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Opportunities and Risks of Disaster Data from Social Media: A Systematic Review of Incident Information

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Abstract. Compiling and disseminating information about incidents and disasters is key to disaster management and relief. But due to inherent limitations of the acquisition process, the required information is often incomplete or missing altogether. To fill these gaps, citizen observations spread through social media are widely considered to be a promising source of relevant information, and many studies propose new methods to tap this resource. Yet, the overarching question of whether, and under which circumstances social media can supply relevant information (both qualitatively and quantitatively) still remains unanswered. To shed some light on this question, we review 37 large disaster and incident databases covering 27 incident types, organize the contained data and its collection process, and identify the missing or incomplete information. The resulting data collection reveals six major use cases for social media analysis in incident data collection: impact assessment and verification of model predictions, narrative generation, enabling enhanced citizen involvement, supporting weakly institutionalized areas, narrowing surveillance areas, and reporting triggers for periodical surveillance. Aside from this analysis, we discuss the advantages and disadvantages of the use of social media data for closing information gaps related to incidents and disasters.

1 Introduction

A disaster is a hazardous incident, natural or man-made, which causes damage to vulnerable communities that lack sufficient coping and relief capabilities (Carter, 2008).[1] Key elements to disaster management are preparedness, early detection, and monitoring a disaster from its sudden, unexpected onset, to its unwinding, and its aftermath. Disaster-related data may be obtained from sensor telemetry, occurrence metadata, situation reports, and impact assessments. Various stakeholders benefit

[1]The International Federation of Red Cross (IFRC, 2017) provides a more detailed definition: "A disaster is a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community's or society's ability to cope using its resources. Though often caused by nature, disasters can have human origins."

from receiving such data, including task forces, relief organizations, policymakers, investors, and (re-)insurers. Not only data about ongoing incidents, but also past ones is crucial to enable forecasting efforts, and to better prepare for future incidents. The broad range of potential incidents and their ambient conditions require an equally broad range of monitoring techniques, each with their benefits and limitations: Remote-sensing data provides spatial coverage, but is often heavily delayed and with low resolution; ground-sensors and scientific staff are fast and precise, but costly and far from ubiquitous; and citizen observers are ubiquitously available, but need training and an incentive to generate reliable, high-quality observations. As a consequence, disaster monitoring is often spatially sparse and temporally offset. In addition, underfunding is a further reason for systematic disaster information gaps.

A rising trend in the disaster relief community is to fill the information gap through citizen observations, ranging from the registration of tornado sightings and the verification of earthquake impact to reporting hail diameters and water levels. The traditional way of acquiring this information is to actively carry out surveys and to operate hotlines, requiring significant staff and a high level of engagement by citizens. In recent years, however, new information sources are increasingly being tapped: blogs, websites, news (Leetaru and Schrodt, 2013; Nugent et al., 2017), and "citizen sensors" on social media. The promise of passively collecting disaster-related information from social media has spawned pioneering research, from detecting earthquakes to estimating the impact of a flood. However, despite several statements of interest (GDACS, 2020) and early applications, like Did You Feel It (DYFI) by the USGS (2020) to validate an earthquake's impact, most practical attempts to utilize disaster-related information from social media have yet to be acknowledged by professionals (Thomas et al., 2019).

Given the many approaches that have already been proposed to exploit citizen observations from social media for disaster-related tasks, it seems prudent to take inventory, and to refine our understanding of the information gap that is supposed to be closed, by shedding light onto the following questions: (1) What information is missing, difficult or expensive to acquire, and what information is frequently but incompletely collected by relief organizations? (2) Can these pieces of information be found in social media? (3) How reliable is the information available from social media, and what risks are associated with them?

