

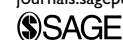
Identifying Crisis Response Communities in Online Social Networks for Compound Disasters: The Case of Hurricane Laura and COVID-19

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Abstract

Online social networks allow different agencies and the public to interact and share the underlying risks and protective actions during major disasters. This study revealed such crisis communication patterns during Hurricane Laura compounded by the COVID-19 pandemic. Hurricane Laura was one of the strongest (Category 4) hurricanes on record to make landfall in Cameron, Louisiana, U.S. Using an application programming interface (API), this study utilizes large-scale social media data obtained from Twitter through the recently released academic track that provides complete and unbiased observations. The data captured publicly available tweets shared by active Twitter users from the vulnerable areas threatened by Hurricane Laura. Online social networks were based on Twitter's user influence feature (i.e., mentions or tags) that allows notification of other users while posting a tweet. Using network science theories and advanced community detection algorithms, the study split these networks into 21 components of various size, the largest of which contained eight well-defined communities. Several natural language processing techniques (i.e., word clouds, bigrams, topic modeling) were applied to the tweets shared by the users in these communities to observe their risk-taking or risk-averse behavior during a major compounding crisis. Social media accounts of local news media, radio, universities, and popular sports pages were among those which heavily involved and closely interacted with local residents. In contrast, emergency management and planning units in the area engaged less with the public. The findings of this study provide novel insights into the design of efficient social media communication guidelines to respond better in future disasters.

Keywords

planning and analysis, social media, sustainability and resilience, disaster response, recovery, business continuity, disaster recovery

Natural, human-caused, and technological disasters have major adverse consequences for society and the economy. Affected communities must be well-informed about the potential distress they may encounter during a disaster to take appropriate preparation mentally and logistically. Emergency management authorities must be aware of the needs and concerns of affected people to respond effectively throughout a crisis (1). Understanding the communication pattern, perspectives, thoughts, and needs of the affected people, as well as proper information dissemination, is pivotal during any disaster or emergency situation.

On August 27, 2020, Hurricane Laura, one of the most powerful and deadliest (Category 4) hurricanes,

made landfall with peak intensity in Cameron, Louisiana, U.S. in the midst of the COVID-19 pandemic (2). An estimated 20 million people were in the path of the storm, with 1.5 million in Texas and Louisiana being ordered to evacuate (3). Hurricane Laura spawned a 15 ft storm surge that drenched some regions with 10 in. of rain (Figure 1) and spawned four tornadoes (4).

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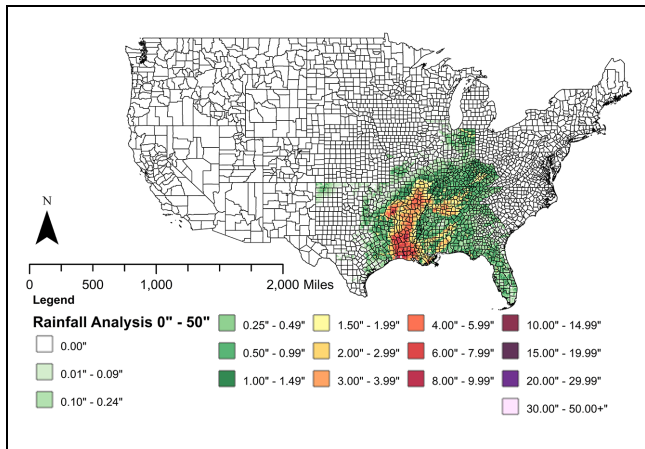


Figure 1. Heavy rainfall caused by Hurricane Laura.

Lesser Antilles, Greater Antilles, the Bahamas, the Gulf Coast of the U.S., and the Midwestern and Eastern U.S. were all heavily affected by Hurricane Laura. It largely affected Louisiana, and 14 people were killed in the U.S. (10 deaths in Louisiana and four in Texas), 31 in Haiti, and three in the Dominican Republic (5–7). More than 750,000 people experienced a significant power outage because of Hurricane Laura, while many refineries in the U.S. were shut down for several weeks pending repairs and power restoration in the hurricane's aftermath (8, 9). Furthermore, this Category 4 hurricane hit the U.S. during a pandemic, when people were advised to socially distance. When there is a communication breakdown between vulnerable communities and emergency management agencies, the crisis worsens (10).

According to the U.S. Census Bureau, approximately 85% of U.S. households own a cell phone, and 80% own a personal computer (11). During a disaster, people can communicate in person or via mobile phone. However, by using online social media platforms (SMPs), they can reach and connect with more people in a much shorter period of time, which is why the use of online social media during disasters has recently increased (12). Many studies have shown that weather and situational awareness information is widely disseminated through SMPs (i.e., Facebook, Twitter, Reddit, Instagram, etc.) (13–17). These SMPs allow users to share ideas, thoughts, and information through virtual networks in a timely manner (18). Users readily share real-time information on social media about a variety of topics, such as disasters, potential crises, weather updates, and traffic updates, among others. According to a recent report, there are approximately 450 million monthly active Twitter users, and among them, more than 80.9 million users are from the U.S. (19, 20). The majority of the emergency management and law enforcement agencies in the U.S. have Twitter accounts where they share important and

relevant information (21). People follow different organizations as well as different celebrities on social media, and a lot of users are directly influenced by who they follow on SMPs (22).

The COVID-19 outbreak saw 29.7% more users spending 1–2 h per day on social media, with 20.5% using SMPs 30–60 min more (18, 23). Even during a power outage, people can still use different social media to keep communication with their friends and family (16). This makes social media a viable data source for user-generated content, particularly during a disaster when traditional surveys are inconvenient. Many literatures have demonstrated the effectiveness of social media data in disaster management, particularly in crisis communication, human mobility, damage valuation, and event detection, among others (16, 24–36). However, there are very few studies that have looked at the social network connectivity of the local people and network-level properties of the local communities along with their crisis narrative analysis during a compound hazard like Hurricane Laura amid the COVID-19 pandemic.

Twitter recently launched its academic application programming interface (API), which provides a full archive of public conversation through full-archive search endpoint, thus making Twitter a reliable social media data source (37, 38). In this study, a user-mention network has been developed from the local Twitter users who tweeted during Hurricane Laura and tweeted from the affected areas. The study is concerned with the following three research questions:

- 1) *Who are the agents of the social network, and what are their communication patterns?*
- 2) *How does crisis communication differ from one community to another community?*
- 3) *What is the role of different agencies in the social network?*

The findings of this study provide novel insights into how to create effective social media communication guidelines so that future disasters can be handled more effectively. The communication pattern in the local community is observed in this study with the local connectivity of different agents.

Related Work

According to the global data portal by Kepois, the emergence of SMPs has been met by a spike in social media users of an excess of 4.70 billion people as of 2022, equating to ~59% of the total global population (18). People are becoming accustomed to relying more on social media than on mainstream news sources (39). SMPs act as a global connecting point for immediate response and

news dissemination; for example, according to a recent study, Twitter alone generates more than 143K trending tweets per second (40). These SMPs are extremely effective communication tools, particularly during emergencies such as hurricanes, and they serve as a hub for public discourse and consolation during crisis situations (41). Many researchers have used social media data in analyzing a variety of natural and human-caused hazards, including fire, flood, tsunami, earthquake, hurricanes, and active shooting, among others (39, 42–48).

Social media play a great role during an emergency such as a hurricane evacuation. The routing decision, evacuation destination, and evacuation decisions can be influenced by social media (49). As a relatively new data source, social media can provide invaluable, real-time insights for flood monitoring (43). Extreme weather consequences can be seen in real-time on social media (50). Mohanty et al. found that a hurricane's per-capita economic impact is significantly correlated with per-capita Twitter engagement (27). In the classical evacuation literature, there have been a lot of studies on disaster response, particularly on hurricane evacuation and wildfire, using traditional survey data, but according to recent studies, social media plays an important role in catastrophes by providing a participative, collaborative, and self-organized structure for communicating and disseminating situational information (25, 51–64). Social networks also have a great influence on decision-making, and decision-makers follow their peers during similar events (65).

Topic modeling, specifically latent Dirichlet allocation (LDA), is used to retrieve disaster-related information from social media narratives. Several studies used Twitter data to identify disaster-related topics using a static or dynamic LDA model (1, 40, 66–68). Yang et al. proposed a method for incorporating sentiment with a topic model. However, none of these studies consider any social network properties (69). Yu et al. explored the network properties of the different local agencies before, during, and after Hurricane Harvey (70). Sadri et al. found that users at the network's core are less eccentric and have higher degrees, and they are more engaged in disseminating information (47). It is pivotal to study how people interact in online social networks to develop and implement more effective guidelines in times of crisis (67, 71).

Very few studies have explored the connectivity of local people on social media during a compound crisis (a hurricane in the midst of a pandemic), as well as their communication patterns from a social network perspective. This study has explored the communication patterns of the locally affected people and connectivity between themselves and with different types of agencies from a user-mention network.

Data Description and Preprocessing

There were several hurricanes in the year 2020. Hurricane Laura was the worst of them for the U.S., killing at least 10 people in Louisiana (72). On August 20, 2020, a tropical depression formed in the Cape Verde islands in the central Atlantic Ocean and was officially named “Laura” on August 21, 2020 (73, 74). It eventually became a Category 4 hurricane and made landfall in Cameron, Louisiana, U.S. on August 27, 2020 (75). People freely express their opinion on social media such as Twitter. Following is one of the tweets generated from Louisiana during the hurricane Laura: “*Me waiting patiently to get the internet and cable fix and back on.... I hate hurricane season.*” One of the news channels tweeted about the devastation in the following tweet: “*@fox4-beaumont Hurricane Laura death toll in Louisiana rises to 10.*” In this study, Twitter data was used to identify crisis response communities in online social networks.

The Twitter academic API, which provides a full archive of public conversation through a complete database search endpoint, was used to obtain Twitter data from August 13, 2020, to September 3, 2020 (37, 38). Different query options have been used to make sure that all location-based data is collected. At first, “*(Hurricane OR Hurricane Laura) has:geo*” query option was used to collect all of the tweets about Hurricane Laura. Secondly, the “*place: ‘Louisiana’*” query option was used to collect all of the generated tweets tagged with Louisiana within the mentioned time frame. Finally, the “*point radius*” query option with a 25 mi radius circle was used to ensure that all location-based tweets were collected from the highly affected locations in Louisiana (Figure 2). The API sets several constraints for geolocation-based data collection, that is, the maximum radius of the “*point radius*” cannot be greater than 25 mi (38). To overcome this constraint, multiple “*point radius*” queries were used on these highly affected locations.

