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Social response and Disaster management: Insights from twitter data Assimilation on Hurricane Ian

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ABSTRACT

During natural disasters, people use social media platforms to share their opinions and general information about the event. Here, we investigate the public response to large and destructive hurricane Ian in late September 2022 by examining the textual content of tweets shared on Twitter across the contiguous United States (CONUS). We mined and processed over twenty million tweets for discovering the main topics of discussion and relationship between them, and classifying tweets into humanitarian topics and categories to help disaster management with thorough sentiment analysis. We employed a variety of algorithms in Artificial Intelligence for Natural Language Processing (NLP) including sentiment analysis, topic modeling, and text classification to assimilate the information content in massive Twitter data. The findings of this study provide insights on how people utilize social media to learn and disseminate information about hurricane events, which accordingly aid emergency responders and disaster managers in mitigating the negative consequences of such catastrophes and improving community preparedness.

1. Introduction

Hurricane Ian, a massive and catastrophic category 4 hurricane [1], has been the deadliest natural disaster hitting Florida and South Carolina states and the western Cuba since 1935. On September 23, Ian developed into a tropical depression. The following morning, when it passed southeast of Jamaica, it strengthened into Tropical Storm Ian. Within a 24-h span, Ian rapidly strengthened into a high-end category 3 hurricane before making landfall in the western Cuba. There was a nationwide power outage in Cuba due to massive flooding brought on by torrential rain. While over land, Ian's strength damped slightly, but was quickly recovered when over the southeast Gulf of Mexico. On September 28, 2022, as hurricane moved near Florida's west coast, it strengthened to a high-end category 4 hurricane. It made landfall on Cayo Costa Island in southwest Florida just before its peak intensity. Ian is now the fifth-strongest hurricane ever to make landfall over the CONUS. It quickly became a tropical storm after arriving inland before heading back out into the Atlantic. Before hitting South Carolina for a second time, it gathered strength and became a hurricane. Soon after making landfall, Ian turned extratropical. After steadily losing strength, it eventually disintegrated over southern Virginia on October 1. Ian caused appalling destruction, with damages estimated over $67 billion.

At the times of natural disasters, millions of people seek updates and share their thoughts and information on social media platforms [2,3]. Studies have demonstrated that social media data can be beneficial for several humanitarian objectives including "situational awareness" [4,5]. A substantial portion of information shared on social media platforms is unavailable through conventional mass media platforms such as TV and newspapers [6]. These findings imply that using social media content during disasters has the potential to promote efficient response, reduce losses, and enhance mitigation strategies [7]. Although information provided on social

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media platforms by individuals may be beneficial for disaster response authorities, it can be challenging to comprehend in time-sensitive situations because of the large volume and velocity of such data streams [8]. Several researchers have examined crisis-relevant information from Twitter during natural disasters by utilizing relevant keywords and geo-tagged tweets [9–11]; Z [12,13]. For example, social media data analysis throughout natural disasters such as floods [14–19], earthquakes [20–22]; Y. [23,24], and wildfires [25–27] have been conducted. Identifying the locations of information extracted from tweets is essential for effective disaster and risk management. Several studies have analyzed geo-tagged disaster-related tweets [28–31]. However, only less than 1% of the tweets are geo-tagged [13]. Several studies employed a phased approach [32–34]; to examine how people respond to disasters at various stages of the event. Researchers have utilized sentiment analysis to determine whether social media content during disasters is positive, negative, or neutral [23,30,35,36]. For instance, analyzing the sentimental changes over time during the disaster [29] and post-disaster recovery [7,37] have been conducted. Although earlier research on social media use during a natural disaster offers helpful insights into social response and disaster management, the sentiment analysis in conjunction with topic classification can yield more valuable information on social response and crisis management. Several studies have utilized text classification to categorize tweets containing valuable information into humanitarian topics [38–42]. Additionally, [33] analyzed textual data posted on Twitter during Hurricane Harvey and classified tweets into humanitarian topics categories. The novelty of this study lies in investigating the dynamic patterns of social response to hurricane Ian. The study aims to provide insights into how people responded to the hurricane as it progressed and evolved, and how social media can be used to understand these responses. The dynamic patterns of social response refer to the changes in sentiment and topic classification of social media posts related to the hurricane over time. By analyzing sentiment and topic classification, the study aims to identify how the public responded to the hurricane, how they perceived the situation, and what concerns they had during different stages of the disaster. Understanding these dynamic patterns can provide valuable insights into the effectiveness of disaster management strategies and help improve response efforts in future disasters. Unlike previous studies that have focused on either sentiment analysis or tweet classification, this study employs both techniques in conjunction to provide deeper insights into the response to Hurricane Ian on Twitter. Specifically, we classify tweets into six distinct humanitarian classes and analyze the sentiment within each class, revealing nuanced patterns of emotional responses to the disaster. Additionally, we perform co-word analysis to uncover the relationship between the main subjects of interest throughout Hurricane Ian on the Twitter sphere, contributing to a better understanding of the collective public discourse surrounding disasters on social media. This multi-faceted approach provides a more comprehensive and nuanced understanding of the ways in which social media can be used in disaster response and management. The aim of this study is to achieve the following objectives:

