



# An assessment of potential improvements in social capital, risk awareness, and preparedness from digital technologies

Tommaso Piseddu, Mathilda Englund, and Karina Barquet

Stockholm Environment Institute, Linnégatan 87D, 115 23 Stockholm, Sweden

**Correspondence:** Tommaso Piseddu (tommaso.piseddu@sei.org)

Received: 23 January 2023 – Discussion started: 9 February 2023

Revised: 20 September 2023 – Accepted: 29 November 2023 – Published: 19 January 2024

**Abstract.** Contributions to social capital, risk awareness, and preparedness constitute the parameters against which applications of digital technologies in the field of disaster risk management should be tested. We propose here an evaluation of four of these: mobile positioning data, social media crowdsourcing, drones, and satellite imaging, with an additional focus on acceptability and feasibility. The assessment is carried out through a survey disseminated among stakeholders. The frame of the analysis also grants the opportunity to investigate to what extent different methodologies to aggregate and evaluate the results, i.e., the Criteria Importance Through Criteria Correlation (CRITIC) model, the (Euclidean)-distance Criteria Importance Through Criteria Correlation (dCRITIC) model, the entropy model, the mean weight model, and the standard deviation model, may influence the preference of one technology over the others. We find that the different assumptions on which these methodologies rely deliver diverging results. We therefore recommend that future research adopt a sensitivity analysis that considers multiple and alternatives methods to evaluate survey results.

## 1 Introduction

The Sendai Framework for Disaster Risk Reduction (UNDRR, 2015) calls for investments in digital technologies and tools to enhance societal resilience. Recent developments in digital technologies and tools offer emerging opportunities for managing disaster risk, i.e., the potential for loss or damages determined by the function of hazard, exposure, and vulnerability (Disaster risk, 2023). More specifically, digital technologies and tools hold significant potential in strength-

ening social capital, risk awareness, disaster preparedness, and, in the end, societal resilience (Latvakoski et al., 2022).

Many scientific fields adopt the concept of resilience (Alexander, 2013), including ecology (Holling, 1973), psychology (Garmezy et al., 1984), and disaster research (Manyena, 2006). As a consequence, resilience is subject to diverse definitions and conceptualizations (see, for example, IPCC, 2014; Johansen et al., 2017; Joseph, 2018; Manyena, 2006; Morsut et al., 2021; UNDRR, 2015; Zhou et al., 2010). Some researchers suggest that resilience refers to the ability of a system to bounce back to its equilibrium (Capano and Woo, 2017; Jurgens and Helsloot, 2018). Other researchers, however, criticize the bounce back metaphor as it fails to capture changes in the social fabric that occur in the wake of a disaster (Dufty, 2012). Accordingly, resilience refers to the ability of a system to bounce *forward* to a new normal i.e., anticipate, recognize, adapt to, and learn from societal disruptions and disasters (Becker, 2014).

There is a plethora of factors that enable or constrain resilience (Javernick-Will and Jordan, 2012). In disaster research, social capital has emerged as a critical determinant of resilience (Kerr, 2018). Social capital refers to “features of social organizations, such as networks, norms and trust that facilitate action and cooperation for mutual benefit” (Putnam, 1993, p. 35).

Greater levels of social capital within a community are linked to higher levels of disaster preparedness and risk awareness (Brunie, 2007; Hausman et al., 2007; Morsut et al., 2021). The nexus between social capital, risk awareness, and disaster preparedness can improve and facilitate collaboration, provide social safety nets, strengthen communication and information sharing, speed up response and recovery efforts, and in the end improve resilience among the most

vulnerable segments of the population (Aldrich and Meyer, 2015).

Despite the demonstrated importance of risk awareness, social capital, and disaster preparedness for effective disaster risk management, their relative degree of importance for enhancing societal resilience remains unclear. An array of weighting models exist, all of which can produce different results (Mukhametzyanov and Pamučar, 2018; Odu, 2019). Most quantitative vulnerability assessments employ a mean weighting approach by default, due to the limited knowledge of the relationship between indicators (Tate, 2012). Comparative studies combining or juxtaposing different weighting methods are found in other fields of research (Jayant and Sharma, 2018) and conclude by warning against the belief that employing a single method may provide sound conclusions (Botvinik-Nezer et al., 2020; Wagenmakers et al., 2022). Similar studies are overall lacking when it comes to digital technologies and tools for improving societal resilience and disaster risk management.

In this paper, we evaluate digital technologies and tools for improving social capital, risk awareness, and disaster preparedness by using a multicriteria analysis. We thereafter assess to what extent the findings are sensitive to different weighting methods. We use five different weighting methods: CRITIC, dCRITIC, standard deviation (SD), mean weights (MW), and entropy. Final scores for these digital technologies are computed using two different approaches, the weighted sum approach (WSA) and the product sum approach (PSA), to test to what extent the results are dependent on this last computational step. This research builds on work carried out within the Horizon 2020 BuildERS project which aims to improve social capital, risk awareness, and preparedness among the most vulnerable segments of the European population through digital technologies and research.

The rest of the paper is organized as follows: Sect. 2 introduces the digital technologies we focus on, Sect. 3 describes the methodology and the data, Sect. 4 presents the results, Sect. 5 comments on the results, and Sect. 6 concludes the study.

## 2 Digital technologies in disaster risk management

Here, digital technologies refer to “tools, systems and devices that can generate, create, store or process data” (Johnston et al., 2022). Digital technologies can support (i) sensing, i.e., collect data with remote sensors; (ii) communication, i.e., transmit data; (iii) processing, i.e., modeling and analysis; and (iv) actuation, i.e., data reconstruction (Bao et al., 2022). Digital technologies can be applied throughout the whole disaster risk management cycle – mitigation, preparedness, response, and recovery (Sakurai and Murayama, 2019; Vermiglio et al., 2022). However, certain digital technologies, such as smartphones, have become ubiquitous in modern life, but their application to disaster risk manage-

ment remains in its infancy and their potential to improve social capital, risk awareness, and preparedness require further attention.

There are many digital technologies relevant to disaster risk management. We zoom in to four digital technologies: mobile positioning data, social media crowdsourcing, drones, and satellite imaging. Previous work in the BuildERS project indicates that mobile positioning data, social media crowdsourcing, drones, and satellite imaging have the greatest innovation potential for disaster risk management (Latvakoski et al., 2022). The identification of these as relevant technologies in disaster risk management is also supported, outside of the framework of the project, by the reviews recently carried out by Izumi et al. (2019), Munawar et al. (2022), and Vermiglio et al. (2022). We therefore proceed by focusing on mobile positioning data, social media crowdsourcing, drones, and satellite imaging. We present an overview of the selected digital technologies below.

### 2.1 Mobile positioning data

Mobile positioning data provides information on the location of a mobile device and its user (Raper et al., 2007). Two forms of mobile positioning data exist: *active*, when the system operator constantly tracks the mobile device, and *passive*, when the system operator only tracks the mobile device while it is being used. The data encompass pseudonymized IDs, timestamps, phone activity, cell tower ID, and the national origin of the SIM card (Latvakoski et al., 2020; Vöik et al., 2021). In a European context, the General Data Protection Regulation (GDPR) prohibits the use of real-time data if not anonymized. Mobile positioning data is often therefore provided with a minimum of 24 h delay to guarantee the anonymity and privacy of mobile device users (Bayardo and Agrawal, 2005; Lasko and Vinterbo, 2010; Terrovitis et al., 2008). Privacy is indeed a concern when operating with this kind of data. For instance, privacy concerns over the sharing of real-time data are identified through the interviews that Bowser et al. (2017) conducted with project managers that handle this kind of data.

Mobile position data can be collected to mitigate disaster risk (Indriasari et al., 2017; Munawar et al., 2022; Hirata et al., 2018; Paul et al., 2021). The ubiquity of smartphones across the globe has made it possible for authorities to use mobile positioning data to alert the population about an approaching hazard by sharing information through SMS messages and others means of communication (Grantz et al., 2020). The application designed by Leelawat et al. (2017) constitutes a good example of such a potential use: risk awareness is increased by providing the population with an assessment of the risk they are exposed to in the event of a tsunami based on their position. Mobile positioning data can also improve data collection, serving as an input when mapping disaster impact, drafting risk and vulnerability assessments, and monitoring mobility. The 2020 Covid-19 pan-

demic accelerated the use of mobile positioning data (Ekong et al., 2020; Ienca and Vayena, 2020; Santamaria et al., 2020), employed to assess the exposure to infection across the population (Grantz et al., 2020). The review performed by Yabe et al. (2022) is an excellent source to understand and classify recent applications of such a technology in the domain of disaster risk management: access to mobile positioning data allows for an understanding of the displacement patterns in the affected population and for a study of the evacuation dynamics, with the possibility to predict post-disaster behaviors of future events based on previous experiences, contributing to better approaches both in the response and in the preparation phases of the disaster risk management cycle. Relocation patterns in the aftermath of a disaster have also been found to correlate with the amount of damage inflicted on the built environment, a condition that allows to proxy the damages estimation by observing relocation behaviors (Andrade et al., 2018). Damage estimates and impacts on local businesses can also benefit from the availability of mobile positioning data (Yabe et al., 2020). The popularity of such an application cannot disguise the challenges that its application entails: the management of the data, which require discretion given their consequences for people's privacy and the difficulty in translating the analysis of the data into insights that can be easily understood by policymakers and hence turned into effective policies (Yabe et al., 2022).

## 2.2 Social media crowdsourcing

Social media crowdsourcing is the practice of contributing to the monitoring of disasters by reporting the presence of incidents related to the event through social media (Phengsuwan et al., 2021). Smartphones and social media use are heavily intertwined. Social media has gained popularity in disaster risk management due to its outreach potential (Reuter and Kaufhold, 2018). The possibility to establish two-way communication in which private citizens interact with official authorities allows for crowdsourcing (Besaleva and Weaver, 2016; Hernandez-Suarez et al., 2019; Kankanamge et al., 2019; Li et al., 2021; Ogie et al., 2019). There are two types of contribution: *active*, when social media users actively share information to support an initiative, and *passive*, when social media users share information independently and irrespectively of an initiative (Besaleva and Weaver, 2016). Typically, social media crowdsourcing generates large datasets that can be analyzed using pre-trained high-level natural language processing software employing artificial intelligence (AI), machine learning, or blockchain technology (Latvakoski et al., 2020).

Social media crowdsourcing has a history of being deployed in disaster risk management, of which some notable examples include the 2010 Haiti earthquake, 2014 North Stradbroke Island bushfires (Australia), and 2015 Houston flooding (USA) (Kankanamge et al., 2019). Social media

crowdsourcing allows the general public to get involved by reporting the conditions they find themselves in and their position: photos and videos can be geotagged once shared on social media, and ad-hoc apps can be downloaded to enable a two-way communication between first responders and those in need. Authorities can use this information to construct hazard maps and alert other citizens about the increasing risks if located in proximity (Zachreson et al., 2021). Besides this flow of information exchange to construct almost-real time maps and inform citizens on the presence of risks (Ogie et al., 2019), the amount of data collected through citizens' engagement in social media can also be exploited to provide rapid assessment of the damage, either through direct observation of the messages shared online (Kryvasheyev et al., 2016) or by applying a sentiment analysis that reveals the correlation between the sentiment level and the impact of the disaster (Li et al., 2021). The experience with past applications of such a technology has helped researchers (Tavra et al., 2021) to identify the challenges that may hinder an effective application: besides the need to constantly train and update the models used for data analysis and interpretation, practitioners will have to design strategies that guarantee a constant, large, and reliable source of data from citizens. While they may appear as the easiest solution, monetary incentives risk undermining the altruistic reasons that push citizens to contribute to the application of this technology (Ogie et al., 2019).