In this way, 1.3 million tweets from around 40 thousand unique users have been collected. Since the study considered both location- and keyword-based data collection approaches, Python's Pandas library was used to check for repetitions and ensure that all tweets in the data set were unique. To address the goal of this research, the study considered tweets created from the highly affected areas only, which in this case is only the state of Louisiana. There are approximately 0.9 million tweets in the raw data, where all of the tweets are geo-tagged. The language of all of the collected tweets was English. The elegant tweet preprocessing “*tweet-preprocessor*” Python package was used to remove noises: character codes, emojis, stop words, html tags, and so forth. Then, all of the tweets were tokenized (broken down into smaller units: individual words or phrases). The study

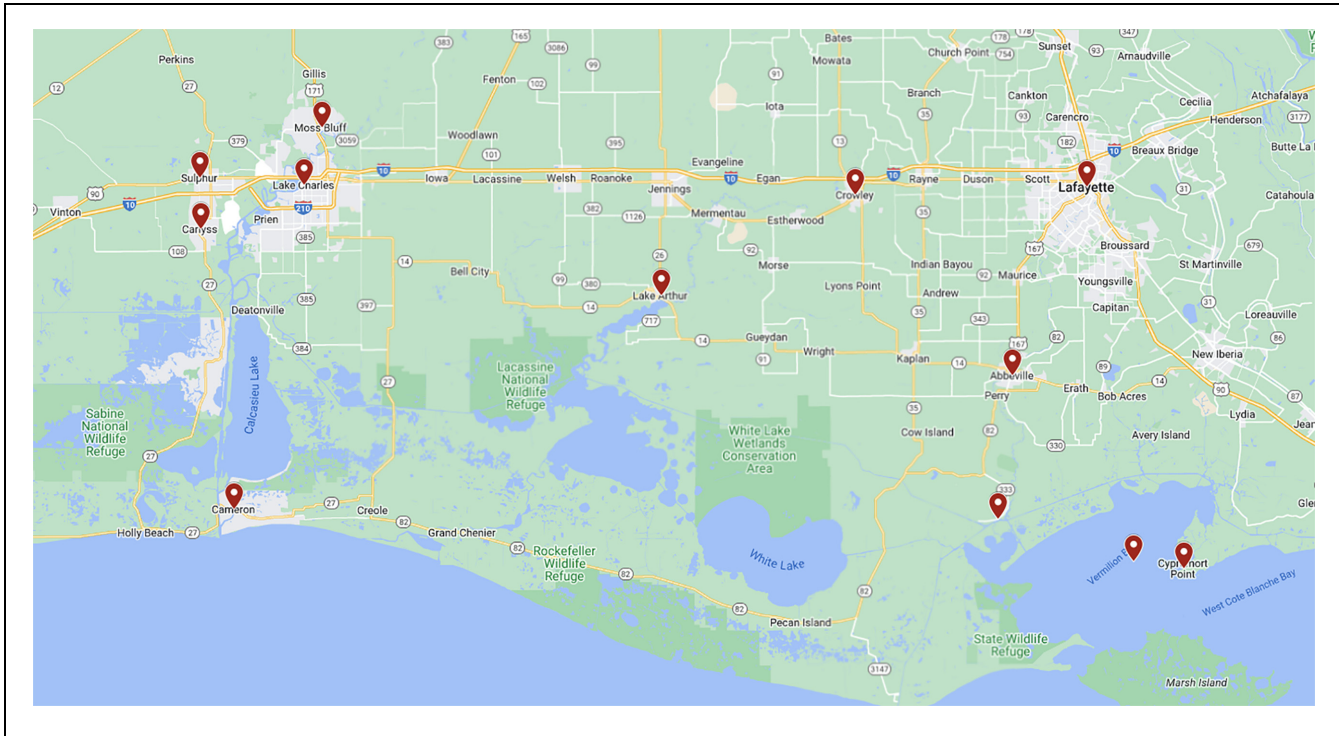


Figure 2. Areas in Louisiana severely affected by Hurricane Laura.

considered tweets relevant to Hurricane Laura only. The relevance of a tweet was determined by identifying tokens within the tweet; more information on the steps and importance of relevance filtering can be found in Kryvasheyeu et al. (34). After all of this sorting and data preprocessing, the study finally obtained 0.4 million tweets from ~20 thousand unique users. The framework of this study is illustrated in Figure 3.

Every collected tweet has a bounding box location. At first, the centroid of the bounding box is determined, then, using the reversed geo-code, these tweets have been mapped with the 2020 census block-level county data. Out of the 64 counties in Louisiana, the study obtained tweets from almost all of them. The following Figure 4 shows the county-level spatial distribution of the collected tweets.

Methodology

Temporal Analysis with Sentiment Ratings

Twitter allows users to share the location of their tweets; if the device's location service is enabled, a confined area known as a bounding box is automatically generated. Tweet geolocation and timestamps were obtained using the associated "geo" and "created at" tweet fields. Temporal analysis is one of the most effective methods for comprehending data trends and temporal variation. Sentiment analysis, also described as "opinion mining,"

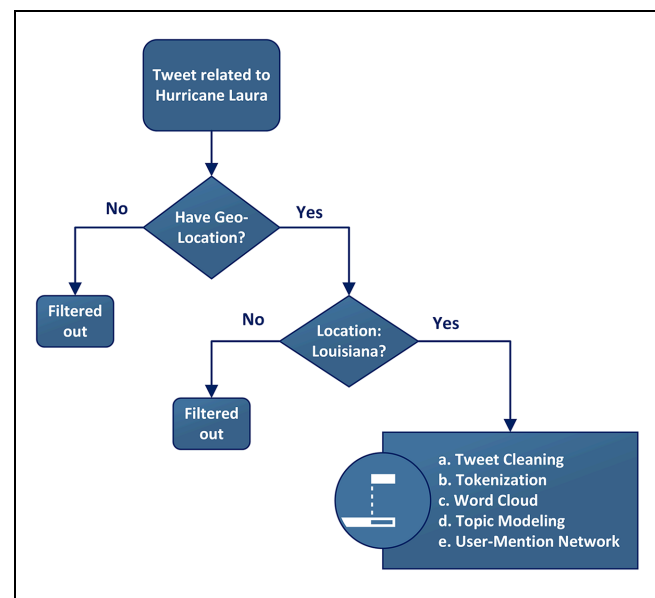


Figure 3. Framework of the study.

is the process of identifying the salient emotions in the opinions of authors about specific entities (76). Sentiment analysis is a form of natural language processing (NLP) that involves classifying emotion detection into three categories—negative, neutral, and positive—which exist within value ranges -1 , 0 , and $+1$,

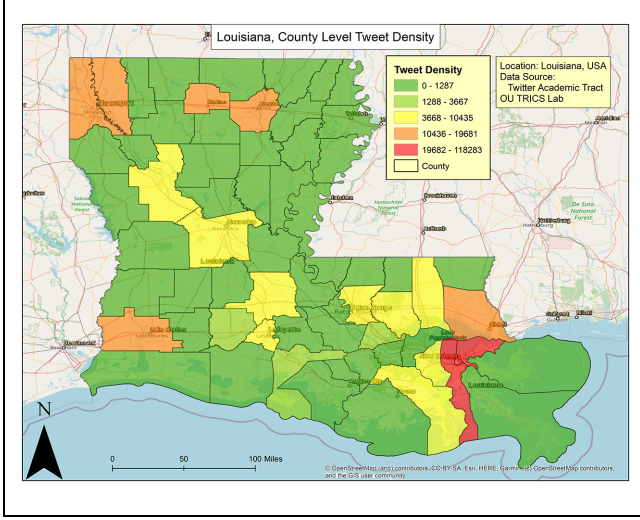


Figure 4. County-level tweet density.

respectively (76, 77). This study uses the *VaderSentiment* analysis tool that is based on the Lexicon approach of sentiment analysis (78). More information about sentiment analysis can be found in Alam et al. (79). Word frequency, a popular NLP technique, counts how often a word appears in a text and orders the counts. A temporal heatmap is a sophisticated pivoting system that shows the term frequency over time. A color bar chart is used to represent frequency. The variations in color sequencing aid in distinguishing the frequency of the words.

Word Bigram Analysis

Word bigram is an NLP concept that examines the likelihood of a duo of words appearing subsequent in a series of texts (80). It is capable of chunking word pairs and predicting the next forum word. The analysis separates the words arrangement $word_1 \dots word_N$ from the sequence of text observations $x_1 \dots x_n$ for which the subsequent probability $P(word_1 \dots word_N | x_1 \dots x_n)$ reaches its maximum. Equation 1 represents the algorithm:

$$\arg \max \{ P(word_1 \dots word_N | x_1 \dots x_n). \\ P(x_1 \dots x_n | word_1 \dots word_N) \}, word_1 \dots word_N \quad (1)$$

where

$P(x_1 \dots x_n | word_1 \dots word_N)$ = the conditional probability of the given word arrangement $word_1 \dots word_N$. Using the conditional probabilities, we obtain the decomposition as Equation 2:

$$P(word_1 \dots word_N) = \prod_{n=1}^N P(word_n | word_1 \dots word_{n-1}) \quad (2)$$

A vocabulary of size W can be divided into G_c word classes. $G_c: w_0 \rightarrow G_w$ represents the category mapping. Every word w in the vocabulary is associated with the word class G_{w0} . We use (G_{v0}, G_{w0}) to denote the equivalent class bigram for a word bigram (v_0, w_0) . The equation for maximum likelihood estimate could be expressed as Equation 3:

$$F_{bi}(\beta) = \sum_w N(w) \log N(w) + \sum_{G_v, G_w} \log \frac{N(G_v, G_w)}{N(G_v)N(G_w)} \quad (3)$$

where

F_{bi} = bigram maximum likelihood,
 N = training corpus size,
 w = size of vocabulary,
 (u, v, w, x) = words in a document, and
 β = number of word classes (80).

Topic Modelling

The topic model framework in NLP examines empirical themes or subjects in text-based data. Blei explained this using LDA (39). It is based on the assumption that the collection of texts exposes a wide range of subjects. A topic model is used to find hidden semantic structures in text bodies. It clusters similar phrases into themes or topics. Based on word statistics in each topic, LDA establishes possible themes and balances the subjects of each document (81, 82). Griffiths and Steyvers proposed using Gibbs collapsed sampling to estimate the posterior distribution of word-to-subject or theme assignments $P(z|w)$ (83). The derivation steps for the update function for a new topic assignment of a word in sampling are summarized in the following equation:

$$P(z = t | z, w, \alpha, \beta) \propto \frac{n(d, t) + \alpha}{n(d, t) + T\alpha} \frac{n(t, w) + \beta}{n(t, w) + W\beta} \quad (4)$$

where

n = number of tokens,
 t = number of topics,
 d = number of documents,
 w = number of distinctive words,
 $\theta = d \times t$ of probabilities; topic distribution in documents,
 $\phi = t \times w$ of probabilities; word distribution in topics,
 $\alpha = d \times t$ of α priors; Dirichlet prior for θ ,
 $\beta = t \times w$ of β priors; Dirichlet prior for ϕ ,
 $w = n$ -vector of word identity w ; words in documents, and
 $z = n$ -vector of topic assignment z ; topic assignment of words.

