IMPROVE DISASTER COMMUNICATION IN HYPERLOCAL ONLINE AND OFFLINE COMMUNITIES USING SOCIAL MEDIA: A CASE STUDY OF THE 2015 NEPAL EARTHQUAKE

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ABSTRACT

This article seeks to go beyond traditional GIS methods used in creating maps for disaster response that commonly look at the disaster extent. Instead, a slightly different approach is taken using social media data collected from Twitter to explore how people communicate during disaster events, how online communities form and evolve, and how communication methods can improve. This study collected the Twitter data during the 2015 Nepal earthquake disaster and applied a spatiotemporal analysis to find any patterns that show shadows or gaps in communication channels in local communities' communication. Linkages in social media can be used to understand how people communicate, how quickly they diffuse information, and how social networks form online during disasters. These can improve communication throughout disaster phases. This study offers a deeper understanding of the kinds of spatiotemporal patterns and spatial social networks that can be observed during disaster events. The need for better communication during disaster events is imperative for better disaster management, increasing community resilience, and saving lives.

Keywords: Disaster, Social Media, Spatial Social Network, Communication, Hyperlocal, Big Data

INTRODUCTION

Disaster management can be approached from many different perspectives. Placing social media communication in a geographic context within the realm of disaster management is useful for analysis of how people communicate during disaster events, how online communities form and evolve, and how communication methods can improve. This opens pathways to determine how to improve communication so community resilience can foster sustainability and lessen vulnerability. Methods to increase resilience continuously grows as a major goal because it determines how a community of people will recover back to their original state after facing a disaster. Resilience reaches beyond the recovery phase and touches upon the mitigation, preparedness, and response phases as well. If community resilience is at least consciously acknowledged in each phase, then it can continuously increase and the sustainability of the community too can strengthen. This has encouraged researchers to analyze communication patterns of social media after disasters *(1)(2)(3)(4)*.

A key component to the success of relief efforts involves providing aid in a timely manner to affected areas as needed. First responders must be able to determine who has been affected and to what severity. Unfortunately, in this lies a wide gap of communication between the affected communities and their formal emergency response institutions *(5) (6) (7) (8) (9) (10)*. Using social media to bridge this gap can improve preparedness and response by providing communities with more resilience to disasters. It gives the community potential to be actively ready for a disaster to occur, and relieves pressure on institutions by improving communication between these institutions and affected communities *(11)*. Because social media acts as an outlet of communication that is free and highly accessible to users - assuming the availability of required devices such as computers/smartphones/internet-, their data can be downloaded and interpreted by emergency responders while also opening direct lines of communication between responders and affected communities or individuals. As the constant advancements in technology have revamped society's methods of communication *(6) (9) (12) (13) (14),* the output from social media significantly increases during a disaster *(5) (6) (7) (8) (9) (11) (13) (15) (16)*. It is possible to utilize these changes to alleviate this communication gap and strengthen relief efforts using social media data in Geographic Information Systems (GIS).

Responding to disasters has seen emergence of new ways of digital humanitarianism. Through the efforts of Ushahidi in the response to the Haiti Earthquake in 2010, SMS messages were translated and classified for responders to best respond to the information provided *(17)*. Ushahidi created a platform that allowed for the use of crowdsourcing to classify messages sent out by the people of Haiti. These messages were put into a format that first responders could react to more quickly to urgent messages because the responders no longer needed to filter through the information. GIS can be used as a tool of information management by gathering various sets of information and sharing it. When this is applied towards disaster management, it can strengthen resilience by bringing affected communities away from being passive victims to being active in relief efforts *(12)*.

In this research, the major focus is to understand the spatiotemporal patterns and structure of online networks from communication that occurred over Twitter during the 2015 Nepal Earthquake between April 25, 2015 and May 18, 2015 (earthquake event: April 25, 2015). The case study is based in Nepal, focusing on its capital of Kathmandu and the surrounding areas. On April 25, 2015, an earthquake whose epicenter was located eastern of the Lamjung District had a moment magnitude of 7.8Mw, which devastated Nepal *(18)*. Its Mercalli Intensity was considered and calculated at IX (United States Geological Survey 2015) with the impact felt in India, China, and Bangladesh. Thus, an avalanche on Mount Everest was set in motion (United States Agency for International Development (USAID) 2015) *(19)* and a multitude of aftershocks were felt throughout the areas for weeks, with a couple only slightly weaker than the initial earthquake; the strongest aftershock occurred on May 12, 2015 (Nepal Earthquakes 2015). The damage to infrastructures produced by this earthquake was catastrophic, but the damage to people's lives was far worse. From this earthquake, there were 8,999 people killed and 19,009 injured. With help from the Nepalese Army, multiple international aid agencies, and countless volunteers and emergency workers, rescue and relief efforts were launched to the areas that experienced trauma. In Nepal, people inside of Kathmandu, the capital city of Nepal, could be reached over social media, even though other areas in Nepal were also heavily damaged.

Similar to the Haiti Earthquake that struck in 2010, the Nepal Earthquake in 2015 brought devastation to a developing nation. Following the idea of "think globally, act locally", the goal of this case study examination is to identify ways of improving communication. This insight has the potential to help increase local community resilience during disaster incidents and to save lives in any future events.

