Utilizing Geo-tagged Tweets to understand Evacuation Dynamics during Emergencies: A case study of Hurricane Sandy

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ABSTRACT

Hurricane evacuation is a complex process and a better understanding of the evacuation behavior of the coastal residents could be helpful in planning better evacuation policy. Traditionally, various aspects of the household evacuation decisions have been determined by post-evacuation questionnaire surveys, which are usually time-consuming and expensive. Increased activity of users on social media, especially during emergencies, along with the geo-tagging of the posts, provides an opportunity to gain insights into user's decision-making process, as well as to gauge public opinion and activities using the social media data as a supplement to the traditional survey data. This paper leverages the geo-tagged Tweets posted in the *New York City* (NYC) in wake of Hurricane Sandy to understand the evacuation behavior of the residents. Based on the geo-tagged Tweet locations, we classify the NYC Twitter users into one of the three categories: outside evacuation zone, evacuees, and non-evacuees and examine the types of Tweets posted by each group during different phases of the hurricane. We establish a strong link between the social connectivity with the decision of the users to evacuate or stay. We analyze the geo-tagged Tweets to understand evacuation and return time and evacuation location patterns of evacuees. The analysis presented in this paper could be useful for authorities to plan a better evacuation campaign to minimize the risk to the life of the residents of the emergency hit areas.

CCS CONCEPTS

• **Information systems → Mobile information processing systems**; • **Networks → Social media networks**; • **Human-centered computing → Social media**;

KEYWORDS

Hurricane evacuation; Geo-tagged Tweets; Evacuation modeling

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1 INTRODUCTION

Hurricanes are a major threat to life and property of coastal residents. The devastation caused in the US by the hurricanes from the 2005 Atlantic hurricane season (Katrina, Wilma, and Rita), Hurricane Sandy in 2012, Hurricane Matthew in 2016 and most recently, hurricanes Irma and Harvey in 2017 have been significant. The loss of lives from these devastating hurricanes highlights the importance of effective evacuation strategy. Hurricane evacuation is a complex dynamic process governed by many factors such as hurricane trajectory, household locations, warning system, and characteristics of the evacuees and their households [18]. Although mandatory or voluntary evacuation orders are issued by the authorities in the wake of a hurricane due to the anticipated storm surge, many people defy these orders risking their lives [2, 9]. Some states in the US have criminal sanctions for failure to comply with the mandatory evacuation orders (e.g. New York), however, these laws are rarely enforced. A variety of factors including risk perception, prior experience, and the severity of the storm itself affect the residents' decision to evacuate or not [2]. Considering the significant risk to non-evacuees as well as the first responders, a better understanding of the factors which influence the evacuation behavior of the coastal residents could be helpful in planning a better evacuation policy. Traditionally, the various aspects of the household evacuation decision, such as whether to evacuate or stay, when to evacuate, where to evacuate, mode of transport, when to come back, etc. have been determined by post-evacuation questionnaire surveys, (usually) months following the hurricane [1, 5, 11, 45]. Using these surveys, researchers aim to find the reason behind various evacuation decisions based on the strong correlation between the decision and the household and individual attributes such as household income, vehicle availability, social circle, previous experience with emergencies, etc. Not discounting the importance of such representative surveys in modeling evacuation decisions, this exercise is usually time-consuming (could take up to a few months after the emergency) and expensive. Also, there are concerns regarding the lack of time to fill the survey questionnaire, inexact recollection of the sequence of events during a stressful activity such as evacuation, the length of the survey, and the emotional, psychological, and physical issues with which coastal residents were coping [23].

With the increased popularity of social media, a large number of users express their opinion, activities, decisions, discussions etc. on popular social media platforms such as Facebook, Twitter, FourSquare etc. During extreme events, there is a spike in the activity of users on social media, where they document the real-time, geo-tagged chain of events and activities [39]. This self-documented, fine-grained spatiotemporal data of residents' experiences during an emergency provides an opportunity to gain insights into their decision-making process, as well as to gauge public opinion as a supplement to the traditional survey data. Although researchers have utilized data from different social media platforms, Twitter is the social media of choice among researchers studying public perception of emergency situations [12, 29, 37]. Twitter is unique in the sense that it has a large number of monthly active users, facility to post geo-tagged tweets, a 140 character limit on the Tweets, and an infrastructure which provides its data easily through APIs.

