International Journal of Disaster Risk Reduction 122 (2025) 105441

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Legal and ethical considerations for demand-driven data collection and AI-based analysis in flood response

Carolin Gilga [a,1], Christoph Hochwarter [b,1], Luisa Knoche [c,1], Sebastian Schmidt [e,h,*], Gudrun Ringler [d], Marc Wieland [f], Bernd Resch [e,g,h], Ben Wagner [i,j,k]

[a] *Institute for Business Law, University of Kassel, Germany*
[b] *Institute for Empirical Social Research - IFES, Vienna, Austria*
[c] *German Federal Agency for Technical Relief (THW), Bonn, Germany*
[d] *Johanniter Österreich Ausbildung und Forschung gGmbH (JOAFG), Vienna, Austria*
[e] *Department of Geoinformatics - Z_GIS, University of Salzburg, Austria*
[f] *German Remote Sensing Data Center (DFD), German Aerospace Center (DLR), Germany*
[g] *Center for Geographic Analysis, Harvard University, USA*
[h] *Geosocial Artificial Intelligence, IT:U Interdisciplinary Transformation University Austria, Linz, Austria*
[i] *AI Futures Lab on Rights and Justice, Delft University of Technology, Delft, the Netherlands*
[j] *ARC Research Center, Inholland University of Applied Sciences, Den Haag, the Netherlands*
[k] *Human Rights and Technology, IT:U Interdisciplinary Transformation University Austria, Linz, Austria*

A R T I C L E I N F O

Keywords:
Disaster response
Artificial intelligence
Ethics
Data privacy

A B S T R A C T

During a disaster, the timely provision of customised and relevant data is of utmost importance. In the case of floods, data from remote sensing (satellite-based or airborne) is often used, but in recent years data from social media platforms has also been increasingly utilised. Focusing on these data sources, this study provides an in-depth assessment of requirements by emergency responders. Furthermore, the paper sheds light on the legal and ethical considerations that need to be taken into account during data collection and processing. A particular focus lies on the use of artificial intelligence (AI) for data analysis in disaster response. Topics such as privacy preservation and AI-informed decision making are highlighted throughout the paper. The investigation was carried out based on expert interviews with scientists, an extensive literature review, and workshops with emergency responders.

1. Introduction

Due to anthropogenic climate change and rising population density in many regions of the world, the number and severity of disasters caused by natural hazards are increasing [1,2]. Consequently, the quantity and quality of data for disaster response is crucial to effectively manage disaster impacts. Disaster response is usually seen as the second step in the disaster management cycle [3] and, according to the Sendai Framework for Disaster Risk Reduction, refers to “actions taken directly before, during or immediately after a disaster in order to save lives, reduce health impacts, ensure public safety and meet the basic subsistence needs of the people affected” [4]. Various data sources are used to generate semantically diverse, high-quality information in a timely manner, including remote

* Corresponding author. Department of Geoinformatics - Z_GIS, University of Salzburg, Austria.
E-mail address: sebastian.schmidt@plus.ac.at (S. Schmidt).
[1] Authors contributed equally.

https://doi.org/10.1016/j.ijdrr.2025.105441
Received 16 July 2024; Received in revised form 26 March 2025; Accepted 28 March 2025
Available online 28 March 2025

sensing (satellite and aerial imagery) and different social media platforms. While the former can be used to create very detailed spatial delineations of disaster extents and evolution from a top-view, the latter can provide texts and imagery that contain precise, albeit often subjective information from the ground. To effectively manage and rapidly analyse vast quantities of heterogeneous data, artificial intelligence (AI) methods are increasingly being used. AI may be pivotal in ensuring that emergency responders receive precisely the information they require at the time they need it. However, numerous questions arise here with regard to ethical or legal implications.

Few scientific publications explicitly address user requirements for data analysis in emergency management and are a direct result of interaction with potential users. Pilemalm et al. [5] present needs and requirements for information system support for collaborative emergency management developed in collaboration with emergency managers in Norway. Also in Norway, Opach et al. [6] work with emergency responders to define requirements for map-based support systems. Hellmund & Moßgraber [7] present the most recent requirements for administrative crisis management collected through questionnaires and workshops in Germany. Fewer publications refer to the specific event of flooding. Hillin et al. [8] identify the needs of rescue personnel during flood disasters by examining the sources and types of information they rely on and information that would improve their responses in the future. While [9,10] have conducted research on AI-based data analytics for disaster management, so far no literature grounded in the direct involvement of emergency responders that addresses user requirements for AI-based data analytics exists. Kuglitsch et al. [11] advocate doing just that: Bring humanitarian organisations and governments into the discussion.

There are already several studies that explore ethical and legal frameworks relevant to disaster management. Kathleen Geale [12] investigates ethical questions and dilemmas concerning disaster management. Since her study predates the widespread use of AI, the application of AI is neglected. The potential use of AI methods in all four phases of the disaster management cycle has already been discussed in detail (e.g. by Sun et al. [9]). However, the focus in the literature is generally on methodology without ethical considerations. Kankanamge et al. [13] investigate the public perception of AI usage in disaster management and identify demographic differences in terms of potential technological acceptance. Gevaert [14] discuss the accountability of AI applications for disaster management, with a particular focus on biases in the analysis of geospatial data. There are also some studies focused on specific data sources: Lovari & Bowen [15] study ethical implications of social media use for disaster management during a flood in South Carolina, USA.

However, they do not consider aspects such as data analysis, big data, or AI. Cinnamon et al. [16] enlist some ethical challenges of using mobile phone data, including individual (geo-)privacy. Crawford & Finn [17] go into detail about ethical questions regarding social media and mobile phone data. As their analysis also took place before the widespread use of AI, this aspect is not taken into account. There has, nevertheless, already been some work on the legal implications of the use of AI in the disaster management process, mentioning some general concerns on data privacy, market monopolies and fake news spreading [18]. However, they do not go into detail about concrete data sources or methodologies and their respective implications. Other studies in the legal context are usually specific to countries (e.g. Butt[19] for Indonesia) or tackle lessons learned from particular events (e.g. Nottage et al. [20] for large-scale disasters surrounding the Pacific).

Consequently, there is a significant research gap concerning the definition of user requirements together with the users as well as the legal and ethical issues related to data acquisition and AI-based analysis during flood disaster response, especially for the aforementioned, relatively new data sources. Given the growing reliance on AI methods for data processing, it is essential to explore the existing regulatory framework and consider the necessary measures for the ethical and lawful collection, preparation, and utilisation of data, specifically addressing the demand-driven data collection needs of emergency responders. Consequently, we will answer the following research questions:

- **RQ1:** What data collection requirements do emergency response organisations have in the context of disaster response?
- **RQ2**: What ethical considerations are necessary for the AI-based analysis of geo-social media and remote sensing data in flood response?
- **RQ3**: What legal considerations are necessary for the AI-based analysis of geo-social media and remote sensing data in flood response?

In this paper, we focus on floods, the most frequent type of disaster caused by a natural hazard in Central Europe [21]. Our investigation was developed against the backdrop of the devastating 2021 Ahr Valley flood, the most severe flood disaster in Germany in six decades, which caused more than 200 casualties and billions of euros in material damage [22–24].

After providing an overview of technical possibilities arising from AI-based methods applied to remote sensing and geo-social media data, we describe the methods employed to derive the statements presented in this paper. Subsequently, we direct our attention to the rationale for collecting, processing, and analysing data, the necessity for precise and timely information that emergency response organisations typically confront during major disaster events. These opportunities are then assessed from ethical and legal perspectives. Finally, the core messages of the study are discussed. Accordingly, this paper aims to to provide an interdisciplinary overview of the ethical and legal implications of the use of AI methods in a disaster context.

2. Technological background

AI has been a hot topic for some time, at the latest since the release of ChatGPT in 2022. However, there is no standardised definition of this concept. In our paper, we characterise AI as “a field of computer science dedicated to the creation of systems performing tasks that usually require human intelligence”. Machine learning (ML) can be seen as a subcategory of AI, which deals with training “machines based on the provided data and algorithms” and thus represents a technical implementation of AI [25].

The use of AI methods for data processing has become widespread. This holds true for both of our central data sources that even share some methodological approaches, mainly in the deep learning domain. Even though model features or explicit tasks might differ severely, many of the general processes for model training and evaluation are relatively similar. Consequently, they also share some coinciding legal and ethical implications. In the following, the most important methods that can potentially be employed in disaster response for both remote sensing and geo-social media data are described.

2.1. Remote sensing

The demand for information products based on remote sensing data in the context of disaster management, especially for rapid decision-making in crisis situations, has increased significantly over the last 15 years [26]. Almost half of the products requested as part of operational emergency mapping mechanisms relate to flooding [27]. Mapping of the spatial extent of the flooding (see Fig. 1), identifying affected infrastructure and assessing related damages are particularly relevant for emergency response [28].

