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A Resilience Assessment Framework of Infrastructure Systems by Integrating Social Equity to Support Disaster Resilience Decision Making

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A RESILIENCE ASSESSMENT FRAMEWORK OF INFRASTRUCTURE SYSTEMS BY INTEGRATING SOCIAL EQUITY TO SUPPORT DISASTER RESILIENCE DECISION MAKING

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To: Dean John L. Volakis
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This dissertation, written by Sunil Dhakal, and entitled A Resilience Assessment Framework of Infrastructure Systems by Integrating Social Equity to Support Disaster Resilience Decision Making, having been approved in respect to style and intellectual content, is referred to you for judgement.

We have read this dissertation and recommend that it be approved.

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ABSTRACT OF THE DISSERTATION

A RESILIENCE ASSESSMENT FRAMEWORK OF INFRASTRUCTURE SYSTEMS BY INTERGRATING SOCIAL EQUITY TO SUPPORT DISASTER RESILIENCE DECISION MAKING

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Resilient infrastructure, which better withstands, adapts, and quickly recovers from disasters, can limit disaster impacts, such as disruptions to infrastructure services and time and efforts needed for recovery. However, in the context of a disaster, the impacts or disruptions on the infrastructure are not evenly distributed across different communities. Thus, we need to account for such disparities (or inequalities) when assessing infrastructure resilience.

To address this need, this dissertation presents a new social-welfare-based infrastructure resilience assessment (SW-Infra-RA) model for quantifying the collective resilience of infrastructure serving multiple communities. This model accounts for (1) disaster inequality – the unequal distribution of disaster impacts on infrastructure across different communities, and (2) disaster vulnerability – the disaster impacts on infrastructure of the communities that suffer from the most severe impacts, both of which have impacts on the collective resilience of infrastructure. The proposed model is theoretically grounded on the social welfare theory and social welfare functions. It also leverages studies related to Social Vulnerability Index and the Resilient Triangle framework. The dissertation presents the conceptual notions and mathematical functions of the SW-Infra-RA model. A set of

hypothetical and real case studies were conducted to illustrate the use of the proposed model to assess infrastructure resilience.

The results generated using this model could be utilized by decision makers to better understand the uneven distribution of disaster impacts across communities and identify communities that are severely impacted from a disaster. Such information about inequalities and vulnerabilities of the impacted region could help decision makers prioritize disaster assistance, resources for recovery, and future infrastructure investment toward the vulnerable communities. Overall, the study has the potential to facilitate equitable resilience planning by allowing both decision makers and community personnel to better understand the links between resilience planning and equity in their communities.

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CHAPTER 1 INTRODUCTION

1.1 Background

Infrastructure systems provide essential services including electricity, water supply, communication, and transportation services to communities. With the increase in frequency and intensity of extreme weather events and natural disasters by climate change, these infrastructure systems serving different communities remain at high risk to from disasters. Failures on infrastructure systems due to disaster impacts could result in severe consequences on the regional economic system and affects people's accessibility to infrastructure services. Past experience in disaster have shown that the disaster accounts for huge economic losses mostly in the form of damage to infrastructure systems (UN 2016). To allow infrastructure to resist or absorb disturbance, and remain basic functional and service capacities, investing on and implementing disaster resilience strategies have become a "national imperative" (NRC 2012). Thus, it is crucial that we focus on improving the resilience of our infrastructure systems, so they offer the essential services to society in the aftermath of disruptive events. Government and scientific scholars in the domain of disaster management have made significant contributions on improving infrastructure resilience (Ouyang and Wang 2015, Chang et al. 2013, UN 2016). However, one of the overlooked problems with infrastructure resilience is that a damaged infrastructure due to disaster could result in varying level of disturbances to the community residents. Such damage is typically not evenly distributed across different communities; the low-income and the minority communities are more vulnerable to disaster risks, and they are more likely to struggle more to recover (Emrich et al. 2019). For example, after Hurricane Harvey, more severe flooding damage was found in communities or households with lower income as lower income Americans are more likely to live in neighborhoods r buildings that are more susceptible to flooding or other impacts from storms (Krause and Reeves 2017).

To reduce or eliminate disparities of access to infrastructure due to disasters, the 2030 Global sustainable development agenda of the United Nations highlights the importance of understanding the interlinkages and integrated nature of infrastructure, inequality, and resilience (UN 2016). For example, how does the infrastructure resilience affect social equity? How is social equity integrated into the infrastructure resilience assessment or planning? How to evaluate resilience of infrastructure systems while accounting for social equity? Benchmarking the definitions of social equity in a number of literature (e.g., Emrich et al. 2019), in my dissertation, social equity is defined as equal opportunities and resources provided to different populations through the functions offered by infrastructure. Achieving social equity means reducing or elimination disparate access to goods, services, and amenities among different populations, including the socially vulnerable populations. Socially vulnerable populations include the economically disadvantaged, racial and ethnic minorities, the elderly, the uninsured, the homeless, the disabled, those with chronic health conditions, and those with language barriers (Rao et al. 2109, AJMC 2006). They often have the fewest resources for disaster preparedness, live in disaster prone areas, and lack social capital, political, and economic capital needed to adapt to and recover from disasters (IWR 2016). Multiple studies (e.g., Frigerio et al. 2019, Fatemi et al. 2017, Constible 2018) have shown that socially vulnerable communities experienced more severe disturbances caused by infrastructure damage, which could exacerbate social inequities if not addressed in a timely manner (Fothergill and Peek 2004).

Resilient infrastructure, which is able to withstand disasters and recover quickly, remains vital in offering stabilized essential services (e.g., water, power, communication, transportation) to socially vulnerable populations. Thus, it plays an important role in supporting social equity in disasters (Doorn 2019, UN 2016). A resilient infrastructure has a potential to reduce “disaster-induced poverty” - such as shortage of supplies, inaccessibility to goods or services. In addition, implementing the disaster resilient strategies in the infrastructure planning could facilitate infrastructure improvement and potentially led to economic growth. This will eventually increase productivity and employment opportunities, reduce poverty and contribute to social equity. It also has better capabilities of offering “disaster equity” by reducing the vulnerabilities and disparities in different regions and communities by allowing less infrastructure damage and access to adequate resources for recovery during disasters. Despite such linkage between infrastructure resilience and social equity, there is a lack of study that provides more explicit understanding of the complex interrelationship between infrastructure resilience and social equity. Without such understanding, our “next generation infrastructure” cannot be planned, constructed and operated with great human awareness and social adaptability.

1.2 Problem Statement

Over the last few decades, many resilience assessment methods and models have been proposed to assess the resilience of infrastructure systems. However, there is still a lack of assessment model that incorporates the quantification of inequalities and vulnerabilities with it. One of the crucial challenges in the domain of disaster resilience is to measure such inequalities and vulnerabilities in the context of infrastructure resilience. This knowledge gap creates the need for a change in resilience assessment approaches. It remains crucial that we develop a better understanding of the relationships between equity and infrastructure resilience as well as improve the assessment of infrastructure resilience by accounting for equity. Based on a comprehensive literature review in the domain of infrastructure, resilience, and social equity, a number of knowledge gaps were identified. These knowledge gaps will be discussed in detail in the following sections.

1.2.1 *Knowledge gaps*

(1) Lack of theoretical and explicit understanding on how infrastructure resilience affects social equity. Scholars in the domain of built environments, transportation systems, design and manufacturing, logistics systems, and systems operation and management have

contributed to understanding, assessing, and enhancing the resilience of infrastructure systems (e.g., Aydin et al. 2018, Zhang et al. 2018, Heinimann and Hatfield 2017). Research in these domains focused on different aspects of infrastructure resilience, such as structural integrity (e.g., Chopra et al. 2016), system reliability (e.g., Nateghi 2018), system recovery (e.g., Aydin et al. 2018), resource allocation (e.g., Zhang et al. 2018), and system resilience measurement (e.g., Heinimann and Hatfield 2017). Social equity, on the other hand, has been extensively studied by social scientists in the domain of social science, political science, psychology, and anthropology. A long history of social equity research in the disaster domain shows that multiple social characteristics are associated with disparate exposures and impacts in disasters -including race, income, age, disability, and language proficiency (Domingue and Emrich 2019, Thomas et al. 2013). Most literature in social equity, in the domain of disasters, focused on studying social vulnerability (e.g., Fatemi et al. 2017, Frigerio et al. 2019, Cutter et al. 2003), equitable recovery (e.g., Emrich et al. 2019), social justice (Shively 2017), and social resilience (e.g., Comes et al. 2019). Collectively, the research efforts in the domain of engineering and social science have offered valuable contributions to infrastructure resilience and social equity in disasters, respectively. However, there is still a lack of study that integrates both infrastructure resilience and social equity, which can offer a holistic understanding of the interrelationships between them to facilitate better infrastructure decision making that account for social equity impacts.

(2) There is a lack of study on the methods for measuring social equity in the context of infrastructure resilience. Many studies in the domain of disasters have focused on assessing social equity in disaster recovery or analyzing the social vulnerability across different regions (Domingue and Emrich 2019, Emrich et al. 2019, Doorn et al. 2019). These studies have emphasized the need to pay special attention to socially vulnerable populations and

facilitate social equity across different phases of disaster. Although these studies contribute to better understanding of social inequality in disasters and support decision makers and practitioners to implement policies to maintain equity in the community, there is a lack of theoretically grounded quantitative method to measure social equity. To improve the collective resilience of infrastructure systems of the communities, it is crucial that we understand the unequal distribution of disaster impacts to infrastructure systems across different communities and potential severe impacts to infrastructure systems experienced by the most vulnerable communities.

(3) There is a lack of study that quantitatively integrates social equity into infrastructure resilience assessment framework. Scholars in the disaster resilience domain have proposed different infrastructure resilience assessment framework for quantifying the resilience of infrastructure systems (Liu et al. 2019, Panteli et al. 2017). In addition, studies in the infrastructure resilience domain have developed multiple resilience metrics to measure the resilience of infrastructure, such as Resilience Star developed by Department of Homeland Security (Kangior 2013), Resilience-based Earthquake Design Initiative (REDi™) rating system (ARUP 2020), RELi rating system (GBCI 2020). Most of the literature in the field of resilience evaluation primarily focuses on evaluating the performance of whole system (e.g., Meerow 2019, Comes et al. 2019), while lacking consideration of social equity conditions. Thus, there is a need to integrate equity and vulnerability into the resilience evaluation framework to develop a better resilience metrics for infrastructure systems.

1.3 Research Objectives

The main goal of this research study is to analyze the interrelationships between infrastructure resilience and social equity and establish an infrastructure resilience assessment framework that accounts for the unequal distribution of disaster impacts on infrastructure serving different communities and potentially severe impacts on infrastructure of the vulnerable communities. In order to achieve this goal, the research objectives along with the research questions are formulated:

Objective 1:

To understand the interrelationships between social equity and infrastructure resilience in the context of a disaster.

Associated Research Questions:

RQ 1: How are infrastructure resilience conditions in the disaster-affected communities reflected by Twitter activities?

RQ 2: How are social equity conditions in the disaster-affected communities reflected by Twitter activities?

RQ 3: Do social equity characteristics of communities have impacts on the infrastructure resilience conditions of the communities?

Objective 2

To develop a new infrastructure resilience assessment framework by integrating equity into the resilience assessment framework.

Associated Research Questions:

RQ 1: How to quantitatively measure the unequal distribution of disaster impacts on infrastructure across different communities?

RQ 2: How to quantitatively measure the potentially severe disaster impacts on infrastructure of the vulnerable communities?

RQ 3: How to mathematically integrate the disparity and vulnerability in disaster impacts with infrastructure resilience assessment?

Objective 3

To validate the proposed resilience assessment framework using real case studies and develop a decision support system that assesses equity-integrated infrastructure resilience automatically.

Associated Research Questions:

RQ 1: How do communities with different characteristics (e.g., coastal vs inland, urban vs rural, more vulnerable vs less vulnerable) compare against each other in terms of disaster inequality?

RQ 2: How do communities with different characteristics compare against each other in terms of disaster vulnerability?

RQ 3: How do communities with different characteristics compare against each other in terms of collective resilience?

To limit the scope of the research work, the dissertation focused on the Florida communities, infrastructure systems that serve Florida communities, and disasters that threatened Florida communities.

1.4 Research Methodology

In order to achieve the above-mentioned research objectives, the research methodology is divided into four main research tasks as follows: (a) understanding the social equity, infrastructure resilience and their interrelationships in the context of a disaster, (b) develop a new infrastructure resilience assessment framework while integrating equity with infrastructure resilience assessment, (c) develop a prototype of a decision support system based on the proposed model for facilitating automatic infrastructure resilience assessment, and (d) validate the proposed assessment framework through multiple case studies. Figure 1-1 shows overview of the research framework.

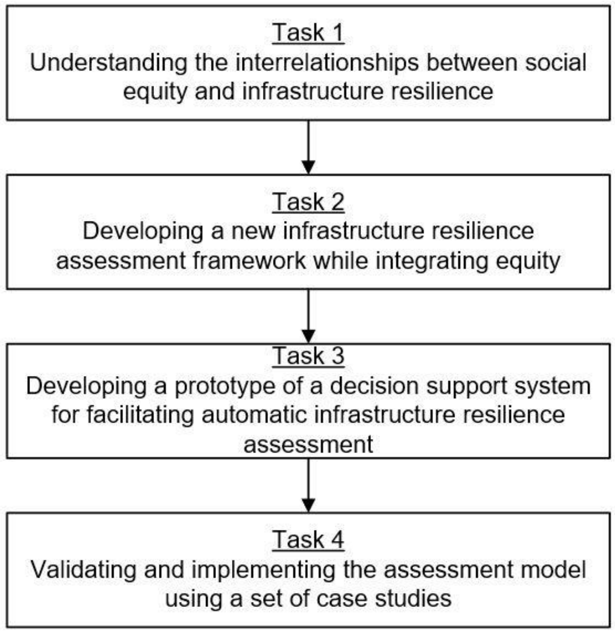


Figure 1-1 Overview of research tasks.

1.5 Research Significance

This research study contributed to (1) advancing the fundamental understanding of the interrelationships between infrastructure resilience and social equity, (2) developing new methods on quantifying the unequal distributions of disaster impacts on infrastructure across different communities and evaluating severe impacts on infrastructure of vulnerable communities, and (3) formulating a theory-based infrastructure resilience assessment model that integrates disaster inequalities and vulnerabilities.

1.5.1 *Benefits to the Society*

The SW-Infra-RA model could allow the decision makers to quantitatively assess the resilience of infrastructure system and facilitate equity-incorporated decision making. The results generated by the model can be utilized to understand the inequalities that exists during disasters and identify communities that are more vulnerable to such disasters. This will help decision makers, emergency managers, and infrastructure planners prioritize disaster aids and funds, resources for recovery, and future infrastructure investments and planning efforts to communities that are more vulnerable to the disasters. With the help of the model, decision makers can better understand the importance of considering inequalities and vulnerabilities in disasters and predict the potential consequences of future disasters. In addition, this model could potentially allow community residents and disaster practitioners to understand the relationship between resilience planning and social equity and help facilitate equitable resilience planning of infrastructure systems.

1.6 Dissertation Organization

This dissertation is organized into six chapters. Each of these chapter consists of its own introduction, methodology, results and analysis, and conclusions. Chapter 1 introduces the research background, knowledge gaps, and problem statement. This chapter also introduces research objectives along with research questions that need to be addressed, methodology adopted to achieve these objectives, and research significance. Chapter 2 provides a comprehensive literature review for all the research tasks. Chapter 3 presents the research task about understanding the interrelationships between social equity and infrastructure resilience in the context of a disaster. This chapter has been published in Dhakal et al. (2021). Chapter 4 presents the research task about developing a new social-welfare-based infrastructure resilience assessment (SW-Infra-RA) model that accounts for disaster inequality and vulnerability. This chapter has been published in Dhakal and Zhang (2022). Chapter 5 presents the research task about the development of a prototype decision support system based on the SW-Infra-RA model. Chapter 6 presents the research task about the resilience analysis of different infrastructure systems using four case studies. Chapter 7 provides a summary of the overall research and conclusions of this dissertation. It also presents the contribution of the research study, limitations, and recommendation for future works.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

The main objective of Chapter 2 is to review the literature related to infrastructure resilience, social equity, and resilience assessment of infrastructure systems. This comprehensive literature review provided a detailed overview of different conceptual notions related to the dissertation topic, explored knowledge gaps, and identified parameters required for formulating the infrastructure resilience assessment framework. The literature review is divided into five parts: (1) review the research about infrastructure resilience, social equity, and their interrelationships, (2) review the research about resilience assessment methods and frameworks, (3) review the research about resilience analysis of infrastructure systems, (4) review the research about social welfare theory and social welfare functions, and (5) review the research about social inequality measurements.

2.2 Interrelationship between Infrastructure Resilience and Social Equity

2.2.1 *Infrastructure Resilience and Social Equity in Disaster Literature*

Over the last decade, disasters caused by natural hazards have resulted in over $900 billion in economic losses worldwide, mostly in the form of damage to infrastructure (UN 2016). Developing resilient infrastructure systems becomes a “national imperative” to address the threat caused by increasingly frequent and intensive disasters (Chopra et al. 2016). In addition, there are still significant disparities in access to infrastructure. For example, over 1.1 billion people still have no access to electricity worldwide, and about one-third of the world’s population is not served by all-weather roads (Badré 2015). Minimizing or closing these disparities would require significant investment and development on infrastructure in a way that not only enhances its resilience but also reduces inequality of the society. While infrastructure resilience and social equity do not automatically go together, facilitating infrastructure resilience could potentially lead to better outcomes of social equity. Disasters cause disproportionate impacts to communities through their impacts on infrastructure, which offers essential services (e.g., water supply, energy, communication, and transportation) to meet basic needs of disaster victims (Lynn et al. 2011). Multiple studies (e.g., Frigerio et al. 2019, Fatemi et al. 2017, Constible 2018) have shown that socially vulnerable communities experienced more severe disturbance caused by infrastructure damage, which could exacerbate social inequities if not addressed in a timely manner (Fothergill and Peek 2004). Resilient infrastructure, which poetically has less functional damage and/or is able to refunctionalize rapidly, may close the inequality gaps across different communities; it plays an important role in catering the necessities of all communities (Braese et al 2019).

On one hand, the concept of infrastructure resilience has drawn significant attention among researchers in the disaster domain (Karamouz et al. 2019). Infrastructure resilience is defined as the ability of infrastructure to withstand, adapt, and quickly recover from the effects of disasters. The concept of resilience, originally, was used to indicate the capacity of a system to return to its original functional level after disruptive events (Rus et al. 2018). It was first introduced by Holling (1973) to define the persistence of relationships within a natural ecosystem and the ability of the system to absorb changes (Holling 1973). It was then widely adapted into different scientific fields, such as engineering, social science, material science, and economics, etc.

Over the last few decades, engineers in the domains of built environments, transportation systems, design and manufacturing, logistic systems, and systems operation and management have contributed to understanding, assessing, and enhancing the resilience of infrastructure systems (e.g., Aydin et al 2018, Zhang et al. 2018, Yodo and Wang 2016, Hosseini and Barker 2016, Heinimann and Hatfield 2017). Research in these domains focused on different aspects of infrastructure resilience, such as structural integrity (e.g., Chopra et al. 2016, Zhao et al. 2015), system reliability (e.g., Nateghi 2018), system recovery (e.g., Aydin et al. 2018, Croope and McNeil 2011), resource allocation (e.g., Zhang et al. 2018, MacKenzie and Zobel 2016), and system resilience measurement (e.g., Heinimann and Hatifield 2017, Yodo and Wang 2016). For example, Chopra and colleagues (2016) developed a multi-pronged framework that analyzes information on the network structure, spatial location, passenger flow, and structural and functional vulnerabilities for improving the resilience of the London Metro system. Nateghi (2018) proposed a predictive tool to assess various investment strategies for enhancing the resilience of electric power systems in hurricanes. Aydin and colleagues (2018) proposed a methodology that evaluates road recovery strategies for restoring the services after blockage due to natural disasters. Zhang and colleagues (2018) proposed a numerical modeling-based approach for allocating restoration resources that could enhance the resilience of infrastructure systems. Yodo and Wang (2016) explored and evaluated the challenges of incorporating resilience into engineering design, which contributes to the development of an engineering resilience analysis framework.

Social equity, on the other hand, has been extensively studied by social scientists in the domains of social science, political science, psychology, and anthropology. In the context of disasters, allowing all disaster-affected individuals, including the socially vulnerable populations, to have equal access to resource distributions and opportunities is the key to achieve equitable resilience (Emrich et al. 2019). A long history of social equity research in the disaster domain shows that multiple social characteristics are associated with disparate exposures and impacts in disasters—including race, income, age, disability, and language proficiency (Domingue and Emrich 2019, Thomas et al. 2013). Most literature on social equity, in the domain of disasters, focused on studying social vulnerability (e.g., Fatemi et al. 2017, Frigerio et al. 2019, Cutter et al. 2003), equitable recovery (e.g., Emrich et al. 2019), social justice (Shively 2017, Gil-Rivas and Kilmer 2016), and social resilience (e.g., Comes et al. 2019, Kim et al. 2018). For example, Cutter and colleagues (2003) studied socioeconomic and demographic conditions of different counties and developed social vulnerability index to encapsulate the socioeconomic conditions associated with disaster inequalities. Emrich and colleagues (2019) explored how social characteristics influenced the equitable disaster recovery process for the 2015 South Carolina floods. Gil-Rivas and Kilmer (2016) proposed an ecological framework that accounts for social justice, empowerment, and diversity in building community resilience. Comes and colleagues (2019) highlighted the role of new information and communication technologies for improving social resilience during crisis across three different eras (1991-2005, 2005-2015, and 2016-onwards).

Collectively, the research efforts in the domains of engineering and social science have offered valuable contributions to infrastructure resilience and social equity in disasters, respectively; research in the engineering domain advances the design, operation, and management of infrastructure systems in ways that improve their capabilities to resist, respond, and adapt to disasters; while research in the social science domain leads to the important recognition and understanding of the disproportionate impacts of disasters on communities. However, researchers focusing on each of these fields are typically from different research backgrounds, making links between infrastructure resilience and social equity less commonly studied than any of the two areas taken in isolation. There is still limited convergence research that integrates both social equity and infrastructure resilience, which can offer a holistic understanding of the interrelationships between social equity and infrastructure resilience to support better infrastructure decision making that accounts for social impacts.

2.2.2 *Social Media Analysis in Disaster Literature*

Social media is a collection of platforms that allow users to create public or semi-public profiles, generate multimedia contents, connect with other users, and share contents, opinions, insights, and perspectives in real time (Houston et al. 2015). Social media is characterized as a low-cost, easy-to-use, scalable, relatively reliable multimedia network that allows for real-time information sharing and exchange (Mills et al. 2009). In addition, with the prevalence of Global Positioning System (GPS)-enabled personal mobile devices, every social media user could become part of a location-enabled large sensor network. Thus, compared with traditional data sources, social media data is more spatially comprehensive and relatively rich in offering situational awareness information (Li et al. 2019). Over the last decade, social media has gained immense popularity for understanding information sharing and exchange in different domains, such as healthcare (e.g., Surani et al. 2017), emergency management (e.g., Harrison and Johnson 2019), marketing (e.g., Shareef et al.2019), politics (e.g., Kwak et al. 2018), and entertainment (e.g., Khan 2017).

In the disaster domain, social media has been proved to be a good alternative to traditional data sources (Beigi et al. 2016, Cobo et al. 2015, Lindsay 2011). The massive data generated from social media can be used to analyze human activities in different spatiotemporal dimensions and provide insights on disaster-related knowledge. Researchers in the disaster field have worked on analyzing social media activities to address a variety of issues, such as damage assessment (e.g., Resch et al. 2018, Chen et al. 2020), disparities of disaster impacts (e.g., Zou et al. 2018b), crisis communication (e.g., Roshan et al. 2016), disaster response and recovery (e.g., Young et al. 2020), and real-time disaster mapping (e.g., Li et al. 2018). For example, Resch and colleagues (2018) conducted a spatiotemporal analysis of social media data using machine learning techniques to analyze the regions with significant damage due to disasters. Chen and colleagues (2020) employed a systematic approach to identify and assess the damage on highways using social media in the context of Hurricane Harvey. Zou and colleagues (2018b) studied the social and geographical disparities that existed in the twitter activities during Hurricane Sandy. Roshan and colleagues (2016) analyzed the use of social media for communication among different organizations in the time of crisis. Young and colleagues (2020) studied social media and its potential use for emergency communication during the response and recovery phases of disasters. Li and colleagues (2018) proposed a novel approach for mapping the flood in real time using social media data.

The previous research has collectively provided important contributions to the utilization of social media data in advancing disaster resilience knowledge. However, existing research also suggests that due to the many inherent issues of social media data, such as false information, lack of validation, malicious use, using social media data alone to draw scientific conclusions or generate new knowledge is still challenging (Li et al. 2018, Zou et al. 2018a). There is a need to integrate social media data with traditional data to provide informative analysis results, and more research is necessary to address the question of synthesizing social media data with other sources of data to offer meaningful knowledge that supports disaster resilience (Zou et al. 2018a).

