Empowering Disaster Response with Social Media and GeoAI: Opportunities and Challenges

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Introduction

Due to the increasing incidence of natural hazards and population growth in hazard-prone areas worldwide, research and practices on improving disaster resilience have gained significant attention from various disciplines, government agencies, and the public (Cai et al. 2018). Disaster resilience varies by location and can be vastly enhanced through effective disaster response, i.e., accurately and rapidly identifying affected people, communities, and infrastructures, and providing immediate assistance. Therefore, disaster response research is of high societal relevance, and findings from this theme would significantly improve social and economic well-being.

Disaster response relies heavily on real-time information describing on-site disaster impacts, which is difficult to obtain during natural hazards. The widely adopted social media offers a unique lens to observe disaster impacts in real-time. Social media such as Twitter provides a convenient platform where users can access, share, and exchange hazard information, ask for assistance, and report local damages and conditions (Zou et al. 2018). Responding agencies and volunteers can monitor user-generated information from social media to infer disaster impacts in real-time and send help. Consequently, the popularity of incorporating social media data and platforms into disaster response continues to grow (Mihunov et al. 2020).

However, extracting valuable, fine-grained geographical information from social media data for disaster response is challenging mainly because of technical difficulties processing such big, biased, and noisy data. The breakthroughs in geographical artificial intelligence (GeoAI) provide solutions. Recent studies have demonstrated that newly developed GeoAI algorithms outperform traditional methods in several tasks relevant to social media uses for disaster response, e.g., place name recognition (Wang et al. 2020) and text classification (Zhou et al. 2022). Thus, analyzing social media data with novel GeoAI algorithms is promising in identifying location-based disaster impacts precisely and can play a vital role in effective disaster response.

This research elaborates on the opportunities and challenges of analyzing social media data with GeoAI in disaster response. We investigated Twitter use during 2017 Hurricane Harvey as a case study to fulfill three objectives: (1) to develop a GeoAI-empowered framework for location-based social media analytics; (2) to demonstrate the applications of analyzing social media in supporting disaster response, including monitoring situational awareness, assisting emergency rescue, and estimating disaster damages; (3) to pinpoint the challenges of using social media in disaster response and propose solutions. This research will significantly advance the methods and applications of GeoAI and location-based social media analytics. The knowledge gained from this study will shed valuable insights into strategies to reduce disaster impacts and build resilience for vulnerable communities.

Method

Twitter data during 2017 Hurricane Harvey were initially collected through Twitter's Application Programming Interface (API). The GeoAI-empowered social media analytics framework consists of three modules, intelligent classifier, geoparser, and text-analyzer. The classifier is used to identify disaster-related messages and categorize them into themes, e.g., help/rescue requests, emergent resources, and damages/impacts. The geoparser is designed to determine the location of each tweet considering geotag, content-mentioned location, and user profile address. The text-analyzer mines in-depth information from tweets of interest to support downstream applications, including situational awareness monitoring, harvesting rescue requests, and assessing disaster damages.

Situational Awareness Monitoring

Whether a community or an individual is sufficiently prepared for an impending disaster depends on if they can access the needed information and perceive the risk, broadly defined as Situational Awareness. Situational Awareness can be measured through Twitter by the Ratio index, which is defined as the number of disaster-related tweets in an area divided by the total number of background tweets in the same area within a period. Its values range from 0 to 1. The Ratio index has been suggested for damage estimation, recovery monitoring, and vulnerability and resilience assessment (Zou et al. 2019; Wang et al 2021).

$$Ratio = \frac{Disaster\ Related\ Tweets}{Background\ Tweets}$$

Harvesting Rescue Requests

Collecting rescue requests from social media takes three steps. The first step, referred to as VictimFinder, is Twitter data classification to identify rescue request tweets. Second, a toponym recognition is used to identify the tweet mentioned locations from the rescue request messages. Finally, the Google API is used as the toponym resolution tool to convert extracted textual addresses into pairs of coordinates. This study designed two models to identify rescue request messages and addresses in those messages by leveraging the latest natural language processing model, Bidirectional Encoder Representations from Transformers (BERT).

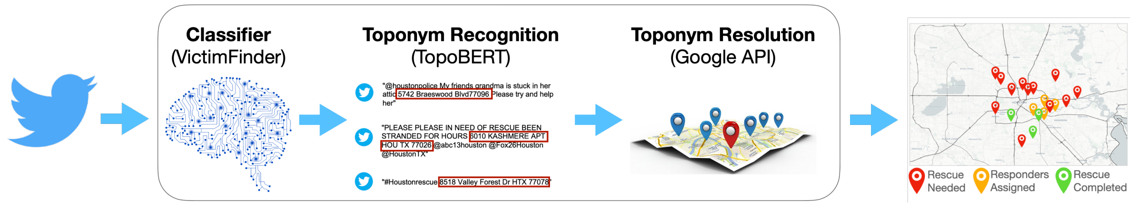

Figure 1: The workflow of harvesting rescue requests from Twitter data.

