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REVIEW ARTICLE

Social media analytics for natural disaster management

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ABSTRACT

Social media analytics has become prominent in natural disaster management. In spite of a large variety of metadata fields in social media data, four dimensions (i.e. space, time, content and network) have been given particular attention for mining useful information to gain situational awareness and improve disaster response. In this article, we review how existing studies analyze these four dimensions, summarize common techniques for mining these dimensions, and then suggest some methods accordingly. We then propose a schema to categorize the gathered articles into 15 classes and facilitate the generation of data analysis tasks. We find that (1) a large part of studies involve multiple dimensions of social media data in their analyses, (2) there are both separate analyses for each dimension and simultaneous analyses for multiple dimensions and (3) there are fewer simultaneous analyses as dimensions increase. Finally, we suggest research opportunities and challenges in fusing social media data with authoritative datasets, i.e. census data and remote-sensing data.

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Social media; dimensions; natural disasters; census data; remote sensing

1. Introduction

Over the past several decades, the frequency and intensity of natural disasters have dramatically increased, causing a huge amount of human injuries, deaths and property damage (Cutter and Emrich 2005, Klomp 2016). This has imposed great challenges on natural disaster management (Klonner *et al.* 2016, Kryvasheyeu *et al.* 2016). To reduce the impact of disasters to humanity, various management tasks during all disaster phases, i.e. mitigation, preparedness, response and recovery, have soaring needs for human-centric information. In recent years, due to the capability of capturing human activities, social sensing techniques featured by various big data sources such as social media data and movement data are gaining increasing attention from geographic information scientists and domain scientists (Goodchild 2007, Liu *et al.* 2015, Wang *et al.* 2016, 2016, Zhao *et al.* 2016).

In natural disaster management, social media has been applied to 'strengthen situational awareness and improve emergency response' (Steiger *et al.* 2015). From a citizen's perspective, through following official natural disaster management agencies on social media, ordinary social media users can be alerted to authoritative situational announcements. From an organizational perspective, disaster response organizations can leverage social media as a platform to communicate with the public in disaster situations and

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potentially solicit on-the-ground information using the public as information sources (Latonero and Shklovski 2011). Social media could be a useful information source for all phases of natural disaster management. However, most studies, with several exceptions, e.g. Haworth *et al.* (2015) and Yan *et al.* (2017), have focused on disaster response instead of other phases (Haworth and Bruce 2015, Klonner *et al.* 2016). This is probably due to the fact that social media activities are less reported before and long after a disaster than during the disaster. This data sparsity problem in phases like preparation, mitigation and recovery may cause unreliable analytical results. Therefore, future work is needed to overcome this limitation and effort needs to be directed toward gaining more useful information for all phases of disaster management through mining social media data.

Social media data are multi-dimensional. For example, each tweet collected via the Twitter application program interface contains multiple metadata fields such as *user ID, timestamp* (i.e. the time when tweet was posted), *text* (i.e. the text message tweeted by a user), *coordinates, retweet* (i.e. whether a tweet is retweeted from others) and so forth. In fact, existing studies mainly focus on four dimensions: space, time, content and network. Still using Twitter as an example, these four dimensions correspond to the Twitter metadata fields of *coordinates/place/location, timestamp, text* and *retweet*, respectively. Notably, besides *retweet*, other relationships such as reply, mention and friends/followers can also be utilized to formulate networks (Lai *et al.* 2015).

Granell and Ostermann (2016), Miyazaki *et al.* (2015), Haworth and Bruce (2015), Imran *et al.* (2015), Steiger *et al.* (2015) and Klonner *et al.* (2016) have reviewed studies on applications of social media and volunteered geographic information (VGI) in disaster management. Compared with these existing reviews, our study provides a unique way to generalize the characteristics of studies related to natural disasters based on the dimensions of social media data. From a methodological perspective, we summarize common techniques used for mining these dimensions and suggest some methods accordingly. We also propose a novel classification schema that is different from existing ones to categorize relevant studies and suggest data analysis tasks. Furthermore, we point out research opportunities and challenges in fusing social media data with authoritative datasets, i.e. census data and remote-sensing data. Notably, although social media has been used in managing man-made crises such as terrorist attacks, current study focuses on disasters caused by natural processes of the earth (e.g. floods, earthquakes and hurricanes). We acknowledge that it might be limiting to emphasize natural disasters alone, but this narrow scope in our study is motived by an attempt to more explicitly deal with nature and society relations and thus contribute to an important subfield of geography, i.e. the human–environment geography.

The remainder of this paper is structured as follows. Section 2 provides a literature review on how existing studies analytically and methodologically explore social media data in natural disaster contexts. Section 3 includes a schema for categorizing existing studies and generating data analysis tasks. Section 4 suggests some research opportunities and gaps in linking social media data with authoritative data, i.e. census data and remote-sensing data. We make our conclusion in Section 5.

2. Four dimensions

Four dimensions in social media data, including space, time, content and network, have attracted particular attention from researchers.

2.1. *Space*

Spatial information in social media data is critical for natural disaster management. Disaster mapping is an important tool for disaster managers to learn where things are happening. It has been acknowledged that spatial information in social media data could be used in disaster mapping to enable disaster managers to better identify risks and assess damages (Huang *et al.* 2015, Kryvasheyeu *et al.* 2016). There are mainly two types of spatial information in social media data: exact coordinates (i.e. longitudes and latitudes) and toponyms (e.g. a city name) (Huang *et al.* 2014, Huang and Wong 2016). Exact coordinates can be solicited if the built-in global positioning systems in users' devices are turned on. Toponyms could come from profile locations or an inference from the content of social media messages.