## 2.3 Drones

There is a growing interest in unmanned aerial vehicles, of which drones represent the most popular example (Gomez and Purdie, 2016). Drones are used in a vast range of sectors, such as warfare and agriculture, and also in disaster risk management (Aydin, 2019). Significant improvements in miniaturization and computerization have enabled the production on a large scale of lighter, safer, and cheaper drones (Hall and Wahab, 2021).

The review carried out by Mohd Daud et al. (2022) highlights the operations in disaster risk management that can be aided by the use of drones. Beyond the standard use of drones to construct real-time maps of the areas affected by disasters such as floods, landslide, wildfires, and earthquakes with a rapidity and a cost-effectiveness that has often justified their adoption over other image-providing tools, drones have also found vast application in difficult-to-access areas. An alternative use is that of using drones to perform a rapid assessment of the damages to the built environment without having to put the personnel at risk. In this sense, drones are often sought by practitioners as drones allow them to perform some tasks in a safer manner (Wankmüller et al., 2021). Mohd Daud et al. (2022) also stress the relevant role that drones can play in search and rescue operations: their review identifies several applications where the accessibility to geographical information on the position of the drone and the use of thermal cameras significantly increased the chances to find

and rescue people that went missing during a disaster. Transportation of medical and emergency supplies during an emergency situation or in areas that would otherwise be difficult to reach is another task that can be performed with drones and that has contributed to the popularity of this tool (Rejeb et al., 2021). Further improvements are, however, needed in order to allow for more efficient helicopter–drone and drone–drone cooperation to reduce the risk of collision; and image and video quality will definitely benefit from future technological developments in image acquisitions (Wankmüller et al., 2021).

## 2.4 Satellite imaging

Satellite imaging is a remote sensing technology that takes pictures with an overhead perspective to detect patterns over large areas (Campbell and Wynne, 2011). Satellite imaging made its debut in the 1960s in the first real program for the acquisition of imagery of earth from space, the Landsat program, which was launched by the U.S. government in 1972 (Hemati et al., 2021). The Integrated Global Observing Strategy (IGOS) initiative was launched in 1988 and provided satellite images to support efforts towards disaster risk management. Several initiatives followed, increasing the number of applications of satellite imaging to disaster risk management: the European “Copernicus” program and its Sentinel missions were deployed in 2014 and constitute, to date, the largest European initiative. Despite such a long history compared with other technologies, satellite imaging has not found an early broad application in the domain of disaster risk management: the first 1 m resolution commercial satellite images were only made available thanks to the IKONOS satellite that was launched in 1999; the acquisition of images still takes around 48 h after the event has occurred despite international efforts and collaborations to guarantee a shorter delivery (Le Cozannet et al., 2020). Current image quality and time of delivery already constitute a significant improvement compared with the standards of the past, and despite these issues, satellite imaging has now emerged as a standard technology in the field of disaster risk management thanks also to recent developments in AI and machine learning analysis of the images (Dubovik et al., 2021; Goniewicz et al., 2020; Tellman et al., 2021; Wheeler and Karimi, 2020).

Le Cozannet et al. (2020) offer several points of view to understand and classify the venues for application of this technology. In particular, the authors argue, satellite imaging can be employed to aid in the prevention as well as in response to disasters. The benefits that such technology brings in the prevention of the disaster are acting on those factors that determine the exposure to disasters, such as the hazards themselves, as well as vulnerability and exposure. We here exemplify how satellite imaging can be useful across all these aspects. Reducing hazards often requires access to hazard maps, which are produced by observing the areas and the territories of interest. This makes satellite imaging particu-

larly useful, such as in the case of understanding the characteristics around a volcanic area (Neri et al., 2013) or in estimating geological processes, such as ground deformation, without the need for in situ observations (Foumelis et al., 2016). Targeting vulnerability requires information to produce vulnerability and fragility curves, such as buildings’ shapes, width of streets, and size of buildings (Menichini et al., 2022). Such data can be collected by direct observations, but evidence from the recent literature shows the limit of such an approach and suggests that combining this with space observations guarantees better results (Geiß et al., 2014; Le Cozannet et al., 2018). Substantial improvements in exposure reduction can be achieved by avoiding exposing assets to the risk of hazards in the first place or by relocating those that are now at risk, and high-resolution satellite images can provide the level of detail needed to understand the dynamics in place (Tellman et al., 2021; Weichenthal et al., 2019). While future improvements in computational methods and data quality will make this technology more attractive (Teodoro and Duarte, 2022, p. 10), current developments will unlikely be able to fulfill this promise immediately and satellite earth observations will probably need to be paired with alternative sources to compensate for issues such as uneven temporal sampling (Frasson et al., 2019). The timing aspect appears to be particularly relevant in those cases where longer observations may be needed as the hazards hit: this is the case, for instance, with floods, i.e., with their typical duration of a few hours which can, at times, hardly be matched by satellites’ capabilities (Almar et al., 2023). The accuracy of the measurements represents another aspect that highlights the limitations of this tool (Almar et al., 2023; Melet et al., 2020).

## 3 Materials and methods

We apply a multicriteria analysis following the standard approach outlined in the previous literature: (i) criteria are identified, (ii) a scale for the scoring options is defined, (iii) criteria weights are produced, and (iv) the final scores are computed using the weights from step (iii) and the results from a survey (Bana e Costa et al., 2004; de Brito and Evers, 2016; Gamper et al., 2006). We perform a local sensitivity analysis where we apply different weighting schemes and different approaches for the aggregation of weights and scores into final figures.

### 3.1 Criteria identification

The criteria are identified by referring to the work of Morcut et al. (2021), as developed within the framework of the BuildERS project. The framework outlines the interlinkage between vulnerability, resilience, risk awareness, and social capital. The selection of the criteria aligns with the theoretical approach of the previous literature that confirms the in-

terlinkage between these terms: Barua et al. (2020) on the connection between preparedness and vulnerability, Bixler et al. (2021) on the link between social capital and preparedness, Hanson-Easey et al. (2018) on the relationship between social capital and risk awareness, and Liu et al. (2022) for a discussion on social capital and resilience. We include two additional categories to better reflect potential practical barriers that may emerge: feasibility and acceptability, with special attention given to regulatory frameworks, costs, and social acceptance (Barquet and Cumiskey, 2018; Georgieva and Kae Yanagisawa, 2015).

Each of these five categories is then further developed into criteria. We identify the criteria in a 1 hour workshop with project partners. The workshop is held online to allow project partners representing different European countries to participate. The participants represent different disciplines and professions all pertaining to the sphere of disaster risk management. In total, nine people participate in the workshop and 15 criteria are identified (see Table 1 for an overview). We juxtapose the criteria with previous research on societal resilience to ensure their relevance (Carone et al., 2018; DFID, 1999; Hernantes et al., 2019; The Rockefeller Foundation, 2016).

### 3.2 Scoring options

We develop a survey to assess the digital technologies against the defined criteria. We first ask respondents about their field of expertise and the countries of operation. The respondents are thereafter presented with Likert scale questions outlining the 15 criteria listed in Table 1. We use a four-point Likert scale. We ask the respondents to express whether they “strongly agree”, “agree”, “disagree”, or “strongly disagree” with the statement. We also add a fifth “I do not know” option. The same questions are asked for the four digital technologies to allow for comparison. The survey is launched online on 5 October 2021 and closes on 21 October 2021. A reminder is sent halfway to increase the response rate.

We invite respondents with expertise in disaster risk management or any of the targeted digital technologies to complete the survey. Respondents are contacted by email and asked to complete an online survey. In total, 118 responses are collected, but only 116 are used as 2 respondents failed to complete the survey. All respondents are anonymous. The respondents represent different geographical regions, including Europe (60 %), Asia (15 %), and North America (5 %). The respondents represent different fields of expertise, including disaster risk management ( $n = 79$ ), remote sensing ( $n = 36$ ), drones ( $n = 18$ ), AI ( $n = 18$ ), social media crowdsourcing ( $n = 16$ ), mobile positioning ( $n = 11$ ), and Internet of Things ( $n = 8$ ). Note that the respondents can indicate more than one field as their domain of expertise.

We then convert the qualitative data into quantitative data to allow for the subsequent quantitative analysis. “Strongly agree” is awarded four points and then decreasing values

down to one for “strongly disagree”. “I do not know” replies are dropped as they do not contain any insightful value for the analysis.

We thereafter proceed with creating a performance matrix. The entry values of the matrix for each of the innovation under each criterion are represented as the mean scores that are attributed to the innovation by the survey respondents. We assume that all criteria represent positive contributions to disaster risk management, and hence a higher score indicates a better performance and a positive contribution.

### 3.3 Weighting of criteria

Weights are normalized values between 0 and 1 and add up to 1 when summed for all criteria within the same method. This may sometimes not be the case due to rounding. We apply a quantitative approach when weighting the criteria, using a multimethod framework which allows us to investigate if different methods will lead to different results. The following weighting methods are considered: the Criteria Importance Through Criteria Correlation (CRITIC) (Diakoulaki et al., 1995; Krishnan et al., 2021; Lai and Liao, 2021; Tuş and Adalı, 2019), the (Euclidean)-distance Criteria Importance Through Criteria Correlation (dCRITIC), the standard deviation method (SD), the mean weight method (MW), and the entropy method (Deng et al., 2000; Xu, 2004), all of which represent common approaches in the literature (Diakoulaki et al., 1995; Xu, 2004; Deng et al., 2000; Tuş and Adalı, 2019; Lai and Liao, 2021; Krishnan et al., 2021; Sun et al., 2020; Odu, 2019). An overview is provided Table 2. We only provide a brief description of these methods, and the reader is invited to refer to the previous literature for an analytical analysis.

We delve into the literature to select the weighting methods. A review by Krishnan et al. (2021) finds the entropy and the CRITIC methods to be the most frequently used methods in the literature. The authors also suggest that the dCRITIC methodology requires more attention as it may deliver results that differ from those of the CRITIC method. We add the MW method, as it is a common method in the vulnerability and resilience literature (Tate, 2012). We also add the SD method, as it makes an interesting case for comparison due to its similarities with the CRITIC and dCRITIC methods (Krishnan et al., 2021).

### 3.4 Aggregation

The weights obtained through the different weighting methods and the mean scores obtained through the survey are used to rank the four alternatives following a weighted sum approach:

$$Q_i = \sum_{j=1}^n x_{ij}^* w_j, \quad (1)$$

where  $x_{ij}^*$  is the average survey score of technology  $i$  under criterion  $j$  and  $w_j$  is the weight of criterion  $j$ . In order to pro-

**Table 1.** Criteria used for the analysis.

Category	Criterion
Risk awareness	$C_1$ : It can strengthen risk and vulnerability assessments.
	$C_2$ : It can improve access to crisis information.
	$C_3$ : It can improve the quality of crisis information by making it more accurate, timely, or relevant.
Social capital	$C_4$ : It can minimize the risk of myopic thinking by strengthening trust and coordination between different organizations.
	$C_5$ : It can support citizen engagement in disaster risk management.
	$C_6$ : It can enable collaboration and coordination of volunteers.
Preparedness	$C_7$ : It can improve data collection, procedures, methods, and sharing.
	$C_8$ : It can contribute to the development of plans and strategies to manage crises.
	$C_9$ : It can improve emergency management exercises.
Feasibility	$C_{10}$ :It can be viewed as financially viable considering costs and revenues.
	$C_{11}$ : It is likely that there is access to necessary human, infrastructure, knowledge, and technical resources for implementing and maintaining the service.
	$C_{12}$ : It is likely to be supported by regulatory frameworks.
Acceptability	$C_{13}$ : It can meet local expectations in relation to the stated aims and services provided.
	$C_{14}$ : It receives local support from civil society and groups.
	$C_{15}$ : The perception of gains and/or needs is likely to outweigh perceptions of risk and/or threats.