The number of assignments of word w in the topic t is $n(t, w)$, and the number of assignments of topic t in

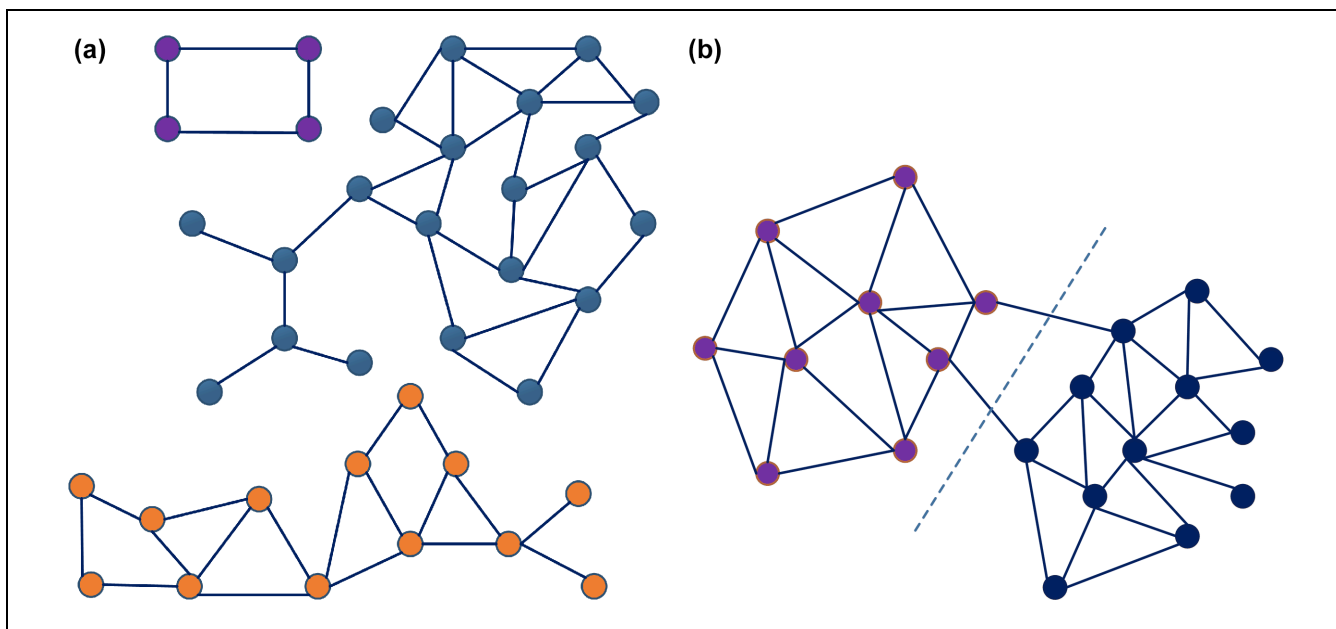


Figure 5 (a) Components in network and (b) communities in network.

document d is $n(d, t)$; all counts exclude the current assignment z .

Graph Theory

Component and Community. In graph theory, a connected subgraph that is not a part of any other bigger connected subgraph is referred to as a “component” of an undirected graph; for example, the network shown in Figure 5a has three components. On the other hand, a “community” is a subset of nodes that are closely connected to one another and distantly connected to the nodes in the other communities. The network shown in Figure 5b has two communities.

Community Detection Algorithm. Communities are a feature of many networks in which a single network may have numerous communities, each with strongly coupled nodes. When examining various networks, it may be necessary to look for communities inside them. Community detection algorithms can be used to find people in online social networks who have similar interests. The two main types of community detection methods are “agglomerative” and “divisive” techniques. Edges are added one after one to a network that only comprises nodes in agglomerative techniques. Edges are added from the stronger to the weaker edge. Agglomerative procedures are followed by dividing methods. There, edges from a whole graph are eliminated one by one. In a particular network, there can be any number of communities, and

they can be of different sizes. These attributes make community detection extremely difficult (84).

For each pair u, v of vertices in the network, a weight $W_{u,v}$ is calculated initially, which denotes how tightly the vertices are related in some way. Because there is an infinite number of paths between any two vertices (unless it is 0), paths of length d are often weighted by a factor a^d with a small, causing the weighted count of the number of paths to converge. If A is the network’s adjacency matrix, and A_{ij} is 1 if an edge exists between vertices u and v and 0 otherwise, then the weights, W , in this formulation are determined by the matrix’s elements:

$$W = \sum (aA)^d = [I - aA]^{-1} \quad (5)$$

Subgraph Generation. There are various types of networks based on the type of social media activity. Follower-follower and user-mention networks are the two most popular social networks (85). The follower-follower network is an unweighted directional network, whereas the user-mention network is a weighted directional network. Here, the weightage is determined by how many times a particular user has been mentioned. Information is passed from the user to the followers in a follower-follower network, and information is passed from the user to the mentioned person in the user-mention network. A user-mention network is more engaging than a follower-follower network because, in a user-mention network, a specific user is directly mentioned, and the specific information is relevant to the

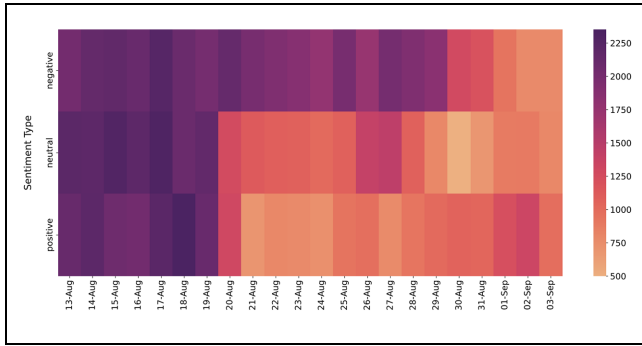


Figure 6. Temporal heatmaps of tweet sentiment type.

user, whereas in a followee-follower network, there is a chance of missing any post or status of the person following, and the information might not be relevant for all of the followers. Based on the largest component, a subgraph was created from the main user-mention network in this study. The study examined various structural properties of the subgraph using network science concepts.

Results

Temporal Heatmaps with Sentiment Type

Figure 6 shows the temporal heatmaps of tweet categories: positive, negative, or neutral. The heatmap shows that the study received at least 500 tweets per day from each category. At first, the number of neutral tweets was high, but, as time passed, the number of negative tweets increased, and then, after Hurricane Laura made landfall on August 27, 2020, negative tweets peaked and then declined. Until August 19, 2020, the number of positive, negative, and neutral tweets was very close, but there was a substantial increase in negative tweets, creating a significant difference between positive and negative tweets. The cause of such an increase could be Hurricane Laura's devastation: property damage, utility disruption, high storm surge, and people's fear. After August 29, 2020, the number of positive and neutral tweets increased in comparison with negative tweets, possibly because the recovery phase began, and people received support and relief from local agencies.

Temporal Heatmaps of Frequently Used Words

The most frequently used words in a pool are sorted using frequent word analysis. The buzzwords in the texts tell the story. Heatmapping frequent words shows how they are stranded over time. It shows how words rise and fall over time. For the top 100 most frequently occurring words (which is nearly 46.45% of the total words), temporal heatmaps have been created and illustrated in two

figures (Figures 7 and 8). The words were deemed in alphabetical order; they act as a contextual "dictionary," incorporating all aspects of conversation that may arise in discussions. The word frequency scale ranges from the most frequently occurring word, "hurricane" to the 100th most frequently occurring word, "work." The top five buzzwords are "hurricane," "emergency," "pandemic," "food," and "covid." The top frequent words of the heatmap reveal some obvious findings with the keywords: it is no coincidence that three of the top five buzzwords are related to COVID-19, indicating a compound hazard situation created by Hurricane Laura's landfall in the midst of the COVID-19 pandemic.

On the other hand, the sequence in which the words show up in the heatmap provides an intriguing picture of the data. In the first heatmap (Figure 7) three distinct patterns are clearly noticeable over three different time periods: before the landfall, days close to landfall, and after the landfall. There are a few words—for example "covid," "emergency," "hurricane," "pandemic," "tornado"—that were constantly repeated during the whole period of Hurricane Laura, but there were a few words—for example "power," "damage," "roof," "center"—that were not used as much in the beginning, but, as the date of the landfall approached, their frequency drastically increased. It acts as evidence of the devastation Hurricane Laura caused. When Hurricane Laura made landfall, people were not initially concerned about power outages, property damage, and utility disruption, but after the hurricane had made landfall, they began discussing those things. A few words—for example "storm," "warning," "water," "wave," "weather," "wind"—were mentioned a lot before the landfall on August 27, 2020, but were less seen after the landfall. Most of the words in the second heatmap (Figure 8) were about the weather, news updates, community, and properties.

User-Mention Directed Network

The user-mention directed network is illustrated in Figure 9. The graph has 10,614 nodes and 16,923 edges. The degree of a node in a network indicates connectivity: a higher degree means it is connected to more other nodes. The average degree of the network is $1.69 \cong 2$, which means that, on average, out of 10,614 people, each person is connected to nearly two others. This indicates that the majority of nodes are isolated and have formed small, scattered groups. The diameter of a network indicates the shortest path between two distant points. This network has a diameter of 12, which means it will take 12 steps to get from one point to the farthest point, which is significantly greater than the six degrees of separation theory (86). There are 78 communities and 21 components in the network. The label of Figure 9 depicts

