# Social Media Analysis in Sudden Onset Disasters and its Usefulness for Decision Makers - Excerpt of a Scoping Review

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## ABSTRACT

**Problem:** Despite the potential of artificial intelligence for rapid social media analysis, practical implementation remains limited. **Approach:** We conducted a scoping review using iteratively developed search terms in two electronic databases. We then conducted a descriptive and thematic analysis to capture the key concepts, findings and methods in the literature. **Results:** After reviewing 130 papers, 27 papers were identified that met our inclusion criteria. Four key themes emerged, including tool development, tool performance comparison, gaining insights from social media data, and usefulness for decision makers. **Conclusions:** While acknowledging the importance of integrating social media into crisis and disaster management, there is a lack of empirical evidence on data reliability and preparation for decision makers. More empirical studies on social media analytics, specifically focusing on usefulness for crisis and disaster management, are recommended.

### Keywords

scoping review, social media, crisis and disaster management, sudden onset disaster, evidence

## INTRODUCTION

Effective disaster relief and management requires a comprehensive understanding of the disaster situation (Fan et al., 2020). As the frequency and intensity of crises and disasters increases, decision makers' knowledge of the situation is becoming ever more important to enhance the effectiveness of response and recovery efforts. Decision makers in the context of crises and disasters are individuals or entities responsible for making critical decisions related to emergency response, recovery, and management. In the digital age, social media (SM) has evolved beyond its role as a platform for personal exchange to become a valuable source of information that can reflect the collective intelligence of the public (Lang et al., 2020). Gaining insights into people's perceptions, reactions and behavior on SM can contribute significantly to crisis and disaster management (Z. Wang & Ye, 2017). Acknowledging the collective intelligence of the public as reflected in social media is a key aspect. This connects with broader discussions on Open Source Intelligence techniques, citizen engagement, and the potential for harnessing distributed knowledge during crisis situations (Pastor-Galindo et al., 2020). However, the sheer volume and variety of information on SM makes manual processing in real time almost impossible (Avvenuti et al., 2015). To overcome this challenge, various artificial intelligence techniques have emerged that offer the possibility of efficiently classifying, analysing and visualizing SM data. This aligns with broader research on the application of AI in disaster response, including natural language processing, machine learning, and data visualization (Abid et al.,

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2021; Fan et al., 2020). The passive collection of information, i.e. without active participation in the conversation or demand for information, allows topics and problems relevant to the population (Ghermandi & Sinclair, 2019). Passive information gathering aims to use existing data sources without disrupting user activity. While numerous studies have examined the technical implementation of these techniques, the integration of SM insights into the overall picture of the situation remains limited in practice due to the complexity of existing algorithms and the lack of comprehensive software solutions. Due to the high number of scientific publications in the field of SM analysis in crises and disasters, there is an increasing need for overviews. However, existing reviews focus unidimensionally on thematic or methodological orientations of the evidence, so that the temporal dimension and usefulness for decision makers are not explicitly considered (Acikara et al., 2023; Luna & Pennock, 2018). This review aims to fill this gap by capturing the available evidence, including the temporal dimension, and providing an overview of the use of passive information gathering from SM for crisis and disaster management in sudden onset disasters. The following research questions guide this review paper:

**RQ1.1** How does the number of publications about social media analyses related to the support of decision makers during sudden onset disasters vary over time?

**RQ1.2** On what data are the publications on social media analytics related to supporting decision makers during sudden-onset disasters based, taking into account the evolution over time?

**RQ2** What methods are used to obtain information from social media to enhance the situation picture for decision makers in sudden onset disasters?

## METHODS

A scoping review was used to capture the key concepts, main sources and types of evidence available in the literature on the passive extraction (observing without active communication) of information from SM in sudden onset disasters for decision makers in crisis management teams and consequently to complement the situational picture. Sudden-onset disasters are events that occur suddenly and unexpectedly, usually with little or no warning, and have an immediate and severe impact on communities and infrastructure, i. e. earthquakes and floods. The focus is intended to provide an overview of direct practical implications and options for disaster management decision-makers in time-critical contexts. The review was based on the methodological guidance for scoping reviews according to the Joanna Briggs Institute (JBI) (von Elm et al., 2019) and conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR guidelines) (Moher, 2009). The overarching research project *#sosmap* focuses on the state of the art regarding the passive derivation of information from SM on the psychosocial needs and resources of the population in any crisis and disaster situation. This work-in-progress paper presents a subset of the results in relation to the knowledge gained from SM for decision makers in sudden onset disaster. As scoping reviews aim to provide an overview of the available evidence, regardless of methodological quality or risk of bias, no critical appraisal was undertaken.