SOCIAL MEDIA DATA COLLECTION AND CLEANING

Nepal Earthquake Data

The GeoViewer tool created by the center for Human Dynamics in the Mobile Age (HDMA) *(20)* was used to collect the Nepal dataset from the dates April 25- May 18, 2015. The GeoViewer is an interactive web mapping tool that allows the user to query tweets on the backend data stored in a MongoDB database *(21)*. The GeoViewer uses Twitter's Streaming API, which returns the tweets that were posted within a user defined bounding box. The bounding box for this case study was created around the impact zone of the earthquake, at southwest latitude/longitude of 84.263207, 26.450917 and northeast latitude/longitude of 87.361352, 28.796561. A total of 33,610 tweets were collected, all of which were geotagged.

TABLE 1 List of data used in Nepal Case Study

Case Study	Date Range	File Size	Number of Tweets	Number of Users	Geotagged Tweets	Keywords	Spatial Boundary
2015 Nepal (StreamingAPI)	April 25- May 18, 2015	3.2 MB	33,610	2,225	100% (all)	N/A	SW: 84.263207, 26.450917; NE: 87.361352, 28.796561

Spatiotemporal Patterns and Social Networks

To explore spatiotemporal patterns and social networks, this study breaks the analysis into the four categories following Couclelis's *(22)* spatiotemporal perspectives: formal, social, empirical, and experiential. The formal perspective temporally analyzes the data's overall properties, and compares Twitter activity to real world events. It then analyzes the changes in Twitter activity over space and time by using Kernel Density Estimation (KDE) to create raster files containing hotspots of highly dense Twitter activity *(23)* during different phases in the case study. Once hotspot maps are created, a differential map can be created to compare the changes in activity by using the raster-based map algebra tool provided by ESRI *(23)*. Following the method used by *(24),* the following formula was applied to the raster formatted maps for the case study.

Differential Map *= (Each Cell Value of Map A/Maximum Cell Value of Map A) –*

(Each Cell Value of Map B/Maximum Cell Value of Map B)

The social perspective focuses on social network analysis to study the structure, content, and evolution of network structures created from the communication in the case study. Data from the GeoViewer was processed through OpenRefine and analyzed through social network graphs created using Gephi. The empirical perspective captures the properties of users by tracking their trajectories throughout the case studies' periods of time. Finally, the experiential perspective refers to geovisualizations created in order to process and display the information.

Data Visualization: Hyperlocal Relationships

To define the hyperlocal relationships, the dataset was separated into communities and mapped to show their spatial relationship through Twitter activity. To emphasize the geographic and geospatial information, geovisualizations are a key component in producing the final products of this research. Combining visualization techniques with geographic data allows the data to be understood more easily and eases in decision-making. One of the real-world applications of this research is to aid emergency response teams in spreading information pertaining to disasters more efficiently throughout social networks (online and offline). The various types of geovisualization products include: 1) Kernel Density hotspot maps showing Twitter activity, 2) differential maps showing the changes in Twitter activity, 3) overall online social network graphs, 4) online social network graphs showing in-degree, 5) online social network graphs showing out-degree, 6) comparison between users' online social network and geographic locations, and 7) individual users' trajectory maps.

DATA ANALYSIS: SPATIOTEMPORAL PATTERNS

In Nepal, the initial earthquake happened on April 25 and the major aftershocks on April 26 and May 12. Since earthquakes are sudden natural disasters that occur, the data could only be collected starting on April 26, 2015 due to data collection restrictions. Despite this, the dataset has plenty of data that displays the temporal trends found in Twitter communication for this case study.

