The anatomy of natural disasters on online media: hurricanes and wildfires

Nicole Olynk Widmar¹ · Kendra Rash¹ · Courtney Bir² · Benjamin Bir³ · Jinho Jung¹

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Abstract

Increasing prevalence and scale of natural disasters fuel the need for new approaches to evaluating, and eventually mitigating, their impact. This analysis quantifies and compares online and social media attention to hurricanes and wildfires over time and geographic space. Hurricanes studied included: Michael, Maria, Irma, Harvey, and Florence. Fires studied included: Woolsey, Mendocino, Carr, and Camp. It was hypothesized that total volume of online media content, measured in posts and mentions, varied measurably over the phases of the disasters. Furthermore, it was hypothesized that the anatomy of the disaster, specifically the number and timing/dates, of posts and mentions varied inside versus outside impacted zones/geographies. Social media content, in sheer volume, related to hurricanes was larger than that devoted to fires. A mismatch between the time periods that people post about natural disasters on social media and the times when aid is needed to rebuild was found. Mentions fell rapidly after landfall for hurricanes, and long before fires were officially contained or extinguished. This rapid fall in media attention may leave directly impacted populations without help and support during the rebuilding process. Greater understanding of volume of posts over time, or the anatomy of disasters in online media space, may help government agencies, private industry, and relief organizations understand public attentiveness before, during, and after various types of natural disasters.

✉ Courtney Bir
courtney.bir@okstate.edu

Nicole Olynk Widmar
nwidmar@purdue.edu

Kendra Rash
rashk@purdue.edu

Benjamin Bir
me.benbir@gmail.com

Jinho Jung
jung104@purdue.edu

¹ Department of Agricultural Economics, College of Agriculture, Purdue University, 403 West State Street, West Lafayette, IN 47907, USA

² Department of Agricultural Economics, Ferguson College of Agriculture, Oklahoma State University, 529 Agricultural Hall, Stillwater, OK 74078-6026, USA

³ Stillwater, USA

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1 Introduction

Due to expected rises in ocean temperature, it is anticipated that hurricanes will increase in frequency and intensity (Fischetti 2018). On land, climate is becoming hotter and drier, resulting in more frequent and stronger fires (Ortiz 2018). As hazards from natural disasters are expected to impact more people with increasing number and severity of events, new avenues of exploring risk and mitigation communication are evolving. Social media and online content is one such measure that is being used in the “citizen as sensor” approach to public safety issues (Martin et al. 2017).

Although there are many sources for news, online and digital media is unique in allowing for real-time distribution, development, and consumption. While providing a broad literature review of disaster-related communications on Twitter, Son et al. (2019) summarized studies evaluating Twitter usage during disasters. They formed three categories, namely studies focusing on tweet content, studies focusing on Twitter users, and studies focusing on Twitter features. Son et al. (2019) highlight that disaster communication work conducted on Twitter “often overlooks the different phases of disaster events that could influence communication patterns among the public and thus affect how people use Twitter.” While focusing on social and online media during a disaster offers usable insights, evaluating communication in preparation phases, as well as during and after the event, would offer a more complete picture.

Gaining understanding of posts/media during disasters enables rapid dissemination of critical information, such as locations for critical rescue efforts and/or directing of aid and medical support, as well as damage assessment. The added value of social listening as a surveillance system for disasters has been documented (Middleton et al. 2014; Imran et al. 2013; Cameron et al. 2012). Previous studies perceived the relationship between ubiquitous characteristic of social media and fundraising potentials for aiding victims. Nagar et al. (2012) found that geographic diffusion of a disaster covers the entire world via social media, which has a significant potential of developing universal fundraising activities.

This analysis quantifies and compares online attention to hurricanes and fires over time and geographic space. This study quantifies the volume, timing, and focus of online media in the time periods before, during and after Hurricanes Irma, Maria, Michael, Harvey, and Florence in addition to online media related to the Woolsey, Mendocino, Carr, and Camp fires. It was hypothesized that total volume of content, measured in posts and mentions related to individual natural disasters, varied measurably over the phases of the disaster. Furthermore, it was hypothesized that number and timing of posts and mentions within versus outside impacted zones/geographies varied. Additionally, whether the amount of attention a hurricane receives online is compared to the amount of attention a hurricane receives in terms of funding for disaster recovery and aid to victims was evaluated.

2 Background information

Beyond the immediacy of communication during the disaster, understanding the patterns, verbiage, and intentions of communication surrounding disasters could enable the development of risk mitigation and preparedness of disaster management. Twitter has been studied

extensively in the areas of emergency management (Panagiotopoulos et al. 2014, 2016). Martin et al. (2017) found that during Hurricane Matthew, peak Twitter response occurred leading up to the hurricane, and quickly decreased after the passage of the storm. Using Twitter, they were able to assess the evacuation response of residents affected by Matthew (Martin et al. 2017). Yin et al. (2012) also showed a positive correlation between peaks in the volume of tweets and the magnitude of 2010 earthquakes in Christchurch, New Zealand. Using Twitter data, Moore and Obradovich (2020) augment current flood standards based on tidal gauges at the county level. Based on their analysis of flood-related posts, they found that some counties experienced nuisance flooding that did not register using standard measures, which has implications for planning and response purposes (Moore and Obradovich 2020).

Studying hurricanes Irene and Sandy as well as tornados and a flood in Louisiana, Niles et al. (2019) found that those with an average-sized Twitter network (people they followed and followers) tweeted more during a natural disaster. Tweets from the average person outnumbered Twitter influencers during the disasters studied. Increases in Twitter use during natural disasters are important information for government agencies and relief organizations that are trying to provide information for those impacted, as well as information on how to help for those who are not. Twitter itself provides tips on Tweeting during a natural disaster through the company's blog, which includes suggestions like following news agencies and using the right hashtags (Reen 2018).

Studying hurricane Sandy, Wang and Zhuang (2017) found that news agencies tweeted more than governmental organizations and non-governmental organizations. Also studying hurricane Sandy, Pourebrahim et al. (2019) found that Twitter users reported receiving news from Twitter sources including, friends, family, and government agencies at a higher rate than non-Twitter users. As the information is distributed to a wide audience, people comment on and contribute additional information to the original source, creating a living breathing document with various viewpoints. For example, during hurricane Sandy in 2012, many states experienced power outages making traditional means of communication difficult, but people continued to use social media for information (Sadri et al. 2018). Using machine learning and Twitter data, Sadri et al. (2018) determined the evolution of communication patterns during hurricane Sandy. They identified three phases-warning, response, and recovery. They also concluded people were concerned about the storm's location, media coverage, and the activities of high-profile people including political leaders and celebrities (Sadri et al. 2018).

Facebook studies are also prevalent in the emergency response domain. Pogrebnjakov and Maldonado (2018) studied nearly a million messages from 997 Facebook pages of US police departments to study text complexity relative to emergency stage. For example, Sakaki et al. (2010) used Twitter data to estimate a spatiotemporal model for earthquake events. Their model worked better at estimating centers for earthquakes, and their accompanying system was able to notify people faster than the Japan Meteorological agency (Sakaki et al. 2010). Earthquake damage intensity was benchmarked using social media in several studies (Avvenuti et al. 2017; Mendoza et al. 2019; Earle 2010). In addition, according to Alexander (2014), after 50 min of an earthquake in northern Italy in 2012, a rapid, clear and relatively comprehensive picture of the earthquake became available with the help of social media. Beyond earthquakes, studying hurricane Sandy, Kryvasheyev et al. (2016) used Twitter data and a spatial-temporal model to compare the online response of 50 metropolitan areas of the USA and found a strong relationship between proximity to Sandy's path and hurricane-related Twitter activity. Kibanov et al. (2017) used Twitter data

to compare the ability of social media posts to complement and supplement information provided by NASA satellite imagery to track haze and fire incidents in Indonesia.

