

Situational Awareness Extraction: A Comprehensive Review of Social Media Data Classification During Natural Hazards

Abstract: Social media (e.g., Twitter and Facebook), can be regarded as vital sources of information during disasters to improve situational awareness (SA) and disaster management since they play a significant role in the rapid spread of information in the event of a disaster. Due to the volume of data is far beyond the capabilities of manual examination, existing works utilize natural language processing methods based on keywords, or classification models relying on features derived from text and other metadata (e.g., user profiles) to extract social media data contributing to SA and automatically categorize them into the relevant classes (e.g., damage and donation). However, the design of coding schema and associated information extraction methods are far less than straightforward and highly depend on: (1) different disaster event types, (2) the analysis purpose of the event, and (3) accordingly the social media platforms that allow user to share different types (e.g., text, and photos) and content of messages for different analysis, which are summarized as content, temporal, user, sentiment, and spatiotemporal analysis in our work. To this end, this paper reviews the literature for extracting social media data and provides an overview of classification schemas that have been used to assess SA in events involving natural hazards from five different approaches and analytical perspectives (content, temporal, user, sentiment, and spatiotemporal) by discussing the prevalent topic categories, disaster event types, purpose of studies, and platforms utilized from each schema. Finally, this paper summarizes classification methods, and platforms that are most commonly used for each disaster event type and outlines a research agenda with recommendations for future innovations.

Keywords: social media, text mining, natural hazards, disaster management

1. Introduction

Social media has been an emerging phenomenon used in many studies to enhance situational awareness (SA) and assist disaster management (DM) in events involving natural hazards. As opposed to traditional media such as newspaper, TV, and radio, using social media has many unique benefits (Al-Saggaf & Simmons, 2015; Sutton, Palen, & Shklovski, 2008; Beigi, Hu, Maciejewski, & Liu, 2016; Mandel *et al.*, 2012):

- 1) Convenience in assessing information and expressing emotions. While traditional news sources have a general focus on crises, people rely on social media to get information on localized impact (Shklovski, Palen, & Sutton, 2008). The public uses social media to communicate and assess the damage and situation without having to deal with filtered information or censorship.
- 2) Participation in an interactive, decentralized, and large-scale discussion. Al-Saggaf & Simmons (2015) suggest that social media may mediate a more decentralized discussion from groups of people who may not have much of a voice in public in the event of a disaster due to heightened emotions.
- 3) Insight to the situation from different perspectives and locations. Having information on people's personal emotions, feelings, opinions, and perspectives may help assist first responders in determining the level of damage and help identify victims' locations, expediting recovery processes because it narrows down where help is needed (Beigi *et al.*,

2016). Utilizing social media can also provide additional information for sentiment analysis, real-time insight, and public perception towards a disaster.

- 4) A cheap and efficient way to receive real-time updates. Sutton *et al.* (2008) describe social media as “backchannel communication,” a secret, unofficial, or irregular means of communication as opposed to the official or formal communications to the public. “Backchannel communications” allow for a wide-scale interaction that can be used to provide the public with additional supporting information because it causes users to be active participants in discussions rather than passive listeners.

Although social media provides a convenient, cheap and efficient way to gain real-time information, there are two major issues should be addressed when using social media for disaster communication: (1) Among the massive of social media data collected during a period for a specific event or topic (e.g., natural hazard), only some of the messages posted by users are relevant to the event, and even much fewer messages contribute to SA. Based on our Twitter data analysis on the 2012 Hurricane Sandy event, less than 3% of collected data were disaster relevant. Among these messages, a majority of them were relevant to personal feelings and emotions, resulting in only 0.75% SA relevant data that could help extract “actionable” information; and (2) although serving as an efficient platform for consistently broadcasting SA information, social media has also been criticized for being a channel to transfer rumors (Hall & Park, 2012; Oh *et al.*, 2010). Because social media has increased the scope of information sharing by opening it up to the public, the risk of getting false or inaccurate information is also increased. Alexander (2004) believes that with having news coming from all types of sources, the information may be misleading, distorted, alarmist, or susceptible to rumor propagation. These issues can become a problem, especially when information sources are scarce because rumors are more likely to be posted and re-posted, increasing the “sense of chaos and insecurity in the local population” (Alexander, 2014).

As such, there should be a methodology to quickly identify and extract the most accurate and relevant information from social media. Due to the volume of data being far beyond the capabilities of manual examination, current approaches utilize natural language processing (NLP) methods based on keywords or classification models relying on features derived from text and other metadata (e.g., user profiles, temporal information) to find social media data relative to disasters and automatically categorize them into the relevant classes (e.g., damage and donation). To build a classification model, a coding schema is necessary to separate them into different categories before they can be made actionable for SA. Information about casualties, damages, donation efforts, or public alerts are more likely to be used and extracted to improve SA during a time-critical event. Correspondingly, many existing works classified social media messages into these major categories (Imran and Castillo, 2015; Vieweg, 2012). To consider the temporal evolution and classify social media data into stages of disaster management (mitigation, preparedness, emergency response, and recovery), Huang and Xiao (2015) designed a coding schema with 42 topic categories. Different types of users (e.g., new reporters, general public, celebrities) may witness and experience different aspects of the disaster event. Therefore, a few studies also develop different classification schema for the message contributors and consider their sentiment, emotions, and personal feelings of message contributor by classifying messages into categories (e.g., subjective, positive, negative, ironic) or ranges of integer (-5 to +5) that express the user’s response to the disaster event (Buscaldi & Hernandez-Farias, 2015; Caragea *et al.*, 2014).

To sum up, the design of the coding schema and associated message extraction methods are far less than straightforward since they highly depend on different disaster event types (Sakaki *et al.*, 2013; Verma *et al.*, 2011; Buscaldi & Hernandez-Farias, 2015), the classification (or

analytical) purpose (CP) of the event (Takayasu *et al.*, 2015; Gurman & Ellenberger, 2015; Vo & Collier, 2013), and the social media platforms (Rosser *et al.*, 2017; Terpstra *et al.*, 2012) that allow users to share different types of messages (e.g., text and photos) for analysis (e.g., content, temporal, user, sentiment, and spatiotemporal analysis) (Figure 1). For example, to detect the occurrence of an earthquake, Sakaki *et al.* (2013) used spatiotemporal analysis and designed a classifier that can identify event-related tweets. Likewise, Verma *et al.* (2011) developed a classifier through content classification for four different crisis events to automatically extract SA messages. Buscaldi & Hernandez-Farias (2015) applied sentiment classification in the event of a flood to identify tweets that may be useful for SA. Despite having the same CP of identifying content relevant to SA, as well as using the same platform (Twitter), these three studies used different classification schemas since they were analyzing different event types. Alternatively, Takayasu *et al.* (2015), Gurman & Ellenberger (2015), and Vo & Collier (2013) had different CPs so they used different classification schemas despite analyzing the same event type and utilizing the same platform. In the event of an earthquake, Takayasu *et al.* (2015) examined the rate of rumor diffusion on Twitter through user classification to determine if social media is a credible source for information on disasters. Gurman & Ellenberger (2015) used content classification to explore communication topics and what people are discussing on Twitter at different phases of an earthquake. Vo & Collier (2013) tracked and analyzed people's emotions during an earthquake through sentiment classification. Finally, studies may also use different classification schemas because they are using different social media platforms despite analyzing the same event for the same CP. Rosser *et al.* (2017) used spatiotemporal analysis to estimate the probability of flood inundation from geotagged images on Flickr, while Terpstra *et al.* (2012) used temporal classification to examine the possibilities of real-time and automated analysis of Twitter messages in the event of a crisis. Both of these studies had the purpose to determine the credibility of social media as an information source during the event of a flood, but used different classification schemas as they were using different platforms.

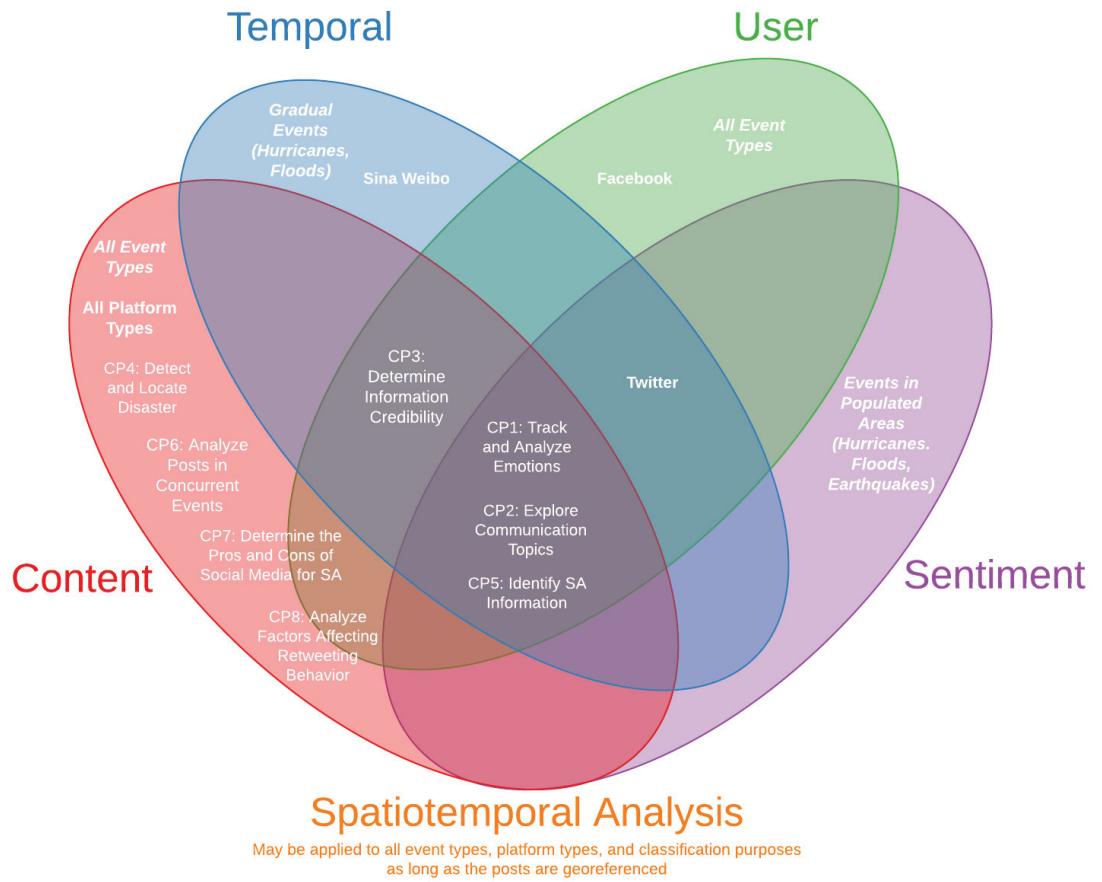


Figure 1. Content, temporal, user, and sentiment, and spatiotemporal analysis of social media data during different event types (bold and italicized), and for different classification (or analytical) purposes (normal text) with different platform types (bold).

Although there are existing reviews of the use of social media and disaster management (Houston et al., 2015; Luna & Pennock, 2018; Wiegmann et al., 2020), there is currently no comprehensive review of the classification schemas and social media platforms most commonly used on different types of natural disaster events. Therefore, this review article intends to fill this gap by providing an overview of classification schemas that have been used to assess SA in events involving natural hazards from five different approaches or analytical perspectives. Four of these approaches analyze the contents from different classification aspects: (1) message content, (2) event temporal evaluation or different stages of DM, (3) user type, and (4) sentiment or emotion expressed by the users. The fifth approach is a general spatiotemporal analysis for social media content that help support SA without the use of classification (Section 2.5).

