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ARTICLE

Space, time, and situational awareness in natural hazards: a case study of Hurricane Sandy with social media data

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ABSTRACT

Various methods have been developed to investigate the geospatial information, temporal component, and message content in disaster-related social media data to enrich human-centric information for situational awareness. However, few studies have simultaneously analyzed these three dimensions (i.e. space, time, and content). With an attempt to bring a space–time perspective into situational awareness, this study develops a novel approach to integrate space, time, and content dimensions in social media data and enable a space–time analysis of detailed social responses to a natural disaster. Using Markov transition probability matrix and location quotient, we analyzed the Hurricane Sandy tweets in New York City and explored how people's conversational topics changed across space and over time. Our approach offers potential to facilitate efficient policy/decision-making and rapid response in mitigations of damages caused by natural disasters.

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Space–time; situational awareness; natural hazards; social media

Introduction

Social media outlets, such as Twitter, Instagram, and Facebook, have evolved beyond platforms for sharing people's personal life toward data sources for leveraging the public's collective intelligence to deal with emergency events (Wang, Wang, Ye, Zhu, & Lee, 2015; Wang, Ye, & Tsou, 2016; Yates & Paquette, 2011). In particular, human-centric information related to people's perceptions, responses, and behaviors in natural disaster context can be extracted from social media and analyzed to assist natural disaster management (Wang & Ye, 2018). The literature on the applications of social media data in natural disaster management has identified several major directions: (1) *Event detection* – social media has proven to be efficient in detecting disaster outbreaks and disseminating notifications to the public (Sakaki, Okazaki, & Matsuo, 2010); (2) *Rapid assessment of disaster damage* – there is a positive relationship between disaster damage and disaster-related social media activities (Guan & Chen, 2014; Kryvasheyeu et al., 2016); (3) *Situational awareness* – social media could enable disaster managers to know what is going on in disaster situations (Vieweg, Hughes, Starbird, & Palen, 2010). As pointed by Vieweg et al. (2010, p. 1), situational awareness "describes the idealized state of understanding what is happening in an event with many actors and other moving parts, especially with respect to the needs of command and control operations". Disaster managers need actionable information associated with disaster situations in order to make sense of the disaster and to facilitate decision-making, policy formulation, and response implementation. The public need authoritative instructions and situational updates as well as a good knowledge on how other people prepare for, respond to, and recover from a natural disaster. Therefore, situational awareness is of particular importance for natural disaster management.

Situational awareness needs to be geographically grounded (MacEachren et al., 2011; Shook & Turner, 2016). Decision-making, policy formulation, and response implementation in natural disaster situations require disaster managers to go beyond knowing what is happening by also being informed of where something is happening, i.e. geographic situational awareness (De Albuquerque, Herfort, Brenning, & Zipf, 2015; Huang & Xiao, 2015; MacEachren et al., 2011). Existing studies have utilized spatial analytical methods such as *k*-means clustering and kernel density estimation to generate spatially relevant information for gaining situational awareness and improving disaster response (Wang et al., 2016). However, one limitation of these studies is that they focused on analyzing the geospatial information in general social media activities related to a disaster while overlooking more detailed

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social responses to it (Guan & Chen, 2014). Actually, these general disaster-relevant messages often contain content reflecting distinct social responses, e.g. damage reports, situational announcements, and help requests that can be extracted with an in-depth analysis such as a topic classification in social media data (Huang & Xiao, 2015). Combining analysis of geospatial information and content in social media data is gaining more attention and has been increasingly practiced in empirical studies (Huang & Xiao, 2015; Hultquist, Simpson, Cervone, & Huang, 2015; Kryvasheyeu et al., 2016; Resch, Usländer, & Havas, 2017; Ye, Li, Yang, & Qin, 2016). The goal of this article is to advance methods for combining geospatial and content data in social media by capturing the spatial concentration and specialization of social responses to Hurricane Sandy on Twitter. More specifically, location quotient (LQ) (its formal definition is given in "Data and methodology" section) is introduced to detect area-specific topic, defined as a topic that has higher concentration than other topics in a specific area as compared to the entire region. LQ can provide additional insights into this field by moving beyond the widely adopted spatial point pattern analysis and simple mapping in current literature, yet its application to natural disaster studies and social media data has not been fully explored.

Social responses to a natural disaster can transit over time. Existing studies have shown a temporal concurrent evolution between disasters and corresponding social media activities (Blanford et al., 2014; Qu, Huang, Zhang, & Zhang, 2011). That is, disaster-related social media activities increased until the disaster unfolded and then decreased. However, these studies also focused on the general disaster-relevant messages instead of analyzing how social responses change over time. Moreover, they rarely combined the geospatial information, time stamp, and message content in social media data to explore the space–time dynamics of social responses (Wang & Ye, 2018). Situational awareness should not be static. That is, disaster managers need to know how people's responses change with the evolution of a natural disaster in order to adjust their coping strategies. Disaster stages (before, during, and after) correspond to different management tasks as people's responses can be significantly different, e.g. from preparation efforts before the disaster to damage reports during the disaster to recovery needs in the aftermath. Hence, the other goal of this article is to investigate how the spatial concentration of topics changes before, during, and after a disaster. More specifically, we aim at embedding a temporal perspective into geographic situational awareness and enable disaster managers to gain better knowledge on the geographic process of social responses.

Notably, the focus of this paper is not on the improvement of situational awareness but on proposing a novel space–time approach to characterize situational awareness in natural disaster situations. The remainder of this article is organized as follows. The data and methodology used in this research are explained in the following section. The "Results" section discusses the findings and their implications. Finally, the conclusion is made in "Discussion and conclusion" section.

Data and methodology

Hurricane Sandy tweets in New York City (NYC)

As one of the most destructive cyclones in the United States since 1900 (Blake et al. 2013), Hurricane Sandy was used as a case study in this research. Making its landfall on 29 October 2012 in New Jersey, Hurricane Sandy caused a vast amount of damage to the northeastern states. It was estimated that the total loss caused by Hurricane Sandy reached $50 billion and that 72 deaths were associated with the storm in the mid-Atlantic and northeastern United States (Blake et al. 2013).

