Equity-Integrated Infrastructure Resilience Analysis: Case Studies of Florida Communities

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ABSTRACT

To mitigate the impacts of climate change on infrastructure, there has been a growing trend toward adopting resilience strategies in infrastructure planning. However, research highlights historical discriminatory practices and biases in policies and investments, resulting in disproportionate disaster impacts on communities. To effectively evaluate infrastructure resilience, it is crucial to consider these disparities. To address this need, this study focuses on assessing infrastructure resilience while incorporating disaster inequality and disaster vulnerability using a proposed equity-integrated resilience evaluation model. The resilience of infrastructure in Florida counties with different characteristics (e.g., spatial, demographic, and socioeconomic statuses) was evaluated and compared. The findings reveal that (1) the more socially vulnerable counties experienced greater disaster inequality, (2) there is a higher percentage of disaster vulnerable counties in the rural group in high-intensity hurricanes, and (3) the infrastructure of the inland counties, collectively, has weaker resilience compared to coastal ones.

INTRODUCTION

To mitigate the impacts of climate change on infrastructure, there has been an increasing trend in adopting resilience strategies in infrastructure planning processes. Resilient infrastructure has the potential to limit the impacts of extreme weather events in terms of physical and financial damage to infrastructure, and it has the capability to recover quickly after such events. Assessing and analyzing infrastructure resilience could help decision makers and infrastructure planners better understand the performance of infrastructure and prioritize infrastructure investment. However, studies on previous infrastructure investment and policies indicate that there have been discriminatory policies and biases in infrastructure planning processes for decades (NASEM 2022). As a result, during extreme events, the disaster impacts on infrastructure, including but not limited to physical damage, financial losses, and service disruption, are not evenly distributed across different communities. Such disparities are typically linked to the variations in community characteristics, such as geographical location, population, and socio-economic status. For example, socially vulnerable communities, including those with a higher percentage of disabled, elderly, poor, uninsured, and minorities populations (Rao et al. 2019), typically experience more severe disaster impacts to their infrastructure and require longer time to recover from disasters (Drakes et al. 2021). However, existing work on infrastructure resilience assessments (e.g., Tonn et al. 2020, Pagano et al. 2019, Chan and Schofer 2016) tends to overlook such disparities and vulnerabilities within different communities. These assessments often assume that infrastructure serving various communities is impacted equally during disasters. Such assessments cannot fully capture the variations in disaster impacts or recovery processes. There is thus a need to account for these disparities and vulnerabilities in infrastructure resilience assessments. By doing so, we can gain a more accurate understanding of the impacts of disasters on different communities and take steps to improve resilience of those communities with greater needs.

Based on a comprehensive literature review in the domain of infrastructure resilience assessment, we identified two main knowledge gaps. First, existing research on infrastructure resilience analysis typically does not account for disaster disparities and vulnerabilities. Extensive studies (e.g., Tonn et al. 2020, Pagano et al. 2019, Chan and Schofer 2016, Yang et al. 2018, Ouyang and Duenas-Osorio 2014) have been conducted in assessing the resilience of various types of infrastructure, such as transportation infrastructure (e.g., Chan and Schofer 2016), electric power systems (Yang et al. 2018), and water supply infrastructure (e.g., Pagano et al. 2019). However, they did not account for the difference in disaster impacts among the diverse communities served by these infrastructures. This lack of consideration may lead to an incomplete understanding of the true resilience of infrastructure systems and hinder efforts to address the specific needs and vulnerabilities of different communities in disaster planning and management. As a result, there is a potential risk of overlooking and neglecting certain communities that may be more susceptible to adverse impacts during disasters. Second, there is a lack of research that investigates how communities with varying characteristics are affected by disasters. By examining the resilience of infrastructure that serves a range of various communities, we can identify vulnerable communities and promote more equitable infrastructure planning. Although previous research has evaluated the effects of disasters on different communities during different stages of a disaster, including preparedness (Kim and Sutley 2021), response (Yabe and Ukkusuri 2020), and recovery (Emrich et al. 2019), there are limited studies that compare infrastructure resilience across communities with different characteristics and explore how these characteristics may influence infrastructure resilience as a whole. Addressing this knowledge gap is crucial for a comprehensive understanding of the relationship between community attributes and infrastructure resilience. By understanding how various community characteristics influence infrastructure resilience, we can work towards creating more robust and inclusive disaster management and recovery plans, ultimately promoting a more resilient and equitable society.