In addition, this paper also summarizes (1) the content topics or information categories are commonly extracted and examined from the social media datasets for the four classification schemas listed previously, (2) what types of social media platforms and events effectively leverage social media for each of the five, (3) what was the most prevalent classification purpose for each event, (4) what social media platforms are most popular, and (5) what classification schemas are most popular for each event. In particular, the analysis results indicate that (1) for content classification, the top five major categories of topics extracted through social media data include

information, others, personal expression and experience, help and requests, and sentiment/emotion; (2) the event type most frequently studied for each classification schema is various event types for content (33%) and user analysis (29%), hurricane for temporal (36%) and sentiment analysis (50%), and flood (37%) and earthquake (37%) for spatiotemporal analysis; (3) among the nine classification or study purposes observed in the literature, the most common ones include: identifying tweets contributing to SA and disaster management for content analysis (33%), exploring communication topics and what people are discussing on social media over the course of a disaster for temporal (40%) and user (37%) analysis, and tracking and analyzing people's emotions and feelings during a time of crisis for sentiment (67%); (4) Twitter has been the most prevalent platform for SA extraction across the majority of event types studied; and (5) the most frequently used classification method is content classification. Finally, this paper introduces a research agenda for SA message classification and extraction methods.

2. Methodology

To develop a framework of social media data for natural disaster analysis, we conducted a comprehensive literature review of relevant articles. We used Google Scholar to search for scientific literature that employed the terms “social media”, “natural hazard”, and “situational awareness”. From our search, we obtained 493 results. Of those results, we manually selected literature that appeared relevant to our topic of interest, based on the title, and examined them further. The reference sections of the articles we reviewed were also searched for additional literature. Ultimately, we retained sources that clearly employed social media on natural disaster detection, response and mitigation. This review article is based on 92 distinctive manuscripts that delineate various aspects of the use of social media during natural disasters. Figure 2 classifies these articles according to the classification method they use (Figure 2a) and the years they were published (Figure 2b). The sum of the number of articles for all classification methods in Figure 2a exceed 92 since multiple manuscripts employ more than one classification method. Shown as Figure 2, previous studies mostly focus on in the content classification and analysis with a peak between 2014 and 2015.

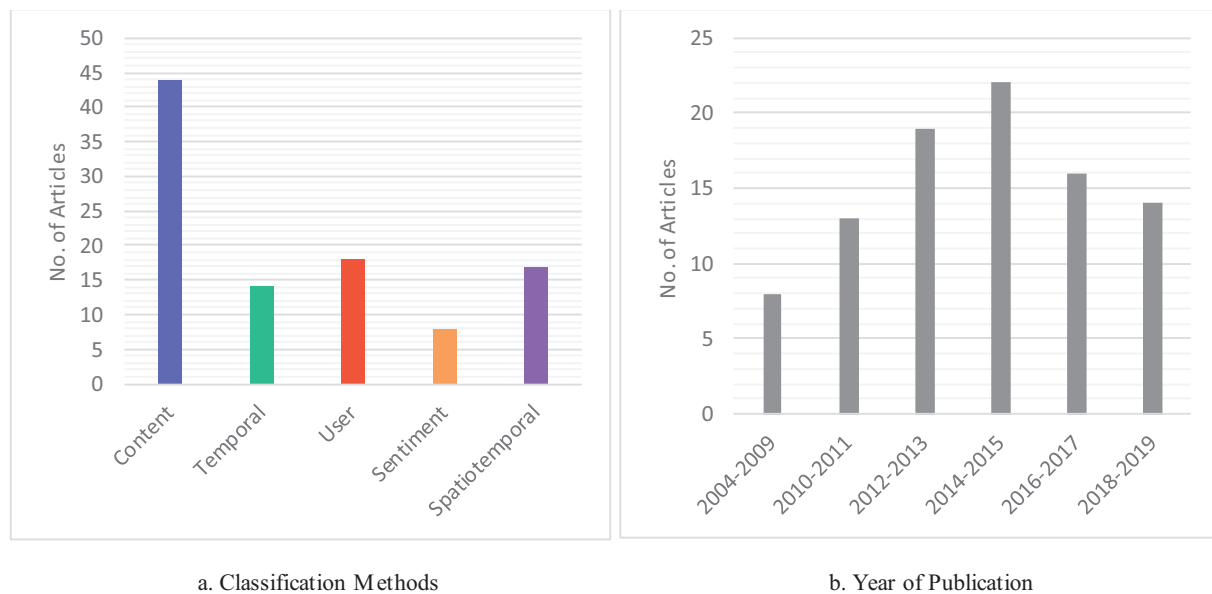


Figure 2. Classification of articles according to classification methods and year of publication of each manuscript

2.1. Classification Methods

This section reviews and summarizes the classification methods for social media content and users. Studies that analyze social media content in more than one approach are listed in more than one categorization type table. For each method, the contents (purpose, event type, platform) from each study will be summarized in one table. Table 1 provides the definition of each CP abbreviation codes listed in the “purpose” column of the contents of the study table. In addition to the contents, the frequency of each topic from all studies will be summarized in another table. For studies that did not specify which social media platforms they used and studies that are review papers, the platform type in the table is listed as just “Various platforms” with no further details. Studies from Shklovski *et al.* (2008, 2010) and Perez-Lugo (2004) conducted interviews and questionnaires on people who use social media rather than collecting data from the social media platform itself. We listed the platform type for this occasion as “Various platforms (Interview data)” due to the multiple platforms that the interviewees may have access to.

Table 1
Classification purpose (CP) abbreviation codes and their definitions

Classification Purpose	Definition
CP1	Tracking and analyzing people’s emotions and feelings during a time of crisis
CP2	Exploring communication topics and what people are discussing on social media over the course of a disaster
CP3	Determining if social media is a credible source for information on disasters
CP4	Detecting and locating disaster events
CP5	Identifying tweets contributing to SA/DM
CP6	Analyzing microblog posts generated during concurrent events
CP7	Determining and analyzing the advantages and disadvantages of using social media for SA
CP8	Showing how thematic content, message style, and number of followers affect retweeting behavior

2.2. Content Classification

Content classification includes studies that classify social media messages by their content or keywords. This classification method is often implemented through an automatic classifier and is used for various event types such as flood, wildfire, hurricanes, tsunamis, and more. The content classification aims to filter out noise and identify tweets/posts relevant to support SA.

Of the reviewed studies, datasets generated various social media platforms are collected and classified, such as Twitter, Sina-Weibo, Facebook, LinkedIn, YouTube, wikis, discussion forums (e.g., Reddit, Tianya), and blogs (e.g., Blogspot, LiveJournal). Specifically, the majority (64%) of the studies used Twitter for content classification (Figure 3a). Twitter is a microblogging platform used by large segments of the population that allows users to write brief text updates and share them with an audience online, which explains why it is popular for content classification. Sina-Weibo is often called the “Chinese Twitter,” and is one of the biggest microblogging platforms in China. Unlike blogging sites that generally have no word limit and updates according to the blogger, microblogging sites usually limit each post to 140 to 150 words and updates in real-time. Flickr is a photo-sharing platform where users share images or videos online rather than text updates. Reddit is a social news and social network site like Facebook, where users can upload content such as links, text posts, and images and start a discussion that other users would then upvote, downvote, and/or comment. Lastly, Tianya is a Chinese internet forum where people can hold discussions online. Most studies use microblogging platforms for content classification since users can casually provide day to day activity updates to other users.

Although there is currently no official list of topics for content classification, studies that use content classification would include similar classification topics as certain words are most frequently used during the disaster. Vieweg *et al.* (2010) classified tweets according to the following categories: warning, preparatory activity, hazard location, flood level, weather, wind visibility, road conditions, advice, evacuation information, volunteer information, animal management, and damage/injury reports. Likewise, Imran *et al.* (2013)'s categories include the following: caution and advice, information source, donation, casualties and damage, and unknown. Wang & Ye (2019) combined geospatial and content data in social media to analyze social responses during the course of the disaster. They extracted informative tweets using an adaptation of Imran *et al.*'s (2013) categories six categories/topics. The adaptation included an addition of a new topic, weather and environment, since many eyewitness reports concerned weather conditions and physical environment. In addition to the five classification categories (caution and advice, casualties and damage, information sources, infrastructure and resource, and donation and aid), Yu *et al.* (2019) employed a convolutional neural network (CNN) to predict the themes of tweets from Twitter. Content classification is most often used to extract informative social media content that contributes to SA, which can be done in copious ways where the methodology would depend on the purpose of the study. Text mining and natural language to categorize social media content into different themes are used for extracting useful information. However, if the study serves a different or a more complex purpose, then incorporating other components (e.g. temporal for trend, geospatial for visualization, user for demographics) would help satisfy the purpose the study. For example, Wang & Ye (2019) also added a geospatial component to their analysis by using location quotient and Markov transition probability matrix to detect topics concentrated in each area. This combination of geospatial and content data enables a space-time approach to identify SA in the course of a disaster.

Furthermore, this classification method is also used on a wide variety of events, with the majority (33%) being more than one type of event (e.g. hurricane and earthquake) within a study (Figure 3b). The top two events include floods and earthquakes. Floods are one of the most common hazards in the United States and are caused by several events including hurricanes and tropical storms. People affected by floods usually experience feelings of helplessness or hopelessness since the physical destruction of floods often include infrastructure damages such as houses, bridges, and cars. Earthquakes are also a common event, but they are usually considered minor. Other natural disasters are not as common as floods and earthquakes but they still cause damages and emotional distress. For example, the 2018 Hurricane Michael caused an estimated 25.1 billion dollars in damages as well as life-threatening conditions for affected residents. Although wildfires are not as common as other disasters and usually occur in remote areas near forests, they are destructive and can still cause emotional distress for people in nearby areas. The 2018 Woolsey Fire in Los Angeles and Ventura Counties of the U.S. state of California burned 96,949 acres of land, destroyed 1,643 structures, killed 3 people, and caused the evacuation of more than 295,000 people. In any of these disaster events, the community can experience disruption due to loss of communication or communication challenges (Simon *et al.*, 2015). When traditional sources of communication channels fail, people can seek and share information through social media. Data extraction from social media streams through content analysis can filter out noise that may be irrelevant to SA and the disaster event as well as sort vast amounts of real-time information into categories that emergency managers can readily access.

Besides being used for a range of different events, the reviewed studies using content analysis also this schema for a variety of classification purposes (CP), which can be referred to in Table 1.

The CP of these studies are listed from most to least prevalent as follows: CP5 (32%), CP2 (30%), CP1 (13%), CP3 (10%), CP6 (7%), CP4 (3%), CP8 (3%), and CP7 (2%) (Table 2).

Finally, the content categories (Table 3) include information, others, personal expression and experience, help and requests, emotion, people, discussion, resources and services, action-related, damage/impact, irrelevant, response, sources, infrastructure and utilities, relief and recovery, safety and security, caution and advice, warnings and alerts, technology or media-related, information seeking, politics and government, community building, donations and fundraising, location/disaster area, and preparation. Due to space limitations, the full version of Table 3, which includes the subcategories, can be seen in the Appendix.

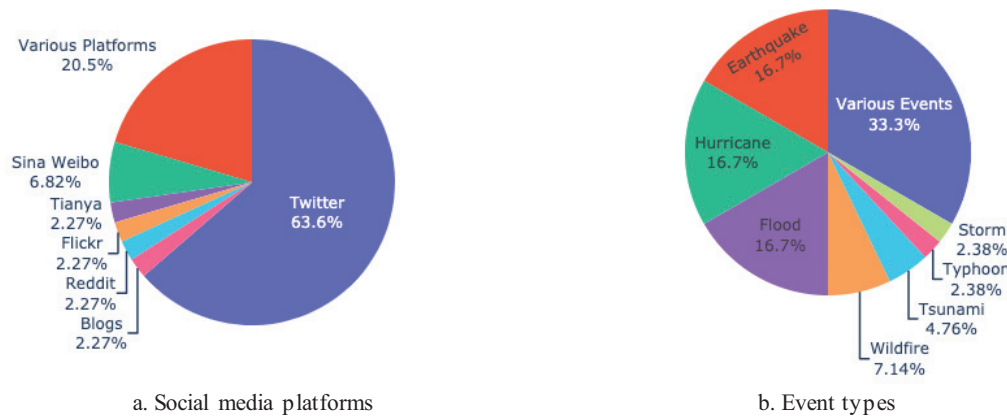


Figure 3. Percentages of different social media platforms (a) and event types (b) for message content classification. Twitter is the most prevalent platform used (63.6%) followed by various platforms (20.5%) for content classification. Other types of platforms alone are not as common, since most articles would use a variety of platforms combined together, with Twitter as an exception. The majority of articles used content classification to analyze various events rather than a single event type, since content classification can be used across all types of events.