2.3 Infrastructure Resilience Assessment in Disaster Literature

Over the last two decades, the concept of infrastructure resilience has gained significant attention from scientific scholars and researchers around the world (Karamoutz et al. 2019, Cimellaro et al. 2010). The concept of "resilience" was first introduced by Holling (1973) to describe the "persistence of relationships within a system" and the ability of the system to "absorb changes of state variables, driving variables, and parameters, and still persist" (Holling 1973). Holling (1996) also explained the difference between engineering resilience and ecological resilience. Ecological resilience measures how a system can persist by absorbing changes and disturbances, while engineering resilience measures the capacity of the system to recovery to its original functional level after a disturbance. Integrating these definitions, infrastructure resilience is typically defined as the ability of infrastructure to anticipate and absorb the shock, adapt to, and quickly recover to its original functional level (Berkeley et al. 2010).

Over the years, many resilience assessment frameworks have been proposed to assess the resilience of different types of infrastructure, such as transportation infrastructure (e.g., Tonn et al. 2020), electric power systems (e.g., Hossain et al. 2019), water and sanitation infrastructure (e.g., Assad et al. 2019), and telecommunication infrastructure (e.g., Mawgaud et al. 2021). These studies used different approaches to assess infrastructure resilience, including simulation-based approaches (e.g., Hossain et al. 2019, Hosseini and Barker 2016, Lam and Tai 2018), mathematical approaches (e.g., Cimellaro et al. 2010, Shin et al. 2018, Bruneau et. al 2003), index-based approaches (e.g., Rehak et al. 2019, Petit et al. 2012, Fisher and Norman 2010), and data-driven approaches (e.g., MacKenzie and Barker 2020, Zhu et al. 2017).

Simulation-based approaches were mostly employed in resilience assessment of system networks, such as water supply networks (e.g., Assad et al. 2019), electric grid networks (e.g., Hossain et al. 2019), and transportation networks (e.g., Hosseini and Barker 2016). In these studies, Bayesian networks, Monte Carlo simulation, and Fuzzy models were commonly used for the analysis. For example, Hossain et al. (2019) employed Bayesian networks to quantitatively assess the resilience of electric infrastructure systems. Similarly, Hosseini and Barker (2016) built a resilience assessment framework to quantify the resilience capacity of an inland waterway network using Bayesian networks. Nogal et al. (2017) proposed a resilience assessment framework to estimate the resilience of a transportation network impacted by extreme events using the Monte Carlo simulation method. Lam and Tai (2018) used a fuzzy modeling approach to model the interdependencies between entities in infrastructure networks by simulating the effects of disruptions.

Using mathematical approaches, the resilience of infrastructure can be assessed through mathematical structures, notions, or equations. The mathematical approaches can be classified into deterministic (e.g., Bruneau et al. 2003, Cimellaro et al. 2010) and probabilistic (e.g., Decò et al. 2013, Nogal et al. 2017) approaches. The deterministic approach utilizes the value of the input parameters to obtain a precise outcome without accounting for uncertainties. In contrast, the probabilistic approach can model the uncertainties that exist in the inputs of metrics to obtain the distributions of infrastructure failure and recovery (Mottahedi et al. 2021). For example, Cimellaro et al. (2010) proposed a comprehensive conceptual model that includes a loss estimation model and a recovery model to quantitatively assess the seismic resilience of a network of health care facilities. Decò et al. (2013) used a probabilistic approach to assess the seismic resilience of bridges.

Using index-based approaches, a resilience index is developed by identifying and aggregating a set of indicators that represent the characteristics of infrastructure resilience. The resilience index can then be used to compare or rank the resilience of several infrastructure alternatives by collecting the data of each infrastructure alternative. To frame the resilience index, both qualitative (measured with ordinal or nominal scales) and quantitative indicators (measured with interval or ratio scales) can be used (Cardoni et al. 2020). Multiple resilience indexes have been developed over the years, such as the Resilience Star developed by the Department of Homeland Security (Kangior 2013), the U.S. Resiliency Council (USRC) Building Rating System (USRC 2021), the Resilience-based Earthquake Design Initiative (REDi™) rating system (ARUP 2021), and the Resilience Action List (RELi) rating system (GBCI 2021). Similarly, many researchers have used the index-based approaches to develop different infrastructure resilience assessment frameworks. For example, Yang et al. (2018) developed the Resilience Index Considering Duration of events (RICD), which assesses the resilience of power transmission systems under typhoon weather. Argyroudis et al. (2020) built a cost-based resilience index that quantifies the seismic resilience of bridges. Cardoni et al. (2020) developed the Power Resilience Index (PRI) that assesses the seismic resilience of urban electric power distribution systems.

Data-driven approaches refer to those methods that rely on collecting, analyzing, and interpreting data to derive insight, knowledge, or solutions. This approach can be used to develop new models to calibrate and reduce uncertainties when assessing infrastructure resilience (Argyroudis et al. 2021). By deriving knowledge from a large amount of data, the data-driven approach may provide a high level of reliability that cannot be achieved through other conventional scientific approaches (Maass et al. 2018). In the last decade, with the advancement on data analytics techniques, there has been a growing tendency of adopting data-driven approaches for resilience assessment. For example, Argyroudis et al. (2021) proposed a data-driven resilience assessment framework for critical transportation infrastructure that is exposed to multiple hazards by interactively analyzing multiscale monitoring data (e.g., terrestrial data, airborne data), crowd data, and environmental measurements. Chandramouleeswaran and Tran (2018) used a data-driven approach for quantitatively assessing the resilience of air transportation networks using publicly available data (e.g., total cancellation flights, average flight delay).

The existing research has offered valuable contributions to advance the understanding and methods of assessing infrastructure resilience. However, one of the major concerns that lie behind the demand for better resilience assessment is the need to pay more attention to equity and vulnerability in resilience assessment (Meerow et al. 2019, Meerow and Newell 2019). Much of the resilience assessment literature focuses on evaluating the performance of a whole (e.g., a complete infrastructure network) while lacking consideration of the inequalities and trade-offs among different parts that compose the whole. Some resilience assessment studies (e.g., RF 2021, GBCI 2021) proposed to integrate equity as one dimension or a characteristic of resilience. These studies tend to mix the conceptualizations of equity and resilience and simplify their relationships. Although disaster resilience and equity are interconnected, they are not the same. Integrating equity with resilience requires us to explicitly assess the unequal distributions of disaster impacts on various communities and evaluate the different levels of vulnerability that these communities face (Wescoat et al. 2018). There is, thus, a need to develop a new resilience assessment framework that assesses the collective infrastructure resilience while accounting for the disparities among the communities and potentially severe impacts on infrastructure of vulnerable communities.

2.3.1 *Resilience Triangle Framework*

The Resilience Triangle framework was based on the work by Bruneau et al. (2003), who defined and quantitatively measured the seismic resilience of communities. According to Bruneau et al. (2003), a resilient system has three key characteristics: (1) reduced failure probabilities, (2) reduced consequences from the failures, and (3) reduced time to recovery. They then proposed to measure the resilience of a community by defining and measuring the area of a resilience triangle (Figure 2-1). In the resilience triangle, the vertical axis represents the quality of infrastructure in a community [Q(t)], which varies with time. Q(t) ranges from 0% to 100%, where 100% represents no degradation in infrastructure quality or service, and 0% means no infrastructure service is available. An earthquake occurring at time t_o would cause damage to infrastructure so that the quality of infrastructure service is immediately reduced. Restoration of infrastructure is a process that takes time, and the quality of infrastructure gradually increases as the restoration process goes on. The infrastructure is completely recovered to its original functional level at time t_t. Therefore, the community loss of resilience is determined by aggregating the degradation of the quality of infrastructure over the total recovery time (t_t -t_o).

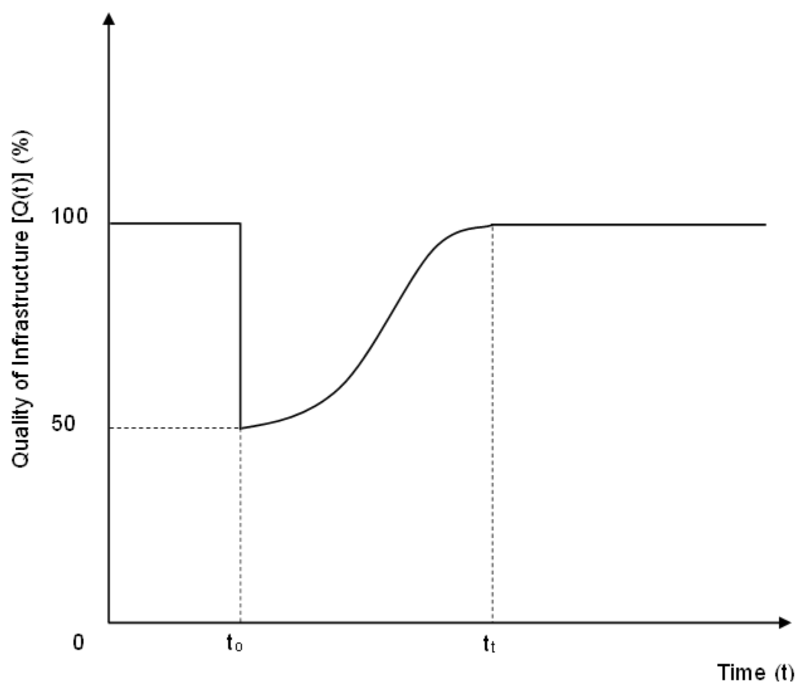


Figure 2-1 A conceptual diagram of resilience triangle

Over the last two decades, many research studies have been conducted to apply or adapt Bruneau et al. (2003)'s framework in assessing the resilience of various types of infrastructure, such as healthcare facilities (Shang et al. 2020), electric power systems (Ouyang and Duenas-Osorio 2014) and transportation infrastructure (Argyroudis et al. 2020). The framework has also been adapted to analyze disruptions caused by disasters other than earthquakes, such as hurricanes (e.g., Ouyang and Duenas-Osorio 2014) and flooding (e.g., Zamanian et al. 2020).

2.4 Resilience Analysis of Infrastructure in Disasters

Over the last decade, changing climatic conditions and frequent extreme weather events have caused a detrimental effect on infrastructure serving different communities in the United States. According to the National Oceanic and Atmospheric Administration (NOAA), there were approximately 323 extreme weather events and other natural disasters since 1980 in which the total damage cost of these events exceeded 2.2 trillion US dollars (NOAA 2022). To mitigate the disaster impacts on infrastructure, researchers and practitioners have been championing for more resilient infrastructure over the last several decades. However, these extreme weather events and natural disasters cause disproportionate impacts on infrastructure serving various communities, which may be linked to the variations in the quality of infrastructure serving communities with different characteristics (e.g., spatial, demographic, and socioeconomic statuses). For example, research shows that socially vulnerable communities bear more than their fair share of the physical and economic burden (e.g., physical damage, service disruptions, economic losses) caused by disasters (Emrich et al. 2019, Domingue and Emrich et al. 2019, SAMSHA 2017). These communities typically lack knowledge and resources in disaster risk reduction, mitigation, and infrastructure resilience planning. They are found to be neglected or left behind in infrastructure planning due to discriminatory policies, practices, and biases within infrastructure planning (NASEM 2022). Thus, it remains crucial that we identify the fundamental disaster inequalities and vulnerabilities across different communities when assessing the resilience of infrastructure.

The concept of resilience has gained significant attentions in disaster risk research and applications over the last few decades. Improving the resilience of infrastructure can enhance the capabilities of infrastructure in resisting, adapting to, and quickly recovering from extreme events. Systematically analyzing the resilience of infrastructure systems and identifying those communities with more vulnerable infrastructure is a first step toward building a universally resilient community. Over the years, extensive studies (e.g., Diao et al. 2016, Shafieezadeh and Burden 2014, Klise et al. 2017, Espinoza et al. 2016, Wei et al. 2020, Zhu et al. 2016) have been conducted to analyze the resilience of various infrastructure, such as water infrastructure (e.g., Diao et al. 2016, Klise et al. 2017), transportation infrastructure (e.g., Zhu et al. 2016, Shafieezadeh and Burden 2014), and electric power system (e.g., Espinoza et al. 2016, Wei et al. 2020). For example, Klise et al. (2017) conducted the resilience analysis of a water distribution system after an earthquake. Zhu et al. (2016) performed an assessment of the resilience of subway and road networks in Hurricanes Sandy and Irene. Espinoza et al. (2016) assessed the resilience of Great Britain's electric power system from the impacts of floods and windstorms. These studies offered valuable contribution to advance the understanding and analyses of infrastructure resilience. However, these studies have not accounted for disparities in disaster impacts on infrastructure serving various communities.

Over the years, scholars (e.g., Yabe and Ukkusuri 2020, Emrich et al. 2019, Mitsova et al. 2018, Zou et al. 2018b, Cutter et al. 2003) in the domain of disasters have highlighted the importance of assessing disparities in disaster impacts to better understand inequities in disaster contexts. Studies on disaster disparity analyses aim to understand unique characteristics and challenges that exist in the various communities and recommend strategies for resilience planning and investment aligned with the severity of needs. Analyzing the disparities of disaster impacts across various communities can be helpful to identify those communities that are the most vulnerable in disasters and facilitate equitable resilience planning in the future. Extensive studies (e.g., Yabe and Ukkusuri 2020, Emrich et al. 2019, Domingue and Emrich 2019, Coleman et al. 2020, Zou et al. 2018b) have been conducted to analyze disparities of disaster management efforts of or disaster impacts on communities or population groups with various characteristics (e.g., income, race, age). For example, Yabe and Ukkusuri (2020) quantified the effects of income inequality on evacuation before disasters and re-entry after disasters, and they found that evacuees from higher income communities were more likely to evacuate from the impacted areas. Emrich et al. (2019) analyzed how social characteristics influenced the federal disaster recovery fund allocation following the 2015 South Carolina floods. Coleman et al. (2020) studied disparities in hardships experienced by different communities due to infrastructure service disruption caused by Hurricane Harvey. Zou et al. (2018b) found social and geographical disparities in social media use during Hurricane Harvey. These studies offer valuable insight and contributions toward better understanding of disparities or inequalities in disasters. However, they have not integrated such disparities with infrastructure resilience assessment. There is also a lack of research on how the integration of disaster inequalities would impact the collective resilience of infrastructure. Furthermore, these studies have not comprehensively studied how the various characteristics of communities (e.g., coastal, inland, urban, rural, more vulnerable and less vulnerable) would impact the level of disaster inequalities and/or the collective resilience of their infrastructure.

2.5 Social Welfare Functions

Welfare economics is the study of how the distribution of resources and goods impacts social welfare; it evaluates well-being (welfare) at the aggregate level (Deardorff 2016). In welfare economics, several functions were proposed to evaluate or compare alternative social states (e.g., income distributions, life expectancy, literacy rate), and these functions are called social welfare functions (SWFs) (Weymark 2016). A SWF can be thus defined as a function that measures or ranks the collective welfare of the society in different social states (Arrow 1963). It can be used to determine the optimal distribution of well-being among individuals to achieve the maximum well-being for the whole society (Arrow 1963). In a SWF, well-being is generally expressed in terms of utilities (e.g., incomes, benefits) or preferences.

In welfare economics literature, SWFs can be generally classified into (1) the Bergson-Samuelson SWFs, (2) the Arrow SWFs, and (3) Cardinal SWFs. The Bergson-Samuelson SWFs determine the social preference (in the form of social ordering or ranking) of alternative social states (Weymark 2016) based on individual utilities (e.g., income, life expectancy). Through the functions, the individual utilities in alternative social states are first determined and further aggregated to determine the collective social preference. With the Arrow SWFs, the social preference of alternative social states is determined as a function of individual preferences (Weymark 2016). Unlike the Bergson-Samuelson SWFs, the Arrow SWFs only use information about individual preferences to determine the social preference.

Cardinal SWFs, on the other hand, are functions that determine the collective welfare (in the form of numerical value) based on individual utilities. They do not necessarily require comparisons among individual utilities in alternative social states, and they yield a numerical representation of the collective welfare for each social state. Some of the Cardinal SWFs found in the literature include Utilitarian SWF (Harsanyi 1955), Rawlsian SWF (Rawls 1971), Bernouli-Nash SWF (Jagtenberg 2017), Sen's SWF (Sen 1997), and Atkinson and Brandoloni SWF (Atkinson and Brandoloni 2010). The Utilitarian SWF measures the social welfare as the average welfare of the individuals in the society. With the Utilitarian SWF, the collective social welfare of a society increases if the welfare of any individual increases and none decreases, with everyone indifferent (Harsanyi 1955, Schneider and Kim 2020). This function does not account for the equality of welfare (e.g., fair distributions of income) among the individuals in a society. With the Rawlsian SWF, the welfare of the society is determined by the welfare of the individuals with the lowest welfare in a society (Rawls 1971). According to the Rawlsian SWF, the social welfare increases if the welfare of the poorest individuals increases; it does not consider the welfare of other individuals in the society. Similar to Utilitarian SWF, the Rawlsian SWF does not consider equality in welfare distributions in a society. The Bernoulli-Nash SWF, in general, can be seen as the mixture of the Rawlsian and the Utilitarian SWFs. With the Bernoulli-Nash SWF, the collective social welfare is calculated as the product of all individual welfare (Jagtenberg 2017).

To account for inequality in welfare distributions, Sen (1997) proposed a SWF (Sens's SWF) that accounts for unequal distributions of welfare across the individuals in a society. In Sen's SWF, a Gini coefficient is used to measure welfare inequality. The Sen's SWF determines the social welfare as the product between average welfare of all individuals and an inequality indicator. According to Sen's SWF, the social welfare increases if the fairness in distributing the welfare increases. However, with Sen's SWF, it is possible that the total amount of welfare increases at the expense of increased equality and reduced average welfare. In another word, the social welfare could increase by allowing all individuals to be equally poorer (Mostafa and El-Gohary 2014). Thus, to account for poverty in social welfare, a poverty line is defined based on the minimum amount of income an individual or a household needs to meet their basic needs (Callan and Nolan 1991). The individual or household whose income falls below the poverty line is considered as being poor. Leveraging the poverty line, Atkinson and Brandoloni (2010) proposed a SWF that accounts for the poorest individuals with the minimum welfare in a society.

Over the year, scholars in the domains of social science and economics have used the SWFs to solve various problems, such as reducing health inequalities (Dolan and Robinson 2001), assessing climate policies (Füssel 2006), and improving cost benefit analysis (Adler 2017). In recent years, the SWFs have been further adapted to address issues in other domains, such as transportation, architecture, engineering, and construction. For example, Zhang and Sanake (2020) proposed a social welfare-based group comfort analysis model to measure the collective comfort level of a group of individuals in the indoor environments. Kinjo and Ebina (2017) developed a mathematical model based on Utilitarian SWF and Nash SWF to determine autonomous vehicle (AV) driving behaviors by evaluating individual utilities of passengers inside the AV and pedestrians on a street. Mostafa and El-Gohary (2014) presented a social welfare-based sustainability benefit analysis model that evaluates the distribution of benefits of infrastructure project alternatives to their stakeholders by accounting for both equality and poverty in benefit distributions.

2.6 Social Inequality Measurements

Inequality refers to an absence of equal distributions of goods, services, opportunities, rights, and/or dignity (UNCTAD 2021). Inequality is often measured by assigning a certain value to a specific distribution in order to facilitate direct and objective comparisons across different distributions (UNCTAD 2021). There are multiple methods to measure inequality, and these methods can be categorized as using "ratios" or using "indices".

Measuring inequality through "ratios" is a relatively easy and straightforward method. The most commonly used ratios for measuring inequality are 20/20 ratio and Palma ratio. 20/20 ratio represents the ratio of average income of the richest 20 percent of the population to the average income of the poorest 20 percent of population (Afonso et al. 2015, UNCTAD 2021). Palma ratio is defined as the ratio of total income of the richest 10 percent of households to the poorest 40 percent of households (Afonso et al. 2015, UNCTAD 2021). Although ratios are relatively easy to understand, these methods do not measure how social welfare (e.g., income) is equally or unequally distributed across the population. For example, they do not consider the welfare (e.g., income) distributions within the highest and lowest percentiles of population (Trapeznikova 2019).

As compared to "ratios", "indices" are more commonly used to measure inequality. Some of the popular indices are Atkinson's index (Afonso et al. 2015), Hoover index (Hoover 1941), Theil index (Theil 1967), and Gini index (Trapeznikova 2019). Atkinson's index is a welfare-based measure of inequality, and it represents the percentage of total income that could be sacrificed to have more equal shares of income among individuals without reducing social welfare (Afonso et al. 2015). Hoover index, also known as Schutz index, defines inequality as the share of total income that needs to be redistributed from the population with income above mean to the those with income below mean to achieve income equality (Afonso et al. 2015). A higher value of Hoover index indicates a higher level of inequality, and more redistributions are needed to achieve equality. Theil index belongs to general entropy (GE) measures; it measures an entropic “distance” the population is away from the ideal equitable state, in which all individuals have the same income (Conceição and Ferreira 2000). Since Theil index is not a relative measure of inequality, the values of this index are not always comparable across different groups and sizes of population (Trapeznikova 2019). Gini index is the most widely used and recognized measure of inequality (Trapeznikova 2019). It can be used to measure the inequality of any distributions. One of the benefits for using Gini coefficient is to allow for direct comparisons of inequality states across different groups of population, irrespective of their sizes (Afonso et al. 2015). A higher Gini coefficient value indicates higher inequality. The Gini coefficient has been used in measuring inequality in various domains, such as energy consumption (Jacobson et al. 2005), water consumption (Wang et al. 2012), indoor environmental quality (Zhang and Sanake 2020), and healthcare resource allocation (Jian et al. 2015).

In our study, we chose to adapt Gini coefficient in measuring the inequality of disaster impacts for the following reasons: (1) it allows for measurement of distributions of disaster impacts across multiple communities, (2) it allows for comparisons of distributions of disaster impacts across communities with different sizes of population, and (3) it is not affected by the characteristics (e.g., poverty) of the communities, and (4) it is relatively straightforward and easy to interpret.

CHAPTER 3 UNDERSTANDING INFRASTRUCTURE RESILIENCE, SOCIAL EQUITY, AND THEIR INTERRELATIONSHIPS: EXPLORATORY STUDY USING SOCIAL MEDIA IN HURRICANE MICHAEL

3.1 Introduction

Resilience has emerged as an increasingly important factor in developing and maintaining infrastructure in response to both acute (e.g., hurricanes, earthquakes) and slow on-set disasters (e.g., sea level rise) (Doorn 2019). Over the last decade, the growing intensity and frequency of disasters have resulted in huge economic losses mostly in the form of damage to infrastructure, which significantly impacts people's access to services, such as clean water, electricity, transportation, and health care (UN 2016). To allow infrastructure to resist or absorb disturbance, and retain basic functional and service capacities, investing in and implementing disaster resilience strategies have become a national imperative for all Americans (NRC 2012). However, one of the overlooked problems with infrastructure resilience is that damaged infrastructure due to disasters could result in varying levels of disturbance to the residents. Such damage is typically not evenly distributed across different communities; low income and minority communities are more vulnerable to disaster risks, and they also struggle more to recover (Emrich et al. 2019). For example, after Hurricane Harvey, more severe flooding damage was found in communities or households with lower incomes as lower income Americans are more likely to live in neighborhoods or buildings that are more susceptible to flooding or other impacts from storms (Krause and Reeves 2017).

To reduce or eliminate disparities of access to infrastructure due to disasters, the 2030 Global Sustainable Development Agenda of the United Nations highlights the importance of understanding the integrated nature of infrastructure, inequality, and resilience (UN 2016). For example, how does infrastructure resilience affect social equity? How is social equity integrated into resilience assessment or planning? Benchmarking the definitions of social equity in the literature (e.g., Emrich et al. 2019, UN 2019, APA 2021), social equity is defined as this study as equal opportunities and resources provided to different populations through the functions offered by infrastructure. Achieving social equity means reducing or eliminating disparate access to goods, services, and amenities among different populations, including socially vulnerable populations. Socially vulnerable population include the economically disadvantaged, racial and ethnic minorities, the elderly, the uninsured, the homeless, the disabled, those with chronic health conditions, and those with language barriers (Rao et al. 2019, AJMC 2006). They often have the fewest resources for disaster preparedness, live in disaster prone areas, and lack social, political, and economic capital needed to adapt to and recover from disasters (IWR 2016). Resilient infrastructure is vital in offering stabilized essential services (e.g., water, power, communication, and transportation) to socially vulnerable populations, thus playing an important role in supporting social equity in disasters (Doorn 2019, UN 2016).

Despite such interlinkage between infrastructure resilience and social equity, there is limited research that provides an explicit understanding about the complex relationships between infrastructure resilience and social equity. Extensive research efforts have focused on either infrastructure resilience or social equity. For instance, on one hand, the research on improving the resilience of infrastructure systems has received significant attention in the engineering circles (e.g., Karamouz et al. 2019, Rasoulkhani et al. 2019, Karamouz et al. 2018, Aydin et al. 2018). On the other hand, social equity has been widely studied in the domains of psychology, social science, political science, and anthropology (e.g., Domingue and Emrich 2019, Rodríguez-Izquierdo 2018, Castillo et al. 2019, Riccucci and Van Ryzin 2017). However, researchers from different research domains or backgrounds usually focus on one of these distinct fields, making links between these two areas less commonly studied than any of these areas taken in isolation (UN 2016). Thus, researchers and organization (e.g., UN 2016, Rockfeller Foundation 2020) have been calling for the need to understand the complex links between infrastructure resilience and social equity to uncover important synergies and tradeoffs.