To address this gap, this paper presents a study that comparatively analyzes infrastructure resilience while accounting for disaster disparities and vulnerabilities. We utilized the social-welfare-based infrastructure resilience assessment (SW-Infra-RA) model proposed by Dhakal and Zhang (2023). SW-Infra-RA model assesses the collective resilience of infrastructure serving multiple communities while accounting for (1) disaster inequality – the unequal distributions of disaster impacts on infrastructure across various communities; and (2) disaster vulnerability– the disaster impacts on the infrastructure of the communities that suffer from the most severe impacts. In this study, we focused on measuring and comparing the levels of disaster inequalities, the levels of disaster vulnerability, and the collective resilience of infrastructure serving Florida counties with various characteristics (e.g., spatial, demographic, and socio-economic characteristics). The remainder of the paper presents the research context, explains the research method, discusses the results, and summarizes the study with conclusions.

RESEARCH CONTEXT

In this study, we selected three hurricanes that made landfall in Florida: Hurricanes Michael, Irma, and Sally. Hurricane Michael is a Category 5 hurricane that made landfall near Mexico

Beach in Florida Panhandle on October 10, 2018. It was one of the strongest hurricanes that hit Florida gulf coast region (NOAA 2019). Hurricane Michael brought catastrophic storm surges ranging from 9 ft to 14 ft on the Florida Panhandle coast (NOAA 2019). It also brought enormous wind gusts that resulted in extensive structural damage and disruption of infrastructure services. Infrastructure such as communication and electric transmission lines were destroyed from fallen trees and flying debris (Burgess 2018). A damage assessment report showed that roads and highways in the coastal region between Panama City and Alligator point were washed out due to flash flooding (NOAA 2019).

Hurricane Irma, another Category 5 hurricane, made landfall in Florida Keys on September 10, 2017. It brought strong winds and storm surges that caused flooding with a maximum inundation level of 5ft to 8 ft above normal level for the lower Florida Keys (NOAA 2018). The hurricane caused extensive damage to the infrastructure serving the communities of South Florida. For example, a report showed that a part of US 1 Highway was washed away due to heavy rainfalls and storm surges.

Hurricane Sally is a Category 2 hurricane that made landfall near the Florida/Alabama state line on September 16, 2020 (NOAA 2021a). The storm brought strong wind speeds (105 mph) and storm surges, causing extensive damage to infrastructure across the northwest coastal region of Florida. Heavy rainfall combined with storm surges resulted in massive flooding and damage to electric power infrastructure serving the communities of western Panhandle region of Florida (Saunders 2020).

RESEARCH QUESTIONS

We conducted three case studies in the context of the three selected hurricanes to address the following research questions:

1. How does disaster inequality vary among counties with different characteristics (e.g., coastal vs inland, urban vs rural, more socially vulnerable vs less socially vulnerable)?
2. How does disaster vulnerability differ among counties with different characteristics?
3. How does collective infrastructure resilience vary among counties with different characteristics?

CASE STUDY DESIGN

We designed the three case studies in a similar manner in terms of structure and content. For each case study, by leveraging the SW-Infra-RA (Dhakal and Zhang 2023), we measured and compared disaster inequalities, disaster vulnerabilities, and collective resilience of one type of infrastructure that serves different groups of communities. The background information as well as the data source of each case study are briefly summarized in Table 1.

