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# Quantitative analysis of social media sensitivity to natural disasters

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ABSTRACT

As the prevalence of social media real-time communication grows among the public, research has increased regarding its use in various domains of study, including human behavior with respect to natural disasters. Various metrics, whether related to message posting frequency, origination proximity to the disaster, and/or the sentiment of the messages themselves are commonly studied. To the best of our knowledge, no study has been conducted to determine the sensitivity of social media to different types or magnitudes of natural disasters under various circumstances. We select four types of natural disasters (tornadoes, winter storms, wildfires, and floods) and for each we examine multiple recent events along with the associated Twitter behavior to evaluate multiple aspects: duration of social media attention, frequency shifts, frequency shifts for different social vulnerability levels, tweet proximity to the disasters, and sentiment. The results demonstrate that Twitter is indeed a social sensor with different sensitivity levels to natural disasters and depending on the event circumstances, a diverse pattern of social media behavior should be expected.

## 1. Introduction

Social media platforms such as Facebook and Twitter have become prevalent communication tools in modern society. These platforms provide a mechanism for collecting dynamic data on human behavior and sentiment. Such data has proven useful to study a variety of activity including crime prediction [1], disease outbreak [2], stock market prices [3], and political election results [4], among other things.

Recent studies consider the use of social media during natural disasters (e.g. Ref. [5], studying mainly either the mood of the population or the various reactions of the public during a specific incident. Furthermore, most of the works that utilize social media data to support emergency management mainly rely on Twitter data for analysis Reuter et al. [6]. One of the first works in social media data analysis during disasters was in 2008 after the wildfires in South Carolina [7]. Since then, many case studies have been related to the Haiti earthquakes [8,9] Hurricane Irene [10,11], or Hurricane Sandy [12–15]. A summary of the ongoing research in the area of emergency management using Twitter as a source of data is provided in Martinez-Rojas et al. [16]. Most of the related analysis, especially those occurring in the United States, rely heavily on data collected from Twitter.

Twitter is a micro-blogging service in which, collectively, users broadcast hundreds of millions of brief messages daily [17]. One major characteristic of Twitter is that the messaging service is conducted in real-time and the day and time that the message is sent is recorded. Twitter messages, known as tweets, can also be labeled with keywords using the hashtag symbol (#) to allow messages to be categorized. The twitter feed (i.e., on-going stream of tweets sent to users) can be filtered based on these labels. Additionally, if the user creating a tweet has permitted location identification services from Twitter, the data include automatic geolocation coordinates embedded within the tweet. The real-time nature of this social media platform, the ability to search for specific keyword labels, and the ability to filter by date, time, and location facilitates data collection regarding how the engaged population react to major events. A wide range of the research conducted considers a specific case study (i.e., one natural disaster) and focuses on one particular aspect of behavior. To the best of our knowledge, no study has been conducted to analyze "Twitter as a sensor" with different sensitivity levels to various types and magnitudes of natural disasters.

The goal of this work is to study multiple natural disasters, compare the results on the same scales, and draw conclusions about Twitter sensitivity levels according to different metrics and different natural disasters. That is, Twitter might be an excellent tool for collecting data and studying population sentiment during a major hurricane, but less so for a large wildfire. Consequently, the main research question is: *How and under which circumstances is social media an effective social sensor during a natural disaster?*

Presently, we aim to broach the subject by looking specifically at how different metrics, derived from Twitter data, do or do not vary with respect to different types of natural hazard events. That is, *sensitivity*, in

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**Table 1**
64 keywords for filtering disaster tweets.

| | | | | | |
|---|---|---|---|---|---|
| affected | disaster | first responders | people dead | redcross | threat |
| breaking news | donate | flash flood | people died | rescuers | tornado |
| bushfire | donation | flooding | people killed | responders | torrential |
| casualties | dramatic | forest fire | people trapped | seismic | tragedy |
| crisis | emergency | hail | power outage | severe | tragic |
| damage | evacuated | hurricane | power supplies | shelter | victims |
| dead missing | evacuees | impacted | prayers | snow | volunteers |
| deadly | explosion | injured | public safety | storm | warning |
| destroyed | fatalities | injuries | ravaged | surviving | wildfire |
| destruction | fire fighters | inundated | recover | survivor | |
| devastating | firefighters | magnitude | red cross | terrifying | |

**Table 2**
Disaster events.

| Event | Date | Location | Disaster ID |
|---|---|---|---|
| Moore Tornado | May 2013 | Moore, OK | DR-4117 |
| Louisville Tornado | Apr 2014 | Louisville, MI | DR-4175 |
| IL Tornado | Nov 2013 | Long point, IL | DR-4157 |
| GA Tornado | Jan 2017 | Albany, GA | DR-4297 |
| OK Tornado | May 2015 | Elk city, OK | DR-4222 |
| NY Winter Storm | November 2014 | Buffalo, NY | DR-4204 |
| SC Winter Storm | February 2014 | Half of the state | DR-4166 |
| ID Winter Storm | December 2015 | Notus, Idaho | DR-4252 |
| NE Winter Storm | December 2016 | New York City, NY | – |
| MA Winter Storm | January 2017 | Boston, MA | – |
| Black Forest Fire | June 2013 | Black Forest, CO | DR-4134 |
| CO Junkins Fire | October 2016 | Pueblo, CO | FM-5157 |
| OR Cornet Fire | August 2015 | Durkee, OR | FM-5097 |
| NH Stoddard Fire | April 2016 | Stoddard, NH | FM-5123 |
| AZ Tenderfoot Fire | June 2016 | Yarnell, AZ | FM-5125 |
| WY Floods | June 2017 | Fremont, WY | DR-4327 |
| NM Floods | September 2013 | Eastern NM | DR-4152 |
| MN Floods | September 2016 | Southern MN | DR-4290 |
| VT Floods | April 2014 | Jericho, VT | DR-4178 |
| US Midwest Floods | April 2013 | MI, AR, TN | DR-4121 |

this context, is defined as observable, statistically significant shifts in Twitter posting frequency and/or user sentiment (specifically, negative sentiments) with respect to disaster events. Furthermore, we consider circumstances relating to social vulnerability (geographically defined) and proximity to the disaster event. This question is a precursor to questions regarding whether or not we can extract useful information from social media regarding various natural disasters. Additionally, we consider how the social vulnerability of the affected populations affects the sensitivity levels.