### Search Strategy

In several iterations, we have developed a search query that covers a range of terms defined by three key topics: (a) SM, (b) decision making and (c) crises and disasters. Two databases were searched from the beginning: IEEE Xplore (until 20.07.2023) and Web of Science (WoS) (until 09.08.2023). When selecting the databases, WoS was chosen because of its in-depth coverage (1945 to the present). IEEE was included due to its technical focus. The review focuses exclusively on primary literature, including published research results in specialized journals, databases, and conference contributions. There is no time limit set, and only English-language literature is considered as no german-language literature was available. The focus on sudden onset disasters was realized by manual title and abstract screening. Table 1 lists the search terms using the syntax for WoS, consisting of the linked topic complexes: extraction of information from SM for decision making in crises and disasters.

**Table 1. Key Search Terms**

| Search terms |
|---|
| (”social media” OR ”user-generated data”) (Title) AND (analy* OR monitor* OR ”social listening”) (Topic) AND (crisis OR crises OR disaster* OR emergenc* OR catastrophe* OR ”extreme event*”) (Topic) AND (”situation* assessment” OR ”situation* aware-ness” OR ”decision mak*”) (Topic) NOT (covid-19 OR marketing) (All Fields) |

### Study Selection

Scientific publications addressing the three key topics were reviewed, with a focus on passive data collection and

