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Measuring Spatio-Temporal Responses to Hurricane Matthew Employing TwitGis

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Measuring Spatio-Temporal Responses to Hurricane Matthew Employing TwitGis

Abstract

This study explores spatio-temporal responses to Hurricane Matthew across the US states by analyzing Twitter data. This study finds that people in different states and periods respond differently to Hurricane Matthew. For instance, people in the Midwest and Northeast regions show a high proportion of tweets in the pre-hurricane period. Those in the Southeast region demonstrate a high proportion of those in the hurricane period, and those in the West region show a high proportion of those in the post-hurricane period. This study also finds that people increase long distance trips (over 100 km) and decrease short distance trips (within 5 km, between 5 and 10 km, and between 10 and 25 km) in the hurricane period. Lastly, people show the most different displacements between the Twitter data and the theoretical model in the hurricane period.

Keywords

human response, trajectories, hurricane, Matthew, natural disaster

1 INTRODUCTION

Natural disasters occur frequently and threaten human's life and property every year. They claimed 10,400 lives and inflicted $160 billion of damage in 2018 across the world (Phys.org 2019). Therefore, minimizing damage from natural disasters has been one of the most important issues for governments and urban planners (see e.g., Haddad and Teixeira 2015; Rus et al. 2018; Zhou et al. 2018). Many countries have developed natural disaster policies and tried to investigate the effects of disaster events on lives and property (see e.g., McAneney et al. 2016; Raikes et al. 2016; Tselios and Tompkins 2017). For example, the US National Committee promotes that state and local jurisdictions review, update, and develop natural disaster policies to improve the quality and ability of hazard and risk management strategies (National Research Council 1991).

However, they have barely explored how natural disasters play an important role in human response and trajectories not only in the damaged regions but also in other regions, while natural disasters are national events rather than local events (see e.g., Ahmouda et al. 2019; Pourebrahim et al. 2019; Qi 2014). For example, Qi (2014) investigates that the human mobility perturbation and Hurricane Sandy only for New York, and Ahmouda et al. (2019) highlight that the effect of Hurricane Harvey on Houston and Hurricane Matthew on Miami-Dade County, and North and South Carolina.

Analyzing the effects of natural disasters at the national level is also very important because people in other regions could also be seriously affected by natural disasters (see e.g., Park et al. 2013; Ye and Abe 2012). For example, Ye and Abe (2012) reveal that the Great East Japan earthquake and the Southeast Asian floods play a significant role in global business environments. Park et al. (2013) highlight that natural disasters seriously affected supply chain disruptions at the company level by exploring four Japanese manufacturing firms (Iryou, Kenki, Sangyo, and Zyuden) in 2011.

Therefore, understanding natural disasters from the national perspective would play an important role in policy development with respect to natural disasters. Not only that, while natural disasters play a different role in regions according to geographical locations and regional characteristics, very few studies have explored how natural disasters play a different role across regions. For instance, Marincioni (2001) shows that natural disasters produce different reactions based on locations by exploring the Mississippi River-Missouri River floods in the US. Yum (2021) highlights that people show different reactions for Hurricane Dorian across US states.

Especially, while some studies explored the effects of natural disasters at the natural level, they have not highlighted the differences between expected mobility patterns and observed patterns for different natural disaster periods (see e.g., Yum 2021; Zhou et al. 2018). In this sense, this study aims to highlight how natural disasters are associated with human response and trajectories across the US states and periods by employing Twitter data based on the case study of Hurricane Matthew.

2 LITERATURE REVIEW

Natural disasters occur across the world and seriously damage lives and property. The global death toll by natural disasters is highly concentrated in developing countries (95% of the total

toll), such as Bangladesh, India, and China (see e.g., Alcántara-Ayala 2002; Alexander 1993). However, they have a considerable impact in developed countries, such as Japan or the US. Especially, the US is extremely vulnerable to natural disasters. All states are damaged by one or more natural disasters: hurricanes, tornadoes, floods, tsunamis, droughts, earthquakes, landslides, volcanoes, and wildfires (National Research Council 1991). Boustan et al. (2017) report that more than 100 natural disasters hit the US every year, causing extreme loss of life and property destruction.

Many scholars have explored how natural disasters play an important role in the US. Masozera et al. (2007) find that Hurricane Katrina has the same effect on New Orleans neighborhoods, regardless of elevation, income, and other social variables. Nix-Stevenson (2013) highlights human response to natural disasters by exploring the connection between socioeconomic status, education, and natural disasters, such as Hurricane Katrina. Boustan et al. (2017) show that severe natural disasters decrease housing prices/rents by 2.5-5.0 percent and increase migration rates by 1.5 percent in the US between 1930 and 2010.

On the other hand, social media have become one of the most useful tools to track the damage of natural disasters and understand human response to them. This is because social media are considered important sources for collection and transmission of natural disaster information (Yamamoto 2015). Social media are regarded as new innovative approaches for developing an emergency risk control for reducing the damage of natural disasters (Velev and Zlateva 2011). Even, Governments utilize social media for communication networks to cope with natural disasters. For instance, the Japanese government uses SNS at the municipal level to promote democratic processes, community buildings, and disaster management (Schellong 2007).

Many scholars have utilized social media to understand the effects of natural disasters on human life and environment (see e.g., Al-Saggaf and Simmons 2015; Martínez–Álvarez and Morales–Esteban 2019; Middleton et al. 2013; Murthy and Gross 2017; Smith et al. 2017; Wang and Ye 2018; Zhang et al. 2019). For instance, Zhang et al. (2019) highlight that social media can better guide scholars and planners to achieve better disaster management and response based on 304 studies conducted from 2008 to 2018. Murthy and Gross (2017) report that Twitter users respond to Hurricane Sandy by employing humor, sharing photos, and checking into locations using 142,786 geotagged tweets. Middleton et al. (2013) show a real-time crisis mapping platform of natural disasters using social media based on gazetteer, street map, volunteered geographic information (VGI) sources, and Twitter data.

