# Understanding Infrastructure Resilience, Social Equity, and Their Interrelationships: Exploratory Study Using Social Media Data in Hurricane Michael

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**Abstract:** The 2030 Global Sustainable Development Agenda of the United Nations highlights the importance of understanding the interlinkages of infrastructure, inequality, and resilience. However, there is limited research that studies the complex interrelationships between infrastructure resilience and social equity. To address the gap, this study aims to understand infrastructure resilience, social equity, and their interrelationships in the context of Hurricane Michael through an integrated analysis of social media data, census data, and disaster damage, relief, and recovery data. The results from the study reveal the following key findings. First, in the context of a disaster, Twitter activities have the potential to be used as an important indicator of infrastructure damage and recovery. Second, socially vulnerable populations are generally less active and represented on Twitter. However, under the same disaster threat level, they were shown to be more active on Twitter, which might be due to more significant hardships they experienced in the disaster. Third, communities with different social equity conditions experienced different levels of infrastructure damage and speeds of recovery. Communities with higher percentages of socially vulnerable populations experienced a relatively higher level of damage and required longer time for recovery. This research contributes to the body of knowledge by offering an improved understanding of social equity and infrastructure resilience in the context of Hurricane Michael using a data-driven approach. The findings from this research further reinforce the fundamental understanding that is needed for practitioners in the emergency management and infrastructure development areas to make human-sensitive decisions that facilitate equitable infrastructure resilience. **DOI: 10.1061/(ASCE)NH.1527-6996.0000512.** 

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## 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-onset 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 2016; APA 2021), social equity is defined in 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 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. 2019; AJMC 2006). They often have the fewest resources for disaster preparedness, live in disaster-prone areas, and lack the 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).

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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 organizations (e.g., UN 2016; Rockefeller 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 study 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 allow 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. 2019; Goldgruber et al. 2017), public awareness (e.g., Martín et al. 2017), and 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 the understanding of the complex relationships between infrastructure resilience and social equity, this paper 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 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 remainder of the paper presents the literature review, explains the research context and methodology, discusses the results and findings, and summarizes the contributions and conclusions.

## Literature Review

### *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 the 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 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).

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.

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;



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MacKenzie and Zobel 2016), and system resilience assessment (e.g., Heinimann and Hatifield 2017; Yodo and Wang 2016). For example, Chopra et al. (2016) developed a multipronged framework that analyzed 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 et al. (2018) proposed a methodology that evaluated road recovery strategies for restoring the services after blockage due to natural hazards. Zhang et al. (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 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 et al. (2003) studied socioeconomic and demographic conditions of different counties and developed social vulnerability index to encapsulate the socioeconomic conditions associated with disaster inequalities. Emrich et al. (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 et al. (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-onward).

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.

### *Social Media Analysis in Disaster Literature*

Social media is a collection of platforms that allow users to create public or semipublic 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 are 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 et al. (2018) conducted a spatiotemporal analysis of social media data using machine learning techniques to analyze the regions with significant damage due to disasters. Chen et al. (2020) employed a systematic approach to identify and assess the damage on highways using social media in the context of Hurricane Harvey. Zou et al. (2018b) studied the social and geographical disparities that existed in the Twitter activities during Hurricane Sandy. Roshan et al. (2016) analyzed the use of social media for communication among different organizations in the time of crisis. Young et al. (2020) studied social media and its potential use for emergency communication during the response and recovery phases of disasters. Li et al. (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).