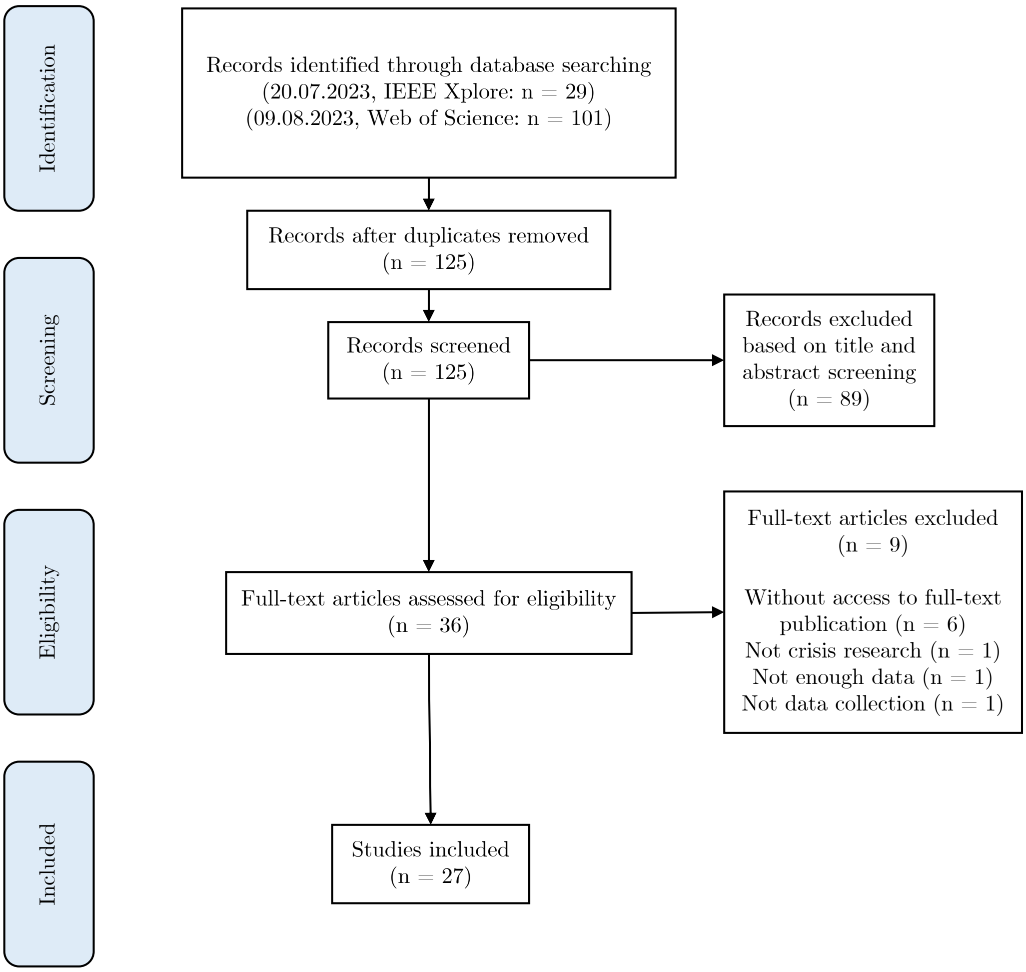



**Figure 1. Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) Flowchart**

analysis via manual, automated, or combined methods. The data sets had to be directly related to sudden onset disasters and support crisis management or complement the situation assessment. Initially, 125 articles were identified, with duplicates removed. Many articles were deemed irrelevant during title and abstract screening, particularly those focusing on active social media engagement or crisis communication. The manual selection of the articles comprised two stages. First, a title and abstract screening was performed to select papers that addressed all three key topics. After the first screening, 36 articles were read in full text. In a second round of full-text screening, data sets were excluded if there was no full-text access and their thematic focus was not sufficiently on all three key topics. A total of 27 studies were identified that were relevant to the research topic. To minimize subjective influences, a second person carried out the two steps on 10 % of the total number of articles. The inclusion and exclusion decisions were identical in 100 % of cases. Figure 1 illustrates the article selection process. The full search protocol is available on request from the authors.

**Data Extraction**
Details of the included studies can be found in Table 2. Here, for each reference included, the disaster analyzed or the data set analyzed, the social media platforms included for data collection, the data analysis methods used and a concise summary of the findings are compiled. Our in-depth analysis of the included literature included an inductive thematic analysis according to Kuckartz to identify, analyze and present recurring focus areas in the articles (Kuckartz, 2018). The derived focus areas are:

- A Development/presentation of tool/framework,
- B Performance comparison of tools,
- C Gaining knowledge from SM (data insights) and
- D usefulness for decision makers.

The presentation of the descriptive summaries takes into account the time dimension.

## RESULTS

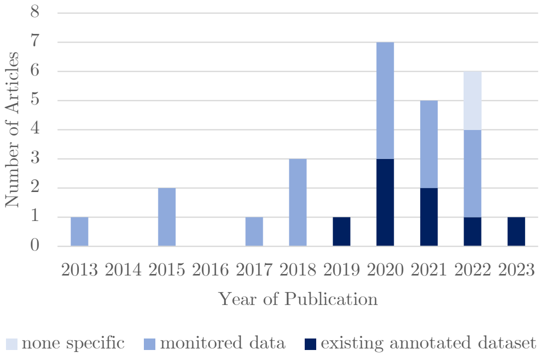
As part of the inclusion and exclusion process, only articles with a publication date after 2013 were integrated. The importance of integrating SM into crisis and disaster management is clearly emphasized by all papers reviewed and beyond. However, very few papers focus on what decision makers really need and adapt the analysis accordingly. Many assumptions are made about what information and presentation methods would be helpful.