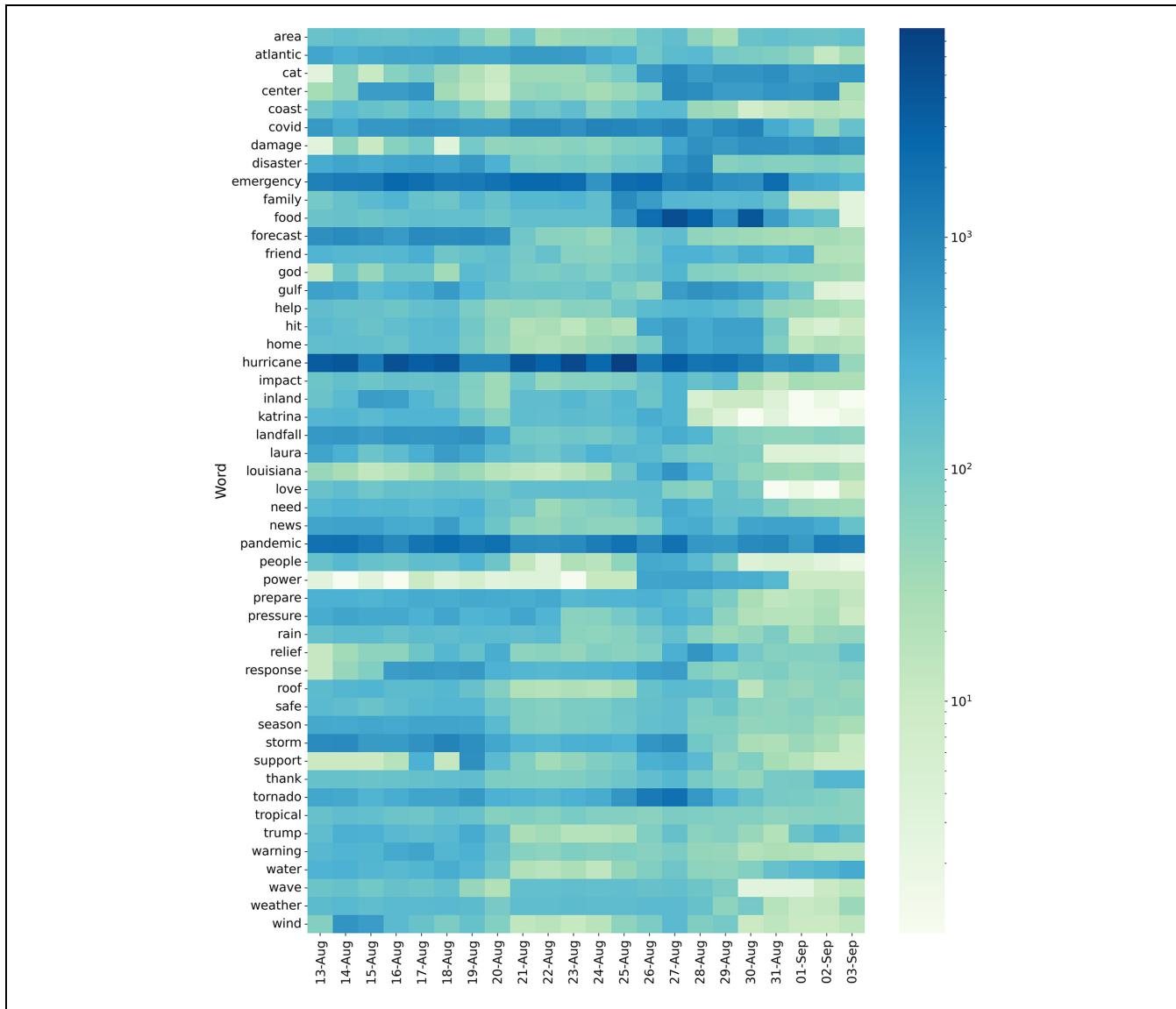


Figure 7. Temporal heatmaps for the top 50 words.

the component number and the number of nodes within that component.

Component 2 has the most nodes, 699, with 578 unique users, while component 10 is the smallest one, with only 243 nodes. This study focused on the largest component for contextual analysis by generating a subgraph from the main user-mention network; however, this study can be scaled up or down depending on the requirements. Figure 10 depicts the largest components of the network. The community determines the network's distinct hue. There are a total of eight communities. The network's node size is proportional to its degree; the higher the degree, the larger the node size. Community 6 has the largest network in relation to the total edges (730) in comparison with other communities.

There is ~21% population alone in community 6, and community 1 is the smallest one with only ~3.5% population. The study also categorized the individuals in this subgraph according to their type, such as incident management, food bank, educator, journalist, online news portal, social organization, television news channel, and so forth. The study also categorized nodes into sixteen distinct agency types. The top five individuals from each community have been labeled in the network.

It is evident from the figure that, in between some nodes, there are two edges. It is because they mentioned each other in their conversation. The single edge between two nodes indicates that the first node has only mentioned the second node, but the second node did not mention the first one. The study also observed each

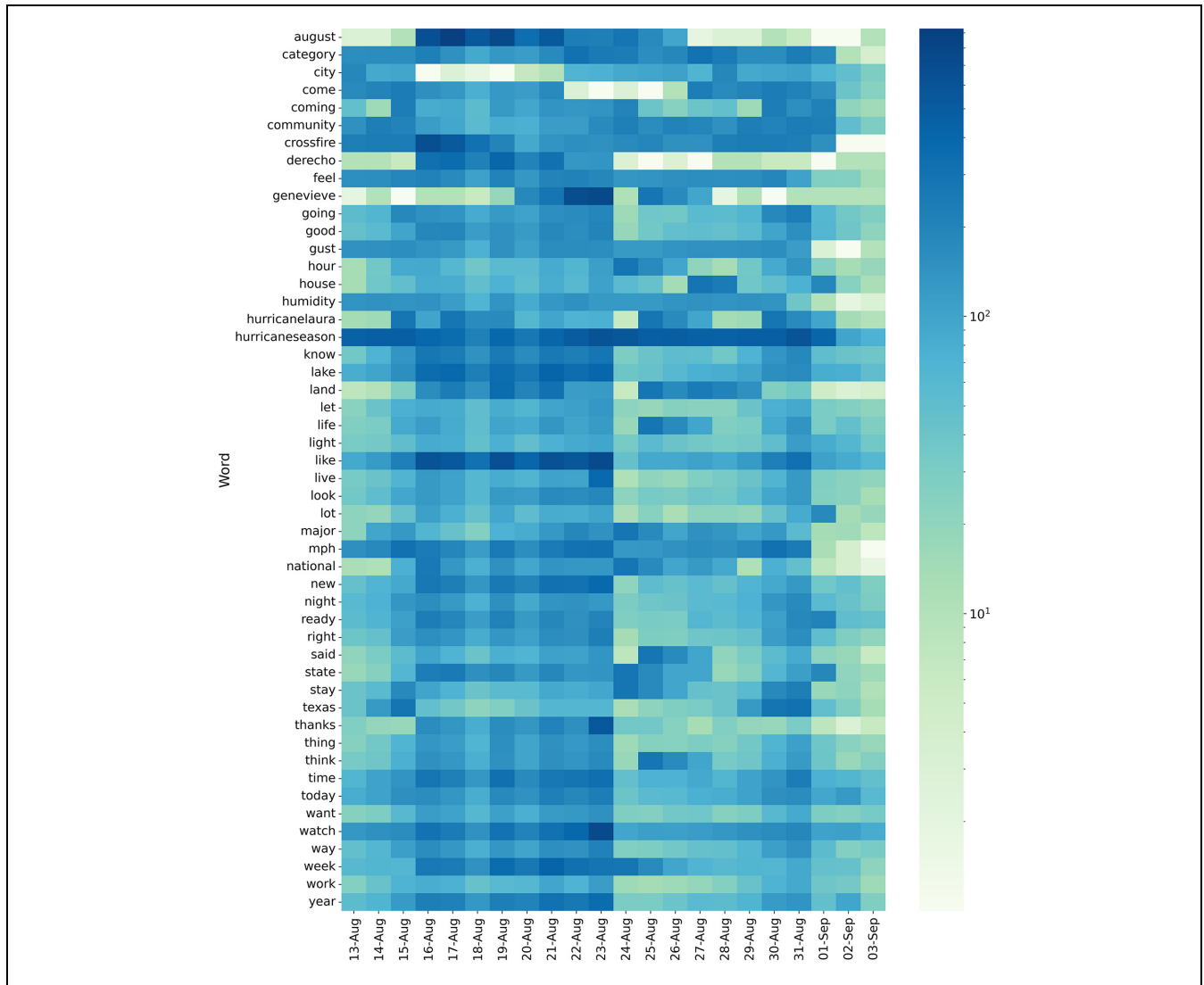


Figure 8. Temporal heatmaps for the top 51–100 words.

community separately to better understand their concern and communication pattern. Figure 11 illustrates the eight communities that comprise the subgraph network. The color of the edges represents high engagement; if the edges are the same color, the nodes are highly engaged with each other. Identifying the agents of the social network is one of the research questions of this study. These are the highly engaged agents in each of the following communities:

Community 1: sports page (L.C. Pride Basketball), athletes, online news portal (12NewsNow), journalist, Food Bank to Fight Hunger

Community 2: T.V. news channel (CNN), educator, Louisiana watershed flood center, social organization (Kappa Sigma)

Community 3: National Weather Service Office Lake Charles, University of Louisiana at Lafayette Black Male Leadership Association, Beacon Club, Radio Station (Mustang 107.1, 1063 radio Lafayette)

Community 4: National Incident Management Systems and Advanced Technologies, Lafayette utilities system, NewsKADN News, Fox 15

Community 5: Louisiana Business Emergency Operations Center, the City-Parish of Lafayette, KPLC7News, Lafayette NewsChan

Community 6: Memorial Health System, Lafayette Utilities System, KATC TV, Latest News

Community 7: KLFY-TV, Utility System, Townsquare Media Station, McNeese Football

Community 8: News @ Lake Charles, McNeese State University, Fox 4, United Way of Acadiana

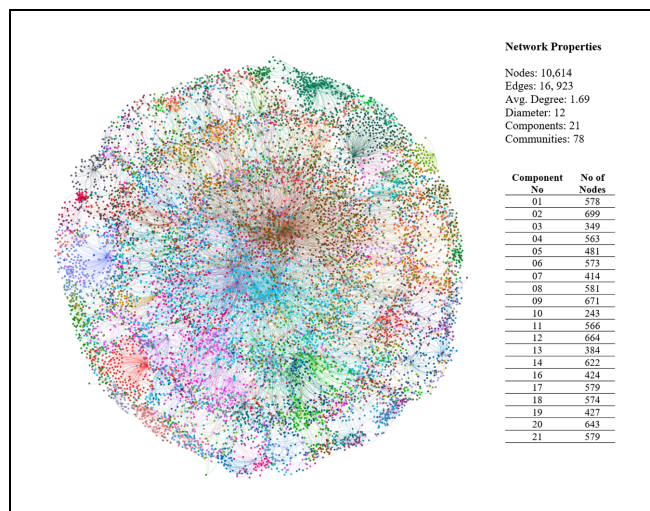


Figure 9. Hurricane Laura user-mention directed network.

Note: The color of the network represents the communities. There are 78 distinct colors in the network.

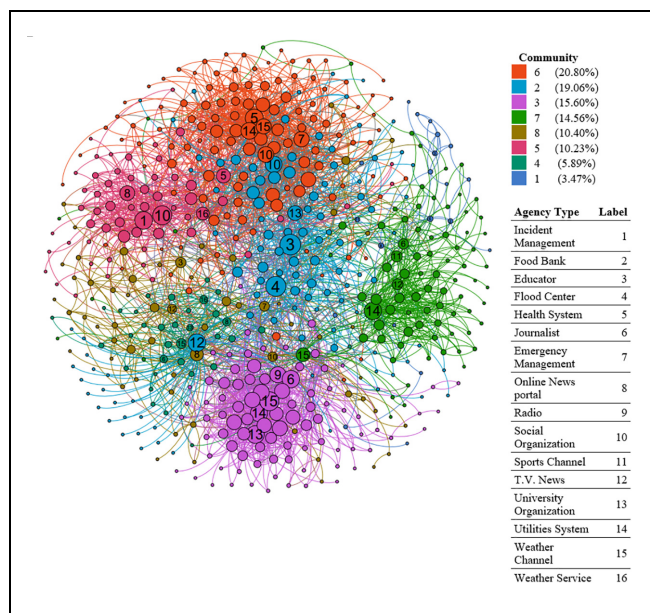


Figure 10. Subgraph: Largest component of user-mention directed network.