Table 2

Studies that use content classification and their purpose, event type, and platform used

Authors	Purpose	Event Type	Platform
(Al-Saggaf & Simmons, 2015)	CP1, CP2	Flood	Various platforms (YouTube, Facebook, online discussion forums)
(Sutton, Palen, & Shklovski, 2008)	CP3	Wildfire	Various platforms
(Arthur, Boulton, Shotton, & Williams, 2018)	CP4	Flood	Twitter
(Verma et al., 2011)	CP5	Various events	Twitter
(Brynielsson et al., 2018)	CP1	Various events	Various platforms
(David, Ong, & Legara, 2016)	CP2, CP5	Typhoon	Twitter
(Vieweg, Hughes, Starbird, & Palen, 2010)	CP5, CP6	Various events	Twitter
(Cho, Jung, & Park, 2013)	CP1, CP3	Earthquake	Twitter
(Qu, Wu, & Wang, 2009; Qu, Huang, Zhang, & Zhang, 2010)	CP1	Earthquake (Qu et al., 2009; Qu, Huang, Zhang, & Zhang, 2010)	Tianya (Qu et al., 2009), Sina-Weibo (Qu et al., 2010)
(Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013a)	CP5	Various events	Twitter
(Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013b)	CP5	Various events	Twitter
(Kongthon, Haruechaiyasak, Pailai, & Kongyoung, 2012)	CP1, CP5	Flood	Twitter

(Vieweg, 2011)	CP1, CP5	Various events	Twitter
(Olteanu, Vieweg, & Castillo, 2015)	CP2, CP6	Various events	Twitter
(Imran, Mitra, & Srivastava, 2016)	CP5	Various events	Twitter
(Acar & Muraki, 2011)	CP2	Tsunami	Twitter
(Amanda L. Hughes, St. Denis, Palen, & Anderson, 2014)	CP2, CP5	Hurricane	Various platforms (Nixle, Twitter, Facebook)
(Imran, Castillo, Diaz, & Vieweg, 2015)	CP5	Various events	Various platforms
(Simon, Goldberg, & Adini, 2015)	CP5	Various events	Various platforms (Twitter, Facebook, Flickr, Other)
(Smith, 2010)	CP2	Earthquake	Twitter
(Z. Wang, Ye, & Tsou, 2016)	CP3	Wildfire	Twitter
(Liu, Palen, Sutton, Hughes, & Vieweg, 2008)	CP6	Various events	Flickr
(Lindsay, 2011)	CP5, CP3	Various events	Various platforms
(Bruns, Burgess, Crawford, & Shaw, 2012)	CP2	Flood	Twitter
(Shaw, Burgess, Crawford, & Bruns, 2013)		(Bruns, Burgess, Crawford, & Shaw, 2012; Shaw et al., 2013)	(Bruns, Burgess, Crawford, & Shaw, 2012; Shaw et al., 2013)
(Leavitt & Clark, 2014)	CP2	Hurricane	Reddit
(Macias, Hilyard, & Freimuth, 2009)	CP2, CP5	Hurricane	Blogs
(Gurman & Ellenberger, 2015)	CP2	Earthquake	Twitter
(Gao, Barbier, & Goolsby, 2011)	CP7	Various events	Various platforms (Twitter, Flickr, Facebook, blogs, YouTube)
(Temnikova & Castillo, 2015)	CP5	Various events	Twitter
(Herfort, de Albuquerque, Schelhorn, & Zipf, 2013)	CP5	Flood	Twitter
(Landwehr, Wei, Kowalchuck, & Carley, 2016)	CP5, CP4, CP2	Tsunami	Twitter
(Spence, Lachlan, Lin, & del Greco, 2015)	CP5, CP1, CP2	Hurricane	Twitter
(Sutton et al., 2014)	CP8	Wildfire	Twitter
(Takahashi, Tandoc, & Carmichael, 2015)	CP2	Typhoon	Twitter
(Tim, Pan, Ractham, & Kaewkitipong, 2017)	CP2, CP3	Flood	Various platforms (Twitter, Facebook, YouTube)
(Valenzuela, Puente, & Flores, 2017)	CP3	Earthquake	Twitter
(Wang & Zhuang, 2017)	CP2, CP8	Hurricane	Twitter
(Yandong Wang, Wang, Ye, Zhu, & Lee, 2016)	CP5, CP2	Storm	Sina-Weibo
(Win & Aung, 2017)	CP5	Earthquake	Twitter
(Xu et al., 2016)	CP2	Typhoon	Sina-Weibo
(Yu, Huang, Qin, Scheele, & Yang, 2019)	CP6	Hurricane	Twitter
(Wang & Ye, 2019)	CP2, CP4, CP5	Hurricane	Twitter

Table 3
Content classification topic categories

Category	Count	Disaster stage: Description
Information	83	All: disaster-related information contributing to situational awareness
Others	73	All: describe about the disaster but not contribute SA
Personal expression and experience	50	All: Any personal updates or opinions expressed by users throughout the course of the disaster
Help and requests	37	Post-disaster: posts involving help, rescue, fundraising, services, and/or support to alleviate disaster impact
Emotion	32	All: User's sentiments and emotions expressed throughout the course of the disaster
People	30	During and post-disaster: posts involving missing, injured, and/or dead people
Discussion	27	All: posts involving discussions and communications throughout the course of the disaster
Resources and services	22	Post-disaster: posts sharing the available resources and services to help alleviate the disaster impact

Action-related	20	All: posts involving action-related events throughout the course of the disaster
Damage/impact	20	During: posts about damages and affected areas from the disaster
Irrelevant	20	All: posts that are not relevant (off-topic or spam) to the disaster
Response	20	Post-disaster: posts involving response to disaster impact and recovery efforts
Sources	18	During: posts classified by user type
Infrastructure and utilities	18	During: posts involving the physical, transportation, and communication components of infrastructures and utilities
Relief and recovery	12	Post-disaster: posts involving disaster relief information and recovery efforts
Safety and security	12	During: posts with safety information, such as shelters
Caution and advice	12	Pre- and during disaster: posts containing caution and advice
Warnings and alerts	11	Pre- and during: posts containing warning, alerts, and announcements
Technology or media-related	10	During: posts involving media sources
Information seeking	8	During: posts containing questions on the disaster
Politics and government	8	During: posts concerning government and politics
Donations and fundraising	8	Post-disaster: posts containing information on donations and fundraisers
Community building	7	Post-disaster: posts concerning community building
Location/disaster area	5	During and post-disaster: posts about locations relating to disaster
Preparation	5	Pre-disaster: information about the preparation for the disaster

2.3. Temporal Classification

Temporal classification categorizes social media content according to the time they are posted in relation to the event of the natural disaster. Most studies divide the duration of the event into three stages: pre-incident, during the incident, and post-incident (Chowdhury *et al.*, 2013, Iyengar *et al.*, 2011, Hughes & Palen 2009, Wang *et al.*, 2016). Houston *et al.* (2015) took the same approach but at a much finer level by adding the categories in between the three general stages such as including the “pre-event to event” stage, which would go in between the pre-incident and during incident stages. Other studies temporally categorize social media posts using the user response during each phase of the disaster: preparedness, response, impact, and recovery (Huang & Xiao 2015, Perez-Lugo 2004). Fang *et al.* (2019) used Pearson correlation coefficient on informative social media data they have collected for each hour with hourly observed precipitation data to examine the relationships between social media activities and the evolution of the storm. By identifying topics that are most prevalent throughout each phase of the disaster, social media can provide information on the disaster’s influence on human activities and psychological activities.

This classification method is most frequently used on hurricane (36%), followed by a tie between floods and various events (14%) (Figure 4b). Hurricanes and floods are both events that happen gradually and require different emergency responses at different stages. The three main stages of response to hurricanes include preparedness (pre-hurricane), response (during the hurricane), and recovery (post-hurricane). During preparedness, people need information on how to handle the disaster such as making evacuation plans and stocking food and water. During the response phase, the main contents of information shift towards action-related tasks such as helping victims, seeking shelter, and preventing further infrastructure damages. Lastly, information surrounding recovery include raising fundraisers or sentimental activities such as memorializing the dead, giving thanks to emergency responders/firefighters, and sending prayers.

Moving on from the events most frequently used, the CP studies using temporal analysis mostly focus on CP2 (40%), CP5 (27%), CP3 (20%), and CP1 (13%) (Table 4). Temporal classification has three main classification categories (Table 5) including pre-incident, during the incident, and post-incident.

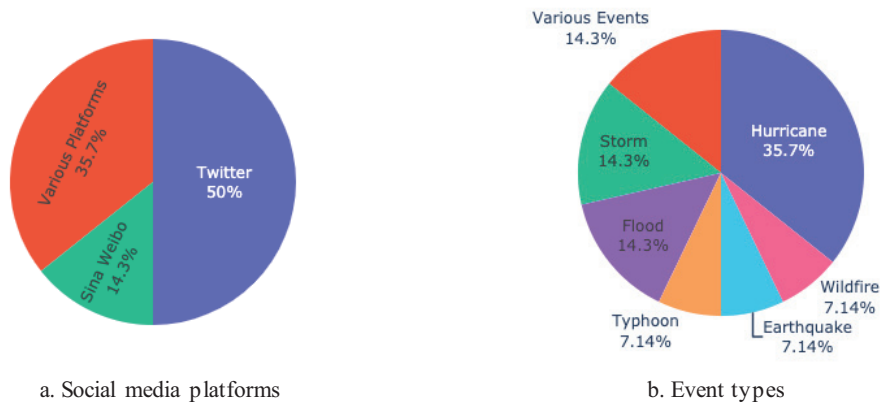


Figure 4. Percentages of different social media platforms (a) and event types (b) for temporal classification. The percentages are mostly divided between Twitter (50%) and various platforms (35.7%). The majority of articles used temporal classification to analyze hurricanes (35.7%), since hurricanes develop gradually and information relating to SA/DM varies at different stages (pre-, during, post-event).

Table 4

Studies that use temporal classification and their purpose, event type, and platform used

Authors	Purpose	Event Type	Platform
(Houston et al., 2015)	CP5	Various events	Various platforms
(Chowdhury, Imran, Asghar, Amer-Yahia, & Castillo, 2013)	CP2, CP5	Typhoon	Twitter
(Iyengar, Finin, & Joshi, 2011)		(Chowdhury et al., 2013),	Twitter
(Amanda Lee Hughes & Palen, 2009)		Various events	(Iyengar et al., 2011),
(B. Wang & Zhuang, 2017)		(Iyengar et al., 2011),	Twitter
(Yandong Wang et al., 2015)		Hurricane	(Amanda Lee Hughes & Palen, 2009),
		(Amanda Lee Hughes & Palen, 2009),	Twitter
		Earthquake (B. Wang & Zhuang, 2017),	Sina-Weibo
			(Yandong Wang et al., 2015)
		Storm	
		(Yandong Wang et al., 2015)	
(Huang & Xiao, 2015)	CP1, CP2, CP5	Hurricane	Twitter
(Perez-Lugo, 2004)		(Huang & Xiao, 2015),	(Huang & Xiao, 2015),
		Hurricane	Various platforms
		(Perez-Lugo, 2004)	(Interview data)
(Terpstra et al., 2012)	CP3	Flood	(Perez-Lugo, 2004)
(Shklovski, Palen, & Sutton, 2008)	CP2, CP3	Wildfire	Twitter
		(Shklovski, Palen, & Sutton, 2008)	(Terpstra et al., 2012)
(Shklovski, Burke, Kiesler, & Kraut, 2010)	CP2	Hurricane	Various platforms (Interview data)
			Various platforms
			(Interview data)

(Tim et al., 2017)	CP2, CP3	Flood	Various platforms (Twitter, Facebook, YouTube)
(Fang et al., 2019) (Zou et al., 2019)	CP2, CP5 CP1	Storm Hurricane	Sina-Weibo Twitter

Table 5

Temporal classification categories

Category	Count	Subcategories
Pre-incident	16	pre-incident(5), preparedness(3), pre-event(1), disaster preparedness information(1), pre-event to event(1), disaster warnings(1), before the incident started(1), pre-disaster(1), warning(1), threat(1)
During incident	22	during incident(5), impact(3), implement traditional crisis communication activities(1), signal and detect disasters(1), event(1), information(1), document and learn what is happening in the disaster(1), news coverage of the disaster(1), during and after the storm(1), damage reporting(1), loss & damage(1), emotion (1), casualty reporting and rumors about deaths(1), during evacuation(1), alert and real-time updates(1), inventory(1)
Post incident	29	post-incident(5), recovery(5), response(3), rescue and relief(2), requests for help or assistance(1), event to post-event(1), disaster response information(1), awareness and help(1), support(1), express feelings(1), recovery and response information(1), post-event(1), connect community members(1), relief(1), rescue(1), readiness and rescue(1), remedy(1), long term(1)

2.4. User Classification

User classification categorizes contents according to the general type/group the author of the post belongs to. Zahra *et al.* (2018) manually categorize users by the type of eyewitness they are, including direct, indirect, vulnerable direct, non-eyewitness. Instead of focusing on the type of eyewitness, Kumar *et al.* (2013) classify users into four categories based on how they relate to the event according to the content of the user's post (topic affinity score) and the user's location (geo-relevancy score). Mandel *et al.* (2012) categorize users by gender (indicated by their names) and location (from user profile and keywords) to determine their level of concern during a natural disaster. Some studies choose to classify users specifically for their situation, such as Dabner's (2012) study which discusses an earthquake that affected a school property, so the categories include staff members, students, and other participants. Other studies classify users by their general group, such as citizens/public/ordinary individuals, journalists, media, agencies, celebrities, government, NGOs, etc. (De Longueville *et al.*, 2009; Choudhury *et al.*, 2012; Diakopoulos *et al.*, 2012; Kim *et al.*, 2018; Kim & Hastak, 2018; Takahashi *et al.*, 2015).

