

Are vulnerable communities digitally left behind in social responses to natural disasters? An evidence from Hurricane Sandy with Twitter data

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ABSTRACT

Social media data is increasingly being used to improve disaster resilience and response. Recent years have seen more efforts to integrate social media feeds with various demographic and socioeconomic variables to gain insight into the geographical and social disparities in social media use surrounding disasters. However, vulnerability concepts and indicators have been largely overlooked despite that they can offer aid in understanding and measuring the communities' sensitivity to natural hazards and their capability of responding to and recovering from disasters. This study addresses a research question: Are vulnerable communities digitally left behind in social responses to natural disasters? Our empirical analysis is based on Hurricane Sandy and is conducted in a pre-disaster setting with spatial regression modeling. We observe that physically vulnerable communities had more intense social responses while socially vulnerable communities were digitally left behind in pre-disaster social responses to Hurricane Sandy.

1. Introduction

Social media has become an important platform for natural disaster communication (Imran, Castillo, Diaz, & Vieweg, 2015; Kryvasheyev et al., 2016; Li, Wang, Emrich, & Guo, 2018; Wang & Ye, 2018a). People are increasingly using social media tools in natural disasters and other emergencies to contact friends and family members as well as to communicate their concerns, fears, and needs. Notably, Hurricane Harvey in 2017 marked an important shift that more disaster victims used social media than the overloaded 911 systems to seek help (Cantu, 2017). Social media is receiving increasing scholarly attention, as researchers take social networking sites as useful social sensing tools for analyzing how to strengthen situational awareness and disaster resilience (Zou et al. 2018a, 2018b pp. 1–20).

Two research streams can be identified in the field of social media analytics for natural disaster management (Wang & Ye, 2018a). In the first stream, studies used social media as stand-alone data source to analyze the patterns and processes of social responses to natural disasters. Huang and Xiao (2015) extracted several topics from Hurricane Sandy tweets to look into detailed social responses to the disaster and then visualized their geographic distributions over three disaster phases (before, during, and after). Also using social media as stand-alone data source, Wang and Ye (2018b) conducted data mining of Hurricane

Sandy tweets to delineate the space-time dynamics of social responses to the disaster. In the second stream, existing work synthesized social media data with authoritative datasets such as census data to reveal the underlying mechanisms shaping the variation of people's digital footprints in natural disaster situations (Zou et al., 2018b). The pioneering work by Li, Goodchild, and Xu (2013) regressed general tweets on socioeconomic and demographic factors and revealed that well-educated people working in management, business, science, and arts were more engaged in social media activities.

In terms of disaster-related social media activities, Kent and Capello (2013) found that young people (age under 18) contributed largely to wildfire Twitter messages. Xiao, Huang, and Wu (2015) found that communities with a larger proportion of young, male, and educated people had more social responses to Hurricane Sandy on Twitter. Although recent years have seen an increasing number of studies linking disaster-related social media data with census data (i.e., socioeconomic and demographic data), existing research has two major limitations. First, most studies did not explicitly differentiate social responses over disaster phases or just focused on social media activities collected after the disaster's breakout, while few of them threw lights on the pre-disaster phase that is of particular importance for disaster preparation. Second, these census variables were subjectively selected from a variety of possible variables, omitting that well-established social vulnerability