Most of the research utilizing social media data during emergency situations belong to one of the two categories: 1) using social media posts' text to assess the users' reaction to the emergency or 2) mining the spatiotemporal variations of the geotagged posts to understand human mobility during extreme events. However, limited research has been done to leverage spatial coordinates, temporal patterns as well as the posted text to understand the rationale behind the evacuation-related behavioral decisions taken by the residents of the emergency-affected areas. In this paper, we leverage the location, time and text of the geo-tagged Tweets posted in the *New York City* (NYC) in wake of Hurricane Sandy to understand the evacuation behavior of the residents. Hurricane Sandy struck New York in October 2012 and remains the second costliest hurricane in the US history with damages costing more than $71 billion [33], more than 100 lives lost, most of them due to drowning [10] and 650,000 houses left damaged or destroyed [32]. During hurricane Sandy, a mandatory evacuation was ordered for the residents of "Zone A" comprising of coastal areas in NYC; while some residents complied with the orders, others refused to leave [4].

In this paper, we leverage the location, time and text of the geo-tagged Tweets posted in the *New York City* (NYC) in wake of Hurricane Sandy (which struck New York in October 2012) to understand the evacuation behavior of NYC residents. We analyze the spatiotemporal patterns and the Tweet content of the users to model various evacuation related decisions. We categorize the Twitter users as evacuee or non-evacuee based on their geo-tagged Tweets locations and show a strong difference between the followers and friends distribution of evacuees and non-evacuees. We also analyze the GPS coordinates of the tweets by evacuees prior, during and post-hurricane to understand evacuation and return time and their evacuation location. Our analysis found large variations in the users' evacuation patterns, most likely due to lack of previous experience of NYC residents to cope with a situation like this. Next, we describe the Hurricane Sandy Twitter dataset used in this study.

2 LITERATURE REVIEW

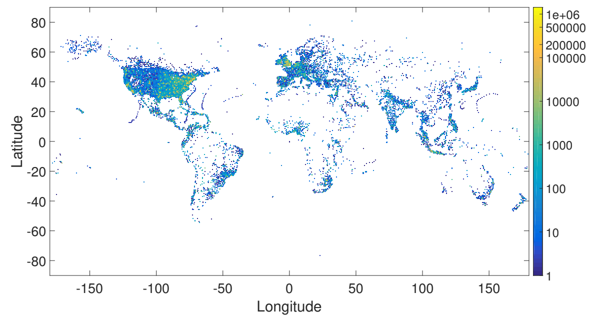
Modeling evacuation behavior of individuals and families during a life-threatening emergency is a challenging task. It depends on a range of underlying factors including but limited to proximity to the coast, socio-economic and demographic characteristics, and past experience with similar disasters. An ever-growing body of literature has investigated the role of various factors to model various evacuation behavior decisions. Most of these studies [3, 13, 14, 17, 19, 44] use face-to-face interviews, and postal or telephone surveys to collect data from affected area residents, a few months after the emergency.

The increased presence of residents, as well as authorities on various social media platforms, have made it a popular source of real-time information sharing during emergencies. Researchers have recently started to value social media as a valuable data source for evaluating various aspects of an emergency evacuation. Civil response to emergencies using social media posts was studied in [24, 34, 35, 41], whereas [8, 36] used temporal patterns in social media response to detect time and location of earthquakes in Japan. Huang and Xiao [20] made an initial attempt to classify social media messages into different themes within different disaster phases such as preparation, response, impact, and recovery. The shift in the behavior of Twitter users before and after Hurricane Sandy was studied in [31], where users responded to the disaster by employing humor, sharing photos, and checking into locations.