Like content classification, user classification is also used on a wide variety of events, with the majority being various events (28%), followed by flood (17%), and then earthquake (17%) (Figure 5b). User classification would be reasonable to use with events that affect a large percent of the population since a variety of news sources and/or organizations would have to be involved. Floods greatly affect communities and individuals, with their impacts including deaths, infrastructure damages, depletion of food and resources, and deterioration of health conditions due to waterborne diseases. The Kerala floods (2018) in India killed more than 350 people and trapped thousands of people ("Why the Kerala floods proved so deadly," 2018). Like floods, earthquakes have a destructive nature and can impact large distances. The 2016 Ecuador earthquake killed 272 people, injured more than 2,500 people, destroyed buildings and highways, and affected areas more than 300 miles away from its epicenter (Ellis, Karimi, Ansari, & Gallon, 2016). With such

large consequences on the community, copious contents on such events would be posted from a diverse range of sources.

Lastly, the purposes of these studies mostly focus on CP2 (37%), CP5 (26%) , CP3 (16%), CP8 (11%), CP7 (5%), and CP1 (5%) (Table 6). The user categories for user classification (Table 7) include government organizations (GO), users by type, agencies, individuals/public, non-governmental organizations, (NGO), eyewitness, journalists, users by location, other, and users by gender.

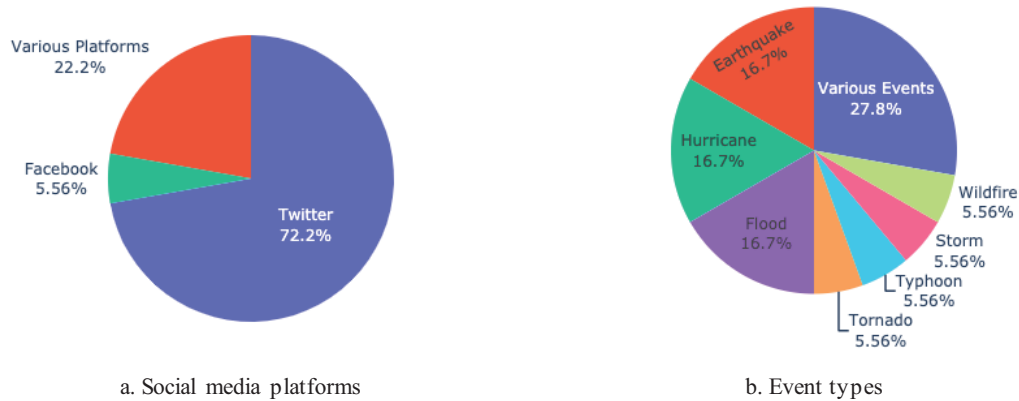


Figure 5. Percentages of different social media platforms (a) and event types (b) for user classification. The most prevalent platform used is Twitter (72.2%), followed by various platforms (22.2%), and Facebook (5.56%), The majority of articles used user classification to analyze various events (27.8%), but the percentages are fairly evenly spread between each events. Like content classification, user classification can be used across all types of events.

Table 6
Studies that use user classification and their purpose, event type, and platform used

Authors	Purpose	Event Type	Platform
(De Longueville, Smith, & Luraschi, 2009)	CP2	Wildfire	Twitter
(Choudhury, Diakopoulos, & Naaman, 2012)	CP2	Various events	Twitter
(Diakopoulos, De Choudhury, & Naaman, 2012)	CP5	Tornado	Twitter
(Zahra et al., 2018)	CP5	Various events	Twitter
(Kumar, Morstatter, Zafarani, & Liu, 2013)	CP5	Various events	Twitter
(Dabner, 2012)	CP3	Earthquake	Facebook
(Kaufhold & Reuter, 2016)	CP2	Flood	Various platforms (Twitter, Facebook, Interview data)
(Kim, Bae, & Hastak, 2018)	CP2, CP7, CP8	Storm (Kim et al., 2018),	Twitter (Kim et al., 2018),
(Kim & Hastak, 2018)		Flood (Kim & Hastak, 2018)	Various platforms (Twitter, Facebook) (Kim & Hastak, 2018)
(Takahashi et al., 2015)	CP2	Typhoon	Twitter
(Takayasu et al., 2015)	CP3	Earthquake	Twitter
(Valenzuela et al., 2017)	CP3	Earthquake	Twitter
(B. Wang & Zhuang, 2017)	CP8	Hurricane	Twitter
(Yeo, Knox, & Jung, 2018)	CP2	Flood	Twitter
(Mandel et al., 2012)	CP1	Hurricane	Twitter
(Simon et al., 2015)	CP5	Various events	Various platforms (Twitter, Facebook, Flickr, Other)
(Houston et al., 2015)	CP5	Various events	Various platforms
(Jamali et al., 2019)	CP2	Hurricane	Twitter

Table 7*User classification categories*

Category	Count	Subcategories
Government Organizations (GO)	22	government(3), go(1), information/weather(1), emergency management/service(1), citizen service/health/environment(1), science/research/survey(1), police department(1), army/military agents(1), foreign affairs(1), economy/trade(1), agriculture/forest service(1), fire department(1), transportation(1), law enforcement(1), lawmaking agent(1), inter-government(1), governmental agencies related to DM(1), disaster response/relief(1), animal protection(1), water level services(1)
Types	13	moderators(1), helper(1), aggregators(1), sympathizers(1), reactive(1), responsive(1), reporter(1), amplifier/retweeter(1), innovative(1), proactive(1), apathetic(1), celebrities(1), topic ignorant(1)
Agencies	10	media(1), news(1), news media(1)] news and media(1), weather agencies(1), news organizations(1), agencies(1), television newscasts(1), news agent(1), federal emergency management agency(1)
Individuals/Public	11	individuals(4), citizens(1), public(1), staff members(1), students and other participants(1), ground state: users who have not encountered the rumor(1), excited state: users who believe the rumor(1), final state: users who already know that the rumor is false(1)
Non-governmental Organizations (NGO)	9	ngos(2), ngos and npos(1), humanitarian(1), faith-based group(1), local and/or public authority group(1), action-focused multi culture group(1), humanitarian nonprofit group(1), private charitable foundation(1)
Eyewitness	7	eyewitness/non-eyewitness(2), eyewitness(1), non-eyewitness and don't know cases(1), vulnerable direct eyewitness(1), direct eyewitness(1), indirect eyewitness(1)
Journalists	4	journalists(2), journalists/bloggers(1), journalists/media bloggers(1)
Location	4	location(1), mid-atlantic states(1), upper-south states(1), new england states(1)
Other	3	other(1), unknown(1), account closed or not accessible to retrieve the information(1)
Gender	3	gender(1), female-indicative names(1), male-indicative names(1)

2.5. Sentiment Classification

Sentiment classification categorizes contents based on expressions of feelings and emotions. The three general categories in sentiment classification are positive, negative, and other (e.g., subjective, ironic, unconcerned). Although these three topics provide broad coverage of emotions, some studies incorporate more detailed categories for a more accurate analysis. For example, Schulz *et al.* (2013) used a 7-class sentiment classifier to develop a fine-grained analysis for sentiment analysis. Other studies implement different algorithms to determine the most accurate one for sentiment analysis. Nair *et al.* (2017) compared the performances of three different algorithms (Random Forests, Naïve Bayes, and Decision Tree) and found Random Forests to have outperformed the others with the least number of misclassification instances during the Chennai Flood in India. Caragea *et al.* (2014) used Naïve Bayes and SVM and found that the performance of SVM provides more accuracy than that of Naïve Bayes. In agreement with Buscaldi and Hernandez-Farias (2015), Vo and Collier (2013) found positive tweets to not be useful in sentiment

analysis during a disaster, so they replaced the categories ‘Happiness’ and ‘Pleasantness’ in tweets that are considered positive to ‘Calm’ instead.

This classification method is used with three events: hurricanes (50%), floods (25%), and earthquakes (25%) (Figure 6). These three events occur quite frequently and have the potential to cause immense damages to infrastructure, property, and resources. Furthermore, these events often affect a large section of the population, since they can occur in populated urban areas and can span over large distances. The 2005 Hurricane Katrina caused an estimated \$108 billion in property damage, killed an estimated 1,200 people, and flooded an estimated 80 percent of the city of New Orleans (Gibbens, 2019). The Chiapas earthquake (2017) killed at least 61 people in Mexico and destroyed an estimated 20 to 30 percent of houses in the city (Villegas, Malkin, & Semple, 2017). With such devastating aftermath, people often experience emotional distress in the face of these events and would seek out information on how to mitigate the disaster.

Finally, the purposes of these studies mostly focus on CP1 (67%), CP5 (22%), and CP2 (11%) (Table 8). The main classification categories (Table 9) that studies use for sentiment classification include negative, positive, and other. Studies that do not classify their contents by categories do so using a range of integers (Wang & Taylor, 2018; Caragea *et al.*, 2014; Zou *et al.*, 2019).

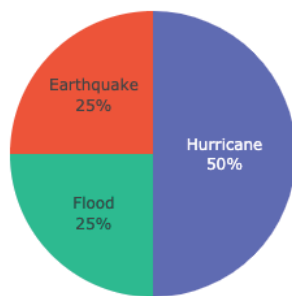


Figure 6. Percentages of different social media platforms for sentiment classification. The most prevalent event that articles used user classification to analyze is hurricane (50%), followed by earthquake (25%), then flood (25%).