The paper in hand contributes to answering these questions by collating the information extraction from social media to date, and the observable gaps in the incident information collected by traditional means:

- We present a systematic, large-scale survey of 37 disaster and incident databases, covering a broad range of disasters, hazardous incidents, regions, and timescales. Each one is categorized by the data collected, its origin, and the spatial and temporal extent of monitoring; and assessed with respect to comprehensiveness per domain.

- We infer six major opportunities for social media-based citizen observations to assist disaster relief: impact assessment and model verification, narrative generation, reinforcing and committing to citizen involvement, supporting weakly institutionalized areas, narrowing surveillance areas, and reporting triggers for periodical surveillance.

- Concluding our assessments, we provide a systematic overview of the uncertainty introduced by social media data to raise awareness of its limitations, i.e., because relevant information is not available, or, because of language ambiguities, misinformation, misuse, and misinterpretation.

https://doi.org/10.5194/nhess-2020-221
Preprint. Discussion started: 17 July 2020

Natural Hazards and Earth System Sciences
Discussions

2 Related Work

Since the current landscape of disaster information systems has a variety of issues, there are also varied attempts at resolving them. Some organizations created curated collections of disasters to provide a unified index (ACDR, 2019) and harmonize disaster data (Below et al., 2010), to study disaster epidemiology (CRED, 2020), to cover new regions (La Red, 2019), or for profit (MunichRe, 2019; SwissRe, 2020; Ubyrisk Consultants, 2020). Other organizations started collaborations (GDACS, 2020), unified subordinates (NOAA, 2019; EU-JRC, 2020), or aggregate other resources (OCHA, 2019; RSOE, 2020). Even citizens contribute collaboratively through the recent disasters list by Wikimedians for Disaster Response (2017), the Wikinews (2020) collection on disasters, and the ongoing events and disaster categories of Wikipedia (2020).

Two recent meta-studies analyze the prerequisites of using social media for relief efforts by outlining the general patterns of social media usage during disasters: According to the first study by Eismann et al. (2016), the primary use case is always to acquire and redistribute factual information, followed by any one of five incident-specific secondary uses: (1) to disseminate information about relief efforts, fundraising activities, early warnings, and to raise awareness on natural disasters, (2) to evaluate preparedness for natural disasters and biological hazards, (3) to provide emotional support during natural disasters and societal incidents, (4) to discuss causes, consequences, and implications of biological hazards and technological and societal incidents, and (5) to connect with affected citizens during societal incidents. According to studies by Reuter et al. (2018) and Reuter and Kaufhold (2017), these usage patterns can be categorized in a sender-receiver-matrix, describing four communication channels: (1) information exchange between authorities and citizens, (2) self-help communities between citizens, (3) inter-organizational crisis management, and (4) evaluation of citizen-provided information by authorities. The operators of disaster information systems consider primarily the uni-directional channel of citizen-to-organization communication. One of those operators, the Global Disaster Alert and Coordination System (GDACS, 2020) of the United Nations and the European Commission remarks that the extraction of citizen observations is the key benefit of social media for their own, sensor-based information system, specifically regarding "assessing the impact of a disaster" on the population to extend and verify traditional models, and "assessing the effectiveness of response" including the extraction of secondary events like building collapses. Reuter et al. (2016) assess in another large survey that "the majority of emergency services have positive attitudes towards social media."

Most academic works since the pioneering publications by, for example, Palen and Liu (2007) conforms with the assessment made by GDACS and focus on extracting information from citizen observations by studying how to infer influenza infection rates (Lampos and Cristianini, 2012), track secondary events (Chen and Terejanu, 2018; Cameron et al., 2012), estimate damages and casualties (Ashktorab et al., 2014), enhance the situational awareness of citizens (Vieweg et al., 2010), coordinate official and public relief efforts (Palen et al., 2010), disseminate information and refute rumors (Huang et al., 2015), generate summaries (Shapira et al., 2017), and create social cohesion via collaborative development (Alexander, 2014). Other research scrutinizes the problem of incident- or region-specific information systems by studying methods to detect earthquakes (Wald et al., 2013; Sakaki et al., 2010, 2013; Robinson et al., 2013; Flores et al., 2017; Poblete et al., 2018), wildfires, cyclones, and tsunamis (Klein et al., 2013) from Twitter streams, map citizen sensor signals to locate these incidents (Sakaki et al., 2013; Middleton et al., 2014), ingest disaster information systems for flash floods and civil unrest exclusively with social media data