Hurricane Sandy was formed on 22 October 2012 and dissipated on 2 November 2012. All geotagged tweets with latitudes and longitudes posted during this time were gleaned by Wang, Hovy, and Dredze (2015) using Twitter Firehose API. A set of bounding boxes were also specified by Wang, Hovy et al. (2015) to ensure that all geotagged tweets were from the affected areas including Washington DC, Connecticut, Delaware, Massachusetts, Maryland, New Jersey, New York, North Carolina, Ohio, Pennsylvania, Rhode Island, South Carolina, Virginia, and West Virginia. Please note that these tweets were general Twitter activates and mostly unrelated to Hurricane Sandy. With an attempt to open this dataset to the public, IDs of all the solicited tweets have been made available by Wang, Hovy et al. (2015) on GitHub. They also indicated which IDs corresponded to tweets that had "sandy" word to help us identify tweets related to Hurricane Sandy. Knowing tweet IDs, a Python program was executed to retrieve all the Sandy-related tweets via Twitter Search API. In total, 83,006 geotagged Sandy tweets were retrieved. Figure 1 shows the spatial distribution of Sandy-related tweets with a kernel density map. As seen in Figure 1, NYC, one of the most severely impacted areas, had the highest cluster of

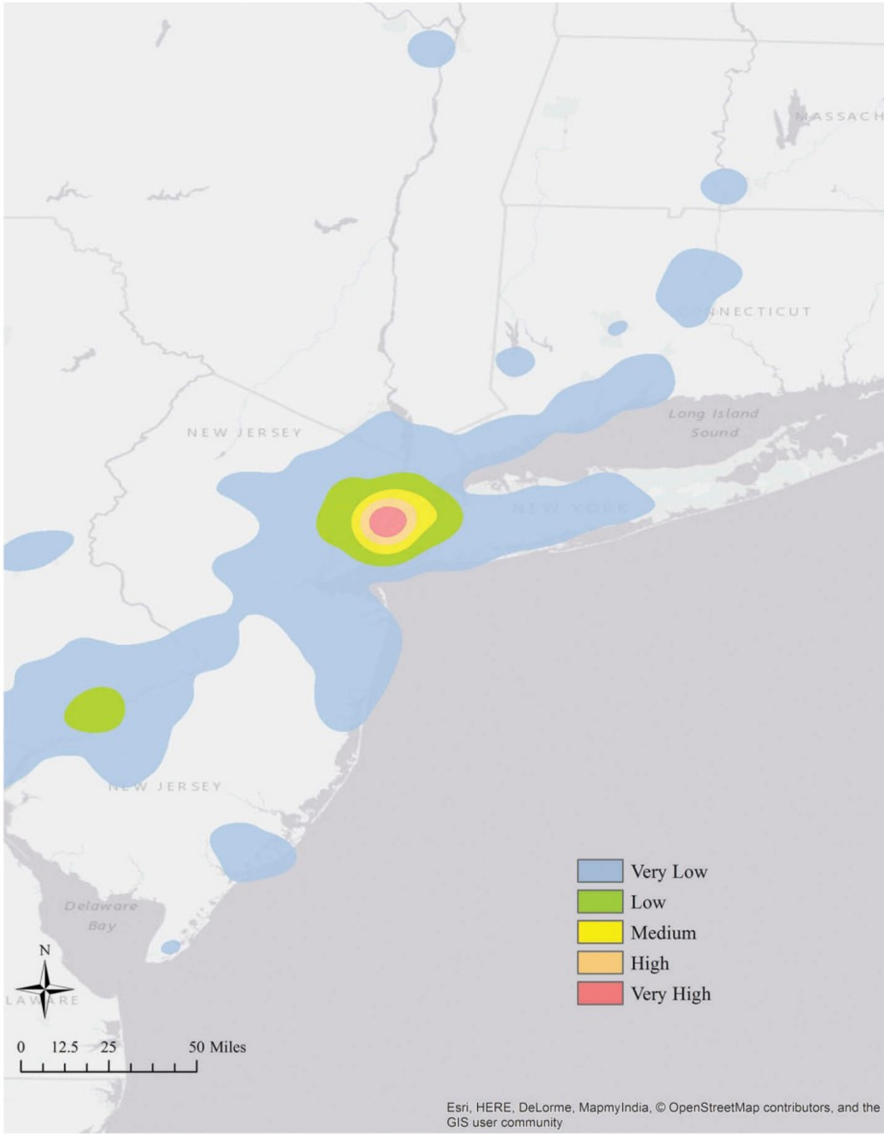

Figure 1. Kernel density map of Sandy tweets (arrow and scale are in the lower left corner).

Twitter activity related to Hurricane Sandy. Therefore, the study area was restricted to NYC where 20,427 geotagged Sandy tweets were posted.

Cleaning and classifying Hurricane Sandy tweets

The collected geotagged tweets were too general to capture detailed social responses to Hurricane Sandy, thus requiring a topic classification based on the textual content of the data. The authors first worked together to manually identify and remove noninformative tweets, reducing the dataset to 8972 geo-tagged Sandy tweets. That is, 43.9% geotagged Sandy tweets from NYC were annotated as informative, which is lower than the ratio of 60% in Imran, Elbassuoni, Castillo, Diaz, and Meier (2013). We found that these noninformative messages were often casually tweeted by users. They could not reflect detailed social responses to the disaster and provided no useful information for disaster preparation, response, and recovery (Imran, Castillo, Lucas, Meier, & Vieweg, 2014). More importantly, they could not be classified into any of these categories in our classification schema (see Table 1). Many of these noninformative messages were check-in tweets. Some check-in tweets are shown as follows:

(1) I'm at Frankenstorm Apocalypse – Hurricane Sandy w/@melissanyc
(2) Oh, hi, Sandy. (@ Hurricane Sandy w/40 others)

Table 1. The classification schema of Hurricane Sandy tweets.