Table 8

Studies that use sentiment classification and their purpose, event type, and platform used

Authors	Purpose	Event Type	Platform
(Buscaldi & Hernandez-Farias, 2015)	CP5	Flood	Twitter
(Nair, Ramya, & Sivakumar, 2017)	CP1, CP2	Flood	Twitter
(Schulz, Paulheim, & Schweizer, 2013)	CP5	Hurricane	Twitter
(Vo & Collier, 2013)	CP1	Earthquake	Twitter
(Wang & Taylor, 2018)	CP1	Earthquake	Twitter
(Mandel et al., 2012)	CP1	Hurricane	Twitter
(Caragea et al., 2014)	CP1	Hurricane	Twitter
(Zou et al., 2019)	CP1	Hurricane	Twitter

Table 9

Sentiment classification categories

Category	Count	Subcategories
Negative	14	fear(3), negative(2), complaints(1), anger(1), disgust(1), sadness(1), negative surprise(1), unpleasantness(1), anxiety(1), very negative(1), apprehension(1)
Other	11	other(2), concerned(2), links to news reports or messages(1), ironic(1), subjective(1), need for help(1), relief measures(1), cannot decide(1), unconcerned(1)
Positive	8	positive(2), express gratitude(1), positive surprise(1), happiness(1), calm(1), very positive(1), relief(1)

2.6. General spatiotemporal analysis without classification

Rather than classifying social media contents into categories, general spatiotemporal analysis utilizes the time and location of the post to support SA by helping relief organizations locate and prioritize their responses. Earle *et al.* (2011) implemented a detector that runs when there is a rapid increase in the frequency of tweets containing keywords relating to the disaster. Information relating to the tweet such as tweet creation time, text, and user location are then used for analysis to identify tweets from users who are within the areas affected by the disaster. Fohringer *et al.* (2015) showed an effective way to create an inundation map of the flood from social media by filtering geolocated posts from social media using keywords related to the disaster. Cervone *et al.* (2016) monitored real-time data from Twitter, remote sensing images, and relevant posts from social media to assess the damages during the course of a natural disaster. Guan & Chen (2014) measured the “degree of disaster” to analyze disaster evolvement temporally and geographically throughout different regions by using the pre-impact phase as the reference point to compare the Twitter activity to the during- and post-impact phases.

This method is used with events including earthquakes (35%), flood (35%), hurricane (6%), wildfire (6%), storm (6%), various events (6%), and blizzard (6%). The spatiotemporal analysis is most typically used with earthquakes and floods (Figure 7b), which may be due to the patterns of the event that change over time. Spatiotemporal analysis can illuminate any outliers and/or anomalies that may occur through time and space.

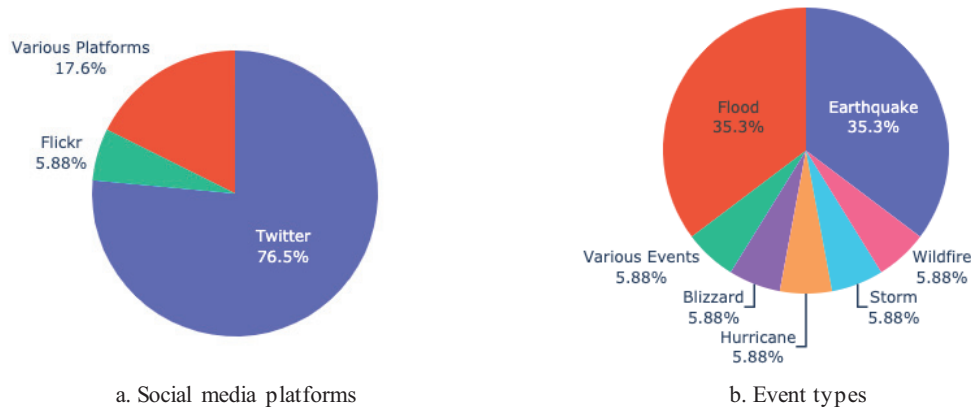


Figure 7. Percentages of different social media platforms (a) and event types (b) for spatiotemporal analysis. The most prevalent platform used is Twitter (76.5%), followed by various platforms (17.6%), and Flickr (5.88%). The majority of articles used user classification to analyze earthquake (35.3%), with flood (35.3%) coming in second. Hurricane, wildfire, storm, various events, and blizzard share the same percentages (5.88%).

Table 10

Studies that use spatiotemporal analysis without classification and their purpose, event type, and platform used

Authors	Purpose	Event Type	Platform
(Crooks, Croitoru, Stefanidis, & Radzikowski, 2013)	Analyzing tweet frequency according to the distance to the epicenter and time intervals	Earthquake	Twitter
(MacEachren et al., 2011)	Analyzing tweet content temporally based on explicit (geotagged) and implicit (inferred) geographic information	Earthquake	Twitter

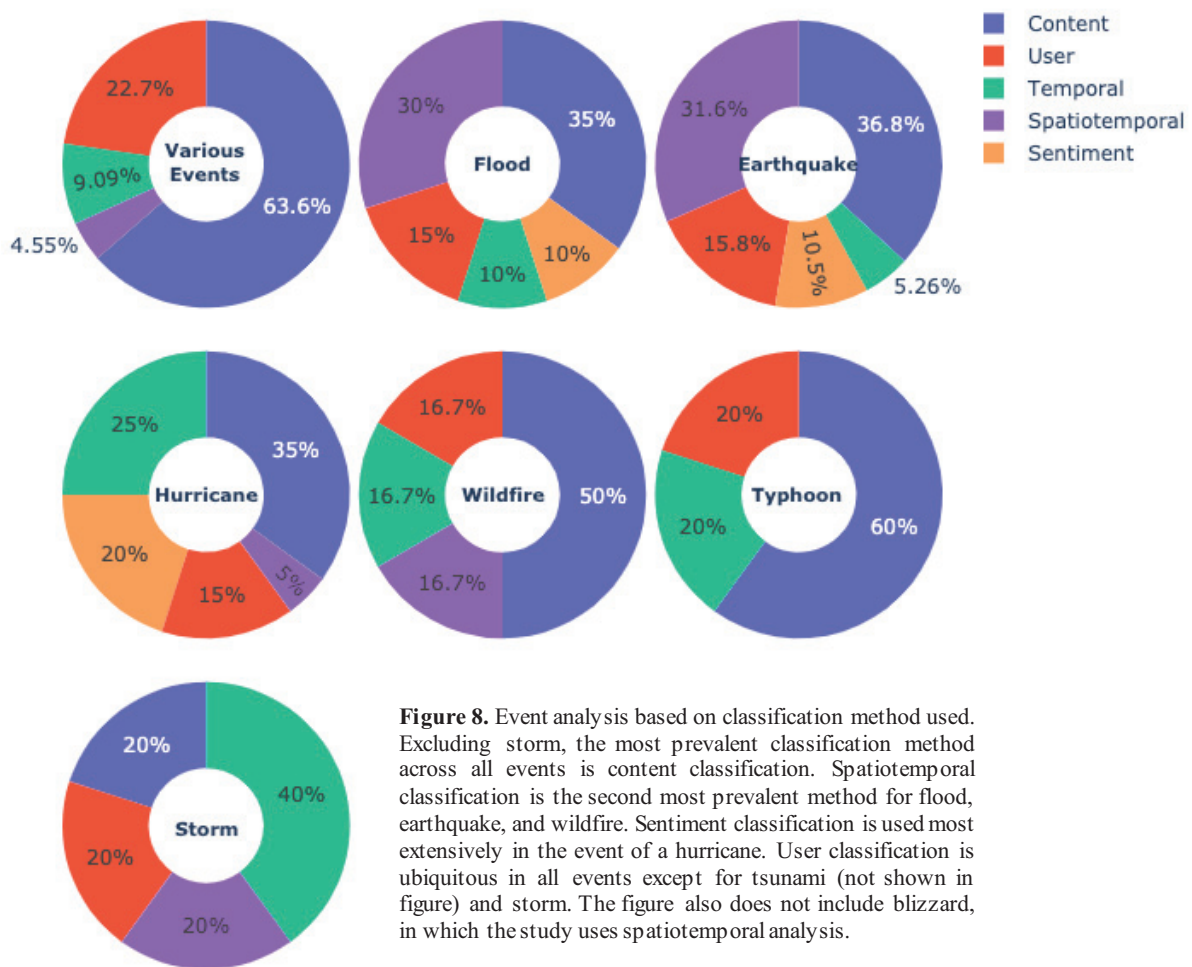
(Earle et al., 2010)	Analyzing geocoded tweet frequency temporally within a set radius from the event	Earthquake	Twitter
(Earle, Bowden, & Guy, 2011)	Analyzing tweet frequency according to time and accuracy/relevance	Earthquake	Twitter
(Fohringer, Dransch, Kreibich, & Schröter, 2015)	Automatically filtering and efficiently supporting the manual extraction of information, including photos, from social media posts	Flood	Various platforms (Twitter, Flickr)
(Cervone et al., 2016)	Using remote-sensing data, tweets, and VGI for damage assessment	Flood	Various platforms (Twitter, Flickr)
(Guan & Chen, 2014)	Demonstrating the temporal-spatial patterns of Twitter activities based on the distance to and phase of the disaster	Hurricane	Twitter
(Jongman, Wagemaker, Romero, & De Perez, 2015)	Demonstrating the potential value of near-real-time satellite and social media information to enhance the speed and effectiveness of disaster response	Flood	Twitter
(Kent & Capello, 2013)	Identifying relevant demographic characteristics of social media users through analyzing spatial patterns	Wildfire	Various platforms (Twitter, Instagram, Flickr, Others)
(Laylavi, Rajabifard, & Kalantari, 2017)	Evaluating tweets using relationship scoring to detect and retrieve event-related tweets	Storm	Twitter
(Li, Wang, Emrich, & Guo, 2018)	Analyzing tweets for spatiotemporal patterns and mapping visualizations	Flood	Twitter
(Lu & Brelsford, 2015)	Analyzing social media content and activity throughout the course of a disaster	Earthquake	Twitter
(Middleton, Middleton, & Modafferi, 2014)	Determining the accuracy of crisis maps generated from social media content	Various events	Twitter
(Restrepo-Estrada et al., 2018)	Using tweets and rainfall to generate a model for rainfall-runoff estimations and flood forecasting	Flood	Twitter
(Rosser, Leibovici, & Jackson, 2017)	Using geotagged photographs from social media, optical remote sensing, and high-resolution terrain mapping to estimate the probability of flood inundation	Flood	Flickr
(Yan Wang, Wang, & Taylor, 2017)	Investigating the effects of severe winter storms on human mobility during a blizzard (pre, during, post) using Twitter geolocations	Blizzard	Twitter
(Sakaki, Okazaki, & Matsuo, 2013)	Using sensor readings on social media to detect real-time events	Earthquake	Twitter

3. Discussion

Based on existing studies we reviewed, we discuss (1) event analysis and (2) category analysis. As shown in Figure 8, content classification has been the most prevalent classification method throughout all types of event: various events (64%), flood (35%), earthquake (37%), hurricane (35%), wildfire (50%), typhoon (60%), tsunami (100%), storm (20%). Events that have a relatively high temporal classification method include hurricane (25%), storm (20%), and typhoon (20%). Spatiotemporal classification is commonly used in earthquake (32%), flood (30%), and storm (20%). Sentiment classification is used most often in the event of a hurricane (20%), followed by earthquake (10%) and flood (10%). Lastly, user classification is used quite evenly between most events: storm (20%), various events (23%), typhoon (20%), wildfire (17%), earthquake (16%), flood (15%), and hurricane (15%). There are only a few studies analyzing wildfire, typhoon, and storm, so the percentages for these events are most likely exaggerated.

The most prevalent platform across all types of events is Twitter (Figure 9). Various platforms are frequently used in various events (36%), flood (35%), hurricane (18%), and wildfire (50%). Studies that use various platforms often include Twitter and Facebook, which are both platforms commonly used for uploading/sharing photos and commenting on other people's posts. Content classification is the most prevalent classification method across all events. Following content, user classification is widely used throughout all events as well.

The figures for both platform and classification method percentages are not shown for storm (3 studies), tsunami (2 studies), and blizzard (1 study) due to the small number of studies reviewed on these events. Both of the two studies on tsunami (Acar & Muraki, 2011; Landwehr *et al.*, 2016) used Twitter and content classification. Likewise, two studies on storm (Kim *et al.*, 2018; Laylavi *et al.*, 2017) used Twitter, using classification by users and spatiotemporal analysis, respectively. The other study on storm (Yandong Wang *et al.*, 2015) used Sina-Weibo and classified posts temporally and by content. Lastly, the study on blizzard (Wang *et al.*, 2017) used Twitter and spatiotemporal classification to investigate the effects of the 2015 blizzard on human mobility using a large volume of Twitter geolocations.