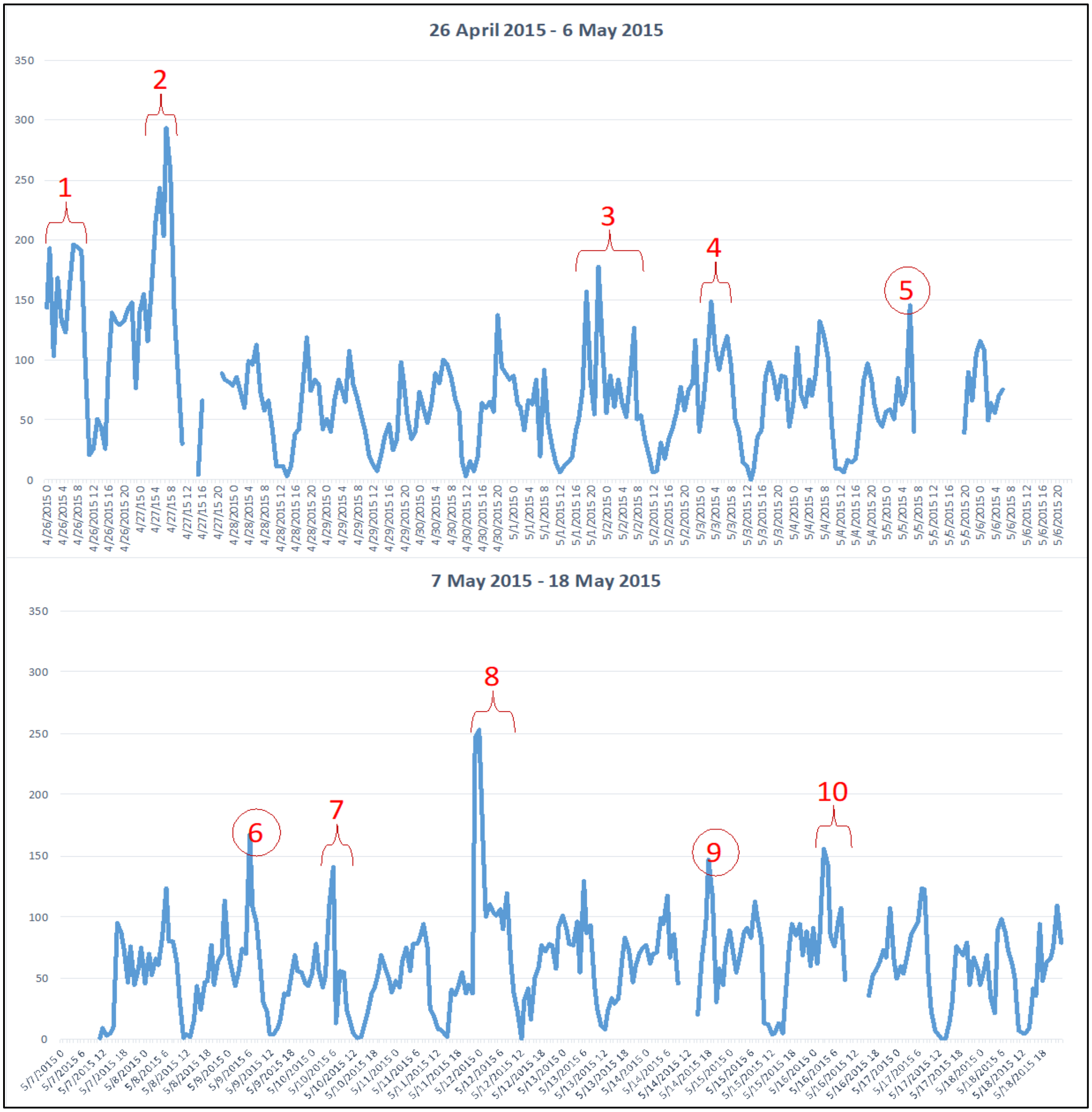

FIGURE 1 Timeline showing major peaks in Twitter activity for the Nepal case study during 26 April - 18 May 2015.

On 26 April 2015, the first peak in tweets was between 0000 and 0100 hours, which is within the same hour that the first of two major aftershocks occurred, the avalanche on Mount Everest and then the landslide on the Koshi highway. The Twitter activity continues to follow real world events, just as reported from the Government of Nepal in the After-Action Report *(18)*, the USGS (United States Geological Survey 2015) *(25)*, and the UNHCR (The United Nations Refugee Agency 2015) *(26)*. The following list corresponds to the red numbers in Figure 1.

1. 26 April 2015 0000-0900: first of two major aftershocks at 6.7Mw (occurred at 00:09); avalanche on Mt. Everest and landslide on the Koshi highway smaller aftershocks experienced throughout the morning

2. 27 April 2015 0000-1000: multiple aftershocks early in the morning ranging from 5.1Mw to 4.1Mw
3. 1 May 2015 1600-2 May 2015 0900: first aftershock at 5Mw after a couple of days
4. 3 May 2015 0000-0800: smaller aftershocks throughout the day ranging from 4.5Mw to 4.2Mw; #gohomeindianmedia becomes a trending hashtag
5. 5 May 2015 0600: flash flood surged the Seti River and caused a landslide
6. 9 May 2015 0600: Natural Resources Conservation Service (NRCS) volunteers deploy in Nepal to support relief efforts; cricket match for the 2015 Indian Premier League
7. 10 May 2015 0500-0600: aftershock of 4.2Mw
8. 12 May 2015 0000-1000: second of two major aftershocks at 7.3Mw (occurred at 0005); aftershocks continued throughout the entire day (0017 - 2353) ranging from 6.3Mw to 4.1Mw; US helicopter carrying six Marines and two Nepalese soldiers crashed during a humanitarian mission
9. 14 May 2015 1800: aftershock of 4.9Mw occurred at 1842
10. 16 May 2015 0300-1000: aftershock of 5.7Mw occurred at 0434 followed by two more aftershocks in the evening