Category	Description
Caution & Advice	Tweets referring to warnings, preparation, advice, and tips (Imran et al., 2013; Imran et al., 2015). Examples: • '@NYCMayorsOffice: Mayor: The peak surge will hit areas along Long Island Sound between 10pm and 2am Tuesday. #Sandy" Everyone be safe.' • 'Stocking up on candles. #hurricanesandy #Hurricane #hurricanesandy2012'
Affected People	Tweets referring to people trapped, injured, missing, and killed (Imran et al., 2013; Imran et al., 2015). Examples: • 'Due to Hurricane Sandy, I am trapped in New York until Wednesday with @Have_aNiceDavis #bummer' • '@CNN: There have been 5 confirmed deaths due to superstorm Sandy in New York'
Infrastructure/ Utilities	Tweets referring to infrastructure damage, services closure, built environment, and collapsed structure (Imran et al., 2013; Imran et al., 2015). Examples: • '@lheron: Massive power outage has turned NYC into city of migrants, from downtown to uptown: http://on.wsj.com/Uhicz8 #Sandy" #mylife' • 'Subways are shut down! #hurricanesandy @Sunset Park, Brooklyn http://instagr.am/p/RXrwc3p5Rw/' • 'Crane on 57 street collapsed. So dangerous! #NYC #Hurricane #Sandy' • 'Kiehl's and Starbucks are closed. #UpperWestSideProblems #sandy'
Needs & Donations	Tweets referring to donations, volunteering, relief, and fundraising (Imran et al., 2013; Imran et al., 2015). Examples: • 'Donating blood w @wandadetroit – our sexiest #ladydate ever! #sandy' • 'RT @PE_Feeds: #SandyVolunteer/UPDATE: NYC volunteer opportunities for #Sandy cleanup efforts'
Weather & Environment	Tweets referring to weather conditions and environment. Examples: • 'The pressure I'm measuring here at @thepodhotel has now dropped through the 97kPa. Winds picking up. #hurricanesandy' • "These winds are pretty strong #Sandy"
Other	Tweets not referring to any of the previous categories (Imran et al., 2013; Imran et al., 2015). Examples: • 'Reports of looting follow Hurricane #Sandy. 15 people have been charged in Queens via @NYMag' • '@billmaher Should/can Election day be postponed for the benefit of Americans still struggling with the aftermath of Sandy?'

(3) Hello Sandy. (@ Frankenstorm Apocalypse – Hurricane Sandy w/2545 others)

Then, the remaining 8972 informative tweets were classified into six categories/topics including Caution & Advice, Affected People, Infrastructure/Utilities, Needs & Donations, Weather & Environment, and Other. This classification schema was a slight modification of Imran et al. (2013) by adding a new topic: Weather & Environment. This modification was motivated by observing that many eyewitness reports were related to weather conditions and physical environment. Although there exist many other types of classification schemas (see Imran, Castillo, Diaz, & Vieweg, 2015 for a survey), we found that the one proposed by Imran et al. (2013) is more useful in revealing information related to situational awareness and is better suited for our case study (i.e. Hurricane Sandy). Note that the authors conducted the classification independently and discussed cases of disagreement in order to reach consensus on the classification of every case. A similar classification procedure has been practiced by De Albuquerque et al. (2015). Nonetheless, we acknowledge that the coding process was not scalable and might suffer from uncertainty as compared to some state-of-the-art classification methods including latent Dirichlet allocation (LDA) and machine learning. However, these new approaches are not without limitations. LDA has been criticized to generate uninterpretable results (Wang & Ye, 2018). Although machine learning is more scalable than the manual approach, it still needs many training data to reach an acceptable accuracy. Aiming to facilitate rapid decision-making in future hurricane situations, we manually classified every Sandy tweet in this research to accumulate training data and obtain an effective classifier. The classification schema is shown in Table 1 where the left column lists the topics and the right column presents descriptions for each topic along with some exemplary tweets. After the classification, we further processed these Twitter messages via conversion of words to lower cases, deletion of stop words, punctuations, URLs, and numbers, as well as word stemming.

LQ: detecting area-specific topic

LQ has been traditionally used in regional economics and economic geography to calculate industrial or employment specification. However, as a useful spatial analytical method, LQ can be exploited to detect the spatial concentration of geographic phenomena or events of interest to other domains. For example, Andresen (2007) adopted

LQ to measure the specialization of three types of criminal activities (automotive theft, break and enter, and violent crimes) in Vancouver. In the present research, LQ was introduced to measure the spatial concentration of disaster-related conversational topics on social media. LQ is represented as a ratio of the percentage of a particular topic in a census tract of NYC in comparison to the percentage of that same topic in NYC as a whole. We used census tract as the spatial unit so that disaster managers can potentially link the analytical results with demographic and socioeconomic data from Census to better their decision/policy making. Moreover, as compared to census block and block group, more census data can be obtained at tract level. The formula of LQ should be as following:

$$LQ_i^k = \frac{X_i^k}{\sum_i^n X_i^k} / \frac{Y_i^k}{\sum_i^n Y_i^k}$$

where X_i^k is the number of tweets under topic k in census tract i, Y_i^k is the amount of all Sandy tweets in census tract i, and n is the count of census tracts in NYC. If the value of LQ_i^k is greater than 1, it represents that the census tract i has a higher concentration of tweets under topic k than the city average; and, the larger the value of LQ_i^k, the more concentrated tweets under topic k are in census tract i. Additionally, for a given census tract, the topic with the highest LQ value larger than 1 is the most concentrated one. Therefore, we selected the topic with highest LQ value as the area-specific topic.

Markov transition probability matrix: measuring temporal transition of area-specific topic

Markov transition probability matrix has been widely used in modeling land use and land cover changes (Gergel & Turner, 2000) as well as regional economic convergence (Quah, 1993a, 1993b, 1996; Rey, 2001). Here, Markov transition probability matrix is introduced to measure how area-specific topics change before, during, and after Hurricane Sandy. We first summarized the cross-sectional distribution of area-specific topics in different disaster stages (i.e. before, during, and after). Then, we obtained a transition probability matrix where each element represents the probability that a spatial unit (here, census tract) with an area-specific topic k in stage t ends up with an area-specific topic l in the following stage. The equation below shows the calculation of transition probability:

$$P_{kl} = \frac{n_{kl}}{n_k}$$

where P_{kl} is the transition probability of area-specific topic k in stage t to topic l in stage $t+1$, n_{kl} is the count of census tracts moving from area-specific topic k in stage t to topic l in stage $t+1$, and n_k is the number of census tracts with area-specific topic k in sate t.