### Data-specific Consideration

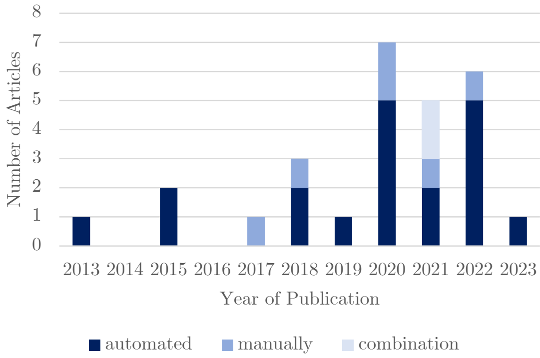
The findings reveal that 63 % of studies relied on monitored data, with annotated datasets comprising 30 %. Notably, the prevalence of existing datasets emerged since 2019. Key datasets included Crisis Benchmark Dataset, CrisisNLP, CrisisLex, MediaEval, European Flood 2013 dataset, Harvard Dataverse, and Hurricane Harvey Twitter dataset, with CrisisNLP being the most used. There's a shift towards utilizing existing and annotated datasets, suggesting a common training basis for models. Figure 2a depicts the trend in data source usage over time. The differentiation was made between already publicly available, annotated datasets of social media data ("existing annotated datasets") and data collected by the authors themselves ("monitored data"). Regarding data formats, 48 % of integrated studies ($n_{total}$ = 27 articles) exclusively used text-based data, while 22 % focused solely on image-based data. Since 2020, there's been a rise in combining text and image data (30 %). The analysis of disaster types showed that 70 % of the studies ($n$ = 19 articles) focused on natural disasters, of which 31.6 % ($n$ = 6 articles) considered several types of natural disasters. Only one study focused on man-made disasters, while 11 % did not focus on a specific crisis and 15 % analyzed several types of disasters. Twitter was the most studied platform (63 %), with Sina Weibo in 7 % of studies. Additionally, 30 % of the studies examined various sources of social media data, including but not limited to Facebook, Instagram, and YouTube. Over time, it can be seen that the consideration of several platforms in one study shows an increasing trend and the singular use of data from Twitter shows a decreasing trend. Since 2020, there's been a decline in studies using Twitter as a data source (-1.6 studies per year).

### Method- and Content-specific Consideration

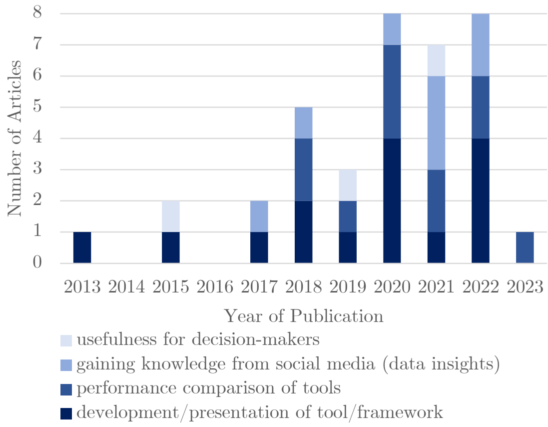
Our analysis revealed that approximately 59 % of articles were case studies. Regarding methodology, 70 % used automated analysis, 22 % manual classification, and only 7 % combined both (Figure 2b). Notable integration of manual and automated analysis is exemplified by Virtual Operations Support Teams (VOST) as highlighted




**(a) Data-specific Consideration (Single Assignment)**




**(b) Method-specific Consideration (Single Assignment)**




**(c) Content-specific Consideration (Multiple Assignment)**

**Figure 2. Stacked Bar Charts of the Considered Articles Integrated into the Review**

by Fathi and Fiedrich 2022. Article foci included tool/framework development (15 articles), tool performance comparison (11 articles), insights from SM (9 articles), and usefulness for decision makers (5 articles). Figure 2c illustrates the distribution of article foci over time. Named Entity Recognition (NER) was the most commonly used algorithm (6 articles), followed by Convolutional Neural Networks (CNN) and Visual Geometry Group (VGG) architectures (5 articles each). However, the temporal distribution of algorithm usage did not provide further insight into preferences over time.

## DISCUSSION OF THE RESULTS

Existing reviews lack a temporal dimension linked specifically to SM in sudden-onset disasters. Therefore, we addressed these gaps by focusing on publications about SM analyses supporting decision makers during sudden onset disasters over time.

**RQ1** The analysis reveals a substantial number of studies (63 %) focusing on passive information extraction from SM, primarily from Twitter, with a decreasing trend observed, especially since 2020, possibly due to API changes. Due to the complete switch from Twitter to X and clear restrictions in the API terms and conditions, there could be a further decline and an increased focus on existing data sets in the future. While text-based data remains prevalent, there is a growing trend, particularly since 2020, towards combined analyses of various data formats. Surprisingly, only one study integrated man-made disasters, with a predominant emphasis on natural disasters. Since 2019, there has been an increasing reliance on existing datasets, facilitating more comparative analyses across different crises.