A typical way of using this spatial information is to map people's responses to a disaster. In most cases, this is done by simply plotting social media messages with geo-coordinates on a map (see Gupta *et al.* 2013, Avvenuti *et al.* 2014, Blanford *et al.* 2014, for examples). Using this method, Avvenuti *et al.* (2014) display the spatial distribution of earthquake-related twitter messages, and Gupta *et al.* (2013) visualize the spatial distribution of Hurricane Sandy tweets on a world map. However, this simple visualization method has very limited capability in detecting spatial patterns. Because of this, natural disaster researchers have started to pay attention to some well-established methods such as kernel density estimation (KDE) that have been widely used in other fields to deal with social media data (Li *et al.* 2013, Spitzberg *et al.* 2013, Tsou *et al.* 2013, Widener and Li 2014, Han *et al.* 2015). Guan and Chen (2014) implement KDE to detect spatial clusters of Twitter activities related to Hurricane Sandy. Wang *et al.* (2015) apply a density-based clustering method to Weibo (a Chinese social media site) messages pertaining to 2012 Beijing Rainstorm to identify spatial hotspots. Notably, a problem may arise when using KDE to deal with social media data, which is that the spatial pattern of social media activities is often a reflection of population distribution, meaning that areas with a larger population tend to report more social media messages. To solve this problem, Wang *et al.* (2016) adopt Dual KDE to exclude the population impact and identify hot spots of wildfire-related Twitter messages. However, spatial analytical tools are still far from being fully exploited to analyze geocoded social media data for natural disasters. It is also important to note that the spatial information that could be retrieved from social media is quite limited. Take twitter for example, geo-tagged tweets only account for a tiny percentage of all tweets (Dredze *et al.* 2013), which possibly undermines any spatial analysis results. More importantly, compared with the accurate and widely used geo-coordinates and toponyms, some place names that have vague boundaries but are largely communicated by social media users have been rarely explored in disaster contexts (Jones *et al.* 2008). For example, 'downtown' and 'city center' are often used to represent the core area of a city (Hollenstein and Purves 2012). These 'vernacular place names' termed by Hollenstein and Purves (2012) in social media messages could be utilized to better enrich the useful geographic information for natural disaster management.

2.2. *Time*

Natural disaster management is often time-critical and thus requires timely information collection and analysis. Event detection is important for natural disaster management, as early detection of disasters could result in an earlier response time and a better mitigation of damages. It has been acknowledged that the real-time nature of social media streams could help detect the outbreak of disasters in a timely manner (Sakaki *et al.* 2010).

Every social media message comes with a high-resolution timestamp. A typical way of using this temporal information in natural disaster management is to analyze how people's responses to disasters change over time. To achieve this, these messages are often temporally aggregated to each time interval. For example, if the time interval is 1 h, then multiple time points in the same hour are aggregated together. In doing so, a frequency distribution is obtained to show the change of related social media activities over time. Existing studies have shown a temporal concurrent evolution between disasters and corresponding social media activities. Blanford *et al.* (2014) note that the frequency of tornado tweets increases until its touchdown and then decreases. Qu *et al.* (2011) also find a similar temporal trend that Weibo messages peak immediately after the earthquake and then drop gradually. However, these traditional methods are unable to distinguish the rich patterns in time series data. Therefore, Wang *et al.* (2015) employ time-series decomposition to disclose the underlying patterns into three components: the overall trend, the cyclical variation and the causal fluctuation.

2.3. *Content*

According to Endsley (1995), situational awareness is 'the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future'. Situational awareness in natural disaster management could be enhanced by social media data, especially the content dimension. As pointed by Huang *et al.* (2015), 'humanitarian Assistance and Disaster Relief (HA/DR) responders can gain valuable insights and situational awareness by monitoring social media-based feeds from which tactical, actionable data can be mined from content'. As people's conversational content on social media varies in terms of topics and emotions, a data reduction process is often required to classify social media messages into distinct categories. Unstructured social media texts should be converted to a structured form such as term-document matrix or unigram feature before being imported to any classification algorithms (Zhao 2012). We discuss two types of classifications: topic-based classification and sentiment-based classification.

2.3.1. *Topic-based classification*

The topic-based classification focuses on mining what people talk about in natural disaster situations. According to the usage of predefined classes, there are mainly two types of classification methods: supervised classification and unsupervised classification.

Supervised classification. When using this method, the categories are predefined by analysts. Analysts should train the classifier with sufficient known social media texts and then apply the classifier to attach labels to all of the text. Although various schemes have been utilized to classify disaster texts, we exemplify them with two types. Some studies use the information provided in social media content to build a classification scheme (Imran *et al.* 2015). A four-tier scheme including situation update (e.g. factual information about situations around the impact area), opinion expression (e.g. criticizing rescue efforts by government agencies), emotional support (e.g. expressing anxiety or other feelings) and calling for action (e.g. requesting help) is adopted by Qu *et al.* (2011) to classify earthquake-related messages from a Chinese social media platform. Imran *et al.* (2013a) and Imran *et al.* (2013b) utilize a five-tier scheme to classify disaster-related Twitter messages into caution and advice (e.g. conveying disaster warnings), casualties and damage (e.g. reporting people injured), donations (e.g. asking for goods or services), people (e.g. reporting people missing) and information sources (e.g. including photos or videos). Some other studies design their classification schemes based on disaster phases. For example, Huang *et al.* (2015) propose a fine-grained classification scheme to categorize Hurricane Sandy tweets into 4 major classes, i.e. preparedness, response, impact, recovery and 47 subclasses. In terms of training methods, multiple techniques could be used to train classifiers, including naïve Bayes, support vector machine and logistic regression (Huang and Xiao 2015, Imran *et al.* 2015).