## Research Context

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

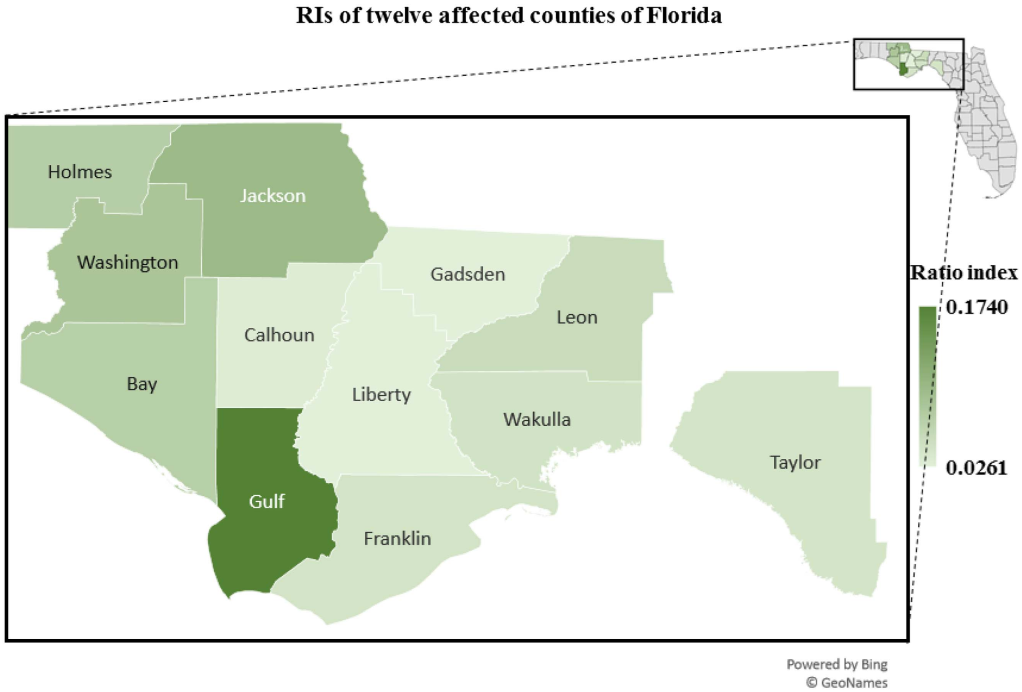


**Fig. 1.** Ratio indices of the disaster affected counties of Florida. [Map powered by Bing, © GeoNames under Creative Commons-BY-4.0 license (https://creativecommons.org/licenses/by/4.0/).]

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 2018). High storm 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, the transportation infrastructure (e.g., roads, 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 declarations as of November 15, 2018. These counties include Bay, Calhoun, Franklin, Gadsden, Gulf, Holmes, Jackson, Leon, Liberty, Taylor, Wakulla, Washington counties (Fig. 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, and Hurricane Irma).

## Methodology

### *Data Collection Methods*

#### 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 share 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, which allows 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) were 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 that were 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 geotagged 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 tweet (e.g., name, screen name, location, number of followers, friend, and list).



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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 the internet archive were combined with extracted geotagged tweets to form the background tweet 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) 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 and inductive approaches. 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 version 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.

### 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 1). Eight infrastructure resilience variables were selected for analysis in this study for two reasons, namely (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), FEMA, Florida Division of Emergency Management (FDEM), Federal Communications Commission (FCC), Florida Department of Economic Opportunity (FDEO), and Florida Office of Insurance Regulations (FOIR).

### Social Equity Data Collection

A total of 18 social equity variables (Table 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 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 12 affected counties were collected from the US Census Bureau (US Census 2019), which provides data that is of high quality, reliability, and consistency (Santos 2019).

## Data Analysis Methods

### 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 12 affected counties in Hurricane Michael. Ratio index is a Twitter index that can be used to represent

**Table 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) | FPSC (2021) |
| | | Percentage of communication service outages (I3) | FCC (2018) |
| Rapidity | Time required to recover to previous functional levels | Power outage recovery time (I4) | FPSC (2021) |
| | | Communication service outage recovery time (I5) | FCC (2018) |
| | Cost required to recover to previous functional levels | Disaster recovery cost per capita (I6) | FDOT (2019) |
| Resourcefulness | 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) |

**Table 2.** Social equity variables

| Dimension | Variable | Data source |
|---|---|---|
| Age | Percentage of population under 18 years (S1) | US Census (2019) |
| | Percentage of population 65 years and above (S2) | |
| Gender | Percentage of male population (S3) | US Census (2019) |
| | Percentage of female population (S4) | |
| Race | Percentage of White population (S5) | US 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) | US Census (2019) |
| Technology | Percentage of households with internet connection (S9) | US Census (2019) |
| | Percentage of households with computer (S10) | |
| Education | Percentage of population having high school degree or higher (S11) | US Census (2019) |
| Health | Percentage of population without health insurance (S12) | US Census (2019) |
| | Percentage of population with a disability (S13) | |
| Economics | Per capita income (S14) | US Census (2019) |
| | Percentage of population under poverty (S15) | |
| | Median household income (S16) | |
| | Median value of owner-occupied housing units (S17) | |
| | Total employment (S18) | |