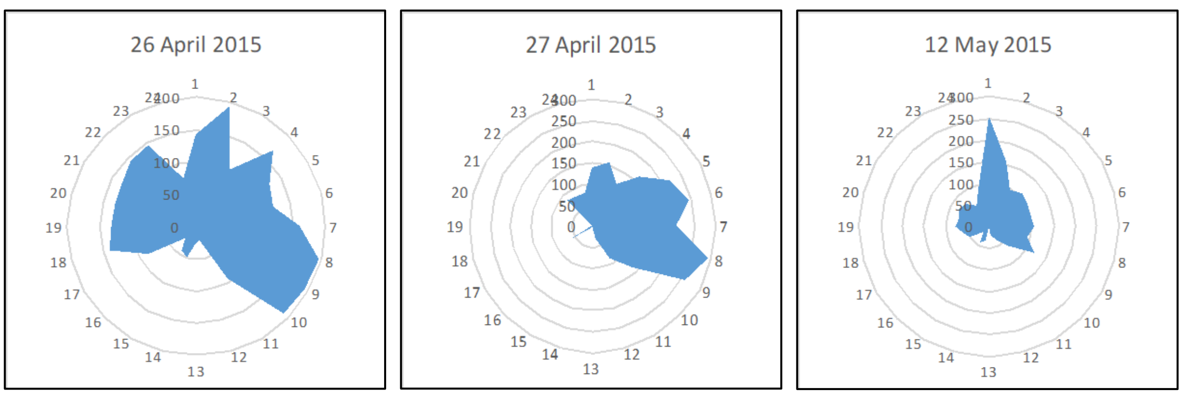

FIGURE 2 Radar graphs depicting the frequency of Nepal tweets count by hour for the dates April 26 and 27 and May 12.

In Figure 1, the highest peaks in Twitter activity are on April 26 and 27 and May 12. To have a more in-depth grasp as to why the Twitter activity is high on these dates, this study creates an hourly radar graph to visualize these temporal patterns. Trends in Twitter activity corresponding to real world events are observed in the Nepal dataset. Referring to Figure 2, there are three days, April 26 and 27 and May 12, with the highest peaks in the number of tweets. The three days with the highest peaks in Twitter activity show that not only do tweets increase during the day of specific disaster events, but also within the exact hour. The radar graphs show increases in twitter activity quickly following aftershocks that occurred. On April 26, the first major aftershock occurred at 0009 and not long after that event, the radar graph shows a spike in Twitter activity. Similarly, the second major aftershock occurred at 0005 and the radar graph shows a spike in Twitter activity around that time.

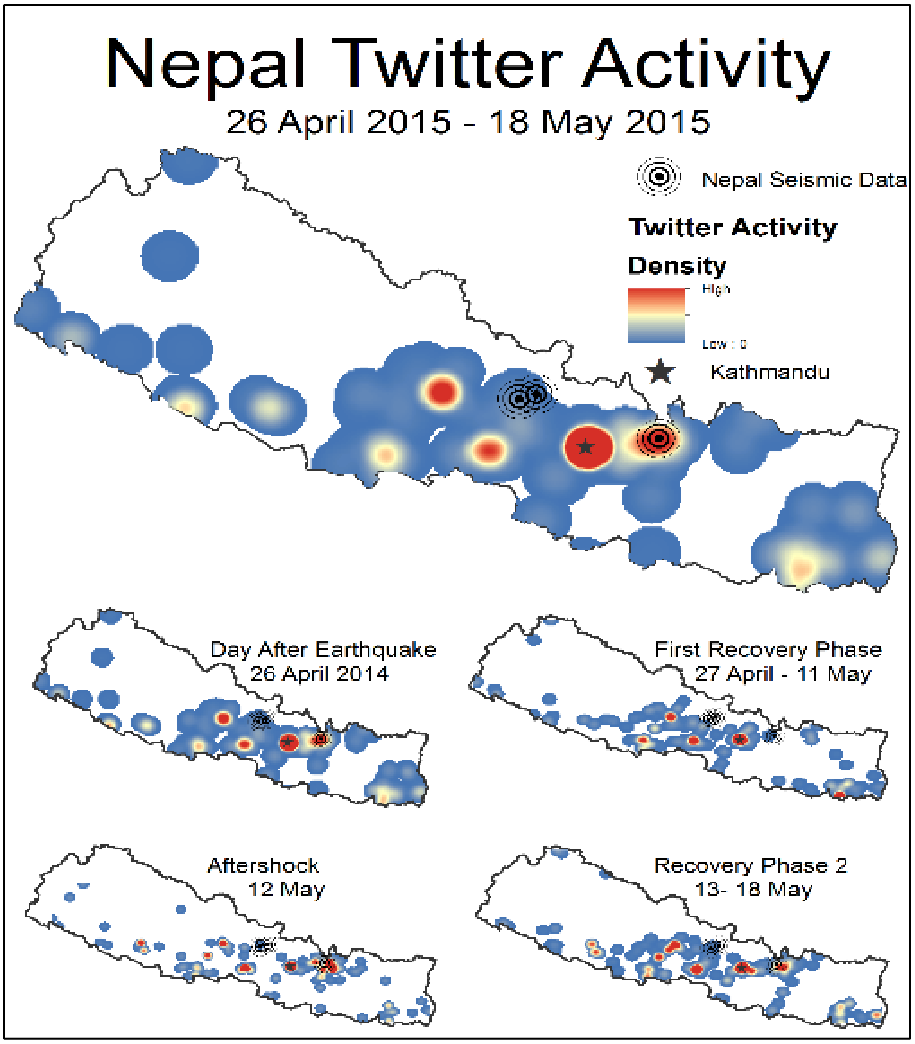

FIGURE 3 The Twitter activity for the Nepal case study depicted using hotspots created with the Kernel Density tool available in ArcMap. The blue regions represent lower densities of Twitter activity, while the red regions represent higher densities.