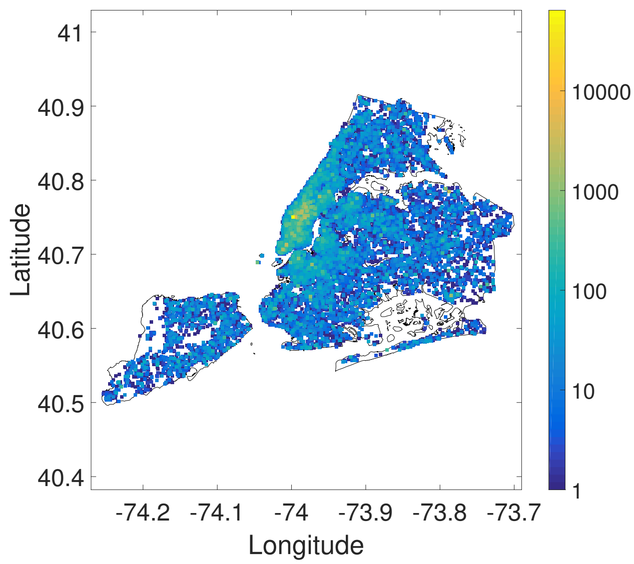
Apart from expressing opinions, many social media platforms let users post their real-time location in terms of geo-tagged posts. With the popularity of GPS enabled devices such as mobile phones, these posts have become common. Geo-tagged social media posts have been successfully used to identify spatial patterns of users during emergency situations [22, 37, 38]. A multi-scale analysis consisting of the relationship between proximity to hurricane Sandy's path and social media activity was performed in [27]. Wang and Taylor [42, 43] explored geo-tagged tweets to extract spatiotemporal human mobility patterns in different disasters such as a hurricane, typhoon, earthquake, storm, and wildfire. Real-time tools for relevant tweet discovery and their spatial visualization during emergency situations were developed in [6, 7]. Martin et al. [30] applied the techniques in [6, 7] to a case study of hurricane Mathew to evaluate the potential for social media to assist in the quantification of evacuation participation and compliance by residents. Next, we describe the Hurricane Sandy Twitter dataset used in this study.

3 HURRICANE SANDY TWITTER DATASET

In this study, we analyze the publicly available data of the tweets posted between October 15 and November 12, 2012, with the hashtag "#sandy" or containing one or more instances of specific keywords, deemed to be relevant to the event and its consequences. Further details about the data collection process and the raw dataset can be found in [25, 26]. The raw dataset consists of ~52.5 million tweets by ~13.7 million users, of which, close to 46% (~24.1 million) tweets by ~6 million users are geo-tagged. These geographical coordinates are distributed across the world as shown in Figure 1(a), which shows the heatmap of the number of tweets by GPS coordinates. Each point in Figure 1(a) represents a square of size 10 km $\times$ 10 km and shows maximum twitter activity in the east half of the USA and more so in NYC area (most affected by Hurricane Sandy). In this study we focus on the evacuation decision making of NYC residents, so we extracted those Tweets, which were posted in NYC region (based on their geo-coordinates). We found 464,478 such Tweets from 39,889 users. The heatmap of the GPS locations of those tweets which are geotagged in NYC is shown in Figure 1(b), where each point represents a square of size 100 m $\times$ 100 m. Manhattan shows highest twitter activity with some 100 m $\times$ 100 m square block having as much as ~64,000 tweets during the study period. Twitter users were quite active during the data collection period as evident by the histogram of the number of tweets per user (Figure 2). As much as 37% of the users posted more than 10 tweets during the data collection period. These sequence of geotagged Tweets



(a) The whole world (each point represent an area of 10 km × 10 km)



(b) NYC (each point represent an area of 100 m × 100 m)

Figure 1: Geotagged Tweets heatmap by location

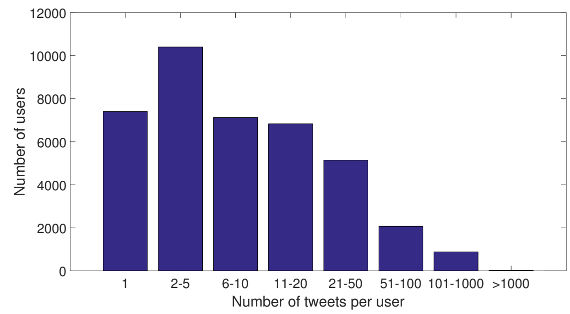


Figure 2: Histogram of the number of tweets per user

posted by the same user help understanding their evacuation decisions. Next, we describe the framework for categorizing users as outside evacuation zone, evacuees, and non-evacuees, based on their spatiotemporal sequence of Tweets.

4 CATEGORIZING USERS FROM TWEETS

To understanding evacuation behavior of users, we first categorize them as an evacuee, non-evacuee, or outside evacuation zone based on their location being outside or inside the evacuation region before, during, and after the hurricane. Specifically, we aim to categorize NYC Twitter users into one of the following three classes:

(1) Outside the evacuation region before, during, and after the hurricane.
(2) Inside evacuation region before and during the hurricane, i.e. asked to but did not evacuate. We call them "non-evacuees."
(3) Inside evacuation region before the hurricane, but moved outside during the hurricane, i.e. "evacuees."