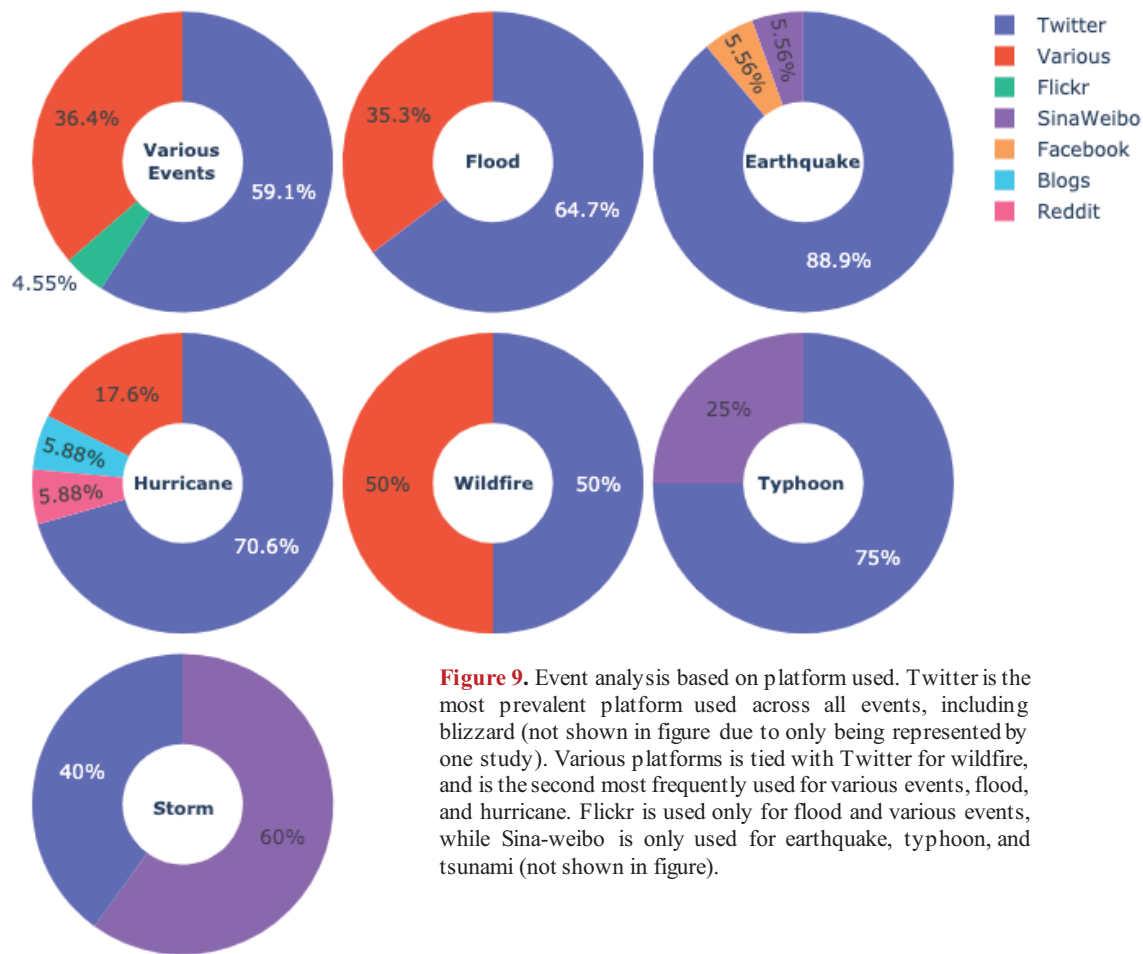


Figure 9. Event analysis based on platform used. Twitter is the most prevalent platform used across all events, including blizzard (not shown in figure due to only being represented by one study). Various platforms is tied with Twitter for wildfire, and is the second most frequently used for various events, flood, and hurricane. Flickr is used only for flood and various events, while Sina-weibo is only used for earthquake, typhoon, and tsunami (not shown in figure).

3.1.Content Classification

Although social media enables us to gain insight into people's emotions and local conditions at different stages during the disaster, there is also a large volume of noise and information not relating to the event, especially in areas with a high population. This noise may be coming from many sources such as individual users, advertisement companies, bots, and more. Arthur *et al.* (2018) avoid this noise by categorizing tweets by time zone, retweets, bot, and relevance. Studies that use content analysis often categorize information-related tweets into different categories, such as hazard information, damage information, mitigation information, and help requests (David *et al.*, 2016; Olteanu *et al.*, 2015; Vieweg, 2011; Imran *et al.*, 2013; Shaw *et al.*, 2013; Temnikova & Castillo, 2015; Spence *et al.*, 2015; Valenzuela *et al.*, 2017; Wang & Zhuang, 2017; Yandong *et al.*, 2016; Qu *et al.*, 2009; 2010; and Vieweg *et al.*, 2010).

By categorizing information-related tweets, these studies were able to not only identify tweets useful to enhance SA, but also to determine the extent of the damages from disasters by analyzing the topics of communication on social media over the course of the disaster. Having subcategories such as 'personal' and 'community' under high-level categories like 'preparation' or 'response to warning' provide an additional filter for different audiences (public, government, emergency responders, etc.) who may find the generated Twitter data useful in an emergency.

Content classification was used across a wide variety of events, with the majority of the studies using the method for more than one natural disaster (various events). The classifications vary from one study to another, but the purpose of the classifications is to categorize different types of relevant information that would benefit different groups of audiences. The category that is most prevalent throughout all event types that use content classification is ‘information’, which describes all contents that provide useful, relevant information about the event. For flood, the most prevalent categories are ‘discussion,’ ‘requests,’ ‘personal,’ and ‘situational.’ The topic ‘personal’ refers to any type of personal experience, feelings, or emotions. From these topics, the group of audience that uses this information would be the general public or individuals who share their own information with one another. For wildfire, the most prevalent categories are ‘evacuation’ and ‘wildfire.’ Wildfire has been the only event that has ‘evacuation’ as one of the most frequent topics. During wildfires, this information would be beneficial to emergency responders to locate areas where people need to be evacuated and would also be beneficial to the general public to know if which areas to avoid. For a hurricane, the most prevalent categories are ‘providing,’ ‘help,’ ‘missing,’ ‘damage,’ ‘assistance,’ and ‘status.’ These categories show an emphasis on relief and recovery efforts in the event of a hurricane, which is useful to emergency responders and organizations. For earthquake, the categories from each existing studies do not show much significance in certain areas over another, showing the most prevalent categories to be ‘action-related,’ ‘opinion-related,’ ‘emotion-related,’ ‘community,’ ‘support,’ and ‘people.’ For typhoons, the most prevalent categories are ‘relief,’ ‘help,’ and ‘personal,’ which shows consistency with the hurricane category’s theme of relief. For various events, the most prevalent categories are ‘people,’ ‘awareness,’ ‘personal,’ ‘situational,’ and ‘infrastructure.’ Although only two of the reviewed studies (Acar & Muraki, 2011; Landwehr *et al.*, 2016) focused on tsunami as their disaster event type, Valenzuela *et al.* (2017) included ‘tsunami’ as a category to classify contents relevant to the earthquake. In addition, Gao *et al.* (2011) studying various events also had an ‘earthquake/tsunami’ category, grouping contents relating to these two events together. Thus, it may be useful for future studies on earthquakes, especially those with high magnitudes, to include a category for tsunamis.

3.2.Sentiment Classification

The study by Verma *et al.* (2011) showed that categorization of tweets by subjectivity, personal or impersonal style, and linguistic (formal or informal) can help predict whether an individual tweet will contain useful/relevant information, where formal and impersonal tweets usually contain SA information. The classification categories within studies using sentiment analyses vary, but most studies include negative tweets within their categories. Negative tweets include different kinds of negative feelings such as fear, anxiety, and concern, which may provide information on affected locations in need of help, as opposed to positive tweets that are not particularly useful in SA analyses during a disaster (Buscaldi & Hernandez-Farias, 2015). Rather than categorizing tweets as negative vs. positive, more fine-grained classification on negative tweets could be used to identify different kinds of negative feelings that may provide important insights to emergency responders (Schulz *et al.*, 2013). Vo and Collier (2013) discarded tweets that fall into the ‘Happiness’ and ‘Pleasantness’ categories because they do not contribute much to negative situations like natural disasters. The authors used 6 different categories to perform sentiment classification on tweets during an earthquake and found that the volume of tweets under the categories Fear and Anxiety correspond to the intensity of earthquakes, and the majority of tweets then fall under the Calm category following the first hours of Fear and Anxiety. Besides using unigrams that express emotions, most studies (Mandel *et al.*, 2012; Caragea *et al.*, 2014;

Buscaldi and Henandez-Faris, 2015; Schulz *et al.*, 2013; Vo & Collier, 2013) also incorporated sentiment features such as emoticons into their machine learning algorithms.

Sentiment analysis should also include demographic attributes to sentiment classification and adjust for demographic bias inherent in social media. For example, Mandel *et al.* (2012) found that women show more levels of concern in tweets than men do. Cho *et al.* (2013) discuss the differences in the characteristic of emotional messages in when the crisis is regionwide as opposed to nationwide. In nationwide crises, social media posts for emotional support generally were not directed towards anyone in particular, while the posts in a more localized crisis usually are personal messages and information directed towards someone related to the user. Sentiment analysis enables us to gain insight into people's emotions as well as the status/intensity of natural disasters during the course of the event to help better mitigation.

Events classified using sentiment analysis include hurricanes, floods, and earthquakes. From the existing studies, there are two main types of sentiment classification used: range (Wang and Taylor, 2018; Caragea *et al.*, 2014) and category (Nair *et al.*, 2017; Schulz *et al.*, 2013; Vo and Collier, 2013; Mandel *et al.*, 2012) classification. Studies that use categories for classification examines the different types of emotions including but not limited to anger, disgust, fear, happiness, and relief. These studies have the same general purpose of identifying tweets that contribute to SA and DM by using categories to filter out relevant content. Other studies (e.g., Wang and Taylor, 2018; Caragea *et al.*, 2014) using range based method, usually classify sentimental contents from negative to positive integers, representing the emotions expressed by the contents. Negative emotions such as anger or fear would be represented as a negative integer, while positive emotions like happiness or gratitude would be represented as a positive integer. The purpose of these studies is to analyze the trend of user response towards the disaster, which would vary according to the phase of the crises. All of the studies using sentiment classification that we analyzed have used Twitter as the social media platform. Twitter is usually used for posting about daily activities, which makes it a convenient platform to update one's daily feelings and emotions.

3.3. User Classification

Distinguishing what group the user is in provides insight on what the social media content may be about. Each study categorizes users in their own ways, but most studies include these three main categories: (1) individuals, (2) organizations (3) journalists/media bloggers (Takahashi *et al.*, 2015; Choudhury *et al.*, 2012; Diakopoulos *et al.*, 2012; Houston *et al.*, 2015). Individuals refer to the general public or private citizens who may or may not be within the disaster-affected region. Organizations are structured groups of people that may be facilitating some events associated with the disaster such as relief organizations. Journalists or media bloggers are small or large organizations in traditional media such as a local community blog or a news organization. Knowing which group the user belongs to may also indicate the level of credibility of the content.

Most studies also include eyewitnesses in their classifications. Kumar *et al.* (2013) found that eyewitnesses generate the most meaningful information in their tweets. Identifying the group of users who provide useful information would make data collection more efficient by filtering more quantity and better quality of tweets to support SA. Both contents from eyewitnesses and sympathizers are relevant to the topic but eyewitnesses show variety in discussion – important for accessing various types of information from within the impact region, while sympathizers are generally talking about the same topics – used for understanding the global impact of the crisis. Zahra *et al.* (2018) classify eyewitnesses into three categories: direct, indirect, and vulnerable direct witnesses. Direct eyewitnesses use words related to perceptual senses such as seeing,

hearing, and feeling, while indirect eyewitnesses mainly express emotions such as thoughts, prayers, worry. Lastly, vulnerable direct witnesses mostly share warnings and alerts about an expected disaster situation. Another method in identifying tweets from direct witnesses is to filter out tweets containing Uniform Resource Locators (URLs) and tweets containing the text “RT” or “@”, which indicates a retweet, often associating to users who are outside the affected areas (Earle *et al.*, 2011).