Al-Saggaf and Simmons (2015) reveal that social media help users communicate the gravity of the damage of floods in Saudi Arabia by exploring YouTube, Facebook, Al-Saha Al-Siyasia and Al Arabiya. Smith et al. (2017) exhibit that social media play a successful role as a data source for flood risk management during two 2012 flood events in the UK. Wang and Ye (2018) report that social media have become prominent in natural disaster analyses based on 94 papers.

Among social media, Twitter is one the most reliable and useful sources to gather information on natural disasters because of the number of users, Twitter API (Application Programming Interface), and Geotagging system. Scholars have tried to highlight the relationship between human response and natural disasters by employing Twitter data. For instance, Doan et al. (2011) highlight that Twitter data can be utilized as a reliable methodology for tracking human response to natural disasters by analyzing over 1.5 million tweets between March 9, 2011 and May 11, 2011 for the 2010 Tohoku Earthquake and

subsequent tsunami, and nuclear emergencies. Chatfield and Brajawidagda (2012) show that Twitter plays an important role in the early warning network for natural disasters by analyzing the 2012 Indonesia Earthquake. Palen et al. (2010) argue that Twitter is used to distribute natural disaster information during the 2009 Red River Valley flood threat by analyzing 20,000 tweet communications.

Pourebrahim et al. (2019) show that Twitter is a highly valuable source of disaster-related information particularly during Hurricane Sandy's power outage. Karami et al. (2020) report that social media enable people to freely communicate their opinions and disperse information during the 2015 South Carolina flood. Stowe et al. (2018) highlight that a large amount of social media data is uploaded during natural disasters, which allows scholars to understand human behavior. Alam et al. (2018) show that people employ social media platforms to post content to report updates about injured or dead people during natural disasters. Takahashi et al. (2015) show that different people utilize social media mostly for dissemination of second-hand information, in coordinating relief efforts, and in memorializing those affected during Typhoon Haiyan in the Philippines. Murthy and Longwell (2013) find that there is a perceived legitimacy of social media during disasters by users in Pakistan during the 2010 Pakistan floods.

3 RESEARCH METHODOLOGY

Hurricane Matthew is the first Category 5 Atlantic hurricane since 2007 and the most powerful storm of the 2016 Atlantic Hurricane Season. Matthew is responsible for 585 deaths and $10.3 billion damage (National Oceanic and Atmospheric Administration 2016a). This study explores Hurricane Matthew by collecting Twitter data in the Twitter Application Programming Interface. Twitter is a real-time microblogging platform for users who post and interact with messages known as tweets. As of the first quarter of 2019, 330 million people are active on Twitter, and 68 million in the US (Statista 2021a; Statista 2021b). Twitter provides the Twitter Application Programming Interface (API), which enables programmatic access to Twitter to analyze, learn from, and interact with Tweets. Twitter limits its API to 1% of Tweets. Twitter API currently consists of two supported versions (Twitter API v1.1 and Twitter API v2). Twitter API v1.1 is the standard service for getting started, testing an integration, validating a concept, or creating solutions. Twitter API v2 is the new Twitter API with a modern and more sustainable foundation as well as an improved developer experience. The new Twitter API v2 replaces the standard v1.1, premium v1.1, and enterprise APIs in the future (Twitter 2021). Given that Twitter API does not provide access to older tweets than seven days for standard service or 30 days of for premium and enterprise service (Twitter 2021), this study creates a new app called "Twitgis" in Twitter developers to collect old tweets more than 30 days by coding a program written in the R language.

This study selects five keywords ("Matthew," "Hurricane," "Storm," "Tropical," and "Cyclone") since hurricanes are also referred to as tropical storms or tropical cyclones (see e.g., Katzberg et al. 2001; Keim et al. 2007; Webster et al. 2005). By employing Twitgis in RStudio, this study collects 1,237,702 tweets between 09-14-2016 and 10-25-2016 (six weeks). The period consists of two pre-hurricane weeks, two hurricane weeks, and two post-hurricane weeks. This study makes some selection criteria for empirical analyses as follows: first, the text in tweets should be posted in English since the author collects the tweets based

on the English keywords. Second, the tweets should include at least one keyword (Matthew, Hurricane, Storm, Tropical, and Cyclone) in the text. Third, the tweets should be located in the US. Fourth, the tweets should have geotagged information to track human responses and mobility. After filtering the data, this study utilizes 44,392 samples, which are about 3.6% of original data (see Table 1). This study first explores human response to Hurricane Matthew across the whole US states.

Table 1. Data samples.

	Original data	Data filtered
Matthew	290,795	10,151
Hurricane	218,333	8,336
Storm	536,271	19,924
Tropical	144,746	4,214
Cyclone	47,557	1,767
Total	1,237,702	44,392

Next, given that the movement of Hurricane Matthew mainly hits the Southeast region, this study selects three study areas to explore human trajectories based on geographical locations, the impacts of the hurricane, and the proportion of tweets: Florida (FL), Georgia (GA), and South Carolina (SC). The boundaries of three study areas are as follows: Florida (latitude: 24.523096 to 31.000888, and Longitude: -87.634938 to -80.031362), Georgia (latitude: 30.357851 to 35.000659, and Longitude: -85.605165 to -80.839729), and South Carolina (latitude: 32.034600 to 35.215402, and longitude: -83.35391 to -78.54203). The number of tweets in the three regions is 11,259 tweets, which is 25.4% of the filtered data.