1. Discover the main subjects of interest in tweets during hurricane Ian by analyzing the patterns of co-occurrence of pairs of words in a corpus of tweets
2. Conduct sentiment analysis on tweets related to the disaster event of hurricane Ian.
3. Utilize a cutting-edge machine learning algorithm to classify tweets into various humanitarian topics.
4. Examine the temporal and spatial patterns of social response to hurricane Ian.
5. Offer valuable insights into the possible employment of social media data by disaster response authorities in enhancing mitigation strategies and minimizing losses.

2. Methods

2.1. Twitter data

In this study, we used Twitter API to collect tweets containing hurricane Ian related keywords as they were posted on the Twitter stream from September 24, 2022, to October 6, 2022. Our dataset contains twenty-one million tweets.

2.2. Textual content pre-processing

Raw tweets are quite disorganized and have redundant features if they are not preprocessed. Tweet preprocessing eliminates stop words, hyperlinks, mentions, retweets, white spaces, emoticons, and illegible characters to fix these problems. Preprocessing is essentially done to remove noise from the dataset prior to further analysis. We used the Natural Language Toolkit (NLTK) to pre-process the tweets dataset. A well-liked framework for creating Python programs that interface with human language data is NLTK. The preprocessing steps involved removing stop words, hyperlinks, mentions, retweets, white spaces, emoticons, and illegible characters. This resulted in a cleaner and more structured dataset that was ready for further analysis. An example tweet before and after preprocessing is provided in Table 1.

As seen in the example, the pre-processing steps have removed stop words, retweets, mentions, hyperlinks, and hashtags, leaving only the relevant words related to the hurricane and evacuation. This clean and structured dataset allowed for easier analysis of the tweets and helped us to extract meaningful insights.

Table 1
Preprocessing example.

Before preprocessing:	After preprocessing
RT @news: Hurricane Ian is a category 4 storm with winds up to 130 mph. Everyone in the area should evacuate immediately! #hurricaneian #evacuation #safety	hurricane ian category storm winds everyone area evacuate immediately

2.3. Sentiment analysis

Understanding people's feelings during disasters and crises can help them understand their concerns, panics, and emotions over a variety of themes connected to the occurrence [43]. It also helps first responders gain a better understanding of the disaster area's circumstances [44]. We performed sentiment analysis on the collected data to gain this knowledge. Due to our inquiry, we anticipate identifying issues that anger and incite negative attitudes in both harmed individuals and non-parties. Humanitarian organizations can use this to track public opinion, uncover pressing issues affecting large populations, and swiftly plan their response. With the use of Valence Aware Dictionary for Sentiment Reasoning (VADER), we aimed to detect the emotions expressed in the Twitter data for this study. A text sentiment analysis model based on VADER is sensitive to both emotion polarity (positive/negative) and intensity (strong) [45]. It can be used directly on unlabeled text data and is part of the NLTK package. The emotional analysis of VADER is based on a lexicon that converts lexical data into sentiment ratings, which measure the intensity of an emotion. The intensity of each word in a text can be added to determine the sentiment score. To further analyze the sentiment scores obtained from VADER, we discretized the scores into three categories: positive, negative, and neutral. This was done to provide a clear picture of the distribution of sentiments in the data, as well as to make it easier for non-technical stakeholders to interpret the results. The positive category includes scores greater than 0.05, while the negative category includes scores less than −0.05. Scores between −0.05 and 0.05 are considered neutral. This categorization allows us to determine the dominant sentiment in each tweet, and also enables us to investigate the relationship between sentiment and different humanitarian classes. Our purpose in using this categorization was to gain a deeper understanding of the emotions expressed by Twitter users during Hurricane Ian and how they relate to different aspects of the disaster.