On the other hand, studies that did not focus on the type of eyewitness categorized the users by their groups instead. Choudhury *et al.* (2012) found that tweets from organizations generally contain the words “headline” and “news,” while tweets from journalists/bloggers would contain second-person pronouns words like “you” to encourage an interactive behavior. Individual tweets would most likely contain sentiment words such as “excited,” “awesome,” or “bad” and first-person pronouns like “my” and “us.” By identifying the content of the tweets, they were able to classify which user category the information source belonged to. While organizations frequently point to external sources of information through URLs in their posts, ordinary individuals tend to be more representative of their personal experiences and feelings about events. Classifying users according to the type of user can expedite DM processes, as the type of social media content (e.g. sentiment, informative, alert) can often be determined by the user group. However, classifying users according to direct or indirect eyewitnesses would be analyzing content posted by individual users and not organizations or journalists. Individual users may provide insight on sentiment and human coping mechanisms, but social media content from individual users may also be biased and subjective.

3.4.Temporal Classification

There are generally three phases in a course of a disaster: pre-incident, during the incident, and post-incident. During the pre-incident, social media contents usually include topics of warning and alert (Chowdhury *et al.*, 2013). During the incident, topics usually include damage and casualty reporting (Terpstra *et al.*, 2012). Post-incident contents include topics on recovery and relief (Chowdhury *et al.*, 2013). The event that is most prevalent for studies using temporal classification is hurricane, accounting for 36% of all studies indicated in this schema. Both floods and hurricanes are considered to develop progressively, as opposed to earthquakes that happen rather instantaneously (Olteanu *et al.*, 2015). We observe a corresponding pattern where temporal classification is most often used with progressive events since these events usually have warning periods and other development phases. Since temporal classification for disaster management is often used to explore communication topics and what people are discussing on social media over the course of a disaster, this classification method complements sentiment classification as people’s emotions correspond to the phase of the disaster.

3.5.Spatiotemporal Analysis

Social media allows for real-time data and information at a local level to be shared at a global level. The scale and location of the natural disaster play an important role in social media activity where the larger the size and significance of the disaster, the higher the frequency of Twitter activity. An example can be seen when Hurricane Ike, estimated to be \$27 billion in damages, had a much higher tweet activity than that of Hurricane Gustav with an estimation of \$4-14 billion in damages (Hughes & Palen, 2009). As for location, there will most likely be fewer social media activity in less-populated areas than areas that are high in population. If the center of an earthquake happens to be in an oceanic area, then it would be difficult to determine its location

from social media threads because of a lack of people (Sakaki *et al.*, 2013). Crooks *et al.* (2013) showed that reaction time tends to increase away from the epicenter, serving as an indicator to estimate the epicenter of the event by considering the temporal stamps of relevant data. Furthermore, the dataset in the study showed that information dissemination through Twitter can reach distant communities and locations faster than the physical event itself, suggesting how social media can be used as an early warning system for large-scale incidents. The most prevalent events used for spatiotemporal classification are earthquakes and floods. Spatiotemporal analysis was used to locate areas affected by the disaster and to assess how heavily it was affected.

4. Research Agenda

Though each classification schema has its own limitations, there are multiple challenges in using social media data for DM that are cross-cutting among all thematic areas. First, the data from individual users are inherently subjective. User's opinion about the disaster condition can vary depending on several factors such as demographics, education level, personal motivation (Jamali *et al.*, 2019). Another challenge is locational errors from using geolocated social media data as the majority of informative disaster-related content is often from people who are physically close to the location of the disaster and not necessarily in the exact location of the disaster (Li *et al.*, 2017). This situation may be due to the lack of internet access and that people experiencing the disaster would be prioritizing their safety before engaging in social media interactions. In addition, this limitation also affects the using social media data for disasters that take place in remote regions. Unlike floods, earthquakes, and hurricanes that could happen in urban areas with a large population size, wildfires usually occur in forested areas that are far away from the majority of the human population so there may be a lack of informative data shared on social media. As such, there are more studies in this review on flood, hurricane, or earthquake compared to studies on wildfire or blizzard. To address this issue, future research should incorporate spatiotemporal analysis when assessing social media data in addition to the classification method (content, temporal, user, and/or sentiment) they may be using. Due to the near real-time nature of social media data, using spatiotemporal analysis can assist data acquisition in weakly institutionalized areas by monitoring the frequency and pattern of social media activity.

Based on the review, a future research agenda is envisioned for SA classification and extraction methods from five different aspects (e.g., content, temporal, user, sentiment, and spatiotemporal) elaborated as below.

Content classification: Current content classification models mostly rely on features derived from text only (Arthur *et al.*, 2018; Verma *et al.*, 2011; David *et al.*, 2016; Vieweg *et al.*, 2010; Cho *et al.*, 2013; Qu *et al.*, 2009; Qu *et al.*, 2010; Imran *et al.*, 2013; Kongthon *et al.*, 2012; Vieweg, 2011; Olteanu *et al.*, 2015; Imran *et al.*, 2016; Acar & Muraki, 2011; Smith, 2010; Wang *et al.*, 2016; Bruns *et al.*, 2012; Shaw *et al.*, 2013; Gurman & Ellenberger, 2015; Temnikova & Castillo, 2015; Herfort *et al.*, 2013; Landwehr *et al.*, 2016; Spence *et al.*, 2015; Sutton *et al.*, 2014; Takahashi *et al.*, 2015; Valenzuela *et al.*, 2017; Wang & Zhuang, 2017; Win & Aung, 2017; Yu *et al.*, 2019). These models are often limited in accuracy due to the variability, uncertainty and succinct characteristics of social media messages. Therefore, more clues or signals are necessary to improve entirely text-based approaches. Others features, especially spatial and temporal information, can potentially be integrated because messages within the same category likely form spatiotemporal clusters (e.g., posts reporting a flood zone and infrastructure damaged by the flood would have close locations; posts about donation and aid are more likely to occur during and after a disaster event) to which spatial and temporal features can improve text classification (Figure 10).

Temporal classification: The process of automatically detecting and classifying tweets by periods is important when using temporal classification on social media data to detect the different phases of a disaster (Chowdhury *et al.*, 2013). Rather than just being able to detect the timeframe of when an event starts and ends, future studies should incorporate more data sources concerning different aspects of the emergency events into their models to develop filters that enable early detection of this information. Combining these additional information sources such as authoritative data (e.g., remote sensing data), real-time weather data, and terrain data may enhance the identification of relevant content from social media to ensure that the model can be used to help better prepare for different types of emergency situations.

User classification: User classification and analysis are important for addressing the challenge of finding reliable data from social media streams. Current models of user classification focus on determining which category (e.g., organizations, journalists/media bloggers, ordinary individuals) the information source is in or determining the relationship between the information source and the event (e.g., direct/indirect eyewitness) (Choudhury *et al.*, 2012; Diakopoulos *et al.*, 2012; Kumar *et al.*, 2012). However, there are still many opportunities to enhance these models by considering additional factors including individual characteristics of users such as demographic information (e.g. gender, age), cognitive variables (e.g. scientific knowledge, language), affective variables (e.g. emotions), other structural factors (e.g. access to Internet, type of technological capacity), and social factors (e.g. culture) (Takahashi *et al.*, 2015). Considering these factors would help determine the reliability of the post, and identify influential users.

Sentiment classification: Although the current machine learning models for sentiment classification provide broad coverage of the ongoing event, the accuracy rate could still be improved due to a high rate of false positives (e.g., ironic tweets) (Buscaldi and Henandez-Faris, 2015; Schulz *et al.*, 2013). To address this issue, future studies should incorporate a larger labeled training set with a finer-grained classification while decreasing potential information overload by post-processing the classified micro posts to reduce noise. In addition, integrating spatiotemporal analysis by providing visualization of these sentiment posts on a geographical map would help reveal the trend of users' responses throughout the event related to their location and distance from disaster.

Spatiotemporal analysis: While examining the spatiotemporal patterns of extracted information from social media, some common limitations are that only a small percentage of users geotag their posts/tweets (Wang *et al.*, 2007) and that the analysis is done after the event (Crooks *et al.*, 2013). Future studies should perform real-time trend detection over the social media stream to be able to access all crawled user-generated content. Moreover, it is important to consider the spatial size and significance of the natural disaster, since the quality of the visualization map corresponds to the number of users in the location of the event.

Lastly, Twitter has been the platform most frequently used for all classification schemas (Figure 8). Therefore, a future study should investigate the characteristics and effectiveness of different social media platforms in relation to their feasibility and reliability as an information diffuser in the event of a natural disaster, and fuse data (e.g., texts, images, and videos) from different platforms for better SA information extraction and establishment.

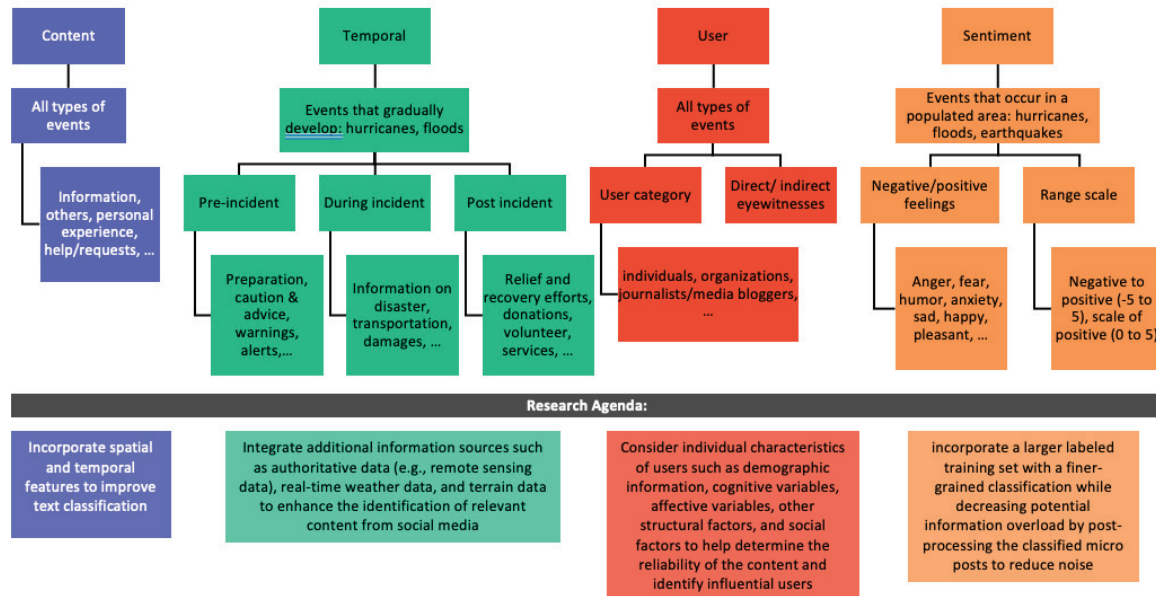


Figure 10. Classification methods and the types of events they are recommended to be used with, along with their subcategories and research agenda. Content and user classification may be used with all types of events. Temporal classification is advised to be used with events that develop over time such as hurricanes and floods. Sentiment classification would be appropriate for events that occur in a populated area, since it depends on user response and emotions. Spatiotemporal classification (not shown in figure) should be used for investigating patterns of events over time and disaster mapping.

5. Conclusion

Identifying relevant information efficiently and accurately to support SA is a main priority during a natural disaster. Effective threat assessment and logical reactions are critical in the disaster mitigation processes (Perry & Lindell, 2003). In this paper, we reviewed studies that use different methods to extract information from social media during natural hazards. These studies include work from across multiple social media platforms, with the most used platform being Twitter. We categorized these studies' methods into five categories (content, sentiment, user, temporal, spatiotemporal), with some studies showing up in more than one category. As shown in Figure 10, content classification can be used for all types of events, as it is efficient and appropriate for filtering relevant tweets that contribute to SA. However, the classification category/topic would vary according to the event itself. Sentiment classification is most often used when the purpose of the study is to analyze the trend of people's emotions and responses to the event, which changes throughout the different phases of the natural disaster. User classification is recommended to check for information credibility and track the main influencers on discussions in social media. Temporal classification is most appropriate for events that develop progressively like hurricanes since there are clear distinctions on the different phases of the event. Lastly, spatiotemporal classification would be most appropriate for disaster mapping.

This paper presents an overview of methods used to analyze social media content across multiple events and social media platforms. Furthermore, this paper also summarizes (1) the content topics or information categories are commonly extracted and examined from the social media datasets for four classification schemas listed previously, (2) what types of events mostly leverage social media for each of the five schemas, (3) what was the most prevalent classification purpose for each event, (4) what social media platforms are most popular, and (5) what classification schemas are most popular for each event.