While data availability was the main limiting factor for a long time, we are currently observing a growing availability of remote sensing data from increasingly numerous and heterogeneous platforms (satellite, plane, helicopter or drone) and sensors (optical, multi-/hyper-spectral, lidar or radar) [29]. While passively sensed optical and multi-/hyper-spectral images provide easily interpretable and highly detailed information about the Earth’s surface, their usage is limited to day-time and good weather conditions. In contrast, Synthetic Aperture Radar (SAR) images are actively sensed and can provide a clear view during day and night that is independent of the cloud coverage. Their preparation and interpretation are, however, more complex than optical images.

Recent progress in ML and the emergence of large-scale remote sensing benchmark datasets [28,30,31] have introduced new opportunities for automating the analysis of satellite, aerial and drone images. This automation is designed to address the escalating volume and complexity of data, as well as the inherent spatio-temporal dynamics observed in disaster situations. Employing automated image processing routines alongside pre-trained ML methods can significantly reduce the time required for generating final products, shrinking the timeline from several hours or days to just a few minutes [32]. This not only accelerates product delivery but also enhances the frequency of analysis, enabling more continuous monitoring of the situation. The effectiveness of the deployed ML models relies heavily on their capacity for generalisation, a critical factor for handling the widely fluctuating data availability characteristic of disaster situations, such as the 2021 floods in Germany [33]. Deep learning methods that are relevant for disaster response can roughly be grouped into semantic segmentation (e.g. to outline the extent of a natural disaster such as flood inundation areas) [34], object detection (e.g. to locate exposed assets such as buildings or vehicles) [35] and change detection (e.g. to locate changes between multi-temporal images that are related to building damages) [36]. At the core of these methods are commonly convolutional neural networks (CNNs) or, more recently, transformer networks of different architectures that are adapted to the specific image analysis task and optimised for the respective application domain. Deep learning for remote sensing in disaster response faces biases from geographic, sensor, and temporal limitations, leading to potentially poor generalization across regions and disaster types. Annotation challenges, class imbalances, and overfitting to specific conditions may further reduce reliability. Mitigating these issues requires

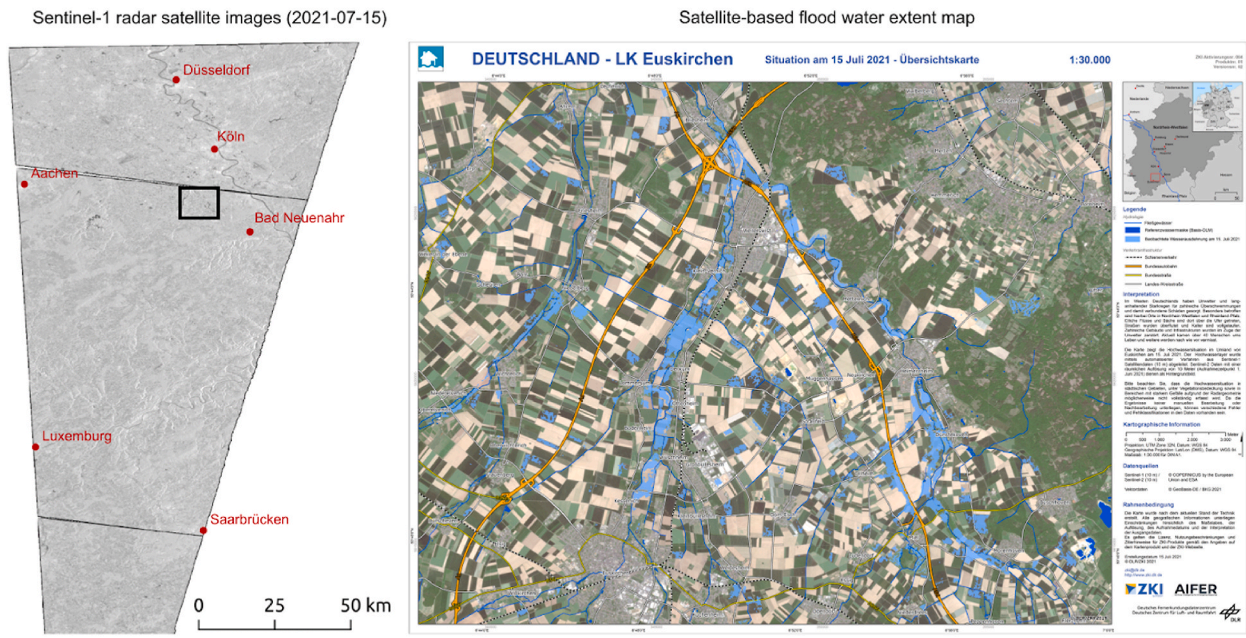

Fig. 1. Synthetic Aperture Radar (SAR) satellite images and corresponding flood water extent map for the floods in Western Germany (15.07.2021). The map has been compiled by the Center for Satellite based Crisis Information (ZKI) (https://activations.zki.dlr.de/de/activations/items/ACT152).

diverse datasets [28], domain adaptation [37], active learning [38], and transparency in model performance across different regions and communities.

2.2. Geo-social media

Social media platforms are an enormously valuable data source for disaster response. Geo-social media refers to any platform that is suitable for connecting people virtually and allows for explicit or implicit georeferencing [39]. The most popular example of this in research is Tweets with geolocation. However, there are also other platforms (e.g. Telegram, Instagram, TikTok) that have similar functionalities. Most of these platforms provide textual and visual (images, videos) information that can be accessed via specific crawling strategies or explicit application programming interfaces (APIs), i.e. concrete connections to the databases of social media platforms [40]. These only enable the acquisition of publicly accessible data, e.g. Tweets or posts in open Facebook groups. Data can be queried and collected using temporal criteria (e.g. a specific day), spatial filters (e.g. the bounding box of a city) or specific keywords and hashtags. The respective possibilities and accuracies vary depending on the social media platform.

A key advantage of data from geo-social media is its high timeliness [41]. When a disaster or similar event occurs, this is usually communicated very quickly online. This means that e.g. concrete images are available on social media much earlier than from external data sources such as remote sensing [42]. In a way, this turns social media users into 'in-situ sensors' [43]. However, the sheer volume of data, demographic biases [44], frequently coarse geolocations [45] and the increasingly prevalent issue of fake news [46] must be mentioned as limitations for the analysis of social media data. Furthermore, text-based ML methods have been shown to exhibit language-specific biases [47]. Even though much progress has been made, colloquial language [48], irony and sarcasm [49] and the use of dialects [50] are still potentially disruptive factors in ML-based text analyses. Additionally, training datasets for disaster-related ML methods are often imbalanced and in English [51].

A variety of methods exist for extracting useable information for disaster response from the unstructured big data of social media. In particular, natural language processing (NLP) approaches and the machine and deep learning methods that build on them should be mentioned here. The enormous amount of data is usually reduced by extensive filtering tailored to the respective use case. This can be done using spatial and temporal filters, but also at a semantic level [41]. Traditionally, keyword filtering approaches are used [52], which are increasingly being replaced by ML methods. This makes it possible, for instance, to classify the relevance of individual posts for disaster management purposes [53–55]. A semantic clustering of post contents is also frequently carried out in the form of so-called topic modelling, which groups semantically similar posts. Latent Dirichlet Allocation [42] or BERTopic [56] are frequently used methods for this. Further analyses, e.g. sentiment analyses, can also generate valuable information [57]. Most of these models are nowadays also based on the transformer architecture, in particular the BERT family [58]. These algorithms can work bidirectionally, i.e. they are able to take context into account for NLP tasks. The models have a basic understanding of human language and can then be finetuned for specific classification or regression tasks. Based on the output of such methods, spatial aggregation can be performed, which enables e.g. spatial hot spot analyses for the rapid identification of affected regions (see Fig. 2) or even early warning purposes [42]. However, this is highly dependent on the availability of data, especially in regions with low population density [59].