2.4. Tweet classification

We use text classification to understand the information content on Twitter data during the crisis and provide useful information to disaster management/response organizations. A text categorization through a machine learning technique [46], assigns unstructured text to one of the specified groups [47]. Text classifiers are used to arrange, classify, and organize almost any type of information, including files, articles, scientific research, and online text. For this assignment, we use six classes that represent the humanitarian classes of concern (Alam et al., 2018):

- Caution: Messages that contain information on warnings and advice about the hurricane.
- Damage: Tweets about damage caused by hurricane over roadblocks, trees, buildings, and infrastructures.
- Evacuation: Tweets about displaced people and evacuation orders.
- Injury: Tweets about injuries and death of individuals.
- Help: Tweets about urgent needs, donation of money, clothing, and food, providing shelters, and acts of voluntary services.
- Sympathy: Tweets about emotional support, prayers, and appreciation for disaster responders.

An example of tweets in each humanitarian category is provided in Table 2.

2.5. Co-word analysis

The co-word analysis method for content analysis, maps the degree of correlation between keywords in textual material [48]. By tracking the co-occurrence of keywords, this method analyzes the textual data for information content. This method was employed to analyze a sizable volume of social media data. To perform this analysis, we first tokenized the pre-processed tweets and generated the co-occurrence matrix. A threshold was used to have the most significant co-occurrences. Keywords appearing in more than 80% of the tweets were ignored, with the ones appearing less than five times in the entire dataset of tweets. Co-word analysis is different from topic classification in that it focuses on the correlation between the keywords rather than assigning a tweet to a particular topic or category. Co-word analysis helps in identifying the most frequently occurring words that have a strong association with each other. The analysis helps in identifying the primary topics or themes that are discussed in the dataset, providing a holistic view of the overall conversations taking place. In contrast, topic classification is a technique that assigns a tweet to a particular category or topic based on predefined rules or machine learning algorithms. It helps in organizing the tweets into meaningful categories, making it easier to analyze and understand the overall trends in the data. In summary, co-word analysis and topic classification are two different approaches to analyze textual data, and both can provide valuable insights depending on the research questions and objectives.

Table 2
Examples of humanitarian classes for hurricane Ian-related tweets.

Class	Example Tweet
Caution	"Heads up guys, hurricane Ian is heading towards our area, make sure to stock up on food and water before its too late!"
Damage	"My neighbor's roof just got blown off by hurricane Ian, this is insane! #hurricaneIan #damage #devastation"
Evacuation	"Just got an evacuation order due to hurricane Ian. Packing up and heading to a shelter with my family. Stay safe everyone!"
Injury	"My heart goes out to those who lost loved ones or were injured during hurricane Ian. Praying for their speedy recovery. #Ian"
Help	"Does anyone know where I can donate clothing and food for those affected by hurricane Ian? Let's all do our part to help out. #Ian"
Sympathy	"Sending love and appreciation to all the first responders and volunteers who are working tirelessly to help those affected by #Ian."

3. Results and discussion

3.1. Co-word analysis

One objective of this study is to discover the top subjects of interest in tweets during hurricane Ian by analyzing the patterns of co-occurrence of pairs of words in a corpus of tweets. Fig. 1a illustrates co-occurrence of top unique keywords in our dataset of tweets for hurricane Ian. Our twitter dataset includes more than two million hurricane Ian related tweets posted by Twitter users in the CONUS and every pair of these top keywords have co-occurrences in our dataset. To discover the topmost topics discussed in tweets, we eliminated pairs with less than two hundred co-occurrences (Fig. 1b). We classified keywords with the same pattern of co-occurrences into clusters. For example, “storm surge”, “landfall”, and “track” only have co-occurrences with “Fort Myers”, and “Tampa”. We label clusters based on the subject keywords in each cluster representing:

- Politicians: “Biden”, and “DeSantis”
- Hurricane info: “landfall”, “storm surge”, and “track”
- Cities: “Tampa”, and “Fort Myers”
- Help: “need”, and “help”
- Funds: “Money”, and “hurricane relief”
- Climate change: “climate change”

The figure shows that during hurricane Ian, people discussed politicians, hurricane information, cities, help, funds, and climate change on Twitter. Politicians and climate change were mostly discussed as political issues, and the relationship between Help, Funds, and Politicians suggests that decisions made by political rivals to provide funding and help for disaster recovery were a main topic of discussion. The significant co-occurrence of hurricane information and cities demonstrates the awareness and preparedness of the community about hurricane updates and its possible threats to key locations. Overall, Fig. 1 provides a visual representation of the co-occurrence analysis results, making it easier to understand the relationship between different topics discussed on Twitter during hurricane Ian.