Assessing Disaster Damages

Figure 3 shows the workflow of integrating Twitter data with building footprints, elevation, and precipitations for rapid damage estimation. The equation below was used to assess if one household was affected by Hurricane Harvey. If the sum of elevation and rainfall depth of the building i is higher than the sum of the two values of the nearest rescue request, the building is labeled as flooded. Otherwise, the building is labeled as non-flooded.

$$flooded_i = \begin{cases} 1, & elevation_i + rainfall_i \geq elevation_0 + rainfall_0 \\ 0, & else \end{cases}$$

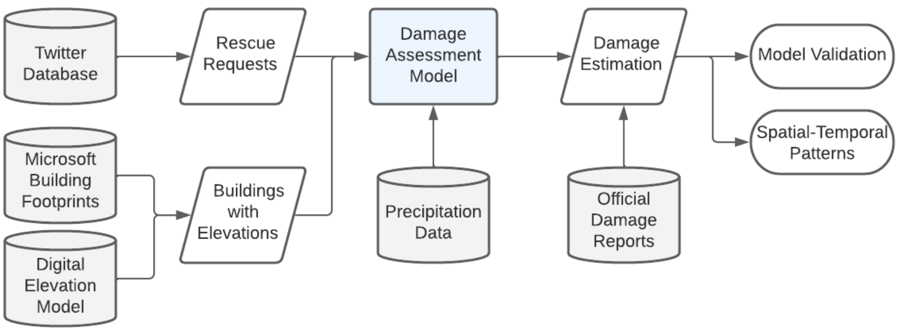

Figure 2: The workflow of using Twitter data for rapid damage estimation.

Results

Situational Awareness during Hurricane Harvey

The situational awareness reflected on Twitter during Hurricane Harvey is displayed in Figure 3. In the United States (Figure 3 left), most of counties with high Ratio index values were concentrated along the Texas coastline, including the metropolitan areas of Corpus Christi, Houston, and San Antonio. Zooming into the severely affected area and tabulating the tweets into three phases (preparedness, response, and recovery) reveals more information on how public awareness changed through the three phases (Figure 3 right). In the affected areas, higher Ratio index values were found mainly in the Houston metropolitan areas in the response phase.

We conducted stepwise linear regression analyses between Ratio indexes and 17 selected social-geographical variables at the three phases and for the entire period to test if communities with better socioeconomic conditions had more disaster-related Twitter use in all three phases of emergency management. The results confirm that Communities with higher situational awareness during Harvey generally were communities of better social-geographical conditions.

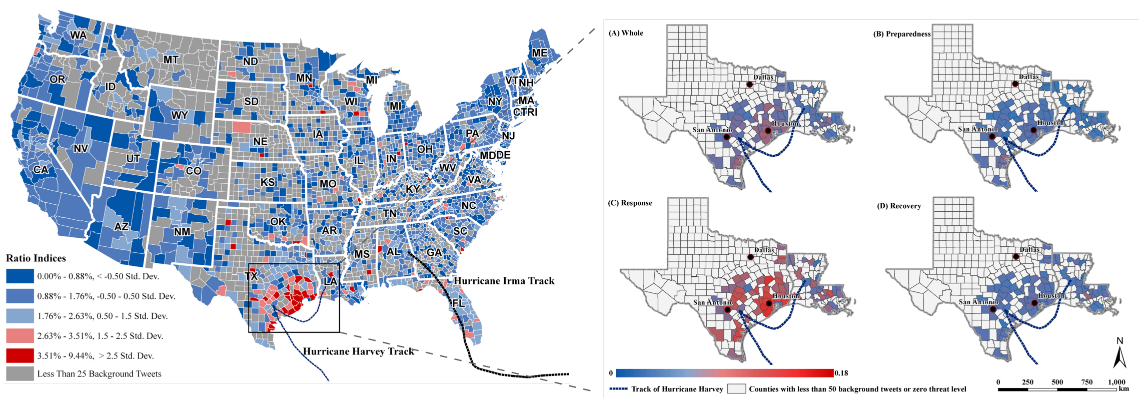

Figure 3: County-level Ratio index in the U.S. and affected communities during Harvey.