3. Methods

In order to understand the information requirements of emergency responders, address ethical considerations, and navigate the

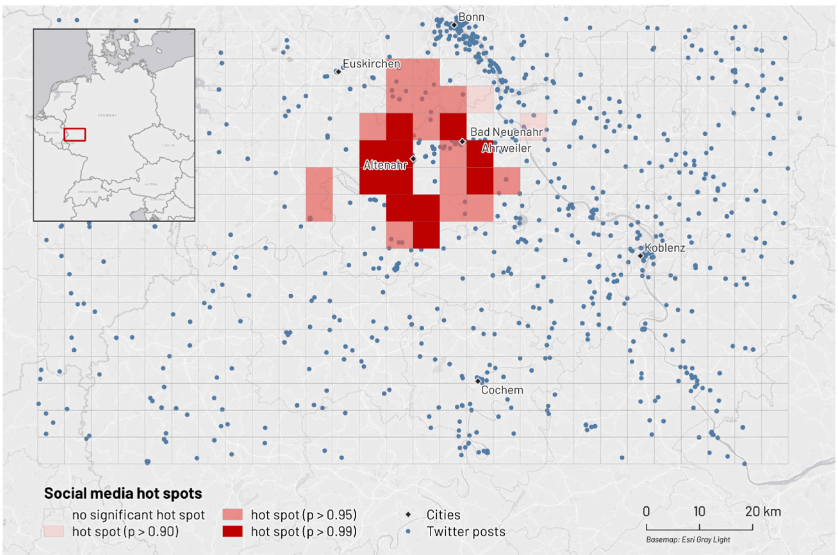

Fig. 2. Social media hot spots for 2021 Ahrtal flood (15.07.2021).

legal framework for data collection and analysis, a variety of methodologies were employed.

For the requirements analysis, we implemented a multi-stage approach. Following an initial literature review and risk assessment, we conducted five workshops and three surveys involving in total 104 experts from various emergency response organisations (German Federal Agency for Technical Relief, Johanniter Austria, Red Cross Salzburg, and the Bavarian Red Cross) to gather and prioritise technically feasible requirements. Furthermore, three focus group discussions with 14, six and five participants and results from a survey (eleven participants), conducted after two practical exercises, during which emergency responders engaged with data from geo-social media and remote sensing, further enriched our findings.

For the ethical analysis of using AI in flood-related disaster events, several methods have been used. In ethics of technology, there are frameworks specifically tailored to applications in domains of information and communication technologies. These frameworks typically comprise sets of ethical questions, often grounded in ethical principles. Those include the general principles of respect for human autonomy, prevention of harm, beneficence, justice [60], as well as the IT-specific concepts of privacy, respect for law and public interest, as well as explainability [61–63]. Such deliberations often require an interdisciplinary approach, involving diverse stakeholders (e.g. developers of a technological innovation, potential users, ethicists or societal spokespersons). To achieve the results presented in this paper, we have drawn upon the sources cited above, established a framework of significant ethical principles, and formulated more immediately applicable questions for reflection. We engaged in regular collective discussions within the context of an ethical board and conducted two workshops within the EESSR (Ethical Evaluation Standard for Security Research) framework [64], involving a diverse interdisciplinary group of scientists and emergency responders. The EESSR model was developed to systematically identify ethical considerations that could arise in technology-human interactions at an early point during development phases, to make them visible to stakeholders and incorporate them into further development. The assessment provides insights into the extent to which a technological development could potentially collide with the ethical values of our society. Furthermore, we conducted four expert interviews with researchers specialising in technology impact assessment.

In order to conduct a legal analysis, the classical legal methodology was applied, i.e. the systematic procedure to interpret and apply legal norms. In order to determine the legal requirements concerning a specific practical case, the relevant norms must first be identified. Subsequently, it is necessary to define the precise content and meaning of the relevant rules in a logical and coherent manner. For this purpose, four distinct methodologies can be employed: grammatical, systematic, historical, and teleological interpretation. In contrast to grammatical interpretation, which is concerned with the wording of the norm, systematic interpretation considers a norm within the context of the law. In the field of historical interpretation, the motives of the legislator are identified to ascertain the content of the norm. Teleological interpretation determines the meaning and purpose of the norm. The respective methods of interpretation complement each other and interlink. Furthermore, the relevant case law and legal literature are consulted to ascertain the legal framework of the specific case.

4. Results

4.1. Data collection requirements

Emergency management typically follows predetermined protocols of actions, including dispatching personnel to the site, establishing a hierarchical order, and identifying additional emergency response organisations that can provide support. In Germany, these standard operating procedures are outlined in the regulation (*Dienstvorschrift*) number 100. However, managing events on a larger scale, where the situation is complex, a large area is affected, many people are at risk, and hundreds of emergency responders are required on the scene, has always been challenging in Germany. This became particularly apparent in the large-scale flood in Western Germany in July 2021.

To ensure the protection and safety of individuals and their possessions, emergency services must make decisions based on the information available at the time. Therefore, effective information management is crucial during operations to enable prompt and best possible decision-making. The exchange of information is a challenge that is frequently discussed in literature [22,65,66]. Normally, the emergency services rely on information from emergency personnel in the field. However, this information is only transmitted once emergency responders have arrived at the scene and may therefore be delayed for minutes or possibly for hours. Sharing large volumes or different formats of data within or between organisations is currently limited by the communication platforms available. Operational control must base their decisions on information obtained via phone, radio, email, oral communication, or even stored on physical media. To provide emergency services with a more comprehensive and efficient overview of the situation on the scene, information sources could be expanded beyond the reports from emergency responders in the field and integrated into a single system.

Despite the differences in emergency organisations, their levels of operation, and personal preferences for situational awareness, we have identified some general requirements for data - especially from remote sensing and social media - in situational awareness systems. According to our findings, timeliness of data is crucial in an emergency. Data from remote sensing and geo-social media must be provided to emergency services as quickly as possible, but no later than three hours after it was requested. It is particularly important to provide timely information at the onset of a situation, but accuracy becomes increasingly important as the situation develops and the facts become clearer. A system for visualising the information must explicitly display the data source and timestamp, enabling emergency responders to verify the data's accuracy and identify any potential discrepancies. Information should be graphically presented to ensure that relevant data is immediately apparent. This visual representation facilitates a quick assessment of the situation, allowing emergency responders to rapidly identify the extent of damage and efficiently allocate resources where they are most needed.

When analysing **geo-social media**, it is useful to employ spatial aggregation methods on the most relevant activities (e.g. spatial hot spot analysis), particularly for larger events, to maintain focus on what is most important. Both an above-average level of social media activity or no social media activity at all can be warning signs. When displaying the individual posts from social media, they should be sorted by descending relevance. Multiple social media posts with similar content can be overwhelming, without adding value. The system must automatically detect these similarities and summarise the information. It should also be possible to filter posts by keywords, source, time and geographic area. Imagery accompanying social media posts hold significant value for emergency responders by offering potentially real-time, detailed visuals of ground conditions. Consequently, there is a need for methods that can automatically analyse photos and videos from social media to extract relevant content effectively. However, measures should be taken to prevent the display of fake news and to raise user awareness.

Data from **remote sensing** holds particular significance when dealing with large-scale affected areas. It should undergo pre-analysis to direct users to essential information. Users should have the capability to quickly understand the geographical extent and consequences of the event. Mapping the flooded area is crucial to enable emergency responders to compare it with existing flood risk and hazard maps, thereby assisting in decision-making and resource allocation. Automatically identified buildings, passable roads, critical infrastructure and cut-off areas should be visible at a high level of detail in order to analyse affected areas and safe access routes. For a more comprehensive understanding of areas of high priority and where immediate action may be required, conducting damage intensity analysis proves beneficial. This analysis allows emergency responders to prioritise their efforts based on the severity of damage observed. Equally, identifying safe zones and exclusion areas is invaluable for ensuring the safety of both responders and affected individuals. In this context, it is important to have imagery that is updated as frequently as possible in the aftermath of a disaster (preferably near real time) to accurately track the progress of an event. Moreover, the level of detail in both data and analysis should be tailored to the scale at which the operator is overseeing the situation. Keeping a detailed record of updates within the system is useful to see how the situation has evolved. In instances where an information source fails to provide data, this should be immediately highlighted to the user. Automated alerts signalling critical changes in the situation from the data are extremely helpful to emergency services. Automatically set thresholds (e.g. with regard to the geographic extent of flooded areas), which can be adjusted manually as needed, can be implemented in the system for this purpose. [67], for example, deploy a spatio-temporal anomaly detection method to identify hazardous flood areas and potentially alert users during continuous surface water monitoring.

4.2. Ethical considerations

While the general purpose of using additional data sources and AI for disaster response is ethically rather uncontested (this can be called the "primary" or "foreseeable usage"), attention must be paid to whether this new approach enables additional "secondary" usages of collected data or developed AI models. Furthermore, it must be inquired whether ethically problematic consequences arise from the (ethically sound) primary usage.

Regarding the aspect of secondary data usage that is potentially ethically unsound, there is the risk that parts of the technology could be repurposed in a new way: e.g. social media data could be collected to systematically determine areas where shops are damaged in order to identify easy targets for criminal activities. Preventing ethically unsound secondary usage can be achieved by setting up usage guidelines for the system, in order to make clear how and when data may be collected to prevent exuberant data acquisition. This could be accompanied by extensive logging procedures to make transparent when and by whom such a system or its components have been used, which is important for respecting the ethical principle of transparency and accountability. Also, guidelines for sharing results of data analysis should be set up, in order to prevent spread of information into unfit hands.