3.2. Tweets distribution and topic classification

In this study, we show how classified tweets on Hurricane Ian were distributed daily at the state level across the CONUS before, during, and after hurricane landfall in the study area. The extracted tweets were divided into six categories, including "Caution," "Damage," "Evacuation," "Injury," "Help," and "Sympathy," which represent the humanitarian topics that Twitter users in the research area are most concerned with. Fig. 2 shows the distribution of classified tweets from September 24, 2022, to October 6, 2022, along with frequency of tweets per one thousand population in each state. People in Florida tweeted the most about hurricane Ian as it made landfall in Florida as a category 4 hurricane that caused billions of dollars in damages. After Florida, South Carolina had the most hurricane related tweets, but with less than 40% tweets compared to Florida. Ian made landfall in South Carolina as a category 1 hurricane and did not cause as much damage as it had in Florida. Overall, the southeastern states participated the most in tweeting about the hurricane. In recent years, there have been numerous natural disasters in this area. This region is vulnerable to financial losses and fatalities due to its frequent exposure to natural catastrophes. “Damage” is the most frequently tweeted topic from all the states about the study area. While “Caution” is the second most discussed topic in the states located in the southeast from Alabama to Virginia, “Help” is the second most discussed subject in the rest of the study area. Those states in the southeast were also at risk of getting impacted by hurricane Ian.

Fig. 3 depicts the temporal fluctuation of each class across the study area during three phases of the hurricane (pre-hurricane, hurricane, and post-hurricane). “Caution” is the most tweeted classified topic during the pre-hurricane phase. Right after hurricane Ian made landfall in Florida on September 28th, the frequency of “Caution” tweets decreased toward the end of post-hurricane phase. “Damage” and “Help” are the most discussed topics after the landfall during hurricane and post-hurricane phases. More “Help” tweets are observed compared to “Damage” during post-hurricane phase. Overall, the variations in tweet topics seem to sub-

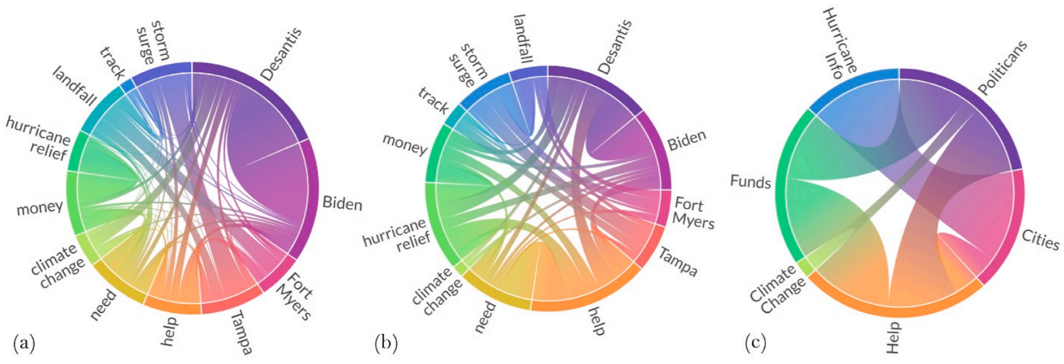

Fig. 1. Chord charts representing top keywords' co-occurrences (a) with no filter, (b) with more than two hundred co-occurrences, and (c) with keywords clustered together and classified into top subjects of interest in tweets.