The smallest community, Community 1, has 30 nodes and 41 edges, a network diameter of 7, and an average degree of 1.367. Community 2 has 227 nodes and 576 edges. Despite having the most nodes, Community 2 has a graph density of only 0.011, with an average degree of 2.537 and a network diameter of 8. With 142 nodes and 667 edges, Community 3 has the highest edge/node ratio of 4.69. Community 3 has the highest graph density of 0.033, trailing only Community 4, which has 51 nodes and 140 edges and a graph density of 0.055. As a result,

Community 4 has the highest population density of all. Community 5 has 108 nodes and 359 edges, with a graph density of 0.031 and a network diameter of 7. With a graph density of 0.031 and network diameter of 7, Community 5 has 108 nodes and 359 edges. Community 6 has the highest number of edges (730) and the second-most nodes (198) after Community 2. The graph density of Community 7 (126 nodes and 356 edges) and Community 8 (116 nodes and 248 edges) is 0.023 and 0.019, respectively.

Word Bigram Network Mapping

A word bigram is a pair of words that are next to each other in a text. Figure 12 shows which two words most frequently appeared together in the corpus. The study used a network to map the bigram words to gain a better understanding of their conversation in each community. The degree determines the color of each node in the network. The centered word has the highest degree; for example, in Community 1, the words “charles,” “Laura,” and “hurricane” have three degrees, and the rest of the words, with the exception of “catastrophic,” “jesus,” “helplakecharles,” and “days,” have two degrees. These words depicted in the bigram are buzzwords in each community and tell what was being cooked in each community.

In Community 1, the word “power” headed by “without” and succeeded by “water” indicates the utility disruption, and the phrases “lake-city-destroyed-completely,” “laura-entire-wiped-city,” and “roof-destroyed” refer to the damage that Hurricane Laura did to Lake Charles in Louisiana. Hurricane Katrina, a Category 5 Atlantic hurricane that made landfall on August 29, 2005, was also a traumatic event for Louisiana. After 14 years, on August 27, 2020, they experienced something similar; the words “august-issued,” and “two-hurricanes” in Community 2 bring up this issue. The bigram network clearly shows that the primary topic of conversation in each community is as follows:

Community 1: Utility disruption, property damage, flooding

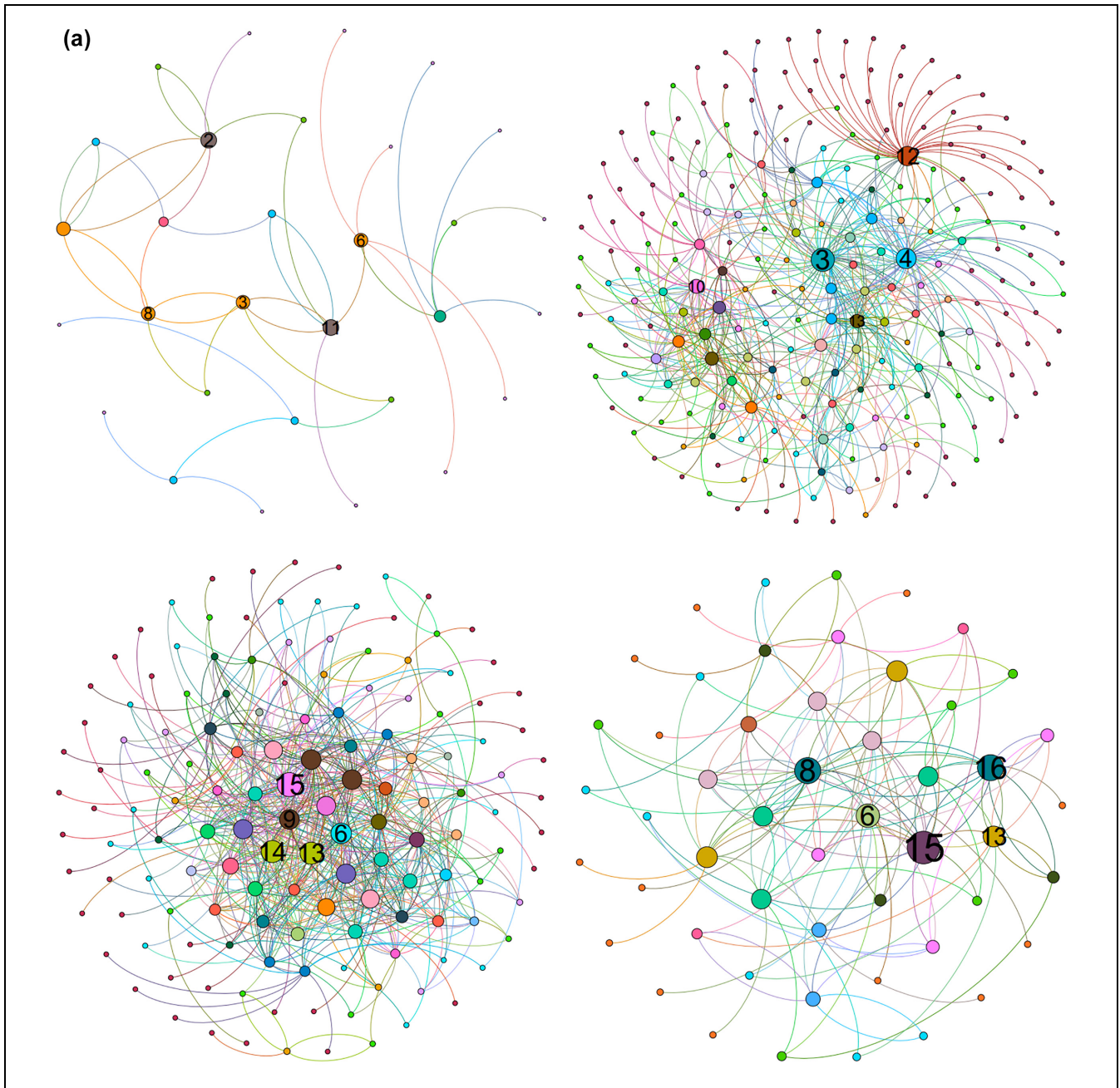
Community 2: Utility disruption, property damage, comparison with Hurricane Katrina

Community 3: Evacuation, utility disruption, relief seeking, COVID-19 pandemic, property damage

Community 4: Seeking donation (fundraising), utility disruption, property damage

Community 5: Compound hazard, utility disruption, Cameron, weather, death

Community 6: Election campaign, public property damage, insurance, relief, recovery

**Figure 11.** (continued)

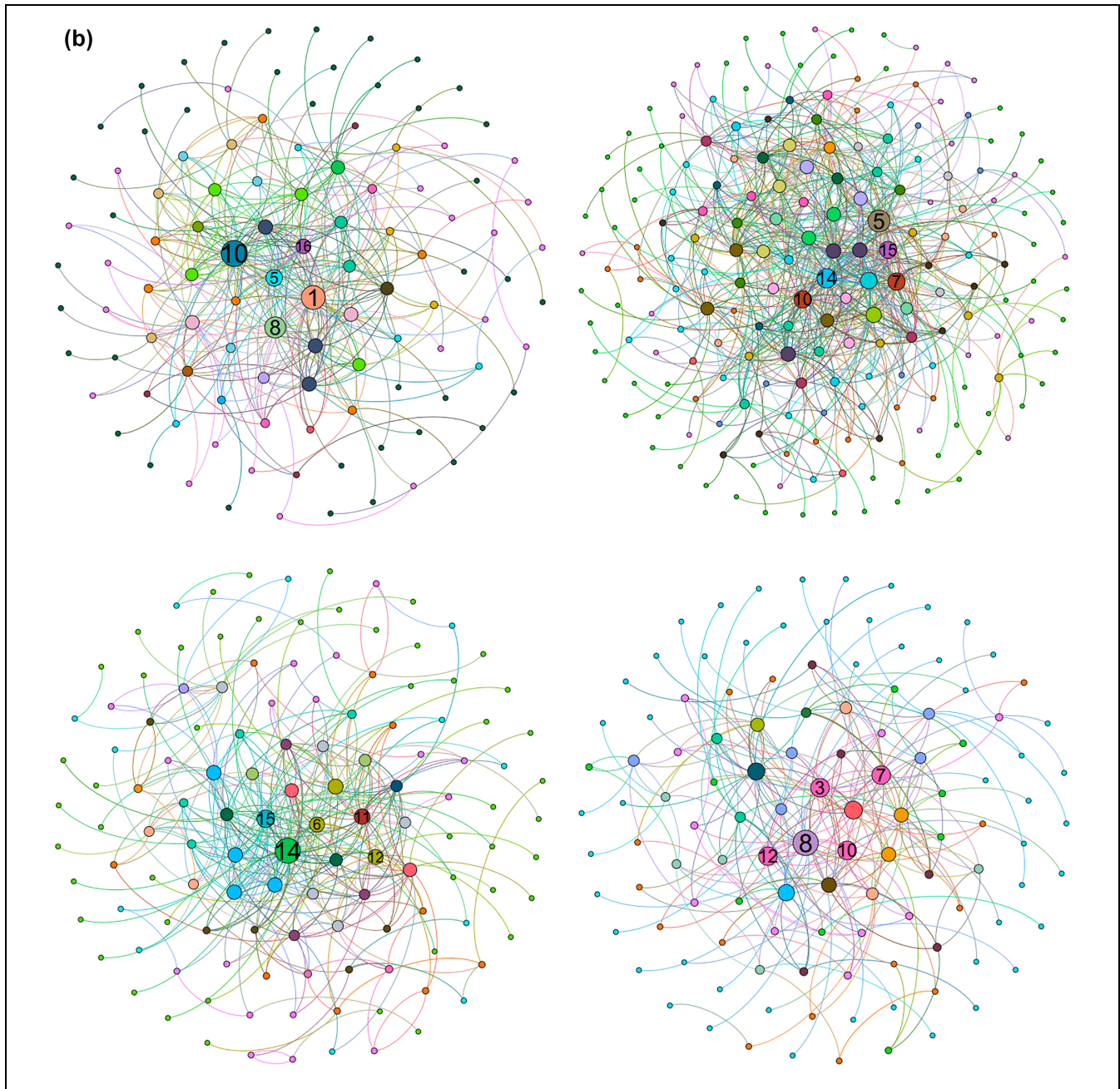


Figure 11. (a) Communities of the network (Communities 1–4): Community 1, Community 2, Community 3, and Community 4 and (b) Communities of the network (Communities 5–8): Community 5, Community 6, Community 7, and Community 8.