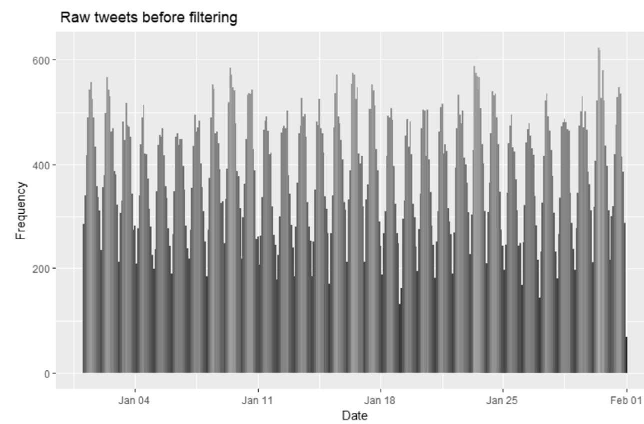


**Fig. 1.** Tweet frequency before filtering.

## 2. Background and related work

If patterns are detectable in Twitter feed data in the presence of natural disasters *and* if those patterns are distinct based on characteristics of the disaster, this provides evidence that Twitter is a "sensor" and is sensitive to distinctions between the different types of disruptive events. For instance, in the case of an oncoming hurricane, one might expect a spike in frequency of Twitter messages related to the event. However, for other less dramatic natural hazards, or those with less lead time, it is possible that very little relevant information will be

**Table 3**
Breakout dates and total observed time for disasters.

| Event | $t_d$ | $t_s$ | $t_f$ | $t_{obs}$ | $t_{rec}$ |
|---|---|---|---|---|---|
| Moore Tornado | 05/19/13 6PM | 05/22/13 12AM | 05/24/13 06AM | 108 | 54 |
| Louisville Tornado | 04/27/14 6PM | 04/29/14 12AM | 04/30/14 12PM | 66 | 36 |
| IL Tornado | 11/17/13 11AM | 11/18/13 05AM | 11/19/13 11AM | 48 | 30 |
| GA Tornado | 01/21/17 12AM | 01/22/17 6AM | 01/23/17 12AM | 36 | 12 |
| OK Tornado | 05/14/17 12PM | 05/15/17 12PM | 05/16/17 6PM | 104 | 36 |
| NY Winter Storm | 11/13/14 5AM | 11/17/14 11AM | 11/20/14 11PM | 186 | 84 |
| SC Winter Storm | 02/12/14 6PM | 02/14/14 12PM | 02/17/14 12AM | 104 | 60 |
| ID Winter Storm | 12/19/15 6AM | 12/20/15 12PM | 12/22/15 12AM | 66 | 36 |
| NE Winter Storm | 12/16/16 6AM | 12/17/16 12PM | 12/18/16 6PM | 60 | 30 |
| MA Winter Storm | 01/07/17 12AM | 01/07/17 6PM | 01/09/17 12AM | 48 | 30 |
| Black Forest Fire | 06/12/13 6AM | 06/13/13 06PM | 06/14/13 12PM | 54 | 18 |
| CO Junkins Fire | 10/22/16 6AM | 10/23/16 6PM | 10/24/16 12PM | 54 | 24 |
| OR Cornet Fire | 08/15/15 12PM | 08/22/15 6PM | 08/24/15 6PM | 222 | 12 |
| NH Stoddard Fire | 04/19/16 6PM | 04/21/16 6AM | 04/21/16 6PM | 48 | 42 |
| AZ Tenderfoot Fire | 06/06/16 12PM | 06/10/16 12PM | 06/12/16 6AM | 138 | 18 |
| WY Floods | 06/11/17 12AM | 06/18/17 12AM | 06/20/17 12PM | 108 | 84 |
| NM Floods | 09/10/13 6PM | 09/12/13 12AM | 09/13/13 12AM | 30 | 30 |
| MN Floods | 09/22/16 12PM | 09/23/16 6AM | 09/24/16 12AM | 18 | 30 |
| VT Floods | 04/15/14 6AM | 04/16/14 12AM | 04/16/14 6PM | 18 | 18 |
| US Midwest Floods | 04/22/13 12PM | 04/23/13 6PM | 04/26/13 12PM | 96 | 36 |

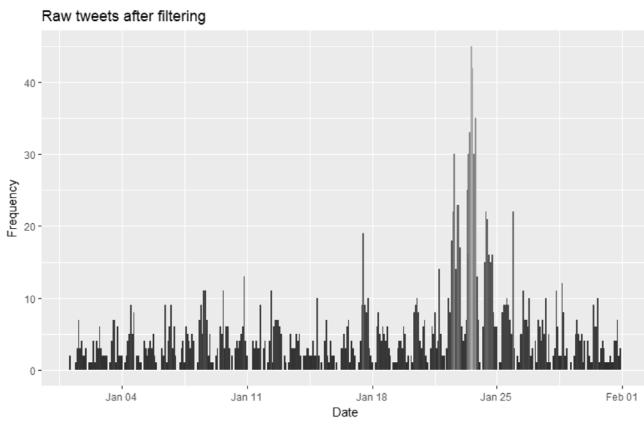


**Fig. 2.** Tweet frequency after filtering.

captured in the Twitter feed. To address the question of the sensitivity of Twitter messaging to various hazards, we consider a variety of elements including, statistical changes in tweet frequency, changes in sentiment polarity, and hazard proximity. This analysis is conducted in such a way to support community resilience research. Each of these elements is now briefly described.

### 2.1. Breakout detection

Breakout detection, also known as change-point or event detection, is a technique for detecting specific points in time series data where certain properties change [18]. There are a variety of ways to determine these change points. For example, Sakaki et al. [19] studied event detection with Twitter during earthquake scenarios. They employed a probabilistic method associated with observing a certain number of keyword-specified positive-sentiment tweets within a given time period. Earle et al. [20] used the ratio of short-term average tweet frequency to long-term average tweet frequency of, again, keyword-specified tweets to determine an event. In both cases, the presence of the keyword “earthquake” was used to filter the tweets. Cheng and Wicks [21] did not filter tweets by keywords but applied a space-time permutation model of the space-time scan statistic technique [22] to all Twitter data during a time frame of disaster events. Several other works conducted analysis on Twitter data to detect the onset of disruptive events [23–26]. A recent technique developed by Twitter called E-Divisive with Medians identifies breakouts by detecting divergence in mean values. According to the authors, their technique is robust to anomalies in the data and notably faster than other competing methods [27]. The E-divisive with Medians algorithm is used on a daily basis at Twitter according to the authors and it has been tested at the University of Louisville School of Medicine to identify past influenza outbreaks from CDC data [28]. We employ this method to identify frequency changes in Twitter messaging with respect to the occurrence of natural disasters.

### 2.2. Spatial analysis

In Caragea et al. [13]; the authors mapped the moods reflected in tweets during Hurricane Sandy. They demonstrated that even if Hurricane Sandy has a regionally limited impact in terms of damage, people have been emotionally affected by the storm far away from the coast. Their maps display the population's response in space and time to the disaster measured through sentiment analysis, showing that the closer people were to the point where the storm made landfall the more they tweeted, with negative sentiment tweets always being clustered in closer proximity to the storm. In Sakaki et al. [29]; the authors performed a trend analysis of the tweets when the Great East Japan earthquake hit Japan in 2011. They showed that the tweet frequency peaked dramatically when the earthquake hit. However, by comparing different regions, they found out that people posted fewer tweets in the heavily damaged areas compared to areas further away with less damage. This is explained by the fact that people were not in a safe situation to tweet or were not technically able to access the Internet.