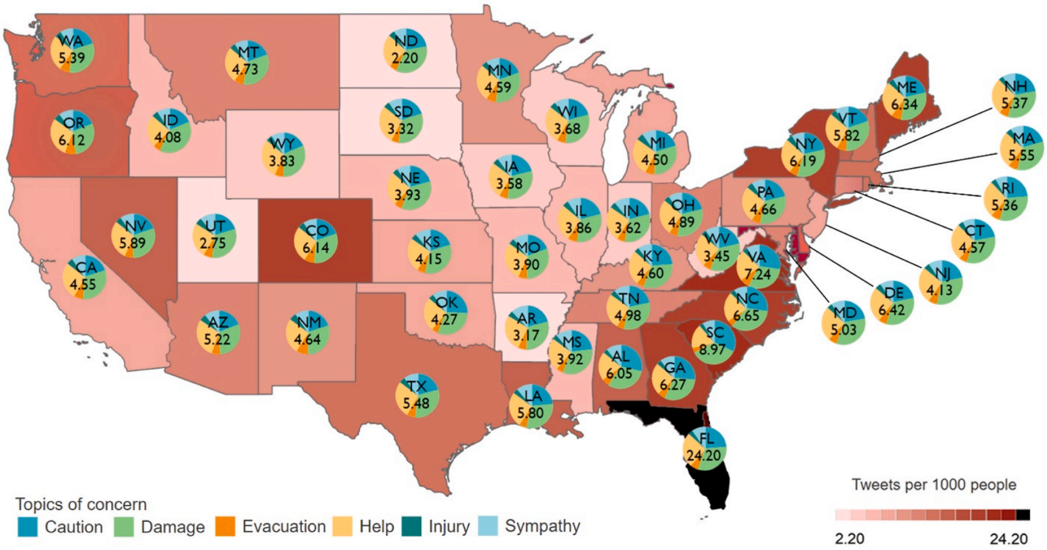

Fig. 2. Distribution of humanitarian topics of concern along with tweets per one thousand population for hurricane Ian written over each circle.

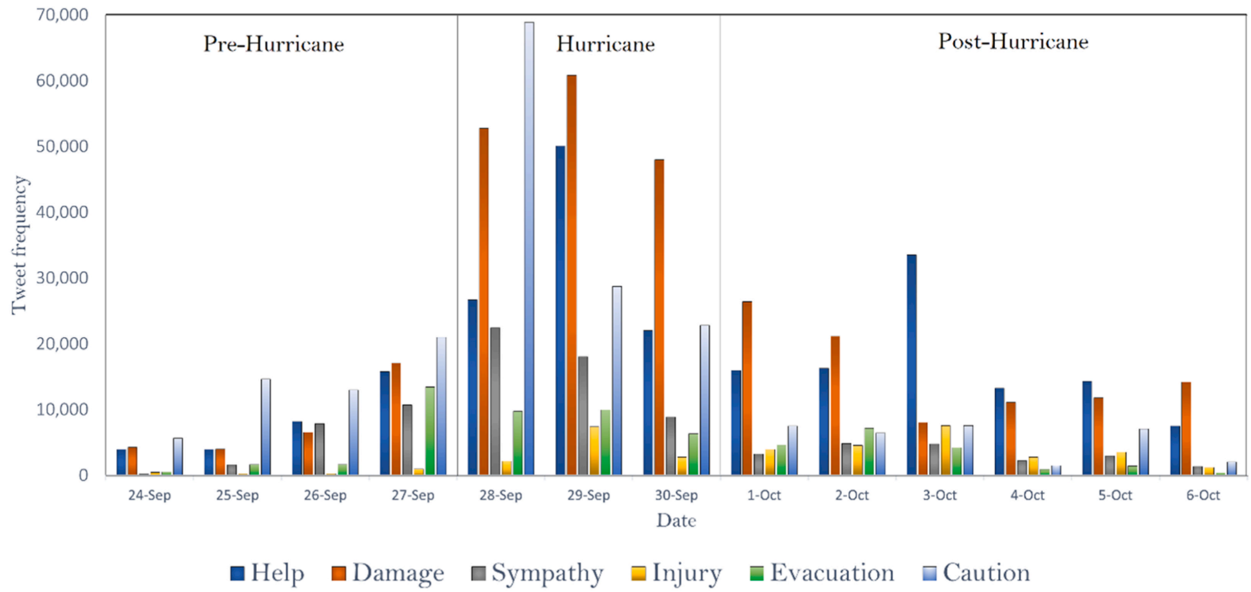

Fig. 3. Temporal distribution of classified humanitarian topics for hurricane Ian.

stantially reflect the development of a crisis in terms of the societal impacts. People's social duty necessitates additional information when they are anticipating something. Pity and prayers beyond the catastrophe affected area start to pour in as the tragedy progresses, and a commensurate gratitude is shown for the local support. Following the calamity, the extent of destruction is revealed, leading to pleas for assistance in the form of monetary donations and volunteerism.