**RQ2** The surge in dataset usage is accompanied by a heightened emphasis on comparing different artificial intelligence (AI) techniques, particularly since 2018. However, there is limited consideration of manual classification in comparative or combined methodologies. While concepts like VOST appear promising (Fathi & Fiedrich, 2022), their validation involving decision makers is lacking. Instead, the focus tends to be on understanding crisis situations rather than collaborating with decision makers.

However, our review has limitations. Snowballing was not employed to identify additional literature, potentially restricting the scope. Additionally, screening was not conducted by both examiners for all titles, abstracts, and full texts, possibly leading to omissions. Furthermore, qualitative content analysis for data extraction was performed by both examiners only about 40 % of the time, introducing potential bias. Lastly, our focus solely on sudden-onset disasters may limit the generalizability of our findings.

However, our findings reveal similarities with existing reviews and studies. For example, Karimiziarani (2023) and Kondraganti (2021) emphasize the potential of integrating multimodal data sources, including SM, to improve disaster response efforts. They highlight the importance of ethical considerations and privacy concerns in SM analytics research, advocating for further research to ensure responsible SM data use.

## CONCLUSION AND FUTURE OUTLOOK

In this scoping review, we aim to provide a overview of the current state of research regarding passive information extraction from social media (SM) in sudden onset disasters for decision makers. By considering the temporal dimension, we seek to identify the current trends in scientific inquiry.

Looking ahead, it is imperative to shift towards addressing the needs of decision makers during crises and disasters, facilitating the translation of research into practical applications. While numerous articles detail the technical implementation of information extraction from SM, there is a dearth of evaluations targeting the intended user group. Future efforts should prioritize comparative presentations of algorithms and evaluation indicators, such as accuracy and performance, with a clear delineation of their intended use.

This work-in-progress paper offers a glimpse into the ongoing evidence presentation within the research project #sosmap. The forthcoming analysis will delve deeper into an expanded database, implementing an enhanced search strategy focused on deriving psychosocial needs/resources, sentiment, and other factors in various crises.

**Table 2. Overview of Selected Article Characteristics**

| *No./ Focus* | *Reference* | *Disaster/ dataset* | *Platforms* | *Data analysis methods* | *Summarized results* |
|---|---|---|---|---|---|
| 1/ B | Alam et al., 2023 | Crisis Benchmark Dataset | Twitter | automated (ResNet18, ResNet50, ResNet101, AlexNet, VGG16, DenseNet, SqueezeNet, InceptionNet, MobileNet, EfficientNet) | Optimization of the algorithms is possible through training using consolidated data sets. Based on performance and computational effort, EfficientNet is the best option for real-time applications. |
| 2/ B | Asif et al., 2021 | CrisisMMD (CrisisNLP) | multiple | automated (YOLOv4, YOLOv3, VGG16) | With an accuracy of 96 %, YOLOv4 shows better results than YOLOv3 for categorizing images. |
| 3/ A | Avvenuti et al., 2015 | Earthquake, Italy, 2012; Flood, Italy, 2014 | Twitter | automated (WEKA, NLP, MLR) | Strong earthquakes can be identified by monitoring SM. The algorithm used showed an accuracy of 83.5 % for English tweets and 90.1 % for Italian tweets. In data processing, term clouds contribute to improved situational awareness. |

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**Table 2 – continued from previous page**

| *No./ Focus* | *Reference* | *Disaster/ dataset* | *Platforms* | *Data analysis methods* | *Summarized results* |
|---|---|---|---|---|---|
| 4/ B, C | Dong et al., 2021 | Hurricane Sandy, 2012; Hurricane Matthew, 2016; Hurricane Harvey, 2017; Hurricane Michael 2018; Hurricane Dorian, 2019 | Twitter | combination of automated + manually (manual classification, LR, NB, DT, SVM, KNN, RF, Adaboost, MNN) | SM is seen as an important platform for gathering information about disasters. It was also found that there is a difference between people's basic needs in natural disasters. The performance of the model adapted to the optimal settings is significantly better than the existing and lexicon-based machine learning models. Moreover, Naïve Bayes is the best performing model in terms of classification accuracy, confusion matrix and ROC-AUC graph in our study. |
| 5/ A, B | Fan et al., 2020 | Hurricane Harvey, United States, 2017 | Twitter | automated (NER, BERT classifier) | The integration of NER and Google Map Geocoding API enables advanced georeferencing. The fine-tuned BERT-based classifier performs best in classifying tweets into different humanitarian categories. Credible identification of situational information can be implemented through a graph-based clustering approach. In addition, the suggested pipeline can be used to map the development and geographical distribution of disaster events. |
| 6/ C, D | Fathi and Fiedrich, 2022 | Floods, Germany, 2021 | multiple | combination of automated + manually (ScatterBlogs + VOST) | Information collected by VOST increases situational awareness. The resulting actionable information can contribute to the crisis team's decision-making. Contributions with a potential impact on the health and safety of those affected and image contributions are prioritized higher than others. |
| 7/ C, D | Fromm et al., 2021 | Storm Dragi, Germany, 2019; Storm Eberhard, Germany, 2019 | Twitter | manually (categorization) | Respondents rate the usefulness of traffic information and eyewitness accounts from private individuals the highest. However, the indication of location and an indicator of relevance and trustworthiness is important. Adaptable filter options are proposed in order to do justice to the disparity between individual assessments of different types of tweets. |