Community 7: Media, reports, weather, property damage, help-seeking

Community 8: Relief transportation, utility disruption, help-seeking, insurance, gas, return to home

The most common topic of discussion in each community is utility disruption (i.e., power, internet, water, gas) and property damage; however, each community has its own distinctive conversations also. A word bigram is a

great tool for understanding the conversation's latent meaning; however, topic modeling is a more established method in natural language processing for understanding the inherent topics.

Topic Modeling

Topic modeling is a statistical model that uses a probabilistic process based on a set of sampling rules to

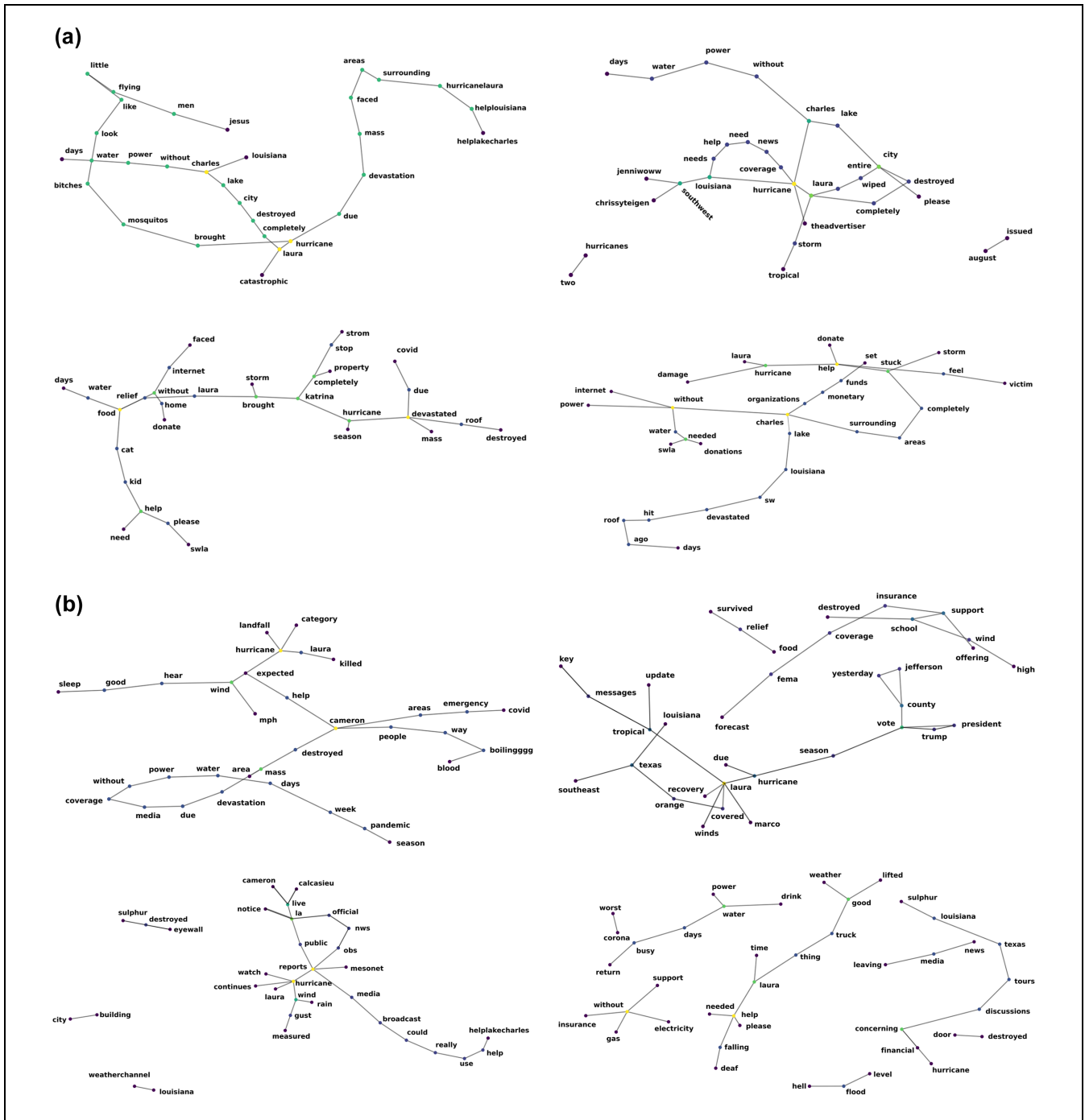


Figure 12 (a) Bigram network: (Communities 1–4): Community 1, Community 2, Community 3, and Community 4 and (b) Bigram network: (Communities 5–8): Community 5, Community 6, Community 7, and Community 8.

generate abstracts of topics (16). This procedure describes how latent variables generate database topics. Perplexity, loglikelihood, coherence value, and so forth, can measure model performance. The study assessed the coherence value for the topic model optimization. There is a global coherence value for each topic model and

individual scores for each word in the model. The model's performance improves as the coherence value increases. When the coherence value reaches its peak, the topics begin to reoccur, which reduces the model's efficiency. Tweets in each community have been analyzed for topic modeling, and each topic generated 10 salient

Table 1. Highlights of Topic Modeling

Community	Probable topic	Most probable words in coherent topic
1	Topic 1	Utility interruption in Lake Charles
	Topic 2	Tropical storm in Louisiana
2	Topic 1	Urging help
	Topic 2	Power interruption
	Topic 3	Aftermath of hurricane
3	Topic 1	Relief for Lake Charles
	Topic 2	Prior experience
	Topic 3	Compound disaster
4	Topic 1	Fundraising
	Topic 2	Water captivity
5	Topic 1	Extent of destruction
	Topic 2	First landfall
	Topic 3	Compound hazard
6	Topic 1	Media coverage
	Topic 2	Recovery update
	Topic 3	Election campaign
7	Topic 1	Weather forecast
	Topic 2	Agency mention
	Topic 3	Damage in school
8	Topic 1	Weather report
	Topic 2	Seeking help
	Topic 3	Utility interruption
9	Topic 1	Seeking help
	Topic 2	Seeking help
	Topic 3	Seeking help
10	Topic 1	Relief
	Topic 2	Home coming
	Topic 3	Utility interruption

words, of which the top five significant words with their probability are listed in Table 1.

From the eight communities, a total of 26 topics were found. Community 1 has the fewest number of topics (2 topics), while Community 6 has the most (5 topics). The majority of the communities talked about utility outages, tropical storms, property damage, seeking assistance, and raising funds.

Conclusions

Hurricane Laura devastated Louisiana and nearby areas in the midst of a pandemic. The local people and agencies had to be prepared to cope with the situation. There are very few studies that have explored the connectivity of the local people in social media during a compound crisis, along with their communication pattern, from a network perspective. This study investigated the communication patterns of locally affected people, as well as their connectivity between themselves and with various types of agencies, using data-driven approaches. The tweets of the local users revealed a crisis communication pattern based on their community. The number of agencies and users connected to a community reveals the nature of their discussion. The study analyzed the

collected tweets using multiple natural language processing: 1) the top 100 frequently used words grasp the most buzzed words in the deliberations, 2) temporal heatmaps show how topics emerge and trend over time during and after the landfall, 3) the directed user-mention network shows how local residents are connected to one another and to various agencies, 4) community detection in the subgraph allows hidden associations among different network nodes to be uncovered, 5) word bigram network captures the centrality and correlation of the discussions, and 6) the topic modeling depicts the overall scenario of the compound hazard.

The crisis communication of the local people on Twitter during Hurricane Laura shows how people interact and engage in social media during a major disaster and how they engage in connectivity with different agencies and organizations. The connectivity of the Twitter users was determined based on their mention in the original tweet. Some key findings of the study are summarized below:

- Based on the subgraph generated within the scope of the study, 21 network components of different sizes were observed in the subgraph network. The largest component included eight well-defined

communities that revealed high levels of engagement between the public and several agencies/organizations. The communities discussed utility outages, seeking assistance, compound disaster, water captivity, fundraising, and returning home.

- One of the communities that primarily comprised of health and utility systems along with some news media (KATC TV) was found to be the most connected, and community that comprised of T.V. news channel (KLFY-TV, Fox 15), National Weather Service Office Lake Charles, University Organization (University of Louisiana at Lafayette Black Male Leadership Association) and radio Station (Mustang 107.1, 1063 radio Lafayette) is the most populous network found in this study.
- Sports channels, university clubs, utility systems, weather channels, social organizations, health systems, and online news portals are the most connected (have the highest node degree) and influential node in their respective communities.
- Although emergency management and law enforcement agencies play a critical role in responding to such emergencies, the online communities found in this study revealed that university-related organizations, such as the University of Louisiana at Lafayette Black Male Leadership Association, Beacon club, social organizations such as Kappa Sigma, distinct journalist, T.V channel., online news portal, electronic media, weather service (National Weather Service Office Lake Charles), sports page such as L.C. Pride Basketball, McNeese Football, and some athletics organizations were found more engaged in the network.
- The most common topic of conversation in each community is utility disruption (i.e., power, internet, water, gas), followed by property damage; however, each community also has its own unique conversations, such as evacuation, insurance coverage, election campaign, fundraising, and so on.

The 21 connected components found in this study indicate that there are 21 isolated groups with poor engagement. In future crisis communications, this communication gap should be addressed. Again, the network diameter ranges from 7 to 9 in the subgraph's eight distinct communities. It indicates that transferring information from one actor to another will take at least seven steps, which exceeds the six-degree separation rule. The more steps required to transfer information from one actor to another, the greater the possibility of information deviation. In the future, the influential entities should be more engaged with each other and connect as

many social media agents, individuals, or both, as possible. Emergency management and law enforcement agencies should be more engaged with social media, in addition to their physical presence. They can reach out to more people in a shorter period of time and learn about their needs through social media.

This study found that the majority of highly engaged nodes include social media presence of the traditional media (such as television channels and radio stations) as well as educators, popular sports pages, university clubs, and other social organizations. However, federal and state-level emergency management agencies such as the Federal Emergency Management Agency (FEMA) and local police departments were not as involved as the other highly engaged nodes except for few government agencies, such as the National Weather Service Office in Lake Charles and the City-Parish of Lafayette. Future research efforts should explore how such agencies can participate in major crisis communication scenarios in a more engaged manner with the local residents to ensure more efficient response in a timely manner.

The findings of this study provide novel insights that would allow developing effective social media communication guidelines so that future disasters can be handled more effectively. The network analysis in this study, however, was limited to the largest component, which can be expanded to investigate other components and communities of the network. In addition, this study considered all topics to be static, that is, time-independent, which cannot explain the topic's evolution over time. Future research may utilize more advanced topic modeling techniques to capture the dynamics of word distribution within a topic.