Unsupervised classification. When there are no predefined classes, the classification of social media messages becomes unsupervised. Clustering is a widely used technique to perform unsupervised classification. The purpose of clustering is to form clusters in such a way that words within a cluster are more likely to reflect the same topic than those that belong to other clusters. Among various clustering algorithms (e.g. *k*-means clustering, hierarchical clustering and logistic regression), Latent Dirichlet Allocation (LDA) is a popular topic modeling method which 'allows a word to simultaneously belong to several clusters with varying degrees' (Imran *et al.* 2015). Using LDA, Kireyev *et al.* (2009) detect several prominent topics including (tsunami, disaster, relief, earthquake), (me, you), (happy, feel), (dead, bodies, missing, victims), (Australia, Indonesia), (Internet, web, online) and (aid, help, money, relief) in tweets related to the 2009 Indonesian earthquake. Wang *et al.* (2015) identify three significant topics, i.e. weather, disaster information, and loss and influence in Weibo messages related to the 2012 Beijing rainstorm.

Both unsupervised classification and supervised classification have advantages and disadvantages. Unsupervised classification, take LDA for example, could automatically generate summaries of topics and thus may be useful for situations where prior knowledge about the topic distribution of the input disaster-related social media messages is lacking. However, it often provides uninterpretable topics and no obvious way of specifying predefined classes into its learning procedure. In contrast, supervised classification could meet the need of disaster responders to specify their own categorization schemes. Nevertheless, it often requires the analysts to manually train enough sample data with the given scheme, which is a time-consuming process and may not be appropriate for rapid decision support. To utilize the strengths from both of them while offsetting weaknesses, we suggest that, for each type of natural disaster (e.g. hurricane), a classification scheme with widespread acceptance should be developed and trained with social media data historically collected. In this way, when the next disaster comes, this well-trained classifier could be directly used to categorize newly collected social media data.

2.3.2. *Sentiment-based classification*

The textual content of social media also reflects people's sentiments. Sentiment classification is a special task in text classification, which aims to categorize given texts based on their conveyed sentimental opinions such as positive, neutral or negative (Pang *et al.* 2002). A large part of sentiment classification algorithms such as SentiStrength (http://sentistrength.wlv.ac.uk) are lexicon-based, meaning that a lexicon of words which are labeled as positive or negative are used to determine the sentiment of a text. In this sense, a straightforward way of doing sentiment classification is to use a specific lexicon of words to measure the frequency of such words in a text. For example, Shook and Turner (2016), although not indicating the lexicon, calculate the ratio of positive and negative words in winter storm-related tweets to capture the temporal change of people's emotions. A more sophisticated way is to use a machine learning method to train sample tweets labeled by annotators using multiple features extracted from tweets. These features usually include the results from lexicon-based sentiment analysis algorithms. In order to classify people's sentiments during Hurricane Sandy, Caragea *et al.* (2014) use sentiment strength based on the SentiStrength algorithm, along with other features such as emoticons, Internet acronyms and unigrams to train labeled sample tweets. Although many sentiment classification methods are well established, there are still few such social media studies on natural disaster management.

2.4. *Network*

One of the most important tasks for natural disaster management is to spread authoritative announcements and situational updates to the community. This requires disaster managers on the social network structure to have better knowledge in which disaster-related information is disseminated. The emergence of online networks provides great opportunities to investigate information exchange behaviors of various agents (e.g. ordinary users, authoritative agencies and news media) in natural disaster situations. Many studies have revealed a hierarchical structure in these networks. Cheong and Cheong (2011) conduct a social network analysis on tweets related to the 2011 Australian floods and find that dominant users in propagating disaster-related information are 'local authorities (mainly the Queensland Police Services), political personalities (Queensland Premier, Prime Minister, Opposition Leader, Member of Parliament), social media volunteers, traditional media reporters, and people from not-for-profit, humanitarian, and community associations'. Kogan *et al.* (2015) indicate that local government authorities and the media were the most important nodes in spreading useful information in the 2012 Hurricane Sandy disaster. Social network analysis has shown its strength in analyzing the components, phases and characteristics of information diffusion process in disasters. Specifically, the results of social network analysis can be visualized to facilitate reasoning (Cheong and Cheong 2011, Chatfield and Brajawidagda 2012, Lu and Brelsford 2014); and various metrics such as betweenness centrality, closeness and PageRank can be used to detect network patterns in a quantitative manner (Starbird and Palen 2010, Chatfield *et al.* 2013).

3. Focusing on social media information

Moreover, few studies have incorporated all the four dimensions in their analyses; most of them analyze no more than three dimensions (Vieweg *et al*. 2010, Zhu *et al*. 2011, Imran *et al*. 2013a, 2013b, De Albuquerque *et al*. 2015, Huang and Xiao 2015). When multiple dimensions are involved, some researchers analyze them separately, whilst others try to examine their interactive dynamics. For example, one study may separately analyze the spatial and temporal dimensions by presenting the temporal component as a histogram of tweets over time and the spatial component as a kernel density map of tweets while another may suggest the simultaneous evolution of tweets across space and over time with a space–time kernel density map.

A classification schema is proposed in this paper to generalize the characteristics of studies, identify research gaps and derive data analysis tasks. Some similar efforts have been developed based on space–time-distributional features of economic datasets (Rey and Ye 2010, Ye and Rey 2013) in order to comprehensively quantify the changes and level of hidden variation of regional economic development datasets across scales and dimensions. By incorporating content and network, the suggested schema in the current study moves beyond the socioeconomic conventional spatiotemporal datasets focusing on macrodynamics and toward the finer scale social media studies integrating physical and virtual spaces.