A significant body of literature has focused on the impact and efficacy of official government social media use for information dissemination. In an analysis of public relations best practices, Freberg et al. (2013) identified “good” social media crisis messages as containing links to further information, use of a strong voice, and multimedia. Liu et al. (2018) found that government organization crisis communication strategies focus on information over blame mitigation, and that Twitter enhances government organization-public crisis communication. Official social media posts as well as citizen posts are interconnected as they are often re-posted and commented on to create the body of natural disaster-related social media.

Existing studies on individual natural disasters spur questions about the anatomy of a category of natural disasters in online and social media broadly. Is the development of social media in response to a hurricane, for example, reflective of hurricanes generally or only that particular hurricane? Hurricanes are increasingly widely publicized; the “terrible trio” of Hurricanes Harvey, Irma, and Maria propelled 2017 to the costliest hurricane season since record keeping began in 1851 at approximately \$370 billion dollars (Halverson 2018). For the first time in recorded history, three Category 4 hurricanes made landfall in the USA, namely Harvey, Irma, and Maria, and five total Category 5 landfalls took place across the Caribbean (Blake 2018).

The effect of the population impacted by the natural disaster, as well as the duration and strength of the event, is likely to influence monetary aid, as well as social media presence. These two factors came to a head when hurricane Harvey stalled over Houston Texas. Houston is the fourth largest metro area in the USA and has experienced large amounts of suburban sprawl resulting in the removal of grass and marshes that would help prevent (Halverson 2018). This geography coupled with a vast plume of low-level moisture combined with a high-pressure system created a storm that resulted in 25 trillion gallons of freshwater falling on the county, 91 fatalities, and 200 billion dollars in damages—40 million more than hurricane Katrina (Halverson 2018). Other geographic features, such as being an island, also influenced the impact of recent hurricanes. Hurricane Irma hits the island of Puerto Rico, killing 97 people (Halverson 2018). Unfortunately, due to difficulties rebuilding structures, and getting aid to the island, it is expected that additional 500 deaths can be attributed to the direct aftermath (Halverson 2018).

In comparison with hurricanes, which have a predicted landfall that is determined sometimes weeks in advance (Cangialosi and Berg 2012), fires appear sporadically. Although weather conditions and fuel buildup may help predict the chances of fires occurring (Andrews et al. 2007), there is less warning than for hurricanes. Evaluating both hurricanes and fires allows researchers to begin determine factors that influence social media response.

3 Materials and methods

Data collection facilitated by in-depth Internet/web searches, often focused on media sources and news outlets, has long been utilized in social science research (for example, via platforms such as LexisNexis (2019)). This analysis employed the Netbase platform, which offers search and analysis capabilities for online media, including blogs, forums, consumer reviews, Twitter, Instagram, News, and other media (Netbase 2018). Netbase ranks among

the top social listening platforms, and has been used for research purposes as well as quantifying interest and sentiment for product development (Carr et al. 2015). Searches across countries and in multiple languages are technologically possible, although limitations surrounding language interpretation, like slang, shorthand, sarcasm, and cultural context must be acknowledged. For this analysis, the geographic area for all searches employed was limited to the USA and US Virgin Islands; posts in English were studied exclusively.

Online search results within search parameters associated with five hurricanes and four wildfires were studied during the time period of 9-16-2016 through 12-16-2018. The 27-month time period studied offered sufficient time for in-depth comparison during an abnormally impactful hurricane period in the USA. Given the fluidity of data collected through social media posts as they may appear, be removed, and/or be reinstated, data collection dates were documented. Data were downloaded and summarized on December 15–16, 2018.

3.1 Parameterization of searches and analysis of hurricanes

By 1979, the USA was using male and female names to identify tropical storms and hurricanes in both the Pacific and the Atlantic (NOAA 2018a). This nomenclature was adopted to avoid previous confusion with the numbering system when storms would occur simultaneously (NOAA 2018a). Due to the use of common names to identify individual storms, careful attention was needed to determine the word set to establish the general hurricane data set. By including, for example, the name *Michael* (a named hurricane), all posts authored by or talking about a person named Michael would be found, as well as hurricane Michael (the targeted media). However, including the search term *hurricane Michael* would not generate additional data points not already captured by the word *hurricane*. Therefore, the terms used to determine the base hurricane data set included: Hurricane, #Hurricane, hurricane, and #hurricane.

Further tuning of the search was done by evaluating individual posts and determining keywords, authors (bots), or domains to exclude. For example, song lyrics such as “rock you like a hurricane” were removed along with references to comic books, Pokémon, and university mascots such as the Tulsa University Hurricanes. Some domains also required extra attention when developing searches to collect the relevant/necessary data. The majority of domains were social media platforms and news sources; however, other blogs such as community.babycenter.com were within the top domains. Upon closer inspection, many of the posts in this particular domain were parents talking about ways to prepare for hurricanes with children, options for evacuations, and other hurricane-related topics. However, some of the posters were describing the behavior of their children as “like a hurricane.” Efforts were made to exclude such posts through the exclusion of phrases such as “my little hurricane.” All inclusions and exclusions for the hurricane topic are available in Appendix 1.

Conversations regarding each hurricane may differ, so efforts were made to isolate posts related to each individual hurricane by employing themes, which were essentially filters placed over top of existing search terms. Due to hurricanes having common names, there were challenges with this process beyond simple search engine use. For example, Michael Jordan made a sizeable donation on behalf of hurricane Florence relief and any post/news story/or blog mentioning this would also appear in the hurricane Michael data set, because of Michael Jordan’s first name. Researcher inspection of the data set revealed that relatively few posts referenced hurricane Michael without the word hurricane. For example,

people were more likely to talk about damage caused by hurricane Michael than they were to talk about damage caused by Michael. Therefore, all hurricane themes were created as hurricane (name) and the associated hashtags. For example, the hurricane Michael theme was comprised of Hurricane Michael, #Hurricane Michael, #hurricanemichael. The named hurricanes included in this data set were gathered from the NOAA (National Oceanic and Atmospheric Administration) website and include hurricanes Florence, Michael, Maria, Irma, and Harvey (NOAA 2018b). Due to limitations in the available data time frame (27 months prior to collection period), collecting data prior to hurricane Harvey was not possible at the time that the research was conducted.

To allow for comparison across areas of different impact potentials such as in Kryvasheyeu et al. (2016), specific geographic regions were identified. Filters employed included hurricane states, defined as states in which there was a historical hurricane landfall (NOAA 2018c), and non-hurricane states, which included all other states. Hurricane states included Texas, Louisiana, Mississippi, Alabama, Florida, Georgia, South Carolina, North Carolina, Virginia, Maryland, Delaware, New Jersey, Pennsylvania, New York, Connecticut, Rhode Island, Massachusetts, New Hampshire, and Maine. It was hypothesized that those in hurricane-prone areas would have different reactions to new hurricanes, for example, they may show solidarity toward others affected. It was also hypothesized that those affected may use different languages in their posts when compared to non-affected areas. For example, perhaps those immediately affected by the hurricane have more financial- or economic-related posts that include words such as recover and aid, while those unaffected may have posts such as pray for, thinking of, and hope for. For each individual hurricane, the affected area was determined as the closest major city to the hurricane's landfall by researchers. For example, the affected area for hurricane Florence was Wilmington, North Carolina, USA.