**Table 2.** Weighting methods.

Name	Description
CRITIC	CRITIC is inspired by the analysis proposed by Diakoulaki et al. (1995), which is based on a correlation analysis of the criteria. The standard deviation method is meant to capture the contrast intensity. Diakoulaki et al. (1995) add a correlation study on top of that to account for emerging conflicts among the criteria.
dCRITIC	dCRITIC, as proposed by Krishnan et al. (2021), represents a small variation in the way correlations, variances, and standard deviations are computed in comparison with the CRITIC method.
Standard deviation	The standard deviation method presents several similarities to the entropy method in the way the weights are computed. The method attributes low weights to the criteria that have similar scores across all the options. The idea behind such a result is straightforward and intuitive: criteria that do not vary across the options do not provide meaningful results and should therefore be assigned a low weight (Zardari et al., 2015).
Mean weight	The mean weight method does not present any computational complexities as every criterion is assigned the same weight, which is just the ratio of 1 over the number of criteria. This method makes no use of the information contained in the performance matrix and just assigns the same weight to all criteria.
Entropy	The entropy method entails a certain degree of uncertainty in the information matrix that is accounted for by making use of probability theory. It suggests that spread and broad distributions contain more uncertainty than the sharply peaked ones (Zardari et al., 2015).

vide additional sensibility to the analysis, we also aggregate the results through the weighted product approach, another methodology that is often employed in the literature (Odu, 2019):

$$Q_i = \prod_{j=1}^n (x_{ij}^*)^{w_j}.$$

(2)

4 Results

In this section, we first present responders’ opinions as we collected them through the survey. We aggregated these opinions into mean score for each technology under each criterion. We then proceed with applying the different weighting methods to investigate their impacts on the findings. Lastly, we present the aggregated findings.

## 4.1 Survey responses

This section presents the survey responses. An overview is provided in Fig. 1. The  $x$  axis presents the criteria, ordered and numbered according to Table 1. The  $y$  axis shows the mean score for each innovation under the corresponding criterion. The range of the  $y$  axis has been reduced to better appreciate the difference in scores that each technology was awarded by the participants in the survey.

Satellite imaging has the highest mean score for criterion 1 (*It can strengthen risk and vulnerability assessments*) and criterion 2 (*It can improve access to crisis information*). Drones score the highest in criterion 3 (*It can improve the quality of crisis information by making it more accurate, timely, or relevant*). Social media crowdsourcing receives the lowest mean score in all criteria related to risk awareness (i.e., criteria 1–3).

Looking at social capital, mobile positioning data holds the highest mean score for criterion 4 (*It can minimize the risk of myopic thinking by strengthening trust and coordination between different organizations*) and criterion 6 (*It can enable collaboration and coordination of volunteers*). Social media crowdsourcing has the highest mean score for criterion 5 (*It can support citizen engagement in disaster risk management*). Both drones and satellite imaging score low in all criteria related to social capital.

When it comes to preparedness, satellite imaging scores the highest in criterion 7 (*It can improve data-collection, procedures, methods, and sharing*) and criterion 8 (*It can contribute to the development of plans and strategies to manage crises*). Drones have the highest mean score in criterion 9 (*It can improve emergency management exercises*). Social media crowdsourcing receives the lowest mean score across all criteria.

In terms of feasibility, all digital technologies receive a high mean score for criterion 10 (*It can be viewed as financially viable considering costs and revenues*), of which drones score the highest. Mobile positioning data have the highest mean score in criterion 11 (*It is likely that there is access to necessary human, infrastructure, knowledge, and technical resources for implementing and maintaining the service*). All digital technologies score low in criterion 12 (*It is likely to be supported by regulatory frameworks*). Social media crowdsourcing scores the lowest in criterion 12.

In the final category, acceptability, most digital technologies scored low across all criteria. Mobile positioning data received the lowest overall score, whereas satellite imaging received the highest overall score. Satellite imaging has the highest mean score in criterion 13 (*It can meet local expectations in relation to the stated aims and services provided*), and social media crowdsourcing has the highest mean score in criterion 14 (*It receives local support from civil society and groups*). Satellite imaging and drones received a high mean score in criterion 15 (*The perception of gains and/or needs is likely to outweigh perceptions of risk and/or threats*).

## 4.2 Weighting methods

This section presents the results from the weighting assessment. The weights are reported in Fig. 2. The  $x$  axis presents the 15 criteria. (See Table 1 for criteria explanations.) The MW method is not included in Fig. 2, as it assigns all criteria the same weight by construction. The weighting methods produce different rankings of criteria and some of these differences are substantial.

Weights' ranges are large in both the CRITIC and the dCRITIC methods. In Fig. 2, under the CRITIC method, the largest weight is about 13.5 % and the smallest weight is about 4 %. Similarly, under the dCRITIC method, the largest weight is about 14 % and the smallest weight is about 3.8 %, i.e., for both methods the largest weight is more than three times the smallest weight. Technologies that score high in the criteria with the largest weights will rank higher. Criterion 6 (*It can enable collaboration and coordination of volunteers*) is assigned the largest weight under the CRITIC method, whereas criterion 8 (*It can contribute to the development of plans and strategies to manage crises*) receives the lowest weight. The distance correlation correction that is introduced by the dCRITIC method seems to bring some changes, though not substantial, when compared with the original CRITIC method: criterion 10 (*It can be viewed as financially viable considering costs and revenues*) receives the largest weight, while criterion 6 still ranks among the top three. Criterion 13 (*It can meet local expectations in relation to the stated aims and services provided*) receives the lowest weight under the dCRITIC method and it ranks 14th under the CRITIC method. In conclusion, some changes are indeed produced by computing a distance correlation instead of the standard Pearson correlation. The changes are, however, minor at the top and bottom of the weights rank.

The SD method and the CRITIC method return similar results in relative terms, i.e., which weights are assigned the largest weights, but the values of these are different. The CRITIC method uses the standard deviations within each criterion to compute the correlation matrix and to correct the values of the final weights, and this could explain the similarity. The SD method assigns the highest weight value to criterion 6 (*It can enable collaboration and coordination of volunteers*), just like the CRITIC method. The smallest weight in the SD method is assigned to criterion 12 (*It is likely to be supported by regulatory frameworks*), which has the third smallest weight under the CRITIC method. In other words, in relative terms, the two methods seem to assign large weights to the same criteria, but the actual weights determined by the SD method are much closer to each other than those observed under the CRITIC method. In fact, we find the SD method to be the one, after the MW method, to return the smallest range of weights.

The SD and MW methods lead to similar distribution of the weights: both methods return a narrow range. The weights defined by the SD method are narrowly distributed:

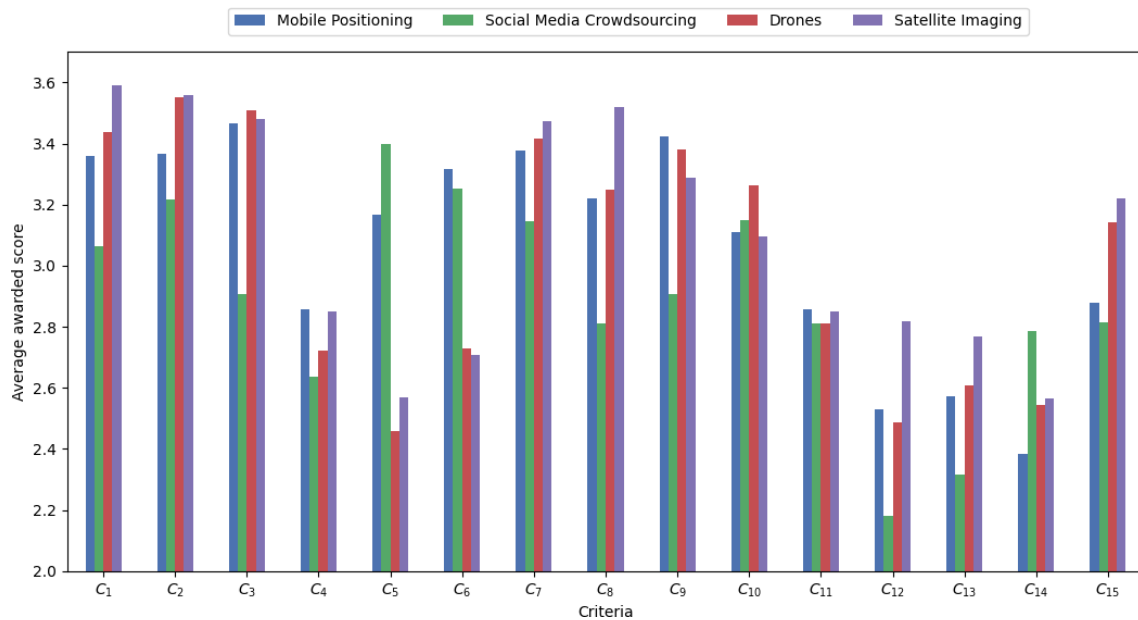


Figure 1. Questionnaire results (average scores).

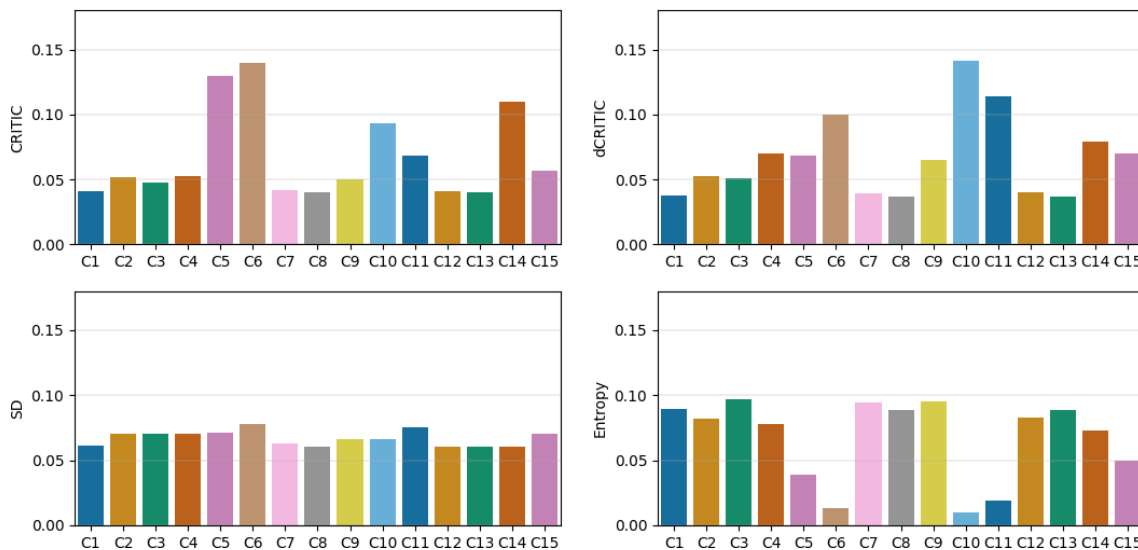


Figure 2. The methods' weights.

the maximum weight is about 7.8 % and the minimum is about 5.9 %, with a difference between the largest and the smallest weight of about 1.9 percentage points. This can be seen in Fig. 2, where although the bars have different heights, overall, the graph looks “flat”, with no criterion being assigned a weight that is much larger than the other criteria and hence no bar being significantly taller than the others. The difference between the largest and the smallest weight in the case of the MW method is 0 as all the criteria are awarded the same weight by construction. Each criterion is assigned a weight of 0.066 % or 6.66 % under the MW method. A bar plot of the MW's weights would show a set of 15 identical

bars. If all the weights are similar, as in the case of the results produced by the SD or MW methods, the innovation with the highest average performance score across all criteria will rank higher, which can be supported by statistical claims. By exploiting the narrow range of the SD and of the MW methods, one could be able to predict, with a significant degree of confidence, which technology will rank first under these methods by simply looking at the survey results as presented in Fig. 1: even without resorting to statistical analysis, it is evident that satellite imaging scores the highest under most of the criteria (7 out of 15), is expected to have a high



average score, and will probably rank high using the weights determined by the SD and MW methods.