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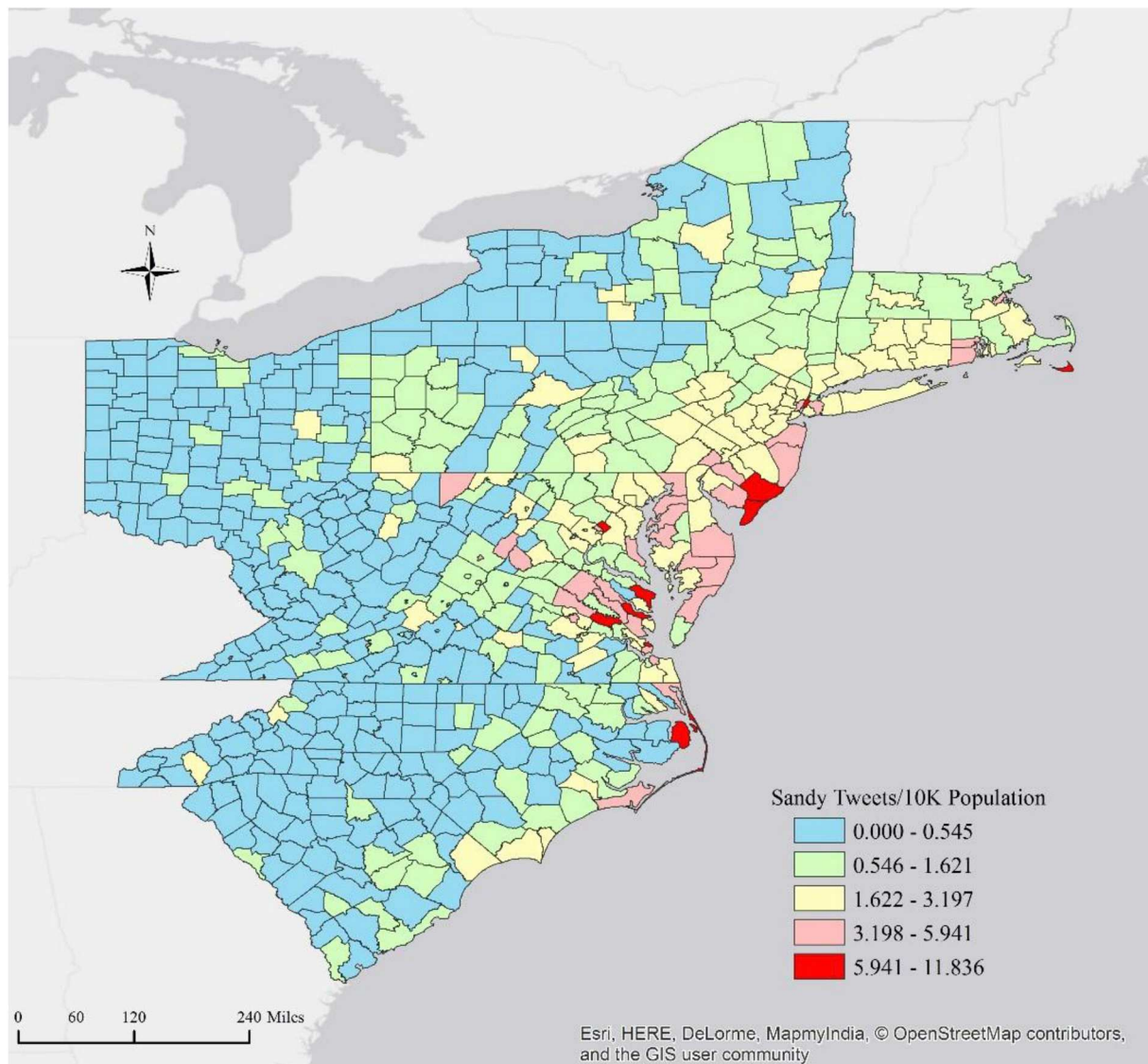


Fig. 1. A map of pre-disaster social responses to Hurricane Sandy on Twitter.

concepts and indicators may provide an integrative way for representing the communities' socioeconomic and demographic characteristics (Wang & Ye, 2018a). In light of this, this article incorporates physical vulnerability and social vulnerability to identify influential factors shaping pre-disaster social responses to a natural hazard.

Vulnerability to disaster is gaining increasing attention in disaster management research and practice. Vulnerability represents the likelihood of communities to be impacted by hazards (Cutter, 2003). It encompasses two components including physical vulnerability and social vulnerability. The physical component often depends on the hazard's physical nature (Cutter, Mitchell, & Scott, 2000). That is, different communities could be physically vulnerable to different natural hazards such as wildfires, tornados, earthquakes, floods, and hurricanes. According to Cutter and Finch (2008), social vulnerability is a “measure of both the sensitivity of a population to natural hazards and its ability to respond to and recover from the impacts of hazards”. It is a composite of multiple variables characterizing communities' demographic and socioeconomic conditions, which increase their sensitivity to the hazards' effects and decrease their capability in responding to and recovering from natural hazards. Vulnerable communities are more likely to become disaster victims and their representation in disaster-related social media communication determines whether their needs

and concerns can gain sufficient attention from disaster responders. Our research question is: are vulnerable communities digitally left behind in social responses to natural disasters? Our attempt to address the research question is critical for assessing the usefulness of social media data in natural disaster management. To the best of our knowledge, this article is one of the first attempts to examine the relationship between vulnerability and online social responses to natural disasters.

2. Data and methodology

2.1. Pre-Sandy Twitter activities

Hurricane Sandy was one of the most destructive cyclones in the United States since 1900 (Blake, Kimberlain, Berg, Cangialosi, & Beven, 2013). After its landfall on October 29, 2012 in New Jersey, Hurricane Sandy caused a vast amount of damage to the eastern states. The total loss caused by Hurricane Sandy was estimated to reach \$50 billion, and 72 deaths was also related to Sandy (Blake et al., 2013).

