496(1987)113:2(191)

Wang, C., Yu, Q., Law, K. H., McKenna, F., Yu, S. X., Taciroglu, E., Zsarnóczay, A., Elhaddad, W., & Cetiner, B. (2021, 2021/02/01/). Machine learning-based regional scale intelligent modeling of building information for natural hazard risk management. *Automation in Construction, 122*, 103474. https://doi.org/https://doi.org/10.1016/j.autcon.2020.103474

Wang, C., Yu, Q., McKenna, F., Cetiner, B., Yu, S. X., Taciroglu, E., & Law, K. H. (2021). *NHERI-SimCenter/BRAILS: v2.0.0 (v2.0.0)*. Zenodo.

Wang, C., Zhang, H., Ellingwood, B. R., Guo, Y., Mahmoud, H., & Li, Q. (2021, 2021/04/03). Assessing post-hazard damage costs to a community's residential buildings exposed to tropical cyclones. *Structure and Infrastructure Engineering, 17*(4), 443-453. https://doi.org/10.1080/15732479.2020.1845215

Wang, H., Mostafizi, A., Cramer, L. A., Cox, D., & Park, H. (2016, 2016/03/01/). An agent-based model of a multimodal near-field tsunami evacuation: Decision-making and life safety. *Transportation Research Part C: Emerging Technologies, 64*, 86-100. https://doi.org/https://doi.org/10.1016/j.trc.2015.11.010

Wang, Y., Liu, Y., Xing, L., & Zhang, Z. (2021). An Improved Accessibility-Based Model to Evaluate Educational Equity: A Case Study in the City of Wuhan. *ISPRS International Journal of Geo-Information, 10*(7), 458. https://www.mdpi.com/2220-9964/10/7/458

Watson, M., Hamidah, S., & Sutley, E. (forthcoming). The Lumberton, North Carolina Flood of 2016, Wave 4: A Community Impact and Recovery-Focused Technical Investigation Following Successive Flood Events. *NIST Special Publication*.

Watson, M., Xiao, Y., Helgeson, J., & Dillard, M. (2020). Importance of households in business disaster recovery. *Natural Hazards Review, 21*(4), 05020008.

Wiebe, D. M., & Cox, D. T. (2014, 2014/04/01). Application of fragility curves to estimate building damage and economic loss at a community scale: a case study of Seaside, Oregon. *Natural Hazards, 71*(3), 2043-2061. https://doi.org/10.1007/s11069-013-0995-1

Williams, T. G., Logan, T. M., Zuo, C. T., Liberman, K. D., & Guikema, S. D. (2020, 2020/09/01/). Parks and safety: a comparative study of green space access and inequity in five US cities. *Landscape and Urban Planning, 201*, 103841. https://doi.org/https://doi.org/10.1016/j.landurbplan.2020.103841

Wu, J., & Dueñas-Osorio, L. (2013). Calibration and Validation of a Seismic Damage Propagation Model for Interdependent Infrastructure Systems. *Earthquake Spectra, 29*(3), 1021-1041. https://doi.org/10.1193/1.4000160

Wu, S.-Y., Yarnal, B., & Fisher, A. (2002). Vulnerability of coastal communities to sea-level rise: a case study of Cape May County, New Jersey, USA. *Climate research, 22*(3), 255-270.

Xu, L., & Brown, R. E. (2008). A hurricane simulation method for Florida utility damage and risk assessment. 2008 IEEE Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century,

Yang, L., Kajitani, Y., Tatano, H., & Jiang, X. (2016). A methodology for estimating business interruption loss caused by flood disasters: Insights from business surveys after Tokai Heavy Rain in Japan. *Natural Hazards, 84*(1), 411-430.

Yavari, S., Chang, S. E., & Elwood, K. J. (2010). Modeling post-earthquake functionality of regional health care facilities. *Earthquake Spectra, 26*(3), 869-892.

Zahran, S., Brody, S. D., Peacock, W. G., Vedlitz, A., & Grover, H. (2008, Dec). Social vulnerability and the natural and built environment: a model of flood casualties in Texas. *Disasters, 32*(4), 537-560. https://doi.org/10.1111/j.1467-7717.2008.01054.x

Zhang, P., & Peeta, S. (2011). A generalized modeling framework to analyze interdependencies among infrastructure systems. *Transportation Research Part B: Methodological, 45*(3), 553-579.

Zhang, W., Lin, P., Wang, N., Nicholson, C., & Xue, X. (2018). Probabilistic Prediction of Postdisaster Functionality Loss of Community Building Portfolios Considering Utility Disruptions. *Journal of Structural Engineering, 144*(4), 04018015. https://doi.org/doi:10.1061/(ASCE)ST.1943-541X.0001984

Zhang, W., & Nicholson, C. (2016, 2016/11/28). A multi-objective optimization model for retrofit strategies to mitigate direct economic loss and population dislocation. *Sustainable and Resilient Infrastructure, 1*(3-4), 123-136. https://doi.org/10.1080/23789689.2016.1254995

Zou, Q., & Chen, S. (2020). Resilience Modeling of Interdependent Traffic-Electric Power System Subject to Hurricanes. *Journal of Infrastructure Systems, 26*(1), 04019034. https://doi.org/doi:10.1061/(ASCE)IS.1943-555X.0000524

Zuzak, C., Goodenough, E., Stanton, C., Mowre, M., Ranalli, N., Kealey, D., & Rozelle, J. (2021). *National Risk Index Technical Documentation*. https://www.fema.gov/sites/default/files/documents/fema_national-risk-index_technical-documentation.pdf