To fill the knowledge gap, this chapter aims to explore the interlinkages between infrastructure resilience and social equity using a data-driven method. Data from different sources were collected and analyzed, including social media data, census data, and disaster damage, relief, and recovery data. In recent years, social media has become one of the emerging data sources to understand human activities and behaviors in a disaster setting (Resch et al. 2018, Zou et al. 2018a). Compared with traditional data sources (e.g., surveys), social media offers real time human generated data with spatiotemporal characteristics. Social media data allows researchers to conduct diverse studies in the context of disasters; the topics range from those that are related to infrastructure, such as damage assessment (e.g., Resch et al. 2018, Cervone et al. 2017, Wu and Cui 2018), infrastructure accessibility (e.g., Hamstead et al. 2018), and infrastructure recovery (e.g., Nazer et al. 2016, Schempp et al. 2019), to those that are relevant to social impacts, such as communication patterns (e.g., Wukich et al. 2019Goldgruber et al. 2017), public awareness (e.g., Martín et al. 2017), social disparities (e.g., Zou et al. 2018b). Among different sources of social media data (e.g., Facebook, Instagram, Twitter, and Tumblr), Twitter is the most widely used data source for conducting research as Twitter data are relatively easy to access, cost-effective, have less privacy concerns, and have proven to be a relatively reliable source of valuable information (Kryvasheyeu et al. 2016, Zou et al. 2018a).

As a first step toward understanding of the complex relationships between infrastructure resilience and social equity, this chapter aims to explore whether social media data can be used as indicators of either infrastructure resilience or social equity conditions in the context of a disaster. It aims to address the following research questions (RQs):

RQ1: How are infrastructure resilience conditions in the disaster-affected communities reflected by Twitter activities?

RQ2: How are social equity conditions in the disaster-affected communities reflected by Twitter activities?

RQ3: Do social equity characteristics of communities have impacts on the infrastructure resilience conditions of the communities?

To address these questions, Twitter activities generated by 12 disaster-affected counties in Florida during Hurricane Michael in 2018 were collected and analyzed. In addition, socioeconomic data were selectively collected to represent the social equity conditions of these disaster affected counties, while infrastructure damage, relief, and recovery data were collected to reveal the infrastructure resilience conditions of these counties. Statistical correlation analyses were then conducted (1) between the social equity variables and Twitter variables, (2) between the infrastructure resilience variables and the Twitter variables, and (3) between the social equity variables and the infrastructure resilience variables. The remainder of the chapter presents the research context and methodology, discusses the results and findings, and summarizes the contributions and conclusions.

3.2 Research Context

Hurricane Michael was a Category 5 hurricane that made landfall near Mexico Beach, Florida on October 10, 2018, with a maximum speed sustained wind speed of 257.50 kph (160 mph) (Wamsley 2019). It is one of the strongest hurricanes to have ever made a landfall in the Florida Panhandle region.

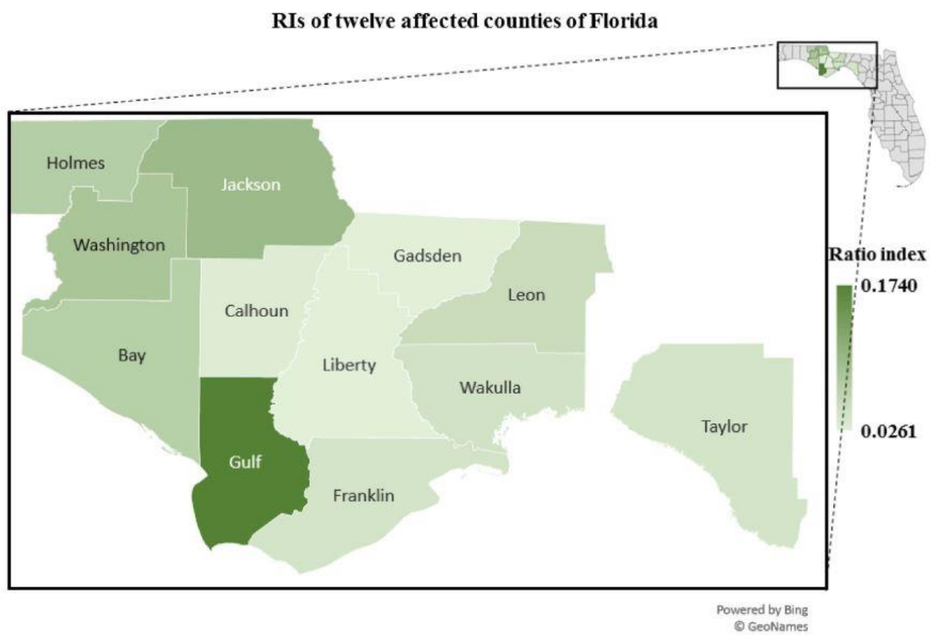


Figure 3-1 Ratio indices of the disaster affected counties of Florida.

Hurricane Michael was selected as the research context for three reasons. First, it caused massive damage and destruction to the infrastructure of coastal communities in the Florida Panhandle region. According to National Oceanic and Atmospheric Administration (NOAA), the storm surges brought floods with water levels rising 2.74-4.27 m (9-14 ft) above the normal level in the Panhandle area (NOAA 2018a). High storms surges and intense wind speeds caused significant damage to buildings and infrastructure. According to a preliminary damage assessment report (NHC 2018), Hurricane Michael caused approximately $25 billion in direct damage. These surges and wind forces caused complete power outages and a significant portion of the communication network outages in the Florida Panhandle region, with some of these outages lasting for more than a month. Physical structures, such as communication towers, electric poles, substations, and transmission towers, were severely damaged due to intense wind forces combined with fallen and flying debris and flash floods. In addition, transportation infrastructure (e.g., roads and bridges), was blocked, damaged, or completely washed away due to fallen trees and flash floods (NHC 2018). Second, the regions struck by Hurricane Michael are among the most socially vulnerable regions in the United States (DirectRelief 2018, Pathak et al. 2020). According to Federal Emergency Management Agency (FEMA 2018), 12 counties in Florida were severely impacted and issued disaster declaration as of November 15, 2018. These counties include Bay, Calhoun, Franklin, Gadsden, Gulf, Holmes, Jackson, Leon, Liberty, Taylor, Wakulla, Washington Counties (Figure 3-1). Third, there is relatively limited disaster research that focuses on Hurricane Michael as compared to studies on other hurricanes (e.g., Hurricane Sandy, Hurricane Harvey, Hurricane Irma).

3.3 Methodology

3.3.1 *Data Collection Methods*

3.3.1.1 Twitter Data Collection

In this study, Twitter was used as the source of social media data. Twitter provides an online social networking platform where people can communicate in short messages, share images, or webpages links, all of which are known as tweets. With 100 million daily active users and around 500 million daily tweets (Forsey 2019), Twitter is one of the most popular social networks that allow for the collection of a huge amount of information on human thoughts and activities in a disaster setting (Zou et al. 2018a). Twitter data collection and processing methods proposed by Zou et al. (2018a) was benchmarked, and the following steps were taken to collect and process Twitter data for analysis:

Step 1: Background Tweets Collection

Background tweets are the tweets generated from the Florida Panhandle area during the preparedness, response, and initial recovery phases of Hurricane Michael. The background tweets were collected by combining two different types of tweets: geotagged and non-geotagged tweets. The geotag of a tweet can be either an exact GPS coordinate (latitude and longitude) that represents the precise location of a user's mobile device or an approximate place name selected by the user from a list of place names suggested by Twitter, such as a city or a neighborhood (Twitter 2020). Tweets are generally not embedded with geolocations unless enabled by the users, and it is estimated that less than 1% of all the tweets are geotagged (Ajao et al. 2015).

Twint is used to collect geotagged tweets generated from Florida Panhandle area. Twint is a twitter scraping tool that utilizes Twitter search operators to scrape tweets from specific users, certain topics, or geographic locations (PyPI 2018). Twint is able to extract all the tweets that fall within a predetermined geographical coordinate and a radius of coverage. A Twitter search query was then scripted to extract all the geo-tagged tweets that were generated from each of the 12 Florida Panhandle counties. The tweets were extracted from October 1, 2018 to November 16, 2018 to cover preparedness, response, and initial recovery phases of Hurricane Michael. Each extracted tweet contains information including the time of creation, tweet ID, tweet content, tweet status (i.e., if the tweet is a reply or retweet), coordinates, place, and information about the user who posted the tweets (e.g., names, screen name, locations, numbers of followers, friend, and list).

The non-geotagged tweets in the background collection are the tweets without geotags but sent by users whose addresses are in the Florida Panhandle area. A publicly available Twitter data archive (Internet Archive 2020) was used to collect these non-geotagged tweets. The Internet Archive provides a chronological collection of tweets randomly selected from general twitter stream since 2012. In the archive, each tweet is stored in JavaScript Object Notation (JSON) format and contains information such as the textual content of the tweet and user profile. To collect non-geotagged tweets, a place-name lexicon was created including all the municipality names of each Florida Panhandle county. For each tweet, the address in the user profile was examined. The tweet was extracted if the address contains any municipality name from the place-name lexicon. Finally, the extracted non-geotagged tweets from Internet Archive were combined with extracted geotagged tweets to form the background tweets collection.

Step 2: Disaster-related Tweets Filtering

After the background tweets were collected, the disaster-related tweets were further filtered. The filtering process includes two main steps. First, all the extracted tweets were filtered to include only the following relevant information to this study: (1) time when the tweet was generated, (2) the tweet content, (3) user name, (4) user's profile information, (5) tweet's geolocation if enabled, and (6) user's location. Second, the disaster-related tweet data were further filtered based on the disaster-related keywords. A total of 39 keywords were used, such as hurricane, Michael, storm, response, preparedness, power, flood, infrastructure, and damage, etc. These keywords were derived through a combination of deductive approach and inductive approach. The deductive approach identifies the keywords based on the terms that are commonly used for filtering disaster-related tweets according to other social media literature (e.g., Zou et al. 2018b, Kryvasheyeu et al. 2016) in the disaster domain. The inductive approach identifies the keywords based on empirical observation of tweet contents. The keywords and the approaches that were used to derive them are listed as follows:

Deductive approach: Hurricane, power, weather, damage, storm, recovery, flood, local government, FEMA, climate, safe, food, and water

Inductive approach: Michael, infrastructure, emergency, rain, wind, surge, panhandle, Panama, Mexico, beach, relief, wave, responder, gulf, federal aid, resource, rebuild, supply, response, mitigate, prepare, highway, pray, rescue, search, and survivor.

For each county, the total number of background tweets and disaster-related tweets were counted and tabulated. A Python 3.6 script was used to filter the original tweets and count the disaster-related and total background tweets for each of the 12 studied counties.

3.3.1.2 Infrastructure Resilience Data Collection

Infrastructure resilience can be characterized by robustness, rapidity, resourcefulness, and redundancy (Bruneau and Reinhorn 2006). Each of these characteristics can be further represented through concrete dimensions and variables (Table 3-1). Eight infrastructure resilience variables were selected for analysis in this study for two reasons: (1) these variables can represent the key characteristics of infrastructure resilience, and (2) their data can be obtained through public sources. The selected variables include damage value per capita (I1), percentage of power outages (I2), percentage of communication service outages (I3), power outage recovery time (I4), communication service outage recovery time (I5), disaster recovery cost per capita (I6), disaster relief and emergency assistance fund per capita (I7), and number of insurance claims per capita (I8). As indicated in Table 1, the data for these variables were collected from different public sources, including Florida Department of Transportation (FDOT), Federal Emergency Management Agency (FEMA), Florida Division of Emergency Management (FDEM), Federal Communications Commission (FCC), Florida Department of Economic Opportunity (FDEO), and Florida Office of Insurance Regulations (FOIR).

Table 3-1 Infrastructure resilience variables

Main characteristic	Dimension	Variable	Data source
Robustness	Functional loss of infrastructure	Damage value per capita (I1)	(FDEM 2019)
		Percentage of power outages (I2)	(POR 2018)
		Percentage of communication service outages (I3)	(FCC 2018)
Rapidity	Time required to recover to previous functional levels	Power outage recovery time (I4)	(POR 2018)
		Communication service outage recovery time (I5)	(FCC 2018)
	Cost required to recover to previous functional levels	Disaster recovery work cost per capita (I6)	(FDOT 2019)
Resourceful-ness	Availability of economic resources	Disaster relief and emergency assistance fund per capita (I7)	FDEO (2019)
Redundancy	Alternate plan to maintain the functional level of infrastructure	Number of insurance claims per capita (I8)	(FOIR 2019)

3.3.1.3 Social Equity Data Collection

A total of 18 social equity variables (Table 3-2) were selected based on two main criteria: (1) they are representative indicators of social equity verified based on the review of literature (e.g., Schneiderbauer et al. 2006, Cutter et al 2010), and (2) they have consistent and high-quality data available from the national sources. These variables include percentage of population under 18 years (S1), percentage of population 65 years and above (S2), percentage of male population (S3), percentage of female population (S4), percentage of white population (S5), percentage of black or African American population (S6), percentage of Hispanic or Latino population (S7), percentage of population speaking other than English language at home (S8), percentage of households with internet connection (S9), percentage of households with computer (S10), percentage of population having high school degree and higher (S11), percentage of population without health insurance (S12), percentage of population with disability (S13), per capita income (S14), percentage of population under poverty (S15), median household income (S16), median value of owner occupied housing units (S17), and total employment (S18). For each variable, the data of each of the twelve affected counties were collected from the U.S. Census Bureau (U.S. Census 2019). The U.S. Census Bureau provides data with quality, reliability, and consistency (Santos 2019).

Table 3-2 Social equity variables

Dimension	Variable	Data source
Age	Percentage of population under 18 years (S1)	(U.S. Census 2019)
	Percentage of population 65 years and above (S2)	
Gender	Percentage of male population (S3)	(U.S. Census 2019)
	Percentage of female population (S4)	
Race	Percentage of white population (S5)	(U.S. Census 2019)
	Percentage of black or African American population (S6)	
	Percentage of Hispanic or Latino population (S7)	
Language	Percentage of population speaking other than English language at home (S8)	(U.S. Census 2019)
Technology	Percentage of households with internet connection (S9)	

	Percentage of households with computer (S10)	(U.S. Census 2019)
Education	Percentage of population having high school degree or higher (S11)	(U.S. Census 2019)
Health	Percentage of people without health insurance (S12)	(U.S. Census 2019)
	Percentage of population with disability (S13)	
Economics	Per capita income (S14)	(U.S. Census 2019)
	Percentage of population under poverty (S15)	
	Median household income (S16)	
	Median value of owner-occupied housing units (S17)	
	Total employment (S18)	

3.3.2 *Data Analysis Methods*

3.3.2.1 Twitter Data Indices

To analyze Twitter activities during Hurricane Michael, the Ratio Index (RI), Normalized Ratio Index (NRI), and Sentiment Index (SI) were calculated for each of the twelve affected counties in Hurricane Michael. Ratio Index (RI) is a Twitter index that can be used to represent the intensity of twitter activities in certain topics or domains. In this study, it is calculated using the number of disaster-related tweets divided by the total number of background tweets [Eq.(3-1)] (Zou et al. 2018b).

$$\text{RI} = \frac{Total\ number\ of\ disaster-related\ tweets}{Total\ number\ of\ background\ tweets} \tag{3-1}$$

In order to eliminate the effects of disaster threat levels on Twitter activities, a normalized ratio index was defined so that disparities of Twitter activities under the same disaster threat level can be investigated. The NRI can be calculated as RI divided by the average sustained wind speed [Eq.(3-2))]. The sustained wind speed data for each of the most affected counties were collected from the National Hurricane Center under NOAA (2018), and the NRI was calculated for each county using Eq. (3-2).

$$\text{NRI} = \frac{RI}{Average\ sustained\ wind\ speed} \tag{3-2}$$

Sentiment analysis aims to evaluate people's opinions, thoughts, and feelings, expressed in Twitter by assigning sentiment scores based on tweet contents (Caragea et al. 2014). Previous studies on social media data analysis have exhibited that sentiment analysis of tweet contents can be used to understand human perceptions, concerns, or psychological impacts during disasters (Caragea et al. 2014, Kryvasheyeu et al. 2016). This study used the valence aware dictionary and sentiment reasoner (VADER), a lexicon and rule-based python tool, to quantify the sentiment score for each of the tweet contents (Hutto and Gilbert 2014). VADER combines a manually created comprehensive sentiment lexicon with a set of grammatical and syntactical heuristics to determine the overall sentiment intensity of an input text (Hutto and Gilbert 2014). The comprehensive lexicon of VADER was constructed by examining existing well-established sentiment word banks [e.g., linguistic inquiry word count (LIWC), affective norms for english words (ANEW), and general inquirer (GI)] and incorporating numerous lexicon features related to sentiment expressions, including a full list of emotion and sentiment related acronyms (e.g., LOL), and commonly used slang with sentiment value (e.g., meh, nah) (Hutto and Gilbert 2014). In developing VADER, twenty independent human raters were employed for the intensity rating of lexical features, where the features were rated on a scale from extremely negative (-4) to extremely positive (+4), with neutral (0) in between (Hutto and Gilbert 2014). VADER has been found to perform exceptionally well in the social media domain and even outperform human raters at correctly identifying the sentiment intensity of tweets (Hutto and Gilbert 2014).

In our study, we employed VADER to determine if the text in the tweet content expresses positive, negative, or neutral opinion. For each tweet, VADER assigns a sentiment score ranging from 1 (extremely positive) to -1 (extremely negative), and a score between -0.05 and 0.05 is considered neutral. For a county, the sentiment index is calculated as the mean sentiment score of each tweet content from the county [Eq. (3-3)].

$$\mathrm{SI} = \frac{Sum\ of\ sentiment\ scores\ for\ disaster - related\ tweets}{Total\ number\ of\ disaster - related\ tweets} \tag{3-3}$$

3.3.2.2 Infrastructure Variable Index

When analyzing the infrastructure resilience conditions of the affected communities with different social equity characteristics, it is acknowledged that the counties that are close to the hurricane path naturally had more severe damage and could also take longer time to recover. Therefore, to eliminate the effects of disaster threat levels on the infrastructure, a set of normalized infrastructure resilience (NIR) variables were developed. Accordingly, the NIR data were calculated by dividing the original infrastructure resilience data with the average sustained wind speed during the hurricane period in each county [Eq. (3-4)]

$$\mathrm{NIR} = \frac{Infrastructure\ resilience\ data}{Average\ sustained\ wind\ speed} \tag{3-4}$$

3.3.2.3 Correlation Analyses

To answer the research questions, three sets of correlation analyses were conducted (1) between Twitter variables (RI and SI) and infrastructure resilience variables, (2) between Twitter variables (RI, NRI and SI) and social equity variables, and (3) between normalized infrastructure resilience variables (NIR) and social equity variables. Both the Pearson's Product-Moment Correlation (Pearson's correlation for short) and Spearman' Rank Order Correlation (Spearman's correlation for short) were used to conduct the correlation analyses. The Pearson's correlation coefficient is a measure of the strength of a linear association that exists between two continuous variables and is denoted by r (Laerd 2020a). The Spearman's correlation is a nonparametric version of the Pearson's correlation. Spearman's correlation coefficient (ρ) measures the strength and direction of monotonic association between two variables rather than strength and direction of the linear relationship between two variables, which is what Pearson's correlation determines (Laerd 2020b). The Spearman's correlation can be used for both continuous variables and ordinal variables. Additionally, compared to Pearson's correlation, Spearman's correlation is more robust to outliers (Mukaka 2012).

The results of the analyses were interpreted based on both the correlation coefficients (Pearson's r and Spearman's ρ) and the probability value (p-value). For the correlation coefficients, an absolute value of 0.50 and higher represents a high association between two variables, while an absolute value between 0.30 and 0.49 represents a medium association, and an absolute value between 0.10 to 0.29 represents a small association (SS 2020, Cohen et al. 2013). For the probability value, most researchers consider a standard significance level as 0.1, 0.05, or 0.01 for hypothesis tests (Frost 2020). In our study, a significance level of 0.1 was selected because (1) it allows the test to be more sensitive to detect significance in the data, (2) it is suitable for exploratory research to identify new hypothesis (Gaus et al. 2015), and (3) it is suitable to use for small sample size data sets (Kim and Choi 2019). Thus, if the p-value is less than 0.1, the association results are considered as statistically significant. The following sections discuss about the main findings of the analyses.

3.4 Results Analysis and Discussion

During the study period (from October 1, 2018, to November 16, 2018), 128 million tweets were collected. A total of 1,827,624 tweets were collected as the background tweets. Among the background tweets, a total of 103,660 disaster-related tweets were identified based on the disaster-related keywords. The RIs for the twelve affected counties were first calculated using Eq. (3-1), as shown in Fig. 1. Similarly, the NRIs and SIs for the twelve counties were calculated using Eq. (3-2) and Eq. (3-3), respectively. The three sets of correlation analyses were then conducted.

3.4.1 *Analyzing Relationships between Infrastructure Resilience and Twitter Activities*

To answer RQ1, the correlation analyses were conducted to assess the relationships between the infrastructure resilience variables and the Twitter activity variables (i.e., RI, SI). **Error! Reference source not found.** and Figure 3-2 present the correlation results that are statistically significant. As per Table 3, three infrastructure resilience variables, including damage value per capita (I1) (Pearson's r =0.750, p=0.058), communication service outage recovery time (I5) (Pearson's r = 0.556, p=0.060), and disaster recovery cost per capita (I6) (Pearson's r = 0.547, p =0.066) show statistically significant, strong positive linear associations with the Twitter activity variable, RI. In general, the results indicate that communities that experienced more severe damage to infrastructure and spent a longer time on recovery were more active on Twitter in Hurricane Michael.

Table 3-3 Statistically significant results of correlation analyses between infrastructure resilience variables and Twitter activities

Relationship[a]	Pearson's correlation		Spearman's correlation	
	r value	p-value	ρ value	p-value
RI vs I1	0.750	0.058[b]	0.149	0.645
RI vs I5	0.556	0.060[b]	0.467	0.125
RI vs I6	0.547	0.066[b]	0.168	0.602
RI vs I7	0.544	0.068[b]	0.224	0.484
RI vs I8	0.626	0.029[b]	0.427	0.167
SI vs I4	0.598	0.040[b]	0.687	0.014[b]

Note: RI = ratio index; and SI = sentiment index
[a]The numbering of infrastructure resilience variables follow that in Table 1.
[b]The p-value is significant at 0.1 level.

These results are consistent with a number of studies (e.g., Zou et al. 2018b, Kryvasheyeu et al. 2016) that indicate disaster-related Twitter activities are higher in those regions that have severe damage and destruction due to disasters. Other studies (Kent and Capello 2013, Starbird and Palen 2010) show that disaster-related Twitter activities originate more from the communities that are proximal to the crisis events compared to the communities located farther away. Social media plays an increasingly important role in the context of disasters. It has changed the ways of crisis communication, and it has turned out to be an important tool for information dissemination and exchange during emergency events. For example, during Hurricane Michael, the Twitter accounts of government officials were used for disseminating hurricane-related news, instructions, and educational resources for hurricane preparedness and response. The community residents were concerned about the damage and destruction that happened in their surroundings, and they turned to Twitter for disaster-related communication and information exchange. In the recovery process, social media is more commonly used for locating friends and families, facilitating volunteering inquiries, requesting and offering resources, and communicating and coordinating the recovery supplies (CivicPlus 2020). After Hurricane Michael, different government officials, public agencies, and non-government organizations (NGOs) used their official Twitter accounts to provide updates on recovery status, coordinate relief and recovery efforts, and offer resources or support.

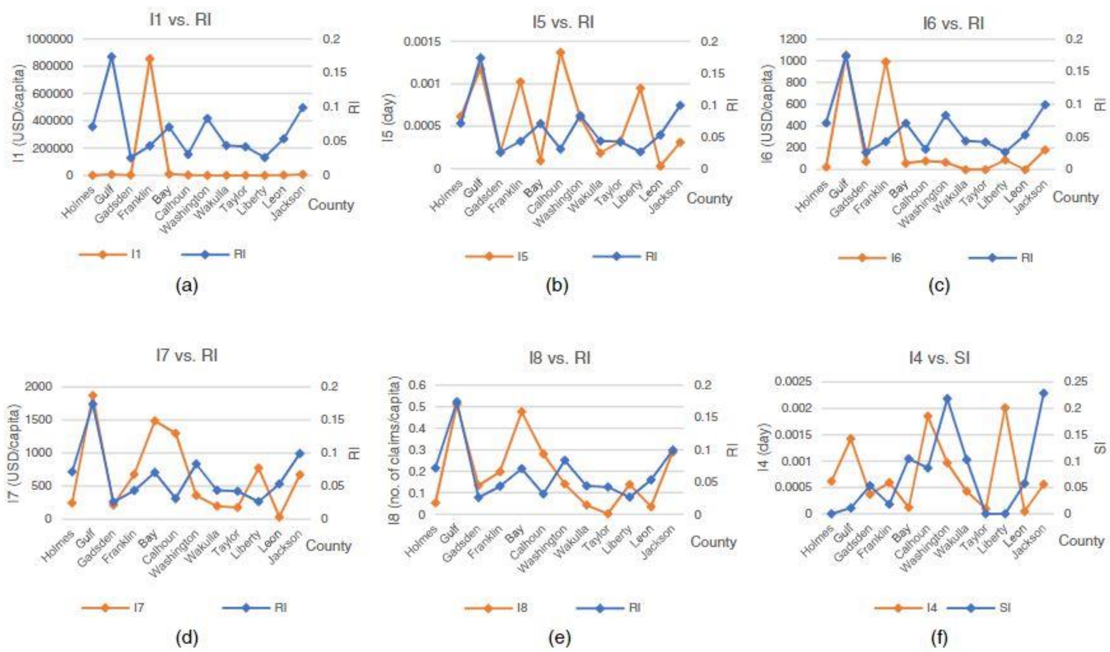


Figure 3-2 Line charts showing the relationships between infrastructure resilience variables and Twitter activities (RI and SI)
(The numbering of infrastructure resilience variable follow that in Table 1): (a) I1 versus RI; (b) I5 versus RI; (c) I6 versus RI; (c) I6 versus RI; (d) I7 versus RI; (e) I8 versus RI; and (f) I4 versus SI.

