Vulnerability in Two-Way Disaster Communication

Looking at Orleans Parish, Louisiana During Hurricane Marco and Hurricane Laura

Abstract

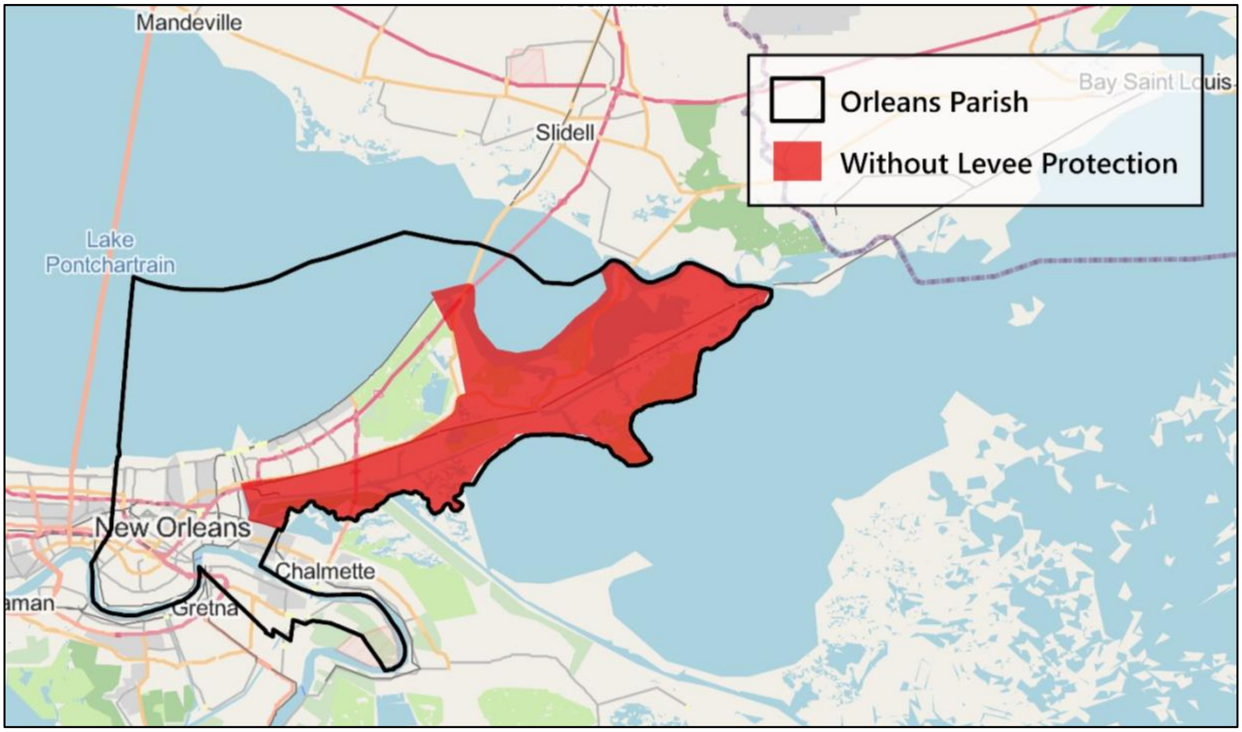
In times of natural disaster, the use of mobile phone can improve communications access and reduce disaster risks. Mobile phones provide additional means for people to call local emergency number and to check on family and friends on social media. For this reason, social media data has been increasingly used in research to investigate community resilience in the three phases of emergency management: preparedness, response, and recovery. However, it has been found that, in social media like Twitter, disaster-related user communities were often associated with a higher socio-economic or higher educational status. What happens to people with poor communication technology during a natural disaster? The primary goal of the project is to examine the vulnerability of disaster communication in the Orleans Parish, Louisiana by analyzing xxx tweets and xxx 311 Calls. The objectives of this project are threefold: (1) to compare the spatial patterns between tweets, 311 calls, (2) to explore how the frequencies of tweets and 311 calls changed over time in relation to the Hurricanes' movements, and (3) finally and most importantly, to develop a risk index that helps identify the most vulnerable communities in the Orleans Parish where people faced disaster risks while lacking disaster communication resources. The results show that the coastal areas received the highest vulnerability score in the City of New Orleans.

Keywords: Hurricane Marco, Hurricane Laura, mobile phone, Twitter, 311 Calls, vulnerability study, disaster communications.

1. Introduction

Natural disasters are catastrophic. Although natural disasters occur across the world, poor areas are usually more vulnerable to certain disasters than the others. Natural disasters turn into tragedies when the lives and livelihoods of people are already disrupted.

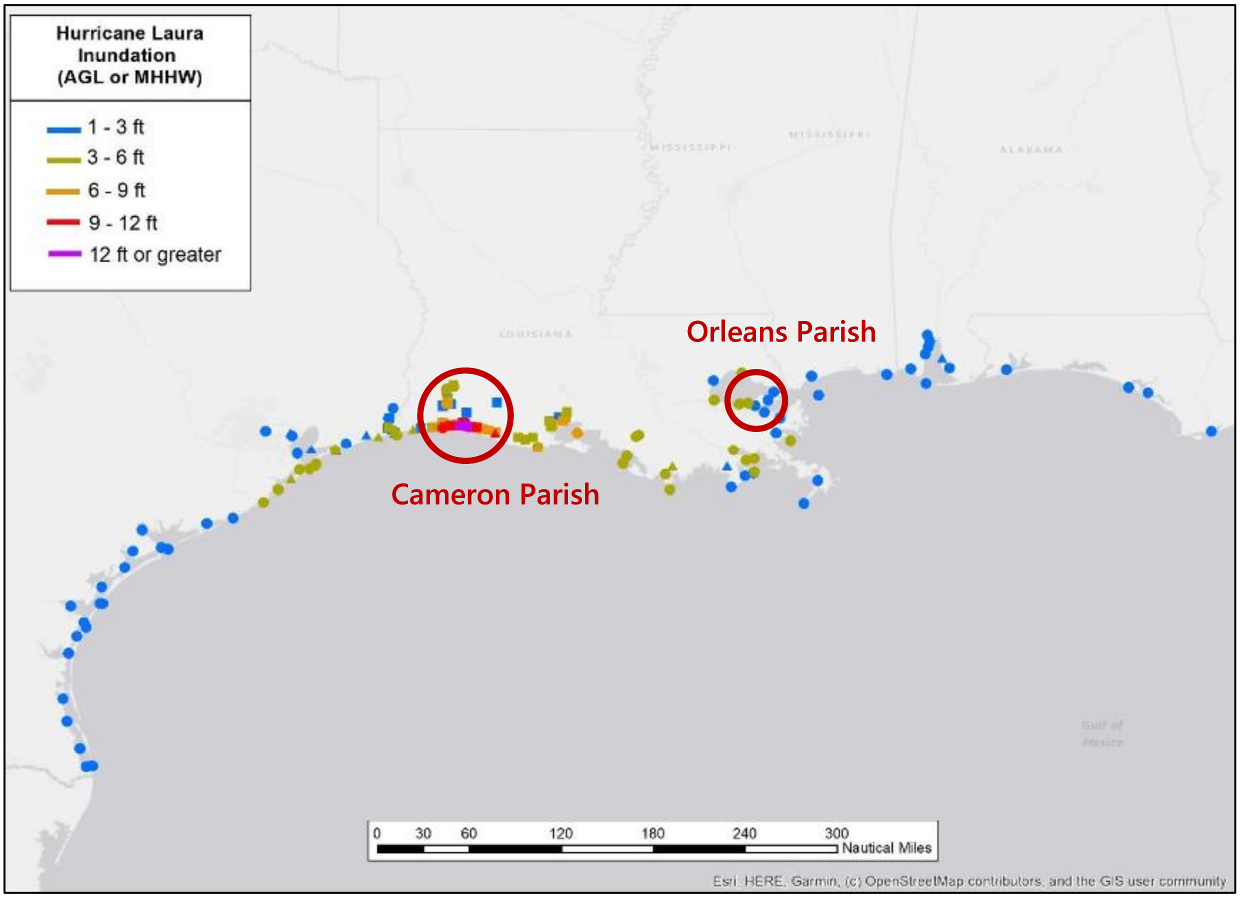
The City of New Orleans, also known as Orleans Parish, is a city located at the Southeast of Louisiana on the Mississippi River. It had a population of 376,971 as of July 1, 2021, of which 33.4% were white and 59.2% were Black or African American (U.S. Census Bureau). However, the city has been vulnerable to flooding and hurricane. In 2005, Hurricane Katrina flooded around eighty percent of the city and caused a fifty percent of decline in population (NASA Earth Observatory, 2005 & The Data Center, 2016).



Map 1. Areas in the City of New Orleans without Levee Protection. *Reproduced from: The City of New Orleans. August 23, 2020.* "*Residents Outside of Levee Protection Should Voluntarily Evacuate." NOLA Ready. Available at: https://ready.nola.gov/incident/tropical-storm-laura/residents-outside-of-levee-protection-should-volun/.*

Seventeen years later, Hurricane Laura made landfall at the Cameron Parish in Louisiana as a category 4 on August 27, 2022 at UTC 0600, three days after a category 1 Hurricane Marco made landfall at the City of New Orleans, with its highest wind speed of 130 kt (Pasch et al., 2021, Page 16). Laura was more powerful than Hurricane Katrina and was, indeed, the strongest hurricane to strike Louisiana since Hurricane Camille in 1969 (Pasch et al., 2021, Page 4). It took 47 lives in total and cost an estimated of $19 billion in damage in the U.S. of which $17.5 billion was in Louisiana (Pasch et al., 2021, Page 1&10).

The Mayor of the City of New Orleans, LaToya Cantrell, filed an emergency proclamation due to Tropical Storm Laura and Tropical Depression Fourteen on August 21, 2020 (The City of New Orleans, 2020a). Two days later, a Storm Surge Warming due to Hurricane Marco was issued to encourage neighborhoods in the City of New Orleans that were without levee protection to evacuate: Venetian Isles, Lake Catherine, and Irish Bayou (See Map 1) (The City of New Orleans, 2020b). On August 25, after Hurricane Marco has left, areas without levee protection were still predicted to be impacted the greatest by Hurricane Laura in the City of New Orleans (The City of New Orleans, 2020c). In addition, a total of seven tornado watches were issued to places including the City of New Orleans.