It was also hypothesized that the posts/blogs/news would differ between the time leading up to and following the hurricane. Martin et al. (2017) also used pre- and post-evacuation time periods when studying hurricane Matthew. Two distinct time frames were determined for each hurricane, before the hurricane, and after the hurricane. Hurricanes start as a weaker storm, for example, a tropical storm, and then build into a hurricane which may not make landfall for days, weeks, or ever (Cangialosi and Berg 2012; Hurricanes: Science and Society 2020). Due to their nature, hurricanes are often followed and talked about prior to landfall, therefore it was important to monitor a period of time prior to and during landfall. The time between the formation of each hurricane and the dissipation of each hurricane as defined by the National Hurricane Center Tropical Cyclone report was used to determine the "lifespan" of each hurricane that occurred prior to 2018 (NOAA 2018b). The NOAA cyclone report for 2018 was not yet available at the time of data collection/date setting, so a Federal Emergency Management Agency (FEMA) report was used to establish the lifespan of hurricane Michael (FEMA 2018a), and a combination of news sources was used to establish the lifespan of hurricane Florence (Larino 2018; CBSa 2018). The halfway point for the hurricane's lifespan was determined; the period before each hurricane was calculated by subtracting 30 days from the midway point of the lifespan. To calculate the time frame after the hurricane, 60 days were added to the midway point of the lifespan. For example, the lifespan of hurricane Maria was September 16–30, 2017. The halfway point (if it was an odd number the extra day was included in the before period) was September 23, 2017. Therefore, the time frame before hurricane Maria was determined as August 24, 2017–September 23, 2017, and the time frame after hurricane Maria was determined as September 24, 2017–November 23, 2017. The timeframes for hurricanes are available in Table 1. All search details for each individual hurricane are available in Appendix 2.

Table 1 Dates designating before and after hurricane and during and after wildfires studied

Hurricane Florence	Before	August 11, 2018–September 10, 2018
	After	September 11, 2018–November 10, 2018
Hurricane Harvey	Before	July 25, 2017–August 24, 2017
	After	August 25, 2017–October 24, 2017
Hurricane Irma	Before	August 8, 2017–September 7, 2017
	After	September 8, 2017–November 7, 2017
Hurricane Maria	Before	August 24, 2017–September 23, 2017
	After	September 24, 2017–November 23, 2017
Hurricane Michael	Before	September 13, 2018–October 13, 2018
	After	October 14, 2018–December 13, 2018
Camp Fire	During	Nov 8, 2018–November 25, 2018
	After	November 26, 2018–December 16, 2018
Carr Fire	During	July 23, 2018–August 31, 2018
	After	September 1, 2018–October 31, 2018
Mendocino Fire	During	July 27, 2018–October 04, 2018
	After	October 05, 2018–December 4, 2018
Woolsey Fire	During	November 11, 2018–November 22, 2018
	After	November 23, 2018–December 16, 2018

Statistical analysis of the number of mentions before and after hurricanes, and during and after fires was completed. The total number of mentions before and after the hurricanes or fires for direct impact states, hurricane/fire states, and non-hurricane/non-fire states were determined. The percentage of posts occurring before and after for each category were calculated, and then statistically compared using the test of proportions. This allowed researchers to determine if the percentage of mentions occurring before and after for the 3 regional categories studied statistically differed. A test of the difference of two proportions $\hat{p}_1$ and $\hat{p}_2$, can be calculated as:

$$z = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\hat{p}_p(1 - \hat{p}_p)\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}} \quad (1)$$

given:

$$\hat{p}_p = \frac{x_1 + x_2}{n_1 + n_2} \quad (2)$$

where x_1 and x_2 are the total number of successes in the two populations (Acock 2018). The tests of proportion were conducted using STATA/SE16 (StataCorp 2019).

3.2 Financial aid and relief for hurricanes

There are many organizations aimed at providing relief efforts and monetary support to individuals and families impacted by natural disasters, such as the Red Cross and FEMA. In order to quantify the impact of monetary relief for various natural disasters, researchers

looked for a source that provided consistent data for the named hurricanes studied. The American Red Cross has monetary data that is updated semi-frequently, providing the number of dollars, donated to a specific cause, across the country. FEMA keeps a public record of information, statistics, and resources for each natural disaster that impacts the USA (or US Territories) (FEMA 2020). The data search began at the FEMA government website (www.fema.gov), using the search toolbar, researchers typed in the name of the natural disaster (ex: Hurricane Maria). For each natural disaster, FEMA has a main website documenting the specific areas that were impacted and the disaster codes associated with each of these areas. Each impacted area is assigned a unique Disaster Declaration Number (DR) by FEMA (FEMA 2009). The DR codes for each hurricane were documented and used as a secondary check that the areas initially used for each disaster were all encompassing. Then, for each hurricane, and each DR area (as recorded by FEMA), there were three numbers recorded for analysis: “Individual Assistance Applications Approved” (FEMA 2019a), “Total Individual & Household Program Dollars Approved” (FEMA 2019a), and “Total Public Assistance Grants Dollars Obligated” (FEMA 2019b). These numbers were aggregated, by hurricane, and across all DR areas to allow comparisons between online mentions and monetary impact. Economic impact in billions of dollars was obtained for Harvey, Irma, and Maria from FEMA (FEMA 2018b). Economic impact for Florence was obtained from Cooper (2018), and the economic impact of hurricane Michael was obtained from NOAA (2018a, b, c, d).

Statistical analysis was completed by determining the total number of approved assistance applications, the total dollar value for assistance (the summation of total individual households program, and total public assistance), the total dollar value of Red Cross donations, and the total economic impact across the 5 hurricanes studied. The percentage of each category for each hurricane was then calculated. For example, the percentage of total assistance from hurricane Maria out of the total assistance provided for the 5 hurricanes was determined. These percentages were then statistically compared using the test of proportions (Eqs. 1, 2) to determine the rank from highest percentage to lowest percentage. The total number of social media and online media mentions was determined across all 5 hurricanes. Again, the percentage of total mentions was determined for each hurricane and statistically compared to establish a rank of hurricanes from highest percentage of mentions to lowest. The rankings across both the financial measures, and social media data were then compared to establish connections between social media chatter, economic impact, assistance provided, and donations.

3.3 Providing a comparison among natural disasters: methodology for studying wildfires

The wildfire topic was built using all variations including hashtags, capitalization differences, and hyphenations of common words used to describe largescale fires including: wildfire, brushfire, grassfire, desert fire, hill fire, vegetation fire, and peat fire. All include and exclude terms for the fire topic are available in Appendix 1. Exclusions included online video games where parts of the fictitious world (often referred to as “map”) may be on fire, and ideas on how to conquer these areas are often discussed in gaming chatrooms, blogs, etc.

Wildfires are named for the area in which they start and can be named after things such as a nearby lake, road, landmark, or town (Morning Edition 2015). Due to this naming structure, the names of the actual fires including variations and hashtags were included

in the creation of the topic. Fires studied were the Mendocino Complex, Carr, Woolsey, and Camp fires. Individual searches for each fire included the fire name and associated hashtags. To compare the reaction of those who live in areas prone to wildfires two geographies were created: fire-prone states, and non-fire-prone states. Fire-prone states were determined using the insurance information institutes' (III) lists of fire-prone states by household and percent of household from 2013, 2015, and 2017 (III 2018). Fire states included California, Texas, Colorado, Arizona, Idaho, Washington, Oklahoma, Oregon, Utah, Montana, New Mexico, Wyoming, Nevada. Non-fire-prone states included all US states excluding the fire-prone states.