Even if the data is collected in a proper way (e.g. by using crawling strategies that do not bypass privacy settings of social media users), and the technology at hand is used correctly (primary usage), the following unintended ethical issues can arise.

- **Privacy threat**: Data collected for disaster response purposes might also include personal information (e.g., in social media posts users might have directly shared personal information; in remote sensing, the high spatial resolution of sensors might allow recognising faces). This is a potential threat to the ethical principle of privacy.
- **Lack of data availability**: Reasons why data is not or only in a limited way available are diverse; e.g.: power failure, poor internet connection, no satellite data in time, or impossible drone-flights (e.g. because of bad weather conditions). However, data gaps not only occur due to acute technical issues but also because of intended circumstances (e.g. critical infrastructure or restricted areas like military installations). Emerging data and information gaps could lead to uncertainties in data as a basis of decision making and, if these gaps are not detected, consequently to wrong decisions.
- **Incorrect evaluation by the system**: Even if data are available in time, the analysis could generate false or incomplete results; affected persons and areas might not be identified as such and be overseen. This could lead to wrong decisions of users, thus violating the principle of beneficence and prevention of harm.
- **Lack of data autonomy and lack of consent of social media users**: From the viewpoint of the ethical principle of autonomy, social media users never explicitly consented to data collection and usage for flood disaster response. While it can be argued that by accepting terms and conditions of social media platforms, they consented in a general way, studies show that terms and conditions are often not completely read and/or understood [68]. Lack of consent is also called the "standard problem in more contemporary Big Data projects" [69].
- **Robustness threat due to commercial social media platforms**: Social media-based data collection requires a certain degree of stability in the platforms that data is collected from. In contrast to platforms operated by public administration, commercial social media platforms might change in ways that negatively impact the utility or availability for disaster-response purposes.

- **Disadvantages inherent to social media posts**: Textual contents harbour the risk of being wrongly interpreted by the reader. Further, posts could be misused by their authors, e.g. by providing fake information or using a higher posting rate to convey the impression to be more in need than others. This could lead to an excessive allocation of responders at the wrong location, while others in need could be affected by undersupply. Additionally, if the social media platform is misunderstood by their users as a communication tool for emergency calls, emergency services could be pressed to react to such posts. Another aspect is that social media users could be motivated to put themselves in danger for the best photos and videos.
- **Robustness threat due to false information**: False information can be a threat to data quality of social media analysis by providing false information. However, according to interdisciplinary discussions in the Ethical Board and the EESSR workshops, false information is expected to be a more frequent problem regarding political topics. While they also occur regarding disaster related topics, aggregating procedures (e.g. spatial hot spot analyses) weaken the impact of singular fake social media posts.
- **Bias of data**: Data gathered from social media can be subject to different kinds of biases, meaning "systematic distortions in the sampled data that compromises its representativeness" [70]. These include population biases (systematic distortions in user characteristics between a population of users represented in a data set and the target population) and temporal biases (systematic distortions across user populations or behaviours over time). In this context, biases also include changing communication cultures on social media platforms, thus posing the risk that a back-then trained AI might not be fit for the change. In remote sensing, bias is also possible, if training data does not represent all the variability in buildings or geographical particularities [71]. Consequences of biases can include both false-positives (i.e. erroneously declaration of areas as flooded) and false-negatives.
- **Contested transparency for the larger society**: Accountability (e.g. concerning data protection) requires transparency. Since AI-based disaster response is only carried out by a specialised core of users, it cannot be taken for granted that general members of society have knowledge of this system, and thus cannot exert their rights of information, thus infringing the ethical principle of explainability.
- **Contested transparency for operators**: A system that allows the application of AI routines on datasets for data analysis still needs human operators who are situated within certain working environments ("socio-technological system"). Operators need to understand how new data has been generated and how to assess the degree of certainty of those information products. Depending on the details of establishing and locating such a system, operators could find it difficult to achieve the necessary level of insight. It is especially important to have an understanding about "blind spots" in the data.
- **Overreliance of emergency responders on AI-based analysis:** While results from AI-based analysis of geo-social media or remote sensing data can be helpful for emergency responders, overreliance on those data sources harbours the risk of reduced operational capabilities in emergency situations in which they might not be available. Therefore, measures should be taken to ensure that AI-based analysis dooes not habitually become the sole foundation of the situational overview. While this might not pose a problem for many years to come, the more common AI usage in disaster-related data analysis becomes, the more acute this issue will be.
- **Contested autonomy of operators**: AI offers not only support in data analysis but also the potential to be developed in a way that includes decision making, coming at the expense of the autonomy of operators.

4.3. Legal considerations

The use of AI assisted methods in disaster response poses various legal challenges, particularly with regard to data from social media platforms, which we focus on below. As large amounts of public data from geo-social media are automatically collected and analysed for disaster management, data protection law is of particular relevance. While not all the information collected can be attributed to an identified or identifiable natural person (data subject), it is generally assumed that this is the predominant case. Importantly, the public availability of that personal data does not preclude the applicability of data protection laws, which apply to all personal data regardless of the number of individuals who have access to it. Therefore, the following elaborations analyse the automated processing of public data from the internet, and data protection law as derived from European law.

For the sake of completeness, it should be mentioned that the legal conformity of the use of social media data is not determined solely by data protection law. Rather, legal challenges can also arise from other areas of law. For example, it is possible that content taken from social media is protected by copyright and therefore copyright law must be taken into account. It is also plausible that automated data collection may violate the terms of use of social media platforms. In this respect, contractual issues may arise. Numerous other legal problems are conceivable, but their comprehensive consideration would go beyond the scope of this paper. The following elaborations are therefore limited solely to data protection law as the most relevant legal matter for assessing the legal conformity of the procedure described.

4.3.1. Data protection in the event of a disaster

The General Data Protection Regulation (GDPR) applies to any processing of personal data in the European Union, regardless of the specific processing situation at hand (Article 2 GDPR). Thus, it also applies to processing in the context of disaster management. While some may consider data protection in disasters negligible, such an approach is not advisable in view of the severe penalties that may be imposed in the event of a breach (Article 82, 83 GDPR).

The GDPR stipulates that the processing of personal data is only permitted if it is based on a legal basis (permission principle). The legal basis for this must be derived from the GDPR, as European regulations take precedence over national law (Article 288 TFEU). The law of a member state can only be used if the GDPR explicitly allows it (e.g. Article 6 (1)(c) or (e) in conjunction with Art. 6 (2), (3) GDPR). However, before the possible legal bases are discussed in more detail, the principles of data processing pursuant to Article 5

GDPR are analysed. These are of particular relevance in the context of the use of AI [72].

4.3.2. Principles relating to processing of personal data and the use of AI

The principles outlined in Article 5 GDPR provide the framework for data protection compliant processing of personal data. In accordance with the transparency principle (Article 5(1)(a) GDPR), it is necessary for AI to be developed in a manner that allows for its mode of operation to be explained. This includes in particular that all steps of the system can be traced, that the reliability of the results can be verified and that there is traceability with regard to the data involved, its use and processing [73]. According to the principle of purpose limitation (Article 5(1)(b) GDPR), the purpose of data processing, even when using AI, must be formulated as narrowly as possible, to ensure that as little personal data as possible is processed, so as to be in line with the principle of data minimisation (Article 5(1)(c) GDPR) [74]. To comply with the principle of data accuracy (Article 5(1)(d) GDPR), it is important to make sure that the processed data is both accessible and correctable by those responsible. In addition, the storage limitation principle requires that deletion concepts are in place, whereby the personal data that is no longer required is deleted (Article 5(1)(e) GDPR). To comply with the principle of integrity and confidentiality (Article 5(1)(f) GDPR), it is necessary to implement technical and organisational measures that ensure data protection in accordance with the risks associated with the use of AI. In addition, the controller must be able to provide evidence of compliance with the principles of data processing (Article 5(2) GDPR).

4.3.3. Legal basis for processing

The GDPR does not explicitly state a legal basis for processing data related to disaster management. Thus, at least one of the general legal bases listed in Article 6(1) GDPR must be applied. A distinction must be made as to whether the data controller is part of a public or non-public body, as this affects the legal bases that come into consideration.

Processing by public bodies.

If a public organisation is responsible for data processing, two legal bases in particular can be considered: a legal obligation (Article 6(1)(c) GDPR) and a task carried out in the public interest (Article 6(1)(e) GDPR). Both processing legal bases require a basis in European or member state law (Article 6(2), (3) GDPR). Whether such a basis exists depends on the specific public authority responsible in each case. However, there is no such basis provided by European law.