Map 2. A Map from the NHC Showing Maximum Water Levels Measured. *Source: Richard J. Pasch, Robbie Berg, David P. Roberts, & Philippe P. Papin. May 26, 2021. HURRICANE LAURA (AL132020). National Hurricane Center (NHC). Available at: https://www.nhc.noaa.gov/data/tcr/AL132020_Laura.pdf. Page 57.*

Laura brought a maximum inundation level of 12 to 18 ft above from ground-level (AGL) along the coast of Louisiana and produced storm surge that ran 20 to 30 n mi inland across southwest Louisiana (Pasch et al., 2021, Page 7). As shown in Map 2, the most impacted areas are in the Cameron Parish located at the Southwest of Louisiana, which experienced 12 ft AGL or greater inundation levels. The Orleans Parish located in the Southeast of Louisiana had inundation levels up to 6 ft AGL, which are similar to what a Category 1 hurricane can produce and can possibly cause damage to roofs and sidings and topple trees with shallow roots and power lines (National Hurricane Center, n.d.).

Both Hurricane Marco and Laura brought sustained impacts upon the Orleans Parish. Although the Orleans Parish did not suffer as much as the Cameron arish during Hurricane Laura, it was still a time when the residents and the local leaders needed to come together – to plan for evacuation for those living without levee protection, to distribute sandbags, to take care of the ones living under the same household, and etc.

	Time Formed	Time Made Landfall at Louisiana	Time Dissipated
Hurricane Marco	8/21/2022	8/24/2022	8/26/2022
Hurricane Laura	8/20/2022	8/27/2022	8/29/2022

Table 1. Timeframe of Hurricane Marco and Hurricane Laura

Some types of disaster communication can be done through a face-to-face in-person conversation. For example, distributing sandbags requires a physical setting. However, during the time of emergency when people were not recommended to go outside, remote communication came into place – television, radio broadcasting, two-way radio, landline telephones, and mobile phone. People with a mobile phone can text “LAURA” to 888777 for updates. From August 23 to August 27, the National Hurricane Center (NHC) provided twenty-three Facebook Live broadcasts with a total of two million views and posted advisories on its Facebook page every three hours. The tweets posted by the National Hurricane Center during Laura received around seventy-one million views. Through the mobile phone, people can also access apps, such as the FEMA Mobile App, which can help with locating shelters, sending notifications to cared ones, and getting real-time weather alerts.

Nevertheless, devices such as television and radio broadcasting can only be used to receive information. Allow for two-way communication requires devices such as a two-way radio, a landline telephone, and a mobile phone. Two-way devices or apps not only provide a means for people to gather information but also a means for people to communicate and to speak for their needs. Two-way devices allow the real-time exchange of information which can protect the safety of people. How many people are injured? LINE, a communication app that is commonly used by people in Japan, Taiwan, and Thailand, was born in the aftermath of the 2011 Japan 311 Earthquake and Tsunami when people had a hard time contacting their loved ones. Its read receipts function was designed specifically for the senders to know that their messages were received when the receivers were not able to respond.

In addition, mobile phones enable people to access apps, the Internet, and social media, which has become one of the live-saving tools when facing disasters although research have found that tweets during the times of disasters were usually posted by communities associated with a higher educational and socioeconomic status (Mihunov et al., 2020). This could mean that people with a lower educational or socioeconomic status do not have the access to a mobile phone or internet during disasters, do not use social media as often in their normal life, or etc.

Therefore, this seeks to develop a risk index that can help identify the most vulnerable communities in the Orleans Parish where people faced disaster risks while lacking proper disaster communications resources. Examining data during and between Hurricane Marco and Hurricane Laura can give a more precise illustration of human behaviors in times of hurricanes. However, due to the constraints of publicly available data, time in the semester, and financial resources, this project only uses Twitter data and 311 data in the risk index. Future work is encouraged to include more datasets from any two-way communication devices or apps for better accuracy for this so-called two-way disaster communication index.

2. Literature Review

Twitter Data in Social Science Research

Twitter data has been used extensively by social researchers because it is free and contains historical and real-time tweets of millions of daily active users. In social research, Twitter data has been used for sentiment analysis, social network analysis, and human mobility analysis. For examples, Agarwal et al. (2011) classified 'tweets' into positive, negative, and neutral classes through models that they built and a 3-way task of classifying. Achrekar et al. (2011) introduced the Social Network Enabled Flu Trends (SNEFT) framework, which monitors messages posted on Twitter with a mention of flu indicators to track and predict the emergency and spread of an influenza epidemic in a population. They showed that social networking media like Twitter can play a key role in seasonal influenza epidemics and other pandemics. Crandall et al. (2010) found that similarity of spatial and temporal information increases likelihood of a social connection between two different contributors. Jurdak et al. (2015) conducted a human mobility study with geotagged tweets to explore the diversity of movement orbits among individuals within and between cities. Ames and Naaman (2007) emphasized on the importance of Mobile and Online media and explained the motivations behind tagging.

Twitter Data in Natural Disaster Research

Besides being used in social media research, Twitter data can also be used for natural disaster management research. Not only can Twitter data show insight about how people communicate during disasters, Pourebrahim et al. (2019) showed that Twitter data can also be highly valuable at helping researchers and emergency managers identify damages (Although the best way to request rescue is still calling 911 or other local emergency numbers (Rhodan, 2017) as Twitter would not tell when the requests were received and when the help would be sent (Mihvnov et al., 2020)).

Similar to how researchers in the social science field have used Twitter data, researchers in natural disaster management have conducted content analysis, temporal analysis, social network analysis, and human mobility analysis. Rajput et al. (2020) conducted a network analysis with twenty-one million tweets in the Houston area; they found that most Twitter users during Hurricane Harvey were government users in the core network, and there is limited interaction between government and non-government users before and after the Hurricane. Yeo et al. (2020) also based their research on network analysis; they analyzed patterns and characteristics of the long-term recovery communication after the 2016 Southern Louisiana flood and found weaning local voices and prolonging negative sentiments over long-term recovery.

In order to collect Twitter data for disaster management research, Ashktorab et al. (2014) introduced a Twitter-mining tool – Tweddr – that extracts actionable information for disaster relief workers during natural disasters. Zhou et al. (2021), emphasizing on the role of natural language processing (NLP) in mining disaster data, proposed a guided Latent Dirichlet Allocation (LDA) workflow to investigate temporal topics from tweets during Hurricane Laura.

However, although Twitter can be a great data source that help improve natural disaster management, it can also be a biased dataset. Examining phases of emergency management, Zou et al. (2015) found that communities with higher Twitter use during Hurricane Harvey were generally having better social status. Mihvnov et al. (2020) also found that those requesting rescue on Twitter were usually better educated, employed (80%), and were homeowners (81%).

311 Data in Social Science Research

Therefore, to reduce the bias in our research, we add in the 311 Calls dataset. There are limited literatures on the 311 Calls data. Minkoff et al. (2016) divided 311 data into three categories (government-provided goods, graffiti, and noise) that are separately analyzed using regression models that account for spatial and serial dependence and investigated the census-tract-level variation 311 data contacting volume with New York City. Chatfield et al. (2018) used 311 data to analyze customer agility and responsiveness in Houston, and they found the importance of a culture of analytics driven by strong political leadership in the data-driven government for greater city-wide public value creation. Schellong et al. (2007) combined 311 calls with emergency management to explore the relationship between citizen relationship management (CiRM) and absorptive capacity (ACAP) and concluded that this setting increases an organization's ability to acquire, assimilate, transform, and exploit information and knowledge regarding citizen's needs. Madkour (2020) generated a forecast for future requests using 311 data. By knowing the future of requests, the city can be prepared in case there is an increase in calls during the next few years by making sure there are enough resources capable of responding rapidly, especially during natural disasters (Madkour, 2020).

Disaster Vulnerability

Disaster vulnerability is influenced by many factors, including housing features, access to social media and signals, income, education level and so on. Morrow (1999) found that poor people are more vulnerable at all stages- preparedness, response, and recovery, and we can observe similar features for ethnic minorities through literature (Morrow, 1999). Juntunen (2005) pointed out that socially vulnerable groups are more likely to die during a disaster event and less likely to recover after a disaster. Meanwhile, the most vulnerable people are likely to be those whose needs are not adequately considered in the plans of local response and relief organizations. During emergencies, real-time evacuation information is generally not provided to people with limited English proficiency, hearing and vision impairments, and other special needs groups (U.S. Department of Transportation, 2006). Additionally, inadequate funding for government and local authorities is another indication of vulnerability. While local authorities are best able to identify vulnerable communities, these agencies are often underfunded, understaffed, and stretched by ongoing health and social service responsibilities (APHA, 2006; USGAO, 2006).

Disaster Risk Indices

For most of the twentieth century, disaster management focused on the physical world, with an emphasis on infrastructure and technology (Flanagan et al., 2011). While disaster management usually included the physical component, the social component was usually ignored. The concept of social vulnerability in disaster management was developed in the 1970s when researchers recognized that vulnerability involves not only physical structures but also socioeconomic factors that affect the resilience of communities (Juntunen et al., 2004). In disaster management studies, academics commonly use a formula for calculating risk factors: *Risk = Hazard * (Vulnerability - Resources)*, where *Risk* is the likelihood of loss; *Hazard* is the condition posing threats of harm (Dwyer et al., 2004). *Vulnerability* represents the degree to which people or objects are liable to be harmed, and *Resources* are assets that can be put in place to lessen the effects of dangers (Dwyer et al., 2004). Putting the idea into practice, Cutter et al. (2010) developed 15 Baseline Resilience Index for Communities (BRIC) while Peacock et al. (2010) developed the Community Disaster Resilience Index to measure disaster vulnerability. Furthermore, to contribute to disaster communication, the Federal Emergency Management Agency (FEMA) introduced the National Risk Index, which identifies communities most at risk to eighteen natural hazards. The index is composed of three components to disaster risk: a natural hazards component (also refers to as Expected Annual Loss), a consequence-enhancing component (also refers to as Social Vulnerability), and a consequence reduction component (also refers to as Community Resilience). (Federal Emergency Management Agency, 2020).