Results

Data description

We first report the classification results of the total 8972 Sandy tweets. As shown in Table 2, half of the total Sandy tweets (50.4%) were about Infrastructure/Utilities, while the second most communicated topic was Caution & Advice (21.2%). Based upon the posted time, we split the tweets into three groups including *Before, During,* and *After*. The *Before* group contained Sandy tweets posted before 28 October 2017, *During* group had Sandy tweets posted on 29 October 2017 and 30 October 2017, and *After* group included Sandy tweets posted after 31 October 2017. Our separation is different from Kogan et al. (2015) where 27 October 2012–31 October 2012 was defined as the *During* stage of Hurricane Sandy. However, their study region covered multiple eastern states while our work focused on a single city, which, to some extent, triggered their adoption of a longer time slice of *During* stage. Meanwhile, after consulting with natural disaster experts, we based our separation mainly upon the time of Sandy's landfall (late 29 October 2017) when it started to intensively affect NYC. We acknowledge that there might be some other ways to separate the data, but none will be exempted from uncertainty. The *Before, During,* and *After* groups have 1664, 5504, and 1804 Sandy tweets, respectively. For each group, the distribution of conversational topics was obtained (Table 2). Before Hurricane Sandy hit NYC, the majority of Sandy tweets (63%) were about Caution & Advice, while this percentage dropped to 15.1% during

Table 2. Classification results of Sandy tweets.

	Caution & Advice	Affected people	Infrastructure/utilities	Needs & Donations	Weather & Environment	Other
Total	1898 (21.20%)	582 (6.50%)	4523 (50.40%)	414 (4.60%)	1395 (15.50%)	160 (1.80%)
Before	1048 (63%)	117 (7%)	368 (22.10%)	8 (0.50%)	105 (6.30%)	18 (1.10%)
During	833 (15.10%)	386 (7%)	2819 (51.20%)	129 (2.30%)	1259 (22.90%)	78 (1.40%)
After	17 (0.90%)	79 (4.40%)	1336 (74.10%)	277 (15.40%)	31 (1.70%)	64 (3.50%)

the disaster and became much smaller in the *After* group (0.9%). In contrast, the percentage of Sandy tweets classified as Infrastructure/Utilities increased before, during, and after the event from 22.1%, to 51.2%, and 74.1%, respectively. Moreover, the share of Weather & Environment topic started at 6.3% *before* Sandy peaked at 22.9% in *During* group and then declined to 1.7% after the disaster. It could also be observed from Table 2 that the share of Affected People topic had little change in the process of Hurricane Sandy.

Top frequent terms

To reveal more details about social responses to the disaster, we summarized the top frequent terms for each topic in total Sandy tweets as well as in the *Before, During*, and *After* groups. Due to the space limitation, we just report the top 15 frequent terms for each topic. Table 3 shows the top frequent terms under each topic in total sandy tweets. Regarding the Caution & Advice topic, there were tweets to raise people's awareness of the disaster and warn them to stay safe, messages about preparation efforts like stocking up on water, food, and other supplies, as well as eyewitness reports such as lines outside grocery stores. The frequent terms of Affected People topic demonstrate that Hurricane Sandy impacted people in ways of human mobility ("stuck", "trap"), emotional status ("bore" and "scare"), and casualty ("kill" and "die"). As shown in the "Infrastructure/Utilities" column, Infrastructure ("tree", "subway"), utilities ("power", "water", "light", "dark"), and services ("close", "open") were largely communicated on Twitter in the process of Hurricane Sandy. The "Needs & Donations" column in Table 3 shows that people posted tweets calling for help, volunteers, donations, expressing their needs, and highlighting relief efforts by Red Cross and NYPD. Under the topic of Weather & Environment, people communicated meteorologic ("wind", "rain"), hydrologic ("Hudson", "water", "flood"), and cognitive ("calm", "empty") information on Twitter in Hurricane Sandy.

Table 2 shows that only eight tweets were classified into Needs & Donations topic in the *Before* group. Therefore, we focus on analyzing the term frequency for other four topics (Table 4). The distribution of frequent terms under Caution & Advice topic in

Table 3. Top frequent terms under five topics of the total Sandy tweets.

Caution & Advice	Affected People	Infrastructure/Utilities	Needs & Donations	Weather & Environment
Prepare (236)	Stuck (73)	Power (877)	Help (102)	Wind (348)
Safe (175)	Scare (48)	Tree (376)	Need (91)	Water (131)
Stay (129)	Die (39)	Close (314)	Victim (45)	Rain (120)
Evacuate (120)	Bore (38)	Manhattan (308)	People (44)	Park (113)
Stock (117)	Day (38)	Park (282)	Donate (42)	Flood (110)
Come (98)	Time (34)	Street (269)	Volunteer (37)	Street (109)
Food (95)	Home (31)	Light (256)	Redcross (34)	Calm (87)
Water (87)	Thank (29)	Brooklyn (207)	Come (34)	East (84)
Zone (77)	People (27)	Thank (200)	Text (31)	Manhattan (78)
Line (77)	Kill (25)	Open (200)	Charge (31)	Brooklyn (67)
Everyone (65)	Make (21)	Dark (187)	Relief (28)	Come (55)
People (65)	Hotel (20)	Subway (182)	Food (28)	Start (52)
Supply (62)	Trap (18)	Day (171)	Can (26)	Empty (52)
Hit (60)	Work (18)	Work (168)	Work (25)	Window (49)
Store (56)	Come (18)	Water (165)	NYPD (25)	Hudson (45)

Table 4. Top frequent terms under four topics of the *before* Sandy tweets.