### 2.3. Sentiment analysis

In research related to the use of social media during natural disasters, several studies measure user sentiment. For example, Nagy and Stamberger [30] and Caragea et al. [13] classify the tweet text as expressing Positive, Neutral or Negative emotions (also referred to as the sentiment polarity). Mandel et al. [10] conducted a demographic analysis of the sentiment using the tweets corresponding to Hurricane Irene. A binary (positive or negative) or three-way (positive, negative, neutral) classification of sentiment are common levels of granularity used in sentiment analysis [12,31–35]. On the other hand, Schulz et al. [36] performed a fine-grained sentiment analysis on the disaster-related tweets. The tweets were classified into 7 categories which include anger, disgust, fear, happiness, sadness, and surprise. Ragini et al. [37] proposed a big data framework to analyze the user sentiment by applying various text mining and machine learning techniques on disaster related tweets. Apart from sentiment analysis on natural hazard related tweets, researchers have analyzed tweet sentiment during other types of emergencies such as the 2013 Boston Marathon bombing [38], the 2017 Las Vegas shooting [39], the Syrian refugee crisis [40] and the Ebola disease outbreak [41].

Polarity analysis is typically conducted by comparing the text of the tweet to a lexicon of “positive” and “negative” words. The lexicon we use was developed by Hu and Liu [42]. Words in the text which are in either of these lists are said to be polarized words and are tagged. A cluster of words before and after each polarized word are selected as a context cluster. The words in the cluster are analyzed to determine if they include words that modify the meaning of the polarized words (e.g., “not”, “barely”, “greatly”). The presence and quantity of such terms is factored into the meaning of each polarized word to provide a numerical score relating to the strength and direction of the polarity. These final scores are aggregated for each polarized word and the message itself is given an overall polarity score [43].

**Table 4**
Results of the frequency analysis for special events.

| Event | Date | $\nu_0$ | $\nu_d$ | $\nu_f$ | % inc. | $p_1$ | $p_2$ |
|---|---|---|---|---|---|---|---|
| NCAA Football 2016 | 1/11/2016 | 10.29 (6.74) | 13.20 (4.96) | 11.10 (7.76) | 28.2 | 0.36 | 0.50 |
| NBA 2015 | 06/16/2015 | 10.29 (5.48) | 8.40 (5.54) | 24.62 (27.49) | −18.4 | 0.48 | 0.20 |
| US Presidential elections | 11/08/2016 | 4.50 (2.37) | 5.33 (7.50) | 4.00<br>2.30) | 18.0 | 0.86 | 0.78 |
| NCAA Basketball 2015 | 4/06/2015 | 24.33 (11.92) | 19.50 (10.60) | 26.40 (17.03) | −19.9 | 0.45 | 0.43 |
| Oscars 2017 | 2/26/2017 | 11.37 (7.26) | 15.50 (10.66) | 7.80 (4.35) | 36.3 | 0.32 | 0.24 |
| East Coast Blizzard | 1/22/2016 | 1.76 (0.14) | **56.00** (34.70) | 13.30 (8.60) | 369.5 | 0.01 | 0.53 |

**Table 5**
Results of the frequency analysis.

| Event | $\nu_0$ | $\nu_d$ | $\nu_f$ | % inc. | $p_1$ | $p_2$ | $t_{rec}$ |
|---|---|---|---|---|---|---|---|
| Moore Tornado | 31.67 (24.96) | **75.90** (50.60) | 27.71 (18.09) | 139.7 | 0.02 | 0.50 | 54 |
| Louisville Tornado | 30.26 (15.91) | **75.50** (44.32) | 29.03 (13.64) | 149.5 | 0.05 | 0.76 | 36 |
| IL Tornado | 39.25 (38.50) | **79.25** (61.61) | 51.35 (31.59) | 101.3 | 0.08 | 0.20 | 30 |
| GA Tornado | 8.77 (4.90) | **14.50** (7.59) | 9.85 (6.23) | 65.2 | 0.05 | 0.48 | 12 |
| OK Tornado | 8.25 (4.30) | 19.33 (10.11) | 8.05 (4.58) | 137.3 | 0.19 | 0.97 | 36 |
| NY Winter Storm | 25.93 (10.43) | **52.28** (33.77) | **40.57** (25.56) | 101.6 | < 0.01 | < 0.01 | 84 |
| SC Winter Storm | 91.31 (50.06) | **206.50** (122.86) | **64.68** (35.63) | 126.2 | 0.03 | 0.03 | 60 |
| ID Winter Storm | 8.59 (5.91) | **14.60** (7.80) | 8.50 (3.70) | 69.9 | 0.01 | 0.80 | 36 |
| NE Winter Storm | 11.25 (7.24) | **21.83** (10.83) | **6.64** (3.64) | 93.9 | < 0.01 | < 0.01 | 30 |
| MA Winter Storm | 10.96 (7.91) | 38.75 (29.40) | 9.60 (6.58) | 253.5 | 0.15 | 0.49 | 30 |
| Black Forest Fire | 26.85 (13.47) | **83.00** (29.02) | 24.21 (12.37) | 209.1 | 0.01 | 0.45 | 18 |
| CO Junkins Fire | 4.77 (2.59) | 11.30 (11.60) | 4.28 (2.40) | 136.3 | 0.28 | 0.50 | 24 |
| OR Cornet Fire | 7.55 (3.40) | 7.40 (4.40) | 7.28 (3.60) | −1.5 | 0.91 | 0.79 | 12 |
| AZ Tenderfoot Fire | 5.90 (2.80) | 8.19 (5.66) | 6.17 (3.62) | 22.1 | 0.21 | 0.78 | 42 |
| NH Stoddard Fire | 7.18 (4.00) | 7.28 (2.69) | 8.53 (5.14) | 1.4 | 0.95 | 0.28 | 18 |
| WY Floods | 5.81 (3.99) | **10.07** (5.50) | **8.44** (5.21) | 72.7 | 0.02 | 0.04 | 84 |
| NM Floods | 22.13 (12.30) | **49.20** (23.20) | 23.30 (12.40) | 122.0 | 0.06 | 0.72 | 30 |
| MN Floods | 5.37 (3.32) | **9.33** (2.33) | 5.57 (3.34) | 73.7 | 0.01 | 0.82 | 30 |
| VT Floods | 35.80 (20.50) | **81.25** (14.30) | 28.50 (3.62) | 126.8 | < 0.01 | 0.15 | 18 |
| US Midwest Floods | 48.22 (45.50) | 121.33 (93.77) | **29.64** 23.58) | 113.0 | 0.12 | 0.06 | 36 |

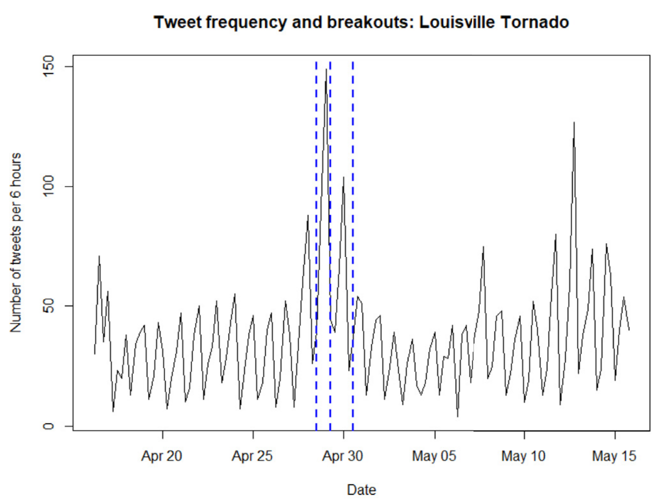


**Fig. 3.** Tweet frequency for the Louisville Tornado.

## 2.4. Social vulnerability

The Social Vulnerability Index (SoVI) was created in 2003 at the University of South Carolina in order to define, for the United States at county-level, the social vulnerability of communities to environmental hazards [44]. Based on demographic and socioeconomic data from the U.S. Census Bureau (e.g., personal wealth, age, race, etc.), the version of the index published in 2010 "emphasizes the constraints of family structure, language barriers, vehicle availability, medical disabilities, and health-care access in the preparation for and response to disasters" [45]. After a principal component analysis, scientists obtained seven components that explain 72% of the variance of the data. Once the index is calculated for each county they are decomposed into percentiles. Scores in the top 20% correspond to the most vulnerable counties and scores in the bottom 20% indicate the least vulnerable. This index can be found in several applications, such as state-level hazard mitigation plans or the Sea Level Rise Coastal Impacts Viewer by the National Oceanic and Atmospheric Administration (NOAA) (see http://coast.noaa.gov/slr/). However, no study has been conducted on social media sensitivity to natural hazards with an emphasis on the social vulnerability level of the concerned areas and its potential effect on the results.