All geotagged tweets posted from October 22, 2012 to November 2, 2012 were retrieved by Wang, Hovy, and Dredze (2015, April) using the Twitter Firehose API. These geotagged tweets came from the affected areas (14 eastern states) including Washington DC, Connecticut,

Delaware, Massachusetts, Maryland, New Jersey, New York, North Carolina, Ohio, Pennsylvania, Rhode Island, South Carolina, Virginia, and West Virginia. With an attempt to open this dataset to the public, IDs of all the solicited tweets have been made available by Wang et al. (2015, April) on GitHub. 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 collected. As Hurricane Sandy's landfall was on October 29, 2012, we defined Sandy tweets posted between October 22 and October 28 as pre-Sandy Twitter activities. Based upon this criterion, 16,913 out of 83,006 geotagged Sandy tweets were identified as pre-Sandy tweets and used to capture the pre-disaster social responses to the hurricane. We then aggregated these 16,913 geotagged messages to county level by counting Sandy tweets that fell into each county within the above 14 states. Please note that counties are considered communities. We used county scale for two reasons: (1) Many social media studies were conducted at the county level. These studies include but are not limited to Zou et al. (2018a, pp. 1–20), Zou (2018b), and Moore, Obradovich, Lehner, and Baylis (2019). Our study results can be comparable with these and other previous studies. (2) Sub-county level analysis is possible but data are not available or reliable. In this study, the aggregation to sub-county units will result in data sparsity, meaning that lots of census tracts/block groups will have no Sandy tweets. Finally, we divided geolocated Hurricane Sandy tweets by the population to calculate the intensity of pre-Sandy Twitter activities as mapped with Jenks Natural Breaks in Fig. 1.

2.2. Precipitation

Hurricanes often bring heavy rainfalls. We hypothesize that pre-disaster social responses on social media can be triggered by precipitation, as people would likely relate rainfalls to the upcoming hurricane. We retrieved daily precipitation data from National Centers for Environmental Information (NECI), National Oceanic and Atmospheric Administration (NOAA). Daily precipitation observations from October 22 to October 28 recorded by 10,274 weather stations located in the 14 eastern states were collected. Following this, we calculated the average precipitation during the pre-Sandy period (October 22–October 28, one week) for each weather station. The one-week average precipitation data were further aggregated to the county level by measuring the mean values for weather stations within each county. This can be demonstrated by the following equation:

$$Pre_i = \frac{1}{7m} \sum_{j=1}^m \sum_{t=1}^7 Pre_{ijt} \quad (1)$$

where i has 628 distinctive values (1–628) representing 628 counties in the 14 eastern states, j denotes the j th weather station in county i , m is the number of weather stations in county i and it varies across the counties. The spatial distribution of the one-week average precipitation before Hurricane Sandy is shown in Fig. 2 with a Jenks Natural Breaks classification.

2.3. Population density

Drawing upon the diffusion of innovation theory, population density facilitates communication and exchange (Klasen & Nestmann, 2006). Denser population creates more opportunities for face-to-face interactions between individuals. Spitzberg (2014) further suggested that population density facilitates social ties and geospatial contact, thereby increasing the potential for information diffusion. In this regard, people's engagement in disaster-related social media communication may also be determined by population density. A population density variable ($Pden_i$) was specified in this research. Fig. 3 displays the geographic distribution of county-level population density within our study area using Jenks Natural Breaks classification.

2.4. Physical vulnerability

Since hurricanes are coastal hazards, people in coastal areas are more likely to be physically affected. Hence, geographic proximity to coastline can represent populations' physical vulnerability to hurricane hazards. With reference to Brody, Zahran, Vedlitz, and Grover (2008), we used geographic distance (Dis_i) to the nearest coastline as a proxy for the physical vulnerability to Hurricane Sandy. Dis_i was specified by calculating the nearest Euclidean distance from the centroid of county i to the coastline. We did not add a map to show each county's proximity to the coastline since it could be easily inspected from other figures.

2.5. Social vulnerability

Researchers have developed multiple indicators to quantify social vulnerability (Cutter, Boruff, & Shirley, 2003; Flanagan, Gregory, Hallisey, Heitgerd, & Lewis, 2011). In this study, we adopted ATSDR's Social Vulnerability Index (Flanagan et al., 2011) that is based upon census variables to help identify places requiring support in preparation for disasters. Although ATSDR's Social Vulnerability Index incorporates fewer variables than other metrics do, it can be easily calculated and has little redundancy. As such, we calculated social vulnerability for each county in the eastern 14 states with ATSDR's 2010 Social Vulnerability Index (Flanagan et al., 2011). Its equation is shown as:

$$\begin{aligned} SVI_i = & PR_POV_i + PR_UNEMP_i + PR_PCI_i + PR_NOHSDIP_i \\ & + PR_AGE65_i + PR_AGE17_i + PR_SNGPRNT_i \\ & + PR_MINORITY_i + PR_LIMENG_i + PR_MUNIT_i \\ & + PR_MOBILE_i + PR_CROWD_i + PR_NOVEH_i \\ & + PR_GROUPQ_i \end{aligned} \quad (2)$$

where SVI_i is the social vulnerability index of county i , and variables on the right-hand side of this equation are county i 's 14 variables which reflect 4 major themes of social vulnerability including socioeconomic theme, household composition theme, minority status/language theme, and housing/transportation theme. These variables are further described in Table 1.