This study employs the Haversine formula to explore how the hurricane affects displacements of individuals in different regions (see e.g., Basyir et al. 2017; Chopde et al. 2013; Ingole et al. 2013; Purbaningtyas et al. 2019; Soe 2020). Displacements are defined as the distance between two consecutive geolocations of people based on the Haversine formula. In other words, displacements are the distance calculated by Twitter users who have changed location. The formula calculates the great-circle distance between two points on a sphere using their latitudes and longitudes measured along the surface. The Haversine formula can be expressed as follows:

$$\mathrm{d} = 2\mathrm{r} \times sin^{-1}\left(\sqrt{sin^2\left(\frac{\emptyset_2-\emptyset_1}{2}\right) + cos\emptyset_1\emptyset_2 sin^2\left(\frac{\varphi_2-\varphi_1}{2}\right)}\right) \qquad (1)$$

where d is displacements, r is the earth radius (6,371km), $\varnothing 1$ and $\varnothing 2$ are the latitudes of origin and destination of individuals, and $\phi 1$ and $\phi 2$ are the longitudes of origin and destination of individuals for a trip in a day. This study divides distance categories into six groups based on prior studies as follows: within 5 km, 5-10 km, 10-25 km, 25-50 km, 50-100 km, and over 100 km (see e.g., Ahmouda et al. 2019; Jurdak et al. 2015).

This study employs the Chi-Square test and the Fisher's exact test to check how Hurricane Matthew is statistically associated with spatial displacements. This study runs the Chi-Square test for the whole region and Florida, respectively, and the Fisher's exact test for Georgia and South Carolina since the latter regions do not meet the condition of the Chi-Square test (the expected values less than five should be less than 20%).

This study further employs the radius of gyration formula to explore people's mobility patterns (see e.g., Gonzalez et al. 2008; Pappalardo et al. 2015; Song et al. 2010). This study defines radius of gyration as the root-mean-square average of the distance traveled by individuals from the origin. The formula allows scholars to highlight the trajectory of individuals during the hurricane period and non-hurricane periods. The formula is as follows:

$$\mathrm{g} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left[2\mathrm{r} \times sin^{-1}\left(\sqrt{sin^{2}\left(\frac{\emptyset_k-\emptyset_o}{2}\right) + cos\emptyset_l\emptyset_o sin^{2}\left(\frac{\varphi_k-\varphi_o}{2}\right)}\right)\right]} \qquad (2)$$

where n is the total number of movements, k is each location, o is the origin, r is the earth radius (6,371km), $\emptyset$ is the latitude, and ϕ is the longitude.

This study employs Quantile-Quantile plots to test the differences of observed values and expected values among the pre-hurricane period, hurricane period, and post-hurricane period (see e.g., Augustin et al. 2012; Dhar et al. 2014; Easton et al. 1990). This study further runs deviations of three periods by employing the Kolmogorov-Smirnov test (two-sample) (see e.g., Fasano and Franceschini 1987; Lilliefors 1967; Massey Jr 1951). The test is a nonparametric test to check if two datasets significantly differ. It is widely adopted for checking differences in both location and shape of the cumulative distribution functions of the two data sets. The equation is as follows:

$$D_{m,n} = \max_{x} |F(x) - G(x)| \qquad (3)$$

where m is the size of the first sample, F(x) is the observed cumulative distribution function of the first sample, n is the size of the second sample, and G(x) is that of the second sample.

4 RESULTS

Figure 1 shows the number of tweets according to days (the yellow box indicates the hurricane period). Each keyword is very fluctuated by days. Overall, the total number of keywords rapidly increases from October 3 and decreases from October 6. The total number of tweets increases from October 7 again, and then sharply drops from October 8 to October 11, which is the end point of the hurricane period.

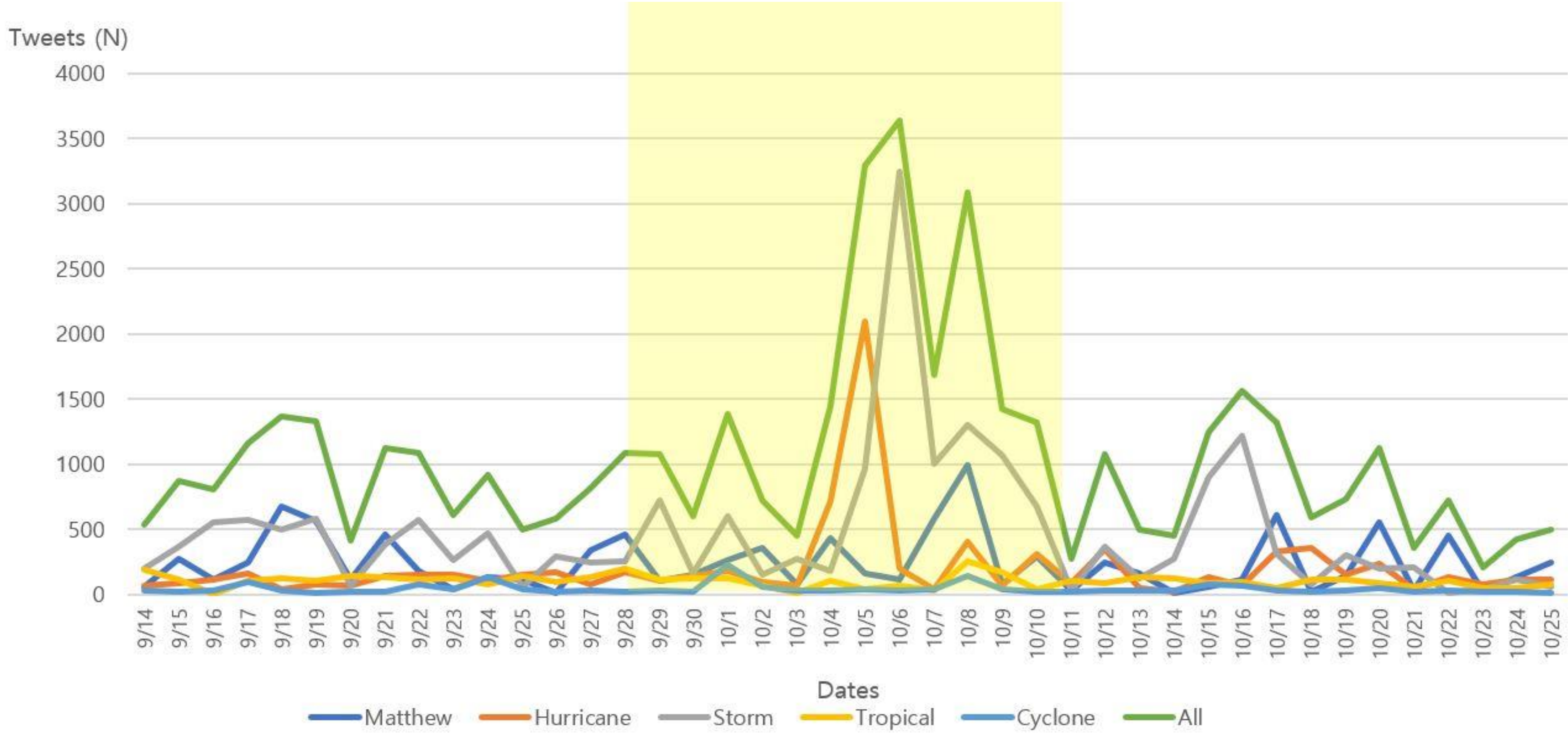
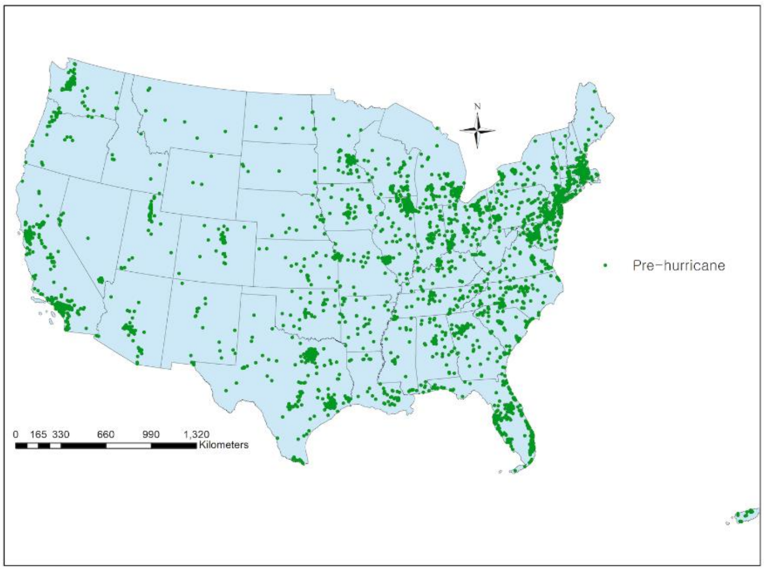