In the case of Germany, only a public body of a federal state is permitted to carry out such processing [75] (Article 30, 70 (1), 71 ff., 83 Basic Law for the Federal Republic of Germany). However, the disaster management laws of the federal states are not standardised and sometimes differ greatly in terms of content. Due to this, it is not possible to make a definitive and universally applicable evaluation of the legality of automatically processing large amounts of public data from geo-social media. However, Hessian state law exemplarily shows that processing of public data from geo-social media can, in principle, be lawful under data protection law (Article 6 (1)(e), Article 9(2)(g) GDPR in conjunction with Section 33(1) Hessian disaster management law, Section 1(1)(No. 2), 20(1), (5) Hessian law on public safety and order, Section 20(1) Hessian Data Protection and Freedom of Information Law). Nevertheless, considerable challenges arise from the fact that in Hessian law only a general clause is available for justification. As a result, only data processing with a limited impact on the rights and freedoms of the data subjects can be justified. The ability of public authorities to manage a disaster is therefore significantly restricted. Furthermore, the use of a general clause for processing of public data from geo-social media is fraught with uncertainty, as it is not a standard measure and involves large-scale data processing. In such cases, it is difficult for the actors responsible for the disaster – especially since they are usually not legal experts – to determine whether processing of public data from geo-social media is legally compliant. This leads to considerable legal uncertainty. In this respect, more specific rules for processing of public mass data by public authorities for disaster management would be desirable.

Processing by non-public bodies.

If a non-public body is responsible for processing of public data from geo-social media, two legal bases are relevant: protection of vital interests (6(1)(d) GDPR) and the weighing of legitimate interests (6(1)(f) GDPR). The former can only be taken into account if no other legal basis is applicable (Article 6 marginal no. 19 GDPR) [76]. Thus, one must first consider the applicability of the legal basis of the weighing of legitimate interests as justification for the data processing. According to the wording of this legal basis, it can justify processing carried out in the interest of the controller or of a third party, not of the data subject. Consequently, the legal basis of protection of vital interests can only justify processing concerning the data subject's interests.

If public data from geo-social media is automatically processed in the context of disaster response, both the controller's interest in participating in disaster management and third parties' interest in ensuring humanitarian aid are pursued. At the same time, however, the interests of the data subjects are also pursued, who themselves suffer directly from the effects of a disaster and have an individual interest in being freed from the situation. With regard to these, the legal basis of weighing legitimate interests cannot apply, which is why the legal basis of protecting vital interests is applicable. Finally, both legal bases are needed to justify the whole processing. On their own, the respective legal bases can only provide a partial justification. However, no general statement can be made as to whether these legal bases can be invoked in individual cases.

In principle, the automated processing of public data from geo-social media by non-public bodies can be justified under data protection law. However, this is accompanied by significant challenges, as there is the need to justify the processing of data on two legal bases. Furthermore, the legal basis of protecting vital interests is fraught with great uncertainty. Understanding the term "vital interest", which is neither defined by law nor specified by criteria, is challenging. As a result, there is legal uncertainty in the application of this legal basis. Courts and supervisory authorities consequently may assess the legality of data processing differently. This carries a significant risk for data controllers of being charged with high fines under Article 83 GDPR or facing compensation claims under Article 82 GDPR. To reduce this legal uncertainty, it is desirable to establish more specific rules for non-public bodies that process data in the event of a disaster.

4.4. Policy recommendations

4.4.1. Raise awareness and provide opt-out possibilities

Existing disaster management big data strategies are not always obvious to end users, who might not expect even highly public social media data to be used for rescuing them in a disaster situation. Conversely, another social media user might be very surprised if they are not rescued based on existing data. To increase user autonomy, we believe greater transparency in data usage is needed to raise awareness of how user data is being utilised. These transparency measures would be most effective if implemented where users create data, i.e. on social media platforms or on mobile phone networks, e.g. via SMS notifications informing users about data usage.

At the same time, it must be clarified to the public that this does not turn the social media platforms into a valid channel for emergency calls. Here, greater outreach on social media both before and during an emergency can be helpful to ensure that the public is aware both how their data might be used and in which situations emergency services will respond to social media data. This ensures that users do not see social media as an emergency service, but rather a space where emergency services collect aggregate data to support rescue efforts. In conclusion, there is a need for opt-out options for users from the collection and processing of their data in these contexts, to strengthen their control over their data and their autonomy, even in disaster situations.

4.4.2. Measures for anonymisation, mitigation and deletion

To significantly reduce data-related risks, we propose that systematic measures should be taken to ensure data anonymisation and deletion after use. Additionally, and especially where the former measures are not possible, e.g. when data anonymisation is not fully effective, other mitigation steps should be implemented. This process already starts with data acquisition, which should ensure the minimisation of data collection, anonymisation procedures, and guidelines for data erasure after the emergency. Whenever possible, data acquisition should focus on social media platforms with an inherently high "public" nature (e.g. Twitter/X).

4.4.3. Awareness of limitations among operators

Another key challenge is for operators to be aware of the limitations of the systems they use. Steps to ensure this can include awareness-building of operators through training and verification of analysis results with other available information, extensive introduction and training of operation personnel as well as developing training curricula that prevent overreliance. This is also important at an operational level, where we recommend implementing procedures that ensure that human oversight of an AI-based system and the overruling of AI decisions by human operators is always possible [61].

4.4.4. Risk-interlinkage

More broadly, the interlinkage between risks related to privacy and AI-bias may present novel risks in the context of disaster management. For example, linking available resources to geo-social media data in a disaster situation may disadvantage those individuals who are less likely to have access to social media, particularly marginalised groups. Moreover, potential bias in the algorithms used to interpret data based on which resources are allocated are also more likely to affect such demographic groups. These types of compounded risks should be considered when AI and big data are used in the context of disaster response.

4.4.5. Technical best practices

There are also some key technical best practices to consider. Due to data quality issues, it is key to implement technological processes for quality assurance and cross checking with complementary and alternative data sources. Additionally, technical procedures like normalisation or data augmentation, regular evaluation of training data and existing ML models should be used to ensure high data quality. Another key principle is to collect social media data not only from one platform, but from several, in order to reduce dependence. Finally, there is a need for the implementation of technical approaches for false information detection [77,78], including additional moderation of data.

4.4.6. Broader jurisdictional issues

When thinking about policy recommendations, it is also important to address broader jurisdictional issues raised in emergency situations. Even though data is typically collected in a specific geographic context, the acquisition usually takes place on international platforms, around which the legal governance is often contested. While many large international social media platforms are formally based in Ireland, the actual legal and physical residence of their data may be difficult to ascertain.

In addition, emergencies are seldom respectful of national or regional borders and may require wide data sharing beyond individual national boundaries of emergency services. In particularly challenging situations, international cooperation between emergency services across borders is common, necessitating efficient and effective mechanisms for data sharing. Corresponding legal regulations that enable the emergency services to act with legal certainty in such cases are still lacking.

We propose to resolving these issues in advance, whenever possible, and not wait until an emergency takes place. To this end, cross-border data sharing agreements between different emergency services as necessary, ideally coordinated by international federations or similar multilateral bodies that already exist. These agreements should also include provisions on necessity, minimisation and deletion, to ensure that data is only stored, when necessary, only as much as is necessary and that the data is deleted afterwards. Such agreements could also include the creation of an ombudsman office to ensure the transparency of these procedures and ensure accountability of data and AI usage in broader society. They should also allow for a wider sharing of best practices on how to enable international collaboration in this area while strengthening transparency, privacy and rights citizens.

5. Discussion and conclusions

In this paper, we elaborated on requirements for data acquisition and analysis in flood disaster response and provided a technical overview of two main sources of data (remote sensing and geo-social media) while explaining AI-based analysis methods. The second part of the paper focused on ethical and legal implications that go along with collecting and processing data from remote sensing and geo-social media.

The findings presented here on requirements and ethical and legal frameworks were largely based on qualitative analysis methods. These included workshops in which between 5 and 14 participants were involved. The number and composition of these participants can certainly be criticised, especially as there was a strong focus on the perspective of emergency services. Consequently, we cannot guarantee that all the statements made, particularly from an ethical standpoint, are valid for all participants or organisations involved in the disaster management process.

The precise requirements for more timely, precise and diverse data in disaster response are not easy to define. In countries like Germany and Austria, disaster response is executed by a variety of different organisations. The exact requirements are diverse depending on organisation, level of operation and personal preferences. However, the need for better information and communication is undeniable. Data from geo-social media and remote sensing can provide timely initial information that becomes increasingly accurate as a situation evolves and can be graphically presented to emergency responders to facilitate verification and rapid understanding of the situation. The added value of such information in disaster response will depend on the integration into established procedures and preferably already used software (**RQ1**). While the extra effort to manage the data must be as little as possible, only testing in realistic exercises and real operations can show how the new data sources will improve the overall disaster response. Decision-making could be negatively impacted by data and information gaps, misinformation (especially fake news in social media channels) and diverse interpretations of data and information which might lead to erroneous decisions.