When Hurricane Sandy made landfall in New York City in 2012, its hurricane contingency plan was based on three evacuation zones (named A, B, and C), consisting of a total of more than two million people [40], which was later revised to six zones (named 1 through 6) covering ∼3 million residents [28]. Figure 3 shows the evacuation zones and the evacuation sites for transport to shelters in NYC during hurricane Sandy [40]. Hurricane evacuation zones are areas of the city that may be inundated by storm surge or isolated by the storm surge water. During hurricane Sandy, a mandatory evacuation was ordered for the residents of "Zone A" and the residents in this region were ordered to evacuate to their friends or families in non-evacuation zones or the evacuation centers. During hurricane Sandy, a mandatory evacuation was ordered for the residents of "Zone A" and the residents in this region were ordered to evacuate. We approach the problem of categorizing the users as one of the

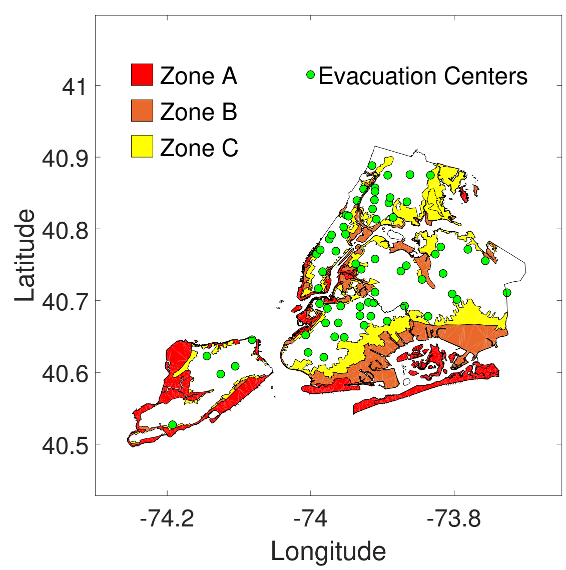


Figure 3: NYC evacuation zones and evacuation centers

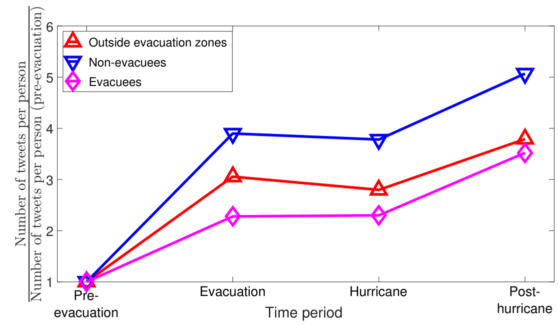
above mentioned three classes by first dividing the time scale into four periods as described below:

(1) Pre-evacuation: From the start of data collection period to the midnight of 25/26 October 2012, since Governor Andrew Cuomo declared the state of emergency on October 26, 2012.
(2) Evacuation: From the midnight of 25/26 October 2012 till 29 October 2012, 8 PM. Sandy made landfall along the coast of New Jersey on the evening of 29 October 2012.
(3) Hurricane: 29 October 2012, 8 PM until the midnight of 31 October/1 November 2012 [15].
(4) Post-hurricane: From the midnight of 31 October/1 November 2012 till the end of the data collection period.

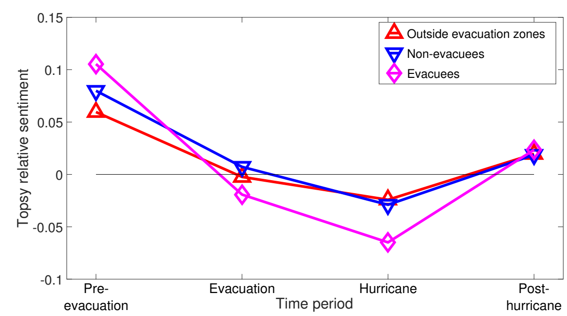
Since the mandatory evacuation orders were issued for the residents of Zone A, we partition the GPS coordinates of the geotagged Tweets as "inside evacuation region" (regions in Zone A) or "outside evacuation region" (not in Zone A). We categorize the users as belonging to one of the three user classes described previously using the *mode* of the Tweet location being inside or outside the evacuation region during the four time intervals. Table 1 list the number of identified users belonging to each of the three user categories. Note that many users out of the total of 39,889, who posted at least one tweet in NYC, cannot be confirmed to belong to any one of the three user categories due to lack of tweeting activity in one or multiple time periods.