Figure 1. The number of keywords (from 14-Sep-2016 to 25-Oct-2016).

Figure 2 illustrates the location of tweets according to periods. The location of tweets is highly located in the coastal areas in Florida, California, and the Northeast region, such as New York, Connecticut, New Jersey, and Maryland. In the pre-hurricane period, tweets are more concentrated in the coastal areas of the Northeast region, such as New York, Connecticut, and New Jersey than other regions, such as Georgia, North Carolina, and South Carolina. In the hurricane period, tweets are more located in the coastal areas in Florida, South Carolina, and North Carolina. In the post-hurricane period, tweets are more uploaded in the coastal areas in the West region, such as Washington, Oregon, and California.

(A)



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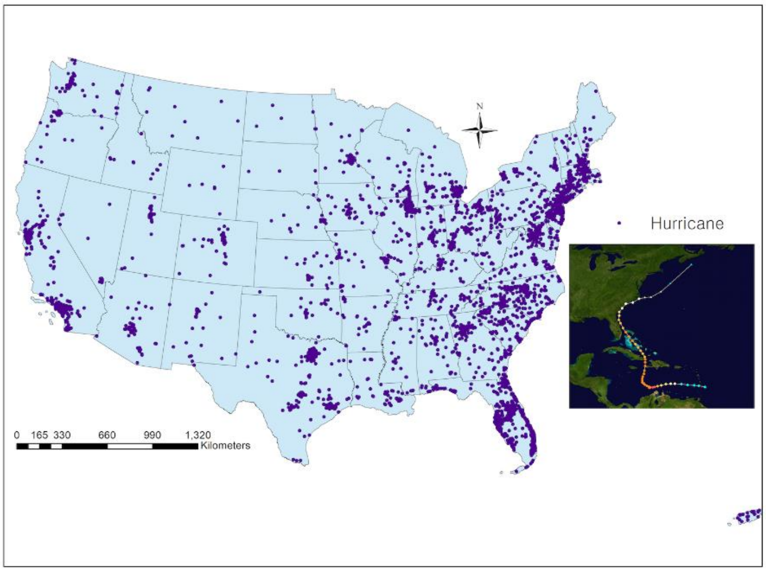


(C)

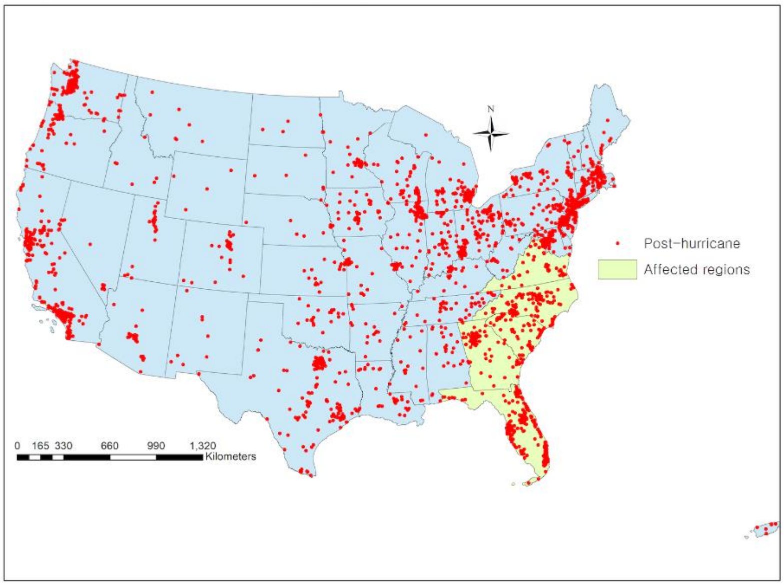


Figure 2. The location of tweets according to periods. (A) pre-hurricane, (B) hurricane, (C) post-hurricane
Source: NOAA (2016b)