From literature we see that work has primarily studied various Twitter derived metrics given a specific disruptive scenario, however no work addresses which types of events can be studied using these social-media based measures. Our work specifically quantitatively evaluates the ability of Twitter to be used as a sensor for various types of natural hazards.

# 3. Methodology

## 3.1. Data pre-processing

The Twitter Sample Stream returns a random sample from all the available tweets for a given query [46]. Data from this stream was collected over multiple years by members of the Archive Team, a group dedicated to preserving online digital content The Archive Team 2017. The broad range of dates available facilitates analysis with respect to several important natural disasters that occurred during the time frame. In this study, we filter the tweets in order to keep only tweets written in English, which are geo-tagged, originate from within the United States, and which were created during the period from 2013 to 2017. Twenty natural hazards occurring during this time frame are selected for analysis and detailed in Section 4.1.

The textual content of a tweet can be "noisy", in that it may include a variety of non-English content such as HTML links, tags, special characters, etc. Consequently, the text must be processed prior to analysis (especially for sentiment analysis). Prior to analysis, we remove all "tags" (tagging someone refers to including a @ character followed by their Twitter user name, e.g., *@UofOklahoma)*, retweet entities (e.g., *RT @UofOklahoma)*, HTML links, and all punctuation, special characters, numbers, line breaks, and any additional whitespace. Let the set of all filtered and preprocessed tweets be denoted by the set *T*.

Due to the massive quantity of diverse message content in Twitter data, a keyword filter is useful to identify the text messages which are germane to the topic of study, namely natural disasters. Such filtering is commonly performed using specific hashtags (e.g., "#Moore Tornado" or "#Hurricane Sandy") to analyze the trend of a particular event on social media. However, such filtering could easily eliminate many relevant tweets. Consequently, we build a catalog of keywords generalized for all types of disasters to broaden the scope of messages in the analysis.

This list of keywords is built in multiple steps: first, a preliminary

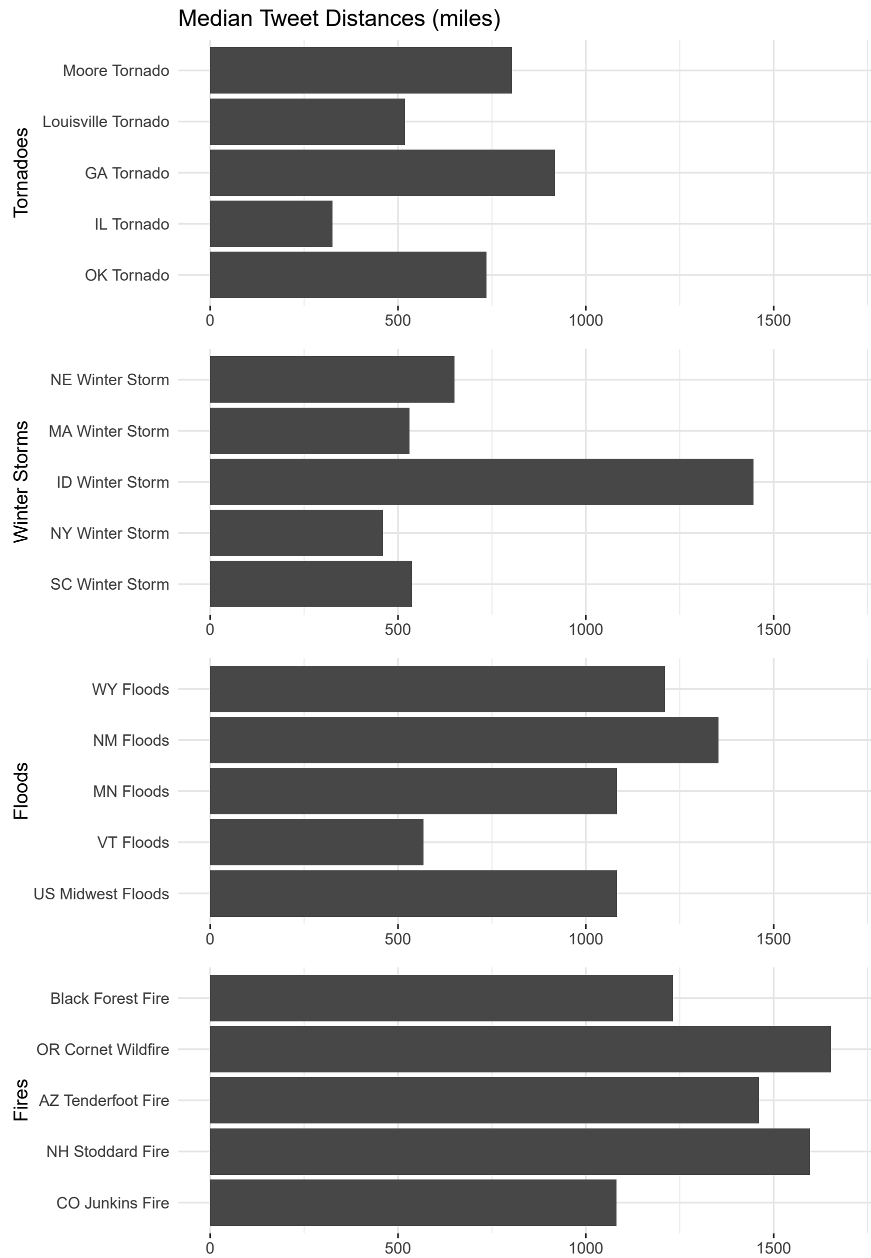


**Fig. 4.** Median tweet distance for events.

list with a dozen basic keywords such as *storm, tornado, flood, hail, wildfire* is used to filter the set of all preprocessed tweets $T$ and create the subset $T' \subseteq T$. All words in $T'$ are stemmed. Stemming is the process of reducing words to their word stem, e.g., "connection", "connections", "connected", and "connecting", each share the same word stem "connect". A document-term matrix $M$ is constructed from set $T'$. The rows in $M$ represent the tweets and the columns represent all stemmed words in $T'$. The entry in the $i^{th}$ row and $j^{th}$ column of $M$ equals 1 if the $j^{th}$ word is found in tweet $i$ and equals 0, otherwise. Next, the matrix $M$ is used as input for Latent Dirichlet Allocation (LDA). LDA is a common unsupervised learning technique for topic discovery within documents [47]. The results of the process allows the identification of a broader list of disaster related keywords in the corpus of documents. This list combined with an appropriate subset of the *CrisisLex* [48], a lexicon used to improve Twitter communications filtering for crisis situations, results in a final keyword list of 64 terms for filtering tweets listed in Table 1. The keywords relate to the vocabulary of natural disasters, consequences, and emergency response. There is no keyword related to a specific event, as we wish to measure the general disaster sensitivity of the social media response.