Please note that, following Flanagan et al. (2011), we ranked each variable except PCI from highest to lowest across all counties in the 14 eastern states and calculated the percentile rank for every county over each of the 13 variables. Since high income represents lower social vulnerability, we ranked PCI from lowest to highest and calculated its percentile rank (PR_PCI) for each county. Finally, an overall percentile rank was obtained for each county to identify its social vulnerability (SVI_i) by summing all 14 variables' percentile ranks. Higher SVI_i indicates higher social vulnerability. A percentile rank is defined as the proportion of scores in a distribution that a specific score is greater than or equal to. Its formula is:

$$Percentile\ rank = (rank - 1)/(N - 1) \quad (3)$$

Where $rank$ is the rank of a variable for a certain county, and N is the number of counties (here, 628). Also using Jenks Natural Breaks classification, a spatial visualization of social vulnerability is shown as Fig. 4.

2.6. Spatial lag model (SLM) and spatial error model (SEM)

Regression analysis aids in examining the relationship between vulnerability and pre-disaster social responses. Prior to the regression analysis, we examined the spatial autocorrelation of the intensity of pre-Sandy Twitter activities (Pre_SR_i) using Moran I. The Moran I index was found to be 0.157 and statistically significant at 1% level. Note that the spatial weight matrix W for calculating Moran I was obtained by using the inverse distance between any two counties. Given the existence of spatial autocorrelation, we adopted two spatial regression