When researching spatial distribution and temporal trends, it is important to utilize geovisualizations so that spatial patterns can be identified. Without these visualizations, spatial patterns would remain hidden behind numerical values. Figure 3 shows the Twitter activity throughout the timeline of the Nepal case study. There are different phases at which the country found itself after the earthquake; they are categorized as the day after the earthquake, the first recovery phase, May 12 aftershock, and the second recovery phase. Displaying the datasets in this manner bring temporal trends into a new light by showing how the Twitter activity changed through space and time.

The differential maps in Figures 4 used the hotspot maps for the Twitter activity on the day after the initial earthquake (April 26, 2015) as Map A and the first recovery period (April 27- May 11, 2015) as Map B. The differential map is used to further showcase the spatial patterns and temporal trends by comparing the hotspot maps in raster format from the two phases. The color scheme shows blue to display a decreased density in Twitter activity from the first map, yellow shows constant activity between both raster files, and red shows increased densities in Twitter activity from the second map. In Figure 4a, there is intense red areas near Kathmandu, the capital of Nepal, and Gathi, the city on the center of one of the earthquakes; the red areas indicate a high level of Twitter activity in the locations during the first recovery phase, possibly due to power outages on the day after the initial earthquake.

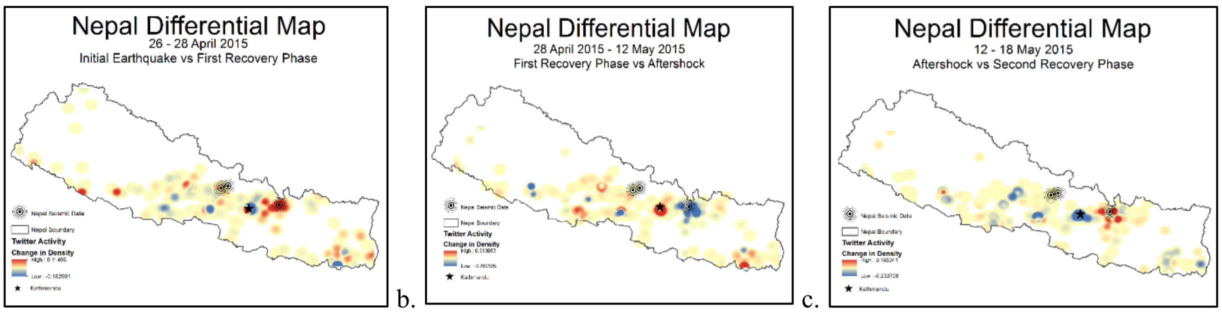

FIGURE 4 Differential map showing the changes in Twitter activity hotspots for the Nepal case study between Initial Earthquake to First Recovery Phase (a), First Recovery Phase to the 12 May Aftershock (b) and the 12 May Aftershock to the Second Recovery Phase (c).

Figure 4 shows the changes from the first recovery phase (April 27- May 11, 2015) to the May 12 aftershock in Figure 4b and shows the changes from the May 12 aftershock to the second recovery phase (May 13-18, 2015 in Figure 4c. In Figures 4b and 4c, similar patterns are revealed in Twitter activity changes between both of the recovery phases and the 12 May aftershock. In both figures, there is high Twitter activity near Gathi, which is located at the epicenter of the aftershock, during the first and second recovery phases. Also, the figures show there is high Twitter activity in Kathmandu on the day of the aftershock (May 12, 2015). While these results may seem to be reversed, the differential maps analyze the overall, aggregated communication during each time-period in the entire country. The capital of Kathmandu has a higher population density than Gathi, resulting in more people tweeting from the capital and having that reflected in the hotspots for each phase.