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. (1)] (Zou et al. 2018b)

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

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 sustained average wind speed [Eq. (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. (2)

$$\mathrm{NRI} = \frac{\mathrm{RI}}{\text{Sustained average wind speed}} \tag{2}$$

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 tweet content (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, 20 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)]

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

## 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 sustained average wind speed during the hurricane period in each county [Eq. (4)]

$$\mathrm{NIR} = \frac{\text{Infrastructure resilience data}}{\text{Sustained average wind speed}} \tag{4}$$

## 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's 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 non-parametric version of the Pearson's correlation. Spearman's correlation coefficient ($\rho$) measures the strength and direction of monotonic association between two variables rather than the 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 with 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 $\rho$) 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 and 0.29 represents a small association (Statistics Solutions 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 the main findings of the analyses.

## 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 12 affected counties were first calculated using Eq. (1), as shown in Fig. 1. Similarly, the NRIs and SIs for the 12 counties were calculated using Eqs. (2) and (3), respectively. The three sets of correlation analyses were then conducted.

### *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). Table 3 and Fig. 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.

These results are consistent with a number of studies (e.g., Zou et al. 2018b; Kryvasheyeu et al. 2016), which 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 nongovernment organizations (NGOs) used their official Twitter accounts to provide updates on recovery status, coordinate relief and recovery efforts, and offer resources or support.

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

| | Pearson's correlation | | Spearman's correlation | |
|---|---|---|---|---|
| Relationship[a] | $r$ value | $p$-value | $\rho$ value | $p$-value |
| RI versus I1 | 0.750 | 0.058[b] | 0.149 | 0.645 |
| RI versus I5 | 0.556 | 0.060[b] | 0.467 | 0.125 |
| RI versus I6 | 0.547 | 0.066[b] | 0.168 | 0.602 |
| RI versus I7 | 0.544 | 0.068[b] | 0.224 | 0.484 |
| RI versus I8 | 0.626 | 0.029[b] | 0.427 | 0.167 |
| SI versus 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.

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 11 affected counties (Fig. 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 19 ft), 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).

### *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). Table 4 and Fig. 3 present the correlation results that are statistically significant. As per Table 4, the RI has statistically significant, strong negative correlations with