Four dimensions have 15 possible combinations (C(4,1)+C(4,2)+C(4,3)+C(4,4)) which are illustrated by Figure 1. The upper left, upper right, lower left and lower right part of Figure 1 graphically shows C(4,1), C(4,2), C(4,3) and C(4,4) combinations, respectively. Regardless of the

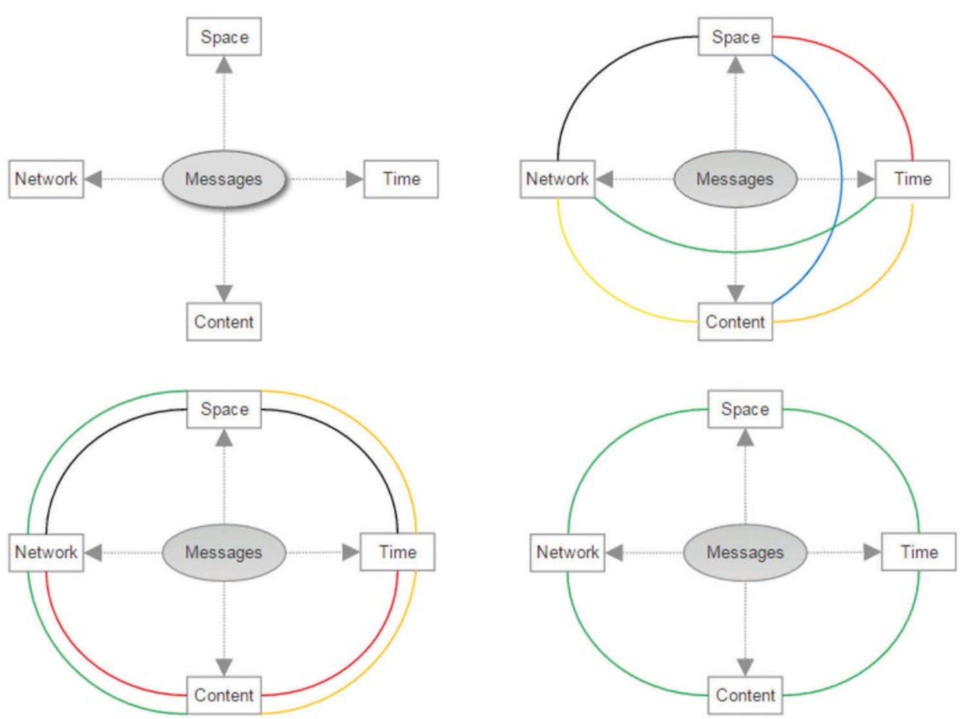

Figure 1. Combinations of four dimensions in social media data.

upper left part in Figure 1 where four dimensions represent four combinations, each colored line connecting dimensions in other three parts of Figure 1 represents one combination. All the combinations are listed in the first column of Table 1 along with the corresponding studies shown in the second column. We use these combinations to classify collected studies into 15 classes. It is important to note that when dimensions are joined together using '∩' (e.g. Space ∩ Time), they represent that those dimensions are simultaneously examined in corresponding studies (e.g. identify space–time hot spots of earthquake-related tweets).

With reference to Granell and Ostermann (2016), we first define the criteria for filtering articles, shown as following:

(1) Written in English.
(2) Explicitly stating that they deal with natural disasters and use social media as their data source.
(3) Empirical studies using quantitative methods.
(4) Published in scientific journals, conferences, book chapters or workshops with full text being accessible.

Based on the criteria, three steps are performed to search and select articles:

(1) Apply the criteria to the references listed in Granell and Ostermann (2016), Miyazaki *et al.* (2015), Haworth and Bruce (2015), Imran *et al.* (2015), Steiger *et al.* (2015) and Klonner *et al.* (2016) to obtain an initial set of papers (44, in total).
(2) For the newly added articles to the collection, retrieve both their reference papers and the papers that cite them and then filter the articles with the criteria.
(3) Repeat step (2) until no new articles could be obtained.

We finished the above process on 2 January 2017 and obtained a final collection of 94 papers. In these papers, various natural disasters such as earthquakes, tornados, wildfires, hurricanes, flooding and tsunamis have been analyzed using data from major social media sites including Twitter, Flickr, Facebook, Weibo etc. The authors work together to classify every article in our collection based on the schema. For each article, we first identify the dimensions involved in its analysis and then decide its combinations by investigating which dimensions are separately analyzed, and which dimensions are simultaneously analyzed, and finally assign the article to categories based on the combinations. Please note that one article could be assigned to different categories because it may involve multiple combinations of dimensions. For a large majority of articles, the authors could easily reach agreement on which categories they should be classified into. Nonetheless, we acknowledge that the coding process is not without uncertainty, and readers and some of the authors of the classified articles may assign these articles differently.

As shown in Table 1, these 94 papers are categorized into 15 classes based on the combination of dimensions. The first four rows in Table 1 list papers in which there are dimensions being separately analyzed, and we observe that 31 of the 94 papers include just 1 dimension in their analyses. Figure 2 is a summary of these 31 papers according to the dimension they analyze. As seen from Figure 2, most studies choose to analyze the space or content dimension when only one dimension is involved.

Table 1. Combinations of four dimensions and corresponding articles.