Caution & Advice	Affected People	Infrastructure/Utilities	Weather & Environment
Prepare (179)	Scare (12)	Close (86)	Calm (36)
Stock (94)	Stuck (11)	School (62)	Wind (33)
Get (91)	Day (11)	Cancel (51)	Rain (14)
Ready (85)	Home (9)	Tomorrow (50)	Start (7)
Food (74)	Get (9)	Subway (41)	Park (7)
Evacuate (73)	Come (9)	Monday (35)	Come (7)
Line (69)	Time (8)	Work (32)	Weather (6)
Water (60)	Make (7)	Thank (31)	Water (6)
Come (55)	Freak (7)	Tonight (27)	Pick (6)
Safe (49)	Thank (6)	Shut (27)	Brooklyn (6)
Zone (47)	Everyone (6)	MTA (27)	River (5)
Store (45)	Today (5)	Flight (27)	Look (5)
Grocery (40)	Plan (5)	Service (26)	Dark (5)
Wine (38)	Like (5)	Class (26)	Sky (4)
Supply (38)	Kill (4)	Train (25)	Make (4)

Table 5. Top frequent terms under five topics of the *during* Sandy tweets.

Caution & Advice	Affected People	Infrastructure/Utilities	Needs & Donations	Weather & Environment
Safe (124)	Stuck (55)	Power (681)	Help (31)	Wind (315)
Stay (98)	Die (34)	Tree (314)	NYPD (20)	Water (125)
Ready (68)	Bore (34)	Close (193)	Need (17)	Flood (110)
Get (56)	Scare (32)	Street (186)	Work (15)	River (108)
Prepare (56)	Get (30)	Light (186)	Thank (15)	Street (104)
Evacuate (46)	Time (19)	Park (185)	FDNY (12)	Rain (104)
Come (43)	Thank (18)	Manhattan (167)	Volunteer (11)	Park (100)
Everyone (40)	Day (18)	Brooklyn (138)	Park (11)	Get (83)
Emergency (33)	Kill (17)	Open (134)	Brooklyn (10)	East (78)
Hunker (31)	Hotel (17)	Flood (128)	Respond (9)	Manhattan (75)
Zone (30)	Home (17)	Water (112)	Can (9)	Like (60)
People (30)	People (15)	Thank (109)	Street (8)	Brooklyn (54)
Hit (30)	Make (13)	Build (109)	First (8)	Look (52)
Home (27)	Family (13)	Crane (99)	People (6)	Empty (52)
Time (26)	Wait (12)	Get (98)	Bridge (6)	Calm (51)

Before group is similar to that in total Sandy tweets, as people tweeted most about their preparedness for Hurricane Sandy, e.g. stocking up supplies ("food", "water"). It is interesting to note from Table 4 that wine was also in the list of people's hurricane provisions. After a comparison of Tables 3 and 4, Affected People topic has some consistency in terms of the word frequency distribution between the total Sandy tweets and the *Before* group. In both cases, people tweeted about human mobility ("stuck"), emotional status ("bore", "scare"), and casualty ("kill"). This comparison also shows that, since power issues and fallen trees had not taken place before the disaster, Infrastructure/Utilities topic in the *Before* group was more about closure ("close", "shut", "school", "subway", "train" and "MTA") and cancellation ("class", "flight") which were notified to the public ahead of time. As already noted, "Manhattan" and "Brooklyn" were frequently tweeted when people communicated Weather & Environment as well as Infrastructure/Utilities in the entire process of Hurricane Sandy (Table 3). This is likely because people tend to report geolocations when tweeting eyewitness reports that were often associated with Infrastructure/Utilities as well as Weather & Environment. Notably, "Manhattan" and "Brooklyn" did not appear in the term frequency list of Infrastructure/Utilities topic in the *Before* group, since these tweets were mainly about the ahead-of-time notifications from authorities instead of eyewitnesses. Meteorologic ("wind", "rain", "sky"), hydrologic ("water", "river"), and cognitive (calm) reports were also covered by the Weather and Environment topic in *Before* group, which is similar to that of the total Sandy tweets.

A comparison of Tables 3 and 5 shows that the total Sandy tweets and the *During* group have an overall similarity in terms of the word frequency distribution. In other words, they share similar frequent terms across the five topics. This is mainly because the *During* group accounted for the largest proportion of total Sandy tweets (Table 2). However, there exist non-negligible distinctions between the *Before* group and *During* group. First, "power" and "tree" that were rarely tweeted before Sandy became the most frequent terms under the topic of Infrastructure/Utilities in the *During* group. Also during the disaster, people communicated their concern on Twitter about the dangling construction

Table 6. Top frequent terms for four topics of the *after* Sandy tweets.

Affected People	Infrastructure/Utilities	Needs & Donations	Weather & Environment
People (9)	Power (185)	Help (71)	Sky (8)
Day (9)	Manhattan (133)	Need (70)	Brooklyn (7)
Time (7)	Dark (100)	Victim (42)	Blue (7)
Stuck (7)	Park (90)	People (38)	Park (6)
Staten (6)	Day (87)	Donate (38)	Sun (5)
Island (6)	Street (79)	Come (32)	Cloud (4)
Death (6)	Blackout (79)	Redcross (31)	Sunshine (3)
Thank (5)	Gas (78)	Charge (31)	Light (3)
Sad (5)	Back (76)	Text (30)	Halloween (3)
Night (5)	Get (74)	Volunteer (26)	Final (3)
Like (5)	Subway (70)	Food (26)	East (3)
Home (5)	Line (70)	Marathon (25)	Aftermath (3)
Halloween (5)	Light (68)	Relief (24)	Weather (2)
Kill (4)	Brooklyn (68)	Thx (23)	Sunrise (2)
Trap (4)	Traffic (66)	Resource (23)	Skyline (2)

"crane" or posted eyewitness reports of its collapse. Second, as compared to the *Before* group, more Needs & Donations tweets calling for and reporting relief efforts emerged in the *During* group.