The goal of this project is to develop a disaster communication vulnerability index. Although many disaster risk indices have been developed to help government and local leaders improve disaster communication, there is no index that specifically focuses on disaster communication vulnerability. This project aims to study how people communicate during a hurricane by incorporating Twitter data along with 311 Calls.

3. Research Questions

To study how two-way communication devices or apps were used during hurricanes, this project asks the following questions:

1. How were Twitter and 311 Calls being used across the City of New Orleans?
2. How had the frequencies of tweets and 311 calls in the City of New Orleans changed over time in relation to Hurricane Laura's movement?
3. Where do people have a higher disaster communication risk score - meaning facing greater disaster risks and lacking disaster communication resources?

4. Data (Source/Data Cleaning Explanation)

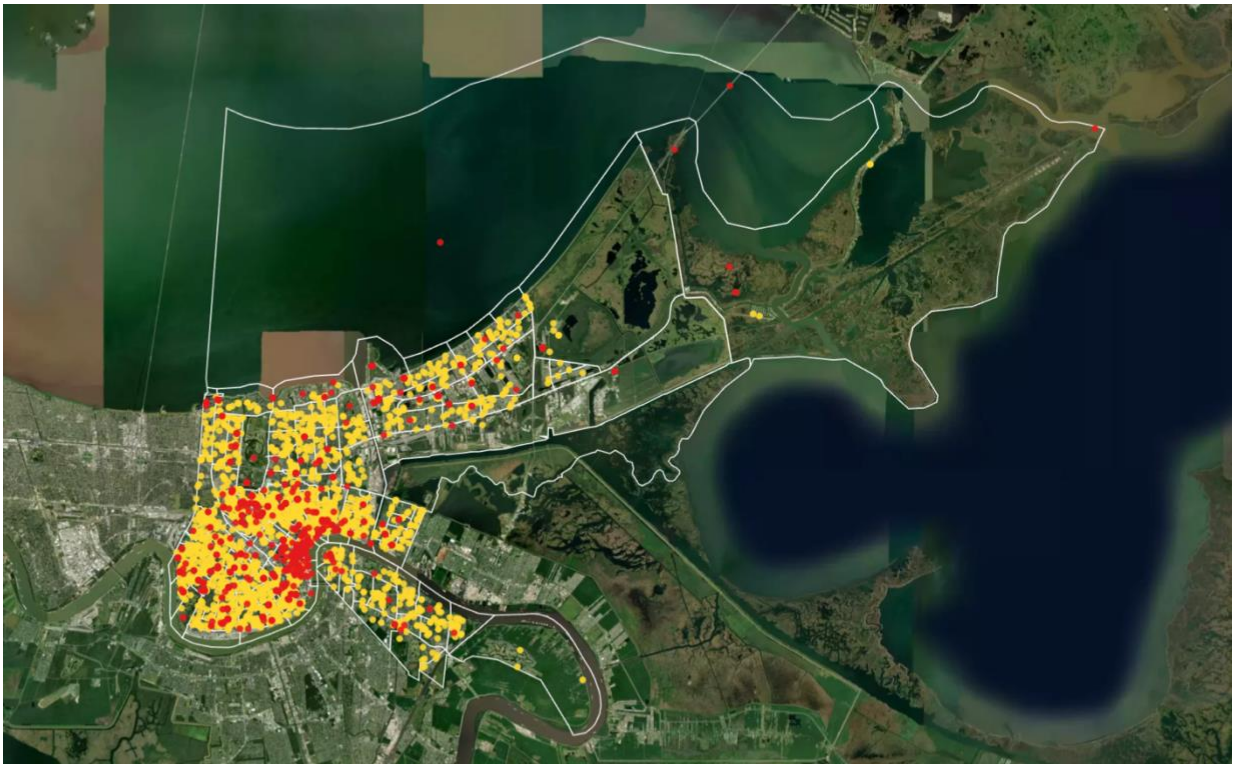
1. Twitter Data

Twitter is a popular social networking site where users broadcast short texts known as tweets, which can contain texts, pictures, links and locations. Thanks to the courtesy of Professor Shan Jian and her Research Team for the Twitter data. The Twitter dataset provided represents tweets from August 20, 2020 to August 29, 2020 within the bounding box of {(30.17457, -89.626938), (29.765921, -90.294479)}. The Twitter dataset includes the following information: userID, timestamp, Latitude, Longitude, tweetID, and tweetContent.

2. NOLA 311 Calls Dataset

NOLA 311 Calls is a dataset that represents calls from residents to request non-emergency services from the Orleans Parish, Louisiana. Examples of request reason include broken roads, street cleaning, COVID-19 business, and property maintenance. 311 allows citizens in the community to help raise awareness of non-emergency issues and ensure that authorities are aware of existing problems. The dataset was downloaded from the City of New Orleans website (See Appendix B, Section 1). The dataset contains calls from 2012 to October 27, 2022 – the latest updated date before the dataset was downloaded – and contains the following example columns: Request Type, Data Created, X, and Y. In pre-processing, we will select the calls made in between August 20, 2020 to August 29, 2020, which were the days when Hurricane Marco was formed and when Hurricane Laura dissipated.

Data source: City of New Orleans Open Data. "311 OPCD Calls (2012-Present)." Available at: https://data.nola.gov/City-Administration/311-OPCD-Calls-2012-Present-/2jgv-pqrq.



Map 3. Twitter (Red) and 311 Calls (Yellow) within the City of New Orleans.

3. Storm Warning Summary

A National Hurricane Center report provides a storm surge watch and warning summary table for Hurricane Marco and Laura, which includes the times and locations of all storm surge watch and warning. We will select relevant storm surge watch and warning to compare with the Twitter data and the 311 Calls in a histogram.

Data Source: (1) John L. Beven II, & Robbie Berg. March 31, 2021. HURRICANE MARCO (AL 142020). National Hurricane Center. Available at: https://www.nhc.noaa.gov/data/tcr/AL142020_Marco.pdf. Page 21-23. (2) Richard J. Pasch, Robbie Berg, David P. Roberts, & Philippe P. Papin. May 26, 2021. HURRICANE LAURA (AL132020). National Hurricane Center. Available at: https://www.nhc.noaa.gov/data/tcr/AL132020_Laura.pdf. Page 46-52.

4. Maximum Sustained Wind Speed

A National Hurricane Center report provides a maximum sustained wind speed summary table for Hurricane Marco and Laura, which includes times, locations, and the maximum wind speed recorded. We transferred the data into an Excel sheet and compared the wind speed data with the Twitter data and the 311 Calls in a histogram.

Data Source: (1) John L. Beven II, & Robbie Berg. March 31, 2021. HURRICANE MARCO (AL 142020). National Hurricane Center. Available at: https://www.nhc.noaa.gov/data/tcr/AL142020_Marco.pdf. Page 14-15. (2) Richard J. Pasch, Robbie Berg, David P. Roberts, & Philippe P. Papin. May 26, 2021. HURRICANE LAURA

(AL132020). National Hurricane Center. Available at: https://www.nhc.noaa.gov/data/tcr/AL132020_Laura.pdf. Page 21-23.

5. FEMA National Risk Index

The FEMA National Risk Index is a dataset that describe the risk in U.S. communities (counties and census tracts) for eighteen natural hazards, including flooding, hurricane, and landslide. The FEMA National Risk Index includes three components: (1) Expected Annual Loss, (2) Social Vulnerability, and (3) Community Resilience. The National Risk Index calculates each of the components as follows: ***Expected Annual Loss * Social Vulnerability / Community Resilience*** (See Appendix B, Section 2). This project uses the total expected annual loss for hurricane to be a part of our risk analysis (See Appendix B, Figure 2, row180).

Data Source: FEMA. National Risk Index Data Resources. Available at: https://hazards.fema.gov/nri/data-resources#spatialTribal.

6. U.S. Census Bureau: The Community Resilience Estimates (CRE)

The 2019 Community Resilience Estimates (CRE) is a U.S. Census Bureau program which provides a metric that measures how individuals and household within a community would response or absorb the impacts made by disasters. The CRE groups the population estimated into three categories: zero risk factors, one-two risk, and three plus risk factors. These risk factors were determined by adding up binary components of 10 risk factors from Census Bureau's ACS American Community Survey (See Appendix B, Section 3). We are using the CRE data to validate the result of our communication risk analysis.

Data Source: U.S. Census Bureau. 2019. "Community Resilience Estimates. [Dataset]" Available at: https://www.census.gov/programs-surveys/community-resilience-estimates.html.

5. Methods

This project seeks to answer the three research questions by conducting a spatial analysis, a temporal analysis, and a risk analysis. Before performing any data analysis, our data needed to be cleaned. We converted timestamp from unit time to date time in pandas, built geometry columns, set coordinate system, selected data points to be within the boundary of the City of New Orleans and to be in between August 20, 2020 and August 29, 2020, created a communication type column (0 represents tweets; 1 represents 311 Calls), and merged all datasets by time or location.

After cleaning data, we created a joint kernel density estimates map (See Appendix C, Example Code #1) and two individual kernel density estimates maps of tweets and 311 Calls in Seaborn (See Appendix C, Example Code #2) to compare the spatial patterns of tweets and 311 Calls.

Next, we plotted a few histograms in Seaborn to see how the frequencies of tweets and 311 calls changed over time in relation to the Hurricanes' movements. We used Seaborn to create a line plot to see the frequencies of tweets and 311 Calls in each hour of the day (See Appendix C, Example Code #3).

Finally, to find where people have a higher disaster communication risk, or where people face greater disaster risks while potentially lacking disaster communication resources, we created a risk map in the unit of census tracts. Our risk map follows the Equation #1. All the calculations were done in pandas (See Appendix C, Example Codes 4 & 5), while a min-max normalization was applied (See Appendix C, Example Code #6).

$$\begin{aligned} &\textit{Hurricane Communication Risk} \\ &\quad = \textit{Expected Annual Economic Loss from Hurricane} \\ &\quad \times \textit{Hurricane Communication Vulnerability Score}\ (\textit{Equation}\ \#1) \end{aligned}$$

The expected annual economic loss from hurricane was estimated by the FEMA National Risk Index (See Appendix B, Section 2), and communication vulnerability was derived from the Twitter data, 311 Calls, and population (See Equation #2).

$$\begin{aligned} &\textit{Communication Vulnerability Score} \\ &\quad = (\textit{Twitter Activity} + 311\ \textit{Calls Activity}) \\ &\quad \div \textit{Number of People in the Census Tract}\ (\textit{Equation}\ \#2) \end{aligned}$$

6. Results (Spatial analysis/statistical analysis)

Type	Count
Tweets	1,640
311 Calls	2,236

Table 2. Counts of Tweets and 311 Calls from August 20, 2020 to August 29, 2020 in NOLA.