Table 2 shows that the proportion of tweets is highly fluctuated by states and periods. In the pre-hurricane period, Texas shows the highest proportion of tweets (9.0%), followed by California (8.9%), Florida (8.7%), New York (6.4%), and North Carolina (4.2%). In the hurricane period, Florida ranks first with the proportion of 28.8, which is 3.3 times higher than the previous period (8.7%) and 2.7 times higher than the second-ranked state (North Carolina: 10.8%). The next states are South Carolina (6.3%) and Georgia (5.2%), and California (4.9%). This result shows that the people in Southeast region respond sensitively to the hurricane event since the movement of Hurricane Matthew mainly hits the Southeast region and they are the most dangerous regions in the study areas. In the post-hurricane period, Washington places first (13.1%), ahead of California (9.5%), Florida (8.8%), Texas (7.0%), and New York (5.9%).

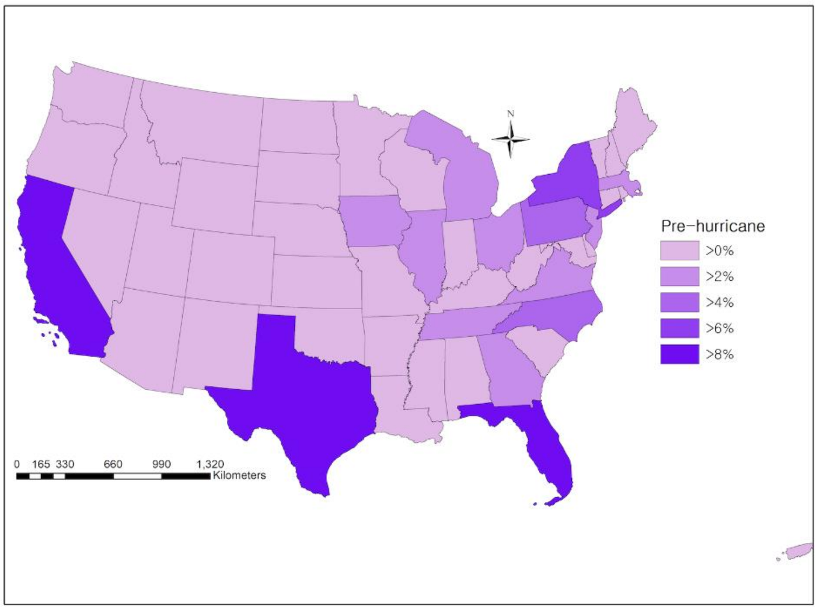
Table 2. The proportion of tweets in top 20 states.

	Pre-hurricane	Hurricane	Post-hurricane
1	Texas (9.0%)	Florida (28.8%)	Washington (13.1%)
2	California (8.9%)	North Carolina (10.8%)	California (9.5%)
3	Florida (8.7%)	South Carolina (6.3%)	Florida (8.8%)
4	New York (6.4%)	Georgia (5.2%)	Texas (7.0%)
5	North Carolina (4.2%)	California (4.9%)	New York (5.9%)
6	Pennsylvania (4.2%)	Texas (4.1%)	North Carolina (5.7%)
7	Georgia (3.8%)	New York (4.1%)	Oregon (3.5%)
8	Illinois (3.5%)	Virginia (3.8%)	South Carolina (3.3%)
9	Ohio (3.3%)	Pennsylvania (2.2%)	Georgia (3.1%)
10	Virginia (3.0%)	Ohio (1.9%)	Maryland (2.9%)

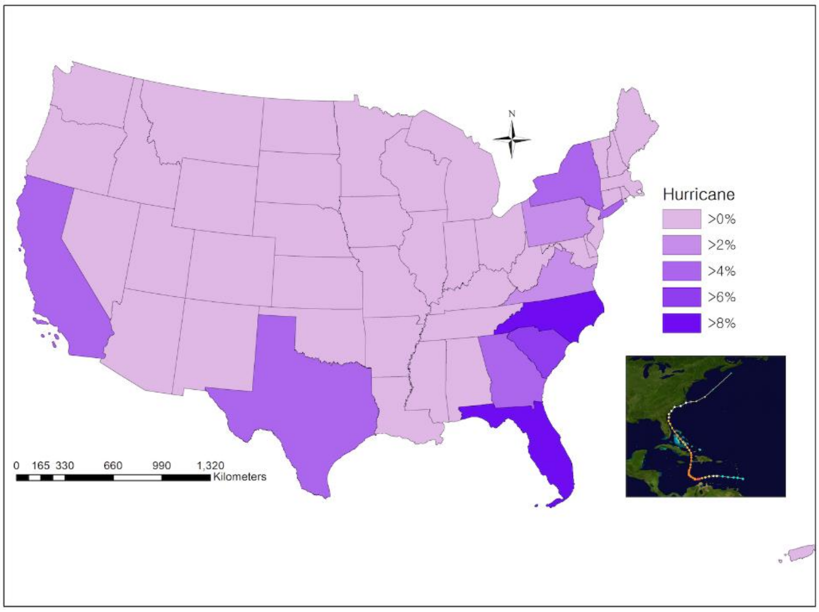
11	Iowa (3.0%)	Iowa (1.9%)	Virginia (2.8%)
12	New Jersey (2.4%)	New Jersey (1.7%)	Ohio (2.6%)
13	Michigan (2.4%)	Illinois (1.6%)	Pennsylvania (2.5%)
14	Massachusetts (2.3%)	Michigan (1.6%)	Michigan (2.5%)
15	Tennessee (2.1%)	Massachusetts (1.5%)	Illinois (2.4%)
16	Arizona (2.0%)	Tennessee (1.5%)	Arizona (1.8%)
17	Minnesota (2.0%)	Arizona (1.3%)	Iowa (1.7%)
18	Louisiana (1.8%)	Maryland (1.2%)	New Jersey (1.6%)
19	South Carolina (1.8%)	Washington (1.1%)	Massachusetts (1.4%)
20	Washington (1.8%)	Colorado (1.1%)	Indiana (1.4%)