Besides the previous findings, in our study, the hurricane damage value data from Franklin County were found to be an outlier; the relatively high damage value per capita was not aligned with the relatively low Twitter activities in that county. A further investigation on the data of damage value showed that Franklin County has a significantly higher damage value compared to the other eleven affected counties (Figure 3-1) of the Florida Panhandle. This is mainly because of the tremendous amount of damage on coastal Highway 98 connecting Carrabelle to Saint George Island in Franklin County; the gulf side of the two-lane roadway was completely washed out (FDEM 2019). As a scenic highway along the shoreline, coastal Highway 98 has fewer coastal barrier protections installed to resist the potential high tides and storm surges. Without adequate and robust barrier protections that serve as the mainland's first line of defense against the impacts of severe storms and erosions, the roadway infrastructure along the gulf coast of the county was especially vulnerable during Hurricane Michael. Hurricane Michael generated strong wind forces and storm surges that ranged from 1.52 to 5.79 m (5 to 19ft), which caused extensive damage to residential buildings, critical facilities, and infrastructure such as roads and highways. The damage value was estimated to be $10 billion for Franklin County (FDEM 2019).

3.4.2 *Analyzing Relationships between Social Equity and Twitter Activities*

To answer RQ2, the correlation analyses were conducted to assess the relationships between the social equity variables and the Twitter activity variables (i.e., RI, NRI, and SI). **Error! Reference source not found.** and Figure 3-3 present the correlation results that are statistically significant. As per Table 4, the RI has statistically significant, strong negative correlations with the percentage of population speaking other than English language at home (S8) (Spearman's $\rho = -0.592$, $p = 0.043$), the percentage of Hispanic or Latino population (S7) (Spearman's $\rho = -0.573$, $p = 0.051$), and the percentage of population with disability (S13) (Spearman's $\rho = -0.565$, $p = 0.056$). In contrast, the RI has a statistically significant, strong positive correlation with the percentage of households with internet connection (S9) (Spearman's $\rho = 0.566$, $p = 0.055$). In general, these results indicate that the communities with a higher percentage of vulnerable populations (e.g., those with language barriers, the minority, the disabled) are less represented on social media, while the communities with relatively high socioeconomic status are more active on social media. The following paragraphs provide the discussion of the main findings from the results.

Table 3-4 Statistically significant results of correlation analyses between social equity variables and Twitter activities

Relationship[a]	**Pearson's correlation**		**Spearman's correlation**	
	r value	**p-value**	**ρ value**	**p-value**
RI vs S7	-0.408	0.187	-0.573	0.051[b]
RI vs S8	-0.383	0.220	-0.592	0.043[b]
RI vs S9	0.390	0.210	0.566	0.055[b]
RI vs S13	-0.267	0.402	-0.565	0.056[b]
SI vs S13	-0.435	0.158	-0.618	0.032[b]
SI vs S15	-0.392	0.208	-0.730	0.007[b]

Note: RI = ratio index; and SI = sentiment index.
[a]The numbering of social equity variables follow that in Table 2.

[b]The p-value is significant at 0.1 level.

Based on the results, the communities with higher percentages of vulnerable populations were less active on Twitter during Hurricane Michael. Despite the efforts and goals to reduce or eliminate disparities in the context of disasters, significant disparities in different aspects such as risk levels, access to capital, and disaster-related knowledge and resources, continue in these disaster-affected communities. Vulnerable populations could face various obstacles that result in their “silence” on social media. For example, people who are disabled are exposed to a higher constant risk in disasters due to personal health concerns, higher chance of injuries and mental health problems, lack of awareness of situations, isolation from communities, and physical barriers in evacuation (Stough 2017). Previous studies (e.g., Morris et al 2014, USDoC 2019) also suggest that people with disabilities show a lower rate of technology use. These obstacles often force disabled people to strive to address physiological needs and maintain their personal safety in disasters, leaving less time and lower chances of using or communicating through social media.

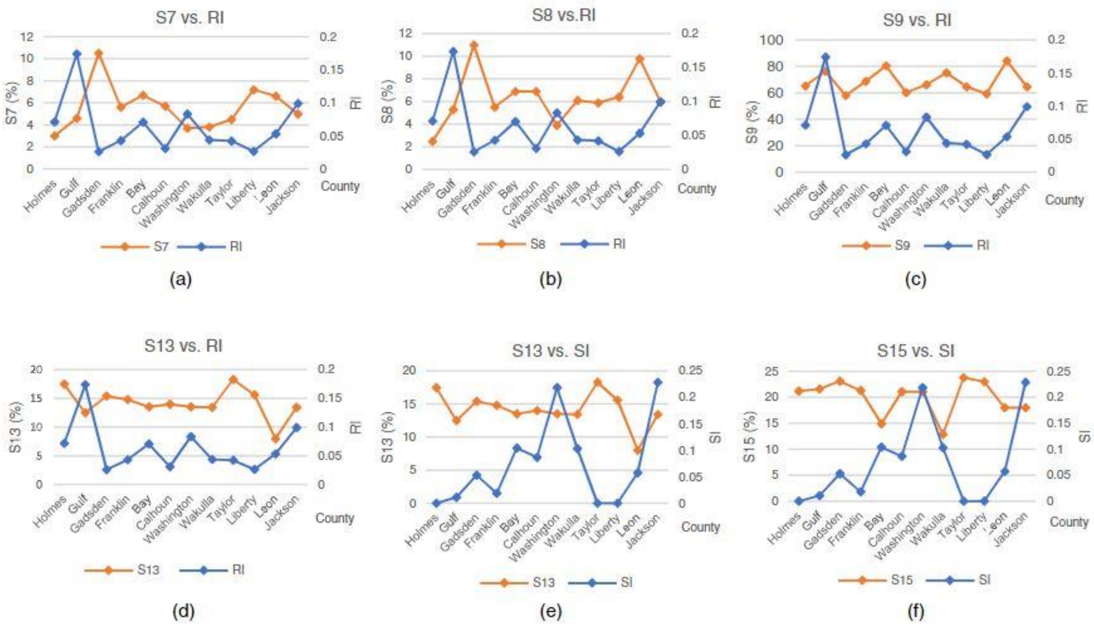


Figure 3-3 Line charts showing relationships between social equity variables and Twitter activities (RI and SI)
(The numbering of social equity variables follow that in Table 2): (a) S7 versus RI; (b) S8 versus RI; (c) S9 versus RI; (d) S13 versus RI; (e) S13 versus SI; and (f) S15 versus SI.

Similarly, the minority populations (e.g., Hispanic populations) and the populations speaking other than English language, were less active on Twitter during Hurricane Michael. Language barriers have a significant impact on how people perceive and prepare for disasters. For example, disaster warning alerts, preparedness strategies, and disaster-related knowledge are mostly communicated through the English language in the United States. People who do not speak English have to rely on the secondary sources of information to prepare for and respond to disasters. Although social media, such as Twitter, is a platform for the global community, the analysis of Twitter user behavior shows that users tend to confine their connectivity within those who speak the same language; the interactions among the users are fragmented and often limited by the language (Young 2020). Language barriers impede effective communication through social media between the affected minority populations and relief operations during disasters.

To eliminate the effects of disaster threat levels on Twitter activities, the correlation analyses between NRI and social equity variables were also conducted to explore the relationships between Twitter activities and social equity variables under the same disaster threat level. Table 3-5 summarizes the correlation results between the social equity variables and (1) RI, and (2) NRI. By comparing the results between (1) social equity variables vs. RI, and (2) social equity variables vs. NRI, it is observed that the correlation coefficients (Spearman's ρ) of three social equity variables, including the percentage of black or African American population (S6), percentage of population without health insurance (S12), and percentage of population under poverty (S15), change from negative values to positive values.

Table 3-5 Correlation coefficients of correlation analyses between social equity variables and Twitter activities

Social equity variable[a]	**Pearson's r value**		**Spearman's ρ value**	
	RI	**NRI**	**RI**	**NRI**
S5	0.243	0.174	0.245	-0.007
S6	-0.212	-0.105	-0.238	0.154
S9	0.390	-0.146	0.566	-0.146
S10	0.128	-0.327	0.329	-0.327
S11	0.129	-0.344	0.252	-0.344
S12	-0.146	0.263	-0.098	0.277
S13	-0.267	0.086	-0.565	-0.028
S14	0.100	-0.329	0.280	-0.329
S15	-0.071	0.182	-0.425	0.242
S16	0.068	-0.446	0.224	-0.446
S17	0.340	-0.215	0.455	-0.215
S18	-0.034	-0.317	0.259	-0.317

Note: RI = ratio index; and NRI = normalized ratio index.
The number of social equity variables follow that in Table 2.

On the other hand, the correlation coefficients of eight social equity variables, such as the percentage of population having high school degree and higher (S11), per capita income (S14), median household income (S16), median value of owner-occupied housing units (S17), and total employment (S18), change from positive values to negative values. Collectively, the shifts in correlation tendencies reveal that, by accounting for the hurricane wind threat levels, communities with higher percentages of vulnerable populations became more active on Twitter. In another word, under the same threat level, vulnerable populations were more active on Twitter during Hurricane Michael. This is probably because, facing with the same level of disaster threat, vulnerable populations perceived a greater level of difficulty and hardship in disasters, and they reflected this hardship by expressing their concerns, needs, and difficulties on social media.

3.4.3 *Analyzing Relationships between Social Equity and Infrastructure Resilience*

To answer RQ3, correlation analyses were conducted between the normalized infrastructure resilience variables and the social equity variables. Table 3-6 and Figure 3-4 present the statistically significant correlation results. Three main findings are discussed in the following paragraphs.

First, according to Table 3-6, under the same disaster threat level, there is a significant and strong positive correlation between the damage value per capita (I1*) and the percentage of Hispanic or Latino population (S7) (Spearman's $\rho = 0.559$, $p = 0.059$), and there is a significant and strong positive correlation between the disaster recovery cost per capita (I6*) and the percentage of population without health insurance (S12) (Spearman's $\rho = 0.518$, $p = 0.084$). In addition, there is a significant and strong positive linear association between disaster recovery cost per capita (I6*) and the percentage of population over 65 years old (S2) (Pearson's $r = 0.738$, $p = 0.006$). Collectively, these results may imply that the communities with higher percentages of vulnerable populations (e.g., the minority, the uninsured, the elderly) might have experienced more severe damage during Hurricane Michael, which also required higher expenses on recovery. Existing research shows that vulnerable populations are often under-prepared before disasters (e.g., lack of home insurances or flooding insurances, inadequate financial resources); thus, they may experience more severe losses (Constible 2018). These populations are also more likely to live in the disaster-prone regions with older and structurally deficient houses. In addition, a large percentage of houses, in the Florida Panhandle, were not able to withstand the strength of Hurricane Michael as they were constructed before the implementation of stricter building codes, which happened after Hurricane Andrew in 1992 (Allen 2018).

Table 3-6 Statistically significant results of correlation analyses between social equity variables and normalized infrastructure resilience variables

Relationship[a]	Pearson's correlation		Spearman's correlation	
	r value	p-value	ρ value	p-value
S1 vs I6[b]	-0.809	0.001[c]	-0.543	0.068[c]
S2 vs I6[b]	0.738	0.006[c]	0.476	0.118
S3 vs I6[b]	0.411	0.184	0.501	0.097[c]
S3 vs I7[b]	0.550	0.064[c]	0.585	0.046[c]
S4 vs I6[b]	-0.411	0.184	-0.501	0.097
S4 vs I7[b]	-0.550	0.064[c]	-0.585	0.046
S7 vs I1[b]	0.010	0.975	0.559	0.059[c]
S10 vs I4[b]	-0.385	0.216	-0.517	0.085[c]
S10 vs I5[b]	-0.494	0.102	-0.531	0.075[c]
S11 vs I5[b]	-0.438	0.154	-0.529	0.077[c]
S12 vs I5[b]	0.424	0.170	0.567	0.054[c]
S12 vs I6[b]	0.330	0.295	0.518	0.084[c]

[a]The numbering of infrastructure resilience and social equity variables follow that in Tables 1 and 2, respectively.
[b]Normalized infrastructure resilience variables by the wind threat levels.
[c] The p-value is significant to 0.1 level.

Second, as per Table 3-6, under the same disaster threat level, the communication service outage recovery time (I5*) has significant and strong negative correlations with the percentage of households with computer (S10) (Spearman's $\rho = -0.531$, $p = 0.075$) and percentage of population with high school degree and higher (S11) (Spearman's $\rho = -0.529$, $p = 0.077$), and it has a significant and strong positive correlation with the percentage of population without health insurance (S12) ($\rho = 0.567$, $p = 0.054$). The power outage recovery time (I4*) also shows a significantly negative correlation with the percentage of households with computer (S10) (Spearman's $\rho = -0.517$, $p = 0.085$). These results may imply that the communities with higher socioeconomic status are more likely to require shorter time for recovery, and vice versa. Previous recovery experiences show that wealthier communities typically receive more reinvestment on their infrastructure compared to low-income communities (Nexus 2017). In addition, communities with highly educated populations tend to take short recovery time after disasters. Highly educated populations are likely to be aware of the ongoing situations in their surroundings during disasters. They have the capability to communicate with local agencies, share information, and seek for aid and resources to recover from disasters.

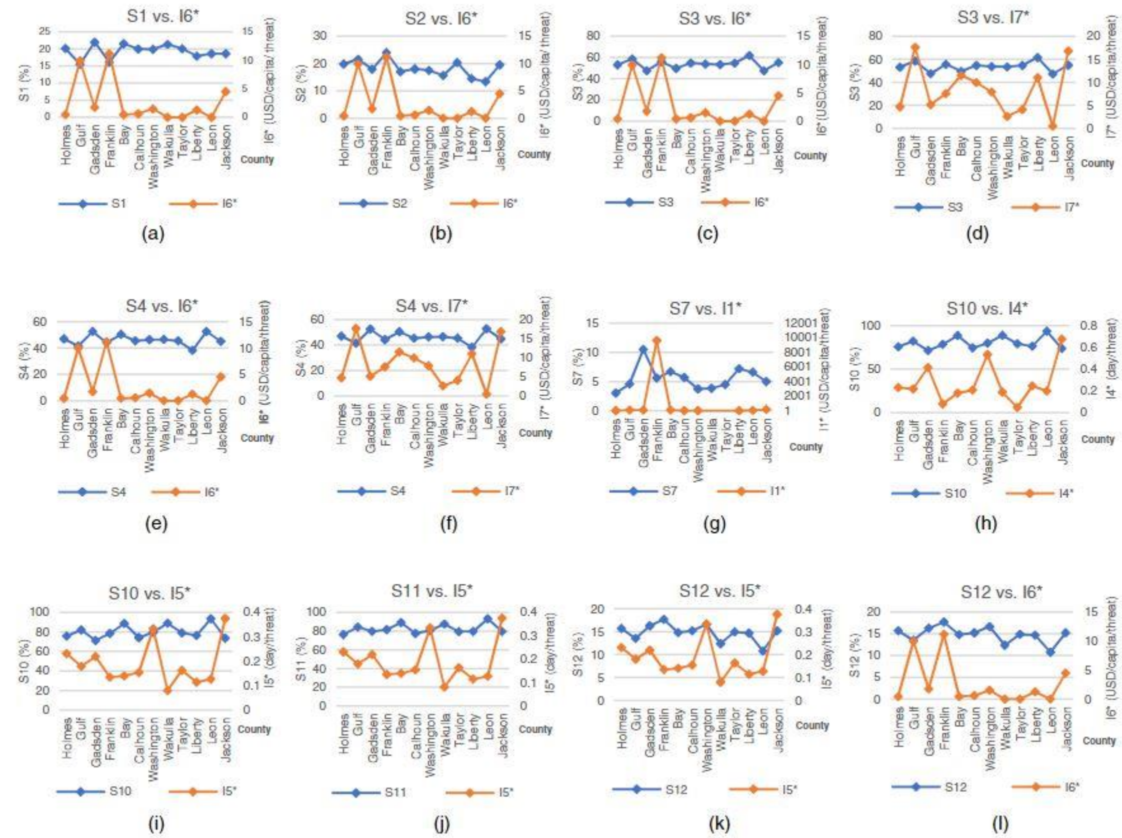


Figure 3-4 Line charts showing relationships between social equity variables and normalized infrastructure resilience variables
(The numbering of infrastructure resilience and social equity variables follow that in Tables 1 and 2, respectively): (a) S1 versus I6*; (b) S2 versus I6*; (c) S3 versus I6*; (d) S3 versus I7*; (e) S4 versus I6*; (f) S4 versus I7*; (g) S7 versus I1*; (h) S10 versus I4*; (i) S10 versus I5* (j) S11 versus I5*; (k) S12 versus I5*; and (l) S12 versus I6*.

Third, the results in Table 3-6 show the significantly positive correlations between the percentage of male population (S3) and (1) the disaster relief and emergency assistance fund per capita (I7*) (Spearman's $\rho = 0.585$, $p = 0.046$), and (2) the disaster recovery cost per capita (I6*) (Spearman's $\rho = 0.501$, $p = 0.097$). In contrast, significantly negative correlations are observed between the percentage of female population (S4) and (1) the disaster relief and emergency assistance fund per capita (I7*) (Spearman's ρ = -0.585, p = 0.046), and (2) the disaster recovery cost per capita (I6*) (Spearman's ρ = -0.501, p = 0.097). In addition, disaster relief and emergency assistance fund per capita (I7*) is found to have a significantly positive linear association with the percentage of male population (S3) (Pearson's r = 0.550, p=0.064), while having a significantly negative linear association with the percentage of female population (S4) (Pearson's r = -0.550, p=0.064). These results may reflect gender-based disparities in disaster recovery and relief efforts in Hurricane Michael. Existing studies suggest that male populations have a higher sense of responsibility in an emergency event (Ariyabandu 2009, Olson 2017); male populations may be more aware of damage in their communities, volunteer to take responsibilities in reconstruction works, and seek aid and support from relief agencies to support recovery. On the contrary, women are more likely to take the role of caregivers; they protect, nurture, and assist family members during emergency events (Ashraf and Azad 2015, Ariyabandu 2009), which may inhibit their participation in community disaster recovery activities. Some studies (e.g., Neumayer and Plümper 2007, Ariyabandu 2009) show that women are marginalized in access to disaster recovery and relief resources compared to men within the same community.

3.4.4 *Analyzing Sentiment Indices, Infrastructure Resilience, and Social Equity*

Sentiment scores of each of the tweets in the affected counties were calculated using VADER and the mean values of these sentiment scores were calculated to determine the SI for each county. In this study, the sentiment scores range from 0.946 (extremely positive) to -0.898 (extremely negative). To further exemplify the tweets associated with the sentiment scores, examples of positive and negative tweets are listed in Table 3-7. According to the tweet contents, most of the negative tweets are related to the damage caused by Hurricane Michael, such as death toll, damaged property, power outages, and fallen trees. For the most positive tweets, the contents are related to the aid, support, supplies, and services people received after Hurricane Michael.

Table 3-7 Partial list of positive and negative Hurricane Michael related tweets with sentiment scores

Rank	Tweet Content	Sentiment score	County
Examples of highly ranked negative sentiment tweets			
1	A closer look at damage in Mexico Beach, FL. The death toll right now is 4 people in Mexico Beach alone. 15 total in Bay County. #hurricanemichael #mexicobeach @ Mexico Beach, Florida	-0.8442	Gulf
2	My thoughts and prayers are with our brothers and sisters along the #Florida #panhandle. #hurricanemichael looks to be devastating. Scary for me to see another storm of this magnitude	-0.8176	Gulf
3	Even when power gets restored finding fuel will still be a problem around Panama City, FL. Hereâ€™s why. @weatherchannel #hurricanemichael @ Lynn Haven, Florida	-0.8126	Bay
4	This is what I #live for. Poor guy lost his #home in the #hurricane, has been outside since #Wednesday and overheated. His temp was 106.8.	-0.8126	Bay
5	Every tree down except the new ones #hurricanemichael #panhandlestrong @vacasarentals @RickyHaskins @ Calhoun County, Florida	-0.8074	Liberty
6	from @WFTV - CRUSHED: @GWarmothWFTV got a bird's eye view of the damage from #HurricaneMichael along the panhandle. #hurricane #mexicobeach #florida #orlando #floridaweather	-0.7739	Gulf
Examples of highly ranked positive sentiment tweets			
1	Inspiring to see the determination and positive attitudes of people hit hard by #hurricanemichael. And the selfless service of those here to help. #recover #rebuild #restore #hope	0.926	Jackson
2	Listen, Tallahassee. This is my spot. The whole family ate for $11. They were opened after the hurricane. No struggling over here. @ Los Compadres Express	0.9168	Leon
3	Our hearts go out to the panhandle and all of the communities terribly affected by #hurricanemichael Today, we witnessed, firsthand, the devastation in Marianna, FL as we delivered 47	0.8885	Jackson
4	@cityofdeltona Our @DeltonaFireRescue deployment team is still working in #calhouncounty They have been doing damage assessments for the local #emergencyoperationscenter	0.886	Calhoun
5	Thank you edwardcutie mr_chad_barnett and fmpolice for driving a truck load of supplies up to Mexico Beach law enforcement officers and first responders today #buyingthekeys @vacasarentals	0.8687	Gulf
6	I love this beautiful bride. She is such a sweet pure soul. During this big mess of a hurricane she offered to help us with anything we needed. I sure she was able to help many others	0.807	Bay

The correlation results between SI and (1) infrastructure resilience variables, and (2) social equity variables are shown in Table 3-3 and Table 3-4, respectively. According to Table 3-3, a significant and strong positive correlation is observed between the SI and the power outage recovery time (I4) (Spearman's $\rho = 0.687$, $p = 0.014$). This may imply that the communities tend to have a positive and optimistic attitude toward the recovery of the communities and the infrastructure services, even though they spend longer time in recovery. This result coincides with another research study on Hurricane Michael (Pathak et al. 2020), which indicates that the impacted communities emphasized that Hurricane Michael opened doors for growth and change. Local residents look forward to more opportunities that Hurricane Michael could bring to their slowly developing communities. In the recovery, they were determined to rebuild stronger structures instead of restoring to pre-disaster conditions. Many local stakeholders called for a change of policies, such as raising the standards of the building codes (Pathak et al. 2020).

In addition, the results in Table 3-4 show significantly negative correlations between the SI and (1) the percentage of population under poverty (S15) (Spearman's $\rho = -0.730$, $p = 0.007$) and (2) the percentage of population with disability (S13) (Spearman's $\rho = -0.618$, $p = 0.032$). These results suggest that the communities with higher percentages of populations that are disabled or under poverty were more likely to show a higher level of anxiety and deeper concerns regarding the impacts of Hurricane Michael. This result is supported by a number of studies (e.g., Shultz and Galea 2017, Galea et al. 2005, Fothergill and Peek 2004) that indicate vulnerable populations are more likely to develop anxiety, depression, and post-traumatic stress disorder (PTSD) as a result of exposure to disasters. For example, people with physical and mental disabilities are disproportionately affected by the impacts of disasters. These people with pre-existing medical conditions are more prone to develop additional mental health problems as a result of disasters. A study conducted after Hurricane Sandy found the residents with chronic health conditions and disabilities developed sleep disorders, pains, and suicidal ideation as the outcomes of adverse mental health problems (Boscarino et al. 2014). Similarly, the financially disadvantaged individuals are at a greater mental and emotional risk in disasters. Previous studies (e.g., Rhodes et al. 2010, Kessler et al. 2008, Mills et al. 2007) show that the lack of access to both social and economic resources is correlated with declining mental health conditions, which may result in serious mental illness and higher perceived stress levels after disasters.

3.5 Conclusions

This chapter presents a study that aims to explore the interrelationships between infrastructure resilience and social equity in the context of Hurricane Michael. As part of the study, this chapter examines whether Twitter data can be used as an indicator of the infrastructure resilience or social equity conditions in a disaster setting. Twitter activities generated by the twelve disaster-affected counties in Florida during Hurricane Michael in 2018 were collected and analyzed. In addition, the socioeconomic data were selectively collected to represent the social equity conditions of these disaster-affected counties, while the infrastructure damage, relief, and recovery data were collected to reflect the infrastructure resilience conditions of these counties. Statistical correlation analyses were then conducted (1) between the social equity variables and the Twitter variables, (2) between the infrastructure resilience variables and the Twitter variables, and (3) between the social equity variables and the infrastructure resilience variables. The results indicate that, in the context of a disaster, Twitter activities have the potential to be used as an important indicator of infrastructure resilience conditions. In general, socially vulnerable populations are less active and representative on social media. However, under the same disaster threat level, the vulnerable populations become more active, and this is probably because of more difficulties and hardship they perceive during disasters. In addition, the impacted counties with different social equity conditions experienced different levels of damage and different speeds of recovery. The communities with higher percentages of socially vulnerable populations experienced relatively higher level of damage and required longer time for recovery. While some of the findings were discovered in other literature (e.g., Krause and Reeves 2017, Emrich et al. 2019, Constible 2018) and in the context of other disasters, this study offers a data-driven understanding by integrating social media data with traditional data and providing synthesized data analysis results that further explore and reinforce the knowledge of infrastructure resilience and social equity in disasters.