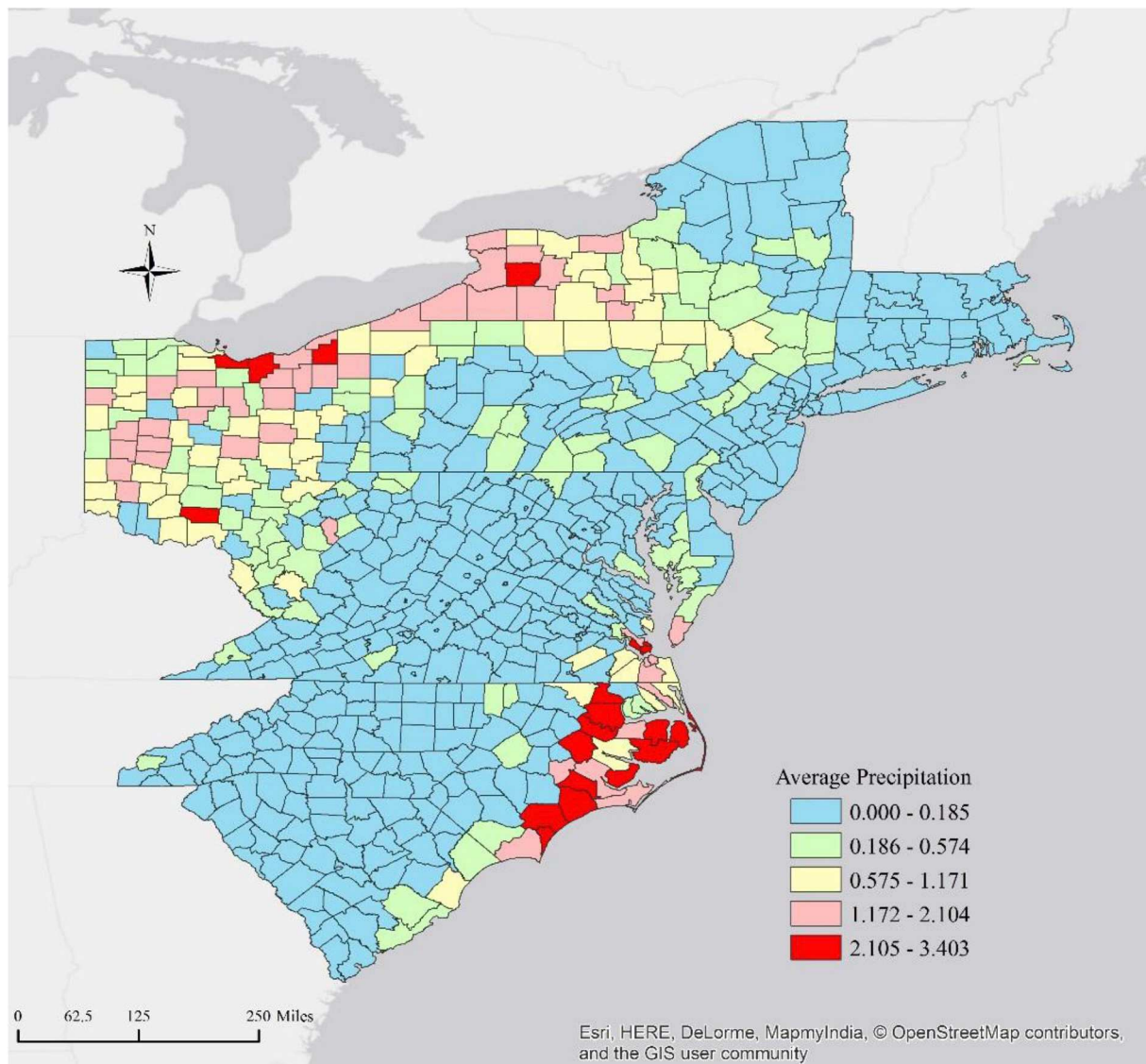


Fig. 2. The one-week average precipitation before Hurricane Sandy.

models including spatial lag model (SLM) and spatial error model (SEM) to control its impact on the estimation of coefficients. The spatial lag model captures substantive spatial dependence spatial interaction. These two models were conducted with the *spdep* package in R. In the specification of SLM, the dependent variable's observations at certain locations are partially dependent on their neighbors' observations (Wang & Ye, 2017). SLM can be specified as:

$$Pre_SR_i = \alpha + \rho WPre_SR_i + \beta_1 Pre_i + \beta_2 Dis_i + \beta_3 Pden_i + \beta_4 SVI_i + \varepsilon \quad (4)$$

where α is the constant term, W is the spatial weight matrix as in the Moran I calculation, ρ is the coefficient of spatial autoregressive term, $\beta_1, \beta_2, \beta_3, \beta_4$ are the parameter coefficients of *Pre*, *Dis*, *Pden*, and *SVI*, respectively. In the specification of SEM, it is hypothesized that spatial dependence exists in the error terms. SEM is given by:

$$Pre_SR_i = \alpha + \beta_1 Pre_i + \beta_2 Dis_i + \beta_3 Pden_i + \beta_4 SVI_i + \varepsilon \quad (5)$$

$$\varepsilon = \lambda W\varepsilon + \mu \quad (6)$$

3. Analytical results

Table 2 reports the estimation results from two spatial regression

models: spatial lag model (SLM) and spatial error model (SEM). With a larger Log likelihood value and a smaller AIC value, SEM has a better model fit than SLM. We also used Lagrange Multiplier (LM) diagnostics for model selection. As seen from Table 3, simple tests of the lag and error i.e., LM error and LM lag are both significant at 0.001 level, suggesting the presence of spatial dependence. We then used their robust versions (Robust LM lag and Robust LM error) to identify which spatial dependence is at work. Robust LM error remains significant at 0.001 level, while the significance of Robust LM lag has dropped from 0.001 to 0.01. Therefore, SEM is more preferred over SLM, and we use the results from SEM for interpretation.

As observed from Table 2, precipitation (*Pre*), population density (*Pden*), physical vulnerability (*Dis*), and social vulnerability (*SVI*) are all statistically significant. Although with a less significance level (0.05) as compared to other three variables (0.001), the positive sign of *Pre* indicates that precipitation is positively related to the intensity of pre-Sandy Twitter activities. That is, counties with heavy rainfalls tend to have more intense social responses to the upcoming Hurricane Sandy. This is likely because individuals were concerned about the unfolding disaster, and the precipitation that often accompanies hurricanes can motivate individuals' responses on social media.