Table 1: Twitter users belonging to different user categories

	Outside evac. zones	Non-evacuees	evacuees
No. of users	13,551	636	98



(a) Twitter activity



(b) Topsy relative sentiment of tweets

Figure 4: Activity and Tweet sentiment by different category users during different periods of time

5 UNDERSTANDING EVACUATION

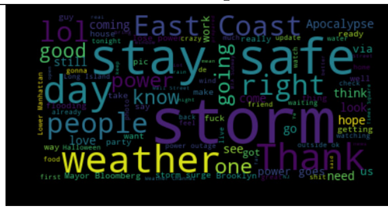
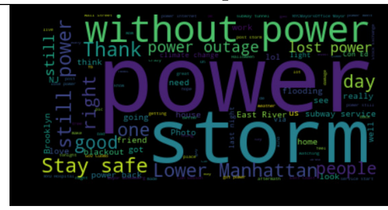
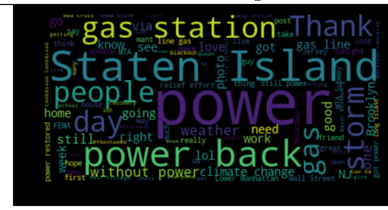
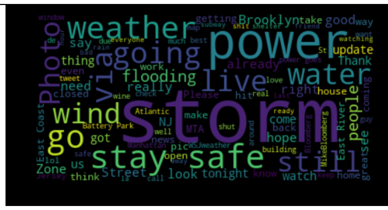
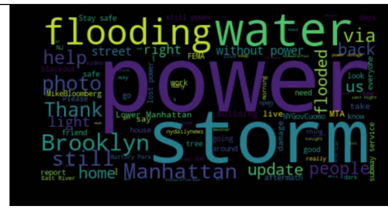
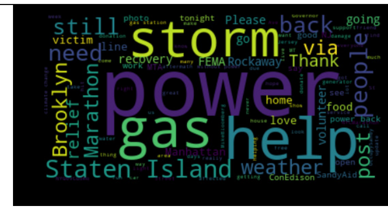
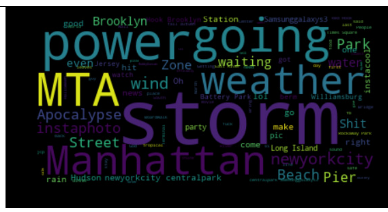
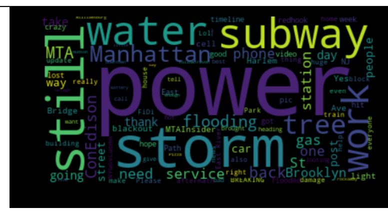
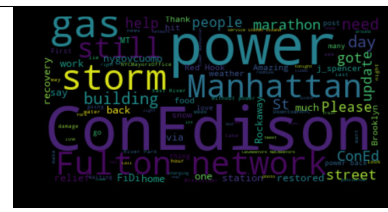
5.1 Twitter activity by periods of time

The Twitter activity of users increased substantially as the state of emergency was declared in NYC on 26 October 2012, dropped a bit during the hurricane period when most of the city did not have any power and become even more drastic in the aftermaths of the hurricane when people took stock of the situation. To put things in perspective, Figure 4(a) shows the ratio of the average number of tweets per person for a time duration to the average number of tweets per person during the pre-evacuation period (representing normal twitter activity). The tweet per person increases by a factor of 4 to 6 for non-evacuees as they were the ones at the frontier of the disaster. For users which were outside evacuation zones, the Twitter activity increased three to four-fold during the hurricane. Users who evacuated tweeted lesser as compared to other two categories, most likely due to being busy in the evacuation process. Figure 4(b) plots the relative sentiment of the tweets posted by different user categories during different time periods. We use the sentiment score for each tweet generated by a proprietary algorithm from the data provider, analytics company Topsy Labs [16], where negative values represent sad/unhappy sentiment and vice versa. As a general trend, the sentiment of tweets dropped gradually to slightly negative territory during evacuation period, when people were scared and uncertain about the impacts of the hurricane. When Sandy finally struck and people felt its fury, the sentiment of tweets became more negative, before bouncing back to positive after the hurricane has passed and recovery process began. One thing to note from Figure 4(b) is that people who evacuated posted tweets with more negative sentiments as compared to other two groups, possibly due to being away from their home and unable to know how much damage they might have suffered and also due to greater concerns such as lack of gas, lack of transportation and/or congested transportation conditions, congested shelters etc.