Rescue Requests during Hurricane Harvey

A total of 824 unique addresses having residents requesting rescue on Twitter were harvested. Figure 4 depicts the spatial patterns of those rescue requests during Hurricane Harvey. The rescue request locations are distributed unevenly with three hotspots based on the point density. A further examination of the geographical and socioeconomic status of communities where people sent rescue requests found that most of them had below-average elevations, received more rainfall from Harvey, and had more socially vulnerable populations. In addition, we analyzed the tweet contents and identified the challenges of using social media for rescue, including users' lack of knowledge on how and who to ask for help online and the need for tools to collect and process rescue requests on social media efficiently.

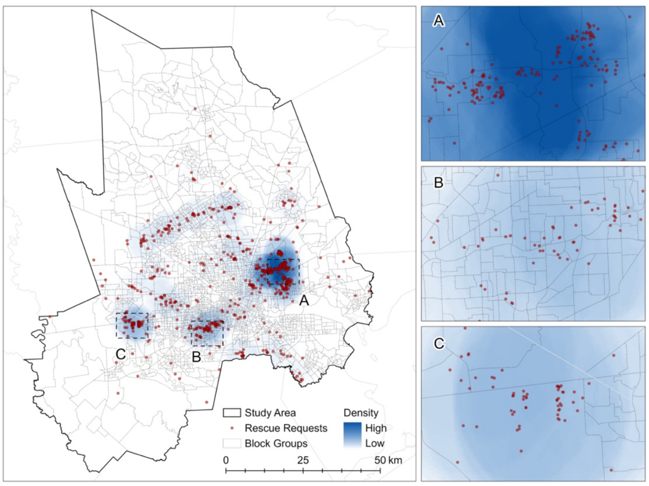

Figure 4: Rescue requests in Houston on Twitter during 2017 Hurricane Harvey.

Damage Estimation

Figure 5 reveals the estimated affected households during Hurricane Harvey through Twitter data. Three significant results were discovered. First, the developed model can accurately identify affected households during hurricanes. The estimated affected households highly agree with the official damage report at the block-group level. Second, the model performs better in communities closer to the locations of people requesting rescue or reporting damage on Twitter, demonstrating the importance of ground-reference data in rapid damage estimation. Finally, the developed model reveals overlooked communities in official damage reports. For example, some communities in the rural areas had people requesting rescue or reporting damage on Twitter but were labeled as having no damage in the official assessment. There is an urgent need to incorporate damage information collected from sources like social media to supplement the official damage estimation process and enhance equality in disaster management.

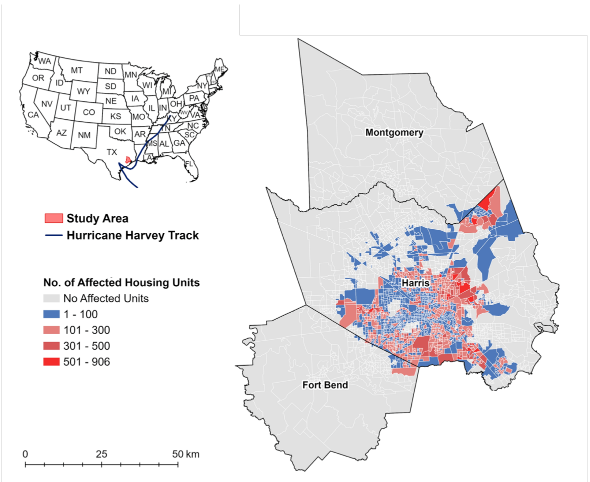

Figure 5: Rescue requests in Houston on Twitter during 2017 Hurricane Harvey.

Discussion and Conclusion

This study established a GeoAI empowered social media analytics framework and applied it for disaster response. Using Twitter data during Hurricane Harvey as a case study, three applications were demonstrated, including monitoring situational awareness, identifying rescue requests, and assessing disaster damages.

However, this study also unravels a few challenges of using social media and GeoAI in supporting disaster response, which necessitates further investigations. First, social media data are biased toward the younger population from communities with better socioeconomic characteristics. Consequently, vulnerable social groups with limited access to social media platforms may be overlooked if disaster response relies only on the information from social media. Second, although GeoAI algorithms can render state-of-the-art performance in analyzing social media, relying entirely on AI algorithms' knowledge may be risky. For instance, although the developed VictimFinder model can capture 92% of rescue requests on Twitter, which is higher than any other classification model, it misclassified 8% of rescue requests from people who need evacuation. Third, social media platforms are awash with noisy information, including fake news. Finally, social media data sharing policies have been changing through time, while users' preference for social media platforms is dynamic. Therefore, finding pathways to establish stable collaborations to transform research outcomes into generalized useable tools on social media platforms is urgently needed.

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