The entropy method returns weights that are different from those found in other methods. A large range of different weight values are observed under this method too, as in the CRITIC and dCRITIC methods, but the criteria awarded the largest weights are different from those of other methods. Five of the criteria alone – criterion 15 (*The perception of gains and/or needs is likely to outweigh perceptions of risk and/or threats*), criterion 1 (*It can strengthen risk and vulnerability assessments*), criterion 13 (*It can meet local expectations in relation to the stated aims and services provided*), criterion 12 (*It is likely to be supported by regulatory frameworks*), and criterion 8 (*It can contribute to the development of plans and strategies to manage crises*) – account for about 40 % of the total weight and satellite imaging scores first under all of these criteria. It is reasonable to expect this innovation to score high under this method. As for the CRITIC and dCRITIC methods, we observe a large distribution of the weights awarded to the criteria. It is interesting to note that some of these receive similar weights under the three methods – CRITIC, dCRITIC, and entropy – such as criterion 14 (*It receives local support from civil society and groups*) and criterion 15 (*The perception of gains and/or needs is likely to outweigh perceptions of risk and/or threats*). However, a striking aspect that should already be observed from Fig. 2 is that the most relevant criteria under the CRITIC and dCRITIC methods, i.e., those that are awarded the largest weights are assigned the smallest weights under the entropy method. Just by looking at these preliminary results, it is reasonable to expect large differences in the final rankings among these methods.

The Spearman correlation matrix in Table 3 provides additional insights for a comparison of the weights that are produced by the different methods. The correlation between the entropy method and the CRITIC and dCRITIC methods is negative and large, meaning that the ranking order may be really inverted and that the weights vary significantly, confirming what is observed in Fig. 2. As expected, the dCRITIC and CRITIC methods have a high positive correlation value as the way in which the correlation matrix is computed constitutes the only difference between the two. No correlation can be computed between the MW method and any of the other methods as there is no variation in the assigned weights of the former, i.e., the variance of the MW method is 0. A null denominator in the correlation formula impedes any computation.

4.3 Aggregation

Figure 3 offers an overview of how the four digital technologies rank under the different weighting methods. Only results from the weighted sum approach are presented as the results produced by the weighted product approach are identical. The rankings are produced according to the final score that is

Table 3. Spearman correlation matrix.

	Entropy	MW	dCRITIC	SD	CRITIC
Entropy	1	–	–0.79	–0.45	–0.76
MW	–	–	–	–	–
dCRITIC	–0.79	–	1	0.575	0.9
SD	–0.45	–	0.575	1	0.65
CRITIC	–0.76	–	0.9	0.65	1

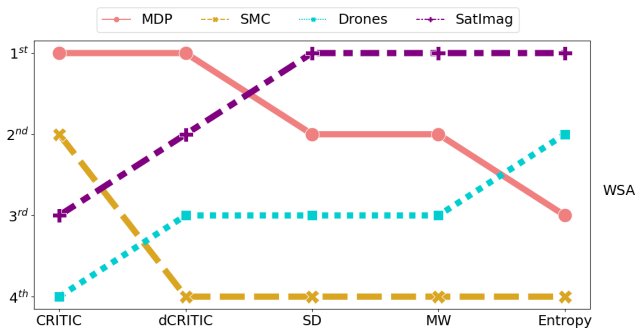


Figure 3. Final ranking of the technologies. MDP stands for Mobile Data Positioning, SMC stands for Social Media Crowdsourcing, and SatImag stands for Satellite Imaging.

computed for every technology: we use the weights produced by the methods, presented in Fig. 2, and the average survey scores in Fig. 1 by feeding these values into Eqs. (1) and (2), presented in the “Materials and methods” section. We find here a confirmation of the correlations that were produced in Table 3: the high negative correlation between the entropy method and the CRITIC and dCRITIC methods results in a complete reversal of the ranking order. The entropy method returns results that are, at the top and bottom, the same as those returned by the SD and MW methods: satellite imaging still ranks as the most preferred innovation and social media crowdsourcing as the least.

As expected from the computation of the Spearman correlation matrix, the CRITIC, dCRITIC, and SD methods are the ones that produce the closest results. Across all weighting methods, with the sole exception of CRITIC, social media crowdsourcing seems to be the least preferred option among respondents. Satellite imaging ranks as the best innovation in three out of five methods (SD, MW, and entropy) with mobile positioning data ranking first in the remaining two. Overall, the results suggest that satellite imaging is the most preferred innovation. It is evident, however, that the results are very sensible to the methodology used. The best innovation according to the entropy method, satellite imaging, ranks third under the CRITIC method. The opposite is true for mobile data positioning, which ranks first under the CRITIC method and the dCRITIC method but then falls to third place under the entropy method.

As we had been able to anticipate, satellite imaging is the technology that ranks first under the SD and MW methods. We attribute this, again, to the small range of weights produced by these two methods. It is also interesting to note that these two are the only methods where the ranking orders are exactly identical.

## 5 Discussion

Below we first discuss the findings in relation to disaster risk management and societal resilience, with a focus on their impact on social capital, risk awareness, and disaster preparedness. We thereafter delve into the weighting methods and make some recommendations for scholars assessing digital technologies for disaster risk management.

### 5.1 Digital technologies for enhancing societal resilience

The different weighting methods produce different results, which makes it difficult to draw conclusions about which digital technologies can improve social capital, risk awareness, and disaster preparedness. In general, the findings show positive or neutral perceptions of the digital technologies under investigation. When juxtaposing the digital technologies, we find some emerging patterns that indicate a preference of some technologies over others.

Social media crowdsourcing received the lowest score in the survey in all criteria except criterion 5 (*It can support citizen engagement in disaster risk management*), criterion 10 (*It can be viewed as financially viable considering costs and revenues*), and criterion 14 (*It receives local support from civil society and groups*). We attribute the poor ranking to the interdependence between social capital, risk awareness, and disaster preparedness in which a negative performance in one of them may reinforce negative performance in the others. It creates a vicious circle of cascades and unintended consequences. In the case of social media crowdsourcing, scholars find that it may generate data inaccuracies due to mis- or disinformation and social biases (Fang et al., 2019; Nguyen et al., 2019). Data inaccuracies may have a negative impact on preparedness if integrated into risk and vulnerability assessments, contingency plans, and emergency exercises. Di Felice and Iessi (2019) note that inaccurate data generated from social media crowdsourcing may exacerbate disaster impacts. In line with previous research (Han et al., 2011; Nicholls and Picou, 2013), we believe that ineffective disaster response can erode social capital and trust as it might cause a loss in confidence in disaster risk management authorities.

Regardless of the weighting method, satellite imaging and drones yield similar benefits for risk awareness and disaster preparedness including improvements in data collection, better input to risk and vulnerability assessments, support to

emergency exercises and contingency plans, and improvements in quality and access to crisis information. Given these similarities, satellite imaging and drones may be considered as alternatives i.e., investments should be made in one or the other, but not both, as they yield similar benefits. However, in line with previous research (Sajjad and Kumar, 2019; Gray et al., 2018; Kucharczyk and Hugenholtz, 2021), we argue that satellite imaging and drones can complement each other when applied in disaster risk management. Satellites and drones can support different aims and offset different challenges with regard to accessibility and feasibility. Our findings indicate that satellite imaging and drones differ in terms of compliance with regulatory frameworks, financial viability, and social acceptance, as also noted by Bansod et al. (2017). Furthermore, satellites and drones offer imagery at different scales and therefore have different purposes and attributes. In disaster risk management, drones are used on a local scale and case-by-case basis, while satellite imaging is more standardized.

Practical barriers seem to pertain to all digital technologies, regardless of the weighting method, and these barriers impede their integration in disaster risk management despite their potential benefits for social capital, risk awareness, and disaster preparedness. Noncompliance with regulatory frameworks, inadequate access to resources, and limited social acceptability apply across all digital technologies. In line with previous research (Gambino and Tuzzolino, 2022; Bu-Pasha, 2018; Tsiamis et al., 2019; Harrison and Johnson, 2019; Santos and Rapp, 2019), this indicates a gap between technological advancements and institutional contexts. Technological development seems to accelerate faster than regulatory frameworks and capacity development. We see a need for going beyond technological solutions and consider the practical constraints faced by actors in disaster risk management, in order to strengthen social capital, risk awareness, disaster preparedness, and societal resilience.

We collected data from respondents representing various regions with differences in disaster exposures and social conditions. Vulnerabilities are represented differently depending on context, hence requiring different types of disaster risk reduction measures. For example, satellite-based remote sensing cannot operate in cloudy conditions, whereas drones can (Emilien et al., 2021). This study does not capture these contextual and situational differences. We therefore recommend that future research investigate social capital, risk awareness, and disaster preparedness in depth and in context, in order to make recommendations for policymakers and practitioners.

### 5.2 Reflections on the weighting of the criteria

We find that the choice of weighting method has a significant impact on the final ranking of the alternatives, while the way in which survey results and weights are aggregated to produce the final scores does not affect the ranking order. The final rankings produced by the methods are the re-

sults of the underlying assumptions on how to better treat the uncertainties and the distributions of stakeholders' opinions. We therefore refrain from recommending one method over another. Instead, we suggest applying different weighting methods to observe what outputs are produced under different assumptions. This can mitigate potential uncertainties and biases. Using different weighting methods can increase robustness, reduce uncertainty, and improve credibility of the results.

Our findings suggest that, when selecting the methods for evaluating alternatives, methods that share similar underlying assumptions and compute scores in a similar way should be avoided as the additional information they provide is not substantial and risk reinforcing the decision bias. The combination of methods with diverging theoretical assumptions can better recognize the uncertainty found in the dataset and account for unseen patterns. In our case, the CRITIC and dCRITIC methods yielded similar results and are hence insufficient on their own, as they both rely on an approach that is based on a correlation analysis among the criteria. The similarity of results under these two methods can be explained by the distance correction that the dCRITIC method adds to the CRITIC method and that has little effect on the computation of the results. It can be said that these two methods belong to the same family, as both stress the analysis of the correlation between the criteria as their main feature. Both methods thus build on similar assumptions. Because of this common trait, they may award similar weights to the same criteria leading then to similar results. We observed that the only two methods that produced the same exact ranking preferences of the technologies are the SD method and the MW method. We argue that this result is due more to a selection choice by the researchers than to the similarity in the computational steps. The MW method returns a null range of weights by construction: all criteria are assigned the same weight. The fact that we observe similar results from the SD method, we argue, is instead linked to the selection of a four-point Likert scale. The selection of such a small scale returns a mean that is significantly close to the median. To provide an example, mobile positioning data has an average score of 3.36 under criterion 1 (*It can strengthen risk and vulnerability assessments*) and the distribution of scores for this technology under this criterion does not differ much from this mean: 51 of the respondents awarded three points and 50 awarded four points. The narrative does not change for the same technology under criterion 2 (*It can improve access to crisis information*), where the mean score is 3.37 and 53 respondents awarded three points and 49 respondents awarded four points. The argument we are stressing is that with these distributions of results from the survey, all the criteria present similar, small, standard deviations. As the SD method awards each criterion a weight that is expressed as the ratio between that criterion's standard deviation and the sum of all standard deviations across all criteria, it is clear that the weights will have close values and will then show a distribution that is

similar to the one obtained with the MW method. The distribution of survey results, centered closely around the mean and therefore all very close to each other, is the reason, we argue, why the SD method returns weights that have similar value, e.g., the "flat distribution" observed in Fig. 2. A larger Likert scale, i.e., with more scoring options, could potentially prevent such a result and return a different range of weights.