(McCreadie et al., 2016), and explore the technical possibilities of combining social media streams with traditional information sources in tailored information systems (Thomas et al., 2019). A comprehensive survey of the academic work in crisis informatics has been presented by Imran et al. (2018). Despite significant prior work on techniques and algorithms to detect hazardous incidents from social media streams and to extract corresponding information, the majority of approaches only explore a narrow selection of disaster types, based on little systematic discussion of the needs of traditional disaster information systems, and ignoring the wealth of established remote sensing methods. As of yet, there is little understanding of the potential of social media in general, and whether computational approaches generalize to the full scope of hazardous incidents.

Several comprehensive monitoring systems have been proposed to generalize from studying particular events or focusing on a singular region or analysis method and to effectively expose disaster management to social media data. Twitcident (Abel et al., 2012) is a framework for filtering, searching, and analyzing crisis-related information that offers functionalities, like incident detection, profiling, and iterative improvement of the situational information extraction. Keyword-based Twitter data gathering and a human-in-the-loop tweet relevance classification and tagging have been implemented for the Artificial Intelligence for Disaster Response (AIDR) system (Imran et al., 2014). McCreadie et al. (2016) propose an Emergency Analysis Identification and Management System (EAIMS) to enable civil protection agencies to easily make use of social media. The system comprises a crawler, service, and user interface layer and enables real-time detection of emergency events, related information finding, and credibility analysis. Furthermore, machine learning is exploited over data gathered from past disasters to build effective models for identifying new events, tracking developments within those events, and analyzing those developments to enhance the decision making processes of emergency response agencies. The recently proposed decision support system Event Tracker (Thomas et al., 2019) aims at providing a unified view of an event, integrating information from news sources, emergency response officers, social media, and volunteers.

There is an obvious need to identify current information gaps and issues of operational disaster information systems as well as to investigate the potential of utilizing social media data to fill these gaps to augment traditionally used data sources, such as in-situ data, satellite imagery, and news feeds with social media data. Recent research on event metadata extraction and management (McCreadie et al., 2016) forms a starting point for their integration into established disaster information systems.

3 Survey Method

The principal prerequisite for a deeper analysis of the gaps in collected incident information is a systematic compilation of the data that is currently collected across disaster types. In a first step, we narrowed the scope of disaster types to a set of the most relevant ones, while maintaining diversity. We started with the de-facto standard top-down taxonomy used by EM-DAT (Below et al., 2009), which is based on work from GLIDE, DesInventar, NatCatSERVICE, and Sigma. It has also been closely adapted by the IRDR (2020) and appears to be more scientifically sound than, for example, the glossary of PreventionWeb, the typology of RSOE, or the bottom-up Wikipedia category graphs. We reduced the dimensionality of the type spectrum to a manageable degree by excluding exceedingly rare incident types (i.e. meteorite impacts) and combining types that are also commonly combined in the other databases (i.e., coastal and riverine floods) without crossing over sub-type hierarchies.

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Preprint. Discussion started: 17 July 2020

Natural Hazards and Earth System Sciences
Open Access
Discussions

Table 1. List of disaster groups with corresponding disaster types and numbers of corresponding disasters in **EM-DAT**, **GLIDE**, **Wikipedia**, **Wikidata**, and in **incident** databases since 2008. Unavailable or not applicable information is marked with **–**, and ∨ denotes that the disaster counts are added to the disaster in the next row, due to type subsumption.