The coefficient of population density (*Pden*) is significantly different

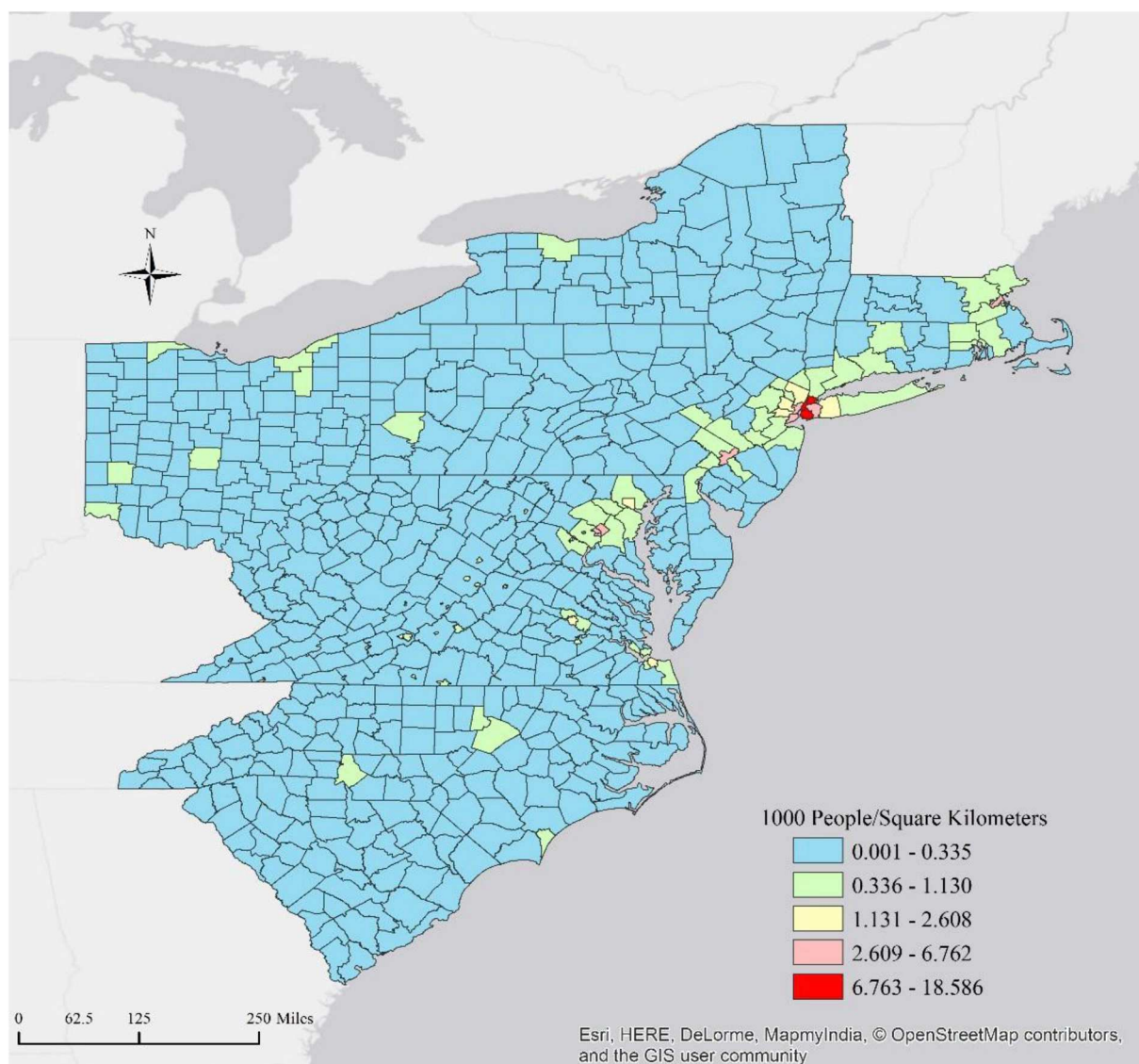


Fig. 3. Population density map.

Table 1

Variables used to calculate social vulnerability.

Source: compiled from <https://svi.cdc.gov/>

Themes	Variable Name	Description
Socioeconomic theme	<i>PR_POV</i>	Percentile rank of the proportion of persons below poverty estimate
	<i>PR_UNEMP</i>	Percentile rank of the proportion of civilian (age 16+) unemployed estimate
	<i>PR_PCI</i>	Percentile rank of per capita income estimate
Household Composition theme	<i>PR_NOHSDIP</i>	Percentile rank of the proportion of persons with no high school diploma (age 25+) estimate
	<i>PR_AGE65</i>	Percentile rank of the proportion of persons aged 65 and older
	<i>PR_AGE17</i>	Percentile rank of the proportion of persons aged 17 and younger
Minority Status/Language theme	<i>PR_SNGPRNT</i>	Percentile rank of the proportion of single parent households with children under 18
	<i>PR_MINORITY</i>	Percentile rank of the proportion minority (all persons except white, non-Hispanic)
	<i>PR_LIMENG</i>	Percentile rank of the proportion of persons (age 5+) who speak English "less than well" estimate
Housing/Transportation theme	<i>PR_MUNIT</i>	Percentile rank of the proportion of housing in structures with 10 or more units estimate
	<i>PR_MOBILE</i>	Percentile rank of the proportion of mobile homes estimate
	<i>PR_CROWD</i>	Percentile rank of the proportion of households with more people than rooms estimate
	<i>PR_NOVEH</i>	Percentile rank of the proportion of households with no vehicle available estimate
	<i>PR_GROUPQ</i>	Percentile rank of the proportion persons in institutionalized group quarters

Note: *PR_AGE65*, *PR_AGE17*, *PR_SNGPRNT*, *PR_MINORITY*, and *PR_GROUPQ* were obtained and calculated from Census 2010 data, while the remaining variables/estimates were from American Community Survey (ACS), 2006–2010.