Figure 3 shows the spatial patterns of human response according to periods. The spatial patterns of human response are visualized by the number of tweets in the states divided by the whole number of tweets in the US. In the pre-hurricane period, the Midwest and Northeast regions near the Great Lakes, such as New York, Pennsylvania, Ohio, and Michigan, show a high proportion of tweets. In contrast, in the hurricane period, the Southeast region, such as Florida, Georgia, South Carolina, and North Carolina, exhibits the heaviest concentration for tweets. In the post-hurricane period, the West region, Washington, Oregon, and California, demonstrates a high proportion of tweets. The results show that the spatial response is differentiated by pre-hurricane, hurricane, and post-hurricane period.

(A)



(B)



(C)

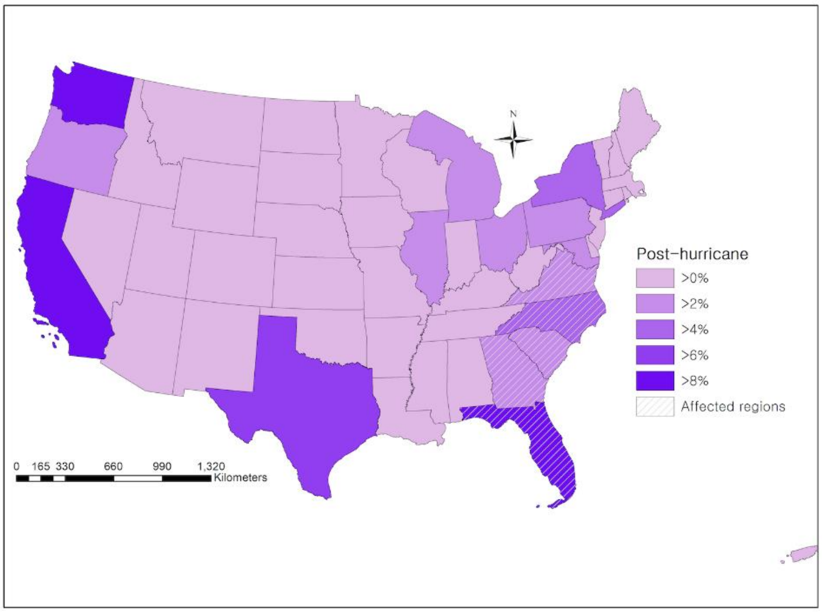


Figure 3. The proportion of tweets across the US states. (A) pre-hurricane, (B) hurricane, (C) post-hurricane.

Figure 4 shows that the number of displacements significantly increases in the hurricane period. For example, displacements in the hurricane period are 430 cases, which are quite higher than those in the pre-hurricane period (78) and post-hurricane period (85). However, the patterns of displacements are differentiated by regions. While Florida and South Carolina show a similar pattern with the whole area, Georgia reveals a different result from the whole sample. Also, Florida demonstrates the second-highest displacements in the pre-hurricane period, whereas the other regions exhibit the second-highest displacements in the post-hurricane period.

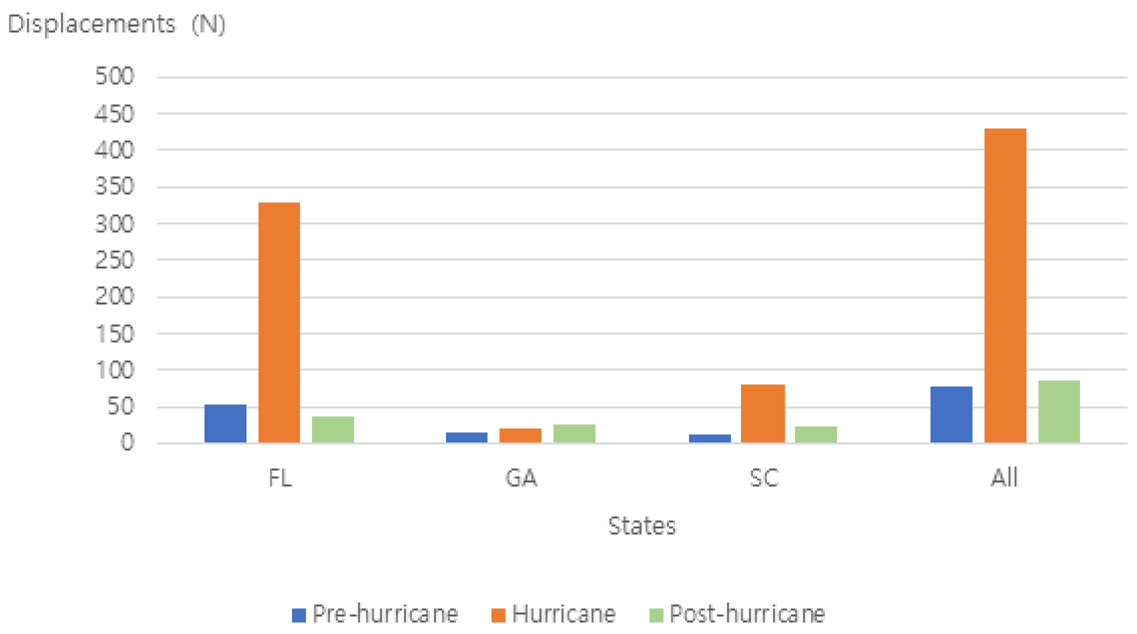


Figure 4. Displacements in the three periods.