DATA ANALYSIS: SOCIAL NETWORKS

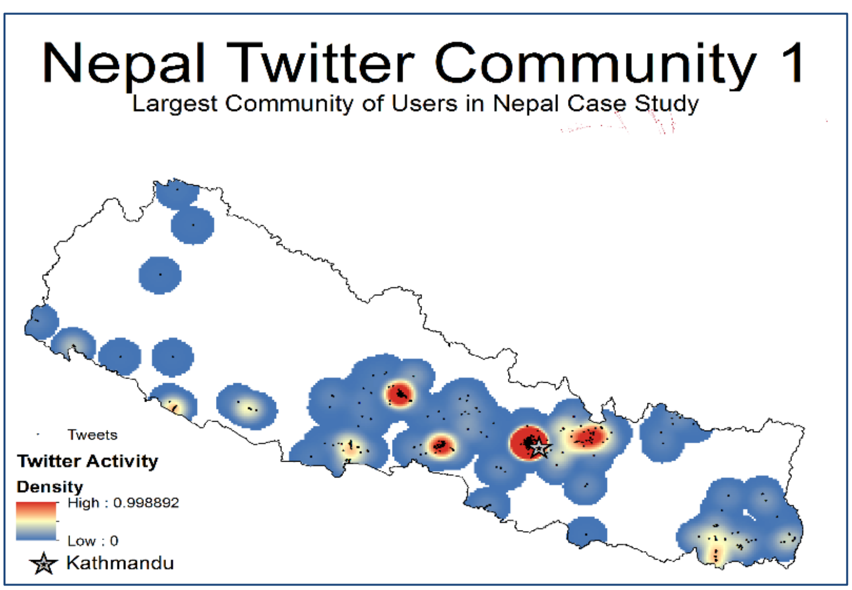

FIGURE 5 Hotspot map of all geotagged tweets and a social network graph of the largest online community in the Nepal case study.

To adapt to this expansion in using social media, such as Twitter, research revolving around using social media data should be refined. The social spatiotemporal perspective for the Nepal case study does just this and focuses on a social network analysis of the dataset. To briefly explain again, in-degree measures the flow of communication from one person to another, while out-degree measures the flow of information coming towards someone; in-degree is the sending of information and out-degree is the receiving of information.

The top three major users with high in-degree are the official accounts of the Prime Minister of India, the Nepal Police headquarters, and a telecommunications company in Nepal. The three users with high in-degree were figures of authority in the area. The Prime Minister (PM) of India, Narendra Modi, was actively using Twitter to communicate with those who were affected by the disaster. Based on the tweets from their official accounts, the Prime Minister of Nepal had been in Bangkok on medical leave and within the hour of the initial earthquake, PM Narendra Modi tweeted in support of Nepal. PM Narendra Modi also used Twitter to communicate openly with PM Sushil Koirala, the Prime Minister of Nepal, so that the general public could follow the latest updates in real-time.

The second highest level of in-degree is the official account of the Nepal Police headquarters located in the capital city of Kathmandu. Although most tweets from this account are in Nepali, there were many tweets that were tweeted in English near the time of the earthquake. According to the Kathmandu Post, the police headquarters were becoming highly active in Twitter to communicate directly with netizens (citizens of the Internet). In this, the Nepal Police could receive information about people who need immediate assistance and then send the appropriate rescue teams directly to the field *(27)*. The Senior Superintendent of Police, Rajib Subba, stated, "There is a convergence of both the physical and the virtual world at this point, and the way to capitalise on it could help coordinate and reach out the affected areas" (Sidgel 2015). Not only did this assist Nepal Police in relief efforts, but also assisted in maintaining the safety of citizens by acting as a method of eyes on the ground. One incident that was reported to the Nepal Police was of a vehicle driving recklessly in attempts to leave the Valley after the earthquake. Through crowdsourcing, the Nepal Police could track down the driver from photos posted online of the vehicle's license plate.

The third user with the highest level of in-degree the official Twitter account for the largest and most prominent telecommunications company in Nepal. After the initial earthquake, there was a surge in communication from people trying to get in touch with loved ones to ensure they were safe. When there is such an increase, the systems that run the lines of communication can become overwhelmed with activity, causing them to work more slowly than usual. They became highly active with using Twitter to communicate with their customers; just like the Nepal Police's Twitter account, most tweets are in Nepali but after the earthquake they posted a few tweets in English giving information on how to communicate more effectively, that they were adding balances to accounts as they ran low, and providing updates and tips on how to make sure the networks did not overload.

Most users with high levels of out-degree are individuals using their personal accounts, so their information will remain anonymous for privacy concerns. The top three users had many tweets in English; they discussed their experiences and carried conversations with other friends in the online social network. The age range for each are within the predominant demographics of Twitter and each of the top three users have high numbers of followers and tweets. These users are important to identify because response agencies can request them to participate in diffusing information during disaster events to ensure that the information can quickly spread to many people. If they assist in information diffusion, there is high potential for the information to travel further and faster in the overall Twitter networks, and even to reach the socially disconnected communities as well.

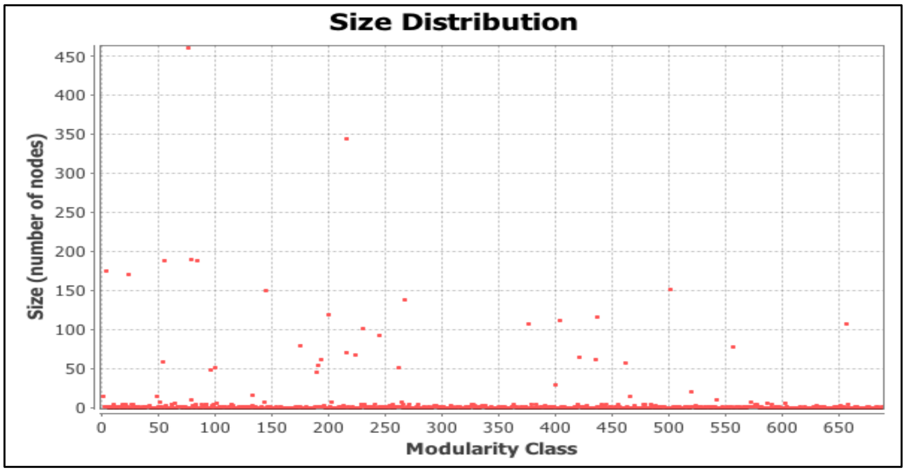

FIGURE 6 Modularity Report provided by Gephi for the Nepal case study.