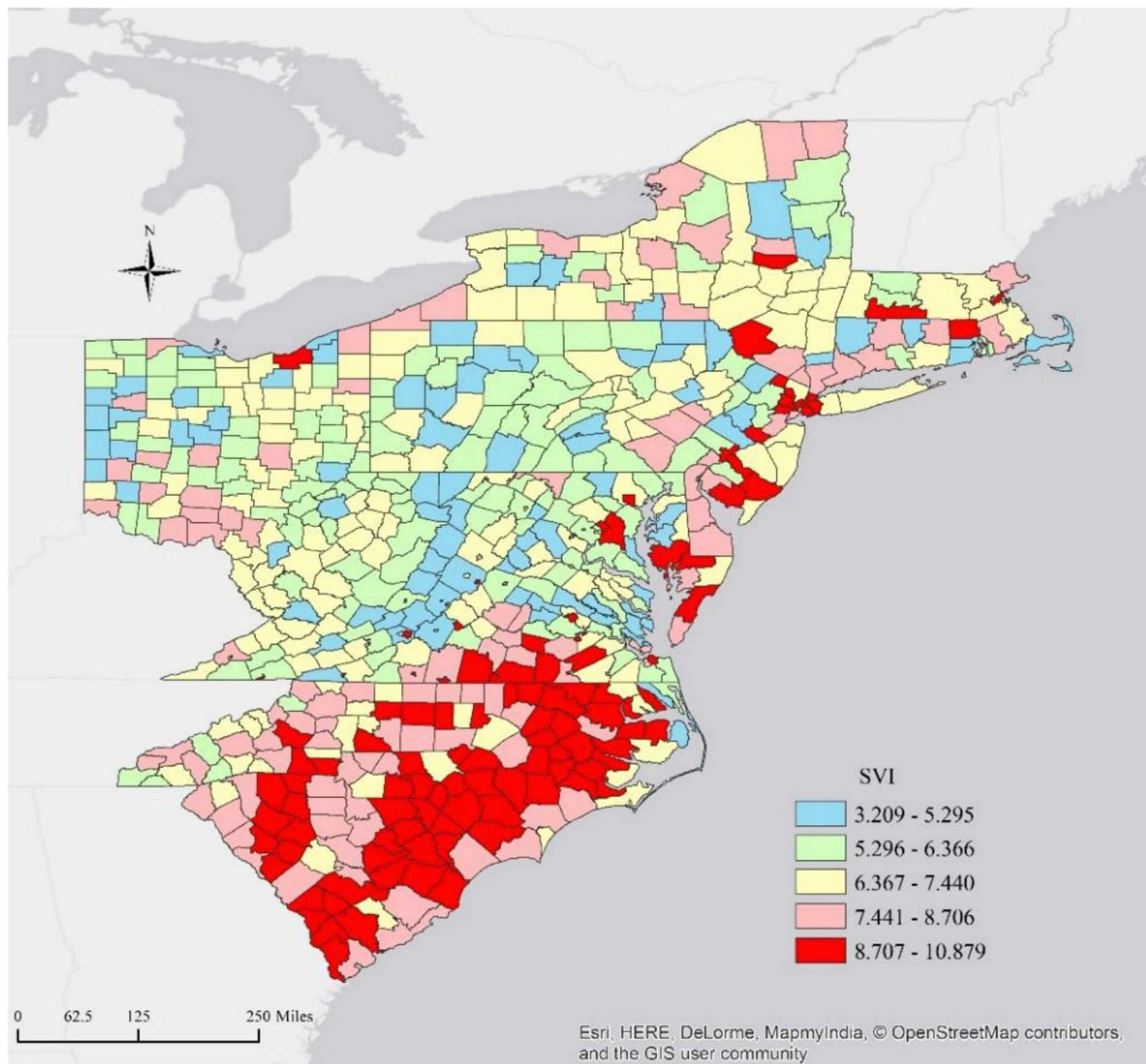


Fig. 4. A map of social vulnerability.

from zero and has an expected positive sign, which indicates that places with high population density are more likely to report Sandy Twitter activities prior to its landfall. Population density can benefit communication and exchange. People in densely populated areas can therefore easily gain access to disaster-related information from various sources and communicate their retrieved information on social media. We can further suggest that the spatial disparity of population density plays a

critical role in shaping the geographic variation of pre-disaster social responses on social media.

As shown by the SEM estimation, the coefficient of *Dis* is significantly negative, indicating that places that are geographically close to the coastline have more intense pre-Sandy Twitter activities. Recall that geographic distance (*Dis*) was used to measure physical vulnerability; that is, more distant from the coastline, people are less

Table 2
Estimation results of SLM and SEM.