Additional methods that consider alternative weight specifications and assumptions should be included to provide a robust analysis of the performance. In this case, we rely both on the entropy method to provide additional insights as it makes use of probability theory instead of correlation or standard deviation analysis, and on the mean weight method, which makes no assumption regarding the uncertainties in stakeholders' opinions by assigning every criterion the same weight. We show that the introduction of a method that builds on a different set of assumptions, the entropy method, may completely change the results of the analysis.

### 5.3 Limitations

The geographical distribution of the responses collected through the survey should stand as a caveat against the external validity of the results presented here. The way local governments, communities, enterprises, and other local actors interact generates a dynamic that makes every application extremely case specific (Maskrey, 2011). Moreover, the adoption and the application of certain digital technologies in areas that are already characterized by uneven distribution of vulnerability and inequalities may risk exacerbating these situations (Hao et al., 2021). The case holds both for the Global North, as shown in Wang et al. (2019), where social vulnerability of certain communities has been exacerbated by the use of social networking sites for information exchange during responses to Hurricane Sandy, and for the Global South as well, as exemplified in the case of the 2015 earthquake that hit Nepal: technological innovations in disaster management were introduced in the context of deep social and digital inequalities, benefitting mostly those less at risk (Mulder, 2020).

## 6 Conclusions

Our study makes a contribution to the literature on disaster risk management by evaluating digital technologies for improving social capital, risk awareness, and disaster preparedness. We applied a multicriteria analysis that incorporated different weighting methods in order to test uncertainties in the relative degree of importance of social capital, risk awareness, and disaster preparedness for societal resilience. The conclusions of our analysis, we hope, will benefit the academic community and practitioners as well. For the former, the warnings we raised on the implications of the choice of the model to aggregate stakeholders' opinions may raise

awareness among researchers working with similar methods, even in a different field; for the latter, the conclusions of the analysis inform practitioners on the suitability of adoption of one or more of the tools to achieve their goals of increasing awareness, social resilience, and disaster responsiveness.

To overcome some of this study's shortcomings, we recommend that future research engage in comparative case studies and provide a contextual assessment of how digital technologies can improve social capital, risk awareness, and disaster preparedness. We suggest looking into an array of empirical contexts to test their application in various geographical areas and situations. Future research can also explore potential negative spillover effects that cascade across social capital, risk awareness, and disaster preparedness when implementing the digital technologies in practice. We argue that the size of the scoring scale also may have a significant impact on the ranking of preferences in a multi-criteria assessment. We therefore encourage further research on this topic to increase the awareness around this issue and prevent selection biases.

In conclusion, our study shows the potential of digital technologies in strengthening social capital, risk awareness, and disaster preparedness. We highlight the importance of using rigorous methodologies when assessing different innovative solutions for disaster risk management. Sensitivity analysis by comparing different weighting methods and testing different assumptions on how to treat uncertainties from survey results can enhance the communication of findings and improve confidence in the reliability of the results. The number of choices that a researcher makes is high, from the selection of a scoring scale to that of the weighting models, and this increases the likelihood of uncertain results that would not be confirmed by an alternative approach. Different assumptions and different approaches should always be considered as a means to increase the robustness of the results. Above all, this can improve decision-making and societal resilience, and in the long run it can protect human lives and economic assets.

*Code and data availability.* The datasets generated during and/or analyzed during the current study are available from the corresponding author.

*Author contributions.* TP: conceptualization, formal analysis, data curation, methodology, visualization, and writing – original draft preparation as well as review and editing; ME: conceptualization, formal analysis, methodology, and writing – original draft preparation as well as review and editing; KB: funding acquisition, supervision, and writing – review and editing.

*Competing interests.* The contact author has declared that none of the authors has any competing interests.

*Disclaimer.* Publisher's note: Copernicus Publications remains neutral with regard to jurisdictional claims made in the text, published maps, institutional affiliations, or any other geographical representation in this paper. While Copernicus Publications makes every effort to include appropriate place names, the final responsibility lies with the authors.

*Financial support.* This work was supported by the Horizon 2020 BuildERS project (grant no. 833496).

*Review statement.* This paper was edited by Daniela Molinari and reviewed by two anonymous referees.

## References

- Aldrich, D. P. and Meyer, M. A.: Social Capital and Community Resilience, *Am. Behav. Sci.*, 59, 254–269, <https://doi.org/10.1177/0002764214550299>, 2015.
- Alexander, D. E.: Resilience and disaster risk reduction: an etymological journey, *Nat. Hazards Earth Syst. Sci.*, 13, 2707–2716, <https://doi.org/10.5194/nhess-13-2707-2013>, 2013.
- Almar, R., Stieglitz, T., Addo, K. A., Ba, K., Ondo, G. A., Bergsma, E. W. J., Bonou, F., Dada, O., Angnuureng, D., and Arino, O.: Coastal Zone Changes in West Africa: Challenges and Opportunities for Satellite Earth Observations, *Surv. Geophys.*, 44, 249–275, <https://doi.org/10.1007/s10712-022-09721-4>, 2023.
- Andrade, X., Layedra, F., Vaca, C., and Cruz, E.: RiSC: Quantifying change after natural disasters to estimate infrastructure damage with mobile phone data, in: 2018 IEEE International Conference on Big Data (Big Data), 2018 IEEE International Conference on Big Data (Big Data), 3383–3391, <https://doi.org/10.1109/BigData.2018.8622374>, 2018.
- Aydin, B.: Public acceptance of drones: Knowledge, attitudes, and practice, *Technol. Soc.*, 59, 101180, <https://doi.org/10.1016/j.techsoc.2019.101180>, 2019.
- Bana e Costa, C. A., Antão da Silva, P., and Nunes Correia, F.: Multicriteria Evaluation of Flood Control Measures: The Case of Ribeira do Livramento, *Water Resour. Manag.*, 18, 263–283, <https://doi.org/10.1023/B:WARM.0000043163.19531.6a>, 2004.
- Bansod, B., Singh, R., Thakur, R., and Singhal, G.: A comparison between satellite based and drone based remote sensing technology to achieve sustainable development: A review, *J. Agric. Environ. Int. Dev.*, 111, 383–407, <https://doi.org/10.12895/jaeid.20172.690>, 2017.
- Bao, H., Zeng, C., Peng, Y., and Wu, S.: The use of digital technologies for landslide disaster risk research and disaster risk management: progress and prospects, *Environ. Earth Sci.*, 81, 446, <https://doi.org/10.1007/s12665-022-10575-7>, 2022.
- Barquet, K. and Cumiskey, L.: Using participatory Multi-Criteria Assessments for assessing disaster risk reduction measures, *Coast. Eng.*, 134, 93–102, <https://doi.org/10.1016/j.coastaleng.2017.08.006>, 2018.
- Barua, U., Mannan, S., Islam, I., Akther, M. S., Islam, Md. A., Akter, T., Ahsan, R., and Ansary, M. A.: People's awareness, knowledge and perception influencing earthquake vul-