To evaluate the posts/news/blogs of those directly affected by the fire, geographies were parameterized for each fire's affected area. Individual details regarding the fires, including regions affected and dates, were collected from different sources. Information regarding the Mendocino Complex and Carr fires was sourced from the California government fire incident information website (Cal Fire 2018). Information regarding the Woolsey fire (CBSb 2018; Hamilton et al. 2018), Camp fire (Dowd 2018; CBSb 2018), and additional information regarding the Carr fire (Sanchez 2018) were sourced from news sites. The affected areas of the fires were more difficult to establish when compared to the hurricanes. Many of the counties that burned were located within national parks or sparsely populated areas. All large cities within the affected county for each fire were individually included within each individual fire's affected area geography. To capture the less inhabited areas, a geofence was placed around the general area of the affected county(s) for each fire. The geofence allows a shape to be drawn directly on a map of the USA, and only posts from the geofenced area are included (Appendix 3). The use of named larger cities and geofence were intended to facilitate capturing all potentially affected people for each individual fire. For example, the Camp fire affected area included geographies were Magalia California, Chico California, Chico-Redding California, Paradise California, Oroville California, Gridley California, and a geofence was drawn around the general area of Butte County, California (Appendix 3).

Unlike hurricanes, there is no standard or expected warning period or watching period for the development of individual/new named fires. However, it was hypothesized that posts would differ during and after each wildfire. Two time periods were established for each fire, during and after. The period during the fire was established as the time between when the fire started and containment. The time period after was defined as the day after containment plus 60 days. For example, the time period during the Carr fire was defined as July 23, 2018–August 31, 2018, and the time period after was defined as September 1, 2018–October 31, 2018. The time periods for each fire are available in Table 1. All search parameters employed for searching individual fires are available in Appendix 3.

4 Results

The percentages of females and males posting on social media regarding natural disasters are fairly equivalent (Table 2). Relatively high percentages of posters were 55–65 of age. There were more posts regarding hurricanes when considering the entire USA compared to the number of posts regarding fires. More posts about hurricanes came from hurricane states than non-hurricane states, while the opposite was true for fires in which more non-fire state posts were found.

Table 2 Inferred demographics of social media (Twitter) posters

	Hurricanes			Fires		
	Hurricane states		Non-hurricane states	Fire states		Non-fire states
	All US			All US		
<i>Gender (n)</i>	13,608,062	7,005,851	6,602,267	3,544,369	1,664,327	1,880,076
Male	51%	51%	51%	49%	48%	50%
Female	49%	49%	49%	51%	52%	50%
<i>Inferred age (n)</i>	13,150,779	6,801,422	6,349,370	3,440,185	1,627,977	1,812,220
< 18	9%	9%	8%	8%	8%	8%
18–24	12%	12%	11%	11%	11%	10%
25–34	17%	17%	16%	16%	16%	16%
35–44	15%	15%	15%	15%	15%	15%
45–54	16%	16%	17%	17%	17%	17%
55–64	20%	19%	21%	21%	20%	21%
65 +	12%	12%	12%	12%	12%	13%
<i>Posts by day of week (n)</i>	11,062,340	6,234,610	4,827,500	1,921,700	949,190	972,470
Monday	12%	12%	12%	15%	15%	14%
Tuesday	15%	15%	15%	19%	19%	19%
Wednesday	16%	16%	15%	17%	17%	17%
Thursday	15%	16%	15%	17%	17%	17%
Friday	16%	16%	16%	13%	13%	14%
Saturday	13%	13%	14%	10%	10%	10%
Sunday	13%	12%	13%	10%	10%	10%
Mentions (n)	39,843,419	14,023,698	25,819,870	11,573,358	3,447,225	8,126,508
All posts (n)	11,062,340	6,234,610	4,827,500	1,921,700	949,190	972,470

Table 3 Domains and sources for posts

	Hurricanes		Fires			
	All US	Hurricane states	Non-hurricane states	All US	Fire states	Non-fire states
Domains						
	twitter.com	96%	98%	95%	91%	94%
	instagram.com	2%	2%	3%	4%	6%
	reddit.com	1%	0%	1%	2%	0%
	tripadvisor.com	0%	0%	1%	1%	0%
	disboards.com	0%	0%	0%	1%	0%
Domains (n)	30,428,290	13,934,660	11,742,097	6,963,920	3,444,683	3,550,904
Sources (n)	30,428,368	13,934,660	16,493,398	11,557,943	3,442,176	8,113,662

Table 4 Top 25 Terms in hurricanes search, by geography

All US		Hurricane states		Non-hurricane states	
n	30,428,076	n	13,934,660	n	16,493,378
hurricane Harvey	3,798,592	Hurricane Harvey	1,594,485	storm	2,321,052
Puerto Rico	3,416,421	Hurricane Irma	1,371,672	Hurricane Harvey	2,204,141
storm	3,402,370	Puerto Rico	1,286,202	Puerto Rico	2,130,316
Hurricane Irma	3,085,931	Florida	1,207,580	Trump	1,904,768
Florida	3,050,337	Trump	1,093,270	Florida	1,842,741
Trump	2,998,020	storm	1,081,239	Hurricane Irma	1,714,259
Hurricane Maria	2,680,143	Hurricane Maria	1,018,740	Hurricane Maria	1,661,509
help	2,544,383	help	942,902	help	1,601,460
hit	2,040,344	Texas	660,186	hit	1,387,901
Texas	1,850,785	hit	652,450	home	1,103,193
Hurricane Matthew	1,480,662	Hurricane Florence	630,323	state	1,070,531
home	1,453,731	Hurricane Matthew	603,381	damages	989,835
Hurricane Florence	1,429,756	#Irma	493,150	island	906,368
state	1,391,836	power	361,854	left	892,447
Powered	1,229,240	hurricane season	361,009	Hurricane Matthew	877,282
left	1,201,381	@realDonaldTrump	360,320	power	867,187
island	1,182,165	donate	360,096	Hurricane Florence	799,463
Updated	1,060,341	BREAKING	332,346	reported	742,299
landfall	998,714	Hurricane Michael	332,037	working	706,286
shows	966,255	landfall	319,240	caused	702,326
caused	888,580	affected	291,956	Updated	688,443
#Irma	875,230	safe	289,533	shows	679,463
@realDonaldTrump	827,022	stay	262,507	landfall	679,430
mph	756,385	hurricane victims	246,552	mph	541,042
Hurricane Michael	723,568	#Harvey	225,425	National Hurricane Center	422,655

Twitter.com encompassed the highest percentage of posts by far for both disasters and all geographies (Table 3). Compared to hurricane posts, there were slightly higher percentages of posts from Instagram.com for both fire and non-fire states. For all regions studied, the top 4 terms included references to hurricane Harvey, Puerto Rico, and Hurricane Irma. For all area categories, the term *help* appeared in the top 10 terms, but unique to hurricane states, the terms *donate*, and *hurricane victims* also appeared (Table 4). Unique to fires, the term *firefighters* appeared in the top 5 terms for all three geographies (Table 5). Also unique to fire states were words that likely described individual situations such as *safe*, *fleeing*, and *lost* although *evacuate* did appear as a top term in both wildfire and non-wildfire geographies. *Climate change* only appeared as a top term for US and wildfire state geographies for wildfires.