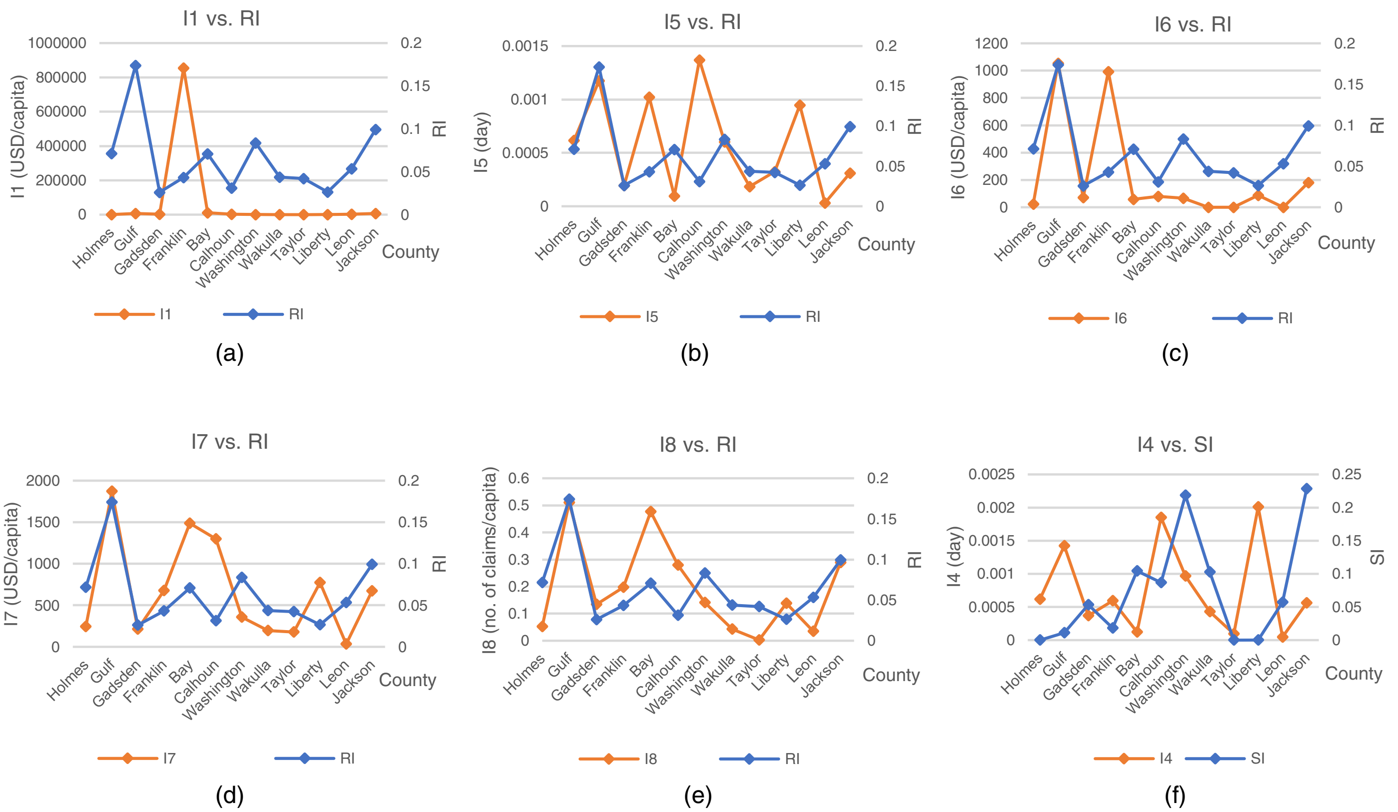


**Fig. 2.** Line charts showing relationships between infrastructure resilience variables and Twitter activities (RI and SI) (The numbering of infrastructure resilience variables follow that in Table 1): (a) I1 versus RI; (b) I5 versus RI; (c) I6 versus RI; (d) I7 versus RI; (e) I8 versus RI; and (f)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

**Table 4.** Statistically significant results of correlation analyses between social equity variables and Twitter activities

| | Pearson's correlation | | Spearman's correlation | |
|---|---|---|---|---|
| Relationship[a] | $r$ value | $p$-value | $\rho$ value | $p$-value |
| RI versus S7 | −0.408 | 0.187 | −0.573 | 0.051[b] |
| RI versus S8 | −0.383 | 0.220 | −0.592 | 0.043[b] |
| RI versus S9 | 0.390 | 0.210 | 0.566 | 0.055[b] |
| RI versus S13 | −0.267 | 0.402 | −0.565 | 0.056[b] |
| SI versus S13 | −0.435 | 0.158 | −0.618 | 0.032[b] |
| SI versus 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.

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, minorities, and 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.

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.