- nerability of a community: A study on Ward no. 14, Myensingh Municipality, Bangladesh, *Nat. Hazards*, 103, 1121–1181, <https://doi.org/10.1007/s11069-020-04028-2>, 2020.
- Bayardo, R. J. and Agrawal, R.: Data privacy through optimal k-anonymization, in: 21st International Conference on Data Engineering (ICDE'05), 21st International Conference on Data Engineering (ICDE'05), Tokyo, Japan, 5–8 April 2005, 217–228, <https://doi.org/10.1109/ICDE.2005.42>, 2005.
- Becker, P.: Chapter 1 – Introducing the Book, in: *Sustainability Science*, edited by: Becker, P., Elsevier, 1–6, <https://doi.org/10.1016/B978-0-444-62709-4.00001-4>, 2014.
- Besaleva, L. I. and Weaver, A. C.: Crowdsourcing for Emergency Response, in: *Int'l Conf. Frontiers in Education: CS and CE | FECS'16*, 248–253, <https://www.proquest.com/openview/42bebl1ea326c3049891613f284cc6349/1?cbl=1976352&pq-origsite=gscholar&parentSessionId=IqwCpMszuuOqQOOkJE9SO8ztsDNgpj8GpJ09kPq1MNk%3D> (last access: 12 July 2021), 2016.
- Bixler, R. P., Paul, S., Jones, J., Preisser, M., and Pas-salacqua, P.: Unpacking Adaptive Capacity to Flooding in Urban Environments: Social Capital, Social Vulnerability, and Risk Perception, *Front. Water*, 3, 728730, <https://doi.org/10.3389/frwa.2021.728730>, 2021.
- Botvinik-Nezer, R., Holzmeister, F., Camerer, C. F., Dreber, A., Huber, J., Johannesson, M., Kirchler, M., Iwanir, R., Mumford, J. A., Adcock, R. A., Avesani, P., Baczkowski, B. M., Bajracharya, A., Bakst, L., Ball, S., Barilari, M., Bault, N., Beaton, D., Beitner, J., Benoit, R. G., Berkens, R. M. W. J., Bhanji, J. P., Biswal, B. B., Bobadilla-Suarez, S., Bortolini, T., Bottenhorn, K. L., Bowring, A., Braem, S., Brooks, H. R., Brudner, E. G., Calderon, C. B., Camilleri, J. A., Castrellon, J. J., Cecchetti, L., Cieslik, E. C., Cole, Z. J., Collignon, O., Cox, R. W., Cunningham, W. A., Czoschke, S., Dadi, K., Davis, C. P., Luca, A. D., Delgado, M. R., Demetriou, L., Dennison, J. B., Di, X., Dickie, E. W., Dobryakova, E., Donnat, C. L., Dukart, J., Duncan, N. W., Durnez, J., Eed, A., Eickhoff, S. B., Erhart, A., Fontanesi, L., Fricke, G. M., Fu, S., Galván, A., Gau, R., Genon, S., Glatard, T., Glerean, E., Goeman, J. J., Golowin, S. A. E., González-García, C., Gorgolewski, K. J., Grady, C. L., Green, M. A., Guassi Moreira, J. F., Guest, O., Hakimi, S., Hamilton, J. P., Hancock, R., Handjaras, G., Harry, B. B., Hawco, C., Herholz, P., Herman, G., Heunis, S., Hoffstaedter, F., Hogeveen, J., Holmes, S., Hu, C.-P., Huettel, S. A., Hughes, M. E., Iacovella, V., Iordan, A. D., Isager, P. M., Isik, A. I., Jahn, A., Johnson, M. R., Johnstone, T., Joseph, M. J. E., Juliano, A. C., Kable, J. W., Kassinosopoulos, M., Koba, C., Kong, X., Kosciak, T. R., Kucukboyaci, N. E., Kuhl, B. A., Kupek, S., Laird, A. R., Lamm, C., Langner, R., Lauharatanahirun, N., Lee, H., Lee, S., Leemans, A., Leo, A., Lesage, E., Li, F., Li, M. Y. C., Lim, P. C., Lintz, E. N., Liphardt, S. W., Losecaat Vermeer, A. B., Love, B. C., Mack, M. L., Malpica, N., Marins, T., Maumet, C., McDonald, K., McGuire, J. T., Melero, H., Méndez Leal, A. S., Meyer, B., Meyer, K. N., Mihai, G., Mitsis, G. D., Moll, J., Nielson, D. M., Nilsson, G., Notter, M. P., Olivetti, E., Onicas, A. I., Papale, P., Patil, K. R., Peelle, J. E., Pérez, A., Pischedda, D., Poline, J.-B., Prystauka, Y., Ray, S., Reuter-Lorenz, P. A., Reynolds, R. C., Ricciardi, E., Rieck, J. R., Rodriguez-Thompson, A. M., Romy, A., Salo, T., Samanez-Larkin, G. R., Sanz-Morales, E., Schlichting, M. L., Schultz, D. H., Shen, Q., Sheridan, M. A., Silvers, J. A., Skagerlund, K., Smith, A., Smith, D. V., Sokol-Hessner, P., Steinkamp, S. R., Tashjian, S. M., Thirion, B., Thorp, J. N., Tinghög, G., Tisdall, L., Tompson, S. H., Toro-Serey, C., Torre Tresols, J. J., Tozzi, L., Truong, V., Turella, L., van 't Veer, A. E., Verguts, T., Vettel, J. M., Vijayarajah, S., Vo, K., Wall, M. B., Weeda, W. D., Weis, S., White, D. J., Wisniewski, D., Xifra-Porxas, A., Yearling, E. A., Yoon, S., Yuan, R., Yuen, K. S. L., Zhang, L., Zhang, X., Zosky, J. E., Nichols, T. E., Pol-drack, R. A., and Schonber, T.: Variability in the analysis of a single neuroimaging dataset by many teams, *Nature*, 582, 84–88, <https://doi.org/10.1038/s41586-020-2314-9>, 2020.
- Bowser, A., Shilton, K., Preece, J., and Warrick, E.: Accounting for Privacy in Citizen Science: Ethical Research in a Context of Openness, in: *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, New York, NY, USA, 25 February 2017–1 March 2017, 2124–2136, <https://doi.org/10.1145/2998181.2998305>, 2017.
- de Brito, M. M. and Evers, M.: Multi-criteria decision-making for flood risk management: a survey of the current state of the art, *Nat. Hazards Earth Syst. Sci.*, 16, 1019–1033, <https://doi.org/10.5194/nhess-16-1019-2016>, 2016.
- Brunie, A.: Household disaster preparedness: assessing the importance of relational and community social capital, University of North Carolina, Chapel Hill, <https://doi.org/10.17615/545T-SS41>, 2007.
- Bu-Pasha, S.: Location Data, Personal Data Protection and Privacy in Mobile Device Usage: An EU Law Perspective, PhD, University of Helsinki, Helsinki, <https://helda.helsinki.fi/handle/10138/251512> (last access: 22 March 2022), 2018.
- Campbell, J. B. and Wynne, R. H.: Introduction to remote sensing, 5th edn., Guildford Press, New York, ISBN 9781609181765, 2011.
- Capano, G. and Woo, J. J.: Resilience and robustness in policy design: a critical appraisal, *Policy Sci.*, 50, 399–426, 2017.
- Carone, M. T., Marincioni, F., and Romagnoli, F.: Use of multi-criteria decision analysis to define social resilience to disaster: the case of the EU LIFE PRIMES project, *Enrgy Proced.*, 147, 166–174, <https://doi.org/10.1016/j.egypro.2018.07.051>, 2018.
- Deng, H., Yeh, C.-H., and Willis, R. J.: Inter-company comparison using modified TOPSIS with objective weights, *Comput. Oper. Res.*, 27, 963–973, [https://doi.org/10.1016/S0305-0548\(99\)00069-6](https://doi.org/10.1016/S0305-0548(99)00069-6), 2000.
- DFID: Sustainable livelihoods guidance sheets, Department for International Development, <https://www.livelihoodscentre.org/documents/114097690/114438878/Sustainable+livelihoods+guidance+sheets.pdf/594e5ea6-99a9-2a4e-f288-cbb4ae4bea8b?t=1569512091877> (last access: 18 May 2021), 1999.
- Di Felice, P. and Iessi, M.: A Citizen-Sensing-Based Digital Service for the Analysis of On-Site Post-Earthquake Messages, *ISPRS Int. J. Geo-Inf.*, 8, 136, <https://doi.org/10.3390/ijgi8030136>, 2019.
- Diakoulaki, D., Mavrotas, G., and Papayannakis, L.: Determining objective weights in multiple criteria problems: The critic method, *Comput. Oper. Res.*, 22, 763–770, [https://doi.org/10.1016/0305-0548\(94\)00059-H](https://doi.org/10.1016/0305-0548(94)00059-H), 1995.
- Disaster risk: <https://www.undrr.org/terminology/disaster-risk>, last access: 7 July 2023.
- Dubovik, O., Schuster, G. L., Xu, F., Hu, Y., Bösch, H., Landgraf, J., and Li, Z.: Grand Challenges in Satel-

- lite Remote Sensing, *Front. Remote Sens.*, 2, 619818, <https://doi.org/10.3389/frsen.2021.619818>, 2021.
- Dufty, N.: Using Social Media to Build Community Disaster Resilience, *Australian Journal of Emergency Management*, 27, 40–45, <https://knowledge.aidr.org.au/resources/ajem-jan-2012-using-social-media-to-build-community-disaster-resilience/> (last access: 19 September 2023) 2012.
- Ekong, I., Chukwu, E., and Chukwu, M.: COVID-19 Mobile Positioning Data Contact Tracing and Patient Privacy Regulations: Exploratory Search of Global Response Strategies and the Use of Digital Tools in Nigeria, *JMIR MHealth UHealth*, 8, 19139, <https://doi.org/10.2196/19139>, 2020.
- Emilien, A.-V., Thomas, C., and Thomas, H.: UAV & satellite synergies for optical remote sensing applications: A literature review, *Sci. Remote Sens.*, 3, 100019, <https://doi.org/10.1016/j.srs.2021.100019>, 2021.
- Fang, J., Hu, J., Shi, X., and Zhao, L.: Assessing disaster impacts and response using social media data in China: A case study of 2016 Wuhan rainstorm, *Int. J. Disast. Risk Re.*, 34, 275–282, <https://doi.org/10.1016/j.ijdr.2018.11.027>, 2019.
- Foumelis, M., Papageorgiou, E., and Stamatopoulos, C.: Episodic ground deformation signals in Thessaly Plain (Greece) revealed by data mining of SAR interferometry time series, *Int. J. Remote Sens.*, 37, 3696–3711, <https://doi.org/10.1080/01431161.2016.1201233>, 2016.
- Frasson, R. P. de M., Schumann, G. J.-P., Kettner, A. J., Brakenridge, G. R., and Krajewski, W. F.: Will the Surface Water and Ocean Topography (SWOT) Satellite Mission Observe Floods?, *Geophys. Res. Lett.*, 46, 10435–10445, <https://doi.org/10.1029/2019GL084686>, 2019.
- Gambino, A. M. and Tuzzolino, D.: Location Data and Privacy, in: *Privacy and Data Protection in Software Services*, edited by: Senigaglia, R., Irti, C., and Bernes, A., Springer, Singapore, 141–152, [https://doi.org/10.1007/978-981-16-3049-1\\_12](https://doi.org/10.1007/978-981-16-3049-1_12), 2022.
- Gamper, C. D., Thöni, M., and Weck-Hannemann, H.: A conceptual approach to the use of Cost Benefit and Multi Criteria Analysis in natural hazard management, *Nat. Hazards Earth Syst. Sci.*, 6, 293–302, <https://doi.org/10.5194/nhess-6-293-2006>, 2006.
- Garnezy, N., Masten, A. S., and Tellegen, A.: The Study of Stress and Competence in Children: A Building Block for Developmental Psychopathology, *Child Dev.*, 55, 97–111, <https://doi.org/10.2307/1129837>, 1984.
- Geiß, C., Taubenböck, H., Tyagunov, S., Tisch, A., Post, J., and Lakes, T.: Assessment of Seismic Building Vulnerability from Space, *Earthq. Spectra*, 30, 1553–1583, <https://doi.org/10.1193/121812EQS350M>, 2014.
- Georgieva, I. D. and Kae Yanagisawa, K. (Eds.): *Disaster Risk Reduction for Economic Growth and Livelihood: Investing in Resilience and Development*, Routledge, London, 312 pp., <https://doi.org/10.4324/9781315739953>, 2015.
- Gomez, C. and Purdie, H.: UAV- based Photogrammetry and Geocomputing for Hazards and Disaster Risk Monitoring – A Review, *Geoenvironmental Disasters*, 3, 23, <https://doi.org/10.1186/s40677-016-0060-y>, 2016.
- Goniewicz, K., Magiera, M., Burkle, F. M., and Goniewicz, M.: Prospective Study on the Potential Use of Satellite Data for Disaster Prevention, Preparedness, and Mitigation in Poland, *Prehospital Disaster Med.*, 35, 331–334, <https://doi.org/10.1017/S1049023X20000321>, 2020.
- Grantz, K. H., Meredith, H. R., Cummings, D. A. T., Metcalf, C. J. E., Grenfell, B. T., Giles, J. R., Mehta, S., Solomon, S., Labrique, A., Kishore, N., Buckee, C. O., and Wesolowski, A.: The use of mobile phone data to inform analysis of COVID-19 pandemic epidemiology, *Nat. Commun.*, 11, 4961, <https://doi.org/10.1038/s41467-020-18190-5>, 2020.
- Gray, P. C., Ridge, J. T., Poulin, S. K., Seymour, A. C., Schwantes, A. M., Swenson, J. J., and Johnston, D. W.: Integrating Drone Imagery into High Resolution Satellite Remote Sensing Assessments of Estuarine Environments, *Remote Sens.*, 10, 1257, <https://doi.org/10.3390/rs10081257>, 2018.
- Hall, O. and Wahab, I.: The Use of Drones in the Spatial Social Sciences, *Drones*, 5, 112, <https://doi.org/10.3390/drones5040112>, 2021.
- Han, Z., Hu, X., and Nigg, J.: How Does Disaster Relief Works Affect the Trust in Local Government? A Study of the Wenchuan Earthquake, *Risk Hazards Crisis Public Policy*, 2, 5, <https://doi.org/10.2202/1944-4079.1092>, 2011.
- Hanson-Easey, S., Every, D., Hansen, A., and Bi, P.: Risk communication for new and emerging communities: The contingent role of social capital, *Int. J. Disast. Risk Re.*, 28, 620–628, <https://doi.org/10.1016/j.ijdr.2018.01.012>, 2018.
- Hao, H., Wang, Y., and Kang, S.: Examining “digital” vulnerability to flooding among subsidized housing residents in Florida, *Int. J. Disast. Risk Re.*, 82, 103302, <https://doi.org/10.1016/j.ijdr.2022.103302>, 2022.
- Harrison, S. and Johnson, P.: Challenges in the adoption of crisis crowdsourcing and social media in Canadian emergency management, *Gov. Inform. Q.*, 36, 501–509, <https://doi.org/10.1016/j.giq.2019.04.002>, 2019.
- Hausman, A. J., Hanlon, A., and Seals, B.: Social capital as a mediating factor in emergency preparedness and concerns about terrorism, *J. Community Psychol.*, 35, 1073–1083, <https://doi.org/10.1002/jcop.20203>, 2007.
- Hemati, M., Hasanlou, M., Mahdianpari, M., and Mohammadianesh, F.: A Systematic Review of Landsat Data for Change Detection Applications: 50 Years of Monitoring the Earth, *Remote Sens.*, 13, 2869, <https://doi.org/10.3390/rs13152869>, 2021.
- Hernandez-Suarez, A., Sanchez-Perez, G., Toscano-Medina, K., Perez-Meana, H., Portillo-Portillo, J., And Luis, V. S., and Javier García Villalba, L.: Using Twitter Data to Monitor Natural Disaster Social Dynamics: A Recurrent Neural Network Approach with Word Embeddings and Kernel Density Estimation, *Sensors*, 19, 1746, <https://doi.org/10.3390/s19071746>, 2019.
- Hernantes, J., Marañá, P., Gimenez, R., Sarriegi, J. M., and Labaka, L.: Towards resilient cities: A maturity model for operationalizing resilience, *Cities*, 84, 96–103, <https://doi.org/10.1016/j.cities.2018.07.010>, 2019.
- Hirata, E., Giannotti, M. A., Larocca, A. P. C., and Quintanilha, J. A.: Flooding and inundation collaborative mapping – use of the Crowdfunder/Ushahidi platform in the city of Sao Paulo, Brazil, *J. Flood Risk Manag.*, 11, 98–109, <https://doi.org/10.1111/jfr3.12181>, 2018.
- Holling, C. S.: Resilience and Stability of Ecological Systems, *Annu. Rev. Ecol. Syst.*, 4, 1–23, <https://doi.org/10.1146/annurev.es.04.110173.000245>, 1973.
- Ienca, M. and Vayena, E.: On the responsible use of digital data to tackle the COVID-19 pandemic, *Nat. Med.*, 26, 463–464, <https://doi.org/10.1038/s41591-020-0832-5>, 2020.