Combination of dimensions	References
Space	Avvenuti *et al.* (2014), Cameron *et al.* (2012), Cervone *et al.* (2016), Chatfield and Brajawidagda (2012), Chatfield *et al.* (2013), Crooks *et al.* (2013), De Longueville *et al.* (2009), Earle (2010), Earle *et al.* (2012), Eilander *et al.* (2016), Fuchs *et al.* (2013), Gao and Liu (2015), Guan and Chen (2014), Gupta *et al.* (2013), Guy *et al.* (2010), Hara (2015), Huang and Cervone (2016), Huang *et al.* (2015), Hultquist *et al.* (2015), Kent and Capello (2013), Kryvasheyeu *et al.* (2016), Landwehr *et al.* (2016), Liang *et al.* (2013), McClendon and Robinson (2013), Panteras *et al.* (2015), Sakaki *et al.* (2010), Schnebele and Cervone (2013), Schnebele *et al.* (2014a), Schnebele *et al.* (2014b), Shelton *et al.* (2014), Sun *et al.* (2016), Triglav-Čekada and Radovan (2013), Wang *et al.* (2015), Wang *et al.* (2016), Xiao *et al.* (2015), Yin *et al.* (2012), Zielinski *et al.* (2013)
Time	Avvenuti *et al.* (2014), Avvenuti *et al.* (2016), Cameron *et al.* (2012), Chatfield and Brajawidagda (2012), Chatfield and Brajawidagda (2013), Chatfield and Brajawidagda (2014), Chatfield *et al.* (2013), Crooks *et al.* (2013), De Longueville *et al.* (2009), De Longueville *et al.* (2010), Earle *et al.* (2012), Eilander *et al.* (2016), Fuchs *et al.* (2013), Guan and Chen (2014), Guy *et al.* (2010), Huang and Cervone (2016), Hughes and Palen (2009), Imran *et al.* (2014b), Jongman *et al.* (2015), Kryvasheyeu *et al.* (2015), Kryvasheyeu *et al.* (2016), Lachlan *et al.* (2016), Landwehr *et al.* (2016), MacEachren *et al.* (2011), Mendoza *et al.* (2010), Middleton *et al.* (2014), Oh *et al.* (2010), Panteras *et al.* (2015), Power *et al.* (2014), Preis *et al.* (2013), Qu *et al.* (2011), Sakaki *et al.* (2010), Schade *et al.* (2013), Terpstra and de Vries(2012), Wang *et al.* (2015), Wang *et al.* (2016), Yin *et al.* (2012)
Content	Ashktorab *et al.* (2014), Avvenuti *et al.* (2014), Cameron *et al.* (2012), Caragea *et al.* (2011), Castillo *et al.* (2013), Chatfield and Brajawidagda (2013), Chatfield and Brajawidagda (2014), Chowdhury *et al.* (2013), De Longueville *et al.* (2009), Gelernter and Mushegian (2011), Gupta *et al.* (2013), Hara (2015), Huang and Xiao (2015), Hughes and Palen (2009), Imran *et al.* (2014a), Imran *et al.* (2014b), Imran *et al.* (2013a), Imran *et al.* (2013b), Kireyev *et al.* (2009), Kongthon *et al.* (2012), Lachlan *et al.* (2014a), Lachlan *et al.* (2014b), Lachlan *et al.* (2016), Lingad *et al.* (2013), Liu *et al.* (2008), Mendoza *et al.* (2010), Olteanu *et al.* (2015), Oh *et al.* (2010), Panteras *et al.* (2015), Qu *et al.* (2011), Saharia (2015), Schulz *et al.* (2013), Starbird and Palen (2010), Truelove *et al.* (2015), Verma *et al.* (2011), Vieweg *et al.* (2014), Vieweg *et al.* (2010), Wang *et al.* (2015), Wang *et al.* (2016), Yin *et al.* (2012), Zielinski *et al.* (2013)
Network	Chatfield and Brajawidagda (2012), Chatfield and Brajawidagda (2014), Chatfield *et al.* (2013), Cheong and Cheong (2011), Gupta *et al.* (2013), Mendoza *et al.* (2010), Sakaki *et al.* (2010), Wang *et al.* (2016)
Space ∩ Time	Blanford *et al.* (2014), Crooks *et al.* (2013), De Longueville *et al.* (2010), Fuchs *et al.* (2013), Gao and Liu (2015), Guy *et al.* (2010), Jongman *et al.* (2015), Liang *et al.* (2013), Mandel *et al.* (2012), Schade *et al.* (2013), Shook and Turner (2016), Terpstra and de Vries (2012)
Space ∩ Content	De Albuquerque *et al.* (2015), Fohringer *et al.* (2015), Hara (2015), Huang and Cervone (2016), Huang *et al.* (2015), Huang and Xiao (2015), Hultquist *et al.* (2015), Kryvasheyeu *et al.* (2016), MacEachren *et al.* (2011), Middleton *et al.* (2014), Musaev *et al.* (2014), Robinson *et al.* (2013), Shanley *et al.* (2013), Shelton *et al.* (2014), Truelove *et al.* (2015), Pohl *et al.* (2012), Wang *et al.* (2015)
Space ∩ Network	N/A
Time ∩ Content	Caragea *et al.* (2014), Chatfield and Brajawidagda (2014), Gupta *et al.* (2013), Huang and Xiao (2015), Kongthon *et al.* (2012), Kryvasheyeu *et al.* (2015), Olteanu *et al.* (2015), Oh *et al.* (2010), Panteras *et al.* (2015), Qu *et al.* (2011), Shanley *et al.* (2013), Shook and Turner (2016), Vieweg *et al.* (2010), Wang *et al.* (2015)
Time ∩ Network	Castillo *et al.* (2013), Kryvasheyeu *et al.* (2015), Lu and Brelsford (2014), Mendoza *et al.* (2010)
Content ∩ Network	Gupta *et al.* (2013), Kogan *et al.* (2015), Qu *et al.* (2011)
Space ∩ Time ∩ Content	Bakillah *et al.* (2015), Caragea *et al.* (2014), Hara (2015), Kryvasheyeu *et al.* (2016), Mandel *et al.* (2012), Spinsanti and Ostermann (2013)
Space ∩ Time ∩ Network	Kogan *et al.* (2015), Kryvasheyeu *et al.* (2015)
Space ∩ Content ∩ Network	N/A
Time ∩ Content ∩ Network	Gupta *et al.* (2013), Zhu *et al.* (2011)
Space ∩ Time ∩ Content ∩ Network	Kryvasheyeu *et al.* (2015)

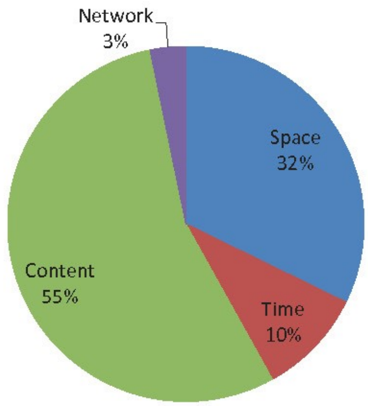

Figure 2. A summary of papers that focus on analyzing one dimension of social media data.