CHAPTER 4 A SOCIAL WELFARE BASED INFRASTRUCTURE RESILIENCE ASSESSMENT FRAMEWORK: TOWARD EQUITABLE RESILIENCE FOR INFRASTRUCTURE DEVELOPMENT

4.1 Introduction

From meeting everyone's basic needs to supporting trade, economy, and technology advancement, infrastructure services are the key enablers of human well-being and development. With climate change and the growth in intensities and frequencies of natural hazards, there is an increasing urgency and priority on investing in and developing resilient infrastructure (Hallegatte et al. 2019). A resilient infrastructure with high quality and robust structural components can potentially limit the impacts from natural hazards in terms of physical damage, economic losses, and functional disruptions (Braese et al. 2019). Over the last two decades, significant efforts have been made for the investment, development, and maintenance of resilient infrastructure to better withstand, adapt to, and rapidly recover from disaster impacts. However, in the context of a disaster, large disparities may exist in the levels of damage and/or recovery processes of the infrastructure across various communities. Such disparities may be caused by the differences in the severity of disaster exposure, and it may also be caused by the variations in the quality and adequacy of infrastructure services across different communities (Coleman et al. 2020). Some communities (e.g., wealthier communities) may have more investment in the development and rehabilitation of existing infrastructure (Hirsch et al. 2016, Nexus 2017). In contrast, some disaster vulnerable communities, which refer to those communities that suffer from the most severe disaster impacts, may struggle with unmet infrastructure needs, such as unreliable electric power systems, lack of adequate water and sanitation systems, overstrained transportation networks, and degraded school buildings, even before the disaster (Huang and Taylor 2019, Hallegatte et al. 2019). Underinvestment, insufficient maintenance, and mismanagement are some of the key factors that result in inadequate infrastructure services in these disaster vulnerable communities (Hallegatte et al. 2019). In addition, research (e.g., Hallegatte et al. 2019, SMASHA 2017) shows that such disaster vulnerability is associated with social vulnerability. Socially vulnerable communities may include those with higher percentages of economically disadvantaged, racial and ethnic minorities, elderly, uninsured, homeless, disabled, those with chronic health conditions, and those with language barriers (Rao et al. 2019, AJMC 2006). These communities often have the fewest resources for disaster preparedness, are located in disaster-prone areas, and lack social, political, and economic capital needed to withstand, adapt to, and recover from a disaster. As a result, they are more likely to suffer from severe disaster impacts (e.g., higher percentages of power outages and traffic disruptions, longer recovery time) (Hallegatte et al. 2019, SAMSHA 2017). Due to the unequal distributions of disaster impacts and potentially more severe impacts on the infrastructure of vulnerable communities, there is sorely a need to systematically integrate disaster inequality and vulnerability with infrastructure resilience assessment.

Despite such need, we have identified a number of knowledge gaps in the domain of infrastructure resilience assessment. Over the last two decades, many research studies (e.g., Panteli et al. 2017, Tonn et al. 2020, Cimellaro et al. 2010, Mao and Li 2018, Yang et al. 2018) have focused on developing models or frameworks to measure or assess infrastructure resilience. Various approaches or methods have been used in resilience assessment, such as simulation-based approaches (e.g., Hossain et al. 2019), mathematical approaches (e.g., Cimellaro et al. 2010), index-based approaches (e.g., Fisher and Norman 2010), and data-driven approaches (e.g., Zhu et al. 2017). These studies have provided valuable contributions toward advancing the understanding and facilitating infrastructure resilience. However, there remains limited research that integrates the disparity and vulnerability in disaster impacts with infrastructure resilience assessment. In another word, there is a lack of study that (1) measures the unequal distributions of disaster impacts (e.g., infrastructure functional loss, infrastructure recovery time) across different communities and potentially more severe impacts on vulnerable communities, and (2) investigates how they would impact the collective resilience of infrastructure that serves multiple communities.

To address these knowledge gaps, we propose a Social-Welfare-Based Infrastructure Resilience Assessment (SW-Infra-RA) model that assesses the collective resilience of infrastructure serving multiple communities by accounting for (1) disaster inequality – the unequal distribution of disaster impacts on infrastructure across the various communities, and (2) disaster vulnerability – the higher severity of disaster impacts on infrastructure serving vulnerable communities. The proposed model is theoretically grounded on the social welfare theory and social welfare functions. It also adapts the methods from Bruneau et al. (2003)'s Resilience Triangle framework and Cutter et al. (2003)'s Social Vulnerability Index. The proposed model aims to address the following research questions: How to quantitatively measure the unequal distributions of disaster impacts on infrastructure across different communities? How to quantitatively measure the potentially more severe disaster impacts on infrastructure of vulnerable communities? How to mathematically integrate the disparity and vulnerability in disaster impacts with infrastructure resilience assessment? This chapter focuses on presenting and discussing the conceptual notions and mathematical functions in the SW-Infra-RA model. The remainder of the chapter first reviews and discusses the relevant literature. It then presents the SW-Infra-RA model, including all the mathematical functions in the model. At the end, it discusses two sets of case studies (including a hypothetical and a real case study) to illustrate the use of the SW-Infra-RA model in determining the collective resilience of infrastructure serving multiple communities.

4.2 Proposed Infrastructure Resilience Evaluation Framework

The proposed SW-Infra-RA model aims to define the collective resilience of infrastructure that serves multiple communities by integrating (1) disaster inequality – the unequal distributions of disaster impacts on infrastructure across the various communities, and (2) disaster vulnerability – the higher severity of disaster impacts on infrastructure serving vulnerable communities. The framework is grounded in the social welfare theory and functions. It also adapts the methods from Bruneau et al. (2003)'s Resilience Triangle framework and Cutter et al. (2003)'s Social Vulnerability Index. The model assesses the collective resilience of infrastructure in five main steps, including (1) determining disaster impacts on individual communities, (2) modeling inequality of disaster impacts, (3) modeling vulnerability in disaster impacts, (4) measuring collective disaster impacts, and (5) assessing collective infrastructure resilience. The following sections discuss about each step in detail.

4.2.1 ***Determining Disaster Impacts on Individual Communities***

Disasters may cause severe damage to infrastructure, which results in the reduction of its functionality, and it may take weeks or months to restore the infrastructure to its original functional level. According to Bruneau et al. (2003)'s Resilience Triangle framework, such characterization of infrastructure performance during a disaster leads to a broader conceptualization of resilience. Resilience can be understood as the ability of infrastructure (1) to reduce the possibility or extent of disaster impacts, and (2) to recover rapidly after a disaster (Bruneau et al. 2003). Such conceptualization of resilience is widely adopted in different disaster literature (e.g., Cimellaro et al. 2010, Rehak et al. 2019, Yang et al. 2018). Benchmarking the Resilience Triangle framework, two main types of indicators were identified to determine the disaster impacts on individual communities. These indicators include those that represent (1) the functional loss of infrastructure (e.g., percentage of power outages, percentage of road closures), and (2) the recovery time of infrastructure (e.g., time required to resume electric power services, time required to resume road and highway services).

Depending on the time of analysis, the selected disaster, the level of analysis (e.g., state level, county level, city level, community level), and data availability, there are two main methods for collecting the data for these indicators (i.e., functional loss and recovery time of infrastructure). For analyzing infrastructure resilience in the context of historical disasters, we can extract the relevant data that are available in public or private sources; the data can be collected directly from (1) public sources, such as state, county, or local Department of Emergency Management, Department of Transportation, Office of Communications Commission, or Office of Insurance Regulations, or (2) private sources, such as electric power companies and telecommunication companies. The data then need to be tabulated by the level of analysis (e.g., state, county, city, community levels). For analyzing infrastructure resilience in the context of ongoing disasters, we need to collect firsthand data on infrastructure damage and recovery works by following damage assessment procedures and using the relevant tools and methods. For example, according to Federal Emergency Management Agency (FEMA)'s Preliminary Damage Assessment Guide (FEMA 2021), damage information of infrastructure needs to be captured by visually and technically inspecting and confirming the conditions of damaged infrastructure and identifying and documenting relevant disaster impacts (FEMA 2021).

In general, damage assessment is conducted using either a rapid approach or a detailed approach (Kwasinski 2011; Massarra 2012). Rapid damage assessment usually takes place as soon as conditions allow inspectors to operate after the occurrence of a disaster. It aims to generally estimate the nature and magnitude of damage and quickly inspect and assess the damage conditions. Thus, rapid assessment typically relies on an exterior observation and investigation of the structures. The magnitude of damage recorded on damage assessment forms (e.g., FEMA 2021) is typically a general estimate of the percentage of damage without accurate measurements (Massarra 2012). In recent years, many technologies have been proposed to facilitate the efficiency of rapid damage assessment. For example, GIS-based hazard modeling platforms (e.g., HAZUS) can be used to estimate potential damage from disasters, such as hurricanes and floods (CCSF 2021). Remote sensing technologies, which detect and monitor the physical characteristics of an area by measuring its reflected and emitted radiation from a certain distance, can be used to quickly estimate locations, causes, and severity of disaster damage conditions (Hao et al. 2020). If more detailed information is required regarding the damage conditions, rapid assessment should be followed by detailed assessments. Detailed damage assessment usually takes place in about two to four weeks after the occurrence of a disaster (Massarra 2012). Detailed damage assessment aims to collect more thorough and accurate information regarding the impacts of a disaster, including estimation of loss value, determination of recovery progress, and identification of recovery needs (Planitz 1999). Detailed damage assessment is based on the inspection of both structural (e.g., girder, column) and non-structural components (e.g., railing, coating) of infrastructure (Massarra 2012). In our research context, both rapid and detailed assessment can be used to collect the data for determining disaster impacts on individual communities. The selection of the methods depends on the level of details that is needed for infrastructure resilience analysis.

4.2.2 *Modeling Inequality in Disaster Impacts*

In our research context, disaster inequality refers to the unequal distributions of disaster impacts (i.e., functional loss, recovery time) on infrastructure of various communities. The unequal distribution of disaster impacts is analogous to the welfare inequality in a society, which is commonly measured through the Gini coefficient (Atkinson and Brandolini 2010). Thus, we adapted Gini coefficient into the domain of infrastructure resilience assessment to measure the unequal distributions of disaster impacts (i.e., functional loss and recovery time) on infrastructure that serves multiple communities.

A Gini coefficient ranges from 0 to 1. A Gini coefficient of 0 means complete equality in disaster impacts – the infrastructure of all communities of analysis has the same level of functional loss, and/or it takes the same length of time for recovery. A Gini coefficient of 1 means complete inequality in disaster impacts – the infrastructure of only one community has the highest level of functional loss and spends the longest time for recovery. Graphically, Gini coefficient can be represented through the Lorentz curve (Figure 4-1). As per Figure 4-1, it is measured by dividing the area between the Lorentz curve and line of complete equality (i.e., Area X) by the area covered under the line of complete equality (i.e., Area X+Y) (Wodon and Yitzhaki 2008, Mostafa and El-Gohary 2014). In the SW-Infra-RA model, the Lorentz curve illustrates the percentage of cumulative infrastructure functional loss (or recovery time) experienced by the percentage of communities in analysis. For example, as per Figure 4-1, a point on the Lorenz curve represents a statement such as, "the bottom 40% of all communities suffered from 10% of the total disaster impacts (e.g., functional loss, recovery time)". A Lorentz curve is always bowed downward from the line of equality or coincides with the line of equality if there exists complete equality among the individuals of analysis. The Lorentz curve being farther away from the line of equality indicates a higher level of inequality (i.e., the value of Gini coefficient becomes closer to 1) and vice-versa.

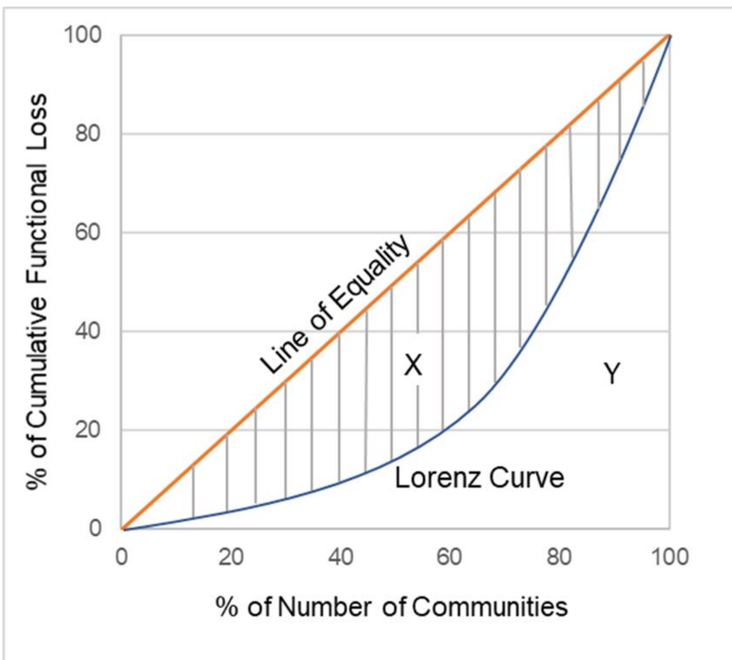


Figure 4-1 A Lorenz curve for the distribution of infrastructure functional loss.

The Gini Coefficient can also be defined through Eqs. (4-1) and (4-2), which are mathematically equivalent to the Lorenz Curve. Eq. (4-1) and Eq. (4-2) define the Gini coefficients that measure the unequal distributions of functional loss and recovery time (i.e., two main indicators of disaster impacts), respectively.

$$G_{k(FL)} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|FL_{ik} - FL_{jk}|}{2n\sum_{i=1}^{n}FL_{ik}} \quad (4\text{-}1)$$

where $G_{k(FL)}$ = Gini coefficient for functional loss of a group k of multiple communities; FL_{ik} = functional loss of infrastructure in an individual community i of group k; FL_{jk} = functional loss of infrastructure in an individual community j of group k; and n= total number of communities in group k.

$$G_{k(RT)} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|RT_{ik} - RT_{jk}|}{2n\sum_{i=1}^{n}RT_{ik}} \quad (4\text{-}2)$$

where $G_{k(RT)}$ = Gini coefficient for recovery time of a group k of multiple communities; RT_{ik} = recovery time of infrastructure in an individual community i of group k; RT_{jk} = recovery time of infrastructure in an individual community j of group k; and n= total number of communities in group k.

4.2.3 *Modeling Vulnerability to Disaster Impacts*

In our research context, vulnerable communities in a disaster refer to those communities that suffer from the most severe impacts from a disaster. The concept of vulnerability to disaster impacts is analogous to the concept of poverty in welfare economics. Thus, benchmarking the methods for measuring poverty in welfare economics, we proposed a "line of vulnerability" to define and measure vulnerability in the SW-Infra-RA model. The line of vulnerability is a benchmark that indicates the vulnerability level of infrastructure serving different communities. If the value of disaster impacts (i.e., infrastructure functional loss and recovery time) is above the line of vulnerability, the community is identified as one of the vulnerable communities in the disaster. However, unlike the poverty line that has been extensively studied, there are no established methods to measure the line of vulnerability in the disaster domain. In our research, we adapted Cutter et al. (2003)'s work on social vulnerability. Cutter et al. (2003) constructed a Social

Vulnerability Index (SoVI) for all the counties in the U.S. based on the county-level socioeconomic and demographic data. The counties with SoVI scores greater than the average plus standard deviation are identified as the most vulnerable counties. In our proposed model, the line of vulnerability can be defined as the sum of the mean and the standard deviation of infrastructure functional loss (or recovery time) experienced by the communities of analysis. Eq. (4-3) and Eq. (4-4) define the line of vulnerability for functional loss and recovery time, respectively:

$$LV_{(FL)_k} = \frac{1}{n}\sum_{i=1}^{n} FL_{ik} + \alpha S_{nk} \tag{4-3}$$

where $LV_{(FL)_k}$= line of vulnerability for functional loss of infrastructure serving a group k of multiple communities; FL_{ij} = functional loss of infrastructure serving an individual community i of group k; n = total number of communities in group k; S_{nk} = standard deviation for the functional losses of infrastructure serving a group k of multiple communities; and α = a coefficient that controls the line of vulnerability ($0 \leq \alpha \leq 1$).

$$LV_{(RT)_k} = \frac{1}{n}\sum_{i=1}^{n} RT_{ik} + \beta S_{nk} \tag{4-4}$$

where $LV_{(RT)_k}$ = line of vulnerability for recovery time of infrastructure serving a group k of multiple communities; RT_{ik} = recovery time of infrastructure serving an individual community i of group k; n = total number of communities in group k; S_{nk} = standard deviation for the recovery time of infrastructure serving a group k of multiple communities; and β = a coefficient that controls the line of vulnerability ($0 \leq \beta \leq 1$).

Depending on the context of analysis, users of the model have the flexibility to define and control the line of vulnerability through the coefficients of α and β. If the value of α (or β) is close to 0, the line of vulnerability is close to the average value. This means the criterion or benchmark for vulnerability is stringent, i.e., approximately half of the communities whose damage (or recovery time) is above the average will be accounted as vulnerable communities. If the value of α (or β) is close to 1, the line of vulnerability is close to the average value plus standard deviation. This means the criterion or benchmark for vulnerability is loose as a relatively smaller number of communities will be accounted as vulnerable communities. Defining such line of vulnerability is important in identifying those communities that experience the most severe impacts during a disaster, and this could allow decision makers to prioritize efforts and investments on those communities in disaster assistance, recovery, and/or future mitigation efforts.

4.2.4 *Measuring Collective Disaster Impacts*

The SW-Infra-RA model measures the collective disaster impacts on infrastructure that serves multiple communities based on the distribution of impacts among individual communities. If we want to reduce the overall impact of a disaster, attention must be given to improve the overall equity and to reduce sensitivity of vulnerable communities to disasters (Nicholson 2014). Previous studies (e.g., Tselios and Tompkins 2019, Ward and Shively 2016) also show that higher inequality is associated with worse losses from disasters. Thus, when modeling the collective disaster impacts, we can assume that inequality and vulnerability are both unfavorable situations. Inequality and vulnerability will then be accounted as factors that will further augment the collective disaster impacts.

In the SW-Infra-RA model, the function of collective disaster impacts includes the Collective Functional Loss (CFL) function (Eq. (4-5)) and the Collective Recovery Time (CRT) function (Eq. (4-6)). Both functions incorporate the unequal distributions of disaster impacts on the infrastructure serving multiple communities and the potentially severe impacts on infrastructure in the vulnerable communities. These two functions are developed by adapting the social welfare functions (e.g., Mostafa and El-Gohary 2014, Zhang and Sanake 2020). The equation for the CFL function is presented as:

$$CFL_k = \frac{1}{n}\sum_{i=1}^{n} FL_{ik} \times \left(1 + \gamma G_{k(FL)}\right) + \delta\,\frac{1}{n}\sum_{i=1}^{n} \max\left[0, \left(FL_{ik} - LV_{(FL)_k}\right)\right] \tag{4-5}$$

where CFL_k= the collective functional loss of the infrastructure that serves a group k of multiple communities; FL_{ik} = the functional loss of the infrastructure that serves an individual community i of group k; n = the total number of communities; $G_{k(FL)}$= the Gini coefficient for the functional loss of group k; $LV_{(FL)_k}$= the line of vulnerability for functional loss of infrastructure serving a group k of multiple communities; γ = a coefficient that controls the degree of accounting for inequality in augmenting the disaster impacts ($0 \leq \gamma \leq 1$); and δ = a coefficient that controls the degree of accounting for vulnerability in augmenting the disaster impacts ($0 \leq \delta \leq 1$).

Similarly, the equation for CRT function is presented as:

$$CRT_k = \frac{1}{n}\sum_{i=1}^{n} RT_{ik} \times \left(1 + \lambda G_{k(RT)}\right) + \mu \frac{1}{n}\sum_{i=1}^{n} \max\left[0, \left(RT_{ik} - LV_{(RT)_k}\right)\right] \qquad (4\text{-}6)$$

where CRT_k= the collective recovery time of the infrastructure that serves a group k of multiple communities; RT_{ik} = the recovery time of the infrastructure that serves an individual community i of group k; n = the total number of communities; $G_{k(RT)}$= the Gini coefficient for the recovery time of group k; $LV_{(RT)_k}$= the line of vulnerability for recovery time of infrastructure serving a group k of multiple communities; λ = a coefficient that controls the degree of accounting for inequality in augmenting the disaster impacts ($0 \leq \lambda \leq 1$); and μ = a coefficient that controls the degree of accounting for vulnerability in augmenting the disaster impacts ($0 \leq \mu \leq 1$).

Each of the CFL and the CRT functions consists of a subfunction for inequality and a subfunction for vulnerability. The inequality subfunction penalizes the unequal distributions of disaster impacts across different communities. In another word, inequality further augments the collective disaster impacts on these communities. The inequality is measured through the Gini Coefficient [$G_{k(FL)}$, $G_{k(RT)}$] using Eq. (4-1) or Eq. (4-2). Additionally, a coefficient γ (or λ) is introduced to allow users to adjust the degree of penalizing unequal distributions of disaster impacts. The value of γ (or λ) ranges from 0 to 1, where γ (or λ) =1 represents the full extent of penalization, and γ (or λ) $= 0$ represents no penalization at all. Thus, users of the model have the flexibility in determining to what extent they want to account for the inequality factor in infrastructure resilience assessment.

The vulnerability subfunction acknowledges that the potentially severe disaster impacts on the infrastructure of vulnerable communities could compromise the overall infrastructure resilience and should be penalized when assessing the collective resilience of infrastructure. In another word, more severe impacts on some vulnerable communities further augment the collective disaster impacts on all communities of analysis. In this function, a coefficient δ (or μ) is introduced, and it allows users to control the degree of accounting for vulnerability in collective disaster impacts. The value of δ (or μ) ranges from 0 to 1, where δ (or μ) =1 represents the full extent of penalization, and δ (or μ) = 0 represents no penalization at all. Thus, users may have the flexibility in determining to what extent they want to account for the vulnerability factor in infrastructure resilience assessment.

4.2.5 *Assessing Collective Infrastructure Resilience*

The collective infrastructure resilience assessment function aims to measure the collective infrastructure resilience based on the collective disaster impacts – collective functional loss and collective recovery time. The function was developed by adapting Bruneau et al. (2003)'s Resilience Triangle framework.

Benchmarking Bruneau et al. (2003), the SW-Infra-RA model measures the infrastructure resilience by defining and measuring the area of a collective resilience triangle (Figure 4-2). In the collective resilience triangle, the vertical axis of the triangle represents the collective functionality of infrastructure, which varies over time. The collective functionality of infrastructure ranges from 0% to 100%, where 100% means no degradation in functions or services and 0% means no service is available. A disaster occurring at time t_0 could cause damage to the infrastructure that the functionality of the infrastructure immediately reduced. The extent to which the functionality is reduced can be measured by the CFL function [Eq. (4-5)]. The recovery of the infrastructure is a process that takes time, and the infrastructure is completely restored to the original functional level when it is time t_t. The collective length of recovery (from time t_0 to t_t) can be measured through the CRT function [Eq. (4-6)].

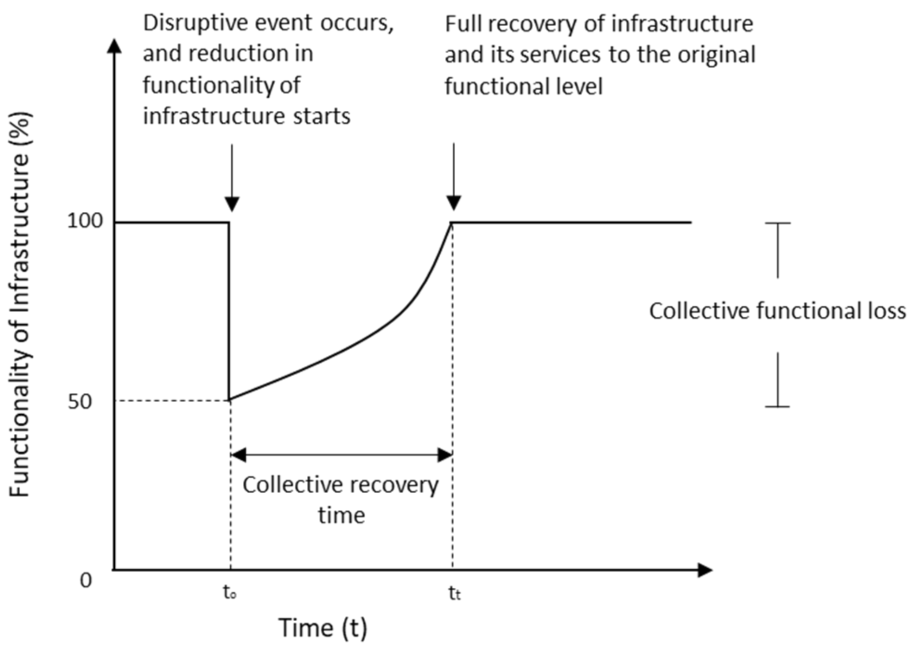


Figure 4-2 A conceptual diagram for a collective resilience triangle (adapted from *Bruneau et al. 2003*).

To measure the area of the collective resilience triangle, the collective loss of infrastructure resilience can be measured through Eq.(4-7):

$$CLR_k = \int_{t_0}^{t_t} (CFL_k)\,dt \tag{4-7}$$

where CLR_k = the collective loss of resilience of infrastructure that serves a group k of multiple communities; CFL_k = the collective functional loss of infrastructure that serves a group k of multiple communities; t_0 = time at which a disruptive event occurs; and t_t = time at which the infrastructure is fully recovered.