Figure 6 is based on a Modularity Report from Gephi regarding the connectedness of the online Twitter networks. In this graph, the report shows that there are a total number of 631 communities detected using the modularity algorithm *(29)*. The report also shows that the measurement of modularity for this dataset is 0.767. There are many socially disconnected communities that are detected in the case study and can be identified from the red dots along the x-axis. One of the socially disconnected communities identified in this case study was given a randomly generated Modularity Class ID of 541. This community consists of 12 people who are connected by links of communication. The main three users, User A, User B, and User C, have the highest out-degree in this community, meaning they each tweeted out to the other people. Although the main language in Nepal is Nepali, many of the tweets were written in English. User A tweeted 75 times, which is the highest number of tweets in this community. The reason that User A tweeted so often was because this person was involved in relief efforts and shared their experiences while constantly keeping a positive demeanor. User A began tweeting on May 7, 2015; on May 8, 2015 at about midnight, this user tweeted, "trying to reached d most affected people by #nepalquake.Very bumpy yet narrow road. Relief items should be delivered be4 monsoon for sure." Another tweet posted by User A was the next day on May 8, 2015 saying, "@[username] yup we just arrive around 9 PM today. Indeed .. Give us 3-4 days we will have an effective operation room *wink winkk". The tweets' content remained consistent in providing information about the relief efforts and staying positive throughout the difficult situations. One example is from May 14, 2015 just after midnight: "Indeed, in emengency operation everybody need to keep calm and stay cool :-) #nepalquakerelief cc @[username] http://t.co/7s0jmd1xdp".

User A frequently mentioned User B in the tweets and vice versa. User B did not tweet as often as User A and only shared short personal experiences. From the communication between the two users, it appears they were involved with the same relief efforts. User C only tweeted twice during the case study to share information about the aftermath such as the building damage and status on the lack of shelters. Using this information on socially disconnected communities allows for a comparison between cyberspace and real space by mapping the Twitter activity from each community and defining the hyperlocal relationship that exists between the online and offline communities.

Hyperlocal Relationships

The largest community in the Nepal dataset shows that the hyperlocal relationship is not so strong between the community's relative online community and its offline geographic locations. The highly dense regions in the map in Figure 3 are major cities throughout Nepal that experienced the magnitude from the earthquake and aftershocks. To the northeast of Kathmandu, the dense region is where the epicenter of the major aftershock on May 12, 2015 occurred; this is the reason for the peak in Twitter activity in that region. If the hyperlocal relationships are seen from a step back, there are strong relationship patterns that emerge based on a city-level. The highly dense areas are located in more densely populated cities; when the hyperlocal relationship is defined based on city-level relationships, there is great potential for community resilience to be improved by people working together in their cities. Moving from a city-level analysis, understanding individuals' movements can help in knowing how resilience can be further improved since this offers a glimpse into how people behave during disaster events and what influences their behaviors.

Trajectories of Individuals

Analyzing the trajectories alongside of tweet content shows how and why people move during a disaster, and can help decision makers know where to set shelters and distribute aid or relief efforts. Understanding the movements of people in the event of a disaster and during the recovery phase can provide insight into how to treat efforts during preparedness and recovery. After selecting 20 users based on their number of tweets and locations, the content of their tweets was analyzed. Many tweets were in English and indicated that each person was either affected by the earthquake or was helping with relief efforts in their communities. In Nepal, there is a need for improvements in communication for disasters that may occur in the future *(28)*, so beginning with the procedures using social media is a good start since its usage constantly increases during disasters *(15) (5) (6) (7) (8) (9) (13) (16)*. Figure 7 illustrated an example of a user's trajectory in our case study using geotagged tweets. We have applied geo-masking methods to randomize the actual geolocations using 50-meter buffer to protect users' locational privacy. Twitter content mainly revolved around sharing the experiences of being in an affected community during the Nepal earthquake and aftershocks. The first tweet collected in this dataset from this person was on April 27, 2015 saying, "The earthquake in Nepal is probably the worst thing i have face in my entire [#] years". This person had tweeted many times and on the same day he/she had tweeted "Its really sweet of you guys praying for my country. The situation is settling down but there are a lot of damages. My house is also damaged". Another tweet from the same user on April 27, 2015 was, "@[another user] my house is all cracked up. Earthquake almost destroyed it. But i am staying in my brothers house so its safe rn".