As NYC entered into the recovery stage, the amount of Caution & Advice tweets in the *After* group became very small (Table 2) and the word frequency of this topic was equally distributed. Therefore, we focused on the term frequency distribution for other four topics (Table 6). Notable changes can be detected for Affected People, Infrastructure/Utilities, as well as Weather & Environment topics. Deaths in Staten Island were highlighted under the Affected People topic in the *After* group. Gas problem was added to the power issues in the aftermath of Hurricane Sandy, as shown in the list of frequent terms of Infrastructure/Utilities topic (Table 6).

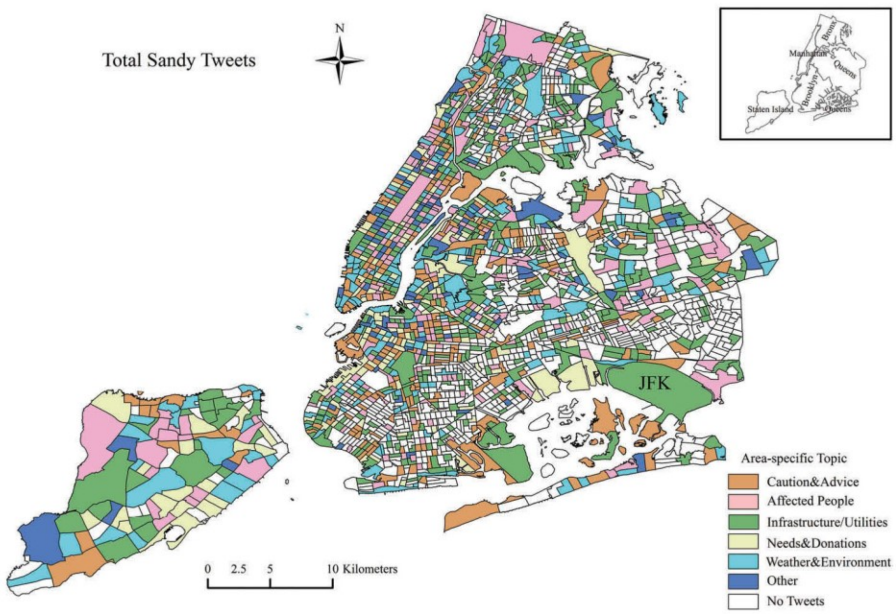

Figure 2. The spatial distribution of area-specific topics for total Sandy tweets.

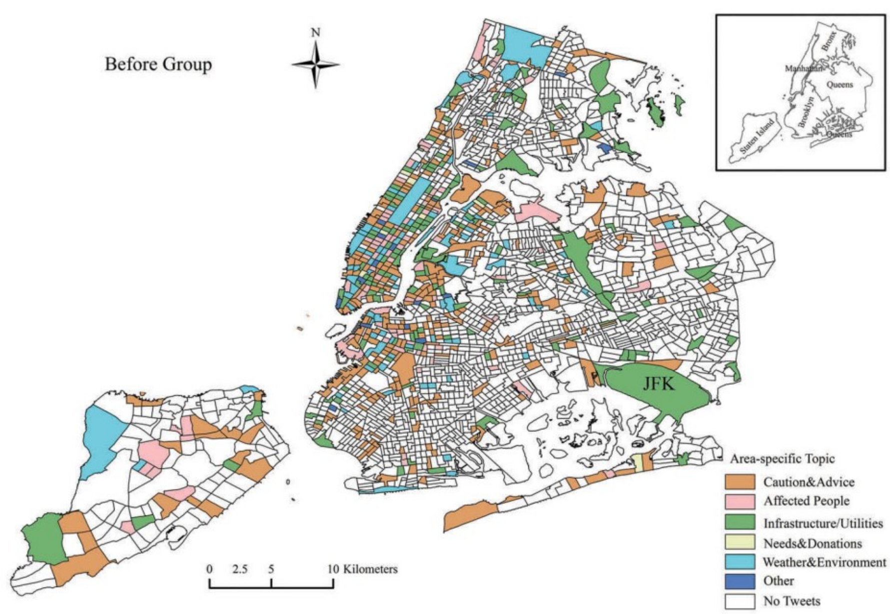

Figure 3. The spatial distribution of area-specific topics in the *Before* group.

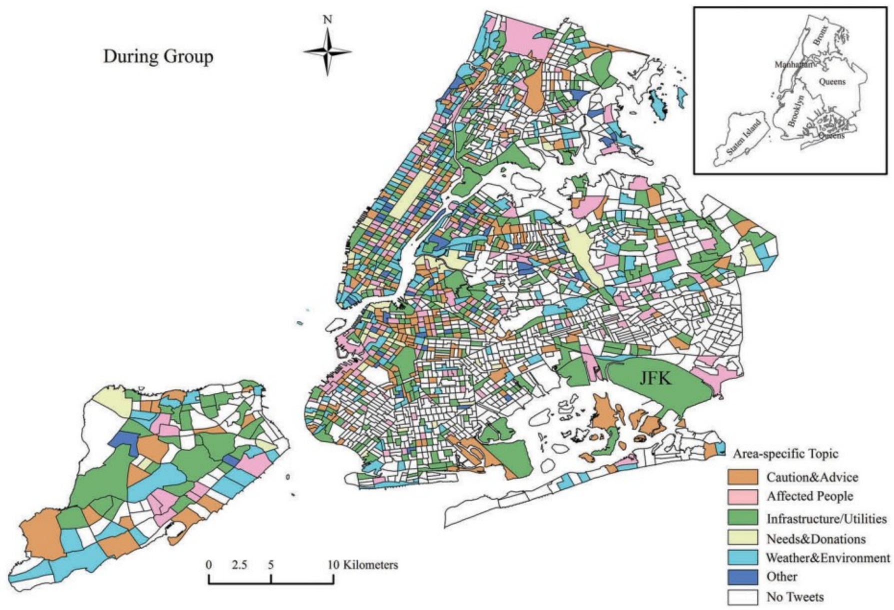

Figure 4. The spatial distribution of area-specific topics in the *During* group.