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| *No./ Focus* | *Reference* | *Disaster/ dataset* | *Platforms* | *Data analysis methods* | *Summarized results* |
|---|---|---|---|---|---|
| 8/ A, B | Jixian et al., 2022 | none specific | multiple | automated (BiLSTM-Attention-CNN-XGBOOST ensemble model for NN and others) | The BiLSTM-Attention-CNN-XGBOOST model proposed in this paper achieves better accuracy than NB MODEL, Ngrams-TFIDF model, charCNN, wordCNN, LSTM model and RCNN model, regardless of whether it is Chinese or English data from WeiBo, Twitter, Wechat or Facebook platforms. |
| 9/ C, D | Kankanamge et al., 2020 | Floods, Australia, 2010-2011 | Twitter | automated (capture-understand-present framework, DT, WEKA, IDW) | The use of Twitter is a promising approach, not specifically to gather new situational information, but rather to capture citizens' knowledge. Tweets could be used to identify variations in disaster severity over time. The spatial analysis of tweets confirms the applicability of geographically located messages to delineate severely affected disaster areas. |
| 10/ A, B, D | Lazreg et al., 2019 | CrisisLex, CrisisNLP | Twitter | automated (NER, NN, CNTM and others) | The proposed framework for obtaining information from SM provides exactly the information required in 70.09 % of cases. |
| 11/ A, B, C | Z. Li et al., 2017 | Floods, United States, 2015 | multiple | combination of automated + manually (text matching + manual checking and selection + ArcPy, ArcGIS geoprocessing tools) | There was an 83.4 % match between the map developed based on SM data and official flood maps from the USGS (United States Geological Survey). People share more on SM when they are closer to the event and when the extent of flooding increases during the flood event. Twitter activity reflects the extent of flooding in the relevant geographic area with no obvious time lag. |
| 12/ A, B | X. Li et al., 2018 | google image data; Typhoon Ruby/H-agupit, Philippines, 2014; Earthquake, Nepal, 2015; Earthquake, Ecuador, 2016; Hurricane Matthew, 2016 | multiple | automated (VGG19, CNN, DDM, GCAM) | The developed Damage Assessment Value in combination with the Damage Detection Map can help assess the severity of damage and identify and prioritize useful information. In addition, the developed tool provides visual explanations for the suggestions made. |