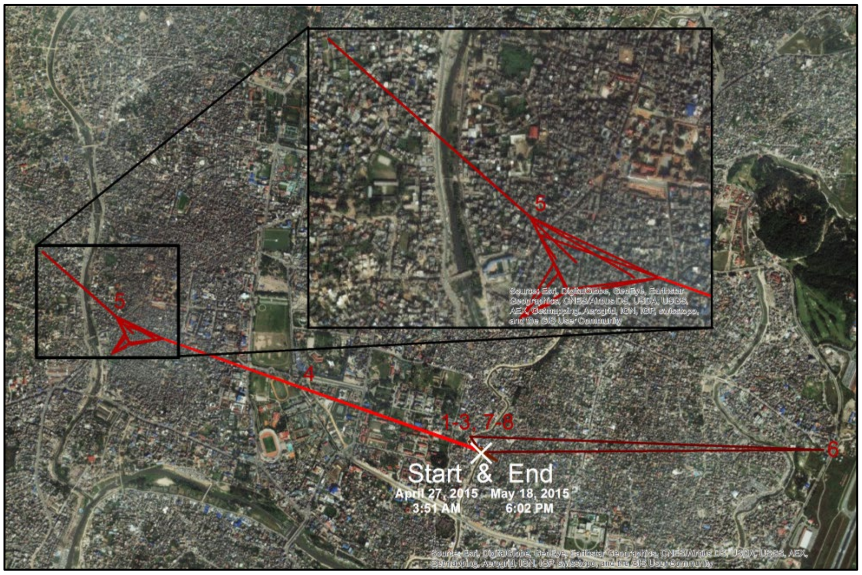

FIGURE 7 Trajectory of one user in the Nepal case study using geotagged tweets. The flow of trajectory shows the temporal changes of the person's movements (1, 2, 3, 4, 5, 7, 8, 9). (Start: April 27, 2015, End: May 18, 2015 at the same location).

CONCLUSION

In this research, the major focus is to understand the spatiotemporal patterns and structure of online networks from communication that occurred over Twitter during the 2015 Nepal Earthquake. The use of social media data from Twitter as a source of Big Data was collected from the 2015 Nepal earthquake. This insight has the potential to help increase local community resilience during disaster events. For this case study, Twitter data was collected from before, during, and after the disasters so that the structure of online communities, spatiotemporal patterns, socially disconnected communities, and hyperlocal relationships could be identified and measured. This research also sought to understand patterns in the case studies' socially disconnected communities.

The two main methods of analyses utilized in this research were spatiotemporal analysis and social network analysis. Through the spatiotemporal analysis, it was noted that the changes in Twitter activity corresponded to events that were reported by the Government of Nepal's Ministry of Home Affairs in their After-Action Report and to aftershocks recorded by the USGS and the UNHCR. In addition, the differential maps showed that the highly populated regions in Nepal had a constant level of Twitter activity, and on the day of the May 12 aftershock, the population near the epicenter in Gathi, Nepal had an increase in the density of Twitter activity. Through social network analysis, it was noted that the influential users were the Prime Minister of India who played a significant role in distributing aid to Nepal, the Nepal Police Headquarters, and Ncell who is the leading telecommunications company. Most social links between people in both online social networks were due to retweets from influential users. Social network analysis also included an examination of the social disconnected communities. The socially disconnected communities mainly comprised of people mentioning other people (mostly friends) instead of retweeting from the overall networks. Finally, the hyperlocal relationship was also included in the examination of social networks. The hyperlocal relationships were defined by mapping the Twitter activity from the community and comparing the spatial distribution of tweets within a community. Tweets that are closer together in geographic proximity represent communities with a hyperlocal relationship.

The hyperlocal relationships were weak in the overall networks because influential users, such as the Prime Minister of India, have wider audiences of followers across large geographic areas.

As we are in a quickly advancing technological age where social media and forms of communication continue to expand every day, it is the responsibility of researchers to learn how to incorporate these changes to improve methods in disaster management. Communication and interactions are two of the major driving forces in human life; the need to communicate with loved ones increases significantly in the event of a disaster. One of the first things that people do when they hear about a disaster is to communicate with other people to make sure they are safe, find out more information, and see how to proceed in the upcoming recovery phase. With advancements and increases in social media use, this method of communication allows people to transcend the barriers of geographic proximity to communicate with others despite their location. Methods of communication progress alongside with advancements in technology and infrastructure; this means that some areas in the world have more access to different forms of communication, like social media. However, not only does the general public's need for communication increase after a disaster, but the same applies to first responders. Their needs are to determine the extent of the disaster and to gain situational awareness. The need for better communication during disaster events is imperative for better disaster management, for saving lives, and for increasing community resilience. Dispersing emergency-related information to the general public and/or affected communities in times of crisis has many difficulties since most disasters are unique and methods of communication change constantly. Due to these difficulties, there remains significant gaps in communication between response institutions and affected communities, and understanding how information about preparedness and disasters spread. This can be mitigated with the incorporation of social media data in preparedness and relief efforts. The potential is limitless, especially when combined with GISciences, so if it can be harnessed now then the future of research can be changed.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Dozier, McFarland, Tsou; data collection and cleaning: Dozier, McFarland, Tsou; analysis and interpretation of results: Dozier, McFarland, Ghanipoor Machiani, Nara, Yang, Tsou; draft manuscript preparation: Dozier, McFarland, Ghanipoor Machiani, Nara, Yang, Tsou. All authors reviewed the results and a pproved the final version of the manuscript.

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