To facilitate the usage of AI-based data analysis in flood-disaster response in an ethical manner (**RQ2**), data has to be collected in a proper way, and ethically unsound "secondary usages" must be prevented (e.g. by usage guidelines and technical measures). Additionally, an outline of different ethical issues that might arise even from proper primary usage, and potential ways to mitigate them, has been given. Most important in that regard are:

- Privacy threats to social media users, which can be softened with minimisation of data collection, anonymisation procedures, guidelines for data erasure after the emergency, and a focus on collecting data from public platforms.
- Contested autonomy of operators, which can be prevented by implementing procedures that ensure human oversight, overruling of AI decisions by human operators, and training curricula to prevent overreliance on AI.
- Contested transparency for operators, which can be softened with extensive introduction and training of the operation personnel.
- Incorrect results coming from the analysis, which require awareness-building of operators through training, the verification of analysis results with other available information, and technical quality assurance measures.

Due to the constraints of this paper, the subject matter of how to ensure that ethical issues can be taken into account during the development stages of a system delineated above was not covered. Furthermore, comprehensive ethical analysis has to take into account all stages of a technology's life cycle: design/development, application, and disposal. The focus within this paper was on aspects of the design and application phase. Finally, ethical issues identified above do not claim to be comprehensive, but rather indicative, because there was no definitive "socio-technological system" to be analysed and thus a final assessment was not possible. Depending on the details of the functionality, modes of data collection, organisational embedding (e.g. of the operators and the training they receive, additional professional guidelines that pertain to them), and other aspects, many other ethical issues in a more fine granularity could be worked out.

From a legal perspective, especially the use of technologies for automated processing of public data from the internet is challenging. In order for such technology to be used in a legally compliant manner, an appropriate legal basis is required. However, at least in German law, the only applicable bases are often laws designed as general clauses for disaster management and emergency responses. This results in legal uncertainty. Therefore, to reduce this uncertainty, the creation of specific rules is desirable. Such rules should explicitly refer to data processing in order to evaluate a disaster situation and establish criteria for the applicability of automated applications (**RQ3**).

Geo-social media and remote sensing data can enhance the information base for decision-making in disaster scenarios, though many ethical and legal considerations must be addressed. In this paper, our focus was on disaster management in the European Union and Germany. The portability of our findings to other regions within and outside of the European Union, should be studied in future work. In the best-case scenario, further studies could result in international policy recommendations to facilitate and standardise the ethically and legally sound exchange of information across borders in disaster events. As technologies and data related to remote sensing, geo-social media, and AI methods are continually evolving, ongoing research into their application for disaster management is crucial.

CRediT authorship contribution statement

Carolin Gilga: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Christoph Hochwarter:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Luisa Knoche:** Writing – review & editing, Writing – original draft, Methodology,

Investigation, Formal analysis, Data curation, Conceptualization. **Sebastian Schmidt:** Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Gudrun Ringler:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marc Wieland:** Writing – review & editing, Writing – original draft, Visualization, Resources, Project administration, Funding acquisition, Conceptualization. **Bernd Resch:** Supervision, Resources, Funding acquisition, Conceptualization. **Ben Wagner:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was funded by the Austrian Research Promotion Agency (FFG) and by the German Federal Ministry of Education and Research through the project AIFER (Grant Numbers 879732 and 13N15525 to 13N15529).

This project has received funding from the European Commission - European Union under HORIZON EUROPE (HORIZON Research and Innovation Actions) under grant agreement 101093003 (HORIZON-CL4-2022-DATA-01-01). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union - European Commission. Neither the European Commission nor the European Union can be held responsible for them.

We extend our gratitude to all emergency responders, scientists, and experts who participated in the workshops, interviews, and surveys. We also appreciate the organisers of the field tests conducted by the Austrian Red Cross and the Bavarian Red Cross. Additionally, we thank Sabrina Scheuer (Johanniter Austria) and Iris Schneider (German Federal Agency for Technical Relief) for their contributions to our analyses.

Data availability

Data will be made available on request.

References

[1] G. Blöschl, A. Kiss, A. Viglione, M. Barriendos, O. Böhm, R. Brázdil, D. Coeur, G. Demarée, M.C. Llasat, N. Macdonald, D. Retsö, L. Roald, P. Schmocker-Fackel, I. Amorim, M. Bělínová, G. Benito, C. Bertolin, D. Camuffo, D. Cornel, O. Wetter, Current European flood-rich period exceptional compared with past 500 years, Nature 583 (2020) 560–566, https://doi.org/10.1038/s41586-020-2478-3.

[2] M. Ionita, V. Nagavciuc, Extreme floods in the Eastern part of Europe: large-scale drivers and associated impacts, Water 13 (8) (2021) 1122, https://doi.org/10.3390/w13081122.

[3] B. Tomaszewski, M. Judex, J. Szarzynski, C. Radestock, L. Wirkus, Geographic information systems for disaster response: a review, J. Homel. Secur. Emerg. Manag. 12 (3) (2015), https://doi.org/10.1515/jhsem-2014-0082.

[4] UNDRR, Sendai Framework Terminology on Disaster Risk Reduction. Response. https://www.undrr.org/terminology/response?quickUrl=true, 2024.

[5] S. Pilemalm, B.E. Munkvold, J. Radianti, Developing information systems for collaborative emergency management: requirements analysis and prototyping, in: T. Gjøsæter, J. Radianti, Y. Murayama (Eds.), Information Technology in Disaster Risk Reduction, vol. 672, Springer, Nature Switzerland, 2023, pp. 153–169, https://doi.org/10.1007/978-3-031-34207-3_10.

[6] T. Opach, J.K. Rød, B.E. Munkvold, Map functions to facilitate situational awareness during emergency events, Cartography and Geographic Information Science 50 (6) (2023) 546–561, https://doi.org/10.1080/15230406.2023.2264759.

[7] T. Hellmund, J. Moßgraber, Evaluating the mismatch between user requirements and existing situation display tools in administrative crisis management, J. Contingencies Crisis Manag. 32 (2) (2024) e12576, https://doi.org/10.1111/1468-5973.12576.

[8] J. Hillin, B. Alizadeh, D. Li, C.M. Thompson, M.A. Meyer, Z. Zhang, A.H. Behzadan, Designing user-centered decision support systems for climate disasters: what information do communities and rescue responders need during floods? J Emerg Manag 22 (7) (2024) 71–85, https://doi.org/10.5055/jem.0741.

[9] W. Sun, P. Bocchini, B.D. Davison, Applications of artificial intelligence for disaster management, Nat. Hazards 103 (3) (2020) 2631–2689, https://doi.org/10.1007/s11069-020-04124-3.

[10] S. Ghaffarian, F.R. Taghikhah, H.R. Maier, Explainable artificial intelligence in disaster risk management: achievements and prospective futures, Int. J. Disaster Risk Reduct. 98 (2023) 104123, https://doi.org/10.1016/j.ijdrr.2023.104123.

[11] M.M. Kuglitsch, I. Pelivan, S. Ceola, M. Menon, E. Xoplaki, Facilitating adoption of AI in natural disaster management through collaboration, Nat. Commun. 13 (1) (2022) 1579, https://doi.org/10.1038/s41467-022-29285-6.

[12] S. Kathleen Geale, The ethics of disaster management, Disaster Prev. Manag. 21 (4) (2012) 445–462, https://doi.org/10.1108/09653561211256152.

[13] N. Kankanamge, T. Yigitcanlar, A. Goonetilleke, Public perceptions on artificial intelligence driven disaster management: evidence from Sydney, Melbourne and Brisbane, Telematics Inf. 65 (2021) 101729, https://doi.org/10.1016/j.tele.2021.101729.

[14] C.M. Gevaert, M. Carman, B. Rosman, Y. Georgiadou, R. Soden, Fairness and accountability of AI in disaster risk management: opportunities and challenges, Patterns 2 (11) (2021) 100363, https://doi.org/10.1016/j.patter.2021.100363.

[15] A. Lovari, S.A. Bowen, Social media in disaster communication: a case study of strategies, barriers, and ethical implications, J. Publ. Aff. 20 (1) (2020) e1967, https://doi.org/10.1002/pa.1967.

[16] J. Cinnamon, S.K. Jones, W.N. Adger, Evidence and future potential of mobile phone data for disease disaster management, Geoforum 75 (2016) 253–264, https://doi.org/10.1016/j.geoforum.2016.07.019.