This reveals that researchers tend to study disaster mapping or situational awareness for natural disaster management when they focus on one dimension of social media data. The remaining 11 rows in Table 1 display papers in which there are dimensions being simultaneously analyzed, and we observe that 63 out of 94 papers involve multiple dimensions in their analyses. Figure 3 is a summary of these 63 papers according to the dimensions they analyze. As seen from Figure 3, among studies where multiple dimensions are involved, nearly half of them (48%) choose to analyze dimensions both separately and simultaneously. This is termed as composite analysis since it consists of both simultaneous analysis and separate analysis. We take Wang *et al.* (2015) as an example to demonstrate how this type of analysis is performed. In terms of separate analysis, Wang *et al.* (2015) analyze the content dimension by classifying rainstorm-related Weibo messages into several topics with associated word frequency distribution, examine the time dimension by checking how the number of Weibo messages change over time and explore the spatial dimension by detecting spatial clusters of geo-tagged Weibo messages. In terms of simultaneous analysis, they combine space and content (denoted by Space ∩ Content in Table 1) to compare the spatial clustering of Weibo messages under different topics.

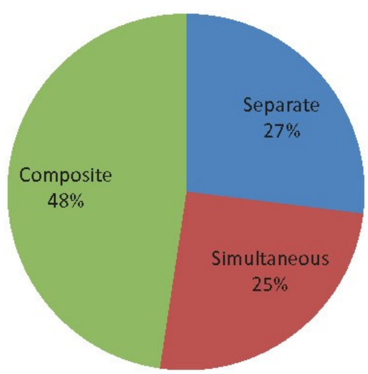

Figure 3. A summary of papers where multiple dimensions are involved.

They also integrate time and content (denoted by Time ∩ Content in Table 1) to compare the temporal trend of Weibo messages under different topics. Researchers usually start with analyzing some dimensions separately and then simultaneously analyze them to gain richer information.

Given the four dimensions in social media data, separate analysis could provide limited information while simultaneous analysis of their combinations could increase the likelihood of gaining more insights. This has implications for natural disaster management, namely that both separate analysis and simultaneous analysis should be conducted to increase the information richness for disaster managers and thus better support the decision-making process in disaster management. For instance, disaster mangers could learn some general information such as where people's responses to the disaster are intensive from a single spatial analysis and what damages the disaster has caused from a single content analysis. Although the general information is equally important, a simultaneous analysis of space and content could enable disaster managers to gain detailed information such as the impact areas or locations of the damage (Huang *et al.* 2015).

Due to some computational constraints, it is challenging to simultaneously analyze many dimensions. As a result, if we compare the first four rows with the remaining 11 rows in Table 1, we can observe that articles containing simultaneous analyses are fewer than those involving separate analyses. Moreover, Table 1 shows that no references correspond to Space ∩ Network and Space ∩ Content ∩ Network, which means that space and network are difficult to simultaneously analyze. For example, it is difficult to build a spatial retweet network, because retweets are usually not geo-tagged (Gupta *et al.* 2013). However, there are two exceptions (i.e. Kogan *et al.* 2015, Kryvasheyeu *et al.* 2015) in our collection of papers, which have overcome the computational constraints and successfully combined space with network (see Table 1). Kogan *et al.* (2015) first glean tweets related to Hurricane Sandy with a bounding box representing the impact area; then, users who have posted geo-tagged tweets within the impact area are identified as geographically vulnerable users; finally, all the retweets posted by geographically vulnerable users are selected to build social networks. In this way, they compare the authors of original tweets and the retweet authors (i.e. geographically vulnerable users) and find an overlap between them, indicating that 'the geographically vulnerable are more likely to propagate tweets from other geographically vulnerable users' (Kogan *et al.* 2015). Kryvasheyeu *et al.* (2015) first identify the impact area of Hurricane Sandy; then, they use profile locations as surrogates for non-geo-referenced tweets to increase the number of geo-tagged tweets; finally, they build a spatial-social network based on friends/followers relationships. In this way, they find that users with strong network centrality tend to be aware of Hurricane Sandy earlier, and that users within the hurricane-affected area show an awareness advantage when compared with those outside the impact area (Kryvasheyeu *et al.* 2015). In view of this, futures efforts could be devoted to overcoming these computational obstacles and toward more simultaneous analyses of dimensions and richer information for natural disaster management.

Aside from serving as taxonomy, these combinations could also guide researchers to derive data analysis tasks. The examples listed in Table 2 are merely illustrative and by no means exhaustive. A major heuristic purpose behind Table 2 is to encourage researchers to reflect on how to fully mine the dimensions to gain useful information and raise new research questions.

4. Fusing social media data with authoritative data

While social media, as one of the most commonly used big data sources, often provides high-volume data, it could lack richness or quality in information if utilized as stand-alone data source (Crampton *et al.* 2013). Therefore, researchers have proposed to complement or synthesize social media data with traditional or authoritative data (Goodchild and Glennon 2010, Crampton *et al.* 2013, Kwan 2016). Although there are some such studies in natural disaster management, current efforts are far from being sufficient and may require further improvement. In these studies, three major data sets, including surveillance data, remote-sensing imagery, and census data, are fused with social media data to provide additional informational richness to analyses (Kent and Capello, 2013, Schnebele and Cervone 2013, Schnebele *et al.* 2014a, Xiao *et al.* 2015, Cervone *et al.* 2016, Sun *et al.* 2016). Although observations recorded by surveillance systems or monitoring networks (e.g. river gauge data) are equally important, remote-sensing imagery and census data have been increasingly integrated with social media data in natural disaster management (Kent and Capello 2013, Schnebele and Cervone 2013, Schnebele *et al.* 2014a, Xiao *et al.* 2015, Cervone *et al.* 2016). As such, we give a particular emphasis on the review of opportunities and challenges of leveraging social media data against remote-sensing imagery and census data.