Disaster Group	Disaster Type	EM-DAT	GLIDE	Wikipedia	Wikidata	Incident DB	Source
Biological	Disease outbreak	301	312	–	67	33,667	CDC (2020); ECDC (2020)
Climatological	Drought	182	94	37	27	29,922	SWDI (2020); EDO (2020); NDMC (2020)
	Wildfire	105	34	195	393	3,402	GWIS (2020); SWDI (2020); GFW (2020) EFFIS (2020); NIFC (2020)
Geophysical	Earthquake	273	196	1,147	1,950	1.6 mio	SWDI (2020); USGS (2020); IRIS (2020)
	Landslide (dry)	6	94	117	78	6,789	SWDI (2020); NASA (2020)
	Tsunami	12	13	89	21	10,094	NCTR (2020)
	Volcanic	44	53	60	72	82	NCEI-V (2020); BGS (2020); GVP (2020)
Hydrological	Landslide (wet)	213	9	78	30	2,011	SWDI (2020); ESSL (2020)
	Flood	1680	848	169	196	61,558	SWDI (2020); Brakenridge (2020) EFAS (2020); GLOFAS (2020)
Meteorological	Blizzard	97	95	123	56	32,901	SWDI (2020); ESSL (2020)
	Cold wave	130	–	75	30	16,737	SWDI (2020)
	Dust storm	5	–	7	4	720	SWDI (2020)
	Hail	16	–	103	13	99,002	SWDI (2020); ESSL (2020)
	Heat wave	63	8	90	58	13,470	SWDI (2020)
	Tornado	56	24	295	123	19,847	SPC (2019); ESSL (2020) MRCC (2017); THP (2020)
	Tropical storm	615	410	–	30	19,253	IBTrACS (2020); OCM (2020)
	Fog/Haze	1	–	–	1	6528	SWDI (2020)
	Thunderstorm	132	–	–	–	145,470	SWDI (2020)
	Rain	1	–	–	–	13,230	SWDI (2020)
	Wind	101	–	–	–	37,671	SWDI (2020)
Industrial	Chemical/Substance	25	∨	–	81	8,655	EFSA (2020)
	Radiation	0	∨	51	34	1,173	CNS (2020)
	Structure hazards	239	47	–	300	–	eMARS (2020)
Transportational	Aviation	183	∨	–	2,165	26,059	ICAO (2020)
	Railway	98	∨	–	20	2,992	ERAIL (2020)
	Maritime	486	∨	–	49	2,336	IMO (2020)
	Traffic	764	154	–	66	–	ITF (2020)

Table 1 shows the resulting taxonomy of disasters, and the number of corresponding entries within EM-DAT and GLIDE as the largest expert-built disaster databases with global reach, as well as in Wikipedia and Wikidata, representing global bottom-up collaborative projects. The table also lists the existing incident databases and information systems of the major academic- and public institutions and NGOs for each disaster type and their cumulative number of entries in the time frame. Only disasters between 2008 and 2019 were counted since social media was relevant enough for the broad public and all surveyed databases had consistent coverage from 2008 onward. The table illustrates the differences in size between disasters recorded by experts in EM-DAT and Glide, by citizens in Wikipedia and Wikidata, and the notion of incidents in the other databases and which incident types are rarely covered systematically in the disaster databases. In total, we surveyed 33 incident databases over 27 disaster types in addition to the four disaster databases.

https://doi.org/10.5194/nhess-2020-221
Preprint. Discussion started: 17 July 2020

Natural Hazards and Earth System Sciences
Discussions

Table 2. Taxonomy of the information commonly collected about disasters.