We collected the data for two main types of infrastructure resilience indicators: infrastructure functional loss and infrastructure recovery time. Here, functional loss is defined as the reduction in functionality of infrastructure due to the impacts of a disaster. Depending on the type of infrastructure, functional loss can be represented through indicators such as percentage of communication service outages, percentage of electric power outages, and percentage of road closures. Recovery time is defined as the time required by infrastructure to resume its services to the original functional level after disasters and can be represented through indicators such as the time required for road reopening and the time required for resuming electric power services. The data for these indicators were collected from both public and private sources, including Federal Emergency Management Agency (FEMA), Florida Public Service Commission (FPSC), Federal Communications Commission (FCC), and Florida Department of Environmental Protection (FDEP).

Table 1. Case Study Information.

Case Study	Hurricane	Type of Infrastructure	Data Source
I	Hurricane Michael	Communication	FCC (2018)
II	Hurricane Sally	Electric power	FPSC (2023)
III	Hurricane Irma	Transportation	FDEP (2023)

The geographical regions in close proximity to disasters often experience more severe impacts compared to the regions located farther away from the same disaster. To account for the effects of varying disaster threat levels on infrastructure serving multiple counties, we used normalized disaster impacts (functional loss and recovery time) in our analysis. We normalized the disaster impacts based on the average sustained wind speeds during the disaster period.

For each case study, we first identified the Florida counties that issued disaster declarations due to the selected hurricane. Then, to conduct the comparative study among communities with different spatial, demographic, and socioeconomic characteristics, we classified the identified counties into multiple groups, including (1) the coastal and inland groups, (2) the urban and rural groups, and (3) the more socially vulnerable and less socially vulnerable groups. The coastal group includes counties that have a coastline bordering the ocean (NOAA 2021b), while the inland group includes counties that share their borders with adjacent counties with no coastline bordering. The urban group includes counties with population densities higher than 100 individuals per square mile, while the rural group includes counties with population densities lower than 10 individuals per square mile (Florida Health 2022). The less vulnerable group includes counties with social vulnerability index (SVI) (CDC/ATSDR 2023) ranging from 0 to 0.5, while the more socially vulnerable group includes counties with social vulnerability index (SVI) ranging from 0.5 to 1. Here, the SVI is an index that is used to assess the vulnerability of a population to hazards and disasters. It takes into account factors such as socioeconomic status, race/ethnicity, language barriers, age, and disability status, which can affect a community's ability to prepare for, cope with, and recover from disasters. (CDC/ATSDR 2023).

We then assessed the infrastructure resilience across multiple counties using the SW-Infra-RA model (Dhakal and Zhang 2023). The SW-Infra-RA model has four key components: (1) a mathematical measure that assesses the unequal distribution of disaster impacts across different counties by adapting the Gini coefficient (Atkinson and Brandolini 2010), (2) a line of vulnerability that identifies those communities that suffer from the most severe impacts from a disaster, (3) a collective disaster impact function that measures the collective functional loss and collective recovery time by incorporating unequal distribution of disaster impacts and the potentially severe disaster impacts on vulnerable communities, and (4) a collective infrastructure resilience assessment function that quantifies collective infrastructure resilience based on the collective disaster impacts. For detailed information about this model, the readers are referred to Dhakal and Zhang (2023).

To conduct the case studies, we followed the following four primary steps:

(1) Measuring the unequal distribution of disaster impacts on infrastructure serving multiple counties by using Gini coefficient, of which the value ranges from 0 to 1, with 0 representing perfect equality and 1 representing complete inequality;
(2) Determining the line of vulnerability to identify disaster vulnerable counties and measuring the percentage of disaster vulnerable counties in each group;
(3) Quantifying the collective disaster impacts on infrastructure serving multiple counties;
(4) Assessing the collective loss of resilience of infrastructure.