4.1. *Fusing with remote-sensing data*

Remote sensing has been widely used to assist disaster management in recent years due to its capability of providing information for poorly accessible areas or areas with sparse ground measurements (Tralli *et al.* 2005, Gillespie *et al.* 2007, Joyce *et al.* 2009). One such example is the application of Landsat Thematic Mapper (TM) imagery and synthetic aperture radar (SAR) data for flood extent estimation and flood volume calculation to support flood management (Sanyal and Lu 2004, Rakwatin *et al.* 2013). However, remote sensing has its own constraints. First, not all remote-sensing data are freely available. Second, vegetation and cloud cover may compromise the quality of some remote-sensing imagery. Third, lengthy revisit times prohibit remote sensing from providing continuous observations with ideal temporal resolution. Quality and reliability issues, unstructured nature, digital divide and privacy are among the most concerned limitations in social media data. Notably, the digital divide implies that social media users could only represent a certain subdivision of the whole population, and vulnerable groups in disasters such as children and elderly people may be underrepresented. The exposure of personal lives, locations and activities may result during the processing of social media data, causing privacy issues (Elwood and Leszczynski 2011, Sui and Goodchild 2011, Zook *et al.* 2015a, Zook *et al.* 2015b). In spite of these limitations, social media data that are virtually in real time and freely accessible could be complementary

Table 2. Combinations of four dimensions and data analysis tasks.

Combination of dimensions	Data analysis tasks
Space	Where is the hot spot of people's responses to a disaster? For example, are the impact areas the hot spots of disaster-related social media activities?
Time	How do people's responses change with the evolution of a disaster (before, during and after)? For example, when do disaster-related social media activities reach peak in the process of a disaster?
Content	How do people's responses vary according to their posted content? For example, how many social media feeds report power outage in a disaster?
Network	Who are the important players in spreading disaster-related information on social media in a disaster? For example, how many reposted messages are originally from emergency management agencies?
Space ∩ Time	How do people's responses to a disaster vary across space and over time? For example, do people's social media activities from the impact area form a significant hot spot immediately after being struck by a disaster?
Space ∩ Content	How do people's conversational topics related to a disaster on social media vary across space? For example, do people proximate to the impact area have more on-topic messages than distant people do?
Space ∩ Network	What is the spatial manifestation of the network structure in a disaster? For example, who are the local opinion leaders in disseminating disaster-related information for a given place?
Time ∩ Content	How do people's conversational topics vary with the evolution of a disaster? For example, do people change their topics from preparedness (e.g. survival kits and food stock) to impact (e.g. damage and casualty)?
Time ∩ Network	What is the temporal manifestation of the network structure in a disaster? For example, is the same set of opinion leaders dominant in all phases of a disaster?
Content ∩ Network	Which topic goes viral in a disaster situation? For example, how do rumor messages spread across the social network?
Space ∩ Time ∩ Content	What is the space–time pattern of people's topics in a disaster? For example, where is the hot spot of transportation-related social media activities when a disaster unfolds?
Space ∩ Time ∩ Network	What is the space–time manifestation of the network structure in a disaster? For example, is the same set of local opinion leaders dominant in all phases of a disaster for a given place?
Space ∩ Content ∩ Network	How does geographical space characterize the diffusion of social media messages under a certain topic? For example, what is the spatial extent of the spreading of rumor messages in a disaster?
Time ∩ Content ∩ Network	What is the temporal dynamics of the diffusion of social media messages under a certain topic? For example, how long do rumor messages last for spreading?
Space ∩ Time ∩ Content ∩ Network	How do space and time jointly characterize the diffusion of social media messages under a certain topic? For example, what is the space–time extent of the diffusion of rumor messages in a disaster?

Table 3. Strengths and limitations of remote-sensing, social media and census data.

	Remote sensing	Social media	Census data
Strengths	Providing information for poorly accessible areas or areas with sparse ground measurements Capturing physical features Data are captured remotely with little risk of lives	Real-time data Freely accessible Recording human activities	Little privacy concern Reflecting demographic and socioeconomic characteristics Most are freely accessible
Limitations	Not all data are freely accessible Could be influenced by cloud and vegetation cover Lengthy revisit time	Quality and reliability problems Unstructured nature Digital divide Privacy Limited spatial information	Long time interval (released yearly or longer) Aggregate data at areal units (e.g. block, block group and census tract)

to remote-sensing data. We summarize the strengths and limitations of social media data, remote-sensing data and census data in Table 3. As seen from Table 3, social media data and remote-sensing data are highly complementary and have a great potential to be fused together to make use of the strengths of both of them while offsetting weaknesses. This has already been confirmed by some existing studies including Schnebele and Cervone (2013), Schnebele *et al.* (2014a) and Cervone *et al.* (2016). As pointed out by Schnebele and Cervone (2013), social media data can verify the presence of water in a specific area and augment the flood hazard map created from Multispectral Landsat ETM+ images by altering water contour lines and reclassifying water pixels. Schnebele *et al.* (2014a) shows that the estimation of flood extent and identification of affected roads during a flood disaster have been augmented with a fusion of social media data with SAR imagery and other data. Cervone *et al.* (2016) have revealed that Twitter can be used to quickly task the collection of remote-sensing imagery and rapidly assess disaster damages. However, studies that fuse social media data with remote-sensing data are still rare and some research gaps need to be filled. Examples of these gaps include but not limited to:

(1) Flooding has been given the most attention by researchers, while studies on other natural disasters are lacking.
(2) Studies should go beyond the spatial dimension and incorporate more dimensions of social media data to refine the fusion. For example, the space–time hot spots of a ‘transportation’ topic will be more refined to task the collection of remote-sensing data for transportation damage assessment in flooding.
(3) Showing all the data on one map is not a good fusion. Studies should go beyond this simple overlay of social media data and remote-sensing imagery by truly fusing these heterogeneous data with different spatial and temporal resolutions.