5.2 Analysis of the Tweet content

To get an idea of what people are tweeting, we constructed a word-cloud of the tweets by different category of users during different periods of time, i.e. evacuation, hurricane and post-hurricane as shown in Table 2. As soon as the state of emergency was declared on 26th October, hurricane Sandy start trending on Twitter. During the period from 26th October till 12th November, Sandy-related keywords such as "Sandy", "HurricaneSandy", "Hurricane Sandy", and "Frankenstorm" were the most tweeted words. To gain insight into what people are tweeting about hurricane Sandy and to have a better picture of the discussion, we remove Sandy-related keywords (mentioned above) while forming the word-clouds shown in Table 2. Users which were outside the evacuation zone (top row of Table 2) tweeted mostly about staying safe and the storm before Sandy made landfall. During hurricane period, most of them were without

Table 2: Word-cloud of the tweets posted by various category users during different stages of Hurricane Sandy

	Evacuation period	Hurricane period	Post-hurricane perio
Outside evacuation zones			
Non-evacuees			
Evacuees			

power and that was the main topic of discussion. After hurricane was over, users were tweeting mostly about getting their power back, long lines at the gas stations and the devastation at Staten Islands. Non-evacuees tweeted about "flooding", "water", "power lost", and "storm" during the hurricane. Post-hurricane, "power," "help," and "gas" were most frequent tweeted words representing non-evacuees who faced flooding and needed help. Evacuees, on the other hand, were tweeting about "subway," "power," and "storm" during the hurricane period but no "flooding" since they evacuated. During the post-hurricane period, evacuees also tweeted about ConEdison, which is the power distribution company in NYC and most likely there was still no power in their houses due to significant infrastructure damage. Analysis of the Tweet content at a more finer temporal scale (for a one-day duration) did not reveal any significant deviation from the results shown in Table 2, hence are not reported here.

5.3 Evacuees versus non-evacuees

Our analysis found a total of 734 users have the home located in the mandatory evacuation zone (Zone A). Of these, 636 are non-evacuees and 98 are evacuees. The mean and the standard deviation of the number of followers and friends (reciprocating followers) of these two category of users is listed in Table 3. We observe

Table 3: Social connectivity (evacuees vs non-evacuees)

	Non-evacuees	evacuees
Followers	12.7 ± 22.1	8.2 ± 11.4
Friends	4.8 ± 9.7	2.5 ± 4.0

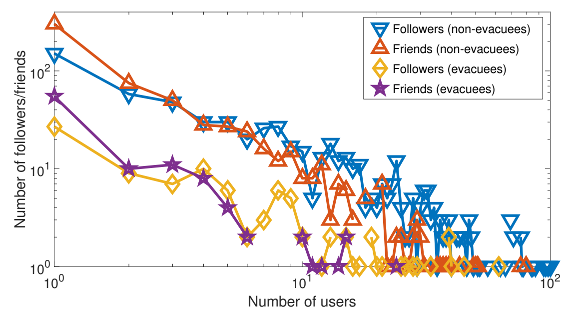
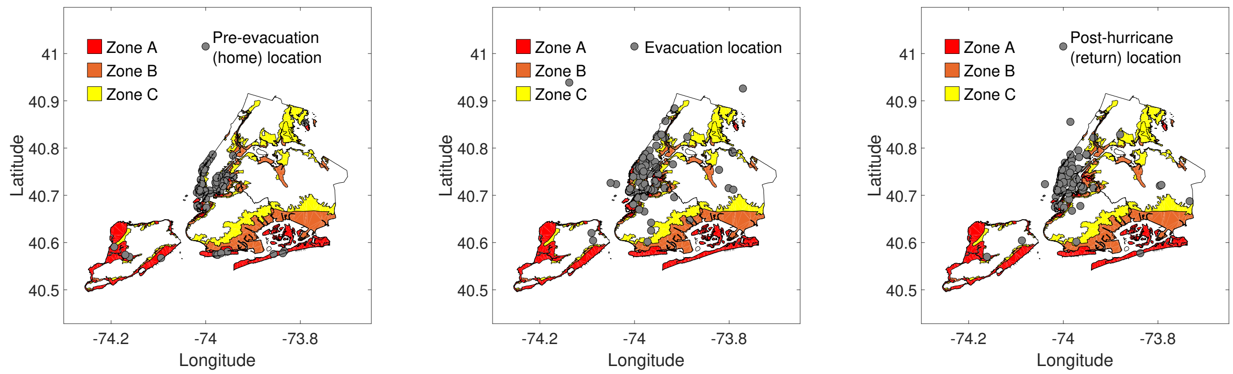


Figure 5: Followers and friends degree distribution for non-evacuees and evacuees

that, in general, people who evacuated, were less connected (by as much as 2 to 3 times) as compared to those who did not. A similar conclusion can be drawn from Figure 5, which shows that the degree distribution of followers and friends for evacuees fall well below that for non-evacuees indicating evacuees are less socially connected as compared to non-evacuees.