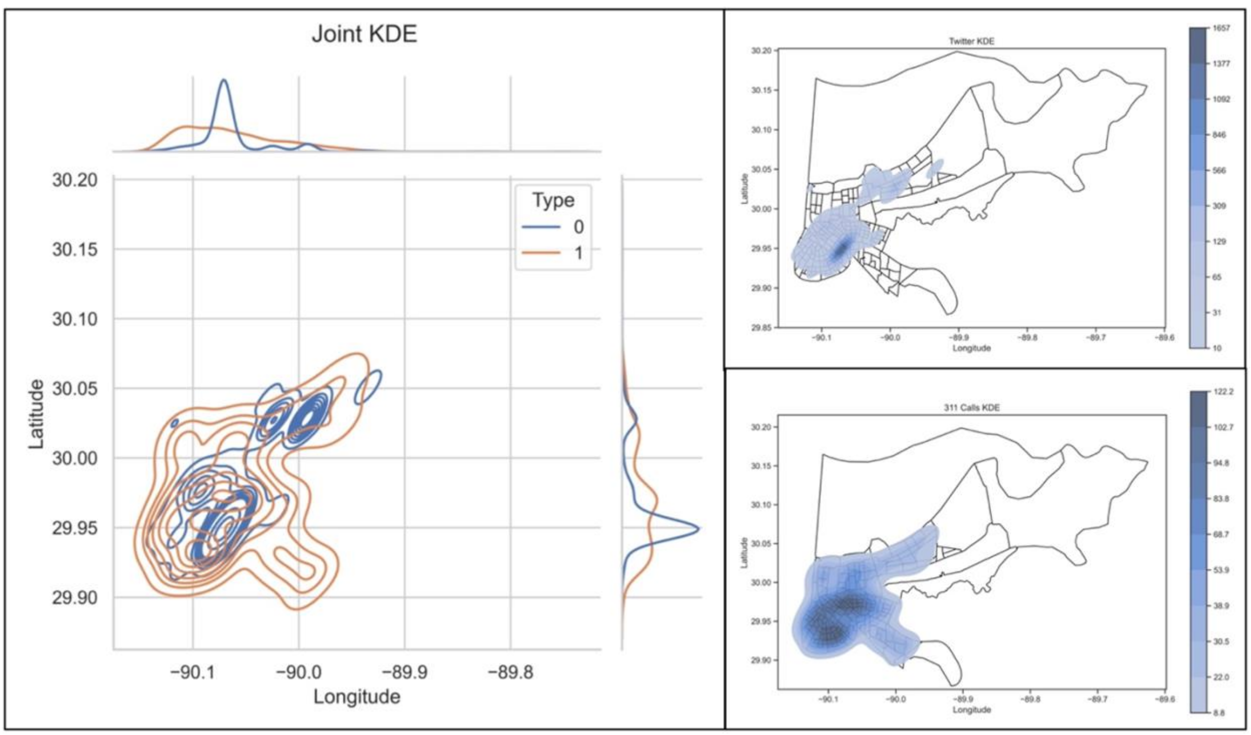


Figure 1. (a) (Left) Joint Kernel Density Estimate of the Tweets and 311 Calls (Legend: 0 represents tweets, and 1 represents 311 Calls). (b) (Upper Right) Kernel Density Estimate of Tweets. (c) (Lower Right) Kernel Density Estimate of 311 Calls.

Around the time of Hurricane Marco and Hurricane Laura, 1,640 tweets were posted on Twitter and 2,236 calls were made to the City of New Orleans (See Table 2). As shown in Figure 1a, almost all tweets posted around Hurricane Marco and Hurricane Laura were concentrated in the area at around -90.08 in longitude and 29.95 in latitude; in contrast, 311 Calls were more dispersed, distributed across most areas in the City of New Orleans. According to Figure 1b, many areas around the ocean and the river did not post any tweets, which could mean that those areas did not have internet access and should be investigated thoroughly. In addition, the areas where tweets and 311 calls concentrated did not overlap (See Figure 1b & 1c). In other words, areas where people tweeted the most are not the areas where people used 311 Calls services the most, and areas where people called 311 the most did not tweet during Hurricane Marco and Laura. This might be that people at different parts of the City of New Orleans had different preferences or that only the people tweeted had internet access.

Figure 2. Maximum Sustained Wind Speed of Hurricane Laura and Marco from August 20, 2020 to August 28, 2020.

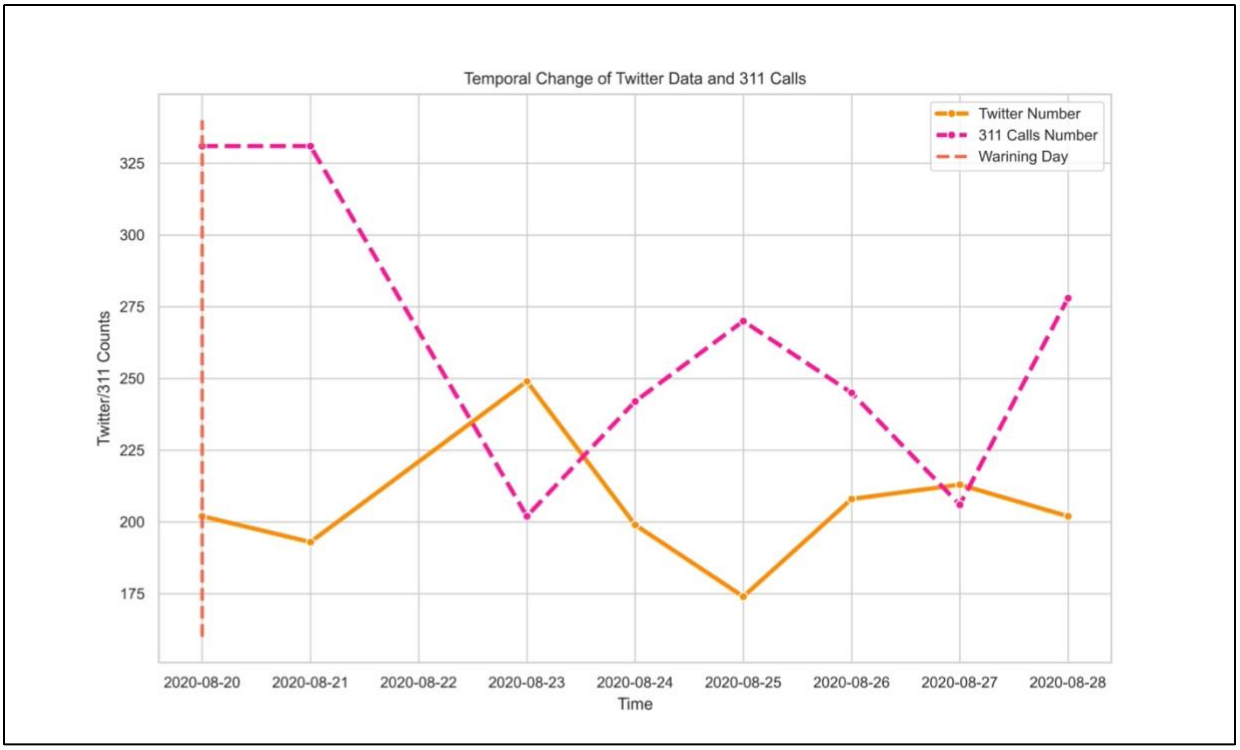


Figure 3. Temporal Change of Twitter Data and 311 Calls from August 20, 2020 to August 28, 2020.

From Figure 3, we can see that the government in New Orleans sent warnings on August 20 before these two hurricanes made landfall. Hurricane Macro made landfall on August 24 and Hurricane Laura made landfall on August 27. Overall, people used 311 Calls more frequently than Twitter during hurricanes, and we can find a huge gap between 311 Calls and Twitter posts after hurricane Macro and Laura made landfall. Twitter posts increased as 311 Calls decreased before August 24, but the number of 311 Calls exceeded the number of Twitter posts on August 23. Hurricanes didn't make any destruction before August 24, so there are no huge demands for help and people tend to use Twitter to send warning messages and hurricane information. There is a shapely increase of 311 Calls after hurricane Marco made landfall. We also can observe the same characteristics after hurricane Laura made landfall. Overall, the 311 Call platform is a major communication tool compared with Twitter platform. People tend to use formal communication platforms like 311 Calls to seek assistance from government and emergency offices. On the other side, people also like to use social media like Twitter to share disaster information before hurricanes made landfall. 311 Calls reached a peak between 12:00 am and 16:00 pm between August 20, 2020 to August 28, 2020. The government and emergency office received the highest number of 311 requests from 12:00 am to 16:00 pm. 311 Calls continued to increase before 12:00 am and reached a peak at 12:00 am or 16:00 pm, but 311 Calls request decreased after 16:00 pm. This changing pattern can be found from August 20, 2020 to August 28, 2020. As for the Twitter posts, the peak time of Twitter Data is later than the peak time of 311 Calls, which often can be found from 17 pm to 20 pm. In addition, the number of Twitter data increased gently before 9 am and decreased subtly dramatically after the peak time (See Appendix D, Figure 1). We also can utilize the wind speed graph to observe the difference between Twitter posts and 311 Calls. When the wind speed decreased from August 20 to August 22, the number of 311 Calls also decreased but we can observe an increase in Twitter Data. 311

Calls followed a similar pattern with Wind Speed Data, but we cannot find the obvious relationship between Twitter Data and Wind Speed Data.