[17] K. Crawford, M. Finn, The limits of crisis data: analytical and ethical challenges of using social and mobile data to understand disasters, Geojournal 80 (4) (2015) 491–502, https://doi.org/10.1007/s10708-014-9597-z.

[18] S. Jolly, G.S.M. Raj, Artificial intelligence and the legal response paradigms in disaster management, in: T.V.V. Kumar, K. Sud (Eds.), AI and Robotics in Disaster Studies, Springer Nature, Singapore, 2020, pp. 133–147, https://doi.org/10.1007/978-981-15-4291-6_10.

[19] S. Butt, Disaster management law in Indonesia: from response to preparedness? in: S. Butt, H. Nasu, L. Nottage (Eds.), Asia-Pacific Disaster Management Springer Berlin Heidelberg, 2014, pp. 183–196, https://doi.org/10.1007/978-3-642-39768-4_9.

[20] L. Nottage, H. Nasu, S. Butt, Disaster management: socio-legal and asia-pacific perspectives, in: S. Butt, H. Nasu, L. Nottage (Eds.), Asia-Pacific Disaster Management, Springer Berlin Heidelberg, 2014, pp. 1–58, https://doi.org/10.1007/978-3-642-39768-4_1.

[21] W. Kron, P. Löw, Z.W. Kundzewicz, Changes in risk of extreme weather events in Europe, Environ. Sci. Pol. 100 (2019) 74–83, https://doi.org/10.1016/j.envsci.2019.06.007.
[22] A. Fekete, S. Sandholz, Here comes the flood, but not failure? Lessons to learn after the heavy rain and pluvial floods in Germany 2021, Water 13 (21) (2021) 3016, https://doi.org/10.3390/w13213016.
[23] M. Kahle, M. Kempf, B. Martin, R. Glaser, Classifying the 2021 'Ahrtal' flood event using hermeneutic interpretation, natural language processing, and instrumental data analyses, Environ Res Commun 4 (2022) 051002, https://doi.org/10.1088/2515-7620/ac6657.
[24] H. Schüttrumpf, J. Birkmann, C. Brüll, L. Burghardt, G. Johann, E. Klopries, F. Lehmkuhl, A. Schütttrumpf, S. Wolf, Herausforderungen an den Wiederaufbau nach dem Katastrophenhochwasser 2021 in der Eifel 5–16 (2022). https://henry.baw.de/handle/20.500.11970/108907.
[25] D. Jakhar, I. Kaur, Artificial intelligence, machine learning and deep learning: definitions and differences, Clin. Exp. Dermatol. 45 (1) (2020) 131–132, https://doi.org/10.1111/ced.14029.
[26] S. Voigt, F. Giulio-Tonolo, J. Lyons, J. Kučera, B. Jones, T. Schneiderhan, G. Platzeck, K. Kaku, M.K. Hazarika, L. Czaran, S. Li, W. Pedersen, G.K. James, C. Proy, D.M. Muthike, J. Bequignon, Guha-Sapir Debarati, Global trends in satellite-based emergency mapping, Science (New York, N.Y.) 353 (6296) (2016) 247–252, https://doi.org/10.1126/science.aad8728.
[27] S. Martinis, A. Twele, S. Plank, H. Zwenzner, J. Danzeglocke, G. Strunz, H.-P. Lüttenberg, S. Dech, The international charter 'space and major disasters': DLR's contributions to emergency response worldwide, PFG – J Photogramm Remote Sensing and Geoinform Sci 85 (5) (2017) 317–325, https://doi.org/10.1007/s41064-017-0032-1.
[28] M. Wieland, F. Fichtner, S. Martinis, S. Groth, C. Krullikowski, S. Plank, M. Motagh, S1S2-Water: a global dataset for semantic segmentation of water bodies from sentinel- 1 and sentinel-2 satellite images, IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 17 (2024) 1084–1099, https://doi.org/10.1109/JSTARS.2023.3333969.
[29] A.S. Belward, J.O. Skøien, Who launched what, when and why; trends in global land-cover observation capacity from civilian earth observation satellites, ISPRS J. Photogrammetry Remote Sens. 103 (2015) 115–128, https://doi.org/10.1016/j.isprsjprs.2014.03.009.
[30] R. Gupta, R. Hosfelt, S. Sajeev, N. Patel, B. Goodman, J. Doshi, E. Heim, H. Choset, M. Gaston, *xBD: a Dataset for assessing building Damage from satellite imagery* (No. arXiv:1911.09296), arXiv (2019). http://arxiv.org/abs/1911.09296.
[31] J. Xia, N. Yokoya, B. Adriano, C. Broni-Bediako, OpenEarthMap: a benchmark dataset for global high-resolution land cover mapping, No. arXiv:2210.10732) (2022). http://arxiv.org/abs/2210.10732.
[32] J. Maxant, R. Braun, M. Caspard, S. Clandillon, ExtractEO, a pipeline for disaster extent mapping in the context of emergency management, Remote Sens. 14 (20) (2022) 5253, https://doi.org/10.3390/rs14205253.
[33] E. Holzheimer, U. Kippnich, M. Kippnich, K. Lechner, M. Wieland, Erkundung im Ahrtal mit Unterstützung von Verfahren der Künstlichen Intelligenz, in: Die Flut im Juli 2021. Erfahrungen und Perspektiven aus dem Rettungsingenieurwesen und Katastrophenrisikomanagement, 2022, pp. 22–26.
[34] V. Hertel, C. Chow, O. Wani, M. Wieland, S. Martinis, Probabilistic SAR-based water segmentation with adapted Bayesian convolutional neural network, Rem. Sens. Environ. 285 (2023) 113388, https://doi.org/10.1016/j.rse.2022.113388.
[35] Y. Pi, N.D. Nath, A.H. Behzadan, Convolutional neural networks for object detection in aerial imagery for disaster response and recovery, Adv. Eng. Inform. 43 (2020) 101009, https://doi.org/10.1016/j.aei.2019.101009.
[36] S. Gholami, C. Robinson, A. Ortiz, S. Yang, J. Margutti, C. Birge, R. Dodhia, J.L. Ferres, On the deployment of post-disaster building damage assessment tools using satellite imagery: a deep learning approach. 2022 IEEE International Conference on Data Mining Workshops (ICDMW), 2022, pp. 1029–1036, https://doi.org/10.1109/ICDMW58026.2022.00134.
[37] V. Hertel, C. Geiß, M. Wieland, H. Taubenböck, Domain adaptation techniques for building damage assessment in rapid disaster response (under review), Rem. Sens. Environ. (2025).
[38] C. Geiß, M. Thoma, M. Pittore, M. Wieland, S.W. Dech, H. Taubenbock, Multitask active learning for characterization of built environments with multisensor earth observation data, IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 10 (12) (2017) 5583–5597, https://doi.org/10.1109/JSTARS.2017.2748339.
[39] S. Zhang, R. Feick, Understanding public opinions from geosocial media, ISPRS Int. J. GeoInf. 5 (6) (2016) 74, https://doi.org/10.3390/ijgi5060074.
[40] S. Alzubi, D. Aqel, A. Mughaid, Y. Jararweh, A multi-levels geo-location based crawling method for social media platforms. 2019 Sixth International Conference on Social Networks Analysis, Management and Security (SNAMS), 2019, pp. 494–498, https://doi.org/10.1109/SNAMS.2019.8931856.
[41] V. Cerutti, C. Bellman, A. Both, M. Duckham, B. Jenny, R.L.G. Lemmens, F.O. Ostermann, Improving the reproducibility of geospatial scientific workflows: the use of geosocial media in facilitating disaster response, Spatial Sci. 66 (3) (2021) 383–400, https://doi.org/10.1080/14498596.2019.1654944.
[42] C. Havas, B. Resch, Portability of semantic and spatial-temporal machine learning methods to analyse social media for near-real-time disaster monitoring, Nat. Hazards 1–31 (2021), https://doi.org/10.1007/s11069-021-04808-4.
[43] B. Resch, People as sensors and collective sensing-contextual observations complementing geo-sensor network measurements, in: J.M. Krisp (Ed.), Progress in Location-Based Services, Springer Berlin Heidelberg, 2013, pp. 391–406, https://doi.org/10.1007/978-3-642-34203-5_22.
[44] Z. Wang, S. Hale, D.I. Adelani, P. Grabowicz, T. Hartman, F. Flöck, D. Jurgens, Demographic inference and representative population estimates from multilingual social media data, The World Wide Web Conference (2019) 2056–2067, https://doi.org/10.1145/3308558.3313684.
[45] E. Williams, J. Gray, B. Dixon, Improving geolocation of social media posts, Pervasive Mob. Comput. 36 (2017) 68–79, https://doi.org/10.1016/j.pmcj.2016.09.015.
[46] O. Ajao, D. Bhowmik, S. Zargari, Fake news identification on Twitter with Hybrid CNN and RNN models. SMSociety '18: Proceedings of the 9th International Conference on Social Media and Society, 2018, pp. 226–230, https://doi.org/10.1145/3217804.3217917.
[47] A. Milios, P. BehnamGhader, *An Analysis of social biases Present in BERT variants across multiple languages* (No. arXiv:2211.14402), arXiv (2022), https://doi.org/10.48550/arXiv.2211.14402.
[48] T. Babaian, J. Xu, Entity recognition from colloquial text, Decis. Support Syst. 179 (2024) 114172, https://doi.org/10.1016/j.dss.2024.114172.
[49] L. Boutsikaris, S. Polykalas, A comparative review of deep learning techniques on the classification of irony and sarcasm in text, IEEE Transactions on Artificial Intelligence (2024) 1–15, https://doi.org/10.1109/TAI.2024.3515935.
[50] A. Joshi, R. Dabre, D. Kanojia, Z. Li, H. Zhan, G. Haffari, D. Dippold, Natural Language processing for dialects of a language: a survey, ACM Comput. Surv. (2025) 3712060, https://doi.org/10.1145/3712060.
[51] J.A. Wahid, M. Xu, M. Ayoub, X. Jiang, S. Lei, Y. Gao, S. Hussain, Y. Yang, AI-driven social media text analysis during crisis: a review for natural disasters and pandemics, Appl. Soft Comput. (2025) 112774, https://doi.org/10.1016/j.asoc.2025.112774.
[52] A. Autelitano, B. Pernici, G. Scalia, Spatio-temporal mining of keywords for social media cross-social crawling of emergency events, GeoInformatica 23 (3) (2019) 425–447, https://doi.org/10.1007/s10707-019-00354-1.
[53] L. Derczynski, K. Bontcheva, K. Meesters, D. Maynard, Helping crisis responders find the informative needle in the Tweet haystack, WiPe Paper – Social Media Studies. Proceedings of the 15th ISCRAM Conference – Rochester, NY, USA May 2018 (2018).
[54] E. Blomeier, S. Schmidt, B. Resch, Drowning in the information flood: machine learning-based relevance classification of flood-related Tweets for disaster management, Information 15 (3) (2024), https://doi.org/10.3390/info15030149.
[55] C.J. Powers, A. Devaraj, K. Ashqeen, A. Dontula, A. Joshi, J. Shenoy, D. Murthy, Using artificial intelligence to identify emergency messages on social media during a natural disaster: a deep learning approach, Inter J Inform Manag Data Insights 3 (1) (2023) 100164, https://doi.org/10.1016/j.jjimei.2023.100164.
[56] N. Veigel, H. Kreibich, J.A. De Bruijn, J.C.J.H. Aerts, A. Cominola, *A transformer-based Analysis of Tweets in Germany to Investigate the Appearance and Evolution of the 2021 eifel Flood in social media* [other], Oral (2023), https://doi.org/10.5194/egusphere-egu23-6038.
[57] S. Behl, A. Rao, S. Aggarwal, S. Chadha, H.S. Pannu, Twitter for disaster relief through sentiment analysis for COVID-19 and natural hazard crises, Int. J. Disaster Risk Reduct. 55 (2021), https://doi.org/10.1016/j.ijdrr.2021.102101.
[58] J. Devlin, M.W. Chang, K. Lee, K. Toutanova, BERT: pre-training of deep bidirectional transformers for language understanding, NAACL HLT 2019 - 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies - Proceedings of the Conference 1 (2019) 4171–4186, https://doi.org/10.48550/arxiv.1810.04805.