The classification of hurricane Ian related tweets into humanitarian classes can provide disaster management authorities with a more comprehensive understanding of the needs of people affected by the disaster. Knowing the exact types of information people are sharing on social media can help authorities better allocate resources and develop more effective strategies to mitigate the impact of the disaster. For example, tweets classified under the 'Help' category can help authorities identify where people need assistance and what kind of resources they require. Similarly, tweets classified under the 'Evacuation' category can help authorities better understand which areas are most vulnerable and require immediate evacuation orders. By analyzing and categorizing social media data, disaster management authorities can be more proactive and efficient in responding to disasters, potentially saving lives and reducing the impact of disasters on affected communities.

3.3. Sentiment analysis

Another objective of this study is to discover the sentimental qualities of tweets and how they evolve over time during various Hurricane phases. Fig. 4 depicts the temporal sentiment of Hurricane Ian-related tweets in the CONUS. Opinions expressed in tweets are classified into three sentiment classes: “Positive”, “Neutral”, and “Negative”. More positive tweets are observed from the beginning of pre-hurricane phase up until the hurricane's landfall in the study area. After the landfall towards the end of the post-hurricane phase more negative sentiments are observed compared to the pre-hurricane phase.

Fig. 4 depicts the temporal distribution of tweet sentiments, whereas Fig. 5 represents the binary sentiments of tweets classified into each humanitarian topic of concern class. The most negative tweets are about "injury". “Help" and "Sympathy" tweets received the highest positive percentage of 70% and 69%, respectively.

The results of this study could be used by various communities such as state/local governments, police, fire departments, and disaster management authorities. For example, the co-word analysis shows that during Hurricane Ian, people discussed politicians, hurricane information, cities, help, funds, and climate change on Twitter. Politicians and climate change were mostly discussed as political issues, and the relationship between help, funds, and politicians suggests that decisions made by political rivals to provide funding and help for disaster recovery were a main topic of discussion. This information could be useful for politicians to better understand the concerns and needs of the community during a disaster and respond accordingly. Disaster management authorities could also use this information to better understand the concerns and needs of the community during a disaster and develop more effective strategies to mitigate the impact of the disaster. The classification of hurricane Ian related tweets into humanitarian classes such as "Caution," "Damage," "Evacuation," "Injury," "Help," and "Sympathy" can also provide disaster management authorities with a more comprehensive understanding of the needs of people affected by the disaster. For example, "Damage" is the most frequently tweeted topic from all the states about the study area, while "Caution" is the second most discussed topic in the states located in the southeast from Alabama to Virginia, "Help" is the second most discussed subject in the rest of the study area. Disaster management authorities could use this information to allocate resources and prioritize their response efforts based on the needs of the community. Overall, the results of this study could be valuable for various communities involved in disaster management and response, including state/local governments, police, fire departments, and disaster management authorities. Overall, the results of this study can be extremely valuable for various communities involved in disaster management and response. By analyzing the data obtained from social media platforms like Twitter, disaster management authorities can gain a better understanding of the needs and concerns of the community dur-

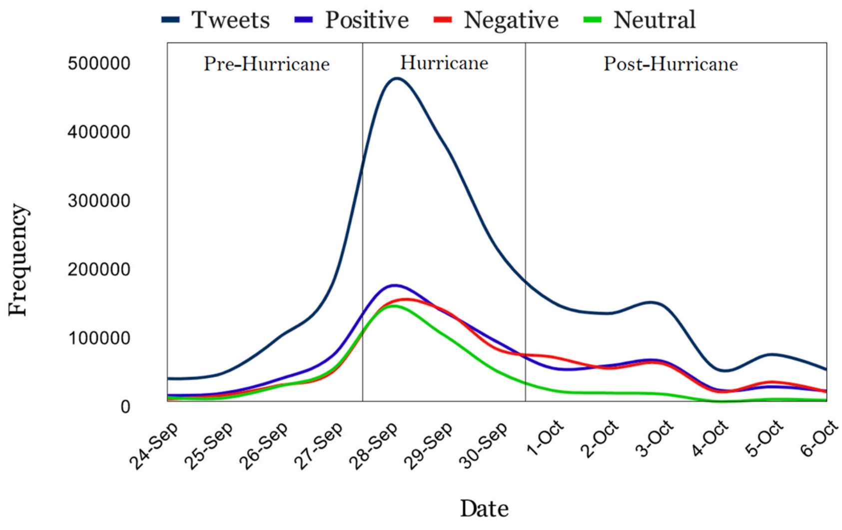

Fig. 4. Temporal tweets and sentiments frequency for hurricane Ian.