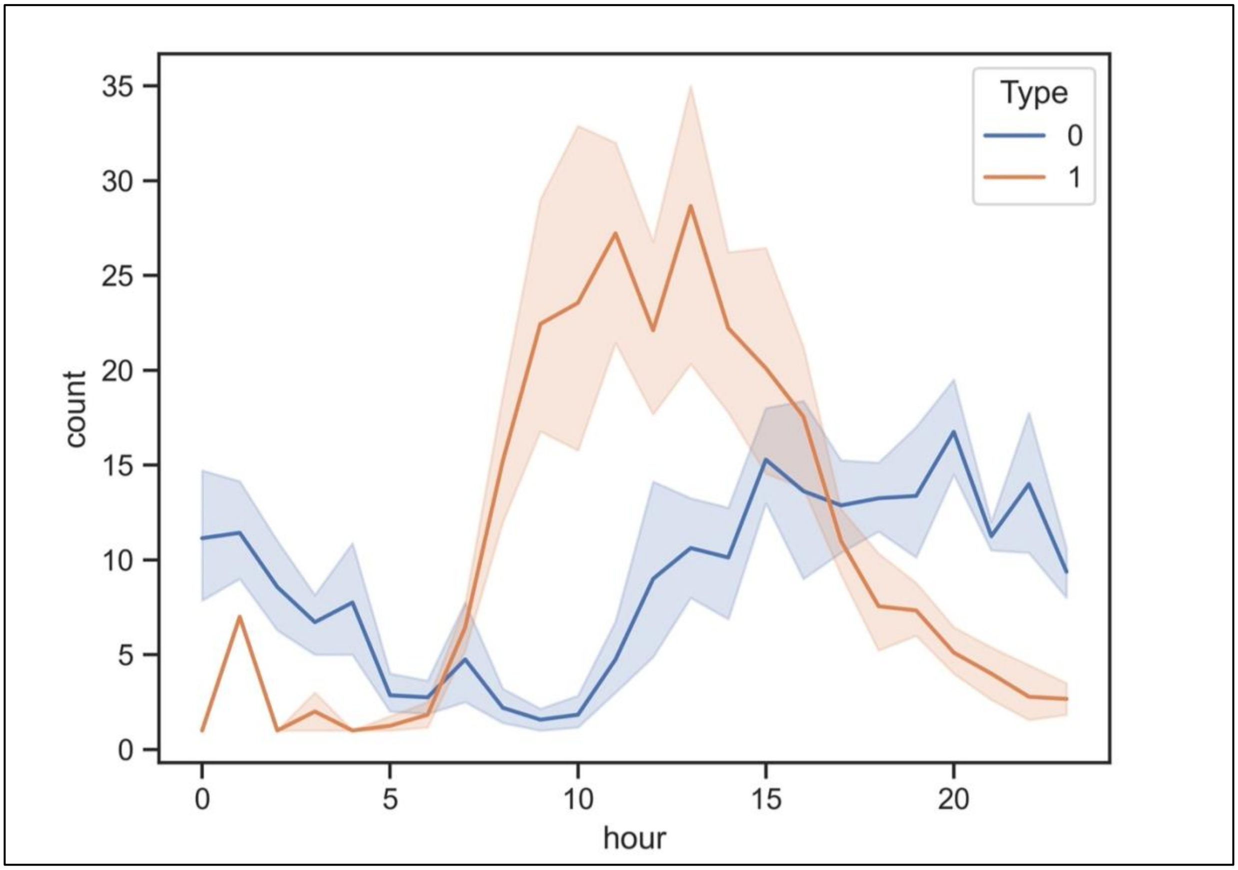


Figure 4. Hour of Day When People Tweeted and Called 311.

As a continuation of our temporal analysis, Figure 4 shows the frequencies of tweets and 311 calls at each hour of the day from August 20, 2020 to August 29, 2020. We see that the number of 311 calls started rising in between six and seven a.m. and the number of tweets started rising later around 10 a.m. In contrast to how tweets and 311 calls were distributed spatially, 311 calls were more concentrated in a certain timeframe while tweets were more spread out temporally.

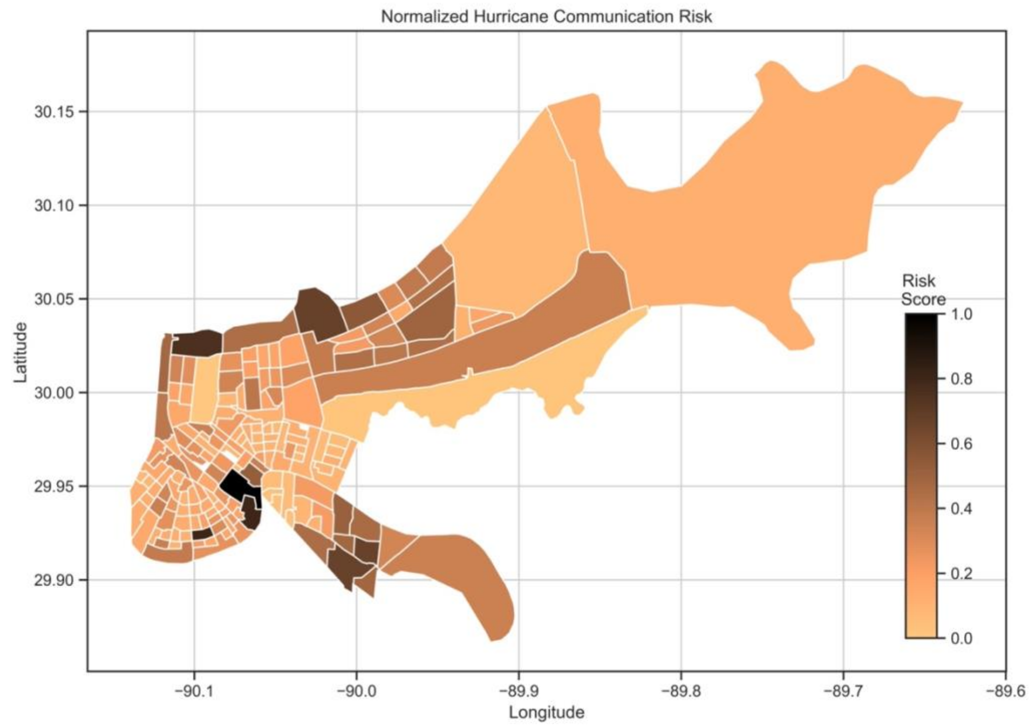


Figure 5. Normalizes Hurricane Communication Risk Map. See Appendix D, Figure 3 for a visualization in CARTO.

In our risk analysis, we produced a risk map using expected annual economic loss from hurricane, twitter activity, 311 Calls activity, and population. Appendix D, Figure 2a is a map that shows the population in the City of New Orleans census tracts. We see that the population in the City of New Orleans were mostly distributed along the ocean and the river. Appendix D, Figure 2b and 2c are maps that show the counts of Twitter data and 311 Calls in census tracts, from which we can see that there was a census tract where there were high numbers of tweets and 311 Calls. Appendix D, Figure 2d shows the total expected annual economic loss from hurricane for each census tract. From Appendix D, Figure 2b & 2d, we see that there was a high correlation between tweets and expected annual economic loss from hurricane, showing that areas where people tweeted the most has a higher expected annual economic loss from hurricane. The final hurricane communication risk map (Figure 5) indicates that the most vulnerable areas are near the ocean and the river, and the inland areas are less vulnerable. Finally, using the 2019 Community Resilience Estimates as our form of validation (See Appendix D, Figure 3), we see that there is only a slight overlap between the two, which might mean that disaster communication or expected economic loss has a low correlation with the Community Resilience Estimates indicators (See Appendix B, Section 3).

7. Discussions (Policy Implications)

Social media data is increasingly being used to improve disaster resilience and response. In order to obtain insight into the regional and social discrepancies in social media usage around disasters, there have been greater initiatives in recent years to connect social media feeds with various demographic and socioeconomic variables. Although they can help in understanding and quantifying the communities' sensitivity to natural hazards and their capacity for responding to and recovering from disasters, vulnerability concepts and indicators have been generally ignored. This study shows that no matter which communication tools are used, they can play different roles in disaster communication. Governments and authorities can apply communication tools like Twitter, 311 Calls, Instagram and Facebook to disaster management in order to gain a better understanding of disaster resilience. The kernel density map for Twitter and 311 Calls can help the government and emergency office to identify the areas where are lacking communication ways and tools. The new index of disaster risk included the communication risk can become more comprehensive for government to identify disaster-vulnerable areas. In addition, our research can help government further determine if socially vulnerable communities were digitally left behind in pre-disaster social responses to Hurricane Marco and Laura. The social and geographical disparities in Twitter and 311 Calls use found in this study imply that communities with better socioeconomic conditions are more likely to have access to hazard information and receive rescue response during emergency. Our study also showed that 311 Calls is a useful platform for people to seek assistance, so government can pay attention to the role of related and similar platforms in disaster management.

8. Conclusion and Future Work

This project has performed a temporal analysis, a spatial analysis, and a vulnerability analysis. The results show that people preferred different ways of communication methods during the time of hurricanes, based on locations and times. People living in the areas along the ocean and the river also suffer from a higher level of communication vulnerability.

However, this study only includes one social media source – Twitter, and one phone data – 311 Calls. For a more accurate estimation in disaster communication vulnerability, future study is encouraged to incorporate more data from other social media platforms, such as Facebook and Instagram, and from other two-way remote communication devices, such as text messages. We would also encourage future study to compare our results with actual hurricane damages to see if there were any correlations between actual damages and communication types. A field trip to the City of New Orleans might also benefit the understanding of the area.

Additionally, to gain a more precise understanding of how Twitter users communicate during a disaster, future study is encouraged to conduct network analysis and to collect and download real-time Twitter data, which would have information about the retweet function on Twitter. Future study can also compare social media data with electricity data to see if there are correlations between them and determine if real-time social media data can predict power outage during a natural disaster.

Gaining a better understanding of the importance of social media in the disaster relief can help policy makers to design more useful evacuation plans which conclude the vulnerable groups (poor people, minorities, children and elderly people). In recent year, the emergency management community has used social media far more frequently, particularly during emergencies and catastrophes. This study hopes to help the government and planners get the most out of social media in disaster management. Every life lost in disasters is unbearable for a family. Our research hopes to make governments and disaster planners aware of the importance of social media in saving lives and property damage, as well as the limitations of social media. Governments should be aware that areas with poor social media and networks accessibility are more vulnerable to and less likely to recover from disasters, and that these areas often do not have a good disaster planning and evacuation plans. It is also one of the objectives of our study to pay attention to vulnerable areas and groups in future planning.