RESULTS AND DISCUSSION

Based on the aforementioned steps and utilizing the functions proposed in SW-Infra-RA (Dhakal and Zhang 2023), the results of the three case studies are summarized in Tables 2, 3, and 4. The next three paragraphs highlighted some of the main findings with relevant discussion.

Table 2. Results of Case Study I.

Variable	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

Table 3. Results of Case Study II.

Variable	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

Table 4. Results of Case Study III.

Variable	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

Analysis of Disaster Inequality across Different Communities. Tables 2, 3, and 4 show the results of the three case studies. As per the results, in the three disasters, the Gini coefficients are all higher in the more socially vulnerable group as compared to the less socially vulnerable group. For example, in the context of Hurricane Michael (Case Study I), both the Gini coefficients for functional loss and recovery time are higher in the more socially vulnerable group (G_{FL}=0.93, G_{RT}=0.89) as compared to the less socially vulnerable group (G_{FL}=0.72, G_{RT}=0.52). The results suggest that counties with higher socially vulnerable tend to experience greater disparities in the distribution of disaster impacts within their communities.

The difference in disaster inequality between the more and less socially vulnerable groups could be attributed to insufficient disaster relief and aid, as well as disparities in the quality and adequacy of infrastructure services. Socially vulnerable communities, which often have a higher percentage of minority, disabled, poor, and unemployed populations, may lack access to the limited disaster aid and assistance, which could impede their recovery processes. Existing studies have shown that socially vulnerable communities face barriers in receiving disaster assistance, leading to longer recovery times and less infrastructure reinvestment and disaster recovery aid (SAMSHA 2017, Nexus 2017). Furthermore, socially vulnerable communities also lack adequate and stable infrastructure services. Previous studies have demonstrated that socially vulnerable communities often have unmet infrastructure needs, such as clean water supply and electricity (SAMSHA 2017). In the event of disasters (e.g., hurricanes), the unstable and substandard infrastructure in the socially vulnerable communities is more likely to suffer from varying levels of damage or service disruptions and has higher uncertainty in recovery. Therefore, socially vulnerable communities may experience higher levels of disaster inequality due to the varying levels of disaster impacts on their infrastructure.

Analysis of Disaster Vulnerability Across Different Communities. The results show that there is a higher percentage of disaster vulnerable counties in the rural group compared to the urban group in Hurricanes Michael and Irma (Case Studies I and III). For example, during Hurricane Irma, the proportion of disaster vulnerable counties was significantly higher in the rural group (66%) compared to the urban group (25%). These results may imply that infrastructure serving the rural area is more vulnerable to disasters compared to the urban area in Hurricanes Irma and Michael.

The greater level of disaster vulnerability across the rural communities may be attributed to various factors, such as aging and substandard infrastructure, insufficient infrastructure investment, and the socio-economic status of individuals residing in rural areas. Generally, rural areas have limited funding to support their infrastructure needs and lack the necessary resources to implement disaster resilience strategies (Kapucu et al. 2013). Furthermore, rural areas often have aging infrastructure that requires significant repair and maintenance. Unfortunately, infrastructure planning and investment programs tend to prioritize urban areas, leaving critical infrastructure services unreliable and inaccessible for rural communities (NCSL 2020). In addition, rural communities tend to have lower socio-economic conditions including higher poverty and unemployment rates and limited education resources. Previous studies have shown that the socio-economic attributes of communities are linked to the extent of damage caused by disasters to infrastructure. For example, during the recovery phase of Hurricane Michael, minority and low-income communities suffered from more severe impacts and lacked essential resources needed for recovery (Moens 2022).

Analysis of Collective Resilience of Infrastructure Serving Different Communities. The results show that, in Hurricanes Michael and Irma (Case Studies I and III), the collective loss of resilience of infrastructure serving the inland group (CLR = 0.14) is higher than the infrastructure serving the coastal group (CLR= 0.07). In contrast, the collective loss of resilience of electric power infrastructure serving both the inland (CLR=0.18) and the coastal groups (CLR=0.19) is similar in Hurricane Sally (Case Study II). These results suggest that greater disparities in collective infrastructure resilience between inland and coastal counites may be observed in the face of more intense hurricanes (e.g., Category 5 hurricanes).