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

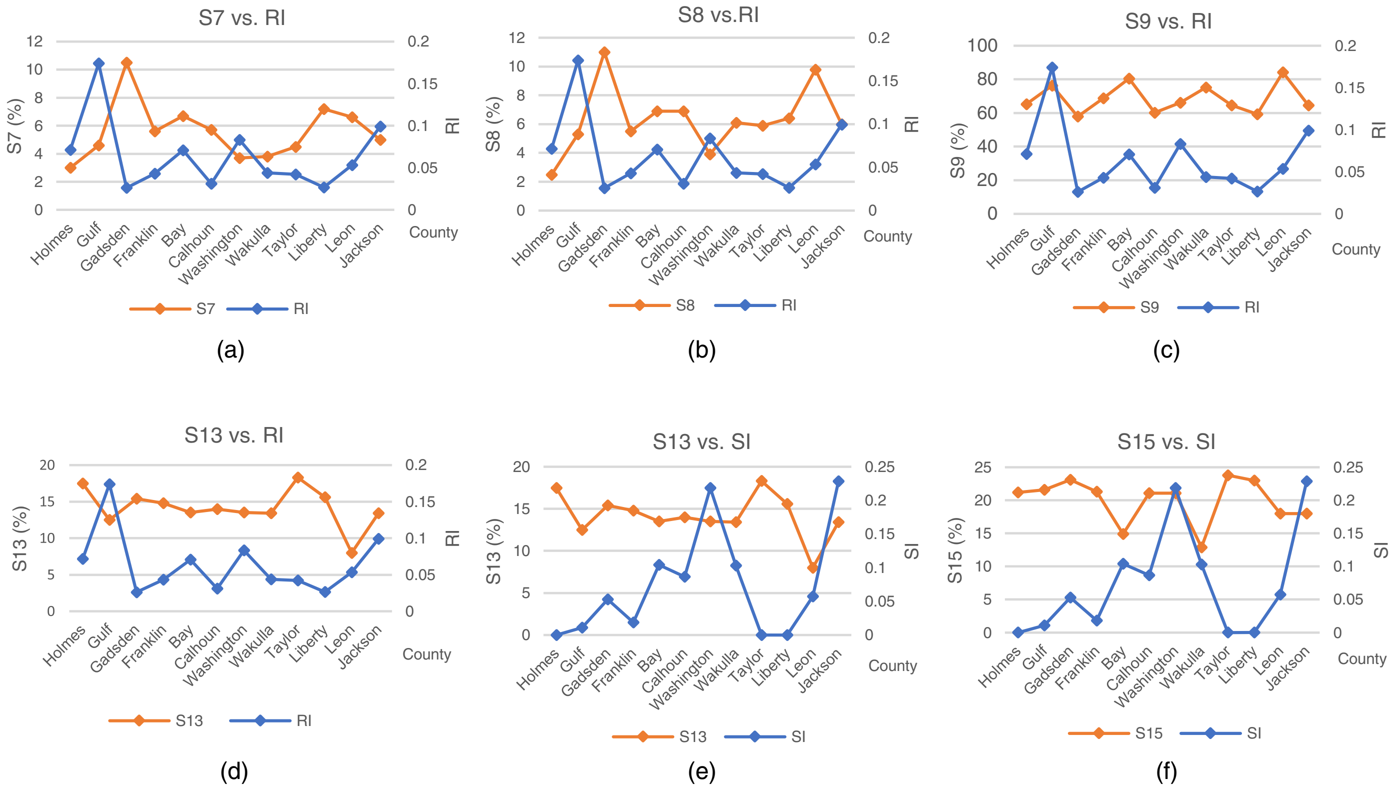


**Fig. 3.** Line charts showing relationships between social equity variables and Twitter activities (RI and SI) (The numbering of social equity variables follow that in Table 2): (a) S7 versus RI; (b) S8 versus RI; (c) S9 versus RI; (d) S13 versus RI; (e) S13 versus SI; and (f) S15 versus SI.

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 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 versus RI, and (2) social equity variables versus NRI, it is observed that the correlation coefficients (Spearman's $\rho$) 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. Conversely, 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 other words, under the same threat level, vulnerable populations were more active on Twitter during Hurricane Michael. This is probably because, faced 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.

**Table 5.** Correlation coefficients of correlation analyses between social equity variables and Twitter activities

| Social equity variable[a] | Pearson's $r$ value | | Spearman's $\rho$ 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.
[a]The numbering of social equity variables follow that in Table 2.

## 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 6 and Fig. 4 present the statistically significant correlation results. Three main findings are discussed in the following paragraphs.

First, according to Table 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

**Table 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 | $\rho$ value | $p$-value |
| S1 versus I6[b] | −0.809 | 0.001[c] | −0.543 | 0.068[c] |
| S2 versus I6[b] | 0.738 | 0.006[c] | 0.476 | 0.118 |
| S3 versus I6[b] | 0.411 | 0.184 | 0.501 | 0.097[c] |
| S3 versus I7[b] | 0.550 | 0.064[c] | 0.585 | 0.046[c] |
| S4 versus I6[b] | −0.411 | 0.184 | −0.501 | 0.097 |
| S4 versus I7[b] | −0.550 | 0.064[c] | −0.585 | 0.046 |
| S7 versus I1[b] | 0.010 | 0.975 | 0.559 | 0.059[c] |
| S10 versus I4[b] | −0.385 | 0.216 | −0.517 | 0.085[c] |
| S10 versus I5[b] | −0.494 | 0.102 | −0.531 | 0.075[c] |
| S11 versus I5[b] | −0.438 | 0.154 | −0.529 | 0.077[c] |
| S12 versus I5[b] | 0.424 | 0.170 | 0.567 | 0.054[c] |
| S12 versus 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 at 0.1 level.