The study contributes to a fundamental understanding of social media communication patterns, that is, how communities are formed, what they are discussing within their communities, and who the influential nodes are in those communities. However, this study focuses on Hurricane Laura crisis communication only. As different hazard events have distinct characteristics, comparing social media communication patterns across multiple events can provide us with more insights. Additional case studies can be conducted in the future by comparing multiple events and verifying whether this methodology provides a general conclusion or if there are any transferable insights or similarities or differences in communication patterns across different events.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: K. Al Momin, H. Kays, A. Sadri; data collection: K. Al Momin, H. Kays, A. Sadri; analysis and interpretation of results: K. Al Momin, H. Kays, A. Sadri; draft manuscript preparation: K. Al Momin, H. Kays, A. Sadri. All

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References

- Roy, K. C., S. Hasan, A. M. Sadri, and M. Cebrian. Understanding the Efficiency of Social Media Based Crisis Communication During Hurricane Sandy. *International Journal of Information Management*, Vol. 52, 2020, p. 102060.
- Freedman, I. L. A. *Hurricane Laura by the Numbers: Winds to 154 mph, a 15-Foot Surge and yet Another Category 4+ on U.S. Soil*. <https://www.washingtonpost.com/weather/2020/08/28/hurricane-laura-peak-winds-surge/>. Accessed July 15, 2022.
- Save the Children. *Hurricane Laura: Facts, FAQs, and How to Help*. <https://www.savethechildren.org/us/what-we-do/emergency-response/hurricane-laura>. Accessed July 15, 2022.
- FEMA. *Louisiana Hurricane Laura*. <https://www.fema.gov/disaster/4559>.
- TeleSUR. *Haiti: Tropical Storm Laura Death Toll Now 31*. <https://www.telesurenglish.net/news/haiti-tropical-storm-laura-death-toll-now-31-20200829-0006.html>. Accessed July 15, 2022.
- BBC News. *Hurricane Laura Death Toll Climbs to 14 in the U.S.* <https://www.bbc.com/news/world-us-canada-53955186>. Accessed July 15, 2022.
- Daily News. *Hurricane Laura Fatally Strikes Dominican Republic, Haiti, Makes Landfall in the U.S.* <https://www.nydailynews.com/photos/ny-tropical-storm-laura-marco-20200824-2saekhf5vrhfjneoxxrcpyhckpu-photogallery.html>. Accessed July 15, 2022.
- PBSorg. *More Than 750,000 Still Without Power in Hurricane Laura's Aftermath*. <https://www.pbs.org/newshour/nation/more-than-750000-still-without-power-in-hurricane-lauras-aftermath>. Accessed July 15, 2022.
- USDoE. *Laura, Sally, and Beta | Update #27*. Final. https://www.energy.gov/sites/default/files/2020/09/f79/TLP-WHITE_DOE%20Situation%20Update_Beta-Sally-Laura_27_FINAL.pdf 2020. Accessed April 20, 2023.
- Comfort, L. K., and T. W. Haase. Communication, Coherence, and Collective Action: The Impact of Hurricane Katrina on Communications Infrastructure. *Public Works Management & Policy*, Vol. 10, No. 4, 2006, pp. 328–343.
- U. S. Census. *Computer and Internet Use in the United States: 2018*. <https://www.census.gov/newsroom/press-releases/2021/computer-internet-use.html>.
- Niles, M. T., B. F. Emery, A. J. Reagan, P. S. Dodds, and C. M. Danforth. Social Media Usage Patterns During Natural Hazards. *PLoS One*, Vol. 14, No. 2, 2019, p. e0210484.
- Imran, M., S. Elbassuoni, C. Castillo, F. Diaz, and P. Meier. Practical Extraction of Disaster-Relevant Information from Social Media. *Proc., 22nd International Conference on World Wide Web*, Rio de Janeiro, Brazil, May 13–17, 2013, Association for Computing Machinery, New York, pp. 1021–1024.
- Oyeniyi, D. How Hurricane Harvey Changed Social Media Disaster Relief. *Texas Monthly*. 2017.
- Xiao, Y., Q. Huang, and K. Wu. Understanding Social Media Data for Disaster Management. *Natural Hazards*, Vol. 79, No. 3, 2015, pp. 1663–1679.
- Sadri, A. M., S. Hasan, S. V. Ukkusuri, and M. Cebrian. Crisis Communication Patterns in Social Media During Hurricane Sandy. *Transportation Research Record: Journal of the Transportation Research Board*, 2018. 2672: 125–137.
- Hasan, S., X. Zhan, and S. V. Ukkusuri. Understanding Urban Human Activity and Mobility Patterns Using Large-Scale Location-Based Data from Online Social Media. *Proc., 2nd ACM SIGKDD International Workshop on Urban Computing*, Chicago, IL, 2013, Association for Computing Machinery, New York, pp. 1–8.
- Kepios. *Global Social Media Statistics*. <https://datareportal.com/social-media-users>. Accessed July 29, 2022.
- Kemp, S. *Essential Twitter Statistics and Trends for 2022*. <https://datareportal.com/essential-twitter-stats>.
- Iqbal, M. *Twitter Revenue and Usage Statistics (2022)*. <https://www.businessofapps.com/data/twitter-statistics/>. Accessed July 15, 2022.
- Heverin, T., and L. Zach. Microblogging for Crisis Communication: Examination of Twitter Use in Response to a 2009 Violent Crisis in the Seattle-Tacoma, Washington, Area. *Proc., 7th International ISCRAM Conference*, Seattle, 2010.
- Zhou, S., P. Kan, Q. Huang, and J. Silbernagel. A Guided Latent Dirichlet Allocation Approach to Investigate Real-Time Latent Topics of Twitter Data During Hurricane

- Laura. *Journal of Information Science*, Vol. 49, No. 2, 2023, pp. 465–479.
23. Samet, A. *How the Coronavirus is Changing U.S. Social Media Usage*. 2020. https://contentstorage-na1.emarketer.com/7b4f01d8ec3cb44704707be5c1d3eaf5/How_the_Coronavirus_Is_Changing_US_Social_Media_Usage_eMarketer.pdf
 24. Lachlan, K. A., P. R. Spence, X. Lin, K. Najarian, and M. Del Greco. Social Media and Crisis Management: CERC, Search Strategies, and Twitter Content. *Computers in Human Behavior*, Vol. 54, 2016, pp. 647–652.
 25. Sadri, A. M. *Social Network Influence on Ridesharing, Disaster Communications, and Community Interactions*. Dissertations and theses. Purdue University, 2016, p. 284. https://docs.lib.purdue.edu/open_access_dissertations/1230/
 26. Sadri, A. M., S. V. Ukkusuri, and M. A. Ahmed. Review of Social Influence in Crisis Communications and Evacuation Decision-Making. *Transportation Research Interdisciplinary Perspectives*, Vol. 9, 2021, p. 100325.
 27. Mohanty, S. D., B. Biggers, S. Sayedahmed, N. Pourebrahim, E. B. Goldstein, R. Bunch, G. Chi, F. Sadri, T. P. McCoy, and A. Cosby. A Multi-Modal Approach Towards Mining Social Media Data During Natural Disasters - A Case Study of Hurricane Irma. *International Journal of Disaster Risk Reduction*, Vol. 54, 2021, p. 102032.
 28. Kryvasheyev, Y., H. Chen, N. Obradovich, E. Moro, P. Van Hentenryck, J. Fowler, and M. Cebrian. Rapid Assessment of Disaster Damage Using Social Media Activity. *Science Advances*, Vol. 2, No. 3, 2016, p. e1500779.
 29. Cheng, Y. How Social Media is Changing Crisis Communication Strategies: Evidence from the Updated Literature. *Journal of Contingencies and Crisis Management*, Vol. 26, No. 1, 2018, pp. 58–68.
 30. Beiró, M. G., A. Panisson, M. Tizzoni, and C. Cattuto. Predicting Human Mobility Through the Assimilation of Social Media Traces into Mobility Models. *EPJ Data Science*, Vol. 5, 2016, pp. 1–15.
 31. Pan, B., Y. Zheng, D. Wilkie, and C. Shahabi. Crowd Sensing of Traffic Anomalies Based on Human Mobility and Social Media. *Proc., 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, Orlando, FL, 2013, Association for Computing Machinery, New York, pp. 344–353.
 32. Rashidi, T. H., A. Abbasi, M. Maghrebi, S. Hasan, and T. S. Waller. Exploring the Capacity of Social Media Data for Modelling Travel Behaviour: Opportunities and Challenges. *Transportation Research Part C: Emerging Technologies*, Vol. 75, 2017, pp. 197–211.
 33. Roy, K. C., M. Cebrian, and S. Hasan. Quantifying Human Mobility Resilience to Extreme Events Using Geo-Located Social Media Data. *EPJ Data Science*, Vol. 8, No. 1, 2019, p. 18.
 34. Kryvasheyev, Y., H. Chen, E. Moro, P. Van Hentenryck, and M. Cebrian. Performance of Social Network Sensors During Hurricane Sandy. *PLoS One*, Vol. 10, No. 2, 2015, p. e0117288.
 35. George, Y., S. Karunasekera, A. Harwood, and K. H. Lim. Real-Time Spatio-Temporal Event Detection on Geotagged Social Media. *Journal of Big Data*, Vol. 8, No. 1, 2021, pp. 1–28.
 36. Dong, X., D. Mavroeidis, F. Calabrese, and P. Frossard. Multiscale Event Detection in Social Media. *Data Mining and Knowledge Discovery*, Vol. 29, No. 5, 2015, pp. 1374–1405.
 37. Statt, N. *Twitter is Opening up its Full Tweet Archive to Academic Researchers for Free*. <https://www.theverge.com/2021/1/26/22250203/twitter-academic-research-public-tweet-archive-free-access>. Accessed July 25, 2022.
 38. Tornes, A. *Product News: Enabling the Future of Academic Research with the Twitter API*. <https://developer.twitter.com/en/blog/product-news/2021/enabling-the-future-of-academic-research-with-the-twitter-api>. Accessed July 25, 2022.
 39. Rusho, M. A., M. A. Ahmed, and A. M. Sadri. Social Media Response and Crisis Communications in Active Shootings During COVID-19 Pandemic. *Transportation Research Interdisciplinary Perspectives*, Vol. 11, 2021, p. 100420.
 40. Sadri, A. M., S. Hasan, S. V. Ukkusuri, and J. E. S. Lopez. Analyzing Social Interaction Networks from Twitter for Planned Special Events. *arXiv preprint arXiv:1704.02489*, 2017.
 41. Liu, B. F., L. Austin, and Y. Jin. How Publics Respond to Crisis Communication Strategies: The Interplay of Information Form and Source. *Public Relations Review*, Vol. 37, No. 4, 2011, pp. 345–353.
 42. Mills, A., R. Chen, J. Lee, and H. Raghav Rao. Web 2.0 Emergency Applications: How Useful Can Twitter be for Emergency Response? *Journal of Information Privacy and Security*, Vol. 5, No. 3, 2009, pp. 3–26.
 43. Palen, L., K. Starbird, S. Vieweg, and A. Hughes. Twitter-Based Information Distribution During the 2009 Red River Valley Flood Threat. *Bulletin of the American Society for Information Science and Technology*, Vol. 36, No. 5, 2010, pp. 13–17.
 44. Kireyev, K., L. Palen, and K. Anderson. Applications of Topics Models to Analysis of Disaster-Related Twitter Data. *Proc., NIPS Workshop on Applications for Topic Models: Text and Beyond*, Whistler, Canada, No. 1, 2009.
 45. Sakaki, T., M. Okazaki, and Y. Matsuo. Earthquake Shakes Twitter Users: Real-Time Event Detection by Social Sensors. *Proc., 19th International Conference on World Wide Web*, Raleigh, NC, 2010, Association for Computing Machinery, New York, NY, pp. 851–860.
 46. Zou, L., N. S. N. Lam, H. Cai, and Y. Qiang. Mining Twitter Data for Improved Understanding of Disaster Resilience. *Annals of the American Association of Geographers*, Vol. 108, No. 5, 2018, pp. 1422–1441.
 47. Sadri, A. M., S. Hasan, S. V. Ukkusuri, and M. Cebrian. Exploring Network Properties of Social Media Interactions and Activities During Hurricane Sandy. *Transportation Research Interdisciplinary Perspectives*, Vol. 6, 2020, p. 100143.
 48. Li, L. T., S. Yang, A. Kavanaugh, E. A. Fox, S. D. Sheetz, D. Shoemaker, T. Whalen, and V. Srinivasan. Twitter Use During an Emergency Event: The Case of the UT Austin Shooting. *Proc., 12th Annual International*