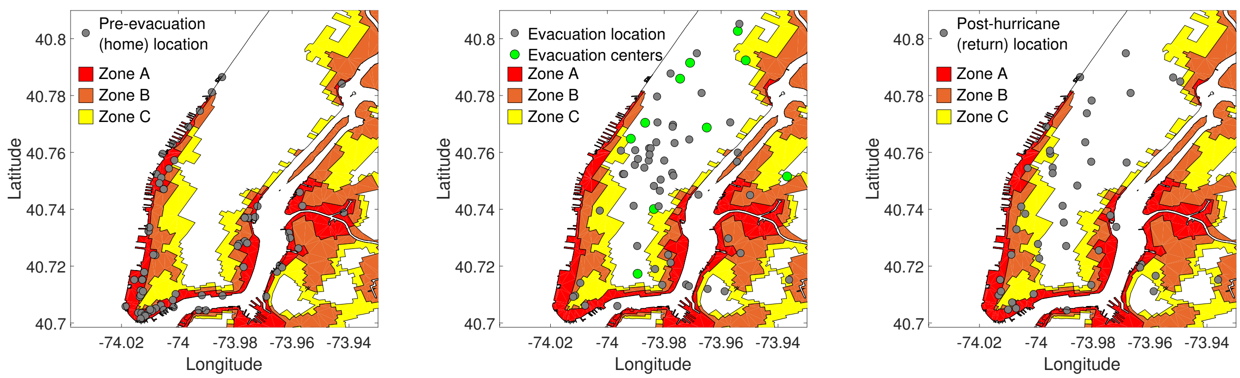
5.4 Evacuation location and time of evacuees

We analyze the time and location sequence of tweets by each user to find the home (pre-evacuation), evacuation, and post-hurricane location and time. To find the home location, we calculated the mean of the location of geo-tagged tweets by users prior to moving to a safe location outside Zone A. Figure 6 shows the home, evacuation and post-hurricane location of the evacuees. It can be



(a) Home location (b) Evacuation location (c) Post-hurricane location

Figure 6: NYC Evacuees' location prior to, during, and post hurricane



(a) Home location (b) Evacuation location (c) Post-hurricane location

Figure 7: Manhattan Evacuees' location prior to, during, and post hurricane

seen from Figure 6(a) that most of the evacuees have their home located in Manhattan, with very few in Staten Island, Brighton Beach (Brooklyn) and Rockaway Park (Queens). Almost all of the evacuees shifted to safe (inland) locations in NYC during evacuation and very few moved outside NYC (Figure 6(b)). An interesting thing to notice from Figure 6(c) is that most of the evacuees did not return to their home location after the hurricane was over, most likely due to the fact that their houses may not be habitable due to the damages caused by the hurricane.

Since most of the evacuees had their homes in Manhattan, we zoom the views in Figure 6 to Manhattan area. These zoomed images are shown in Figure 7. All of the evacuees have their home located along the coastline of Manhattan and Brooklyn. Figure 7(b) shows the evacuation location of these users, which are the inland location within Manhattan. View (b) also shows the location of government announced evacuation centers by green circles. It can be seen that hardly any user evacuated to these centers. Most likely they moved to a friend's or family's place or choose to stay at a commercial establishment (hotel, motel etc.). The post-hurricane location of these evacuees shown in Figure 7(c) shows some of them returning to their home location, whereas others decided to stay away.

Figure 8 shows the evacuation and return dates of the evacuees. The evacuation started on 27 October (20 users) and their numbers