For the five hurricanes included in this analysis, there were more mentions after the hurricane than before (Table 6). For hurricanes, the total number of mentions for direct impact states was 2,246,566, for hurricane states 4,346,500, and for non-hurricane states 9,226,759. For direct impact states, hurricane states, and non-hurricane states mentions before the hurricanes accounted for 99.93%, 99.28%, and 99.30% of posts, respectively. For

Table 5 Top 25 Terms in wildfires search, by geography

All US		Wildfire states		Non-wildfire states	
n	8,535,219	n	3,413,636	n	5,121,629
homes	1,056,816	California wildfires	326,385	homes	778,768
California wildfires	961,057	home	251,439	burn	664,672
burns	898,853	help	249,151	California wildfires	634,691
Firefighters	796,758	acres	238,488	state	577,398
area	734,567	firefighters	229,926	Firefighters	566,839
helped	732,635	burned	222,823	area	545,705
spread	638,229	areas	190,263	helped	483,343
acres	618,474	smoke	176,233	spread	478,177
smoke	490,436	update	163,058	destroyed	390,856
Updated	487,027	spread	160,063	acres	379,987
destroying	470,135	evacuate	124,061	official	366,568
evacuated	412,548	lost	121,103	AP	356,789
report	409,480	fighting	105,429	blaze	346,942
blazes	395,562	affected	101,167	report	329,532
killed	390,509	working	97,047	killed	324,452
working	385,039	battling	94,052	Updated	323,639
AP	385,021	contained	92,557	smoke	314,206
started	384,096	Southern California	81,139	started	305,511
battling	378,468	safe	77,949	work	283,654
fighting	367,835	climate change	77,768	evacuate	279,552
flames	335,895	using	72,178	battle	275,782
contained	330,736	@realDonaldTrump	64,181	flames	272,980
Southern California	313,679	flames	62,922	residents	271,109
cause	306,700	#california	56,752	fighting	262,411
climate change	268,529	fleeing	50,431	contained	238,180

all three regions studied, the percentages of mentions occurring before were statistically different from the percentage of mentions occurring after using the test of proportions.

There were more mentions during the fires and fewer after for all fires studied (Table 6). It is difficult to compare across the hurricanes and fires because each has a unique time-frame, with some lasting much longer than others. To visualize the volume of mentions, Figs. 1, 2, 3, 4, 5, 6, 7, 8, and 9 present the number of mentions weekly for the duration of the natural disaster. For all hurricanes studied, the number of posts was the highest for all geographic categories, the week of landfall and the following week, with the number of posts quickly diminishing. Hurricane Harvey had the highest number of mentions in the USA when compared to the other hurricanes. Interestingly, despite the horrible devastation caused by hurricane Maria, the peak number of mentions in the USA was less than 600,000 (Fig. 4) almost 5 times less than the peak number of mentions for hurricane Harvey (Fig. 2).

The Camp fire had the largest number of mentions, when compared to all other fires (Fig. 6). Conversely, the Mendocino complex fire had the highest number of mentions (Fig. 8). For all fires, the largest number of mentions typically occurred weeks before the

Table 6 Mentions before and after natural disasters

	Mentions
Hurricane Florence	
2,138,477 ^a	
16% ^b	
Direct impact area	
Before	30
After	1,986,969
Hurricane states	
Before	8678
After	679,057
Non-hurricane states	
Before	19,989
After	1,430,753
Hurricane Harvey	
4,266,391	
31%	
Direct impact area	
Before	10
After	36,644
Hurricane states	
Before	50
After	1,443,532
Non-hurricane states	
Before	1407
After	2,821,402
Hurricane Irma	
4,413,792	
32%	
Direct impact area	
Before	1341
After	166,014
Hurricane states	
Before	21,096
After	1,383,482
Non-hurricane states	
Before	39,803
After	2,969,411
Hurricane Maria	
1,589,297	
12%	
Direct impact area	
Before	113
After	42,607
Hurricane states	
Before	1178
After	438,069
Non-hurricane states	
Before	3154

Table 6 (continued)

	Mentions
After	1,146,896
Hurricane Michael	
1,165,302	
9%	
Direct impact area	
Before	–
After	12,838
Hurricane states	
Before	192
After	371,166
Non-hurricane states	
Before	385
After	793,559
Camp Fire	
925,751	
55%	
Direct impact area	
During	7048
After	719
Fire states	
During	332,268
After	33,437
Non-fire states	
During	498,912
After	61,134
Carr Fire	
294,966	
18%	
Direct impact area	
During	3373
After	448
Fire states	
During	95,393
After	3296
Non-fire states	
During	188,295
After	7982
Mendocino Fire	
44,573	
3%	
Direct impact area	
During	117
After	6
Fire states	
During	11,596
After	193
Non-fire states	

Table 6 (continued)

	Mentions
During	29,814
After	2970
Woolsey Fire	
409,905	
24%	
Direct impact area	
During	18,147
After	2610
Fire states	
During	172,542
After	13,883
Non-fire states	
During	206,506
After	16,974

^aTotal number of mentions for the disaster for the period studied

^bPercentage of total mentions across all hurricanes or fires

Fig. 1 Mentions for Hurricane Florence by geographic area. *Note* Box indicates week of midway point

end of the fire. Mentions increased at the beginning of fires, and then decreased. Total mentions occurring during the fires for direct impact states were 32,468, for fire states 662,608, and for non-fire states 1,012,587. For direct impact states, the percentage of mentions occurring during the fires accounted for 88.35% of mentions. For fire states, mentions during fires accounted for 92.33%, and for non-fire states 91.20%. Using the test of proportions, it was determined that the percentage of mentions for all regions occurring during the fires was statistically different than the percentage occurring after the fires. The Mendocino Complex fire took almost 3 months to put-out, and by the end of the fire, very few people were posting about it on social media.

FEMA and Red Cross aid as well as reported economic impact for the hurricanes studied are available in Table 7. Using the test of proportions, the percentage of FEMA assistance application, FEMA aid, Red Cross donations, economic impact, and mentions were statistically compared between the hurricanes studied. Irma had the highest percentage of

Fig. 2 Mentions for Hurricane Harvey by geographic area. *Note* Box indicates week of midway point

Fig. 3 Mentions for Hurricane Irma by geographic area. *Note* Box indicates week of midway point

FEMA assistance applications (46%), followed by Maria (28%), and Harvey (22%). Florence and Michael tied for lowest percentage of applications (2%). For total FEMA aid, Maria had the highest percentage of aid dollars (58%), followed by Harvey (21%), and Irma (14%). Again, Florence and Michael tied for last at 3% each. Hurricane Harvey had the highest percentage of Red Cross donations (68%) followed by Irma (12%). Hurricane Maria and Florence tied for 3rd with 9%, and hurricane Michael had the lowest percentage (5%). Harvey had the highest economic impact (40%), followed by Maria (29%), and Irma (16%). Michael and Florence were tied for last at 8%. Hurricanes Irma (33%) and Harvey (31%) tied for first in terms of highest percentage of mentions (Table 6). Florence was second (16%), followed by Maria (12%) and Michael (9%).

Fig. 4 Mentions for Hurricane Maria by geographic area. *Note* Box indicates week of midway point

Fig. 5 Mentions for Hurricane Michael by geographic area. *Note* Box indicates week of midway point

5 Discussion

In a 2015 survey, Perrin (2015) found that roughly equal percentages of men (62%) and women (68%) were using social media. Natural disasters impact geographic areas independent of gender, so it is unsurprising that such events would be of equal concern/interest to both men and women. Although young adults between 18 and 29 years old are more likely to be social media users, 35% of people 65 and older are using social media, which has more than tripled since 2005 (Perin 2015). Looking specifically at Twitter, for which this study has demographic information, in a 2012 study 27% of those 18–29 used Twitter while only 2% of those 65 and older used Twitter (Duggan and Brenner 2013). The increased interest in participating in natural disaster discussion on social media of older posters may be the result of making disaster plan decisions for their families, or being more likely to have property that could be impacted by a disaster.