- Digital Government Research Conference: Digital Government Innovation in Challenging Times*, College Park, MD, 2011, Association for Computing Machinery, New York, NY, pp. 335–336.
49. Fischer-Pfeßler, D., C. Schwemmer, and K. Fischbach. Collective Sense-Making in Times of Crisis: Connecting Terror Management Theory with Twitter User Reactions to the Berlin Terrorist Attack. *Computers in Human Behavior*, Vol. 100, 2019, pp. 138–151.
 50. Sadri, A. M., S. V. Ukkusuri, and P. Murray-Tuite. A Random Parameter Ordered Probit Model to Understand the Mobilization Time During Hurricane Evacuation. *Transportation Research Part C: Emerging Technologies*, Vol. 32, 2013, pp. 21–30.
 51. Murray-Tuite, P., and B. Wolshon. Evacuation Transportation Modeling: An Overview of Research, Development, and Practice. *Transportation Research Part C: Emerging Technologies*, Vol. 27, 2013, pp. 25–45.
 52. Urbina, E., and B. Wolshon. National Review of Hurricane Evacuation Plans and Policies: A Comparison and Contrast of State Practices. *Transportation Research Part A: Policy and Practice*, Vol. 37, No. 3, 2003, pp. 257–275.
 53. Wolshon, B. Evacuation Planning and Engineering for Hurricane Katrina. *Bridge*, Vol. 36, No. 1, 2006, pp. 27–34.
 54. Alsnih, R., J. Rose, and P. Stopher. Understanding Household Evacuation Decisions Using a Stated Choice Survey: Case Study of Bush Fires. Presented at 84th Annual Meeting of the Transportation Research Board, Washington, D.C., 2005.
 55. Howell, S. E., and D. E. Bonner. *Citizen Hurricane Evacuation Behavior in Southeastern Louisiana: A Twelve Parish Survey*. Southeast Louisiana Hurricane Taskforce, Survey Research Center, 2005. https://scholarworks.uno.edu/src_pubs/10
 56. Hasan, S., S. Ukkusuri, H. Gladwin, and P. Murray-Tuite. Behavioral Model to Understand Household-Level Hurricane Evacuation Decision Making. *Journal of Transportation Engineering*, Vol. 137, No. 5, 2011, pp. 341–348.
 57. Yin, W., P. Murray-Tuite, S. V. Ukkusuri, and H. Gladwin. An Agent-Based Modeling System for Travel Demand Simulation for Hurricane Evacuation. *Transportation Research Part C: Emerging Technologies*, Vol. 42, 2014, pp. 44–59.
 58. Mesa-Arango, R., S. Hasan, S. V. Ukkusuri, and P. Murray-Tuite. Household-Level Model for Hurricane Evacuation Destination Type Choice Using Hurricane Ivan Data. *Natural Hazards Review*, Vol. 14, No. 1, 2013, pp. 11–20.
 59. Sadri, A. M., S. V. Ukkusuri, P. Murray-Tuite, and H. Gladwin. Analysis of Hurricane Evacuee Mode Choice Behavior. *Transportation Research Part C: Emerging Technologies*, Vol. 48, 2014, pp. 37–46.
 60. Wong, S. D., J. C. Broader, and S. A. Shaheen. *Review of California Wildfire Evacuations from 2017 to 2019*. Institute of Transportation Studies, Berkeley, CA, 2020.
 61. Wong, S. D., J. L. Walker, and S. A. Shaheen. Trust and Compassion in Willingness to Share Mobility and Sheltering Resources in Evacuations: A Case Study of the 2017 and 2018 California Wildfires. *International Journal of Disaster Risk Reduction*, Vol. 52, 2021, p. 101900.
 62. Wong, S. D., J. C. Broader, J. L. Walker, and S. A. Shaheen. Understanding California Wildfire Evacuee Behavior and Joint Choice Making. *Transportation*, 2022, pp. 1–47. <https://doi.org/10.1007/s11116-022-10275-y>
 63. Page-Tan, C. An Analysis of Social Media Use and Neighbor-Assisted Debris Removal in Houston Following Hurricane Harvey. *International Journal of Disaster Risk Reduction*, Vol. 63, 2021, p. 102450.
 64. Park, D., W. G. Kim, and S. Choi. Application of Social Media Analytics in Tourism Crisis Communication. *Current Issues in Tourism*, Vol. 22, No. 15, 2019, pp. 1810–1824.
 65. Jeng, A. B., and C. L. Lee. *A Study on Online Game Cheating and the Effective Defense*. Recent Trends in Applied Artificial Intelligence. IEA/AIE 2013. Lecture Notes in Computer Science, Springer, Berlin, Heidelberg, Vol. 7906, 2013. https://doi.org/10.1007/978-3-642-38577-3_53.
 66. Patel, V. H. Topic Modeling Using Latent Dirichlet Allocation on Disaster Tweets. 2018. <http://krex.k-state.edu/dspace/handle/2097/39337>
 67. Sadri, A. M., S. Hasan, S. V. Ukkusuri, and M. Cebrian. Understanding Information Spreading in Social Media During Hurricane Sandy: User Activity and Network Properties. *arXiv preprint arXiv:1706.03019*, 2017.
 68. Resch, B., F. Usländer, and C. Havas. Combining Machine-Learning Topic Models and Spatiotemporal Analysis of Social Media Data for Disaster Footprint and Damage Assessment. *Cartography and Geographic Information Science*, Vol. 45, No. 4, 2018, pp. 362–376.
 69. Yang, M., J. Mei, H. Ji, W. Zhao, Z. Zhao, and X. Chen. Identifying and Tracking Sentiments and Topics from Social Media Texts During Natural Disasters. *Proc., Conference on Empirical Methods in Natural Language Processing*, Copenhagen, Denmark, September 7–11, 2017, Association for Computational Linguistics, pp. 527–533.
 70. Yu, M., Q. Huang, H. Qin, C. Scheele, and C. Yang. Deep Learning for Real-Time Social Media Text Classification for Situation Awareness—Using Hurricanes Sandy, Harvey, and Irma as Case Studies. *International Journal of Digital Earth*, Vol. 12, No. 11, 2019, pp. 1230–1247.
 71. Sadri, A. M., S. Hasan, and S. V. Ukkusuri. Joint Inference of User Community and Interest Patterns in Social Interaction Networks. *Social Network Analysis and Mining*, Vol. 9, No. 1, 2019, pp. 1–23.
 72. Berg, R. P. *Richard Hurricane Laura Tropical Cyclone Update*. Report. National Hurricane Center, Miami, FL, 2020.
 73. Cangialosi, J. *Tropical Depression Thirteen Advisory Number 1*. Report. National Hurricane Center, Miami, FL, 2020.
 74. Pasch, R. *Tropical Storm Laura Tropical Cyclone Update*. Report. National Hurricane Center, Miami, FL, 2020.
 75. Blake, E. *Tropical Storm Laura Discussion Number 22*. Report. National Hurricane Center, Miami, FL, 2020.
 76. Feldman, R. Techniques and Applications for Sentiment Analysis. *Communications of the ACM*, Vol. 56, No. 4, 2013, pp. 82–89.
 77. Medhat, W., A. Hassan, and H. Korashy. Sentiment Analysis Algorithms and Applications: A Survey. *Ain Shams Engineering Journal*, Vol. 5, No. 4, 2014, pp. 1093–1113.

78. Hutto, C., and E. Gilbert. Vader: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 8, No. 1, 2014, pp. 216–225.
79. Alam, M. R., A. M. Sadri, and X. Jin. Identifying Public Perceptions Toward Emerging Transportation Trends Through Social Media-Based Interactions. *Future Transportation*, Vol. 1, No. 3, 2021, pp. 794–813.
80. Martin, S., J. Liermann, and H. Ney. Algorithms for Bigram and Trigram Word Clustering. *Speech Communication*, Vol. 24, No. 1, 1998, pp. 19–37.
81. Griffiths, T. L., and M. Steyvers. Finding Scientific Topics. *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 101, Supplement 1, 2004, pp. 5228–5235.
82. Lau, J. H., N. Collier, and T. Baldwin. On-Line Trend Analysis with Topic Models: Twitter Trends Detection Topic Model Online. *Proc., 24th International Conference on Computational Linguistics - Proceedings of COLING 2012: Technical Papers*, Mumbai, India, December, 2012, The COLING 2012 Organizing Committee, Vol. 2, pp. 1519–1534.
83. Saxton, M. D. A Gentle Introduction to Topic Modeling Using Python. *Theological Librarianship*, Vol. 11, No. 1, 2018, pp. 18–27.
84. Traag, V. A., R. Aldecoa, and J. C. Delvenne. Detecting Communities Using Asymptotical Surprise. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, Vol. 92, No. 2, p.022816. 2015.
85. Alam, M. R., and A. M. Sadri. Examining the Communication Pattern of Transportation and Transit Agencies on Twitter: A Longitudinal Study in the Emergence of COVID-19 on Twitter. *Transportation Research Record*, 2022. <https://doi.org/10.1177/03611981221082564>
86. Zhang, L., and W. Tu. *Six Degrees of Separation in Online Society*. 2009. <https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=1febc4cc5199d36e50ec7d3533a8ac8a32889d7c>