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., minorities, the uninsured, and the elderly) might have experienced more severe damage during Hurricane Michael, which also required higher expenses during recovery. Existing research shows that vulnerable populations are often underprepared before disasters (e.g., lack of home insurance or flood insurance, inadequate financial resources), and 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 implementation of the

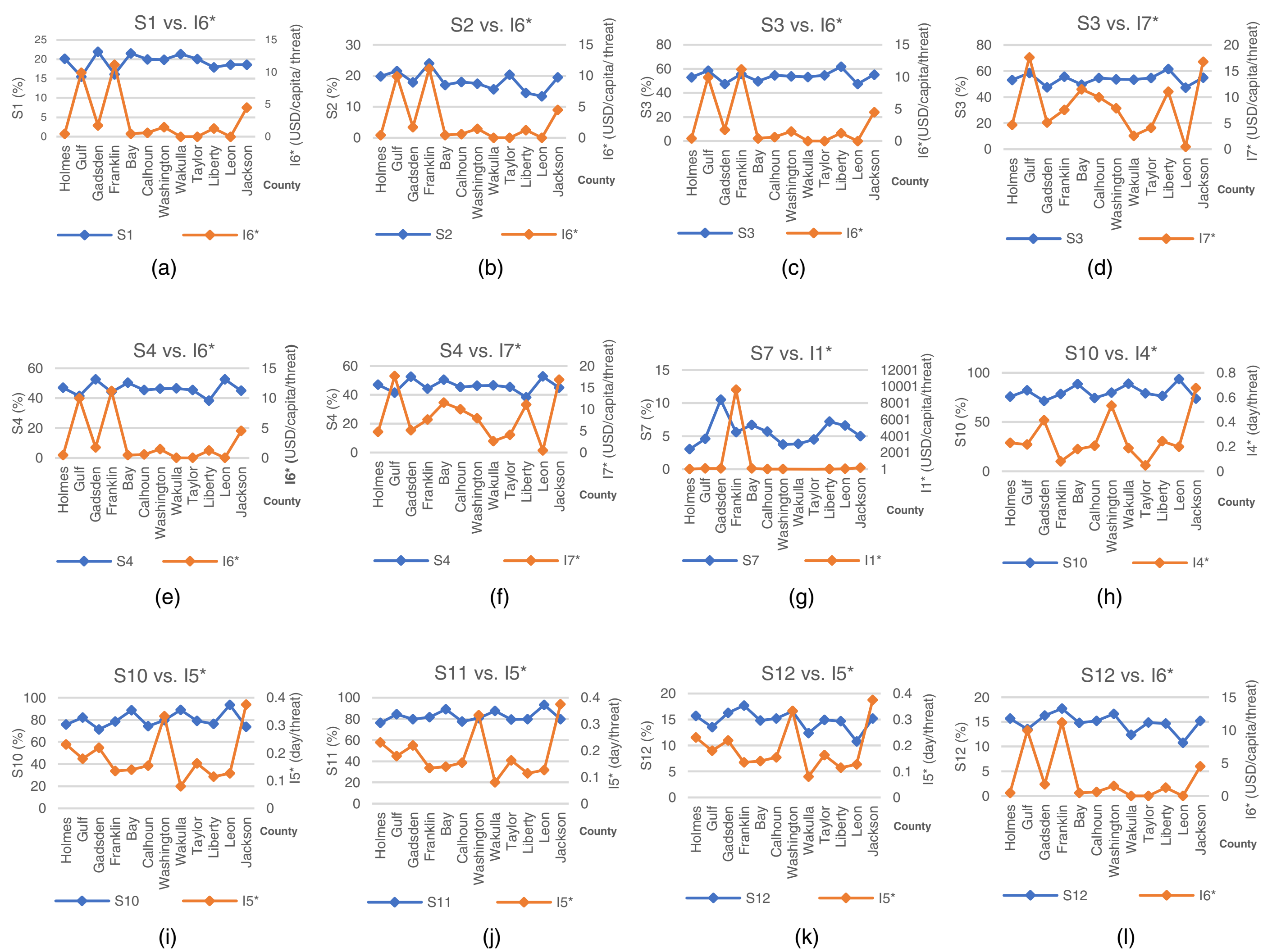


**Fig. 4.** Line charts showing relationships between social equity variables and normalized infrastructure resilience variables (The numbering of infrastructure resilience and social equity variables follow that in Tables 1 and 2, respectively): (a) S1 versus I6*; (b) S2 versus I6*; (c) S3 versus I6*; (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*.

stricter building codes that happened after Hurricane Andrew in 1992 (Allen 2018).

Second, as per Table 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 a 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 with low-income communities (Nexus 2017). In addition, communities with highly educated populations tend to have shorter 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 aid and resources to recover from disasters.

Third, the results in Table 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 $\rho = -0.585$, $p = 0.046$), and (2) the disaster recovery cost per capita (I6*) (Spearman's $\rho = -0.501$, $p = 0.097$). 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.

### *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 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 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. Here'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 Tables 3 and 4, respectively. According to Table 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 conducted by the authors' research group 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 looked 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 predisaster 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 4 show significantly negative correlations between the SI and (1) the percentage of population living in poverty (S15) (Spearman's $\rho = -0.730$, $p = 0.007$); and (2) the percentage of population with a 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 living in 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 posttraumatic 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. 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, financially disadvantaged individuals are at 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.

## Recommendations

Based on the results of this study, some possible actions to improve disaster resilience are provided as follows:

1. Use social media as one data source to complement traditional data sources and offer rapid assessment on infrastructure conditions in disasters. The results of this study suggest that Twitter can be used as one data source for analyzing the damage conditions and recovering efforts in the context of disasters. Compared to traditional assessment methods (e.g., disaster damage value modeling, postdisaster surveying, and data collection from multiple agencies), social media data-based damage assessment could offer many advantages, including easy accessibility, cost-effectiveness, and real-time analysis. This is especially important in the context of disasters, given all decisions (e.g., road reopening, and funding and resource allocation) need to be made and implemented in a fast and timely manner to offer