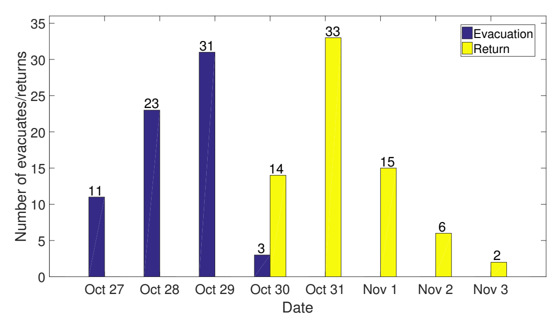


Figure 8: Evacuation and return timing of evacuees

keep on increasing until 29 October, when the landfall occurs (44 users on 28 October and 71 users on 29 October 2012). Although, three users decided to evacuate on 30 October after seeing the devastation caused by the hurricane. For returning behavior, users started to come back and take stock of the situation form 30 October (21 users), but a majority of them returned back on 31 October (39 users). The number of users who returned later keep on decreasing as the time passed (25, 10, and 2 users returned on November 1, 2, and 3 respectively). In this analysis, we did not consider the *multiple-return* phenomenon, where users come back and leave multiple times based on their social connectivity and the condition of physical infrastructure in their locality [21].

To analyze the risk perception of users from Hurricane Sandy, we explored the relationship between how far the evacuees evacuated to, in terms of the distance of their home from the coastline and the evacuation time. We found that users whose home is up to 400m from coastline tend to evacuate longer distance, with some up to 25 km (the average evacuation distance being 7km). There is a lot of variation in the evacuation time of the users and they were not able to make up there mind sooner. A possible reason for such an observation is the lack of experience of NYC residents in dealing with hurricanes since these are not very frequent in this region. We also could not find any definite relationship between evacuation time and home location distance from the coastline, probably due to the same reason. Also, users who tend to evacuate late moved little as compared to people who evacuated early. One possible reason for such an observation could be the lack of time they could travel before the hurricane struck and the congested traffic conditions during that time. Figure 9 plots the best-fitted surface representing evacuation distance of users as a function of the distance of their home from the coastline and evacuation time. Users whose home

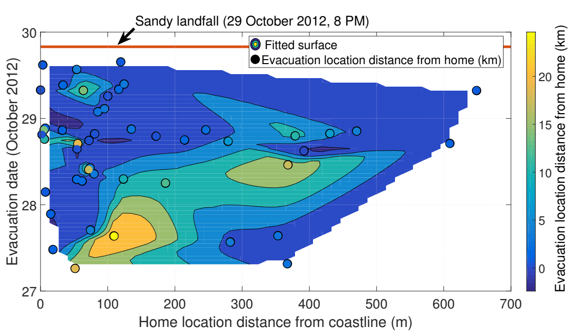


Figure 9: Evacuation distance fitted surface as function of evacuation time and home location distance from coastline

is very close to the coastline (< 200m) and who evacuated early (on 27th or early hours of 28th October 2012), evacuated to longer distances (15-20 km). On the contrary, users whose home is a bit far from the coastline (>400m) choose to evacuate late, and moved little (< 5 km). Users whose home is very close to the coastline (< 200m), but who evacuated late (late hours of 28th or 29th October 2012), couldn't move much due to time and traffic constraints and their evacuation distance is less than 10 km. Note that there are hardly any evacuees whose home location from the coast is more than 500m. The reason for such an observation is the fact that the width of the Zone A strip is less than 500m for most of the regions (at some places as small as 50m), and only at very few locations, it reaches up to 700m. Also, the risk perception of residents decreases as the distance of their home from the coast increases.

6 CONCLUSIONS

Hurricanes are a major threat to the life of coastal residents, however, some residents ignore the evacuation orders issued by the authorities in the wake of the anticipated storm surge. Given the risk to non-evacuees as well as the first responders, a better understanding of the factors which influence the evacuation behavior of coastal residents could be helpful in planning a better evacuation policy. The traditional post-evacuation surveys to understand the cause of evacuation choices of residents are usually time-consuming and expensive and could be a drag on the emotional, psychological, and physical issues with which coast residents were coping. Voluntarily posted social media posts provides a valuable supplementary data to understand evacuation behavior of the residents of emergency hit areas. This paper leverages the spatiotemporal distribution and the contents of the geo-tagged tweets posted by NYC residents during Hurricane Sandy to model various evacuation related decisions. We classified the Twitter users as one of three classes: outside evacuation zone, evacuees and non-evacuees using the geotagged Tweets and analyzed the tweets posted by the different category of users to understand how the narrative changes with time during the life-cycle of the hurricane. Our experiments show a strong correlation between the social connectedness of the users to their decision to evacuate. We also use the GPS coordinates of the tweets by evacuees to understand evacuation and return time and evacuation location patterns. The techniques presented in this paper provide an alternative (fast and voluntary) source of information for modeling evacuation behavior during emergencies apart from the traditional surveys and could provide potential inputs for the authorities to plan a better evacuation campaign.

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