9. References

Achrekar, H., Gandhe, A., Lazarus, R., Yu, S. H., & Liu, B. (2011, April). Predicting flu trends using twitter data. In *2011 IEEE conference on computer communications workshops (INFOCOM WKSHPS)* (pp. 702-707). IEEE.

Agarwal, A., Xie, B., Vovsha, I., Rambow, O., & Passonneau, R. J. (2011, June). Sentiment analysis of twitter data. In *Proceedings of the workshop on language in social media (LSM 2011)* (pp. 30-38).

Akhil Anil Rajput, Qingchun Li, Cheng Zhang & Ali Mostafavi. 2020. "Temporal network analysis of inter-organizational communications on social media during disasters: A study of Hurricane Harvey in Houston." International Journal of Disaster Risk Reduction, 46, 101622. Available at: https://doi.org/10.1016/j.ijdrr.2020.101622.

Ames, M., & Naaman, M. (2007, April). Why we tag: motivations for annotation in mobile and online media. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 971-980).

Ashktorab, Z., Brown, C., Nandi, M., & Culotta, A. (2014, May). Tweedr: Mining twitter to inform disaster response. In *ISCRAM* (pp. 269-272).

Chatfield, A. T., & Reddick, C. G. (2018). Customer agility and responsiveness through big data analytics for public value creation: A case study of Houston 311 on-demand services. Government Information Quarterly, 35(2), 336-347.

City of New Orleans Open Data. "311 OPCD Calls (2012-Present). [Dataset]" Available at: https://data.nola.gov/City-Administration/311-OPCD-Calls-2012-Present-/2jgv-pqrq.

Crandall, D. J., Backstrom, L., Cosley, D., Suri, S., Huttenlocher, D., & Kleinberg, J. (2010). Inferring social ties from geographic coincidences. *Proceedings of the National Academy of Sciences*, *107*(52), 22436-22441.

Cutter, S. L., Burton, C. G., & Emrich, C. T. (2010). Disaster resilience indicators for benchmarking baseline conditions. Journal of homeland security and emergency management, 7(1).

Dwyer, A., Zoppou, C., Nielsen, O., Day, S., & Roberts, S. (2004). Quantifying social vulnerability: a methodology for identifying those at risk to natural hazards.

Federal Emergency Management Agency. (2020, November). Determining Risk | National Risk Index. Mapping Information Platform. Retrieved November 16, 2022, from https://hazards.fema.gov/nri/determining-risk.

FEMA. “Data Source. [Dataset]” National Risk Index. Available at: https://hazards.fema.gov/nri/data-resources#hdrDownload.

Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., & Lewis, B. (2011). A social vulnerability index for disaster management. Journal of homeland security and emergency management, 8(1).

Jungwon Yeo, Claire Connolly Knox & Qian Hu. 2020. “Disaster Recovery Communication in the Digital Era: Social Media and the 2016 Southern Louisiana Flood.” Risk Analysis, 42, 8. Available at: https://doi-org.ezproxy.library.tufts.edu/10.1111/risa.13652.

Jurdak, R., Zhao, K., Liu, J., AbouJaoude, M., Cameron, M., & Newth, D. (2015). Understanding human mobility from Twitter. *PloS one*, *10*(7), e0131469.

Juntunen, L. (2004). Addressing social vulnerability to hazards (Doctoral dissertation, University of Oregon).

Madkour, N. (2020). Predicting Non-Emergency 311 Requests for an Efficient Resource Allocation After a Disaster in Houston, Tx (Doctoral dissertation, Lamar University-Beaumont).

Mihunov, V. V., Lam, N. S., Zou, L., Wang, Z., & Wang, K. (2020). Use of Twitter in disaster rescue: lessons learned from Hurricane Harvey. *International Journal of Digital Earth*, *13*(12), 1454-1466.

Momin, K. A., Kays, H. M., & Sadri, A. M. (2022). Identifying Crisis Response Communities in Online Social Networks for Compound Disasters: The Case of Hurricane Laura and Covid-19. arXiv preprint arXiv:2210.14970.

Morrow, B. H. (1999). Identifying and mapping community vulnerability. Disasters, 23(1), 1-18.

NASA Earth Observatory. 2005. “Hurricane Katrina Floods New Orleans.” Available at: https://earthobservatory.nasa.gov/images/15445/hurricane-katrina-floods-new-orleans.

Nastaran Pourebrahim, Selima Sultana, John Edwards, Amanda Gochanour & Somya Mohanty. 2019. “Understanding communication dynamics on Twitter during natural disasters: A case study of Hurricane Sandy.” International Journal of Disaster Risk Reduction, 37, 101176. Available at: https://doi.org/10.1016/j.ijdrr.2019.101176.

National Hurricane Center. N.d. “Saffir-Simpson Hurricane Wind Scale.” Available at: https://www.nhc.noaa.gov/aboutsshws.php.

Peacock, W. G., Brody, S. D., Seitz, W. A., Merrell, W. J., Vedlitz, A., Zahran, S., ... & Stickney, R. (2010). Advancing resilience of coastal localities: Developing, implementing, and sustaining the use of coastal resilience indicators: A final report. Hazard reduction and recovery center, 1-148.

Rhodan, Maya. August 30, 2017. “'Please Send Help.' Hurricane Harvey Victims Turn to Twitter and Facebook.” TIME. Available at: https://time.com/4921961/hurricane-harvey-twitter-facebook-social-media/.

Richard J. Pasch, Robbie Berg, David P. Roberts, & Philippe P. Papin. May 26, 2021. HURRICANE LAURA (AL132020). National Hurricane Center. Available at: https://www.nhc.noaa.gov/data/tcr/AL132020_Laura.pdf.

Schellong, A., & Langenberg, T. (2006, May). Effective citizen relationship management: hurricane wilma and miami-dade county 311. In Proceedings of the 2006 international conference on Digital government research (pp. 452-453).

The City of New Orleans. 2020a. "Mayor Cantrell Issues Emergency Proclamation Due To Tropical Systems." NOLA Ready. Available at: https://ready.nola.gov/incident/tropical-storm-laura/mayor-cantrell-issues-emergency-proclamation-due-t/.

The Data Center. 2016. "Facts for Features: Katrina Impact." Available at: https://www.datacenterresearch.org/data-resources/katrina/facts-for-impact/.

U.S. Census Bureau. 2019. "Community Resilience Estimates. [Dataset]" Available at: https://www.census.gov/programs-surveys/community-resilience-estimates.html.

U.S. Census Bureau. 2021. "QuickFacts New Orleans city, Louisiana." Available at: https://www.census.gov/quickfacts/neworleanscitylouisiana.

U.S. Department of Transportation. June 1, 2006. Catastrophic Hurricane Evacuation Plan Evaluation: A Report to Congress.

U.S. Census Bureau. "American Community Survey. [Dataset]" Available at: https://www.census.gov/programs-surveys/acs.

Volodymyr V. Mihunov, Nina S. N. Lam, Lei Zou, Zheye Wang & Kejin Wang. 2020. "Use of Twitter in disaster rescue: lessons learned from Hurricane Harvey." International Journal of Digital Earth, 13, 12, 1454-1466. https://doi.org/10.1080/17538947.2020.1729879.

Zou, L., Lam, N. S., Shams, S., Cai, H., Meyer, M. A., Yang, S., ... & Reams, M. A. (2019). Social and geographical disparities in Twitter use during Hurricane Harvey. *International Journal of Digital Earth*, *12*(11), 1300-1318.

Appendix A

Contribution to Project: Grace and Youshuang had run the analysis, written the report, and completed the presentation together.

Member Task Assignment

Data Cleaning: Grace, Youshuang

Histogram: Grace, Youshuang

Kernel Density Estimates: Grace, Youshuang

Vulnerability Analysis: Grace, Youshuang

Report – Introduction: Grace (Lead), Youshuang

Report – Literature Review: Grace, Youshuang (Lead)

Report – Result: Grace, Youshuang

Report – Discussion: Grace, Youshuang

Report – Conclusion: Grace, Youshuang

Report – Citations: Grace, Youshuang

Report – Final Edits: Grace, Youshuang

Presentation Slides: Grace, Youshuang

Appendix B

Metadata

<u>Section 1: 311 Calls</u>

	OBJECTID *	Shape *	Service Request #	Request Type	Request Reason	Date Created	X	Y
40	40	Point	2021-782811	Trash/Recycling	Replace Trash Cart	06/04/2021 01:07:44 PM	3677261.22459	540753.054859
41	41	Point	2021-782810	Property Maintenance	Property Maintenance	06/04/2021 01:06:25 PM	3661512.74522	530987.585922
42	42	Point	2021-782807	Property Maintenance	Property Maintenance	06/04/2021 01:03:23 PM	3661417.96768	530888.72621
43	43	Point	2021-782800	Trash/Recycling	Replace Trash Cart	06/04/2021 12:47:04 PM	3674398.71348	526667.72051
44	44	Point	2022-858754	Roads/Drainage	Catch Basin - Clogged	02/03/2022 09:08:30 PM	3719515.24729	569711.089126
45	45	Point	2022-858751	Roads/Drainage	Man hole cover issue	02/03/2022 08:28:07 PM	3682471.06448	547167.10132

Figure 1. Snapshot of the 311 Calls Dataset. *Data source: City of New Orleans Open Data. "311 OPCD Calls (2012-Present)." Available at: https://data.nola.gov/City-Administration/311-OPCD-Calls-2012-Present-/2jgv-pqrq.*

<u>Section 2: FEMA National Risk Index</u>

- **Expected Annual Loss** is defined as the average economic loss in dollars resulting from natural hazards each year. The National Risk Index has calculated the total expected annual loss and expected annual losses in building value, population, population equivalence, and agriculture value. It is calculated by using a multiplicative equation:

  Expected Annual Loss = Exposure * Annualized Frequency * Historic Loss Ratio

  - Exposure represents the values of buildings, population, or agriculture that might be exposed to a natural hazard occurrence.
  - Annualized Frequency represents the expected probability of natural hazard occurrence per year.
  - Historic Loss Ratio represents the estimated percent of lost values of buildings, population, or agriculture due to an expected natural hazard occurrence.