If we assume the infrastructure is recovered in a steady pace, the collective loss of infrastructure resilience (CLR) function can be further simplified, as shown in Eq. (4-8)

$$CLR_k = \frac{CFL_k \times CRT_k}{2} \tag{4-8}$$

where CLR_k = the collective loss of resilience of infrastructure that serves a group k of multiple communities; CFL_k = the collective functional loss of infrastructure that serves a group k of multiple communities; and CRT_k = the collective recovery time of infrastructure that serves a group k of multiple communities.

As per Eq. (8), a higher value of collective loss of resilience indicates poorer resilience performance of the infrastructure against disasters. In other words, the infrastructure is more likely to experience severe damage, resulting in longer disruptions to the functions and services of infrastructure.

4.3 Case Studies

4.3.1 *Hypothetical Case Study*

A hypothetical case study was first conducted to illustrate the use of the SW-Infra-RA model in assessing and comparing collective infrastructure resilience across different communities. Hypothetical case studies have been widely used in research in different domains to evaluate or illustrate the use of new methods, models, or frameworks (Balaei et al. 2018, Mostafa and El-Gohary 2014, Zhang and Sanake 2020). This case study aims to analyze and compare the collective resilience of transportation infrastructure in two cities that are composed of various neighborhoods. In this process, we account for the inequality in and vulnerability to disaster impacts among these neighborhoods.

In the case study, Hurricane X caused major damage to the highway infrastructure of City A and City B, which were designed as two hypothetical cities that were composed of twenty neighborhoods each. The highway infrastructure (e.g., roads, highways, bridges) of both cities connects the neighborhoods and supports socioeconomic development of the local communities. In the event of a disaster, the highway infrastructure plays a vital role by offering links to emergency services, relief, and evacuation routes. The highway infrastructure, however, were in different conditions in City A and City B before struck by Hurricane X. According to a report on the quality of highway pavement and bridges of City A, approximately 22% of pavement in City A's highway infrastructure was in "poor" pavement ride quality, and around 17% of bridges were inspected as "structurally deficient". The majority of the pavement and bridges in poor conditions are located in the neighborhoods with lower average household income. Further investigation found that these neighborhoods received less financial support on maintaining, repairing, or rehabilitating their highway infrastructure over the last decade. For City B, the report shows that only 4% of pavement in the city was in "poor" pavement ride quality, while 56% was in "good" quality, and 40% was in "fair" quality. Similarly, only 6% of bridges were inspected as "structurally deficient". The generally good performance of highway infrastructure in City B is attributed to the higher financial support and expenses on maintenance and repair, which may be partially due to relatively better socioeconomic backgrounds (e.g., higher average income, higher housing prices, higher percentages of educated population) of all the neighborhoods in City B.

In the event of Hurricane X, the highway infrastructure of both City A and City B suffered from severe disaster impacts, such as strong wind forces, storm surges, and flash flooding. The damage on the roads, highways, and bridges ranged from pavement failures or structural damage to completely washed off road sections, which resulted in road and highway closures lasting days to weeks. In City A, disparities on the road and highway damage were observed across the twenty neighborhoods. Some neighborhoods suffered from more severe impacts on their highway infrastructure. The roads and bridges were blocked, damaged, or partially washed away due to fallen trees, flying debris, strong storm surges, and flash floods. The road and highway services were disrupted and took three to four weeks to repair before resuming normal operation. On the other hand, some neighborhoods had relatively mild damage, such as erosion of road pavement, poles, and trees fallen down on roads. After removing the debris and repairing the damaged roadway segments, the highway infrastructure resumed its normal function. In City B, the road and highway infrastructure across all neighborhoods experienced a similar level of disaster impacts. Table 4-1 presents the hypothetical data on the disaster impacts on the highway infrastructure in the twenty neighborhoods of each city. The data include (1) the percentage of road closures (functional loss), and (2) the time required to resume road services (recovery time).

Table 4-1 Functional loss and recovery time of highway infrastructure of City A and City B.

City A			City B		
Neighborhood	Percentage of road closures (FL) (%)	Time required to resume road services (RT) (days)	Neighborhood	Percentage of road closures (FL) (%)	Time required to resume road services (RT) (days)
A	78	20	a	67	19
B	68	19	b	65	19
C	85	24	c	62	18
D	82	20	d	65	18
E	96	24	e	72	12
F	6	8	f	63	16
G	20	17	g	46	13
H	14	9	h	42	13
I	10	8	i	44	17
J	21	8	j	45	12
K	95	24	k	51	16
L	92	19	l	57	18
M	97	23	m	58	15
N	88	18	n	54	12
O	97	18	o	58	11
P	94	19	p	52	15
Q	18	10	q	56	15
R	28	9	r	49	10
S	13	13	s	60	14
T	44	6	t	61	17

Utilizing the dataset from Table 4-1, we followed five steps to assess the resilience of highway infrastructure in Cities A and B. In Step 1, normalization of the values of functional loss (percentage of road closures) and recovery time (time required to resume road services) was conducted to ensure that their units and scales are comparable (the values range between 0 to 1 after normalization). In Step 2, the Gini coefficients of functional loss and recovery time were determined through the Lorentz curve. The Lorentz curves that represent the distributions of road closures and time required for road reopening across the twenty neighborhoods in Cities A and B are depicted in Figure 4-3 and Figure 4-4, respectively.

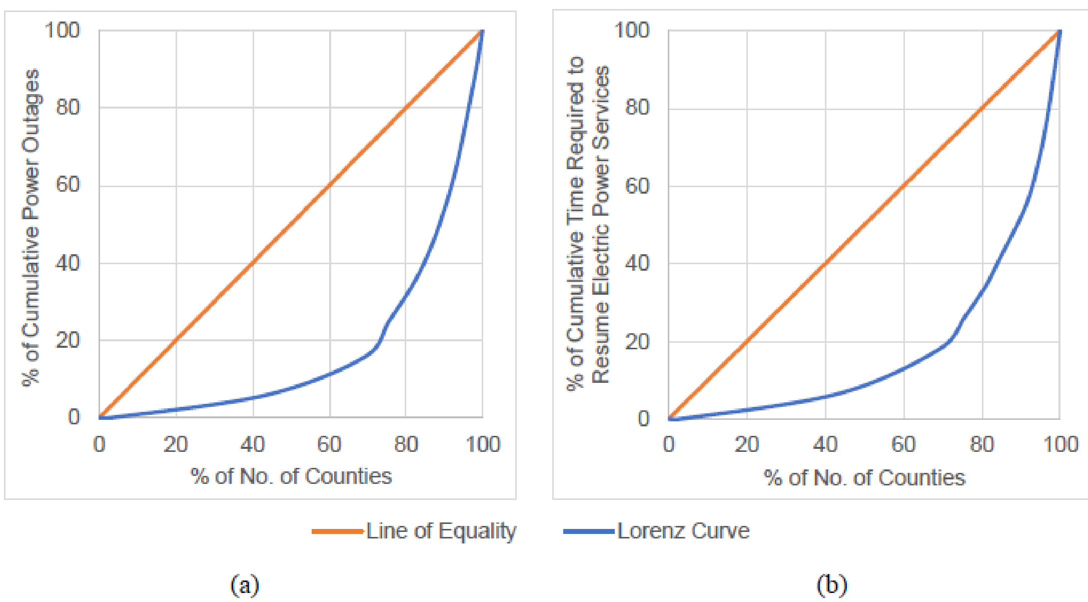
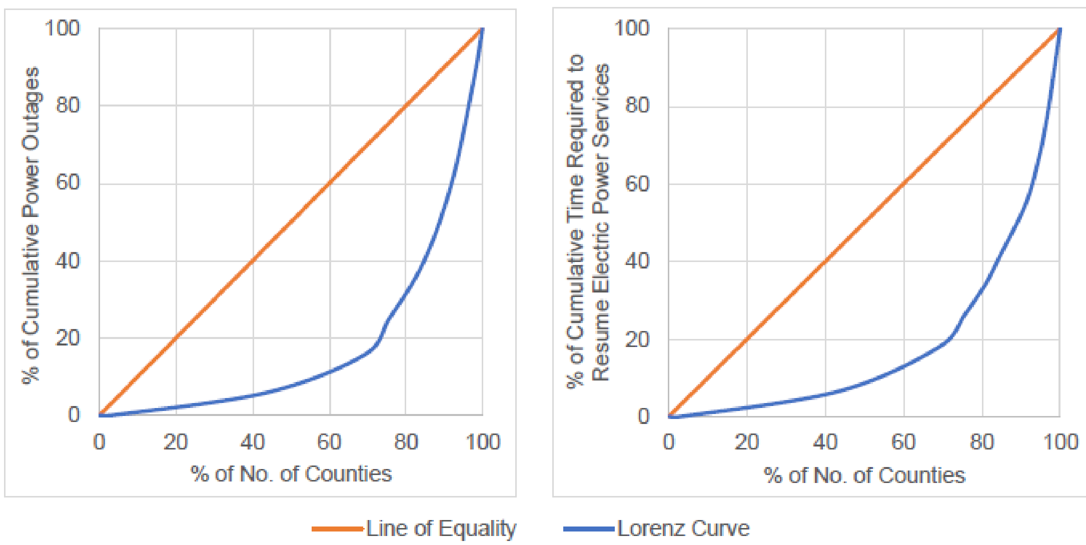


Figure 4-3 Lorenz curves for the distribution of disaster impacts in City A due to Hurricane X (a) A Lorenz curve for the distribution of road closures across neighborhoods in City A due to Hurricane X. (b) A Lorenz curve for the distribution of time required to resume road services across neighborhoods in City A due to Hurricane X.

The results of Gini coefficients are summarized in Table 4-2. As per Table 4-2, although the average disaster impacts on the highway infrastructure were found to be similar for both cities, higher inequality in disaster impacts was found in City A. In Step 3, the lines of vulnerability for disaster impacts on highway infrastructure were determined using Eqs. (3) and (4). In Step 4, the collective disaster impacts on highway infrastructure in Cities A and B were calculated using Eqs.

(5) and (6). A 0.5 coefficient γ (and λ) was employed for the analysis; it represents a medium extent of penalization on the unequal distributions of disaster impacts on highway infrastructure across the twenty neighborhoods in each city. Similarly, a 0.5 coefficient δ (and μ) was used; it represents a medium extent of accounting for the severe impacts on the vulnerable neighborhoods in collective impact analysis. In Step 5, the collective resilience of highway infrastructure for Cities A and B were calculated using Eq. (8). The results of lines of vulnerability, collective disaster impacts, and collective loss of resilience for Cities A and B are summarized in Table 4-2.



(a) (b)

Figure 4-4 Lorenz curves for the distribution of disaster impacts in City B due to Hurricane X. (a) A Lorenz curve for the distribution of road closures across neighborhoods in City B due to Hurricane X. (b) A Lorenz curve for the distribution of time required to resume road services across neighborhoods in City B due to Hurricane X

These results indicate that the overall resilience performance of highway infrastructure of City B is better than that of City A as lower value in loss of resilience represents better resilience performance. The results imply that, collectively, the highway infrastructure of City B had less damage and was more likely to resume its services within a short period of time. It is worth noticing that although the disaster impact data for the twenty neighborhoods of each city have similar average value, City A receives a higher score on collective loss of resilience by using the SW-Infra-

RA model. This is mainly due to the inequality or unequal distributions of disaster impacts across different neighborhoods of City A. As per Table 4-1, neighborhoods M, O, P of City A had much higher percentages of road closures and also required almost three weeks to fully resume road services, whereas neighborhoods like F, I, S of City A had minimum road closures and resumed road services within 8 to 10 days. Furthermore, the low resilience performance of City A could be attributed to the severe impacts on the highway infrastructure of some vulnerable neighborhoods in City A, which further augments the collective disaster impacts. For example, a high percentage of road pavement and bridges in neighborhoods E, K, and M of City A were in poor conditions even before the strike of Hurricane X. Hurricane X further damaged these roads and bridges that were in vulnerable conditions, resulting in longer time for resuming road services. Thus, more neighborhoods were accounted as vulnerable neighborhoods as the disaster impacts on these neighborhoods from Hurricane X were above the line of vulnerability.

Table 4-2 Results of resilience assessment of highway infrastructure of City A and City B

Parameter	City A		City B	
	Functional loss	Recovery time	Functional loss	Recovery time
Gini coefficient	0.38	0.35	0.32	0.31
Line of vulnerability	0.76	0.72	0.62	0.71
Collective disaster impact	0.71	0.68	0.61	0.67
Collective loss of resilience	0.24		0.19	

4.3.2 *Hurricane Michael Case Study*

A real case study on Hurricane Michael was conducted to assess the collective resilience of electric power systems in twelve counties in the Florida Panhandle region. Hurricane Michael was a Category 5 hurricane that made landfall in Florida Panhandle region on October 10, 2018 (NOAA 2019). Twelve counties (Figure 4-5) in this region issued disaster declarations, including Bay, Calhoun, Franklin, Gadsden, Gulf, Holmes, Jackson, Leon, Liberty, Taylor, Wakulla, and Washington Counties. Hurricane Michael brought devastating winds and strong storm surges to these counties, and it caused massive damage and destruction to the infrastructure of the local communities (NOAA 2019). According to a report (NOAA 2019), the inundation height due to the storm surges was estimated to be 9 to 14 feet above ground level in the Florida Panhandle region. It was estimated that Hurricane Michael caused $18.4 billion in damage, primarily incurred due to damage on infrastructure (NWS 2018). The strong wind forces and storm surges caused damage to power substations, resulting in power outages lasting for weeks (FPSC 2021). The physical structures, such as utility poles and transmission towers, were severely damaged and destroyed due to fallen trees, flying debris, and flash flood (Dhakal et al. 2021, Pathak et al. 2020).

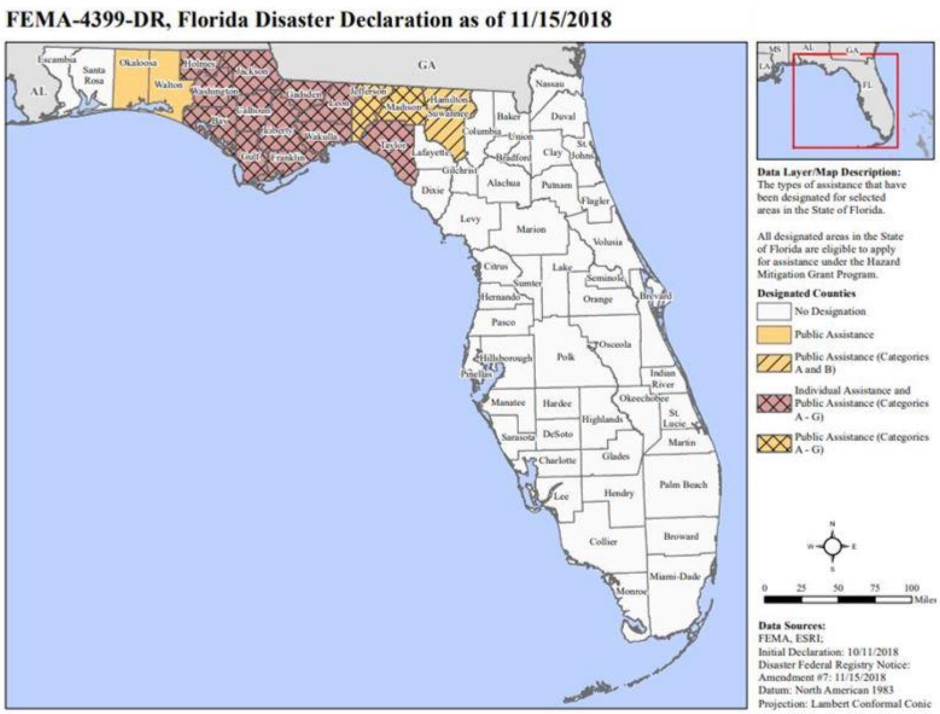


Figure 4-5 Counties of Florida Panhandle region that issued disaster declarations (FEMA 2018).

In this case study, we selected two disaster impact indicators for analysis: (1) percentage of electric power outages, and (2) time required for resuming electric power services. The data on electric power systems of the twelve Florida counties that issued disaster declarations were collected from Florida Public Service Commission (FPSC 2021). The data are summarized in Table

4-3. As per Table 4-3, Hurricane Michael caused disproportionate impacts to the electric power systems of the twelve counties. For example, Calhoun, Gulf, and Jackson, and Washington Counties suffered from more severe impacts on their electric power systems, with power outages ranging from 96.19% to 100%. It took more than three weeks for these counties to fully resume their electric power services (FPSC 2021). On the other hand, Taylor County had a relatively lower percentage of power outages (20.14%), and the county was able to resume power transmission and supply rapidly after the hurricane (FPSC 2021).

Table 4-3 Functional loss and recovery time of electric power infrastructure in Hurricane Michael

County	Percentage of electric power outage (FL) (%)	Time required to resume electric power services (RT) (days)
Bay	96.6	23
Calhoun	100	27
Franklin	96.79	7
Gadsden	92.12	17
Gulf	99.05	23
Holmes	93.82	12
Jackson	99.78	27
Leon	65.69	14
Liberty	65.94	17
Taylor	20.14	2
Wakulla	93.49	14
Washington	96.19	24

By using the data in Table 4-3 and following the five steps as described in the Hypothetical Case Study section, we performed the resilience assessment of the electric power system of the twelve disaster impacted counties in three contexts. In Context I, we did not account for inequality in or vulnerability to disaster impacts in infrastructure resilience assessment. Thus, the coefficients of γ, δ, λ, and μ were assigned to 0, and the coefficients of α and β were assigned to 1. In Context II, we accounted for disaster inequality and vulnerability in a medium extent. Thus, all the coefficients, including α, β, γ, δ, λ, and μ, were assigned to 0.5. In Context III, we fully accounted for disaster inequality and vulnerability in our analysis. Thus, the coefficients of γ, δ, λ, and μ were assigned to 1, and the coefficients of α and β were assigned to 0. Figure 4-6 shows the Lorenz curves for the distributions of power outages and time required to resume electric power services. Table 4-4 summarizes the results of the resilience assessment in the three defined contexts.

Table 4-4 Results of resilience assessment of electric power infrastructure in Hurricane Michael.

Parameter	Context I		Context II		Context III	
	Functional loss	Recovery time	Functional loss	Recovery time	Functional loss	Recovery time
Gini coefficient	0.64	0.63	0.64	0.63	0.64	0.63
Line of vulnerability	1.00	0.93	0.96	0.77	0.81	0.61
Collective disaster impact	0.81	0.61	1.08	0.83	1.44	1.12
Collective loss of resilience	0.25		0.45		0.81	

As per Table 4-4, the results of collective loss of resilience are 0.25, 0.45, and 0.81 in Context I, II, and III, respectively. These results show that the performance of the model is sensitive to the intensity of accounting for disaster inequality and vulnerability. The model is designed in a way that allows users to flexibly choose the coefficients that controls the intensity of accounting for disaster inequality and vulnerability. For example, if an engineer focuses solely on analyzing the functional loss and recovery time of infrastructure systems without emphasis on inequality and vulnerability among the impacted communities. He/she may assign the coefficients of γ, λ, δ, and μ to 0. Thus, as per Eqs. (5), (6), (7), and (8), the collective loss of resilience of these counties under study would be only based on the average disaster impacts on infrastructure of those counties. On the other hand, if a planner or a mitigation expert would like to consider disaster inequality and vulnerability, which may inform future recovery and mitigation efforts, he/she may choose to assign a relatively high value (e.g., 1) for the coefficients of γ, λ, δ, and μ, thus placing a higher emphasis on the impacts of disaster disparities and vulnerabilities on the collective loss of resilience. In this case, the collective loss of resilience would be augmented as the disproportionate disaster impacts across the counties and the potentially severe disaster impacts on the vulnerable counties are considered as negative factors that could exacerbate the collective loss of resilience. It is thus recommended to use a consistent set of coefficients when assessing the resilience of a set of infrastructure alternatives.

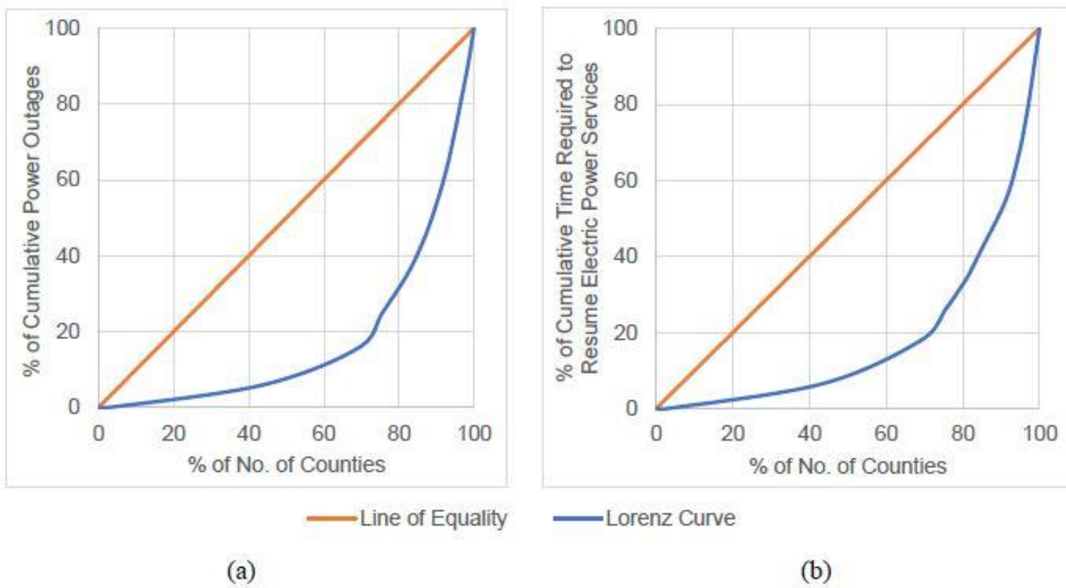


Figure 4-6 Lorenz curves for the distribution of disaster impacts due to Hurricane Michael. (a) A Lorenz curve for the distribution of power outages of Florida Panhandle counties due to Hurricane Michael. (b) A Lorenz curve for the distribution of time required to resume electric power services of Florida Panhandle counties due to Hurricane Michael.

In addition, the results show that, in the case of Hurricane Michael, the impacts of disaster inequality and vulnerability on the collective loss of resilience of electric power infrastructure was relatively high. The unequal distributions of disaster impacts on electric power infrastructure (including both power outages and time required to resume electric power services) across different counties in Hurricane Michael can be observed through the relatively high Gini coefficients (G_{FL} = 0.64 and G_{RT} =0.63). Such disparities in disaster impacts could primarily be caused by the counties' different levels of disaster exposure. In this case study, Hurricane Michael impacted a large geographic region. Counties that are located in close proximity to the hurricane path experienced much significant wind and storm forces compared to counties that are relatively farther away. For example, counties including Calhoun, Gadsden, Gulf, Jackson, and Washington counties experienced strong storm surges and had an average windspeed of approximately 74 mph (Senkbeil et al. 2020). The percentage of power losses in these counties range from 92.12% to 100%. On the other hand, counties, such as Taylor and Leon counties, had relatively lower average wind speeds of approximately 39 mph and 57 mph, respectively (Senkbeil et al. 2020), and their power losses are 20.14% and 65.69%, respectively. Thus, in a large-scale disaster such as Hurricane Michael, the different levels of disaster exposure are one of the primary reasons that contribute to the disparities in disaster impacts.

Another hidden reason may be the social inequality of these counties. The social inequality situation in Florida is among the worst in the U.S. and has been getting worse over time (Johnson 2019). In our case, some of the counties (e.g., Gadsden, Calhoun, Franklin, Holmes, Jackson counties) whose electric power infrastructure suffered from the most severe impacts are also among the most socially vulnerable counties in the region (CDC/ASTDR 2022). In addition, previous research (Dhakal et al. 2021) has found that counties with different socioeconomic and demographic characteristics (e.g., age, race, income, health) experienced different levels of infrastructure damage and speeds of recovery. Those counties with higher percentages of socially vulnerable populations experienced a relatively higher level of damage and required longer time for recovery (Dhakal et al. 2021). Research on other disasters (e.g., Ward and Shivley 2016, Yoon 2012, Flanagan et al. 2011) also show that disaster vulnerability is interrelated with social vulnerability; many social factors (e.g., age, gender, income, education) may impact the resilience of communities. Under the same level of exposure, communities that are socially vulnerable are more likely to suffer from severe impacts (e.g., higher power outages, traffic disruptions, higher congestion) (Hallegatte et al. 2019). This may be attributed to the fact that socially vulnerable populations often have the fewest resources for disaster preparedness, live in disaster-prone areas, and lack social, political, and economic capital needed to withstand, adapt to, and recover from a disaster (SAMSHA 2017).

4.4 Conclusions

This study presents a new social welfare-based infrastructure resilience assessment (SW-Infra-RA) model for assessing the collective resilience of infrastructure serving multiple communities while accounting for inequality in and vulnerability to disaster impacts. The SW-Infra-RA model is theoretically grounded on social welfare theory and social welfare functions. The Gini coefficient was adapted to model unequal distributions of disaster impacts on infrastructure of different communities. The line of vulnerability was proposed and measured by leveraging Cutter et al. (2003)'s work on Social Vulnerability Index to model disaster vulnerability. The collective disaster impact function was then defined by aggregating the impacts on infrastructure of individual communities, while integrating unequal distributions of disaster impacts and potentially more severe impacts on the vulnerable communities. The collective disaster impacts were then considered as input into the collective resilience assessment function, which was developed by adapting Bruneau et al. (2003)'s Resilience Triangle framework. The application of the SW-Infra-RA model was first illustrated through a hypothetical case study, which compares the collective resilience of highway infrastructure of two cities impacted by the same disaster. A real case study was further conducted to illustrate the use of the model for assessing the collective resilience of electric power systems in the context of Hurricane Michael.