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| *No./ Focus* | *Reference* | *Disaster/ dataset* | *Platforms* | *Data analysis methods* | *Summarized results* |
|---|---|---|---|---|---|
| 13/ B | Lopez-Fuentes et al., 2020 | MediaEval 2018 | Twitter | automated (double-ended NN and others) | By reducing the number of composite models to 30, the number of networks can be reduced. This makes the solution faster and easier, while at the same time improving the results. |
| 14/ A, B | Mao et al., 2018 | power outage (keywords), United States, 2016 | Twitter | automated (BiLSTM model coupled with a CRF top layer, and others) | The developed algorithm shows a classification accuracy of 86 % in identifying genuine blackout tweets. In addition, about 20 times more tweets can be georeferenced than are already geotagged. Capturing the number of geo-referenced SM data related to the power outage allows to derive the number of people without power. |
| 15/ A, B | Ning et al., 2020 | Floods, United States, 2017; Floods and Florence hurricane, United States, 2018 | Twitter | automated (VGG16 with integrated YOLOv3 object detector and a face recognition model) | In general, the developed RIASM system has the potential to be integrated into conventional flood mapping systems to close knowledge gaps and provide additional evidence of the extent of a disaster (total accuracy of flooding photo detection was 93 %). |
| 16/ B | Pereira et al., 2020 | European Flood 2013 dataset, MediaEval 2017 (YFCC100m), MediaEval 2018 | multiple | automated (DenseNet, EfficentNet, AGDenseNet) | All three models compared showed very similar results. It was found that the number of images available for model training influences the quality of the results. When assessing the water depth, the best results were achieved with the DenseNet model. |
| 17/ A, B | Pohl et al., 2013 | Flood, United States, 2011; Bombing, Norway, 2011; Riots, United Kingdom, 2011; Hurricane Irene, United States, 2011 | multiple | automated (SOM, AC, 2PG, and 2PGT) | Social multimedia in combination with clustering can be used as part of crisis and disaster management to identify partial events. This allows SM to be integrated into crisis and disaster management without the need for time-consuming manual monitoring. AC and SOM can be used in particular for a quick overview, 2PG and 2PGT for a more user-friendly visualization. |

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| No./ Focus | Reference | Disaster/ dataset | Platforms | Data analysis methods | Summarized results |
|---|---|---|---|---|---|
| 18/ B | Styve et al., 2022 | CrisisLex (CrisisLexT6), Harvard Dataverse (Flood Tweet IDs) | Twitter | automated (LR, RF, CNN, ULMFiT, NER) | 90 % of tweets were categorized as relevant by at least one classifier, however only 20-40 % were categorized as relevant by all classifiers. This shows that there are differences in the way individual tweets are classified and implies that the same tweets are not necessarily classified as relevant by each classifier, raising questions about the reliability of their predictions. |
| 19/ A, B | Sufi and Khalil, 2022 | none specific | Twitter | automated (NER, CNN, Getis-Ord Gi*, AR) | The purposed method can pinpoint a disaster location with 0.93 precision, 0.88 recall, 0.90 F1-Score, and 0.97 accuracy. |
| 20/ C | Tavra et al., 2021 | Forest fire, Croatia, 2017 | multiple | manually (filtering, analysis and georeferencing) | The advantage of using multiple types of crowdsourcing data is that all age groups of citizens are covered and technical limitations can be overcome, such as a poor mobile connection. Data from the Crowdmap platform showed a low quantity but high spatial and temporal quality. |
| 21/ D | Thom et al., 2015 | Floods, Germany, 2013 | Twitter | automated (ScatterBlogs) | decision makers confirm that analytical tools are helpful to manage the volume of data, identify eyewitness accounts and engage with citizens more broadly. However, it is important that analytical tools build on existing systems, language and identifiers. Classification, automatic event recognition, real-time capability, data protection and geo-referencing are considered particularly important. The aim should be to gather information from unmonitored areas as well as public opinion on response measures. |
| 22/ C | Z. Wang and Ye, 2018 | Hurricane Sandy, United States, 2012 | Twitter | combination of automated + manually (annotation, LQ and Markov transition probability matrix) | The chosen approach of combinatorial evaluation of space, time, place and topic makes it possible to derive the focus of the population during the course of the disaster. In the period before and during the disaster, the main topics were infrastructure/utilities and weather/environment. During and after the disaster, donations/environments were discussed in particular. |