In particular, the analysis results indicate that the major topics used to classify social media data include *information, others, personal expression and experience, help and requests, and sentiment/emotion*. For content classification, the majority of the reviewed literature analyzed various event types with the purpose of identifying tweets contributing to SA and disaster management. Likewise, various event types was most commonly used for user classification. For both temporal and sentiment classification, the event type studied most frequently is hurricane. However, the most prevalent study purpose observed in the literature that used temporal classification was exploring communication topics throughout the course of the disaster, while the purpose for sentiment classification was more focused on analyzing people's emotions and feelings. Lastly, studies that employed spatiotemporal analysis mostly studied flood and earthquake. Across the majority of the event types studied, Twitter has been the most prevalent platform for SA extraction, while the most frequently used classification method is content classification.

Finally, a future research agenda for SA classification and extraction methods are envisioned from five different aspects (e.g., content, temporal, user, sentiment, and spatiotemporal) in Section 3.2. We hope this paper would contribute to future studies of analyzing social media content by providing a framework on which categorization to use based on the purpose of the study, the social media platform, and the type of event. The main limitation of this review is the uneven distribution of studies for each type of event as well as the classification methods, causing some exaggerations in the percentage analysis and lack of information to perform analysis on as seen with tsunami and storm. Despite the limitations of this paper, we were able to see the general classification methods and categories used on each type of natural disaster.

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Appendix

Table 3

Content classification topic categories

Category	Count	Subcategories (count)	Disaster stage: Description
Information	83	weather(6), information-related(3), situational awareness(3), earthquake(2), info space(2), information source(2), information sources(2), other useful information(2), situational information(2), eyewitness reports(2), reporting(2), factual(1), water levels(1), fire(1), disaster/events update(1), current situation(1), future situation(1), relevance(1), the magnitude of the storm(1), earthquake/tsunami(1), tsunami(1), information(1), typhoon information(1), local information about impact or status of storm(1), information based on personal experiences(1), general area information(1), general hazard information(1), informativeness(1), informative(1), information type(1), information or updates about the event(1), information about government response(1), providing information about damage(1), providing information about missing that had been found(1), providing information to help locate missing(1), providing information about how to get help(1), information dissemination(1), credible information(1), collection and distribution of critical disaster notifications and situational information(1), information source tips/recommendations(1), information collection(1), disaster information(1), related and informative(1), hazard-related warning(1), hazards location(1), hazard(1), hazard impact(1), reports about environment and self(1), professional news report(1), relative(1), technology/media-related(1), flood-related(1), related to disaster(1), guidance and tips(1), tips(1), visibility(1), health/environment(1), environmental cues and receiver characteristics(1)	All: disaster-related information contributing to situational awareness
Others	73	other(5), general(4), found(3), other opinion(2), moderation-related(2), flaming(2), retweet(2), time(2), anti-social(2), unspecified(2), closures(2), other environmental conditions(1), other on-line social convergence activity(1), screenshots of map mashups and other social media sites(1), class suspension(1), possible exploitation(1), disaster tourism/witness to the devastation(1), corrections(1), children and education(1), cancellations(1), relational(1), international messages(1), general comments(1), containment percentage(1), time zone(1), historical(1), immediate(1), formal(1), social context(1),	All: describe about the disaster but not contribute SA

Personal expression and experience	50	foreign states(1), precise(1), siren heard(1), discounts(1), seen(1), official(1), property(1), reassurance(1), reference(1), subjective(1), credibility(1), threat(1), aftermath(1), new incidents(1), disclosure(1), references to haiti(1), risk(1), care for the sick and elderly(1), affect display(1), advisories(1), re-entry(1), unsure(1), secondhand(1), valid cases(1), religious activities(1), allah(1) personal(4), opinion-related(3), thanks(3), criticizing(2), personal updates(2), personal narrative(2), personal reaction(2), direct experience(2), expressing(2), prayers(2), personal relief(1), personal loss(1), personal community(1), personal experiences(1), personal opinion and interest(1), personalize issues(1), personal belongings(1), documenting personal experience(1) thoughts(1), status(1), people with previous experience(1), personal information(1), impersonal(1), objective(1), expressions of support(1), expressions of opinions(1), expressions of fear(1), praying for the dead(1), memorialize(1), memorializing(1), expressing wishes and memorializing(1), appreciation to firefighters(1), gratitude(1), expressions of gratitude(1), insult(1), complaints(1) support(4), help and fundraising(2), requesting help(2), requests for assistance(2), offer of help(1), for help(1), helping(1), organization of rescue help(1), offer rescue help(1), help tips(1), offering assistance(1), organizing assistance(1), financial assistance(1), volunteers(1), fundraising(1), specific calls for help(1), help requests(1), request(1), requests(1), (support request(1), citizens requirements(1), needs(1), offers(1), providing social support(1), volunteering(1), providing counseling(1), rescue activities(1), call for rescue(1), rescue request(1), rescue efforts and volunteering/collaboration(1), rescue information(1)	All: Any personal updates or opinions expressed by users throughout the course of the disaster
Help and requests	37	emotion-related(3), users emotional content(1) positive(3), emotional support(2), sadness(2), anger(2), fear(2), negative(2), expressing feelings and emotions(1), sentiment/emotional classes(1), emotions(1), sympathy & emotional support(1), sympathy and emotional support(1), emotional content(1), jokes(1), humor and sarcasm(1), joy(1), concern(1), despair and anger(1), humor(1), sympathy(1), unspecified indications of worry or fear(1), anxiety and/or sadness of the writers towards others(1) missing(4), affected individuals(3), injury(2), deaths(2), unaffected people(1), people(1), displaced people(1), injured	Post-disaster: posts involving help, rescue, fundraising, services, and/or support to alleviate disaster impact
Emotion	32	emotion-related(3), users emotional content(1) positive(3), emotional support(2), sadness(2), anger(2), fear(2), negative(2), expressing feelings and emotions(1), sentiment/emotional classes(1), emotions(1), sympathy & emotional support(1), sympathy and emotional support(1), emotional content(1), jokes(1), humor and sarcasm(1), joy(1), concern(1), despair and anger(1), humor(1), sympathy(1), unspecified indications of worry or fear(1), anxiety and/or sadness of the writers towards others(1) missing(4), affected individuals(3), injury(2), deaths(2), unaffected people(1), people(1), displaced people(1), injured	All: User's sentiments and emotions expressed throughout the course of the disaster
People	30	missing(4), affected individuals(3), injury(2), deaths(2), unaffected people(1), people(1), displaced people(1), injured	During and post-disaster: posts involving missing, injured, and/or dead people

Discussion	27	people(1), dead people(1), trapped people(1), displaced and evacuated people(1), people who have lost their homes(1), missing people(1), victims homestays(1), victims(1), injuries(1), missing persons and related resources(1), the whereabouts of others(1), help finding people(1), Sanitation and hygiene(1), health(1), lifeline status(1), medical(1) discussion and reaction(2), adjunctive discussion(2), meta-discussion(2), communication(2), sharing(2), gathering and integrating(2), media sharing(2), participation by new discussants(1), conversational posts for meta-discussions including questions(1), discussion(1), discussing causes(1), discussions(1), situational awareness and citizen communication(1), communicating through blog(1), telecommunications(1), flexible communication and collaborations between diverse occupational communities(1), communications and the media/viña festival(1), connectivity(1), comment on looting(1), reconnecting(1)	All: posts involving discussions and communications throughout the course of the disaster
Resources and services	22	money(2), food(2), water(2), services(2), free emergency survival kits distribution(1), goods(1), non-japanese resources(1), resources(1), medical supplies(1), supplies needed or offered(1), education/supplies and basic services(1), equipment(1), free parking availability(1), free consulting services for home repair(1), utilities/services(1), available services(1), services needed or offered(1), food and nutrition(1)	Post-disaster: posts sharing the available resources and services to help alleviate the disaster impact
Action-related	20	action-related(3), animal management(3), coordinating(2), norm shaping(2), sense-making(2), coping with stress(1), checking on status of loved ones area(1), checking status of ones home(1), engagement(1), promote involvement(1), call to action(1), involvement(1), voluntary work(1)	All: posts involving action-related events throughout the course of the disaster
Damage/impact	20	damage information(2), damage(2), casualty and damage(1), no damage(1), casualties and damage(1), communicating wildfire damage(1), asking about damage(1), casualties and damages(1), magnitude of impact(1), impact(1), impact of crisis(1), loss of assets(1), loss and influence(1), burned acres(1), the extent to which it threatened life or property(1), disaster sighting(1), damage & injury report(1), infrastructure damage(1)	During: posts about damages and affected areas from the disaster
Irrelevant	20	off-topic(3), trolling(2), spam and irrelevant information to the event(1), misinformation(1), not informative(1), related and not informative(1), not situational awareness(3) spam(1), not related(1) non flood-related(1), irrelevant(1), bot(1), ads(1), rumor(1), marketing and advertising(1)	All: posts that are not relevant (off-topic or spam) to the disaster

Response	20	evacuation(6), response(4), who is responsible(1), responding to dearth(1), foreign response(1), response to warning(1), wildfire response(1), post-impact response and recovery efforts(1), comment on government response(1), response agencies in place(1), response/preparing tips(1), evacuation centers(1)	Post-disaster: posts involving response to disaster impact and recovery efforts
Sources	18	individual participation(2), news media(2), back-channel information providers(1), news(1), posting official news(1), citizen journalism(1), women(1), rappers(1), source(1), eyewitness(1), ngos(1), business(1), media(1), outsiders(1), source organization(1), witnesses accounts(1)	During: posts classified by user type
Infrastructure and utilities	18	infrastructure(2), transportation(2), infrastructure & utilities(2), infrastructure and utilities(1), infrastructure and housing/transport/public works(1), infrastructure and resources(1), buildings(1), traffic conditions(1), road conditions(1), traffic(1), road(1), roads(1), both infrastructure and people(1), logistics and transportation(1), stores and facilities(1)	During: posts involving the physical, transportation, and communication components of infrastructures and utilities
Relief and recovery	12	recovery(2), recovery efforts(1), cleanup(1), disaster relief(1), relief of others(1), relief coordination(1), relief(1), relief efforts(1), relief services(1), emergency or crisis relief(1), coordinating relief(1)	Post-disaster: posts involving disaster relief information and recovery efforts
Safety and security	12	Safety(2), calls for safety(1), safety and security(1), safety enquiry(1), public safety and crisis information(1), sheltering(1), shelter open or available(1), shelter(1), sheltering status(1), camp and shelter(1), food/shelter(1)	During: posts with safety information, such as shelters
Caution and advice	12	Caution and advice(6), advice(4), caution(1), caution & advice(1)	Pre- and during disaster: posts containing caution and advice
Warnings and alerts	11	warnings(2), warning components(1), warning issued or lifted(1), emergency warnings(1), warnings issued or lifted(1), emergency warnings and alerts(1), situational announcements and alerts(1), support announcements(1), notifications(1), announcement(1)	Pre- and during: posts containing warning, alerts, and announcements
Technology or media-related	10	multimedia(2), link(2), radio station(1), photo(1), video(1), website(1), tv channel(1), technology and others(1)	During: posts involving media sources
Information seeking	8	Requests for information(4), seeking(2), questions about the event/subject(1), question about looting(1)	During: posts containing questions on the disaster
Politics and government	8	politics(2), government(2), political(1), political activities(1), governmental authorities(1), criticizing government(1)	During: posts concerning government and politics
Donations and fundraising	8	donations(3), donation and offer(1), donations & volunteer(1), donations and volunteering(1), donation and aid(1), fundraising information(1)	Post-disaster: posts containing information on donations and fundraisers
Community building	7	community(2), community building(2), connect with a community of supporters(1), attempts to foster community(1),	Post-disaster: posts concerning community building

Location/disaster area	5	development of a sense of community engagement and association(1) location(2), geographical areas(1), locations(1), disaster area(1)	During and post-disaster: posts about locations relating to disaster
Preparation	5	Preparation(3), risk reduction(1), protocol(1)	Pre-disaster: information about the preparation for the disaster