	Spatial lag model (SLM)			Spatial error model (SEM)		
	coefficient	z-value	p-value	coefficient	z-value	p-value
Constant	1.4516	6.3048	0.0000***	3.3882	8.6538	0.0000***
	0.2384	2.9945	0.0028**	0.1882	2.0646	0.0390*
	0.3650	8.0598	0.0000***	0.4056	8.2524	0.0000***
	−2.4705	−8.8583	0.0000***	−3.2689	−9.9418	0.0000***
	−1.1013	−6.3504	0.0000***	−1.1269	−6.0834	0.0000***
	0.0035 (0.000***)					
λ				0.0045 (0.000***)		
Log likelihood	−1007.873			−1005.255		
AIC	2029.7			2024.5		

Significance level: ‘***’ 0.001, ‘**’ 0.01, ‘*’ 0.05.

Table 3
Lagrange Multiplier (LM) diagnostics for spatial dependence in linear models.

	statistic	p-value
LM error	74.9582	0.0000***
LM lag	38.5510	0.0000***
Robust LM error	44.3645	0.0000***
Robust LM lag	7.9573	0.0048**

Significance level: '***' 0.001, '**' 0.01, '*' 0.05.

physically vulnerable to hurricane disasters. As such, this modeling result demonstrates that physically vulnerable people contributed largely to the intensity of social responses to Hurricane Sandy as it coming onshore. Existing studies have shown a significantly positive correlation between physical vulnerability and hurricane risk perceptions (Peacock, Brody, & Highfield 2005). Hence, social media could serve as a suitable platform for physically vulnerable communities to communicate their concerns, fears, and needs to better prepare for the hurricane disaster.

According to its calculation process, larger SVT value represents higher social vulnerability. SEM estimation reported in Table 2 shows that the coefficient of SVT is significantly negative, indicating that socially vulnerable groups were less represented in online social responses at the pre-Sandy phase. One important reason is that some socially vulnerable communities are also groups with limited accessibility to computers, smartphones, and internet. For example, elderly people (aged 65 and older) are both socially vulnerable (Table 1) and less digitally literate. Studies have shown that socially vulnerable communities often experience heightened levels of risk perception (Fothergill & Peek, 2004). This modeling result, nevertheless, suggests that they were not equally engaged in disaster-related communication on social media. In other words, those who have more worries and concerns about the upcoming hurricane disaster were digitally left behind, and their needs would barely attract sufficient attention from disaster managers on social media. Another possible reason is that a large amount of before-sandy tweets was about people's preparedness (Wang & Ye, 2018b) while some socially vulnerable groups such as poor people have been claimed to be less prepared at the pre-disaster phase (Wendel, 2014).

4. Concluding remarks

Our results suggest that physically vulnerable communities had stronger influence on social responses to Hurricane Sandy than the other three factors (precipitation, population density, and SVI). People with a large likelihood of being impacted would shift their attention to this life-threatening event and engage more in disaster-related social media conversations such as preparedness and situational updates. One may suppose that socially vulnerable groups should be more active in disaster-related social media conversations.

On the contrary, our modeling results disclose that these socially vulnerable communities were digitally left behind in the pre-disaster social responses to Hurricane Sandy. This implies that the use of social networking sites for information exchange in natural disaster situations has introduced new inequality where groups with disadvantaged socioeconomic and demographic status were less represented in disaster-related communication on social media. It is critical to examine the underlying socioeconomic and demographic characteristics in order to better mine actionable and effective data from disaster-related crowd-sourced content. This research cautions that information or subsequent management policies derived from social media response may be biased towards those who are less socially vulnerable.

This study is not without limitations. First, we simply specified four variables in the regression modeling as our focus is on the examination of the relationship between vulnerability and pre-disaster social

responses, while future work will have more variables such as wind speed to improve the explanatory power.

Second, studies have shown that only a tiny percent of Twitter messages have precise longitudes and latitudes (Wang, Ye, & Tsou, 2016; Yang & Mu, 2015; Yang, Mu, & Shen, 2015). Therefore, when only those Sandy tweets with accurate longitudes and latitudes were utilized, the analysis might lack generalizability to the population. Although our data were originally collected with Twitter Firehose API that is not subject to the 1% sampling limitation imposed by Twitter, there are still several counties that have no geolocated Sandy tweets. Future work should not only incorporate the precise longitudes and latitudes but also extract other spatial information from the user profiles and content of Sandy messages to improve the sample size and generalizability.

Third, and relatedly, the demographic vulnerability information we employed is based on census data, not data drawn from individuals themselves. Because of this, we cannot rule out that those individuals in our sample are systematically different from their neighbors, introducing a risk of biased ecological inference.

Finally, this study focused on using the spatial information inherent in Hurricane Sandy Twitter activities without examining their content from which we can mine detailed social responses to the disaster. For example, a classification of Sandy tweets based on their content can enable us to differentiate social responses into several categories such as help requests, preparedness, and damage reports. In next step, we will use state-of-the-art machine learning technique i.e., Convolutional Neural Network (CNN) to classify Sandy tweets into several classes and then examine how social vulnerability and physical vulnerability relate to them.

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