Dimension	Category	Definition	Examples
Data	Metadata	Structured data about an event	Date, time, location, disaster type, verification status, common name
	Sensory	Measured, type-specific information	Magnitude, depth, and severity
	Impact	Effects on the population	Damages caused, fatalities, injuries, displacements
	Causal relations	What caused the event	Trigger, follow-up
	Narrative	Detailed description of the event	Episode narrative, description
	Assessment	Reaction to the event	Response action taken, lessons learned
Source	Surveillance system	Automatic detection	Seismographs, buoys
	Expert	Assessment by trained persons	Meteorologists, park rangers
	Citizen observations	Observations by untrained persons	Call-ins, social media, newspaper
Resolution	Spatially dense	All areas are surveilled	Satellite imagery, weather stations
	Spatially punctual	Only relevant areas are surveilled	Plate boundaries, plane terminals
	Temporally periodical	Area is preemptively surveilled, without the need for a trigger	Seismograph, thermomether, buoys

To gain an overview of the data collected for the different incidents, we devised a taxonomy of incident data in Table 2, selected the largest database of each incident type as a representative, and judged the existence and completeness of each category in Table 3. The taxonomy organized the relevant information within three dimensions relevant to our research questions: (1) The *data* collected for each incident type shows which information is in demand and which is difficult to acquire. (2) The *source* of the occurrence information and who detected the incident shows where citizen observations are meaningful and where surveillance systems or experts are preferable. (3) The spatial and temporal *resolution* shows the gaps in the acquisition process that can be filled by social media data. Other dimensions, such as the typical presentation used for analysis, the involvement of post-processing and validation, and weather reports are qualitatively or quantitatively, are beyond our scope.

We scrutinized the pieces of information compiled in the aforementioned databases and organized them into unified categories to allow for rating across all databases, as shown in Table 2. The gaps in the collected data were determined by checking each database for all categories and whether information from that category exists and is complete. To acknowledge the diversity of disaster types, and to avoid exaggerated expectations, a data category was rated existent if the database contains at least one piece of information from that category. A data category was rated incomplete when less than 90% of the entries contained the respective information. A source was rated existent, if it contributes to the acquisition process, either with a reference to the source in the database or by analyzing the database owner's description of the acquisition process. We did not mark any sources as incomplete, but we noted the distribution of the participating sources whenever possible. Spatial resolution was rated punctual if only selected areas are surveyed (e.g., airports or forests), and dense otherwise. Temporal resolution was rated periodical if surveillance is scheduled in intervals instead of on-demand and if it does not require a trigger event. The resolution was marked incomplete if the surveillance strategy does not fully cover the target, e.g., when some areas are not surveyed due to technical, jurisdictional, or financial constraints, and if incidents might be missed altogether.

https://doi.org/10.5194/nhess-2020-221
Preprint. Discussion started: 17 July 2020

Natural Hazards and Earth System Sciences
Discussions

Table 3. Assessment of the information collected in incident databases following our information taxonomy in Table 2. The **x** denotes existing, the ***** incomplete information. The abbreviations correspond to the categories in the taxonomy. Data: **M**etadata, **S**ensory and **I**mpact data, **R**elations, **N**arrative, **A**ssessments. Sources: **S**urveillance, **E**xperts, **C**itizens. Resolution: spatially dense (**S/D**) or punctual (**S/P**) and temporally periodical (**T/P**).