4.2. *Fusing with census data*

Natural disasters have been analyzed under a ‘sociopolitical ecology of disasters’ framework, because ‘disasters do not affect members of society equally’ (Fothergill and Peek 2004). In other words, people’s vulnerability to natural disasters varies with their demographic and socioeconomic characteristics. Although social media can capture people’s varied responses to disasters, it provides limited or inaccurate information about their demographic and socioeconomic characteristics such as income, education and so on. In this sense, research questions such as how disaster responses vary among social classes could hardly be addressed using social media as single data source. Additionally, demographic and socioeconomic characteristics are evidenced as important factors for shaping risk perceptions (Botzen *et al.* 2009). Therefore, when analyzing the variations of people's responses to disasters, demographic and socioeconomic data can provide more explanatory power. It also provides an opportunity for emergency responders to learn the effects of inequality among different socioeconomic groups in disaster situations to make diversifying interventions. Using the census as an important source of demographic and socioeconomic data, in spite of some limitations, could provide quality information to complement social media data, as shown in Table 3. Kent and Capello (2013) reveal that demographic features (e.g. age under 18, population residing in rental property and the population density) at the census block level could explain the spatial variation of people's responses to wildfires on Instagram, Twitter, Flickr and Picasa. Similarly, Xiao *et al.* (2015) find that people's responses to Hurricane Sandy represented by tweet frequency at the census tract level are related to socioeconomic and demographic factors such as age, gender and income. There are also research gaps in current literature. Examples of these gaps include but not limited to:

(1) Existing studies have simply aggregated the geo-referenced social media data to census area units and related them to demographic and socioeconomic variables at the same level. Refined indicators should be developed to go beyond this spatial aggregation and exclude the influence of population and geo-technical factors. One preliminary indicator may be the ratio of disaster-related social media feeds to the general feeds.
(2) The social vulnerability (Cutter *et al.* 2003) may be a good framework for choosing demographic and socioeconomic variables from census data.
(3) Studies should go beyond the spatial dimension and incorporate more dimensions of social media data. For example, risk perceptions could be analyzed via a content analysis of social media feeds, and then an examination of how they differ across demographic and socioeconomic groups could follow.

5. Conclusion and discussion

As natural disasters become more frequent and severe, their management has increasing needs for human-centric information to facilitate better decision-making toward the reduction of human and property loss. In this context, social media, which records a large amount of human activities, has attracted increasing attention from researchers. Reviewing a set of recently published papers, we propose a framework to classify existing studies and facilitate the generation of data analysis tasks. We also suggest a fusion of social media data with remote-sensing data and census data to gain more useful information for natural disaster management.

This study is not without limitations. First, as we mainly focus on four dimensions, other dimensions might have been overlooked. Hence, we encourage people to update our framework by incorporating more dimensions. Second, the content analysis is only on text, while other contents such as pictures and videos posted by social media users can also be informative to natural disaster management. Third, aside from social media data, informative user generated content and VGI could also be found in OpenStreetMap, Smartphone apps and other sources (Ye *et al.* 2016). Fourth, the classification results may be slightly different depending on the people who carry out the classification of articles. Thus, it merits future efforts to better deal with this uncertainty. Fifth, current classification schema is based on the combinations of dimensions, but another framework by which studies are categorized based on disaster management phases they most closely correspond to could also be useful. We will shed more light on the development of social media analytics to satisfy the diverse needs from different disaster management phases in the next step. Finally, we emphasize the analyses of social media data but rarely mention how these analyses could be more efficiently conducted. Due to its capability of collecting, storing and processing massive, unstructured and real-time datasets (Wang 2010, Wang *et al.* 2013, Huang *et al.* 2015), CyberGIS could provide a scalable solution for analyzing social media data in natural disaster contexts. According to Wang (2013), CyberGIS 'represents a new-generation GIS based on the synthesis of advanced cyberinfrastructure, geographic information science, and spatial analysis and modeling'. Therefore, to gain a high performance computing power for natural disaster management, the analyses of four dimensions in social media data as well as the fusion of social media data with census data and remote-sensing imagery could be embedded in CyberGIS.

In spite of these limitations and drawbacks, our work goes beyond a simple review of existing studies and has great potential for guiding future efforts in the domain of natural disaster management. Specifically, this study shows that simultaneous analyses of multiple dimensions of social media data are rare in current literature. Therefore, it might be helpful for future studies to put more emphasis on overcoming the computational constraints to analyze more dimensions simultaneously. Generally, other things being equal, with more data being analyzed, more information richness could be gained. We find that data fusion of social media data with authoritative datasets (especially census data and remote-sensing imagery) is far from being mature. The spatial dimension in social media data has been given particular attention, while other dimensions have not been fully exploited in data fusion. Additionally, the fusion of social media data with census data and remote-sensing imagery is mainly about simple overlay and aggregation. To solve this problem, Linked Data and Semantic Web technologies that are capable of integrating various and heterogeneous data sources could serve as a good starting point toward a more meaningful data fusion (Purves *et al.* 2007, Goodwin *et al.* 2008, Janowicz *et al.* 2012, Grütter *et al.* 2017). Aside from disaster management, we believe that the general structure of our framework could be extended to other fields such as politics and public health to serve as guidance for better data mining.

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