immediate relief to the impacted communities. Practitioners can use Twitter data to identify the regions that are hit the hardest in real time, and they can then focus on the areas that require the most aid and assistance. In addition, our results suggest that strengths in correlations are not uniformly definitive for all counties or regions, and we need to pay special attention to the outliers in the data sets. In practice, more detailed virtual or field investigations need to be conducted to understand the actual damage conditions in certain regions.
2. Enhance understanding of vulnerable populations on social media to improve social equity. The results of this study indicate that numerous social variables, such as age, gender, ethnicity, language, health, income, and employment status, are associated with the intensity of social media activities during disasters. In general, socially vulnerable populations are quiet on social media. However, under the same disaster threat level, socially vulnerable populations may become more active on social media, which could be due to the more severe conditions they faced or difficulties they experienced in disasters. As social media is becoming an important communication tool in disasters, we need to be aware of and further explore the communication patterns of vulnerable populations in order to understand the needs, concerns, or difficulties vulnerable people experience in disasters. Along with the technological advancement in recent years, social media can offer additional assistance, especially to vulnerable populations. For example, different communities could identify vulnerable individuals through their user profiles on social media, and they could delegate responsibility to specialized government officials to allocate additional resources and provide support to these individuals before, during, and after disasters. In addition, formal policies and programs can be implemented to encourage and assist vulnerable populations experiencing difficulties during disasters and ensure their needs and concerns are systematically accounted for and prioritized.
3. Account for the impacts on social equity in infrastructure planning and development. The results of this study show that, given the same threat level from a disaster, communities with different socioeconomic statuses experienced different levels of damage and different speeds in recovery. The communities with higher percentages of vulnerable populations generally experienced more severe damage and took longer time to recover. The results suggest that infrastructure planners and practitioners need to place more emphasis on offering essential services to marginalized and disadvantaged communities through infrastructure development or investment. For either new infrastructure projects or redevelopment, initiatives can be undertaken to analyze the social equity conditions of all potentially impacted communities during the planning stage of the project. It is worth noting that the implementation of such initiatives could be time-consuming and require a standard procedure or method. Thus, there is a need to develop new methods to quantitatively analyze the impacts of new or rehabilitated infrastructure projects on social equity conditions of the impacted communities. This will allow for more efficient and easy comparisons among multiple design alternatives. Accounting for the impacts on social equity is especially important in the context of disasters, as it facilitates equitable access to goods, infrastructure services, amenities, and economic opportunities for all community residents.