  (Federal Emergency Management Agency, 2020)

- **Social Vulnerability** refers to the susceptibility of social groups to the adverse effects of natural hazards, including disproportionate death, injury, loss or disruption of livelihoods (Federal Emergency Management Agency, 2020). Social Vulnerability Index (SoVI) utilized 29 socioeconomic variables (See Appendix B, Figure xxx) to conduct location-specific assessments to contribute to a community's recovery ability (Federal Emergency Management Agency, 2020).
- **Community Resilience** is the ability of a community to prepare for anticipated natural hazards, adapt to changing conditions, and withstand and recover rapidly from disruptions (Federal Emergency Management Agency, 2020).

165	HRCN_EVNTS	Hurricane - Number of Events
166	HRCN_AFREQ	Hurricane - Annualized Frequency
167	HRCN_EXPB	Hurricane - Exposure - Building Value
168	HRCN_EXPP	Hurricane - Exposure - Population
169	HRCN_EXPPE	Hurricane - Exposure - Population Equivalence
170	HRCN_EXPA	Hurricane - Exposure - Agriculture Value
171	HRCN_EXPT	Hurricane - Exposure - Total
172	HRCN_HLRB	Hurricane - Historic Loss Ratio - Buildings
173	HRCN_HLRP	Hurricane - Historic Loss Ratio - Population
174	HRCN_HLRA	Hurricane - Historic Loss Ratio - Agriculture
175	HRCN_HLRR	Hurricane - Historic Loss Ratio - Total Rating
176	HRCN_EALB	Hurricane - Expected Annual Loss - Building Value
177	HRCN_EALP	Hurricane - Expected Annual Loss - Population
178	HRCN_EALPE	Hurricane - Expected Annual Loss - Population Equivalence
179	HRCN_EALA	Hurricane - Expected Annual Loss - Agriculture Value
180	HRCN_EALT	Hurricane - Expected Annual Loss - Total
181	HRCN_EALS	Hurricane - Expected Annual Loss Score
182	HRCN_EALR	Hurricane - Expected Annual Loss Rating
183	HRCN_RISKS	Hurricane - Hazard Type Risk Index Score
184	HRCN_RISKR	Hurricane - Hazard Type Risk Index Rating

Figure 2. All the Hurricane Economic Loss Columns from the FEMA National Risk Index. *Source: FEMA. National Risk Index Data Resources. Available at: https://hazards.fema.gov/nri/data-resources#spatialTribal.*

Section 3: U.S. Census Bureau: The Community Resilience Estimates (CRE)

Risk Factors (RF) for Households (HH) and Individuals (I)

- RF 1: Income-to-Poverty Ratio (IPR) < 130 percent (HH).
- RF 2: Single or zero caregiver household - only one or no individuals living in the household who are 18-64 (HH).
- RF 3: Unit-level crowding defined as > 0.75 persons per room (HH)
- RF 4: Communication barrier defined as either
  - Limited English-speaking households[1] (HH) or
  - No one in the household over the age of 16 with a high school diploma (HH)
- RF 5: No one in the household is employed full-time, year-round. The flag is not applied if all residents of the household are aged 65 years or older (HH).
- RF 6: Disability posing constraint to significant life activity
  - Persons who report having any one of the six disability types (I): hearing difficulty, vision difficulty, cognitive difficulty, ambulatory difficulty, self-care difficulty, and independent living difficulty.
- RF 7: No health insurance coverage (I)
- RF 8: Being aged 65 years or older (I)
- RF 9: Households without a vehicle (HH)
- RF 10: Households without broadband Internet access (HH)

Figure 3. Risk Factors Used in the Community Resilience Estimates. Source: U.S. Census Bureau. 2019. “Community Resilience Estimates.” Available at: https://www.census.gov/programs-surveys/community-resilience-estimates.html.

Appendix C

Codes

Example Code #1: joint_kde = sns.jointplot(data=complete_nola, x="Longitude", y="Latitude", hue="Type", kind="kde")

Example Code #2: twitter_kde = sns.kdeplot(data=twitter_nola, x="Longitude", y="Latitude", fill=True, alpha=0.9, cbar=True)

Example Code #3: hour_of_day = sns.lineplot(x="hour", y="count", data=ultimate_count, hue="Type")

Example Code #4: nola_clean_geojson.loc[:,'Communication Accessibility %'] = (((nola_clean_geojson['Twitter Count']+nola_clean_geojson['311 Calls Count']) / nola_clean_geojson['POPUNI'])*100)

Example Code #5: nola_clean_geojson.loc[:,'Hurricane Communication Risk'] = ((100-nola_clean_geojson['Communication Accessibility %']) * nola_clean_geojson['HRCN_EALT'])

Example Code #6: nola_clean_geojson.loc[:,'Normalized Hurricane Communication Risk']=((nola_clean_geojson['Hurricane Communication Risk']-nola_clean_geojson['Hurricane Communication Risk'].min())/(nola_clean_geojson['Hurricane Communication Risk'].max()-nola_clean_geojson['Hurricane Communication Risk'].min()))

* Please see the complete code in our Box folder: https://tufts.app.box.com/folder/183063549762.

Appendix D

Additional Figures & Graphs

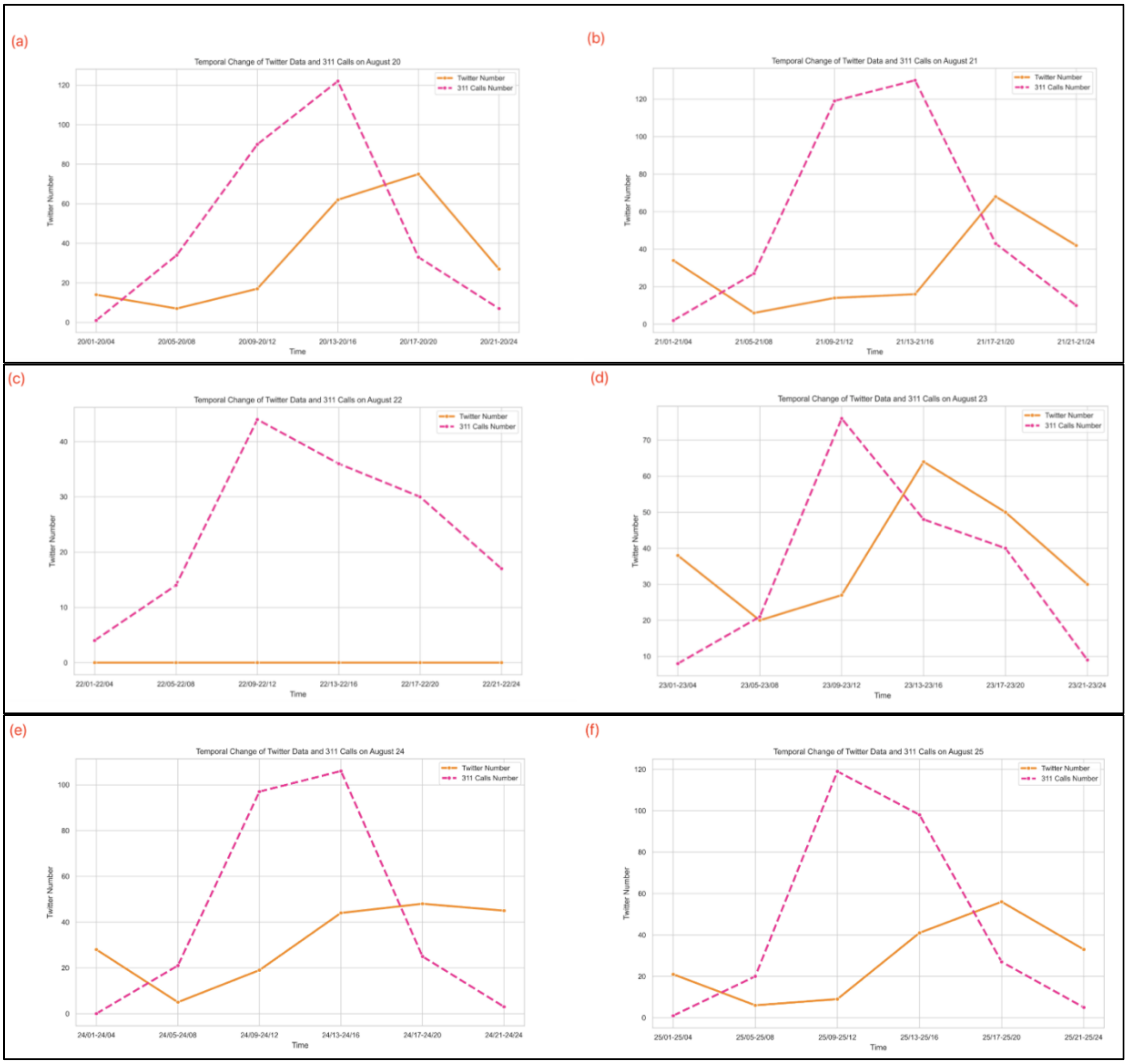


Figure 1. (a) Temporal Change of Twitter Data on August 20, 2020. (b) Temporal Change of Twitter Data on August 21, 2020. (c) Temporal Change of Twitter Data on August 22, 2020. (d) Temporal Change of Twitter Data on August 23, 2020. (e) Temporal Change of Twitter Data on August 24, 2020. (f) Temporal Change of Twitter Data on August 25, 2020.