Figure 5 shows that displacements over 100 km significantly increase in the hurricane period. The proportion of displacements over 100 km in the hurricane period is 37.4%, which is quite higher than those of the pre-hurricane period (6.4%) and post-hurricane period (29.4%). In contrast, displacements within 5 km significantly decrease in the hurricane period (23.7%), compared to the pre-hurricane period (35.9%) and post-hurricane period (27.1%). The trend continues until displacements within 25 km (within 5 km, between 5~10 km, and between 10~25 km). The results show that Hurricane Matthew significantly affects long distance trips (increase) as well as short distance trips (decrease). However, displacements are differentiated by regions. To be specific, Florida shows a similar pattern with the whole result. Displacements over 100 km highly increase in the hurricane period (42.1%), which are quite higher than those in the pre-hurricane period (7.7%) and post-hurricane period (29.7%). Displacements within 5 km (26.7%) and between 5 km and 10 km (10.6%) show the lowest proportion among the three periods (pre-hurricane period: 38.5% and 17.3% and post-hurricane period: 40.5% and 13.5%, respectively). In contrast, Georgia shows the lowest proportion of displacements within 5 km (15.8%) (pre-hurricane period: 33.3% and post-hurricane period: 28.0%, respectively), but it does not show the highest proportion of displacements over 100 km, inconsistent with Florida. South Carolina reveals the highest proportion of displacements between 50 km and 100 km and the lowest proportion of those between 10 km and 25 km among three periods.

The Chi-Square test and the Fisher's exact test show that there is a significant relationship between Hurricane Matthew and displacements for the whole area and Florida, not Georgia and South Carolina (see Table 3). This may be because Hurricane Matthew exerts a weaker impact on Georgia and South Carolina than Florida. The results highlight that Hurricane Matthew plays a different role in displacements according to regions.

Table 3. The Chi-Square test and the Fisher’s exact test.

	Chi-Square		Fisher’s exact test	
	All	FL	GA	SC
Coefficient	24.344	22.917	3.436	2.501
P-value	0.000	0.000	0.646	0.799
N	634	420	99	115

Note: DF is 5 for Chi-Square

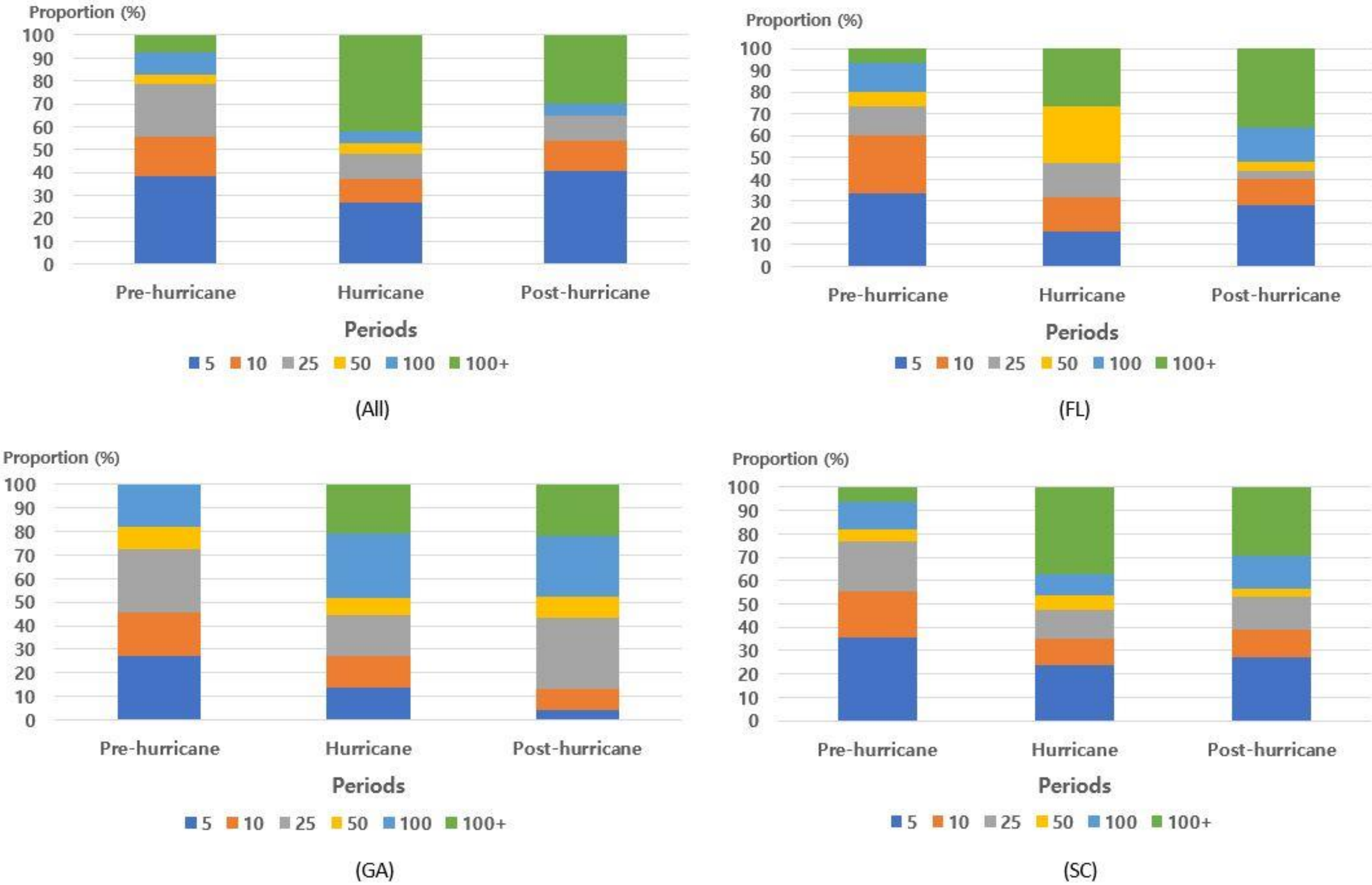
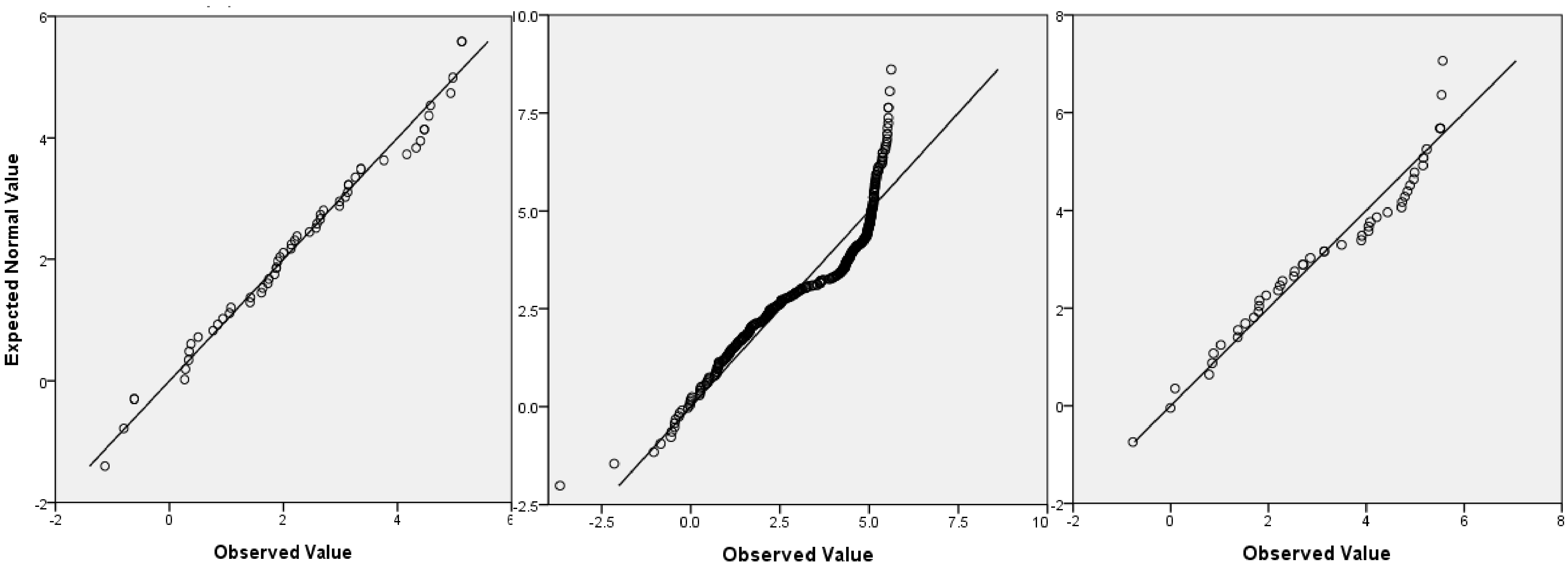