After filtering out all but the geo-tagged, contiguous U.S. based tweets written in English which have at least one of the specified keywords in the text message, the percentage of remaining tweets is approximately 0.84% of the original sample. For every natural disaster considered there are thousands of filtered tweets occurring within a few days of the event onset, ranging from about 3500 to nearly 7600 tweets.

### 3.2. Metrics analyzed

Using breakout detection, three time periods will be identified: (i) the *disruptive time* $t_d$, when a change is observed in the normal activity (e.g., a significant increase in the tweet frequency); (ii) *recovering start*

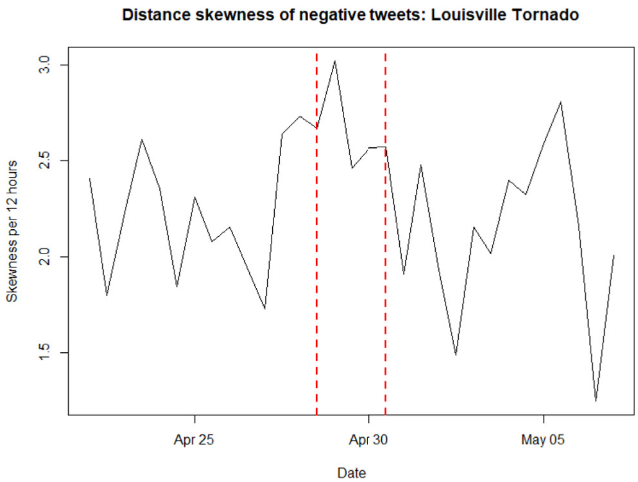


**Fig. 5.** Skewness of negative tweet distance distribution for the sample events.

*time* $t_s$, when a second change is observed, (e.g., a decreasing trend in the tweet frequency); and (iii) the *stabilization time* $t_f$, when the activity obtains a new stable form and thus reaches a recovered state. Note that these times do not necessarily align exactly with the dates of the disruptive event itself. For example, there may be a delay between the event occurrence and the change in Twitter behavior. These dates will be used throughout the different analysis, and will help to define any variations in some metrics over time. In particular, $t_d$, $t_s$, and $t_f$ are used to define the following *tweet frequency* metrics: $\nu_0$ denotes the pre-event tweet frequency and is defined as average number of tweets occurring during the 7 days prior to $t_d$; $\nu_d$ denotes the event-specific tweet frequency and is defined as the average tweet count occurring between time periods $t_d$ and $t_s$; and $\nu_f$ is the post-event tweet frequency after stabilization computed for the 7 days after $t_f$.

To conduct the spatial analyses, the central geospatial location of each disaster is estimated. While events are not generally stationary, (e.g., a tornado moves along a path), an approximate location of each event is defined depending on the type of event. For tornadoes and hurricanes, we use the first location of impact/landfall; for winter storms, the city most impacted; for forest fires, the closest city to the fire. Based on the identified location, the distance from the tweet origin to the center of the event is computed. The median and third quartile values for distance of tweets to disaster are compared across disasters.

**Table 7**
Events that show a significant rise in skewness.

| Disaster Type | Events with statistical significance in skewness |
|---|---|
| Tornadoes | Louisville Tornado |
| Winter Storms | NY Winter Storm and SC Winter Storm |
| Wildfires | – |
| Floods | New Mexico Floods, Vermont Floods and US Midwest Floods |

**Table 8**
Percentage of tweets by level of social vulnerability.

| Event | Low (%) | Medium (%) | High (%) |
|---|---|---|---|
| Moore Tornado | 11.59 | 60.11 | 28.30 |
| Louisville Tornado | 14.71 | 53.33 | 31.96 |
| GA Tornado | 12.91 | 50.08 | 36.99 |
| IL Tornado | 14.23 | 53.52 | 32.24 |
| OK Tornado | 10.66 | 54.77 | 34.55 |
| NY Winter Storm | 13.54 | 55.83 | 30.63 |
| SC Winter Storm | 15.55 | 55.17 | 29.28 |
| MA Storm | 12.94 | 52.17 | 34.87 |
| ID Storm | 15.15 | 53.13 | 31.71 |
| NE Winter Storm | 13.66 | 52.25 | 34.08 |
| Black Forest Fire | 13.34 | 54.26 | 32.39 |
| CO Junkins Fire | 8.51 | 53.31 | 38.17 |
| OR Cornet Fire | 10.01 | 51.69 | 38.29 |
| AZ Tenderfoot Fire | 9.51 | 49.37 | 41.07 |
| NH Stoddard Fire | 13.20 | 52.20 | 34.60 |
| WY Flooding | 10.99 | 54.20 | 34.71 |
| NM Floods | 15.72 | 50.25 | 34.02 |
| MN Floods | 10.21 | 47.84 | 41.93 |
| VT Floods | 13.47 | 52.16 | 34.35 |
| US Midwest Floods | 14.15 | 60.09 | 25.75 |

Additionally, the Social Vulnerability Index associated with each U.S. county in which the tweet was created is overlaid on the data. This allows analysis of potential trends or variations in Twitter sensitivity based on low, medium, and high social vulnerability. The sentiment analysis is based on a three-way classification of message polarity (positive, neutral, negative). In particular, we examine the negative tweets and the skewness over time of the distance to the center of the disaster. The idea is to observe if negative sentiment tweets cluster in closer proximity to the disaster location during the event. For an example of the polarity, consider the three following tweets identified as an expressing a positive, negative, and neutral sentiment, respectively, during a devastating tornado breakout in April of 2014:

**Table 6**
Results of the sentiment analysis.

| Event | $\gamma_0$ | $\gamma_d$ | $\gamma_f$ | % inc. | $p_1$ | $p_2$ |
|---|---|---|---|---|---|---|
| Moore Tornado | 2.40 (0.52) | **1.84** (0.46) | 2.19 (0.57) | −23.67 | 0.01 | 0.30 |
| Louisville Tornado | 2.23 (0.32) | **2.75** (0.20) | 2.21 (0.50) | 23.32 | < 0.01 | 0.92 |
| GA Tornado | 1.95 (0.48) | 1.97 (0.40) | 2.06 (0.55) | 1.12 | 0.94 | 0.60 |
| IL Tornado | 2.36 (0.33) | **3.33** (0.81) | 2.38 (0.33) | 40.59 | 0.03 | 0.93 |
| OK Tornado | 1.91 (0.44) | 1.98 (0.16) | 1.80 (0.30) | 3.55 | 0.66 | 0.47 |
| NY Winter Storm | 2.34 (0.41) | **2.83** (0.28) | **2.93** (0.71) | 21.02 | < 0.01 | 0.01 |
| SC Winter Storm | 2.48 (0.50) | **3.04** (0.46) | 2.53 (0.60) | 22.60 | 0.01 | 0.80 |
| MA Winter Storm | 2.04 (0.29) | **2.90** (0.29) | 2.07 (0.57) | 42.05 | < 0.01 | 0.88 |
| ID Winter Storm | 2.01 (0.42) | 1.66 (0.48) | 2.13 (0.58) | −17.44 | 0.21 | 0.54 |
| NE Winter Storm | 1.89 (0.43) | 2.19 (0.63) | 1.95 (0.30) | 15.35 | 0.26 | 0.72 |
| Black Forest Fire | 2.01 (0.43) | **1.48** (0.54) | **2.73** (0.37) | −26.1 | 0.08 | < 0.01 |
| CO Junkins Fire | 1.77 (0.23) | 1.76 (0.14) | 1.84 (0.17) | 0.6 | 0.80 | 0.21 |
| OR Cornet Fire | 1.88 (0.52) | 1.76 (0.32) | 2.03 (0.51) | −6.2 | 0.48 | 0.47 |
| AZ Tenderfoot Fire | 1.80 (0.30) | 1.70 (0.35) | 1.96 (0.44) | −3.0 | 0.84 | 0.66 |
| NH Stoddard Fire | 2.42 (0.37) | 2.19 (0.14) | 2.28 (0.45) | −9.5 | 0.25 | 0.37 |
| WY Floods | 2.03 (0.40) | 2.12 (0.30) | 2.11 (0.40) | 3.4 | 0.60 | 0.61 |
| NM Floods | 2.00 (0.57) | **1.47** (0.39) | 1.93 (0.33) | −26.9 | 0.04 | 0.75 |
| MN Floods | 1.58 (0.17) | **1.90** (0.63) | 1.63 (0.25) | 20.5 | 0.09 | 0.50 |
| VT Floods | 2.04 (0.50) | **2.88** (0.30) | **1.68** (0.30) | 41.2 | 0.01 | 0.03 |
| US Midwest Floods | 2.21 (0.23) | **2.59** (0.42) | 2.10 (0.55) | 17.1 | 0.01 | 0.52 |

**Table 9**
Results of the social vulnerability analysis.

| Event | $\nu_0^{low}$ | $\nu_d^{low}$ | % inc. | $p_{low}$ | $\nu_0^{med}$ | $\nu_d^{med}$ | % inc. | $p_{med}$ | $\nu_0^{high}$ | $\nu_d^{high}$ | % inc. | $p_{high}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Moore Tornado | 3.48 | **8.10** | 132.7 | 0.07 | 19.19 | **48.90** | 154.9 | 0.01 | 9.00 | **18.70** | 107.8 | 0.06 |
| Louisville Tornado | 4.19 | **17.00** | 306.2 | 0.05 | 15.89 | **42.00** | 164.3 | 0.07 | 10.19 | **16.50** | 62.0 | 0.02 |
| GA Tornado | 1.18 | 2.25 | 90.67 | 0.11 | 3.92 | **7.25** | 84.9 | 0.04 | 3.66 | 4.75 | 29.78 | 0.39 |
| IL Tornado | 5.70 | 15.00 | 163.0 | 0.29 | 20.50 | **43.00** | 109.8 | 0.06 | 13.07 | 21.25 | 62.58 | 0.29 |
| OK Tornado | 0.81 | **2.66** | 228.39 | < 0.01 | 4.40 | **12.00** | 172.7 | < 0.01 | 2.92 | 4.66 | 59.58 | 0.11 |
| NY Winter Storm | 3.78 | **7.50** | 98.5 | 0.01 | 13.52 | **29.22** | 116.2 | < 0.01 | 8.56 | **15.44** | 80.5 | 0.01 |
| SC Winter Storm | 14.69 | **38.50** | 162.0 | 0.02 | 53.12 | **105.38** | 98.39 | 0.05 | 23.50 | **62.50** | 166.0 | 0.04 |
| MA Winter Storm | 1.40 | 5.50 | 290.8 | 0.19 | 5.96 | 19.00 | 218.8 | 0.17 | 3.59 | 14.25 | 296.9 | 0.18 |
| ID Winter Storm | 1.59 | 2.00 | 25.8 | 0.48 | 4.44 | **7.60** | 71.2 | 0.01 | 2.55 | **4.90** | 92.2 | < 0.01 |
| NE Winter Storm | 1.70 | 2.16 | 27.2 | 0.51 | 5.70 | **11.66** | 104.6 | 0.01 | 3.77 | **8.00** | 112.2 | < 0.01 |
| Black Forest Fire | 3.85 | **12.60** | 227.1 | 0.07 | 13.59 | **50.20** | 269.3 | 0.01 | 9.41 | **20.20** | 114.7 | < 0.01 |
| CO Junkins Fire | 0.44 | 0.60 | 36.4 | 0.59 | 2.44 | 7.20 | 195.1 | 0.35 | 1.85 | **3.40** | 83.8 | 0.05 |
| OR Cornet Fire | 0.62 | 0.86 | 38.7 | 0.27 | 3.96 | 3.77 | −4.8 | 0.80 | 2.55 | **4.90** | 92.2 | < 0.01 |
| AZ Tenderfoot Fire | 0.57 | 0.56 | −2.5 | 0.95 | 3.11 | 4.00 | 30.4 | 0.29 | 2.80 | 3.18 | 13.6 | 0.59 |
| NH Stoddard Fire | 1.03 | **0.42** | −58.7 | 0.04 | 3.70 | 3.71 | 0.27 | 0.98 | 2.40 | 3.14 | 30.8 | 0.31 |
| WY Floods | 0.81 | 1.04 | 28.4 | 0.44 | 2.77 | **5.84** | 110.8 | < 0.01 | 2.22 | 3.16 | 42.3 | 0.11 |
| NM Floods | 3.07 | 8.60 | 179.0 | 0.11 | 10.80 | **25.00** | 131.5 | 0.07 | 8.14 | **15.40** | 89.2 | 0.01 |
| MN Floods | 0.55 | 0.33 | −40.0 | 0.50 | 2.77 | **5.16** | 86.3 | 0.01 | 2.03 | **3.83** | 88.7 | < 0.01 |
| VT Floods | 5.33 | 10.75 | 101.7 | 0.15 | 18.30 | **44.00** | 140.4 | 0.07 | 12.07 | **26.50** | 119.6 | < 0.01 |
| US Midwest Floods | 6.03 | 20.80 | 255.9 | 0.12 | 26.90 | **77.66** | 188.7 | 0.10 | 15.11 | 22.66 | 50.0 | 0.22 |