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| *No./ Focus* | *Reference* | *Disaster/ dataset* | *Platforms* | *Data analysis methods* | *Summarized results* |
|---|---|---|---|---|---|
| 23/ A, B | R.-Q. Wang et al., 2020 | Hurricane harvey twitter dataset | Twitter | combination of automated + manually (NeuroNER, CV, CNN, ResNet v2) | The manual data check of automated classification shows significant advantages for credibility and reliability. By extracting information that official media may ignore, an orthogonal dimension can be opened up. In particular, information on street-level locations in SM can play a passive hotline that can support decision makers in the distribution of emergency response teams. |
| 24/ A, B, C | Wu et al., 2022 | Typhoon Lekima, China, 2019 | Sina Weibo | automated (LDA, SnowNLP, OPTICS) | By linking multiple sources with SM data, deeper insights can be gained. In addition, negative sentiment extracted through sentiment analysis from microblogs can roughly show the spatial distribution of injuries and victims. The accuracy of extracting information about the actual victims at district level reached 31.8 % in the analysis conducted 72 hours after the typhoon hit. |
| 25/ A, B | Yang et al., 2022 | Flooding, China, 2020 | Sina Weibo | automated (HanLP, NER) | One cannot get more disaster information by only paying attention to the posts with uploaded location tags, as there are few or no SM in some severely affected areas. The social network can be effectively combined with remote sensing image data and can help to gain more disaster information, such as assessing the disaster situation in different areas and analyzing the spatial distribution of people paying attention to flooded areas. By effectively combining data from multiple sources, the advantages of different data sources can be better utilized, contributing to a comprehensive description of disaster progression. |

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| *No./ Focus* | *Reference* | *Disaster/ dataset* | *Platforms* | *Data analysis methods* | *Summarized results* |
|---|---|---|---|---|---|
| 26/ A, B, C | Zhang et al., 2020 | Hurricane Harvey, United States, 2017 | Twitter | combination of automated + manually (SocialDISC: WSD, BiLSTM, SLPA) | SM analysis should (a) filter out irrelevant data, (b) sort information based on sub-events, needs, or user-defined categorizations, (c) reflect societal reactions to the impact of the disaster, (d) provide concise and easy-to-read results, and (e) ensure timely data processing. Analyzing the impact of Hurricane Harvey revealed that the disruption of housing and goods had the greatest impact on people's lives. In particular, tweets about relief and rescue were the most frequent among the nine categories and showed the most positive emotional signals. Information on societal impact, differences between expectations and realities, can be used in conjunction with other data as a reference for evaluating mitigation and preparedness plans for future disasters. Societal impact information derived from SM posts has the potential to improve disaster-specific models and assessment tools, contributing to increased community resilience. |
| 27/ A, B | Zou et al., 2021 | CrisisMMD and RESOURCE #9 (CrisisNLP) | Twitter | automated (adjusted VGG16, FastText model, Multimodal Fusion) | The presented multimodal approach consisting of deep learning method, FastText framework and data fusion model shows a better performance than the unimodal approach with 87.6 % and shows a better accuracy than the existing multimodal approach. |

Abbreviations:
2PG: 2PhaseGeo, 2PGT: 2PhaseGeoTime, AC: Agglomerative Clustering, AGDenseNet: Attention Guided DenseNet, AR: automated regression, GIS: geographic information system, BERT: Bidirectional Encoder Representations from Transformers, BiLSTM: bidirectional Long Short-Term Memory, CNN: convolutional neural network, CNTM: Conditional Neural Turing Machine, CRF: Conditional Random Field, CV: Computer Vision, DDM: Damage Detection Map, DenseNet: Dense Convolutional Network, DT: Decision Tree, GCAM: Gradient-weighted Class Activation Mapping, IDW: Inverse Distance Weighted, KNN: KNeighbor, LDA: Latent Dirichlet Allocation, LQ: Location Quotient, LR: Logistic Regression, MLR: multiple linear regression, MNN: Multiple Neutral Network, NB: Naïve Bayes, NER: Named Entity Recognition, NLP: Natural Language Processing, NN: neural network, OPTICS: Ordering Point to Identify the Cluster Structure, ResNet: residual neural networks, RF: Random Forests, SLPA: Uncovering Overlapping Communities in Social Networks via A Speaker-listener Interaction Dynamic Process, SocialDISC: semiautomated SM analytics approach for social sensing of Disaster Impacts and Societal Considerations, SOM: Self-Organizing Maps, SVM: Support Vector Machine, ULMFiT: Universal Language Model Fine-tuning, VGG: Visual Geometry Group, VOST: Virtual Operations Support Team, WEKA: Waikato Environment for Knowledge Analysis, WSD: word sense disambiguation, XGBOOST: Extreme Gradient Boosting, YOLO: You Only Look Once, Py: Python
Focus:
A: development/presentation of tool/framework, B: performance comparison of tools, C: gaining knowledge from SM (data insights), D: usefulness for decision makers

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