[59] S. Schmidt, M. Friedemann, D. Hanny, B. Resch, T. Riedlinger, M. Mühlbauer, Enhancing satellite-based emergency mapping: identifying wildfires through geo-social media analysis, Big Earth Data (2025) 1–23, https://doi.org/10.1080/20964471.2025.2454526.
[60] T.L. Beauchamp, J.F. Childress, Principles of Biomedical Ethics, sixth ed., Oxford University Press, 2009.
[61] European Commission, High-level expert group on artificial intelligence. https://ec.europa.eu/newsroom/dae/document.cfm?doc_id=60651, 2019.
[62] Homeland Security, The menlo report. Ethical Principles Guiding Information and Communication Technology Research, 2012. https://www.dhs.gov/sites/default/files/publications/CSD-MenloPrinciplesCORE-20120803_1.pdf.
[63] D. Wright, A framework for the ethical impact assessment of information technology, Ethics Inf. Technol. 13 (3) (2011) 199–226, https://doi.org/10.1007/s10676-010-9242-6.
[64] C. Geyer, G. Ringler, G. Aumayr, N. Sturm, The Ethical Evaluation Standard for Security Research (EESSR) Model [Application/pdf] (2023) 10, https://doi.org/10.35011/IDIMT-2023-39.
[65] M. Knodt, E.K. Platzer, Lessons Learned: Koordination im Katastrophenmanagement, Zenodo, 2023, https://doi.org/10.5281/ZENODO.7756274.
[66] F.C. Nick, N. Sänger, S. Van Der Heijden, S. Sandholz, Collaboration is key: exploring the 2021 flood response for critical infrastructures in Germany, Int. J. Disaster Risk Reduct. 91 (2023) 103710, https://doi.org/10.1016/j.ijdrr.2023.103710.
[67] F. Fichtner, N. Mandery, M. Wieland, S. Groth, S. Martinis, T. Riedlinger, Time-series analysis of Sentinel-1/2 data for flood detection using a discrete global grid system and seasonal decomposition, Int. J. Appl. Earth Obs. Geoinf. 119 (2023) 103329, https://doi.org/10.1016/j.jag.2023.103329.
[68] B. Custers, S. Van Der Hof, B. Schermer, Privacy expectations of social media users: the role of informed consent in privacy policies, Policy Internet 6 (3) (2014) 268–295, https://doi.org/10.1002/1944-2866.POI366.
[69] A.S. Franzke, A. Bechmann, M. Zimmer, C.M. Es, Internet research: ethical guidelines 3.0. https://aoir.org/reports/ethics3.pdf, 2019.
[70] A. Olteanu, C. Castillo, F. Diaz, E. Kıcıman, Social data: biases, methodological pitfalls, and ethical boundaries, Frontiers in Big Data 2 (2019) 13, https://doi.org/10.3389/fdata.2019.00013.
[71] D.-H. Kim, G. López, D. Kiedanski, I. Maduako, B. Ríos, A. Descoins, N. Zurutuza, S. Arora, C. Fabian, Bias in deep neural networks in land use characterization for international development, Remote Sens. 13 (15) (2021) 2908, https://doi.org/10.3390/rs13152908.
[72] C. Gilga, AIFER: Künstliche Intelligenz zur Entscheidungsunterstützung im Katastrophenschutz, Zeitschrift Für Datenschutz-Aktuell (2024) 01519.
[73] DSK, Hambacher Erklärung zur Künstlichen Intelligenz. Sieben datenschutzrechtliche Anforderungen (2019). https://www.datenschutzkonferenz-online.de/media/en/20190405_hambacher_erklaerung.pdf.
[74] T. Krügel, J. Pfeiffenbring, Datenschutzrechtliche herausforderungen von KI. Künstliche Intelligenz Und Robotik: Rechtshandbuch, 2020, pp. 413–441.
[75] A. Thiele, §54 Katastrophenschutzrecht im deutschen Bundesstaat, in: I. Härtel (Ed.), Handbuch Föderalismus—Föderalismus als demokratische Rechtsordnung und Rechtskultur in Deutschland, Europa und der Welt, Springer Berlin Heidelberg, 2012, pp. 69–94, https://doi.org/10.1007/978-3-642-15525-3_3.
[76] E. Ehmann, M. Selmayr, J.P. Albrecht, U. Baumgartner, N. Bertermann, M. Braun, H. Heberlein, D. Heckmann, *DS-GVO: Datenschutz-Grundverordnung: Kommentar* (3. Auflage), C.H. Beck, 2024.
[77] R.K. Kaliyar, A. Goswami, P. Narang, FakeBERT: fake news detection in social media with a BERT-based deep learning approach, Multimed. Tool. Appl. 80 (8) (2021) 11765–11788, https://doi.org/10.1007/s11042-020-10183-2.
[78] Z. Qu, Y. Meng, G. Muhammad, P. Tiwari, QMFND: a quantum multimodal fusion-based fake news detection model for social media, Inf. Fusion 104 (2024) 102172, https://doi.org/10.1016/j.inffus.2023.102172.