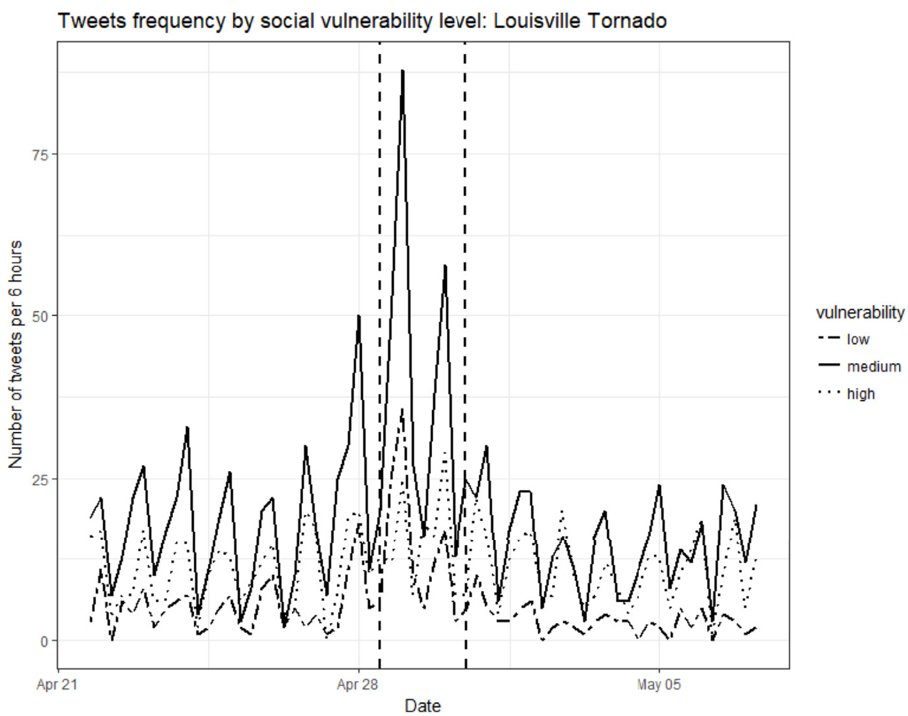


**Fig. 6.** Tweet frequency by social vulnerability level for the sample events.

**Table 10**
Example negative tweets from different distances.

| Message | State | Distance (miles) |
|---|---|---|
| "Just drove through Moore, OK and the view of the tornado damage made my heart drop. My prayers go out to all those impacted" | Oklahoma | 0.5 |
| "what happened in Oklahoma is tragic I have no idea why anyone chooses to live in tornado alley" | Massachusetts | 1510.4 |

- Positive: "thunderstorm naps are the best"
- Negative: "i hate storms so much"
- Neutral: "i ain't seen no tornado"

## 4. Analysis and results

### 4.1. *Case studies*

The event scenarios included in this analysis are grouped into categories used by the Federal Emergency Management Agency (FEMA) to classify disaster declarations: *tornadoes*, *winter storms*, *wildfires* and *floods*. We have selected five examples of each type for analysis which occurred between 2013 and 2017. Table 2 lists the event type, date, location, and the US Federal Emergency Management Agency (FEMA) disaster declaration ID if available. All processed tweets have been grouped by 6 h time windows to determine the breakout time points. Table 3 list the breakouts detected for each case study. The last two columns provide the *total observed time*, $t_{obs} = t_f - t_d$ and *total recovery time*, $t_{rec} = t_f - t_s$, in hours. Observed times vary among all the disaster events. The longest event impact on Twitter was the Oregon Cornet fire (222 h). The shortest events were the Minnesota and Tennessee floods (18 h).

### 4.2. Filter quality

Prior to considering the specific impacts on tweet behavior with respect to natural disasters, we first address the effectiveness of the preprocessing approach discussed in Section 3. In particular, are the 64 keywords sufficient to allow the filtering of non-disaster related events. If not, then any "signal" detected could simply be related to an overall increase in tweet volume due to other significant events. To address this, we have identified 5 non-disaster events occurring during the tweet time frame and applied the filter to determine if the stated approach is effective. Ideally, after applying the filter, there will be no change in tweet frequency before, during, or after the non-disaster events.

As an illustration of the filtering, consider Fig. 1 which depicts tweet frequency from January 2016 before filtering and Fig. 2 after filtering. For purposes of visualization, the tweets are binned in 2-h blocks. The 2016 College Football Playoff National Championship was held on January 11, 2016. After filtering, there is no noticeable change in the tweet behavior around January 11. However, there is a noticeable spike that occurs near January 22. This spike corresponds to a blizzard that hit the US Northeast and Mid-Atlantic causing multiple governors to issue a state of emergency.

All five special events as well as the East Coast Blizzard are listed in Table 4 along with the date of the event, the 7-day average pre-event tweet frequency $\nu_0$, the event specific tweet frequency $\nu_d$, the 7-day average post-event tweet frequency $\nu_f$, and the percent change between $\nu_0$ and $\nu_d$ (% inc.) is shown. For all analyses, except for the skewness analysis (Section 4.5), tweets are grouped in 6-h time windows. The standard deviations are reported in parenthesis. The significance of the difference between $\nu_0$ and $\nu_d$ or between $\nu_0$ and $\nu_f$ is statistically evaluated using an independent two-sample *t*-test (with unequal sample sizes and either equal or unequal variances based on the results of Levene's test for homogeneity of variances) and the resulting *p*-values, $p_1$ and $p_2$, are respectively obtained.

Table 4 provides statistical evidence that the filter is working as expected. After filtering, there are no statistically significant changes in tweet frequency before, during, or after the non-disaster events. However, for the East Coast Blizzard, there is considerable statistical evidence of a frequency change during the event, i.e., the value for $\nu_d$ is statistically different from $\nu_0$. Afterwards, the tweet frequency returns to pre-event levels (there is insufficient evidence that $\nu_f$ differs from $\nu_0$).

### 4.3. Frequency analysis

Table 5 summarizes the tweet frequency variations for each case study using the same calculations as in Table 4. Note that $\nu_0$ is the average tweet frequency over the 7 days prior to $t_d$; the disrupted frequency, $\nu_d$, is the average frequency between the time points $t_d$ and $t_s$; and $\nu_f$ is the average over the 7 days after time point $t_f$ and the percent change between $\nu_0$ and $\nu_d$ (% inc.). For the tornado events, the observed increase from $\nu_0$ to $\nu_d$ range from 65% to 149% and four out of five of the events reflect statistically significant frequency changes with 90% confidence (statistically significant results are in bold). Fig. 3 depicts one example of the tweet frequency, derived breakout points, and impact to tweet frequency based on a disaster event (i.e., Louisville Tornado). For each event, the recovered stable state frequency is not statistically different from the pre-event frequency. For the winter storms, again four of the five events show a statistically significant frequency difference when comparing the $\nu_0$ with $\nu_d$. However, the recovered stable state frequency for the NY, SC, and Northeast Winter Storms is statistically different than the pre-event level.

Among the wildfire events only the Black Forest Fire reflects a statistically significant difference from $\nu_0$ to $\nu_d$. However, there is insufficient evidence that $\nu_f$ differs from $\nu_0$ for any of these events. For Flood events, four of five events have sufficient data to demonstrate statistically valid changes in pre-disaster to post-disaster tweet frequency. Two floods have recovered tweet frequencies that are statistically different from the pre-disaster levels (WY and US Midwest Floods).

### 4.4. Proximity analysis

The proximity analysis is based on tweets posted between $t_d$ and $t_s$ for each disaster. Fig. 4 depicts a bar chart of the median tweet distances for each disaster in the study. Tornadoes and winter storms appear to have relatively lower median distances for most events, ranging from 325 to 918 miles and 460 to 1450 miles, respectively. For floods, the median distances are between 567 and 1352 miles and for wildfires, the median values are from 1081 to 1652 miles.