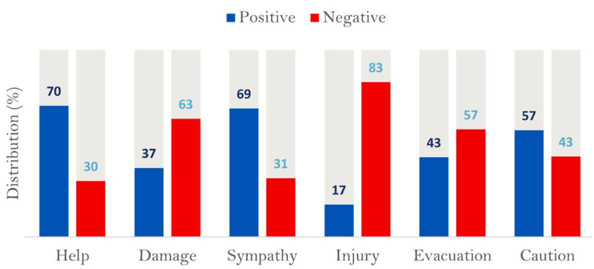

Fig. 5. Classified tweets sentiments for hurricane Ian.

ing a disaster and develop more effective strategies to mitigate its impact. State and local governments, police, fire departments, and other authorities can all benefit from this information and use it to plan for disasters and respond to them more effectively.

As with any study, there are certain limitations to our research that should be taken into consideration when interpreting our results. Firstly, our study relied solely on Twitter data, which may not be fully representative of the broader population's attitudes and behaviors. The users on Twitter are not a completely random sample, and there may be biases in terms of age, gender, and socioeconomic status that could affect the generalizability of our findings. Additionally, Twitter users may not accurately reflect the sentiments and experiences of people who are affected by natural disasters but do not use social media. Another limitation of our study is that our sample was limited to tweets related to Hurricane Ian during a specific time frame. While this allowed us to focus specifically on the impacts of the hurricane and the community's response during that period, it may not be fully representative of the long-term effects of the disaster or the ongoing concerns and needs of the affected community. Future studies could consider a more extensive time frame or multiple disasters to provide a more comprehensive understanding of the community's attitudes and behaviors during and after natural disasters. Finally, while the co-word analysis and classification of tweets into humanitarian classes provide valuable insights, it is worth noting that such analysis is computationally expensive and can not be done in real-time to aid in disaster management. Therefore, further research is needed to develop more efficient and scalable methods to analyze social media data during disasters. In summary, while our study provides valuable insights into the community's response to Hurricane Ian on Twitter, there are certain limitations that should be considered when interpreting our findings. These limitations do not detract from the relevance and significance of our study but rather suggest avenues for future research to further enhance our understanding of the impacts of natural disasters on communities.

4. Conclusions

By offering useful information on the social dimensions and effects of a natural disaster, social media data can satisfy the information needs of disaster management institutions and crisis responders and provide vital insights into how society reacts to disasters. This study has thoroughly investigated the public response, sentiments, and main topics of concern on Twitter during hurricane Ian.

Our findings show that the state that experienced the most economic loss as a result of hurricane Ian was where most tweets were produced. States with a chance of getting on the path of hurricane also had a higher frequency of tweets compared to other states in the study area. Distribution of tweets on humanitarian topics of concern shows different patterns in distinct phases of hurricane. “Caution” was the most discussed topic before the hurricane landfall and then “Damage” and “Help” were the most discussed topics towards the end of post-hurricane phase.

Furthermore, the community's sentiment in tweets showed more positive responses before the landfall while an increase in negative sentiments was observed after the landfall towards the end of post-hurricane phase. Tweets, classified into” Damage” and “Injury” topics, were posted with the most negative sentiment while “Help” and “Sympathy” tweets had the highest rate of positive sentiment.

Moving forward, this line of research can uncover more details about public response to natural disasters, help disaster management, and increase awareness and preparedness in the community. However, it still requires efficient and effective computational resources that can operate in real-time to properly interpret the massive volume of disaster-related content on Twitter, especially during an active natural hazard. It is essential to address issues with the scalability of the methodology utilized in this work for processing real-time streams of textual content in order to implement practical disaster management. Systems that use humans-in-the-loop for machine learning must also deal with humans' limited processing power to maintain high throughput. For scholars and the disaster informatics society, this represents potential future work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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