CHAPTER 5 PROTOTYPE DEVELOPMENT OF DECISION SUPPORT SYSTEM TO FACILITATE EQUITABLE INFRASTRUCTURE PLANNING

This chapter presents completed work of Research Task 3- Developing a decision support system to facilitate automatic infrastructure resilience assessment. The following paragraphs present the development of prototype for decision support system.

The proposed system consists of four main modules: (1) disaster inequality module (2) disaster vulnerability module (3) collective disaster impact module, and (4) collective infrastructure resilience module. The main modules of the proposed system are depicted in Figure 5-1. Figure 5-2 shows a flowchart that illustrates the main functions and flow of information of the proposed system.

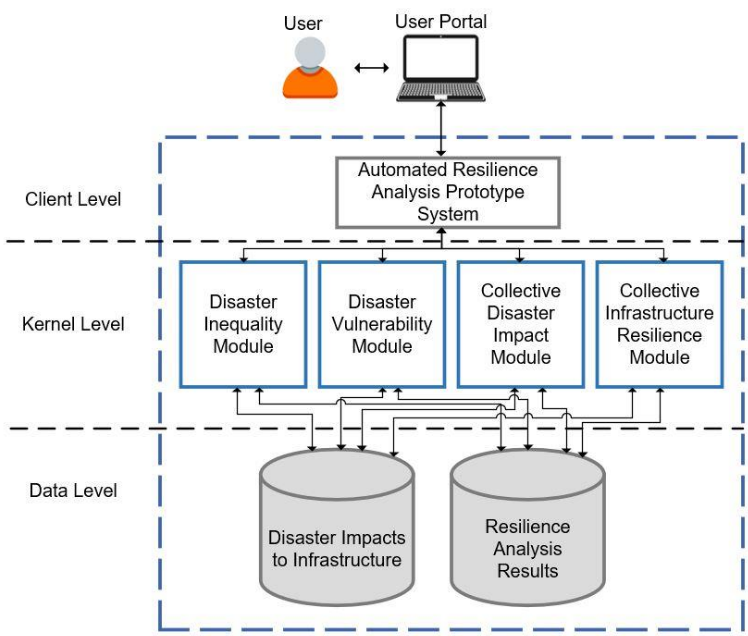


Figure 5-1 Main modules of the proposed prototype system

The disaster inequality module aims to analyze the unequal distribution of disaster impacts on infrastructure of various communities. The input of this module includes the data of disaster impacts on infrastructure of each individual communities of analysis, which are manually loaded into the system. The output of the module is disaster inequality, which is represented by the Gini coefficient. A screenshot of the user interface of the disaster inequality module is shown in Figure 5-3.

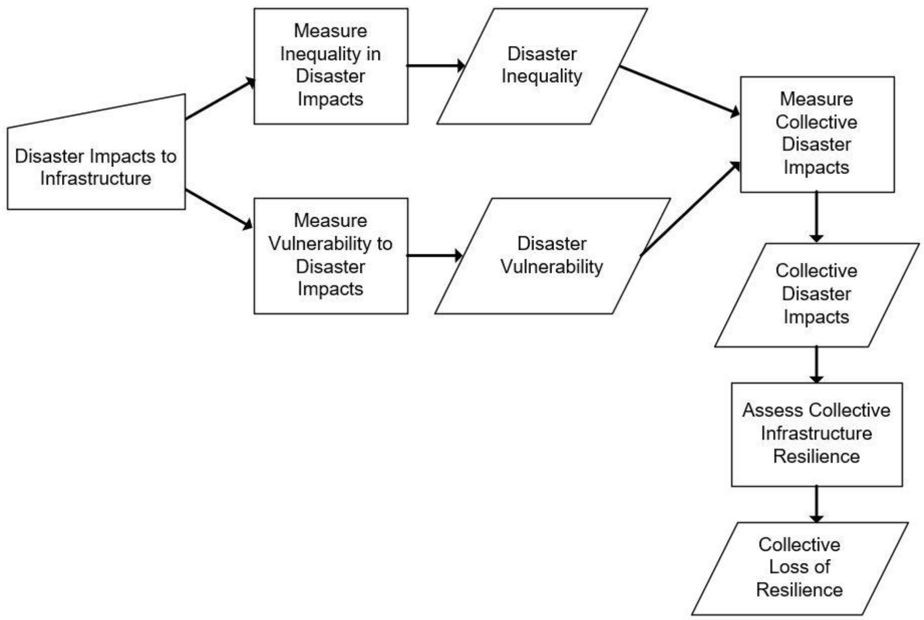


Figure 5-2 A flowchart of the proposed prototype system

The disaster vulnerability module aims to analyze the potential severe impacts on infrastructure of the vulnerable communities. The input of this module includes the data of disaster impacts on infrastructure of each individual communities of analysis. The output of this module includes (1) the line of vulnerability, and (2) the percentage of vulnerable communities.

The collective disaster impact module aims to quantify and analyze the collective disaster impacts on infrastructure serving multiple communities based on disaster impacts on infrastructure serving individual communities while accounting for disaster inequality and vulnerability. The input of the module is the disaster impacts on infrastructure of each individual communities of analysis, disaster inequality, disaster vulnerability, and coefficients that control the degrees of accounting for disaster inequality and disaster vulnerability. The output of the module is collective disaster impacts.

The collective infrastructure resilience module aims to analyze the collective resilience of infrastructure serving multiple communities while accounting for disaster inequality and disaster vulnerability. The input of the module is collective disaster impacts. The output of the module is the collective loss of resilience. A screenshot of the user interface of the collective infrastructure resilience module is shown in Figure 5-4.

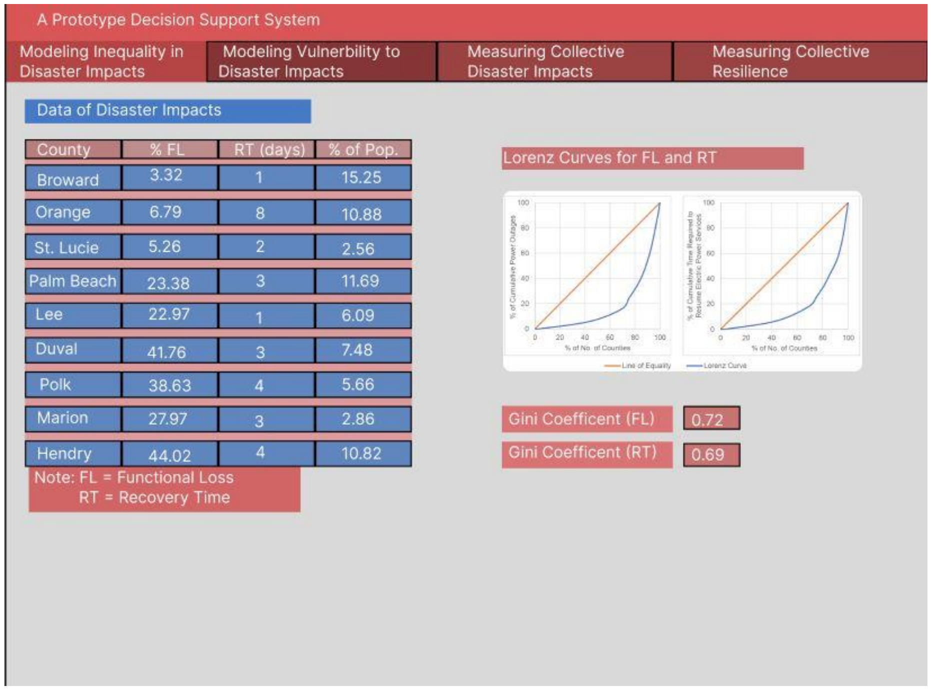


Figure 5-3 A user interface of the disaster inequality module

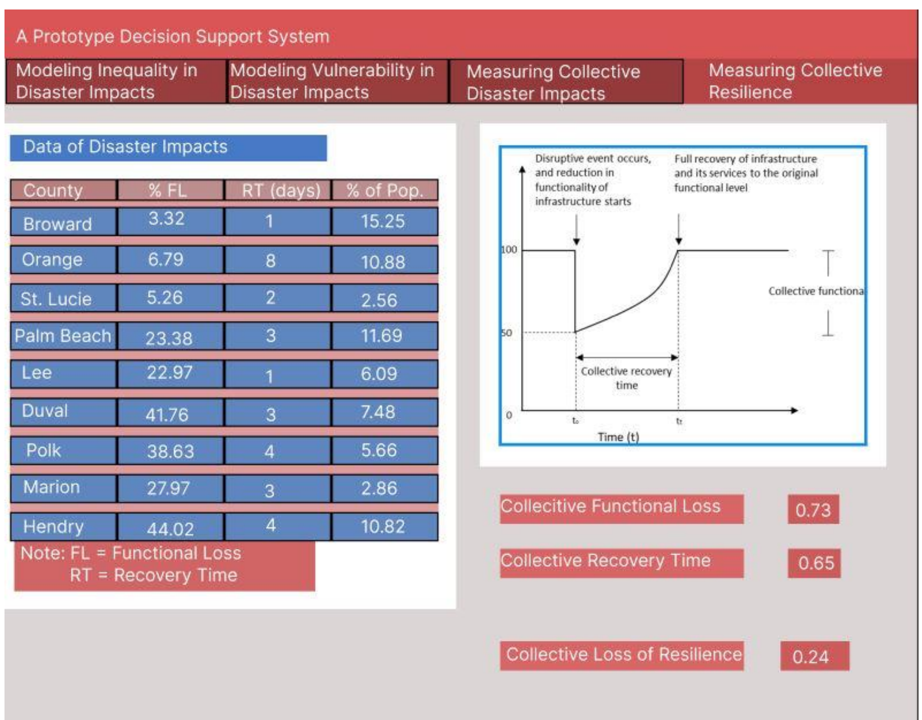


Figure 5-4 A user interface of the collective infrastructure resilience module

The main platform of the proposed prototype system was developed through Figma. Figma is an open source, web-based application that primarily focuses on user interface design utilizing a variety of graphic designing and prototype tools (Kopf 2022). The proposed prototype system was utilized to conduct a comparative analysis to analyze the resilience of infrastructure serving different communities with various characteristics, which is further discussed in Chapter 6.

CHAPTER 6 RESILIENCE ANALYSIS OF INFRASTRUCTURE SYSTEMS INTEGRATING SOCIAL EQUITY: CASE STUDIES USING HISTORICAL DISASTERS

6.1 Introduction

To adapt and thrive in the face of climate change, there has been an increasing trend of adopting resilience thinking and/or strategies in infrastructure planning processes. Assessing and analyzing infrastructure resilience help planners and decision makers better assess the performance of infrastructure and provide the foundation for prioritizing infrastructure investment. However, investigation on previous infrastructure investment and policies shows that there have been discriminatory policies, practices, and embedded biases within infrastructure planning processes for decades (NASEM 2022). As a result, in disasters, large disparities exist in terms of disaster impacts (e.g., physical damage, economic losses, service disruption) on infrastructure across the various communities (Zou et al. 2018b, SAMSHA 2017). Such disparities, also known as disaster inequalities (Dhakal and Zhang 2022), are linked with the variations in infrastructure quality and services across different communities, which may be affected by the various characteristics (e.g., location, population, socioeconomic status) of communities. For example, socially vulnerable communities, which include those with higher percentages of economically disadvantaged, racial and ethnic minorities, elderly, uninsured, homeless, disabled, those with chronic health conditions, and those with language barriers (Rao et al. 2019), typically experience a disproportionate share of physical and economic burden caused by disasters; they may need more time, assistance, support, or investment for coping with and recovering from a disaster (Drakes et al. 2021). However, when assessing the resilience of infrastructure that serves multiple communities, such disparities and vulnerability are often neglected, and the infrastructure of all communities is treated as equally impacted by a disaster. Such resilience assessment may not fully reflect the actual damage level and/or recovery processes. Thus, there is a need to account for disaster inequalities and vulnerabilities in infrastructure resilience assessment.

A comprehensive literature review in the disaster domain shows that there are two main knowledge gaps. First, research that focuses on analyzing infrastructure resilience does not typically account for disaster inequalities or vulnerabilities. Extensive studies (e.g., Ouyang and Duenas-Osorio 2014, Chan and Schofer 2016, Diao et al. 2016, Pagano et al. 2019, Tonn et al. 2020) have been conducted to assess the resilience of infrastructure of various types, such as transportation infrastructure (e.g., Chan and Schofer 2016), water infrastructure (e.g., Pagano et al. 2019), and electric power infrastructure (e.g., Ouyang and Duenas-Osorio 2014), etc. These studies have offered valuable contributions toward understanding and analyses of infrastructure resilience. However, these studies have not incorporated the varying levels of disaster impacts on infrastructure serving different communities into their resilience assessment. Second, there is a lack of research that focuses on analyzing disaster impacts experienced by communities with different characteristics. Studying disparities in disaster impacts would help understand the existing challenges faced by different communities and recommend infrastructure investment and resilience planning strategies that are prioritized based on the severity of needs. Over the years, research in the disaster domain have focused on assessing disaster impacts and/or emergency management efforts across various communities during disaster preparedness (Kim and Sutley), response (Yabe and Ukkusuri 2020) and recovery (Emrich et al. 2022) phases to better understand disaster inequalities. Assessing the resilience of infrastructure serving multiple communities with various characteristics could potentially help identify the vulnerable communities and facilitate more equitable planning in the future. Currently, there is still limited studies that comprehensively analyze or compare infrastructure resilience across communities with different characteristics and how such characteristics might impact the collective resilience of infrastructure.

To address these gaps, this chapter presents a study that analyzes infrastructure resilience while accounting for (a) disaster inequality: the unequal distribution of disaster impacts on infrastructure across the communities with various characteristics, and (b) disaster vulnerability: the potentially more severe disaster impacts on infrastructure of certain (e.g., socially vulnerabilities) communities (Dhakal and Zhang 2022). By utilizing the social welfare-based infrastructure resilience assessment (SW-Infra-RA) model proposed by Dhakal and Zhang (2022), the analyses focus on exploring and comparing (a) the levels of disaster inequalities, (b) the levels of disaster vulnerabilities, and (c) the collective resilience of infrastructure serving communities with various characteristics (e.g., spatial, demographic, and socioeconomic statuses). This chapter presents four case studies that assesses the resilience of four different types of infrastructure (i.e., electric power, communication service, transportation, and wastewater infrastructure) in the context of three hurricanes. The following sections of the chapter describe the background of the research, present and discuss the results of the case studies, and conclude with the summary and contributions of the study.

6.2 Case Study Design

We conducted four case studies in the context of three hurricanes, in order to answer the following research questions:

(1) How do counties with different characteristics (e.g., coastal vs inland, urban vs rural, more vulnerable vs less vulnerable) compare against each other in terms of disaster inequality?

(2) How do counties with different characteristics compare against each other in terms of disaster vulnerability?

(3) How do counties with different characteristics compare against each other in terms of collective resilience?

We designed the four case studies in a similar manner in terms of structure and content. For each case study, by leveraging the SW-Infra-RA, we measured and compared disaster inequalities, disaster vulnerabilities, and collective resilience of infrastructure that serves different groups of communities in the context of a hurricane disaster. Case Study I focuses on communication infrastructure in the context of Hurricane Michael. Case Study II focuses on electric power infrastructure in the context of Hurricane Sally. Case Study III focuses on transportation infrastructure in the context of Hurricane Irma. Case Study IV focuses on wastewater infrastructure in the context of Hurricane Irma.

6.2.1 *Contexts of Cases studies*

We selected three hurricanes for analysis, including Hurricanes Michael, Irma, and Sally. Hurricane Michael was a Category 5 hurricane that made landfall near Mexico Beach in Florida Panhandle on October 10, 2018. It was one of the strongest hurricanes on record, and the maximum sustained windspeed was 161 mph at landfall (NOAA 2019). Hurricane Michael brought catastrophic storm surges ranging from 9 to 14 ft above ground level along the portion of Florida Panhandle coast with the highest inundation occurring in Mexico Beach (NOAA 2019). In addition to life threatening storm surges, Hurricane Michael produced devastating wind gusts that caused extensive structural damage and service disruptions to different infrastructure. For example, the damage to communication service infrastructure was catastrophic (Burgess 2018). Cellular services were knocked down as communication service towers, transformers, and power lines were destroyed by falling trees and flying debris (Burgess 2018). In addition, road and highways in the coastal region were washed out due to flash flooding in several locations between Panama City and Alligator point (NOAA 2019).

Hurricane Irma was a Category 5 hurricane that made landfall in Florida Keys on September 10, 2017. The southern region of Florida, especially Florida Keys experienced severe damage from

Hurricane Irma. The combined effect of strong winds and storm surges brought flood with maximum inundation level of 5 to 8 ft above the normal level for the portions of Lower Florida Keys (NOAA 2018b). According to a damage assessment report (NOAA 2018b), Hurricane Irma caused approximately $50 billion in damage in the U.S., which made Hurricane Irma the fifth-costliest hurricane to affect the U.S. The infrastructure serving the communities of South Florida experienced the most severe impacts. For example, the strong storm surges and heavy rain from Hurricane Irma washed away part of US 1 highway (Lazo 2017). Most of the road and highways in southern part of Florida were shut down due to flooding and resumed after clearing debris and restoring traffic signals (Lazo 2017). In addition, the floodwater from Hurricane Irma damaged wastewater infrastructure, resulting in the sewage flowing from the wastewater systems to the surrounding water bodies (Gardner 2019). For example, according to a city record of St Augustine, the sewage spill caused the leakage of about 388,116 gallons of waste from the wastewater system to the nearby waterways (Gardner 2019).

Hurricane Sally was a Category 2 hurricane that made landfall along the coast of Alabama (immediately west of the Alabama/Florida state line) on September 16, 2020, with a sustained windspeed of 105 mph. Hurricane Sally's strong winds and storm surges caused extensive damage and destruction across the northwest coastal regions of Florida. Housing and infrastructure in Escambia and Santa Rosa Counties suffered from significant damage by the strong wind and storm surges (NOAA 2021a). Furthermore, strong storm surges along with heavy rainfall brought by Hurricane Sally caused massive flooding and damage to electric power infrastructure mostly in the western Panhandle region of Florida (Saunders 2020). A preliminary report on power outages by an electric power company suggests that hurricane Sally caused power outages for about 285,000 customers (Saunders 2020).

We selected these three hurricanes as our research context for three main reasons. First, all three hurricanes have impacted Florida communities, which are the geographic focus of our study. Second, these disasters caused devastating impacts (e.g., physical damage, service disruptions) on various infrastructure, such as electric power infrastructure, communication service infrastructure, and roadway infrastructure. Third, the regions that are impacted by these disasters have different spatial, demographic, and socioeconomic characteristics that can offer better understanding of in terms of how the characteristics of communities influence the resilience of infrastructure.

6.2.2 *Community Groups under Analysis*

To compare the resilience of infrastructure serving communities with different spatial, demographic, and socioeconomic characteristics, we classified all the counties under analysis into multiple groups, including (1) the coastal and inland groups, (2) the urban and rural groups, and (3) the more vulnerable and less vulnerable groups. In this study, the coastal group include those counties that have a coastline bordering of the ocean or contain coastal high hazards areas (NOAA 2021b). The inland group include those counties that share their borders with other adjacent counties with no coastline bordering. The rural counties are those with population densities lower than 100 individuals per square mile (Florida Health 2022), while the urban counties have population densities higher than 100 individual per square mile. To classify the counties based on their socioeconomic statues, we leveraged the Social Vulnerability Index (CDC/ATSDR 2022) (ranging from 0 to 1), which uses 15 U.S. census variables (e.g., poverty, access to transportation, housing to help identify communities that are vulnerable to disasters (CDC/ATSDR 2022). We then classified the counties into two groups based on SVIs; the less vulnerable group include those counties with SVIs ranging from 0 to 0.5, and the more vulnerable group include those with SVIs ranging from 0.5 to 1.

6.2.3 *Case Study Data Collection*

Based on the SW-Infra-RA model, to conduct the resilience analysis of infrastructure, we need to collect the data for two main types of infrastructure resilience indicators: (1) functional loss of infrastructure, and (2) recovery time of infrastructure. Functional loss is broadly defined as the reduction of functionality of infrastructure due to the impacts of a disaster, and it can be represented through different parameters, such as the percentage of electric power outages, the percentage of communication service outages, the percentage of wastewater system failures, and the cost in road debris removal. Recovery time is defined as the time required to resume infrastructure services to the original functional level, such as the time required to resume electric power and communication services, and the time required for road reopening. The data for both types of indicators (i.e., functional loss and recovery time) were collected from different public and private sources, including Florida Public Service Commission (FPSC), Federal Emergency Management Agency (FEMA), Federal Communications Commission (FCC), and Florida Department of Environmental Protection (FDEP). Table 6-1 summarizes the data we collected for the case study.

Table 6-1 List of disaster, infrastructure system and source of infrastructure damage data

Case Study No.	Infrastructure	Disaster context	Infrastructure damage and recovery data	Data source
I	Communication service	Hurricane Michael	% Communication service outages	FCC (2018)
			Time required to resume communication services	FCC (2018)
II	Electric power	Hurricane Sally	% Electric power outages	FPSC (2020)
			Time required to resume electric power services	FPSC (2020)
III	Transportation	Hurricane Irma	Cost of road debris removal	FEMA (2017)
			Time required for road reopening	FDOT (2017)
IV	Wastewater	Hurricane Irma	% Sewage spill from wastewater systems	FDEP (2017)
			Time required to resume normal functioning of wastewater systems	FDEP (2017)

6.2.4 *Case Study Data Analysis*

6.2.4.1 Data Preprocessing

During disasters (e.g., hurricanes), the geographical regions that are close to the hurricane path naturally experience more severe impacts compared to the regions that are located farther. In our analysis, we want to analyze the distribution of disaster inequality and disaster vulnerability across different counties assuming that all disaster-impacted counties experience the same or similar level of disaster impacts. Thus, to eliminate the effects of disaster threat level on infrastructure serving different counties, we first determined the normalized disaster impacts. The normalized disaster impacts were calculated by dividing the disaster impacts (i.e., functional loss and recovery time) experienced by infrastructure across different counties with the average sustained wind speeds during the disaster period across each impacted county.

6.2.4.2 Resilience Assessment

By leveraging the SW-Infra-RA framework developed in Chapter 4, we assessed infrastructure resilience by following four main steps. First, we measured the unequal distributions of disaster impacts on infrastructure serving multiple counties by calculating the Gini coefficients. For the infrastructure serving each group of counties, we calculated the Gini coefficients of functional loss and recovery time using Eqs. ((4-1)1) and (4-2), respectively. Second, we measured the line of vulnerability for functional loss and recovery time, using Eqs. (4-3) and (4-4), respectively. We then identified those counties whose infrastructure suffered from disaster impacts that are above the line of vulnerability as "vulnerable counties" and determined the percentage of vulnerable counties in each group. Third, we determined the collective disaster impacts (i.e., collective functional loss and collective recovery time) on the infrastructure serving multiple counties, using

Eqs. (4-5) and (4-6). Fourth, we quantified the collective loss of resilience of infrastructure serving a group of counties by using Eq (8).

6.3 Case Study Results

6.3.1 *Results of Case Study I*

The results of Case Study I are presented in Table 6-2. As per Table 6-2, in terms of comparisons between the coastal counties and inland counties in the context of Hurricane Michael, the Gini coefficients of communication infrastructure serving the group of coastal counties (G_{FL} =0.93, G_{RT} =0.84) and inland counties (G_{FL} =0.92, G_{RT} =0.92) are generally similar, indicating a similar level of disaster inequality between the coastal group and the inland group. By comparing the disaster impacts on communication infrastructure of each county to the line of vulnerability, the inland group has a higher percentage of vulnerable counties (71%) as compared to the coastal group (62%). In addition, the collective loss of resilience of communication infrastructure serving inland group (0.29) is higher as compared to that of the coastal group (0.16), which implies that the communication infrastructure serving the inland counties had poorer resilience performance against the impacts from Hurricane Michael compared to the one serving the coastal counties.

In terms of comparisons between the urban counties and rural counties, the results show that differences exist in the Gini coefficients for the urban group (G_{FL} =0.75, G_{RT} =0.83) and the rural group (G_{FL} =0.92, G_{RT} =0.92), and more severe disaster inequality exists in the rural group. There is also a higher percentage of vulnerable counties in the rural group (45%) as compared to that in the urban group (25%). In addition, there is a higher collective loss of resilience for communication service infrastructure serving group of rural counties (0.24) compared to urban counties (0.18).

In terms of comparisons between the two groups of counties with different levels of social vulnerability, the results show that the group with more vulnerable counties (G_{FL} =0.93, G_{RT} =0.89) have higher Gini coefficients compared to the group with less vulnerable counties (G_{FL} =0.72, G_{RT} =0.52), indicating a higher level of disaster inequality across counties that are more socially vulnerable. In contrast, there is a higher percentage of disaster vulnerable counties in the less vulnerable group (66%) compared to the more vulnerable group (41%). In addition, the collective loss of resilience is higher in the less vulnerable group (0.37) comparing to the more vulnerable group (0.2).