Fig. 6 Mentions for Camp Fire by geographic area. *Note* Box indicates week fire was declared over

Fig. 7 Mentions for Carr Fire by geographic area. *Note* Box indicates week fire was declared over

Given the destruction related to hurricane Harvey and the destruction Hurricane Irma caused in Puerto Rico (Halverson 2018), top terms for hurricanes related to these storms were unsurprising. Terms related to helping and providing relief were common in the hurricane states. Anecdotally, hurricane-impacted zones, and in particular those which faced devastation in recent memory are featured as providing relief for newly impacted zones. For example, southern states' residents aided others along the Gulf Coast in recent years in the aftermath of hurricanes Harvey, Irma, and Florence in Texas, Central Florida, and North Carolina. For example, the Cajun navy is a volunteer relief and rescue group that uses personal boats to aid in the relief and rescue of those in Louisiana and surrounding

Fig. 8 Mentions for Mendocino Fire by geographic area. *Note* Box indicates week fire was declared over

Fig. 9 Mentions for Woolsey Fire by geographic area. *Note* Box indicates week fire was declared over

states (Cajun Navy 2019). The Cajun Navy self-describes as, “Rescue and relief is our way of sharing our South Louisiana cultural tradition (of neighbors helping neighbors) with people in need across the United States” (Cajun Navy 2019).

There are many possible explanations for the increased number of posts regarding hurricanes in comparison with fires found in this research. The impacts, financially, socially, and culturally, of natural disasters are partially driven by geographic locale of the disaster. The US coasts are highly populated (Wilson and Fischetti 2010), which may result in higher numbers of people being directly impacted by hurricanes than fires. This population factor may influence the number of social media posts, and possibly the content of posts regarding hurricanes in comparison with fires. Hurricane Harvey had the highest percentage of Red Cross donations, and was tied with Irma for highest percentage of mentions. The high population of the Houston area, and severity of the storm resulted in high economic impact. It may be assumed that denser populations and greater disaster severity

Table 7 FEMA disaster relief, Red Cross donations, and economic impact for hurricanes

FEMA disaster relief codes	Harvey				Irma				Maria				Michael			
	DR-4393	DR-4394 Total	DR-4332	DR-4335	DR-4336	DR-4338	DR-4337 Total	DR-4339	DR-4340 Total	DR-4399	DR-4400	DR-4406	Total			
FEMA disaster relief	34,675	5169	39,844 (2%) ^b	373,654 (22%)	8891	1662	9399	777,235 (46%)	797,187 (46%)	470,469	11,702	482,171 (28%)	31,348	5073	–	36,421 (2%)
Individual assistance applications approved	132	24	156	1657	41	13	14	1022	1090	1309	44	1353	144	12	–	156
Total individual & household program (millions of dollars of dollars approved)																
Total public assistance grants (millions of dollars obligated)	240	53	293	1610	60	10	118	930	1118	5760	1796	7556	216	25	6	241
FEMA total ^c (millions of dollars)	372	77	449 (3%)	3267 (21%)	101	23	132	1952 (14%)	2208 (14%)	7069	1840	8909 (58%)	360	37	6	397 (3%)
Red Cross donations (millions of dollars)	69.3 (9%)			518.8 (65%)	96.7 (12%)							71.4 (9%)		36.2 (5%)		
Reported economic impact (billions of dollars)	24 (8%)			125 (40%)	50 (16%)					90 (29%)				25 (8%)		

^aFlorence also had distinction EM 3403 but no financial numbers were available

^bPercentage of total applications or dollars across hurricanes studied included in parenthesis

^cFEMA total is the summation of total individual and household programs and total public assistance grants

would result in a higher storm impact and media attention. However, it would be difficult to measure the individual impact of any one variable, given the population clusters along the shore, and the fact that hurricanes impact the coast. Conversely, although hurricane Maria ranked second in terms of economic impact, it was third in terms of donations, and 3rd in terms of social media mentions, giving credence to the idea there are other factors involved beyond the amount of devastation.

Posts peaked in volume the week of landfall and quickly diminished. Previously, Martin et al. (2017) found that peak Twitter response happened leading up to hurricane Mathew and quickly decreased after its passage. Hurricane Harvey and Irma had the largest percentage of total mentions, even though other hurricanes including Maria were also destructive. This is likely due to the amount of destruction caused by hurricane Harvey. Kempton (2019) analyzed Newspaper coverage of hurricanes Harvey and Maria and found that news coverage may be biased by geographic, social, and racial inequalities. Hurricane Maria was framed with more political intent in newspapers and hurricane Harvey was more often framed as human interest (Kempton 2019). More research would be needed to determine the prevalence of such biases in social media coverage. Additionally, Harvey, Irma, and Maria all hit roughly within a 1-month period which may have resulted in compassion fatigue for those not directly impacted.

Monetary aid decreased from Harvey to Maria which did not align with storm severity or prevention (Conway 2019). Reasons for staggered decreases in donations could have been the result of donor fatigue, difficulty in accessing unfamiliar geographic areas such as Puerto Rico and the US Virgin Islands, and potential racial bias or donor perception (Conway 2019). “Offering ‘thoughts and prayers’ has become a standard response from both US policy makers and the public to major catastrophes—including hurricanes, wildfires, mass shootings, and disease outbreaks.” (Thunstrom and Noy 2019). A survey conducted by Taylor et al. (2012) reported that people undergoing a disaster feel more supported and optimistic about their situation when social media were extensively involved, supporting the argument. While social media and peer-to-peer communication may facilitate the outpouring or expression of concern, including offering up thoughts and/or prayers, recent work has been critical in the sense that nonreligious people have been found to negatively value such gestures from Christians and are indifferent to receiving them from other non-religious people (Thunstrom and Noy 2019). More importantly, one might argue that gestures meant in goodwill could actually replace other communications and/or other aid. In short, regardless of the specific value of a thought and/or prayer to an individual person or group of people, in total are those offering such gestures doing so in place of or alongside other assistance.

Wildfires, particularly in the Western US are, in contrast to hurricanes, more local in their impacts, yet terrifying due to their destructive unpredictable nature. Oftentimes wildfires, particularly in the western states of the USA occur in relatively unpopulated areas; however, as populations grow in these areas, especially California, the impact could become greater (Schoen and McDonald 2019). The recent number of lives lost in large, fast-moving fires through residential and more populated zones along with the fires occurring outside of the traditional wildfire season, has driven attention to the devastation that wildfires cause (Boghani 2019). The Camp fire was the deadliest wildfire in California’s history with 85 people losing their lives (Boghani 2019). Over 18,800 structures were destroyed, with the vast majority of them being residences (Boghani 2019). The differences between the populations affected by hurricanes and fires may in part explain why higher numbers of hurricane states posted about hurricane disasters than non-states, while

the reverse is true for fires. Despite not residing in a fire state, many people were still joining in the conversation regarding the fires included in this analysis.