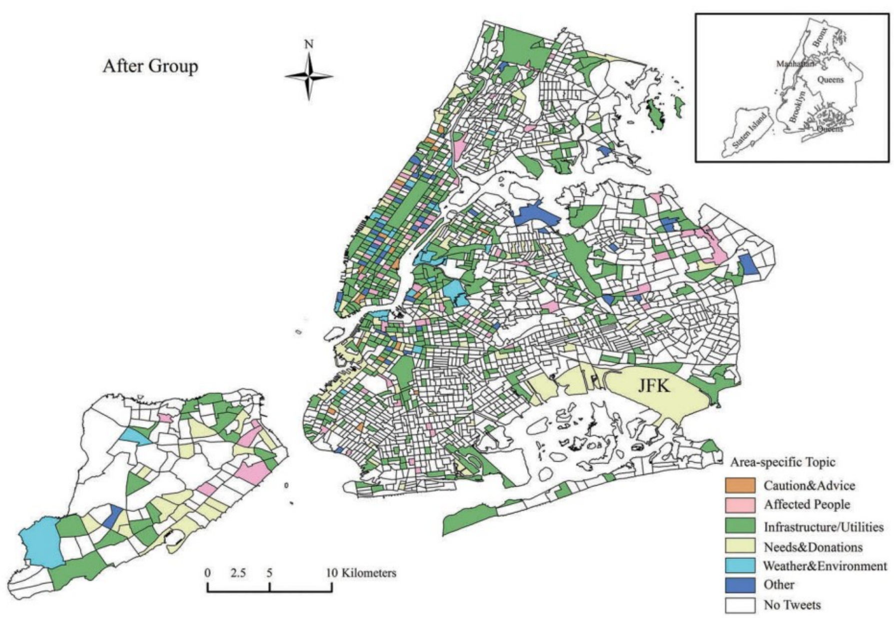

Figure 5. The spatial distribution of area-specific topics in the *After* group.

Additionally, the weather and environment conditions became better ("blue", "sky", "sun", "sunshine", "sunrise") after the disaster.

Spatial visualization of area-specific topic

We map the area-specific topics at census tract scale for total Sandy tweets, *Before* group, *During* group, and *After* group in Figures 2–5, respectively. It is difficult to summarize the spatial characteristics of area-specific topics for total Sandy tweets from Figure 2. However, the spatial pattern becomes clear when it comes to the *Before* group (Figure 3), *During* group (Figure 4), and *After* group (Figure 5). We can easily observe that the Caution & Advice topic played a dominant role in the geographic distribution of area-specific topics in the *Before* group as the majority of census tracts in NYC were colored in orange. This could be explained by the fact that people focused more on tweeting cautions and warnings as well as their preparations for the upcoming disaster. A comparison of Figures 3 and 4 reveals that the prevalent topic shifted to Infrastructure/Utilities during the disaster, as eyewitness reports regarding hurricane impacts such as power outage and service closure became major communicated messages on Twitter.

This spatial pattern becomes more easily identifiable in the aftermath of Hurricane Sandy (Figure 5). As noted from the above term frequency analysis, Manhattan and Brooklyn were two places most communicated on Twitter in Hurricane Sandy context. This can be reflected in the four maps of area-specific topics where Manhattan and Brooklyn (especially the north part) are significant clusters of Sandy Twitter messages. Moreover, the spatial pattern of area-specific topics in Manhattan and Brooklyn is congruent with the general structure of NYC, as the prevalent topic shifted from Caution & Advice before Sandy to Infrastructure/Utilities during and after the disaster. Notably, the census tract where John F. Kennedy International Airport (JFK) is located had Infrastructure/Utilities as its prevalent topic in total Sandy tweets, *Before* group, and *During* group, because people tweeted about delayed and cancelled flights. Yet, with the restoration of JFK after Sandy, people were updated with more information on Needs & Donations.

Temporal transition of area-specific topics

We report the transition probability matrices to demonstrate how the area-specific topics transited throughout the three disaster phases, i.e. before, during, and after. The first seven rows in Tables 7–9 are the transition probability matrices where each element represents the transition probability between area-specific topics from *Before* to *During*, *During* to *After*, as

Table 7. The transition probability matrix for area-specific topics from *Before* to *During*.

Before \ *During*	Caution & Advice	Affected People	Infrastructure /Utilities	Needs & Donations	Weather & Environment	Other	No Tweets
Caution & Advice	*17.73%*	12.49%	16.90%	5.69%	19.97%	4.02%	**23.20%**
Affected People	**18.63%**	7.64%	18.42%	20.67%	*17.38%*	5.70%	11.56%
Infrastructure/Utilities	13.36%	12.83%	**22.41%**	10.42%	*16.69%*	4.12%	20.16%
Needs & Donations	8.97%	*20.23%*	0.00%	6.95%	29.72%	0.00%	**34.14%**
Weather & Environment	11.81%	*17.39%*	**25.06%**	13.26%	17.95%	4.01%	10.52%
Other	12.02%	11.12%	6.37%	**29.07%**	*13.15%*	25.67%	2.61%
No Tweets	*8.11%*	7.35%	16.09%	1.75%	7.85%	1.46%	**57.38%**
Total	10.59%	9.05%	17.05%	4.58%	*11.30%*	2.51%	**44.92%**

The largest, second largest, and third largest values in each row were highlighted in bold, with underline, and in italic, respectively.

Table 8. The transition probability matrix for area-specific topics from *During* to *After*.

During \ *After*	Caution & Advice	Affected People	Infrastructure /Utilities	Needs & Donations	Weather & Environment	Other	No Tweets
Caution & Advice	1.03%	2.49%	27.51%	*13.04%*	2.22%	7.64%	**46.06%**
Affected People	0.94%	*9.79%*	29.93%	8.55%	1.75%	2.05%	**46.98%**
Infrastructure/Utilities	1.02%	5.84%	26.10%	*6.66%*	1.54%	0.81%	**58.02%**
Needs & Donations	4.81%	4.45%	**39.41%**	10.17%	*5.96%*	4.35%	30.86%
Weather & Environment	1.22%	3.01%	29.00%	*9.70%*	3.60%	1.66%	**51.83%**
Other	0.00%	7.64%	**37.99%**	5.93%	0.00%	*12.19%*	36.24%
No Tweets	0.03%	1.21%	9.76%	*3.07%*	0.17%	0.72%	**85.05%**
Total	0.74%	3.42%	20.49%	*6.38%*	1.41%	2.15%	**65.41%**

The largest, second largest, and third largest values in each row were highlighted in bold, with underline, and in italic, respectively.