Tornadoes and storms have the lowest median values among all the disasters. We hypothesize that since the damage is confined to a smaller region, more tweets cluster close to the disaster area. The wide spread of the tweets in case of wildfires may be related to the fact that since a forest fire does not directly hit a large population area (at least not at the beginning), tweets are less clustered close to the disaster. On the other hand, since floods affect a larger area, we see a difference in the proximity of tweets with respect to the disaster location. For example, the majority of the tweets come from relatively nearby in case of the Vermont Floods but a much further distance for tweets associated with the New Mexico Floods.

### 4.5. Sentiment analysis

In Neppalli et al. [35]; the positive skewness of the tweet distance distribution was tracked over time to see if the tweet locations clustered near the event (in their case, the landfall point of Hurricane Sandy). High positive skewness indicates a tendency to cluster and they found negative sentiment tweets to have higher skewness values than positive sentiment tweets (at least during the earlier part of the storm). For the current analysis, we examine the skewness trends of negative sentiment tweets across multiple events corresponding to different disaster types. Since we are filtering the data again by negative polarity, thereby diminishing the amount of available data over time, tweets have been grouped into 12-h time windows for the skewness analysis. Fig. 5 depicts the skewness trends in negative tweet distances (aggregated in groups of 12 h) for one of the Louisville Tornado event.

From Table 7 it is seen that in the case of tornadoes, we observe a statistically significant increase of the skewness only for the Louisville Tornado. For the winter storms, both the NY Winter Storm and SC Winter Storm show a significant rise in the skewness. While none of the wildfires show a significant rise in the skewness, New Mexico Floods, Vermont Floods and US Midwest Floods show a significant increase in the skewness. The increase lies in the range of 21–42% regardless the type of disaster.

To help evaluate these changes, the tweets distance distributions can be aggregated into three groups: pre-event, during, and post-event time frames. Let $\gamma_0$, $\gamma_d$ and $\gamma_f$ represent the skewness of negative sentiment tweets during the stable pre-event state (computed for the 7 days prior to $t_d$), the disrupted state (the time between $t_d$ and $t_s$), and the recovered stable state (computed for the 7 days after $t_f$). Table 6 reports these values for each disaster event.

### 4.6. Social vulnerability analysis

Based on the county of origin for a tweet, we overlay the SoVI indices to associate a level of social vulnerability (low, medium, high). Table 8 shows the percentage of all tweets originating from the three vulnerability classes for each event. There is good representation for all events and for all SoVI classes. Approximately 30%–40% of the tweets are from high vulnerability areas.

For each SoVI class, in Table 9 we report the 7-day pre-disaster average tweet frequency ($\nu_0^{low}$, $\nu_0^{med}$ and $\nu_0^{high}$), the disrupted tweet frequency ($\nu_d^{low}$, $\nu_d^{med}$ and $\nu_d^{high}$) between $t_d$ and $t_s$, the percent change, and the $p$-value from the $t$-test to determine whether or not the difference in means is statistically significant ($p_{low}$, $p_{med}$ and $p_{high}$). Statistically significant differences at a 90% confidence level are in bold. For nearly every event, statistical shifts in tweet frequency are observed in at least one vulnerability class. The evidence for the shifts have a different profile by class. For example, consider the frequency analysis in Table 5 for the OK Tornado event. Overall, there is insufficient evidence to support a statistical change in the tweet frequency. However, in Table 9, there is considerable evidence ($p < 0.01$) for a frequency shift among both the low and medium SoVI classes, although this is not true for the high vulnerability tweet origins. As an example, Fig. 6 shows the tweet frequency based on various SoVI classes for the Louisville Tornado.

Additionally, for both the ID and NE Winter Storms, there is considerable evidence for tweet frequency changes in the medium and high SoVI classes but not in the low vulnerability class. For the fires, a tweet frequency shift is detectable among all three classes for the Black Forest Fire. The Colorado and Oregon fires only show a shift in the high SoVI class, whereas the New Hampshire fire only impacts tweet frequency among the low SoVI class. Finally, for the flood events, the low SoVI class shows no statistically different impacts for any event, whereas both the medium and high groups reflect several statistically valid shifts.

## 5. Summary and discussion

The validity of using Twitter as a sensor is dependent on the ability to extract informative content from the vast amount of unrelated content in social media. In this study we collect and analyze Twitter feed data for multiple natural hazards: 5 tornadoes, 5 forest fires, 5 wildfires, and 5 floods. The Twitter data is filtered with general disaster related keywords as opposed to event specific keywords to help generalize the research and to not focus on single events or depend on hashtags. These keywords were shown to effectively ignore non-hazard events yet successfully capture major natural hazards even when both events occur during the same general time frame.

Breakout detection is used to identify when the social media begins (and ends) its response to the disaster events. The expectation is that for disaster events in which the tweet frequency increases from the stable to disrupted states, there is potential of crowd-sourcing informative disaster information. That is, the increase in social media activity can be attributed to the event and thus the signal to noise ratio increases during the disrupted periods.

Overall, we notice that wildfires are less likely to shift tweet frequencies or impact negative sentiment than the other three hazard types. This is possibly due to their locations further from highly populated areas. However, areas with higher levels of social vulnerability may be more sensitive to wildfire events than others. Twitter behavior associated with tornado events is observed to return to its pre-event norms in all cases studied. This is possibly due to the fact that tornado events are generally shorter in duration than the other hazards considered.

The distances from tweet origins and the disaster centers is specific to the nature of the event. We expect that traditional media plays a large role in this. If the natural hazard is widely covered in the news, and especially if the damage reports are significant, it is more likely that Twitter users will comment on the disaster even if they are not directly impacted. The trends in distance skewness for negative sentiment tweets is not consistent across the events. In some scenarios, the negative tweets cluster closer to the disaster, but for others this is not the case. We hypothesize that the tweets which are closer to the disaster will have higher information content than those further away. Consider, for example, the two negative sentiment tweets in Table 10 referring to the 2013 Moore Tornado event. The first, originating at ground zero, comments on the level of devastation from an eyewitness; the second, originating from 1500 miles away, makes a general comment regarding the tragedy. During the analysis, we also notihengce that the negative tweets closer to the various disaster events are more likely related to the disaster itself. As the distance increases, the amount of messages not related to the event also increase. This is an important issue to note when conducting such social media analyses since it affects the signal to noise ratio.

The level of social vulnerability is also a factor which influences sensitivity to natural disasters. The empirical analysis demonstrates that the expected social media reactions should not be assumed to be homogeneous among the three levels analyzed. The shifts in tweet frequency are distinct in magnitude with respect to the disaster and the social vulnerability.

It is clear that Twitter can be considered a sensor for natural hazards. However, the results indicate that the various Twitter behaviors and metrics (duration of attention, frequency, frequency based on vulnerability, proximity, and polarity) are sensitive in different ways to the different types of natural disasters. It is critical that researchers understand that Twitter response patterns for a certain natural hazard type will not necessarily translate to other hazard types. Careful consideration should be employed when evaluating Twitter response to wildfires, for example, as compared to tornadoes. Furthermore, the social vulnerability of the effected population will play a distinct role in the user's social media behavior. Certain events have a broader impact in terms of distance, may be sustained for a longer time, and be observed differently among subgroups. Future work will leverage this finding to further analyze the quality of the information and actionable content within such social media feeds.

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