- Indriasari, T. D., Anindito, K., Julianto, E., and Pangaribuan, B. L. P.: A Mobile and Web Application for Mapping Disaster Volunteers' Position in Indonesia, *Int. J. Interact. Mob. Technol.*, 11, 98–112, <https://doi.org/10.3991/ijim.v11i3.6477>, 2017.
- IPCC: Annex II: Glossary, in: *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, IPCC, Geneva, 117–130, [https://www.ipcc.ch/site/assets/uploads/2018/02/AR5\\_SYR\\_FINAL\\_Annexes.pdf](https://www.ipcc.ch/site/assets/uploads/2018/02/AR5_SYR_FINAL_Annexes.pdf) (last access: 19 September 2023), 2014.
- Izumi, T., Shaw, R., Djalante, R., Ishiwatari, M., and Komino, T.: Disaster risk reduction and innovations, *Prog. Disaster Sci.*, 2, 100033, <https://doi.org/10.1016/j.pdisas.2019.100033>, 2019.
- Jayant, A. and Sharma, J.: A comprehensive literature review of MCDM techniques ELECTRE, PROMETHEE, VIKTOR, and TOPSIS applications in business competitive environment, *Int. J. Curr. Res.*, 10, 65461–65477, 2018.
- Johansen, C., Horney, J., and Tien, I.: Metrics for Evaluating and Improving Community Resilience, *J. Infrastruct. Syst.*, 23, 04016032, [https://doi.org/10.1061/\(ASCE\)IS.1943-555X.0000329](https://doi.org/10.1061/(ASCE)IS.1943-555X.0000329), 2017.
- Johnston, K., Kervin, L., and Wyeth, P.: Australian Research Council Centre of Excellence for the Digital Child, *Defin. Digit. Technol.*, <https://www.digitalchild.org.au/blog/defining-digital-technology/> (last access: 13 January 2023) 2022.
- Javernick-Will, A. and Jordan, E.: Measuring Community Resilience and Recovery: A Content Analysis of Indicators, *Construction Research Congress 2012*, 2190–2199, <https://doi.org/10.1061/9780784412329.220>, 2012.
- Joseph, J.: *Varieties of Resilience: Studies in Governmentality*, 1st edn., Cambridge University Press, <https://doi.org/10.1017/9781316551028>, 2018.
- Jurgens, M. and Helsloot, I.: The effect of social media on the dynamics of (self) resilience during disasters: A literature review, *J. Conting. Crisis Man.*, 26, 79–88, <https://doi.org/10.1111/1468-5973.12212>, 2018.
- Kankanamge, N., Yigitcanlar, T., Goonetilleke, A., and Kamruzzaman, M.: Can volunteer crowdsourcing reduce disaster risk? A systematic review of the literature, *Int. J. Disast. Risk Re.*, 35, 101097, <https://doi.org/10.1016/j.ijdr.2019.101097>, 2019.
- Kerr, S. E.: Chapter 22 – Social Capital as a Determinant of Resilience: Implications for Adaptation Policy, in: *Resilience*, edited by: Zommers, Z. and Alverson, K., Elsevier, 267–275, <https://doi.org/10.1016/B978-0-12-811891-7.00022-0>, 2018.
- Krishnan, A. R., Kasim, M. M., Hamid, R., and Ghazali, M. F.: A Modified CRITIC Method to Estimate the Objective Weights of Decision Criteria, *Symmetry*, 13, 973, <https://doi.org/10.3390/sym13060973>, 2021.
- Kryvasheyeu, Y., Chen, H., Obradovich, N., Moro, E., Van Hentenryck, P., Fowler, J., and Cebrian, M.: Rapid assessment of disaster damage using social media activity, *Sci. Adv.*, 2, e1500779, <https://doi.org/10.1126/sciadv.1500779>, 2016.
- Kucharczyk, M. and Hugenholtz, C. H.: Remote sensing of natural hazard-related disasters with small drones: Global trends, biases, and research opportunities, *Remote Sens. Environ.*, 264, 112577, <https://doi.org/10.1016/j.rse.2021.112577>, 2021.
- Lai, H. and Liao, H.: A multi-criteria decision making method based on DNMA and CRITIC with linguistic D numbers for blockchain platform evaluation, *Eng. Appl. Artif. Intel.*, 101, 104200, <https://doi.org/10.1016/j.engappai.2021.104200>, 2021.
- Lasko, T. A. and Vinterbo, S. A.: Spectral Anonymization of Data, *IEEE T. Knowl. Data En.*, 22, 437–446, <https://doi.org/10.1109/TKDE.2009.88>, 2010.
- Latvakoski, J., Bäck, A., Parmes, E., Öörni, R., Ceylan, Ö., Tominga, A., Orru, K., Siim, E., Klaos, M., Galvani, A., Schieffellers, A., Myllylä, M., Jukarainen, P., Berawi, M. A., and Max, M.: D2.4 catalogue of tools, technologies and media opportunities for disaster management, Horizon BuildERS project, <https://buildersproject.eu/assets/content/attachments/BuildERS%20-%20deliverables/D2.4.pdf> (last access: 5 July 2021) 2020.
- Latvakoski, J., Öörni, R., Lusikka, T., and Keränen, J.: Evaluation of emerging technological opportunities for improving risk awareness and resilience of vulnerable people in disasters, *Int. J. Disast. Risk Re.*, 80, 103173, <https://doi.org/10.1016/j.ijdr.2022.103173>, 2022.
- Le Cozannet, G., Raucoules, D., de Michele, M., Benaichouche, A., Gehl, P., Monfort, D., Negulescu, C., Rohmer, J., Pierdicca, N., Albano, M., Giovinazzi, S., and Fomelis, M.: Potential of Satellite Remote Sensing to Monitor Vulnerability of Buildings to Earthquakes Within a Semi-Empirical Macroscopic Approach, in: *IGARSS 2018 – 2018 IEEE International Geoscience and Remote Sensing Symposium*, IGARSS 2018 – 2018 IEEE International Geoscience and Remote Sensing Symposium, 2956–2959, <https://doi.org/10.1109/IGARSS.2018.8519531>, 2018.
- Le Cozannet, G., Kervyn, M., Russo, S., Ifejika Speranza, C., Ferrier, P., Fomelis, M., Lopez, T., and Modaresi, H.: Space-Based Earth Observations for Disaster Risk Management, *Surv. Geophys.*, 41, 1209–1235, <https://doi.org/10.1007/s10712-020-09586-5>, 2020.
- Leelawat, N., Suppasri, A., Latcharote, P., Imamura, F., Abe, Y., and Sugiyasu, K.: Increasing tsunami risk awareness via mobile application, in: *IOP Conference Series: Earth and Environmental Science*, <https://doi.org/10.1088/1755-1315/56/1/012001>, 2017.
- Li, L., Bensi, M., Cui, Q., Baecher, G. B., and Huang, Y.: Social media crowdsourcing for rapid damage assessment following a sudden-onset natural hazard event, *Int. J. Inform. Manage.*, 60, 102378, <https://doi.org/10.1016/j.ijinfor.2021.102378>, 2021.
- Liu, Y., Cao, L., Yang, D., and Anderson, B. C.: How social capital influences community resilience management development, *Environ. Sci. Policy*, 136, 642–651, <https://doi.org/10.1016/j.envsci.2022.07.028>, 2022.
- Manyena, S. B.: The concept of resilience revisited, *Disasters*, 30, 434–450, <https://doi.org/10.1111/j.0361-3666.2006.00331.x>, 2006.
- Maskrey, A.: Revisiting community-based disaster risk management, *Environ. Hazards*, 10, 42–52, <https://doi.org/10.3763/ehaz.2011.0005>, 2011.
- Melet, A., Teatini, P., Le Cozannet, G., Jamet, C., Conversi, A., Benveniste, J., and Almar, R.: Earth Observations for Monitoring Marine Coastal Hazards and Their Drivers, *Surv. Geophys.*, 41, 1489–1534, <https://doi.org/10.1007/s10712-020-09594-5>, 2020.
- Menichini, G., Nistri, V., Boschi, S., Del Monte, E., Orlando, M., and Vignoli, A.: Calibration of vulnerability and fragility curves from moderate intensity Italian earthquake damage data, *Int. J. Disast. Risk Re.*, 67, 102676, <https://doi.org/10.1016/j.ijdr.2021.102676>, 2022.