Group	**Type**	**Data**						**Source**			**Resolution**			**Reference**
		M	S	I	R	N	A	S	E	C	S/D	S/P	T/P	
Biological	Disease outbreak	x	–	x	–	x	x	–	x	–	x*	–	–	CDC (2020)
Climatological	Drought	x	–	x*	x	x*	–	.73	.26	.01	x*	–	x	SWDI (2020)
	Wildfire	x	–	x*	x	x	–	–	.83	.17	–	x*	–	SWDI
Geophysical	Earthquake	x	x	x*	x	x*	–	x	–	–	–	x	x	NCEI-EQ (2020)
	Landslide (dry)	x	–	x	x*	–	–	–	.69	.31	–	x	–	NASA (2020)
	Tsunami	x	x	x*	x	x*	–	.22	.56	.22	–	x	x	NCEI-T (2020)
	Volcano	x	–	x*	x	x*	x*	x	x	–	–	x	x	NCEI-V (2020)
Hydrological	Landslide (wet)	x	–	x	x	x	–	.01	.83	.16	–	x	–	SWDI
	Flood	x	–	x*	x	–	–	.31	.51	.18	x*	–	x*	Brakenridge (2020)
Meteorological	Blizzard	x	–	x*	x	x	–	.46	.38	.16	x	–	–	SWDI
	Cold wave	x	–	x	x	x	–	.31	.51	.18	x*	–	x	SWDI
	Dust storm	x	–	x	–	x	–	.06	.73	.21	x*	–	–	SWDI
	Hail	x	x	x	x	x	–	.02	.51	.47	x*	–	x	SWDI
	Heat wave	x	–	x*	x	x	–	.83	.06	.11	x*	–	x	SWDI
	Tornado	x	x	x	–	x	–	–	.86	.14	–	x*	–	SWDI
	Tropical storm	x	x	x*	–	x	–	.22	.61	.17	x	–	x	SWDI
	Fog/Haze	x	–	x	x	x	–	.93	.05	.02	x*	–	x	SWDI
	Thunderstorm	x	x	x*	–	x	–	.09	.57	.34	x	–	x*	SWDI
	Rain	x	–	x*	–	x	–	.37	.28	.34	x*	–	x	SWDI
	Wind	x	x	x*	–	x	–	.61	.29	.10	x*	–	x	SWDI
Industrial	Chemical/Substance	–	–	–	–	–	x	–	x	–	–	x*	x*	Kovarich et al. (2020)
	Radiation	x	x	–	–	x	–	–	x	–	–	x*	x*	CNS (2020)
	Structure hazards	x	–	x	x	x	x	–	x	–	–	x*	–	eMARS (2020)
Transportational	Aviation	x	–	x	–	x	x	–	x	–	–	x	x	ICAO (2020)
	Railway	x	–	x	x	x	x	–	x	–	–	x	x	ERAIL (2020)
	Maritime	x	–	x	x	x	x	–	x	–	–	x	x	IMO (2020)
	Traffic	–	–	x	–	–	–	–	x	–	–	x*	–	ITF (2020)
Social Media		x*	–	x*	x*	x*	x*	–	x*	x	x	x	x	

4 Results

By analyzing the results of the survey shown in Table 3, we can infer six primary opportunities of social media data for incident databases: (1) To more precisely assess the impact of an incident and verify model predictions across all types of incidents, (2) generate narratives or short descriptions, especially for droughts, geophysical incidents, and floods, (3) strengthen acquisition processes that already involve citizens, which is the case for more than half of the natural disasters surveyed, (4) support weakly institutionalized areas and get a broader coverage of surveyed areas, (5) narrow the areas for punctual surveillance, and (6) notice trigger events and start periodical surveillance.

Furthermore, the survey hints at areas of either limited interest or limited practicality that require further attention: Inferring causal relations between incidents, especially for sub-events and consequences, and generating detailed assessments of response, recovery, and mitigation efforts. An automated assignment or grouping of database entries describing the same event, like NOAA's *episodes*, might also be of interest. Conversely, we observe areas of little immediate relevance: The extraction of metadata and sensory or measured information for known incidents, the surveillance of regionally limited incidents, like earthquakes, and volcano eruptions, and the scrutiny of incidents that have reliable surveillance systems in place like transportational incidents. To assess the opportunities, below, we comment on uncertainty as a main obstacle for the incorporation of social media data in high-reliability applications, and on the limitations of our investigation.