Unlike hurricanes, fire content included fairly high Instagram usage. This difference, may be in part due to the large impact of recent wildfires in California. Despite all of the positive uses of social media during a natural disaster, the phenomenon of “keyword squatting,” using keywords or hashtags related to an event to promote unrelated products, became common during the California wildfires (Ma 2018). Influencers were using previous pictures of locations in California or posting things like wine Wednesday while using the tag #californiafires and promoting items (Ma 2018). Although there are some people using social media for personal gain in light of natural disasters, the ability to help people and disseminate information likely outweighs this downside.

There is no way to put-out or stop a hurricane; however, firefighters can help stop or mitigate damages related to wildfires, and firefighters appeared as a top term related to fires. The US forest service employs approximately 10,000 wildland firefighters with specific roles and training (USDA 2020). Due to chronic understaffing and the longer fire season, firefighters are working overtime, and some firefighters say working 32 days straight is the new normal (Morris 2018). Although public concern for firefighters as seen through social media may rise during natural disasters, the conversations regarding solutions to the understaffing and overworking problem likely need to occur during non-disaster times.

Despite being the largest fire in California history (Solomon 2018), the Mendocino Complex fire had the lowest number of peak mentions (Fig. 8). However, the Camp fire was one of the deadliest and costliest fires of all time (Solomon 2018). This point demonstrates that many measures of natural disasters are needed to portray the entire impact on communities, natural places, and the economy. A key finding across all fires was that the chatter related to fires died out long before the fires themselves. This pattern may cause issues for those seeking recovery help, as the chatter on social media has died down by the time recovery efforts are underway. Words related to fleeing appeared only in wildfire states. Monitoring language such as this can help rescue and aid organization know where help is needed. Despite potential links to climate change and increased hurricane activity (Halverson 2018), the word climate change only appeared in relation to wildfires. Observed warming and drying have resulted in significant increases in fire-season fuel aridity, half of which Abatzoglou et al. (2016) have attributed to human-caused climate change.

In talking about the 2017 hurricane season, Halverson (2018) states and answers a key question, “How much did climate change factor into the season’s destructiveness? The densely populated targets of Harvey, Irma, and Maria undoubtedly played the largest factor of economic and life losses. And while no single storm is ever caused by global warming, aggregate, long-term changes in the storm environment (both oceanic and atmospheric) might be creating a statistical uptrend in factors such as storm frequency, size, wind intensity, geographic coverage, storm duration, and rainfall.” In short, the location of natural disasters has a clear and obvious impact on the amount of damage, both economically and in loss of life. But, the uptrend in total numbers of hurricanes and fires also points toward the need for increased preparation and research on risk mitigation and disaster communication regardless of the causes, or the quantity of occurrences.

6 Conclusion

Online media responses to natural disasters vary based on the type of disaster, geography, population impacted, and severity of damage. Social media mentions related to hurricanes outnumbered fires, which mostly can be attributed to higher population densities in coastal areas (Wilson & Fischetti 2010). Analysis of social media terms related to natural disasters can be helpful to those monitoring and disseminating aid; however, there are many potential pitfalls to be aware of. There are those who prey on the rise in natural disaster social media content to increase promotion for unrelated products. Additionally, content may not be directly related to the devastation of an event, as compassion fatigue may play a role with increasing frequencies of natural disasters. Future research can further analyze the potential effects of compassion fatigue, as well as demographics associated with those impacted and social media content. There is a mismatch between the time periods that people post about natural disasters on social media and the times when aid is needed to rebuild. Mentions fall rapidly after the event for hurricanes, and long before fires are officially put-out. This may leave populations without help and support when struggling with the rebuilding process after the online media attention dissipates.

Appendix 1: Primary search terms

Hurricane Primary Terms

Hurricane, #Hurricane, hurricane, #hurricane.

Hurricane Exclude terms

penis, porn, Pat O'Brien, Pat O'Brien's, wallbangers, lottery, Thanksgiving in the Park, @mcp_polm, hurricane pike, Galaxy Note 8, iPhone, Apple, iphone, cowlick, my little hurricane, rain dance, hurricane swing, gut punches, limousine, leafsnet, football, player, hockey, baseball, life is like a hurricane, rock you like a hurricane, shithuts, Scorpions, spitfire, swirl inside you, gay ass, atsushi, stormrazor, Dota, Dota2, Dota 2, pissing in the wind, hard shiny, void, Oscars, Academy Awards, asshole, AKR Princess, Commander, Equestria, Monsters, Meaty, bowl, bowl game, Cotton Bowl, Orange Bowl, Heroes of the Storm, Heros of the Storm, @tnbuckeye44, xmen, X-men, Magento, Marvel, Marvel Comics, League of Legends, Elder Scrolls, Skyrim, NHL, hat trick, hat-trick, Martinook, @golf_mansion, @lamaritzan, WillHaftawaite, Detroit, AIDS, zombie, zombies, Fortnite, Jim Weltzin, basketball, Gregory Helms, WWE, pokemon, hoothoot, flying type, Mr4DoubleO, rugby, Huntly, Nightingale, grammy, RIAA, music, StateOfTheU, StateOfTheU.com, @evanjm02, cyandy, Possible_Indeed, SevenSport, kiosport, @LoriPlanken, Tulsa, TU, Tulsa University, @SMarcLeger_MBA, Thor Industries, Winnebago.

Hurricane Geographies

USA.

Wildfire primary terms

wildfire, wild-fire, #wildfire, Wildfire, #Wildfire, brushfire, Brush Fire, Wild Fire, wild fire, brush fire, brush-fire, Brushfire, #brushfire, #Brushfire, grassfire, grass-fire, Grassfire, grass fire, Grass Fire, #Grassfire, #grassfire, desert fire, Desert Fire, desertfire, Desertfire, #desertfire, #Desertfire, desert-fire, Hill Fire, Hillfire, hill fire, hill-fire, #hillfire, #Hill-fire, hillfire, vegetation fire, Vegetation Fire, vegetationfire, Vegetationfire, vegetation-fire, #vegetationfire, peat fire, peatfire, peat-fire, Peat Fire, #Peatfire, #peatfire, Peatfire, Camp Fire, #Campfire, Woolsey Fire, #Woolseyfire, Carr fire, #Carrfire, Mendocino Complex Fire, #Mendocinocomplexfire, Fergusen Fire, #Fergusenfire, Thomas Fire, #Thomasfire, Tubbsfire, Lodegpole Complex Fire, #Lodegpolecomplexfire, Lolo Peak Fire, #Lolopeak-fire, Anderson Creek Fire, #Andersoncreekfire.

Wildfire exclude terms

penis, porn, @jaesyun_, @AssangeJohn, @carleigh1985, @Schmeltz79, @nessuhhx, @BetteMidler, @RebeccaRage33, @dicaprioofdn, @CaliforCode, Fortnite, #Fortnite, @Fortnite, Epic Game, EpicGames, @KurtSchlichter, @salianij, @chicksaction, xxxtentacion, kaunis, cynycal, #NetNeutrality, Kalaniana'ole, flooding, flash flooding, racist, nuclear, Doznotcomputer, SmackDown, El Greco, PSG, @haydenblack, @AndOneTech, TheKuman717, @CoyoteWildfire, mini-Ice Age, Whoader95, Miocene, Pakistan.

Wildfire Geographies

USA.

Wildfire Exclude domains

Steamcommunity.com.

Appendix 2: Individual hurricane search parameters

Florence-specific terms

Include: Hurricane Florence, #HurricaneFlorence, #hurricaneflorence.

Florence before date range: August 11, 2018–September 10, 2018.

Florence after date range: September 11, 2018–November 10, 2018.

Florence area

Include geography: Wilmington, North Carolina.

Florence non-area

Exclude geography: Wilmington, North Carolina.