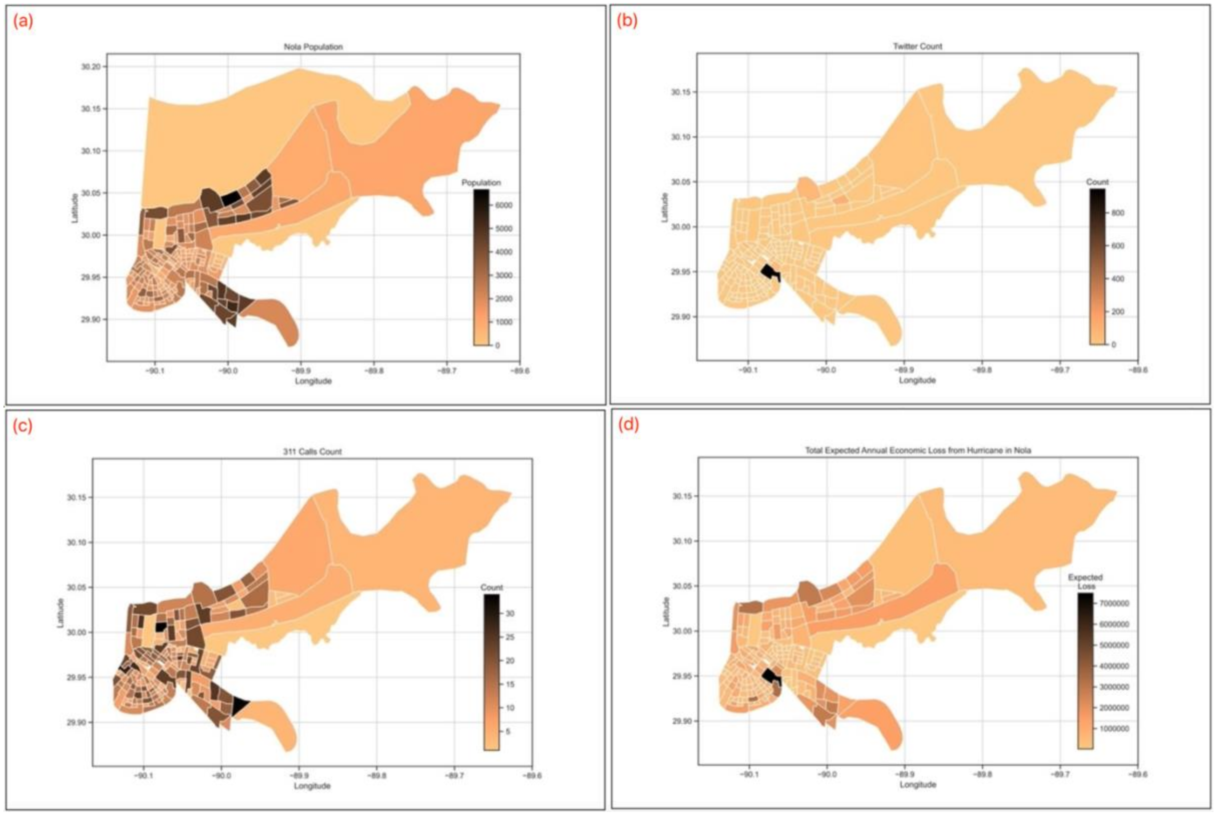


Figure 2. (a) Nola's population within in census tracts. (b) Count of Tweets from 8/20/2020 – 8/29/2020 within Census Tract. (c) Count of 311 Calls from 8/20/2020 – 8/29/2020 within Census Tract. (d) Expected Annual Economic Loss from Hurricane.

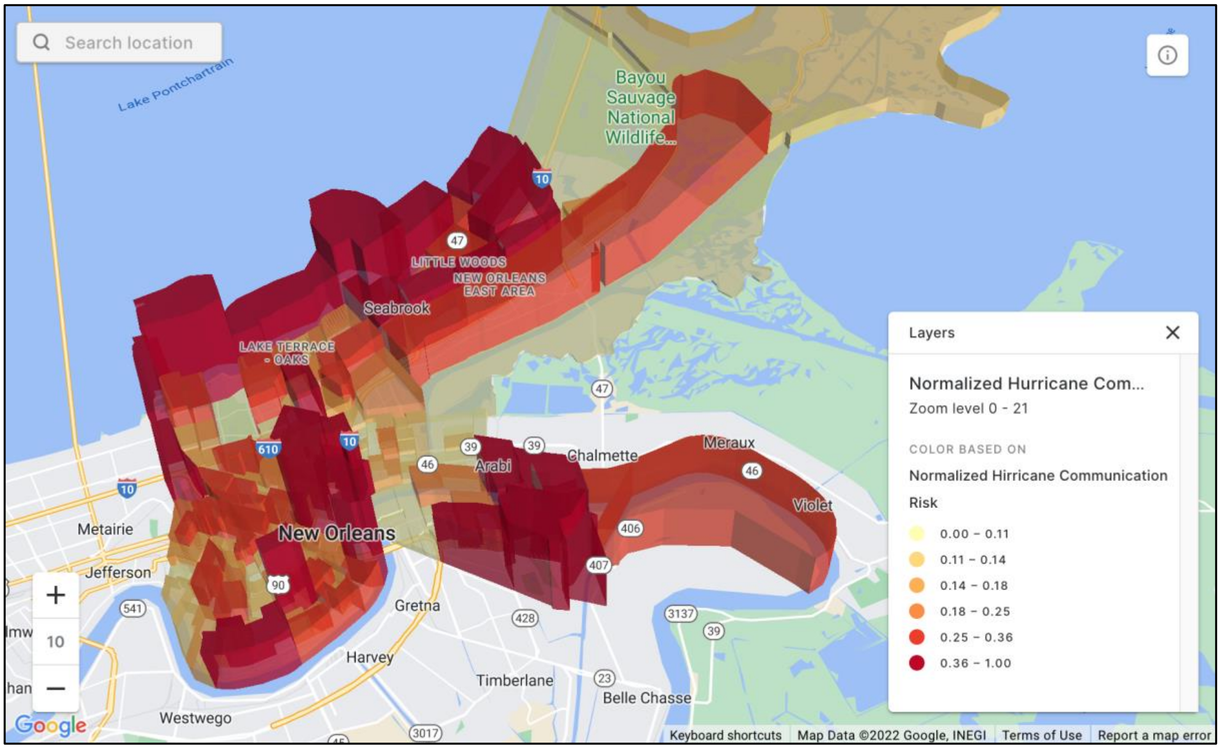


Figure 3. Normalized Hurricane Communication Risk Map in CARTO. Link to map: https://clausa.app.carto.com/map/f111a085-89cf-4aca-9a7b-cc52fb0abaf8.

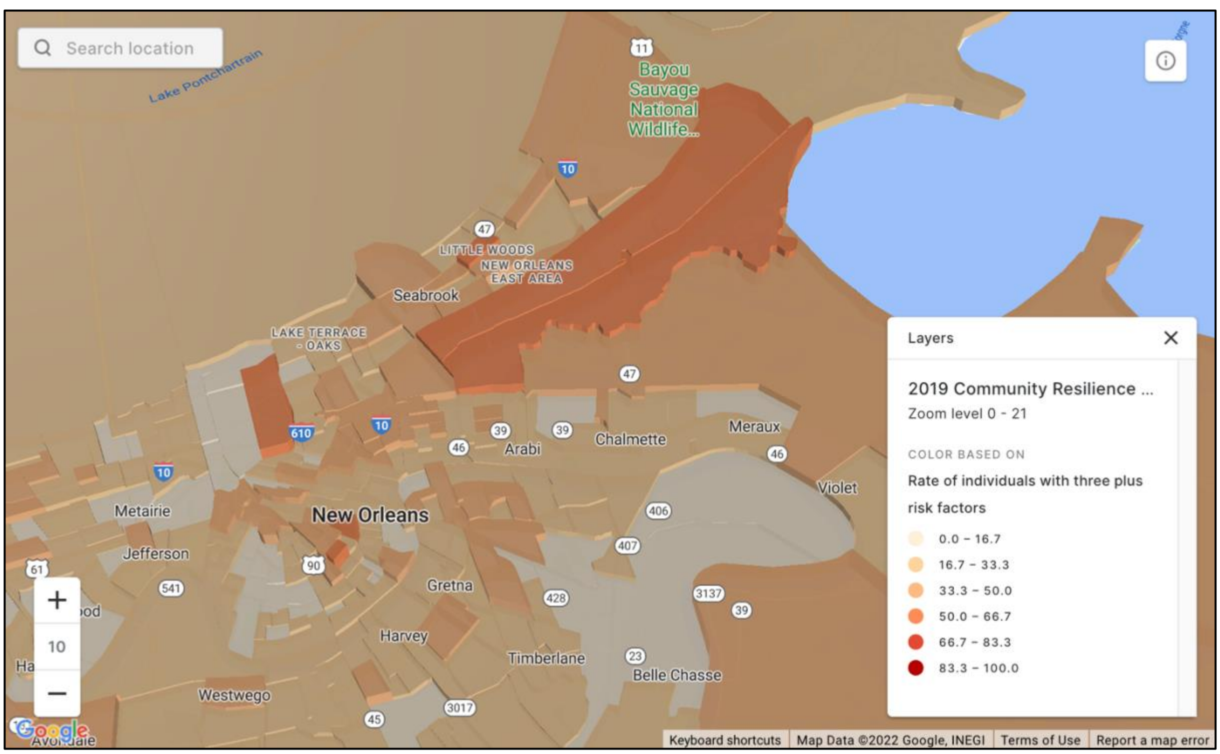


Figure 3. 2019 Community Resilience Estimates Visualization in CARTO. Link to map: https://clausa.app.carto.com/map/f111a085-89cf-4aca-9a7b-cc52fb0abaf8.

Appendix E

Additional Data Sources

National Hurricane Center GIS Archive - Storm Surge Watch/Warming: https://www.nhc.noaa.gov/gis/archive_wsurge_results.php?id=al13&year=20&name=Hurricane%20LAURA.

Wind Speed: https://today.ttu.edu/posts/2020/09/Stories/Hurricane-Laura-data-collection.

Wind and Pressure Reports: https://www.weather.gov/lch/2020Laura-WindPressure.

Employment, wage, and establishment counts in hurricane flood zones: https://www.bls.gov/cew/publications/hurricane-flood-zones-maps/hurricane-maps.htm.

National Flood Layer Resources: https://www.fema.gov/flood-maps/national-flood-hazard-layer.

Where Can I find Flood Maps? (USGS): https://www.usgs.gov/faqs/where-can-i-find-flood-maps.

Global Active Archive of Large Flood Events, 1985-Present: https://floodobservatory.colorado.edu/Archives/index.html.