4.1 Opportunities of Social Media Data

The primary opportunities for social media data in incident databases that can be inferred from surveying the currently collected data are impact assessment and narrative generation. Impact information is collected about almost all (93%) incidents, but incompletely almost half of the time (44%). This is especially true for natural disasters, which have more records than the more qualitatively assessed man-made incidents. Quantifying the impact of an incident is mostly done by local observations, which are also frequently shared on social media in images and discussions, as first- or third-party observations. Impact assessment is also closely related to model validation schemes like DYFI. Narratives are short summaries of the episode and are included for 85% of the surveyed incident types and completely collected for most of them. Given their frequent occurrence, generating narratives from social media data would be highly valuable, not least to reduce the effort required from experts in creating them and to complete the narratives for geophysical events, droughts, and floods as has been showcased by Shapira et al. (2017).

The survey also highlights information gaps in the data collected about incident causality and assessment of the response, recovery, and mitigation efforts, although we are cautious to point to social media data as a potential solution without significant prior academic effort. The causal references included in the databases are mostly mentions of the main cause, which is naturally missing if the cause is the normal operation of earth systems. However, causal inference through social media data is sought after for sub-events (Chen and Terejanu, 2018), like road-blocks caused by a storm, which is in this granularity not captured by our survey. Assessment of the response, recovery, and mitigation efforts are frequent and complete for man-made disasters, but rare for natural ones. Reasons for this might be that there is a greater focus on individual incidents for man-made disasters, since there is also more agency in prevention efforts, while assessments for natural disasters are only created for very significant or groups of incidents, for example in annual reports. There is an apparent value in generating assessments for individual natural incidents, but it is not clear yet if this is possible, especially regarding social media as a source. The survey shows no apparent need to consider metadata and sensory information any further. Metadata are largely (93%) existent and complete if the incident is known, however, there is pioneering work studying crowdsourcing opportunities to gain sensory information from citizen observations; for example, inferring hail diameters or flood levels from posted images (Assumpção et al., 2018).

The surveyed sources, surveillance systems, experts, and citizen observations describe how the incidents were originally reported and in turn how the acquisition process works for individual incident types. Interpreting the findings is straightforward: If citizen observations are already used, social media data can contribute significantly to the acquisition process, which is the case in 75% of the surveyed natural disasters, especially where surveillance systems contribute the least. Precise examples for this are the severe weather reports collected by NOAA and ESWD, as well as the crowdsourcing efforts by NASA to collect landslide data (Juang et al., 2019). Citizen observations barely contribute to databases of man-made incidents and all reports are done by involved parties like train operators or plane engineers. It is conceivable to involve citizens via social media in the acquisition process of traffic, industrial, and extreme transportation incidents. However, research in this area is as of yet too sparse to reach a conclusion.

The spatial and temporal resolution may be the best opportunity for social media data: They are not limited by technical, jurisdictional, or financial issues and thus better cover the spatial and temporal domains, while traditional data acquisition relies on existing networks of sensors and/or experts. Regarding the spatial resolution, social media data can aid the data acquisition process by more densely covering weakly institutionalized areas and determining areas for punctual surveillance. Incident types that favor dense spatial surveillance are often marked incomplete (77% of the total) due to a limited regional focus. For example, meteorological stations are frequent in densely settled areas in wealthy regions, but sparse beyond. Similar problems exist for floods, droughts, and, to a certain degree, for disease outbreaks.[2] There is no apparent need to use social media data to increase the spatial resolution if the incidents are surveyed globally through earth observation techniques and have reliable forecasting models, for example, in the case of hurricanes. Incident types that favor punctual spatial surveillance are marked incomplete (43% of the total) if it is difficult to determine the area in need of surveillance. Examples are fire watches and tornado spotting, but also monitoring substance pollution, and structural hazards. There is no apparent need for incidents with static or strictly tracked punctual extent, like geophysical and most transportation incidents. Social media observations can also improve the temporal resolution for the 33% of incident types without periodical surveillance. Specifically, the trigger events required to initiate and guide detailed surveillance can be detected through social media, for example, for wildfires, floods, and diseases. Similarly, social media can complement space-based earth observation or motivate tests for substance contamination and thus assist the 22% of periodically surveyed incidents with potentially long intervals in their periodical surveillance.