Michael-specific terms

Include: Hurricane Michael, #HurricaneMichael, #hurricanemichael.

Michael before date range: September 13, 2018–October 13, 2018.

Michael after date range: October 14, 2018–December 13, 2018.

Michael area

Include geography: Tallahassee Thomasville metro area.

Michael non-area

Exclude geography: Tallahassee Thomasville metro area.

Maria-specific terms

Include term: Hurricane Maria, #HurricaneMaria, #hurricanemaria.

Maria before date range August 24, 2017–September 23, 2017.

Maria after date range September 24, 2017–November 23, 2017.

Maria area

Include geography: Puerto Rico.

Maria non-area

Exclude geography: Puerto Rico.

Irma-specific terms

Include term: Hurricane Irma, #HurricaneIrma, #hurricaneirma.

Irma before date range August 8, 2017–September 7, 2017.

Irma after date range September 8, 2017–November 7, 2017.

Irma area

Include geography: Miami-Ft. Lauderdale metro area.

Irma non-area

Exclude geography: Miami-Ft. Lauderdale metro area.

Harvey-specific terms

Include term: Hurricane Harvey, #HurricaneHarvey, #hurricaneharvey.

Harvey before date range July 25, 2017–August 24, 2017.

Harvey after date range August 25, 2017–October 24, 2017.

Harvey area

Include geography: Miami-Ft. Lauderdale metro area.

Harvey non-area

Exclude geography: Miami-Ft. Lauderdale metro area.

Appendix 3: Individual wildfire search parameters

Camp fire-specific terms

Include term: camp fire, #campfire, #CampFire.

Camp fire during date range: November 8, 2018–November 25, 2018.

Camp fire after date range: November 26, 2018–December 16, 2018.

Camp fire area *all available cities in Butte Co.

<https://www.worldatlas.com/na/us/ca/c-butte-county-california.html>.

Include geographies: Magalia California, Chico California, Chico-Redding California, Paradise California, Oroville California, Gridley California.

Geofence: Butte County.

Actual County: <https://www.google.com/maps/place/Butte+County,+CA/@39.7220807,-122.1332831,9z/data=!4m5!3m4!1s0x809cd6015b7e73ab:0x856e36710c15f993!8m2!3d39.6253952!4d-121.5370003>.

Geofence area:

Woolsey fire-specific terms

Include term: Woolsey fire, #WoolseyFire, #woolseyfire.

Woolsey fire during date range: November 11, 2018–November 22, 2018.

Woolsey fire after date range: November 23, 2018–December 16, 2018.

Woolsey fire area *all available cities in Los Angeles County and Ventura County.

<https://www.worldatlas.com/na/us/ca/c-los-angeles-county-california.html>.

<https://www.worldatlas.com/na/us/ca/c-ventura-county-california.html>.

Include geographies: Lancaster, Santa Clarita, Thousand Oaks, Los Angeles-metro, Los Angeles, Long beach, Santa Ana, Glendale, Palmdale, Pomona, Torrance, Pasadena, El Monte, Downey, Inglewood, West Covina, Norwalk, Burbank, Oxnard, Simi Valley, Ventura, Camarillo, Newbury Park, Moorpark, Santa Paula, Port Hueneme, Ojai, Whittier, Van Nuys, North Hollywood.

Geofence: Los Angeles County and Ventura County.

Los Angeles County:

<https://www.google.com/maps/place/Los+Angeles+County,+CA/@34.0923658,-119.2669184,8.75z/data=!4m5!3m4!1s0x80dd2ad30164cd31:0x837d28d6cfbd392a!8m2!3d34.0522265!4d-118.2436596>.

Ventura County: <https://www.google.com/maps/place/Ventura+County,+CA/@34.0963627,-120.1756938,8z/data=!4m5!3m4!1s0x80e962d2b20077a9:0xdd9590f047c3b0b3!8m2!3d34.3704884!4d-119.1390642>.

Geofence.

Carr fire-specific terms

Include term: Carr fire, #Carrfire, #CarrFire.

Carr fire during date range: July 23, 2018–August 31, 2018.

Carr fire after date range: September 1, 2018–October 31, 2018.

Carr fire area *all available cities in Shasta County, Trinity County, California.

<https://www.worldatlas.com/na/us/ca/c-shasta-county-california.html>.

<https://www.worldatlas.com/na/us/ca/c-trinity-county-california.html>.

Include geographies: Redding, Anderson, Lake Shasta.

Geofence: Shasta County and Trinity County, California.

Shasta County:

https://www.google.com/search?rlz=1C1GGRV_enUS757US757&ei=_8oKXJzZLcvPjwSL_rbwBA&q=shasta+county+map&oq=shasta+county+map&gs_l=psy-ab.3..35i39j0l3j0i22i30l6.2667.3117..3366...0.0..0.88.336.4.....0....1..gws-wiz.....0i71j0i67j0i131j0i20i263.Ktyuvb0RcV4

Trinity County:

<https://www.google.com/maps/place/Trinity+County,+CA/@40.6712222,-123.5951061,9z/data=!3m1!4m5!3m4!1s0x54d2148e7c7152b5:0x492e195d1bbbaea6!8m2!3d40.6329485!4d-123.0622553>

Geofence.

Mendocino Complex fire-specific terms

Include term: Mendocino Complex fire, #MendocinoFire, #Mendocinofire, #Mendocino-complexfire, #MendocinoComplexFire.

Mendocino Complex fire during date range: July 27, 2018–October 04, 2018.

Mendocino Complex fire after date range: October 05, 2018–December 4, 2018.

Mendocino Complex fire area *all available cities in Colusa County, Glenn County, Lake County, Mendocino County; California.

<https://www.worldatlas.com/na/us/ca/c-colusa-county-california.html>.

<https://www.worldatlas.com/na/us/ca/c-glenn-county-california.html>.

<https://www.worldatlas.com/na/us/ca/c-lake-county-california.html>.

<https://www.worldatlas.com/na/us/ca/c-mendocino-county-california.html>.

Include geographies: Williams, Orland, Willows, Clearlake, Ukiah.

Geofence Colusa County, Glenn County, Lake County, Mendocino County.

Colusa County: <https://www.google.com/maps/place/Colusa+County,+CA/@39.1526764,-122.1389416,9.25z/data=!4m1!3m1!3m6!1s0x80837eeb7d4d3e45:0x29ab73b8d3d7ea34!2sColusa+County,+CA!3b1!8m2!3d39.1040645!4d-122.2653887!3m4!1s0x80837eeb7d4d3e45:0x29ab73b8d3d7ea34!8m2!3d39.1040645!4d-122.2653887>.

Glenn County: <https://www.google.com/maps/place/Glenn+County,+CA/@39.5904073,-122.9578337,9z/data=!3m1!4b1!4m5!3m4!1s0x8082571656c4308f:0xcc5b77cde9471bee!8m2!3d39.6437813!4d-122.4467238>.

Lake County:

<https://www.google.com/maps/place/Lake+County,+CA/@39.1231112,-123.2776318,9z/data=!3m1!4b1!4m5!3m4!1s0x8083dd999b415793:0x89fe1db4886beff!8m2!3d39.0839644!4d-122.8084496>.

Mendocino County: <https://www.google.com/maps/place/Mendocino+County,+CA/@39.3789503,-124.0385592,9z/data=!3m1!4b1!4m5!3m4!1s0x80818e30be51e887:0x2367b369f26e0115!8m2!3d39.5500194!4d-123.438353>.

Geofence.

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Declarations

Conflict of interest The authors declare that there is no conflict of interest.

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