## Conclusions and Contributions

This paper 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 paper 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 12 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 less represented on social media. However, under the same disaster threat level, the vulnerable populations become more active, and this is probably because of the greater 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 a relatively higher level of damage and required a longer period of 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.

This research contributes to the body of disaster resilience knowledge in two primary ways. First, this research uses a data-based approach to derive useful information from data, which leads to improved understanding of social equity and infrastructure resilience in the context of Hurricane Michael. The social media data analysis allows for easy collection of timely data, and it could potentially allow practitioners and decision makers to analyze how disasters could impact people and infrastructure in a more efficient and timely manner. Second, this research advances the understanding of the interrelationships between infrastructure resilience and social equity in the context of Hurricane Michael. It shows how the communities with different social characteristics may experience disproportionate impacts from disasters 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 impacted communities. The study can also spur more dialogue and research on further important questions: How do we evaluate the impacts of infrastructure (re)development on social equity? How do we better integrate the consideration of social equity in infrastructure (re)development? How do we systematically compare the impacts of alternative infrastructure (re)development strategies on social equity? From a practical perspective, this study may potentially support more effective and efficient emergency management by offering a method to assess infrastructure damage in a relatively quick and timely manner. It may offer insights for communities to identify vulnerable populations in disasters through new methods, thus orienting additional resources and assistance to these individuals. It may also support more equitable infrastructure planning by facilitating equity-incorporated infrastructure (re)development plans that prioritize the investment for vulnerable communities.

## Limitations and Future Work

In this study, four main limitations of the work are acknowledged, which may indicate the necessity of future work. First, the Twitter data collected between October 1, 2018 and November 16, 2018 for this study do not reflect the complete disaster management cycle of Hurricane Michael; they do not include the mitigation and the complete recovery phases. Similarly, the data for the eight infrastructure resilience variables were collected up until December 2019 and do not reflect the complete recovery phase of Hurricane Michael either. Continuous data collection together with longitudinal studies are needed to further improve the understanding between infrastructure resilience and social equity. Second, the Twitter data only include the tweets that were either geotagged or whose users included geolocation information in their profiles. Although having geoinformation is essential for this study to understand the differences across different impacted counties, it is acknowledged that this may exclude tweets posted by users who chose not to include any geolocation information. Third, the analysis is conducted on a county level, which may not reveal the infrastructure resilience and social equity conditions within different communities in the same county. This can be further addressed by collecting data based on zip codes or different types of communities by grouping several zip codes together. Fourth, even though Twitter data analysis supports real-time data collection and analysis, in this study, the Twitter data were collected after Hurricane Michael. More extensive studies are needed to generalize the findings of this study and validate the methods, thus supporting the use of Twitter data to offer real-time analysis of infrastructure resilience and social equity conditions of communities in disasters.

In future and ongoing work, the authors will further expand this current study to different phases of disasters (e.g., preparedness, response, recovery, and mitigation), different types of communities (e.g., urban versus rural), and different types of rapid-onset (e.g., earthquake) or slow-onset disasters (e.g., sea level rise). Further analyses will be conducted, such as using natural language processing techniques to understand the trending topics throughout different phases of disasters. This will allow an understanding of local communities' values and concerns toward disasters. Besides these analyses, the authors will further improve the understanding of the interrelationships between built environments and our society by developing new models that can quantitatively measure infrastructure resilience while accounting for the impacts of infrastructure development on social equity of local communities.

## Data Availability Statement

Some data that support the findings of this study are available from the corresponding author (Lu Zhang) upon reasonable request. These data include the Twitter data, the infrastructure resilience data, and the social equity data.

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