Figure 5. Displacements according to distances.



(Pre-hurricane) (Hurricane) (Post-hurricane)

Figure 6. Quantile-quantile plots of displacements for pre-, during-, and post-hurricane periods (data were natural log-transformed).

Figure 6 shows that people show the most different displacements between the Twitter data and the theoretical model in the hurricane period. For instance, the points plotted in a Q–Q plot show the most dispersed patters in terms of the 45-degree line in the hurricane period, compared with the pre-hurricane period and post hurricane period. The result implies that Hurricane Matthew plays an important role in the human mobility patterns. This study also shows an association for the pre-hurricane period and hurricane period and the pre-hurricane period and post-hurricane period based on the Kolmogorov-Smirnov test (see Table 4). For instance, the association between the pre-hurricane period and hurricane period is 2.421 and between the pre-hurricane period and post-hurricane period is 0.894.

Table 4. The Kolmogorov-Smirnov test.

	Pre-hurricane	Hurricane	Post-hurricane
Pre-hurricane		2.421***	0.894**
Hurricane	2.421***		1.395
Post-hurricane	0.894**	1.395	

Note: * p-value <0.1, ** p-value <0.05, *** p-value <0.01 (N= 493)

5 CONCLUSIONS

Natural disasters do not only damage a region, but also affect multiple regions. Therefore, governments should develop natural disaster policies through a national level perspective to understand the relationship between human response and trajectories and natural disasters. In this sense, this study sheds new light on how people respond to natural disasters across the US states by exploring the case study of Hurricane Matthew based on Twitter data.

The findings of this article provide new perspectives to natural disaster literature by employing integrated empirical big data analyses across the US states. The governments should consider the findings of this article in their decision-making processes. For instance, this study highlights that people in different states and periods respond differently to natural disasters, and governments should investigate residents' response and develop emergency management programs according to regional characteristics and different periods.

Also, people increase long distance trips and decrease short distance trips during the hurricane period. They show the most different mobility patterns between the observed values and expected values in the hurricane period. Therefore, governments and disaster planners should establish transportation policies for the emergency evacuation of long trips and investigate the mobility patterns in the hurricane period. Exploring the relationship between human response and trajectories and natural disasters would be a good strategy for preparing, warning, and reducing natural hazard and risks.

This study has some limitations as follows: First, this study only collects tweets data by employing English keywords. In other words, this study did not consider other Twitter users who use other languages. Second, this study employs Twitter to explore the effects of Hurricane Matthew on human behavior. Other social media, such as Facebook, Instagram, or YouTube, may show different results. Third, this study might lack generalizability to the population since Twitter API has the 1% sampling limitation imposed by Twitter (see e.g., Wang et al. 2019). Future research should explore the effects of natural disasters on human behavior and responses for a multitude of Twitter users, social media, and more samples.

Data Availability Statement

The data is available upon reasonable requests

Conflict of Interest Statement

There is no conflict of interest

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