This phenomenon may be explained by the characteristics of these hurricanes. First, both Hurricanes Irma and Michael were Category 5 hurricanes, capable of travelling up to 100 to 200 miles inland after making landfall (Raizner 2021). These hurricanes brought strong winds and extreme rainfall, leading to severe inland flooding. For instance, Hurricane Michael maintained Category 3 intensity as it moved across seven inland counties in Florida, including Calhoun, Liberty, and Gadsden counties (NOAA 2019). It continued to bring excessive rainfall, causing flash floods in the inland counties which resulted in substantial damage to roads and highways and interrupted communication and electric power services. In contrast, Hurricane Sally, a Category 2 hurricane, primarily caused damage to infrastructure in coastal areas due to storm surges and heavy rainfall (NOAA 2021a). After making landfall, Hurricane Sally weakened and moved towards inland areas of Florida as a tropical storm, resulting in less severe impacts on electric power infrastructure serving inland counties than those serving coastal counties.

CONCLUSIONS AND FUTURE WORK

This paper presents three case studies that analyze infrastructure resilience while accounting for disaster inequality and disaster vulnerability. We leveraged the social-welfare based infrastructure resilience assessment (SW-Infra-RA) model introduced by Dhakal and Zhang (2023) to evaluate the level of disaster inequality, disaster vulnerability, and overall resilience of infrastructure serving counties with different spatial, demographic and socio-economic characteristics. The study reveals three key findings. First, infrastructure serving socially vulnerable counties experienced greater levels of disaster inequality. Second, in high-intensity hurricanes, a higher percentage of disaster vulnerable counties were found in the rural group. Finally, infrastructure serving inland counties had poorer resilience performance compared to infrastructure serving coastal counties in high-intensity hurricanes.

This study makes a valuable contribution to the existing body of knowledge on infrastructure resilience assessments by integrating the crucial equity-related factors – disaster inequality and disaster vulnerability. By incorporating these factors, we gained a systematic understanding of (1) how disaster impacts are distributed unevenly among communities, (2) the types of communities that may experience more severe impacts, and (3) the collective resilience of infrastructure. In addition, the study offers comparative analyses across communities with different spatial, demographic, and socio-economic characteristics. These analyses enhance our understanding of the complex relationship between community attributes and infrastructure resilience in a quantitative manner.

Practically, our study offers theoretical and quantitative analyses that can inform more equitable and effective infrastructure planning and resilience strategies. By considering disaster inequality and vulnerability, decision-makers can better prepare for and address the diverse challenges posed by disasters, leading to more resilient and inclusive outcomes for communities at risk. For example, our findings highlight the need to consider the spatial, demographic, and socio-economic characteristics of communities when assessing infrastructure resilience. This can help decision-makers identify communities that are more vulnerable and in need of additional support during and after disasters. Additionally, the results can be used to guide the allocation of resources and investments in infrastructure improvements that can enhance resilience and reduce disparities.

The present study focuses on hurricane disasters in Florida counties, and a primary limitation of the study is the relatively small number of counties analyzed. Consequently, the generalizability of the results to other disaster contexts or geographic locations is restricted. Moreover, due to the scarcity of available data, the analysis was limited to the county level, thereby preventing the examination of disaster inequality at finer scales such as the city or community levels. In the future/ongoing work, the authors will conduct additional case studies to analyze the resilience of diverse types of infrastructure serving a more extensive range of communities across various regions in the country. Additionally, the authors will further explore methods for modeling the interdependencies among infrastructure systems serving multiple communities, with the goal of integrating such interdependencies into the analysis.

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