- Mohd Daud, S. M. S., Mohd Yusof, M. Y. P., Heo, C. C., Khoo, L. S., Chainchel Singh, M. K., Mahmood, M. S., and Nawawi, H.: Applications of drone in disaster management: A scoping review, *Sci. Justice*, 62, 30–42, <https://doi.org/10.1016/j.scijus.2021.11.002>, 2022.
- Morsut, C., Kuran, C., Kruke, B. I., Orru, K., and Hansson, S.: Linking resilience, vulnerability, social capital and risk awareness for crisis and disaster research, *J. Conting. Crisis Man.*, 30, 137–147, <https://doi.org/10.1111/1468-5973.12375>, 2021.
- Mukhametzyanov, I. and Pamučar, D.: A Sensitivity analysis in MCDM problems: A statistical approach, *Decis. Mak. Appl. Manag. Eng.*, 1, 51–80, <https://doi.org/10.31181/dmame1802050m>, 2018.
- Mulder, F.: Humanitarian data justice: A structural data justice lens on civic technologies in post-earthquake Nepal, *J. Conting. Crisis Man.*, 28, 432–445, <https://doi.org/10.1111/1468-5973.12335>, 2020.
- Munawar, H. S., Mojtahedi, M., Hammad, A. W. A., Kouzani, A., and Mahmud, M. A. P.: Disruptive technologies as a solution for disaster risk management: A review, *Sci. Total Environ.*, 806, 151351, <https://doi.org/10.1016/j.scitotenv.2021.151351>, 2022.
- Neri, M., Le Cozannet, G., Thierry, P., Bignami, C., and Ruch, J.: A method for multi-hazard mapping in poorly known volcanic areas: an example from Kanlaon (Philippines), *Nat. Hazards Earth Syst. Sci.*, 13, 1929–1943, <https://doi.org/10.5194/nhess-13-1929-2013>, 2013.
- Nguyen, Q. N., Frisiello, A., and Rossi, C.: The Design of a Mobile Application for Crowdsourcing in Disaster Risk Reduction, *ISCRAM 2019: 16. International Conference on Information Systems for Crisis Response and Management*, Valencia (Spain), 19–22 May 2019, 607–618, [https://iscram2019.webs.upv.es/wp-content/uploads/2019/09/ISCRAM2019\\_Proceedings.pdf](https://iscram2019.webs.upv.es/wp-content/uploads/2019/09/ISCRAM2019_Proceedings.pdf) (last access: 3 January 2023), 2019.
- Nicholls, K. and Picou, J. S.: The Impact of Hurricane Katrina on Trust in Government, *Soc. Sci. Quart.*, 94, 344–361, 2013.
- Odu, G. O.: Weighting methods for multi-criteria decision making technique, *J. Appl. Sci. Environ. Manag.*, 23, 1449–1457, <https://doi.org/10.4314/jasem.v23i8.7>, 2019.
- Ogie, R. I., Clarke, R. J., Forehead, H., and Perez, P.: Crowdsourced social media data for disaster management: Lessons from the PetaJakarta.org project, *Comput. Environ. Urban*, 73, 108–117, <https://doi.org/10.1016/j.compenvurbsys.2018.09.002>, 2019.
- Paul, J. D., Bee, E., and Budimir, M.: Mobile phone technologies for disaster risk reduction, *Clim. Risk Manag.*, 32, 100296, <https://doi.org/10.1016/j.crm.2021.100296>, 2021.
- Phengsuwan, J., Shah, T., Thekkummal, N. B., Wen, Z., Sun, R., Pullarkatt, D., Thirugnanam, H., Ramesh, M. V., Morgan, G., James, P., and Ranjan, R.: Use of Social Media Data in Disaster Management: A Survey, *Future Internet*, 13, 46, <https://doi.org/10.3390/fi13020046>, 2021.
- Putnam, R. D.: What makes democracy work?, *Natl. Civ. Rev.*, 82, 101–107, <https://doi.org/10.1002/ncr.4100820204>, 1993.
- Raper, J., Gartner, G., Karimi, H., and Rizos, C.: Applications of location-based services: a selected review, *J. Locat. Based Serv.*, 1, 89–111, <https://doi.org/10.1080/17489720701862184>, 2007.
- Rejeb, A., Rejeb, K., Simske, S., and Treiblmaier, H.: Humanitarian Drones: A Review and Research Agenda, *Internet Things*, 16, 100434, <https://doi.org/10.1016/j.iot.2021.100434>, 2021.
- Reuter, C. and Kauffhold, M.-A.: Fifteen years of social media in emergencies: A retrospective review and future directions for crisis Informatics, *J. Conting. Crisis Man.*, 26, 41–57, <https://doi.org/10.1111/1468-5973.12196>, 2018.
- Sajjad, H. and Kumar, P.: Future Challenges and Perspective of Remote Sensing Technology, in: *Applications and Challenges of Geospatial Technology*, edited by: Kumar, P., Rani, M., Chandra Pandey, P., Sajjad, H., and Chaudhary, B. S., Springer International Publishing, Cham, 275–277, [https://doi.org/10.1007/978-3-319-99882-4\\_16](https://doi.org/10.1007/978-3-319-99882-4_16), 2019.
- Sakurai, M. and Murayama, Y.: Information technologies and disaster management – Benefits and issues, *Prog. Disaster Sci.*, 2, 100012, <https://doi.org/10.1016/j.pdisas.2019.100012>, 2019.
- Santamaria, C., Sermi, F., Spyros, S., Iacus, S. M., Annunziato, A., Tarchi, D., and Vespe, M.: Measuring the impact of COVID-19 confinement measures on human mobility using mobile positioning data. A European regional analysis, *Safety Sci.*, 132, 104925, <https://doi.org/10.1016/j.ssci.2020.104925>, 2020.
- Santos, C. and Rapp, L.: Satellite Imagery, Very High-Resolution and Processing-Intensive Image Analysis: Potential Risks Under the GDPR\*, 44 *Air and Space Law*, 275–295, <https://ssrn.com/abstract=3413014> (last access: 26 August 2022), 2019.
- Sun, R., Gong, Z., Gao, G., and Shah, A. A.: Comparative analysis of Multi-Criteria Decision-Making methods for flood disaster risk in the Yangtze River Delta, *Int. J. Disast. Risk Re.*, 51, 101768, <https://doi.org/10.1016/j.ijdr.2020.101768>, 2020.
- Tate, E.: Social vulnerability indices: a comparative assessment using uncertainty and sensitivity analysis, *Nat. Hazards*, 63, 325–347, <https://doi.org/10.1007/s11069-012-0152-2>, 2012.
- Tavra, M., Racetin, I., and Peroš, J.: The role of crowdsourcing and social media in crisis mapping: a case study of a wildfire reaching Croatian City of Split, *Geoenviron Disasters*, 8, 10, <https://doi.org/10.1186/s40677-021-00181-3>, 2021.
- Tellman, B., Sullivan, J. A., Kuhn, C., Kettner, A. J., Doyle, C. S., Brakenridge, G. R., Erickson, T. A., and Slayback, D. A.: Satellite imaging reveals increased proportion of population exposed to floods, *Nature*, 596, 80–86, <https://doi.org/10.1038/s41586-021-03695-w>, 2021.
- Teodoro, A. C. and Duarte, L.: Chapter 10 – The role of satellite remote sensing in natural disaster management, in: *Nanotechnology-Based Smart Remote Sensing Networks for Disaster Prevention*, edited by: Denizli, A., Alencar, M. S., Nguyen, T. A., and Motaung, D. E., Elsevier, 189–216, <https://doi.org/10.1016/B978-0-323-91166-5.00015-X>, 2022.
- Terrovitis, M., Mamoulis, N., and Kalnis, P.: Privacy-preserving anonymization of set-valued data, in: *Proceedings of the VLDB Endowment*, *Proceedings of the VLDB Endowment*, 115–125, <https://doi.org/10.14778/1453856.1453874>, 2008.
- The Rockefeller Foundation: Measuring city resilience, The Rockefeller Foundation, New York, <https://www.rockefellerfoundation.org/report/city-resilience-framework/> (last access: 18 May 2021), 2016.
- Tsiamis, N., Efthymiou, L., and Tsagarakis, K. P.: A Comparative Analysis of the Legislation Evolution for Drone Use in OECD Countries, *Drones*, 3, 75, <https://doi.org/10.3390/drones3040075>, 2019.
- Tuş, A. and Adalı, E. A.: The new combination with CRITIC and WASPAS methods for the time and atten-



- dance software selection problem, *OPSearch*, 56, 528–538, <https://doi.org/10.1007/s12597-019-00371-6>, 2019.
- UNDRR: Sendai Framework for Disaster Risk Reduction 2015–2030, in: UN World Conference on disaster risk reduction, Sendai, Japan, 18 March 2015, <https://www.undrr.org/publication/sendai-framework-disaster-risk-reduction-2015-2030> (last access: 2 May 2022), 2015.
- Vermiglio, C., Noto, G., Rodríguez Bolívar, M. P., and Zarone, V.: Disaster management and emerging technologies: a performance-based perspective, *Meditari Account. Res.*, 30, 1093–1117, <https://doi.org/10.1108/MEDAR-02-2021-1206>, 2022.
- Võik, E. J., Tominga, A., Klaos, M., Silm, S., Orru, K., Lusikka, T., Keränen, J., and Schobert, M.: BUILDERS D4.3 Practice & product innovation “Applying mobile positioning data for more precise rescue planning and emergency management under cyber-hazard in Estonia”, Horizon2020 BuildERS project, <https://buildersproject.eu/assets/content/attachments/BuildERS%20-%20deliverables/D4.3.pdf> (last access: 7 July 2021), 2021.
- Wagenmakers, E.-J., Sarafoglou, A., and Aczel, B.: One statistical analysis must not rule them all, *Nature*, 605, 423–425, <https://doi.org/10.1038/d41586-022-01332-8>, 2022.
- Wang, Z., Lam, N. S. N., Obradovich, N., and Ye, X.: Are vulnerable communities digitally left behind in social responses to natural disasters? An evidence from Hurricane Sandy with Twitter data, *Appl. Geogr.*, 108, 1–8, <https://doi.org/10.1016/j.apgeog.2019.05.001>, 2019.
- Wankmüller, C., Kunovjanek, M., and Mayrgündter, S.: Drones in emergency response – evidence from cross-border, multi-disciplinary usability tests, *Int. J. Disast. Risk Re.*, 65, 102567, <https://doi.org/10.1016/j.ijdr.2021.102567>, 2021.
- Weichenthal, S., Hatzopoulou, M., and Brauer, M.: A picture tells a thousand... exposures: Opportunities and challenges of deep learning image analyses in exposure science and environmental epidemiology, *Environ. Int.*, 122, 3–10, <https://doi.org/10.1016/j.envint.2018.11.042>, 2019.
- Wheeler, B. J. and Karimi, H. A.: Deep Learning-Enabled Semantic Inference of Individual Building Damage Magnitude from Satellite Images, *Algorithms*, 13, 195, <https://doi.org/10.3390/a13080195>, 2020.
- Xu, X.: A note on the subjective and objective integrated approach to determine attribute weights, *Eur. J. Oper. Res.*, 156, 530–532, [https://doi.org/10.1016/S0377-2217\(03\)00146-2](https://doi.org/10.1016/S0377-2217(03)00146-2), 2004.
- Yabe, T., Zhang, Y., and Ukkusuri, S. V.: Quantifying the economic impact of disasters on businesses using human mobility data: a Bayesian causal inference approach, *EPJ Data Sci.*, 9, 36, <https://doi.org/10.1140/epjds/s13688-020-00255-6>, 2020.
- Yabe, T., Jones, N. K. W., Rao, P. S. C., Gonzalez, M. C., and Ukkusuri, S. V.: Mobile phone location data for disasters: A review from natural hazards and epidemics, *Comput. Environ. Urban*, 94, 101777, <https://doi.org/10.1016/j.compenvurbsys.2022.101777>, 2022.
- Zachreson, C., Mitchell, L., Lydeamore, M. J., Rebuli, N., Tomko, M., and Geard, N.: Risk mapping for COVID-19 outbreaks in Australia using mobility data, *J. R. Soc. Interface*, 18, 20200657, <https://doi.org/10.1098/rsif.2020.0657>, 2021.
- Zardari, N. H., Ahmed, K., Shirazi, S. M., and Yusop, Z. B.: Weighting Methods and their Effects on Multi-Criteria Decision Making Model Outcomes in Water Resources Management, Springer International Publishing, Cham, <https://doi.org/10.1007/978-3-319-12586-2>, 2015.
- Zhou, H., Wang, J., Wan, J., and Jia, H.: Resilience to natural hazards: a geographic perspective, *Nat. Hazards*, 53, 21–41, <https://doi.org/10.1007/s11069-009-9407-y>, 2010.