Table 6-2 Results for case study I

Communication service infrastructure												
Parameter	Coastal		Inland		Urban		Rural		More vulnerable		Less vulnerable	
	FL	RT	FL	RT	FL	RT	FL	RT	FL	RT	FL	RT
Gini coefficient	0.93	0.84	0.92	0.92	0.75	0.83	0.92	0..92	0.93	0.89	0.72	0.52
Line of vulnerability	0.56	0.46	0.56	0.46	0.56	0.46	0.56	0.46	0.56	0.46	0.56	0.46
% Vulnerable counties	62%	12%	71%	28%	25%	25%	45%	36%	41%	25%	66%	66%
Collective disaster impacts	0.78	0.42	0.87	0.67	0.8	0.46	0.73	0.65	0.74	0.55	0.92	0.81
Collective loss of resilience	0.16		0.29		0.18		0.24		0.2		0.37	

Notes: FL = functional loss; RT = recovery time

6.3.2 *Results of Case Study II*

The results of Case Study II are presented in Table 6-3. As per Table 6-3, comparing the results between the coastal group and the inland group, the Gini coefficients of electric power infrastructure serving the coastal group (G_{FL}= 0.74, G_{RT} =0.77) and the inland group (G_{FL}= 0.76, G_{RT} =0.8) are similar. This implies that there is a similar level of disaster inequality across both the coastal and inland counties. Comparing the disaster impacts on electric power infrastructure serving different counties to the line of vulnerability, the inland group has a higher percentage (50%) of vulnerable counties as compared to the coastal group (40%). Furthermore, the collective loss of resilience for electric power infrastructure are similar for both inland (0.18) and coastal counties (0.19), which shows a similar level of resilience performance of electric power infrastructure for both inland and coastal counties in the context of Hurricane Sally.

Comparing the results between the urban and rural counties in the context of Hurricane Sally, the Gini coefficients of electric power infrastructure serving urban group (G_{FL}= 0.74, G_{RT} =0.76) and rural group (G_{FL}= 0.76, G_{RT} =0.78) are generally similar, indicating a similar level of disaster inequality between the urban and rural counties. As per Table 3, there is a higher percentage of disaster vulnerable counties in the urban group (40%) compared to the rural group (25%). In addition, the collective loss of resilience of electric power infrastructure is higher within the urban counties (0.21) compared to the rural counties (0.15).

In terms of comparisons between the more vulnerable group and the less vulnerable group, the results show that the Gini coefficients are higher (G_{FL}= 0.86, G_{RT} =0.92) within the more vulnerable counties as compared to within the less vulnerable counties (G_{FL}= 0.6, G_{RT} =0.59), which indicates a higher level of disaster inequality in the more vulnerable counties. In addition, the percentage of disaster vulnerable counties is much higher within the more vulnerable group (50%), in comparison to within the less vulnerable group (33%). Overall, the collective loss of resilience of electric power infrastructure serving the more vulnerable (0.2) and the less vulnerable (0.21) groups are similar in the context of Hurricane Sally.

Table 6-3 Results for case study II

Electric power infrastructure												
Parameter	Coastal		Inland		Urban		Rural		More vulnerable		Less vulnerable	
	FL	RT	FL	RT	FL	RT	FL	RT	FL	RT	FL	RT
Gini Coefficient	0.74	0.77	0.76	0.8	0.74	0.76	0.76	0.78	0.86	0.92	0.6	0.59
Line of vulnerability	0.43	0.52	0.43	0.52	0.43	0.52	0.43	0.52	0.43	0.52	0.43	0.52
% Vulnerable counties	40%	20%	25%	50%	40%	20%	25%	25%	30%	50%	33%	33%
Collective disaster impacts	0.59	0.66	0.51	0.71	0.59	0.7	0.51	0.59	0.5	0.79	0.67	0.63
Collective loss of resilience	0.19		0.18		0.21		0.15		0.2		0.21	

Notes: FL = functional loss; RT = recovery time

6.3.3 *Results of Case Study III*

Table 6-4 shows the results of Case Study III. As per Table 6-4, in terms of comparisons between the coastal group and the inland group, the Gini coefficients of the transportation infrastructure serving the coastal counties (G_{FL}= 0.83, G_{RT} =0.96) and the inland counties (G_{FL}= 0.89, G_{RT} =0.8) are similar. There is a higher percentage of disaster vulnerable counties in the group of inland counties (57%) in comparison to the group of coastal counties (41%). In addition, the transportation infrastructure serving the inland counties (0.18) has a much higher collective loss of resilience compared to the one serving the coastal counties (0.08) in the context of Hurricane Irma.

In terms of comparisons between the urban and rural counties, the Gini coefficients of the urban group (G_{FL}= 0.95, G_{RT} =0.94) is higher compared to those of the rural group (G_{FL}= 0.76, G_{RT} =0.52), which indicates a higher level of disaster inequality within the urban counties. In contrast, there is a higher percentage of disaster vulnerable counties in the rural group (66%) than in the urban group (25%). In addition, the transportation infrastructure serving the rural counties (0.34) has a much higher collective loss of resilience compared to the one serving the urban counties (0.06) in the context of Hurricane Irma.

In terms of comparisons between the more vulnerable and less vulnerable groups of counties, the Gini coefficients for the more vulnerable group (G_{FL}= 0.95, G_{RT} =0.91) is higher compared to the less vulnerable group (G_{FL}= 0.77, G_{RT} =0.85). In addition, there is a higher percentage of disaster vulnerable counties within the more vulnerable group (54%) in comparison to the less vulnerable group (50%). Similarly, the transportation infrastructure serving the more vulnerable counties has a higher collective loss of resilience (0.16) compared to the one serving the less vulnerable counties (0.06) in the context of Hurricane Irma.

Table 6-4 Results for case study III

Transportation infrastructure												
Parameter	Coastal		Inland		Urban		Rural		More vulnerable		Less vulnerable	
	FL	RT	FL	RT	FL	RT	FL	RT	FL	RT	FL	RT
Gini Coefficient	0.83	0.96	0.89	0.8	0.95	0.94	0.76	0.52	0.95	0.91	0.77	0.85
Line of vulnerability	0.33	0.37	0.33	0.37	0.33	0.37	0.33	0.37	0.33	0.37	0.33	0.37
% Vulnerable counties	41%	16%	57%	28%	25%	25%	66%	33%	54%	15%	16%	50%
Collective disaster impacts	0.43	0.38	0.55	0.66	0.31	0.36	1.14	0.59	0.77	0.42	0.38	0.31
Collective loss of resilience	0.08		0.18		0.06		0.34		0.16		0.06	

Notes: FL = functional loss; RT = recovery time

6.3.4 *Results of Case Study IV*

The results for Case study IV is presented in Table 6-5. As per Table 6-5, in terms of comparisons between the coastal and inland counties, the Gini coefficients of the wastewater infrastructure serving the coastal group (G_{FL}= 0.92, G_{RT} =0.9) and the inland group (G_{FL}= 0.9, G_{RT} =0.85) are similar, indicating a similar level of disaster inequality between the coastal and inland counties. There is a much higher percentage of disaster vulnerable counties (60%) in the inland group as compared to in the coastal group (20%). Furthermore, the wastewater infrastructure serving the inland counties (0.14) has a higher collective loss of resilience as compared to the one serving the coastal counties (0.07).

In terms of comparisons between the urban and rural groups, the results show that the Gini coefficients of the urban group (G_{FL}= 0.94, G_{RT} =0.95) is higher compared to those of the rural group (G_{FL}= 0.8, G_{RT} = 0.85). There is also a higher percentage of disaster vulnerable counties in the rural group (80%) in comparison to the urban group (26%). In addition, the wastewater infrastructure serving the rural group (0.29) is higher comparing to the one serving the urban group (0.07).

In terms of comparisons between the more vulnerable and less vulnerable groups, the results show that the more vulnerable counties (G_{FL} =0.96, G_{RT} =0.94) have higher Gini coefficients compared to the less vulnerable counties (G_{FL} =0.68, G_{RT} =0.77), which indicates a higher level of disaster inequality within the counties that are more socially vulnerable. In contrast, there is a higher percentage of disaster vulnerable counties in the less vulnerable group (50%) in comparison to the more vulnerable group (37%). In addition, the wastewater infrastructure serving the less vulnerable counties (0.17) has a higher collective loss of resilience compared to the one serving the more vulnerable counties (0.1) in the context of Hurricane Irma.

Table 6-5 Results for case study IV

Wastewater infrastructure												
Parameter	Coastal		Inland		Urban		Rural		More vulnerable		Less Vulnerable	
	FL	RT	FL	RT	FL	RT	FL	RT	FL	RT	FL	RT
Gini Coefficient	0.92	0.9	0.9	0.85	0.94	0.95	0.8	0.85	0.96	0.94	0.68	0.77
Line of vulnerability	0.49	0.29	0.49	0.29	0.49	0.29	0.49	0.29	0.49	0.29	0.49	0.29
% Vulnerable counties	20%	20%	60%	30%	20%	26%	80%	40%	37%	25%	25 %	50%
Collective disaster impacts	0.42	0.37	0.74	0.38	0.44	0.31	1.17	0.49	0.74	0.27	0.54	0.63
Collective loss of resilience	0.07		0.14		0.07		0.29		0.1		0.17	

Notes: FL = functional loss; RT = recovery time

Overall, the results of Gini Coefficients are similar in both the coastal and inland counties across the three hurricane disasters. Higher percentages of disaster vulnerable counties are found in the inland group in Hurricanes Michael and Irma. Similarly, the infrastructure serving the inland counties tend to have higher collective loss of resilience as compared to the one serving the coastal counties in these two hurricanes. However, the context of Hurricane Sally, the coastal group has a higher percentage of disaster vulnerable counties and a higher collective loss of resilience in its infrastructure.

For comparisons between the urban and rural counties, the Gini coefficients vary across the three hurricane disasters. Higher percentages of disaster vulnerable counties are found in the rural group in Hurricanes Michael and Irma. Similarly, the infrastructure serving the rural counties tend to have higher collective loss of resilience as compared to the one serving the urban counties in these two hurricanes. However, the context of Hurricane Sally, the urban group has a higher percentage of disaster vulnerable counties and a higher collective loss of resilience in its infrastructure.

For comparisons between the two groups of counties with different levels of social vulnerability, the Gini coefficients are higher within the more vulnerable groups in all three disasters. However, the percentages of disaster vulnerable counties and the collective loss of resilience of the infrastructure serving these groups of counties vary in different contexts of disasters.

6.4 Results Discussion

6.4.1 *Analysis of disaster inequality across different communities*

As per the results presented in the above section, in the context of all three selected hurricanes, disaster inequality is at a similar level between the infrastructure serving the inland counties and the one serving the coastal counties. The results also show that disaster inequality is more severe within the socially vulnerable counties, which may imply that the disaster inequality is associated with social vulnerability.

The difference in disaster inequality between the groups of counties with varying levels of social vulnerability may be due to differences in (1) the quality and adequacy of infrastructure services and (2) disaster relief and aid for recovery. First, socially vulnerable communities, in general, lack adequate and stable infrastructure services. Studies show that socially vulnerable communities with higher percentages of minorities and disabled, poor, or unemployed populations have inadequate and substandard infrastructure, unmet infrastructure needs, and may lack even basic infrastructure services such as stable water supply, uninterrupted electricity, and safe and durable sanitation, etc. (SAMSHA 2017, Constible 2018). During disasters, such unstable infrastructure is more likely to experience varying levels of physical damage and/or service disruption. As a result, there is a higher possibly that these communities may experience varying levels of disaster impacts to their infrastructure, thus suffering from more severe disaster inequality. For example, in the aftermath of Hurricane Michael, Bay County experienced significant damage to public infrastructure (e.g., transportation), and a preliminary damage assessment showed that Bay County spent more fund for debris removal compared to other disaster impacted counties (Moline 2019). Second, socially vulnerable communities may lack access to disaster relief and assistance, which results in many uncertainties in their recovery. Previous studies show that socially vulnerable communities, following a disaster, face barriers in interacting with bureaucratic systems to receive disaster assistance (SAMSHA 2017). Socially vulnerable communities typically receive less reinvestment or recovery aid compared to those communities with higher socioeconomic statuses, thus they generally spend longer time in recovery (Nexus 2017). For example, in Hurricane Irma, the regions with higher percentages of minorities (Latinos and Hispanic populations) and disabled populations experienced longer electric power outages in the wake of Hurricane Irma (Mitsova et al. 2018).

6.4.2 ***Analysis of disaster vulnerability across different communities***

As per above presentation of the results, we found that there are higher percentages of disaster vulnerable counties in the rural group as compared to those in the urban group in the contexts of

Hurricanes Michael and Irma. This may be due to lack of infrastructure investment funds, delay in disaster aid and relief, aging and substandard infrastructure, and socioeconomic statuses of individuals living in the rural areas. First, urban areas, comparing to rural areas, are more likely to receive federal assistance and funds for developing new infrastructure and maintaining existing ones (Todoroff 2022), and they are more likely to implement resilience strategies in new infrastructure planning and development (Venema 2017) due to adequacy in funds. In contrast, rural areas, with limited funding and support, may have limited capabilities in implementing disaster mitigation practices or resilience strategies (Kapucu et al. 2013). Second, rural areas are generally left behind in receiving disaster recovery assistance, aid, and resources (Todoroff 2022). For example, in the aftermath of Hurricane Irma, comparing to urban counties, rural counties (e.g., Taylor County) of Florida were delayed in receiving recovery resources and aid (Stofan 2017). Third, rural communities typically have aged, obsolete and substandard infrastructure that requires significant repair and maintenance. Unlike urban areas, rural areas lack diverse economic resources (e.g., tax base from large corporations and businesses) and may experience difficulty in attracting developers (Browne 2022). The infrastructure needs of rural areas are not adequately addressed as the infrastructure planning and initiatives have mostly focused on the urban areas. As a result, rural communities lack access to reliable essential infrastructure services (NCSL 2020). Fourth, the residents in the rural areas generally have lower socioeconomic statuses, such as higher level of poverty and unemployment rates, and fewer educational opportunities (Lowe 2017, The Conversation 2017). For example, according to the United States Department of Agriculture (USDA) Economic Research Service (USDA-ERS 2022), there is a higher poverty rate of rural communities (18.8%) in Florida compared to that of the urban communities (12.6%). (USDA-ERS 2022). In addition, variations in the severity of disaster impacts to infrastructure are found to be related to the socioeconomic characteristics of the communities. For example, poor communities and minority communities experienced severe impacts from Hurricane Michael and are deprived of necessary resources during the recovery period (Moens 2022).

6.4.3 *Analysis of collective resilience of infrastructure serving different communities*

As per above presentation of the results, in the context of Hurricanes Michael and Irma, the infrastructure serving the inland counties has relatively worse overall resilience performance compared to the one serving the coastal counties. However, in the context of Hurricane Sally, the electric power infrastructure serving both coastal and inland counties has similar resilience performance. Such differences may be attributed to the characteristics of the hurricanes. First, Hurricanes Irma and Michael were both Category 5 hurricanes. Such hurricanes with high intensities have more potential to travel up to 100 to 200 miles inland after their landfall and they could bring extreme rainfall and wind forces resulting in extreme inland flooding (Raizner 2022). For example, after making landfall in Mexico Beach, Hurricane Michael remained at Category 3 strength while travelling through seven inland counties of Florida, such as Calhoun, Liberty and Gadsden Counties (NOAA 2019). It kept brining extreme rainfall that resulted in flash flooding in the inland counties. The combination of strong winds and heavy rainfall caused significant damage to roads and highways, interrupted the services of wastewater and communication infrastructure.

In contrast, as a Category 2 hurricane, Hurricane Sally caused extensive damage and destruction to infrastructure mostly across the coastal regions (NOAA 2021). The storm surges along with rainfall brought by the Category 2 hurricane caused widespread flash and river flooding on coastal counties (e.g., Pensacola and Escambia Counties) resulting in significant damage to electric power lines (NOAA 2021). Hurricane Sally started to lose its strength after landfall and travelled toward inland regions of Florida as a tropical storm (NOAA 2021). Thus, the electric power infrastructure serving inland counties experienced less severe impacts from the hurricane as compared to the one serving the coastal counties.

6.5 Conclusions

This chapter presents four case studies that analyze infrastructure resilience while accounting for disaster inequalities and vulnerabilities. By utilizing the social welfare-based infrastructure resilience assessment (SW-Infra-RA) framework proposed by Dhakal and Zhang (2022), the study analyzed (1) the levels of disaster inequality, (2) the levels of disaster vulnerability, and (3) the collective resilience of infrastructure serving counties with different characteristics (e.g., spatial, demographic, and socioeconomic statuses). These results indicate that the infrastructure serving the more vulnerable group of counties experience higher levels of disaster inequality. In the context of hurricanes with high intensity (Hurricanes Michael and Irma), there is a higher percentage of disaster vulnerable counties in the rural group. Also, the infrastructure of the inland group of counties, collectively, has poorer resilience performance compared to that of the coastal group of counties.

From practical perspectives, the results generated through the equity-incorporated resilience analysis could facilitate decision makers to better understand the level of inequality in disaster impacts across different communities and identify the communities that are highly vulnerable in a disaster. The analysis results could help decision makers and infrastructure planners better understand the links between collective resilience of infrastructure and the communities with various characteristics (e.g., spatial, demographic, and socioeconomic statuses). This study has the potential to promote equitable planning by allowing decision makers to prioritize infrastructure resilience initiatives and investment and disaster relief resources to those communities that are in dire need.

CHAPTER 7 CONCLUSIONS

7.1 Summary

This dissertation aims to facilitate equitable infrastructure resilience planning by providing a new infrastructure resilience assessment framework that accounts for disaster inequality and vulnerability. The dissertation presents four chapters to achieve research objectives that includes (1) understanding the interrelationships between infrastructure resilience and social equity in the context of a disaster, (2) developing a new infrastructure resilience assessment framework that incorporates disaster inequality and vulnerability, (3) developing a prototype decision support system that facilitates automatic infrastructure resilience assessment, and (4) implementing the model by conducting resilience analyses of different infrastructure systems in the context of various hurricane disasters.

The first task of this dissertation focused on understanding infrastructure resilience, social equity, and their interrelationships in the context of Hurricane Michael. To perform this task, Twitter activities generated by the disaster impacted counties were utilized to examine the social equity conditions and infrastructure resilience conditions. Statistical correlation analyses were conducted across Twitter activities, social equity conditions, and infrastructure resilience conditions in the context of Hurricane Michael. In general, the results indicate that counties with different social equity conditions experienced different level of impacts from disasters. In other words, social equity factors could potentially impact the infrastructure resilience conditions.

The second task of this dissertation focused on developing a social-welfare-based infrastructure resilience assessment (SW-Infra-RA) framework while accounting for disaster inequalities and vulnerabilities. The proposed assessment framework is theoretically based on the social welfare theory and social welfare functions. This model utilized Gini coefficient to measure the unequal distributions of disaster impacts on infrastructure serving various communities. It proposed the "line of vulnerability" to model disaster vulnerabilities. Two sets of case studies, a hypothetical and a real case study, were conducted to illustrate the application of the SW-Infra-RA model. This proposed model could potentially support the development of resilient infrastructure and facilitate equitable resilience planning.

The third task of this dissertation focused on developing a prototype of a decision support system that could potentially facilitate automatic infrastructure resilience assessment. This prototype system allows decision makers to measure infrastructure resilience while accounting for disaster inequalities and vulnerabilities. The input of the system is disaster impacts (e.g., functional loss, recovery time) data of infrastructure, and the output is the collective resilience of infrastructure serving multiple communities.

The fourth task of this dissertation focused on implementing the proposed infrastructure resilience assessment model (SW-Infra-RA) in the context of real disasters. This task analyzed the levels of disaster inequality, levels of disaster vulnerability, and resilience performance of infrastructure serving counties with different characteristics (e.g., spatial, demographic, and socioeconomic). The resilience of four different infrastructure (e.g., communication service, electric power, transportation, and wastewater infrastructure) in the context of three hurricanes (e.g., Hurricane Michael, Hurricane Irma, and Hurricane Sally) was analyzed.

7.2 Research Contributions

This dissertation offers contributions to the body of knowledge in advancing the understanding and methods of assessing infrastructure resilience; these contributions include:

1. This research advances the understanding of the interrelationships between infrastructure resilience and social equity in the context of a hurricane disaster. It shows how the communities with different social characteristics may experience disproportionate impacts from Hurricane Michael due to varying levels of infrastructure damage or time for recovery. This knowledge is

critical as it could support the (re)development and (re)investment of infrastructure in a way that not only addresses disaster resilience challenges but also facilitates social equity in the impacted communities.

2. This research utilized a data-based approach to derive useful meaning. Social media data analysis, which allows for easy collection of timely data, could potentially allow practitioners and decision makers to analyze how disasters could impact people and infrastructure in a more efficient and timely manner.

3. This research developed a new infrastructure resilience assessment framework that measures the collective resilience of infrastructure serving multiple communities while accounting for disaster inequality and vulnerability. It adapted methods from the social science and economics domains to mathematically measure the unequal distributions of disaster impacts across various communities and proposed new ways of evaluating the severe impacts on vulnerable communities.

4. The proposed model (SW-Infra-RA) provides a theoretical basis for equity-incorporated decision making by allowing decision makers to quantitatively assess infrastructure resilience while accounting for inequality and vulnerability. The results generated using this model can be utilized by decision makers to better understand the inequalities during disasters and to identify the communities that are more vulnerable in these disasters.

7.3 Limitations and Recommendations for Future Research

Based on the research development in this study, some research directions can be further investigated to improve the performance of the proposed assessment framework and its applications. The recommendations for future research are presented as follows.

First, this research study explored the interrelationships between infrastructure resilience and social equity and proposed a new social-welfare-based infrastructure resilience assessment framework that accounts for disaster inequality and disaster vulnerability. Although the SW-infra model focuses on assessing collective resilience of infrastructure through aggregating the disaster impacts on the infrastructure of each individual community, it currently doesn't account for the interdependencies of infrastructure serving these communities. Other methods such as system of systems approach or system network analysis can be used to measure such interdependencies and can be further integrated to the proposed assessment framework.

Second, the findings about the interrelationships between social equity and infrastructure resilience cannot be generalize to the general population. The findings are based on data collected from Twitter, which may not fully represent the opinions of the general population. For example, previous research shows that, comparing to the older population, younger adults aged 15-34 years old are more represented in social media (e.g., Twitter). In general, vulnerable populations (e.g., minorities, disabled, low-income, elderly) are more likely to be unaware of communication tools and use of social media, and they may be less representative on social media (e.g., Twitter). Therefore, further investigations on the communication patterns of vulnerable populations are needed to analyze the behaviors of vulnerable populations in disasters.

Third, the proposed model (SW-Infra-RA) is designed to assess the collective resilience of a single type of infrastructure. Assessing the resilience of multiple types of infrastructure may be conducted, depending on the input of the data. For example, if the collected data on disaster impacts are for multiple types of infrastructure, it may be possible to derive the collective resilience of multiple infrastructures.

Fourth, the SW-Infra-RA model was implemented in analyzing the resilience of different types of infrastructure serving communities within Florida. In future studies, there is a need to further apply the model in analyzing the resilience of different types of infrastructure serving a larger number of communities in other parts of the country. Such application would offer more insight and understanding of how inequalities in and vulnerabilities to disaster impacts could impact infrastructure resilience.

Fifth, the resilience analysis of infrastructure is conducted on a county level, which may not reveal the actual infrastructure resilience and social equity conditions within different communities in the same county. This can be further addressed by collecting the disaster impacts data based on zip codes or different types of communities by grouping several zip codes together.

Sixth, although multiple sets of case studies have been conducted to implement the proposed model in various hurricane disasters, the model requires further validation. Validation of the proposed model is a challenging task as there is no agreed upon “gold standard” for the results generated by the proposed model to be compared with. Previous studies (e.g., Ouyang and Wang 2015, Singhal et al. 2020, Argyroudis et al. 2021) show that infrastructure resilience assessment models or methods may lack validation approaches. Some research (e.g., Feldmeyer et al. 2020, Anderson et al. 2020, Cai et al. 2016) suggests the use of an empirical approach. In this research, expert-involved experiments can be conducted to validate the proposed model. For example, a set of case studies that involve domain experts can be conducted to validate the proposed model. The experts may include people from government, non-government and private sectors that hold expertise in the domain of disaster resilience and social equity. First, the data of a disaster, disaster impacts, and infrastructure in the impacted communities will be provided to the experts. Second, the experts will be instructed to focus on inequality and vulnerability in the disasters, and they will be asked to evaluate how disaster impacts are distributed across different communities and how infrastructure of vulnerable communities are impacted during the disaster. Third, through open discussion, the experts will be asked to rank the communities based on the collective resilience of their infrastructure. Fourth, the collective resilience of infrastructure in different communities will be measured using the SW-Infra-RA model, and a ranking of these communities will be provided. The correlation between the expert-based ranking and the model-based ranking will be evaluated.

Seventh, the proposed prototype system has not been used by the general public or decision makers. To address this limitation, community outreach programs can be implemented in the future. For example, seminars and workshops can be held at FIU to engage interested stakeholders and community collaborators. In these seminars and workshops, this research work including the findings and results will be presented. The participants will then have the opportunity to test use the prototype system. Additionally, seminars and information sessions regarding this research can be held with local resilience-focused organizations, such as 100 Resilient Cities, and the County's Office of Resilience. These meetings and workshops could potentially provide effective venues for reaching out to different sectors as they bring together representatives from public, private, and non-profit sectors in local communities.

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