Table 9. The transition probability matrix for area-specific topics from *Before* to *After*.

Before \ *After*	Caution& Advice	Affected People	Infrastructure /Utilities	Needs & Donations	Weather & Environment	Other	No Tweets
Caution & Advice	1.60%	5.52%	29.76%	*10.30%*	1.45%	3.21%	**48.17%**
Affected People	1.94%	6.55%	**36.58%**	*18.28%*	5.58%	6.14%	24.93%
Infrastructure/Utilities	2.68%	6.22%	28.58%	*9.88%*	5.40%	5.46%	**41.78%**
Needs & Donations	6.95%	29.72%	0.00%	0.00%	*20.23%*	8.97%	**34.14%**
Weather & Environment	0.00%	6.25%	**43.40%**	*14.74%*	1.78%	3.13%	30.71%
Other	6.26%	0.00%	**29.54%**	1.07%	*13.15%*	29.38%	20.62%
No Tweets	0.21%	2.14%	15.03%	*3.88%*	0.42%	0.89%	**77.44%**
Total	0.74%	3.42%	20.49%	*6.38%*	1.41%	2.15%	**65.41%**

The largest, second largest, and third largest values in each row were highlighted in bold, with underline, and in italic, respectively.

well as *Before* to *After*, respectively. The "Total" row in each of the Tables 7–9 records the total transition probabilities to a certain topic. For each row in Tables 7–9, we highlighted the largest value in bold, the second largest one with underline, and the third in italic. A glimpse of Figures 3–5 reveal that, in all three groups, there exist a large number of census tracts from where no georeferenced Sandy tweets were reported. Therefore, census tracts have a very high probability of transiting into "no tweets" status, which is congruent with the fact that the largest total probability value is always from the "No Tweets" columns. Notably, the "Infrastructures/Unities" column records the second largest total probability value in all three scenarios, suggesting that census tracts were more likely to transit into Infrastructure/Utilities topic upon reaching the during and after stages. The "Weather & Environment" column has the third largest total transition probability in Table 7, indicating that places also shifted their attention to Weather & Environment in the *Before* to *During* scenario. The third largest total transition probability values in Tables 8 and 9 are both found in the "Needs & Donations" column, implying that Needs & Donations topic became more important for many places in NYC at the recovery stage of Hurricane Sandy. More specifics can be obtained from the transition probability matrices: "Infrastructure/Utilities" and "Weather & Environment" columns in Table 7 as well as the "Infrastructure/Utilities" and "Needs & Donations" columns in both Tables 8 and 9 concentrate the majority of transitions from their previous stages.

Discussion and conclusion

We propose a novel approach for area-based detection of topical hotspots of social media conversations in natural disaster context. Moving beyond the spatial analytical methods in most existing studies, this approach uses LQ and Markov transition probability matrix to integrate space, time, and content dimensions in social media data and enable a space–time analysis of detailed social responses to a natural disaster. We contribute to the literature by characterizing situational awareness in space and time and thereby expanding it to a dynamic understanding of what is happening across geographic space in the whole process of a natural disaster. The case study based on Hurricane Sandy tweets in NYC discloses how the spatial pattern of area-specific topics changes with the evolution of Hurricane Sandy. Area-specific topics mainly transit to Infrastructure/Utilities and Weather & Environment in the *Before* to *During* scenario. In contrast, upon reaching the recovery stage of Hurricane Sandy (*Before* to *During* and *During* to *After*), Donations & Environment starts to play a role and Infrastructure/Utilities still attracts significant transitions. Our approach enables disaster responders to compare what people in an area are most concerned about and to identify how they change in the process of a natural disaster. Although our classification is human-annotated and time-consuming, it provides useful reference for rapid topic categorization of social media data related to similar natural disasters. For example, when another hurricane comes, the classifier developed in this study can be modified and applied to categorize the newly generated social media messages. Hence, when this space–time approach is jointly employed with fast topic modeling, it offers more potential to facilitate efficient policy/decision-making and rapid response in mitigations of damages caused by natural disasters. Furthermore, despite that we focus on natural disasters, this approach can be applied to social media activities related to other phenomena and events.

The current study is not without limitations. We utilized a six-tier classification schema to categorize the Hurricane Sandy tweets, while a fine-grained classification schema with more categories can reveal much detailed social responses to the disaster. However, an effective fine-grained classification is costly and not feasible in current research due to the time and resource constraints. Moreover, existing studies have not reached an agreement on the classification of disaster-related social media massages. As noted by De Albuquerque et al. (2015, p. 685), "thematic categorization is indeed generally problematic in social media analysis, as it can be noticed from the lack of standards for categories in the existing work, in particular in the context of disaster management." Therefore, an interesting direction for future work is to develop a set of standards to assist thematic classification of disaster-related social media data and mitigate the errors resulted from human annotation. Additionally, our topic classification is based on the texts in social media messages and thus may overlook the useful information in accompanying images that can also be relevant to situational awareness. Thus, image processing can be incorporated in the categorization of social media messages into different topics in order to gain more information richness. Finally, our space–time analysis is mainly based on the topic with the largest LQ value and discards other topics with smaller LQ values in the same area. However, these topics may also play a role in revealing situational awareness especially when they have larger LQ values than the area-specific topics from other areas do. Hence, the next step will incorporate all topics with LQ values larger than 1 in the Markov transition method. Some interesting questions could be raised accordingly. For example, what is the likelihood that the second ranked topic in the *Before* group would become the area-specific topic in the *During* group?

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