4.2 Uncertainty of Social Media Data

In contrast to surveillance systems or expert assessments, social media data is unintentionally contributed by people with limited expertise. These factors introduce an inherent uncertainty to the acquisition of incident information from social media in the form of Type I and Type II errors, depending on the platform and the type of data collected. Type I errors include the uncertainty about the existence of the data: The required information may not exist in general, as for sparsely settled regions or low impact incidents; the information may be uninformative if only shallow discussions or sentiment is shared; and the information may lack precise geographical information (Montello et al., 2003). Type II errors include the uncertainty about the reliability of the data: The collected information may be ambiguous since disaster vocabulary has been liberally adopted into the general vocabulary; the data may contain misinformation like rumors (Mondal et al., 2018), misuse like fake news (Zhang and Ghorbani, 2020), phishing (Verma et al., 2018), clickbait, and hoaxes (Zannettou et al., 2019); or it may be prone to misinterpretation due to the expertise gap of social media data. A survey by the United States Homeland Security (2018)

[2]Anecdotally, the Covid-19 outbreak was heavily discussed on social media before it was officially acknowledged by official institutions.

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illustrates several false and inaccurate depictions on social media during crisis events and highlights the harmful effects on victims and relief efforts. When the inherent uncertainties in social media data are not appropriately and sufficiently addressed, their respective analysis leads to inconclusive, incoherent, and misleading outcomes.

In several related works, various methods have been utilized to assess these inherent uncertainties in social media data. Senaratne et al. (2017) created a taxonomy of these methods based on the following four categories of approaches: (1) crowd-sourcing approaches which involve a group of participants to validate and correct the errors made by data contributors (Haklay et al., 2010), (2) social approaches where experts act as gatekeepers to maintain and validate the data contributed on social media platforms by, for example, using linguistic decision making approaches (Bordogna et al., 2014), (3) machine-learning approaches which automate decision making from past examples, for example, using supervised classifications to assess the credibility of data (Castillo et al., 2011), and (4) geographic approaches that use laws and knowledge from geography.

Going forward, the research efforts invested into uncertainty assessment should not only focus on improving the coping mechanism and exploring new event types, but also on mitigating the uncertainties by building trust between users and relief institutions, incorporating feedback, and motivation mechanisms to increase the number and velocity of shared observations, and acknowledge ways of self-policing within the social media communities.

4.3 Limitations

In favor of following a reproducible and data-driven approach to surveying, we do not consider information that may be needed but is never contained in any of the databases. This also means that we do not suggest to limit innovation or research when rejecting use cases like earthquake detection or metadata extraction. There may be novel uses for social media data which are not revealed by our survey. Additionally, our analysis does not consider the uses of social media analysis to reduce detection times and applications that use social media to retrieve other sources, like shared news articles. Note that we limited our conclusions about traffic incidents due to the limited data in IRTAD and that we mostly ignored uncommon and unforeseen events because of the naturally limited data to survey.

5 Conclusions

This work attempts to answer which role social media data can play in disaster management by systematically surveying the currently available data in 37 disaster and incident-databases, assessing the missing and sought-after information, pointing out the opportunities of information spread via social media to fill these gaps, and ponder the risks introduced by uncertainty. The identified gaps hint at six primary opportunities: impact assessment and verification of model predictions, narrative generation, enabling enhanced citizen involvement, supporting weakly institutionalized areas, narrowing surveillance areas, and reporting triggers for periodical surveillance. Additionally, we point to potential opportunities warranting further research: determining causality between incidents and sub-events, and generating assessments about the response, recovery, and mitigation efforts. Given proper awareness of the risks, seizing the determined opportunities and including social media-based citizen observations in incident data collection can greatly improve our ability to analyze, cope with, and mitigate future disasters.

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