BuildERS

BUILDERS D5.4: RECOMMENDATIONS ON RESOURCE ALLOCATION FOR ADDRESSING RISKS

Project acronym: BuildERS
Project title: Building European Communities' Resilience and Social Capital
Call: H2020-SU-SEC-2018-2019-2020/H2020-SU-SEC-2018

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Disclaimer

The content of the publication herein is the sole responsibility of the publishers and it does not necessarily represent the views expressed by the European Commission or its services.

While the information contained in the documents is believed to be accurate, the authors(s) or any other participant in the BuildERS consortium make no warranty of any kind with regard to this material including, but not limited to the implied warranties of merchantability and fitness for a particular purpose.

Neither the BuildERS Consortium nor any of its members, their officers, employees or agents shall be responsible or liable in negligence or otherwise howsoever in respect of any inaccuracy or omission herein.

Without derogating from the generality of the foregoing neither the BuildERS Consortium nor any of its members, their officers, employees or agents shall be liable for any direct or indirect or consequential loss or damage caused by or arising from any information advice or inaccuracy or omission herein.

Project no.	833496
Project acronym:	BuildERS
Project title:	Building European Communities' Resilience and Social Capital
Call:	H2020-SU-SEC-2018-2019-2020/H2020-SU-SEC-2018
Start date of project:	01.05.2019
Duration:	36 months
Deliverable title:	BuildERS D5.4 *Recommendations on resource allocation for addressing risks*
Due date of deliverable:	February 2022
Actual date of submission:	28.03.2022
Deliverable Lead Partner:	Stockholm Environment Institute (SEI)
Work Package:	5
No of Pages:	57
Keywords:	Disaster risk management, cost-benefit analysis, multi criteria decision analysis, investment strategy, mobile positioning data, social media crowdsourcing, drones, satellite imaging

Name	Organization
Mathilda Englund	SEI
Tommaso Piseddu	SEI
Karina Barquet	SEI
Abdi Mehvar	SEI
Jennifer Hinton	SU
Mark Rhinard	SU
Maira Schobert	EKUT
Friedrich Gabel	EKUT
Jyri Hanski	VTT
Margo Klaos	ERB

Dissemination level

PU	Public

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

History

Version	Date	Reason	Revised by
01	13.09.2021	Interviews with experts	SEI
02	05.10.2021	Online survey is launched	SEI
03	21.10.2021	Online survey is closed	SEI
04	22.10.2021	Analysis of survey data	SEI
05	17.12.2021	First draft sent to WP leader	SEI, SU
06	13.01.2022	Comments received from WP leader	SEI, SU
07	16.02.2022	Submission for internal and ethical review	SEI, EKUT, VTT, ERB
08	22.02.2022	Comments received from internal reviewer	VTT
09	25.02.2022	Comments received from ethical reviewer	EKUT
10	28.02.2022	Submission D5.4 to the Coordinator	SEI
11	04.03.2022	Technical check-up	VTT
12	08.03.2022	Comments received from the Coordinator	VTT
13	11.03.2022	Updated version	SEI
14	28.03.2022	Some technical modifications	VTT
Final	28.03.2022	Submission	VTT

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No. 833496

Executive Summary

This report D5.4 aims to provide advice on how new resource allocations for disaster risk management can be considered. We develop a new economic assessment approach to investigate how different emerging technologies and tools can strengthen social capital, risk awareness, disaster preparedness, and in the long run societal resilience. We focus on usage, costs, benefits, risks and methods of provisions. These aspects are considered to construct cost-benefit ratios.

We illustrate our approach by applying it to four technologies. Focus lies on understanding how these technologies can be applied in European societies and communities. Note that all figures are estimates and based in a European setting.

Mobile positioning data can support mitigation, preparedness, and recovery in disaster risk management. Investing in mobile positioning data yields key benefits for risk awareness and disaster preparedness. It is best provided through a public-private partnership. Some risks do exist. This technology may malfunction during disruptive events as it depends on critical infrastructure. As a result, data access and accuracy may be limited during such events. Mobile positioning data cannot locate those without phones.

Social media crowdsourcing can be applied across the disaster risk management cycle. Social media crowdsourcing generates large datasets that can be analysed using pre-trained AI software. It is recommended to integrate social media crowdsourcing into existing communication structures. Key risks include messy datasets; disinformation or misinformation; AI bias and discrimination; and exclusion of the most vulnerable individuals who might not use social media.

Drones can support preparedness, response, and recovery efforts. It is best provided through public procurement, as the collected data can be sensitive and hence not to be shared with private partners. There are several limitations and risks. Drones cannot operate in some environments, for example during storms or heavy precipitation. Changes in regulations can adversely affect the use of drones in disaster risk management, ultimately challenging its future effectiveness. Lastly, the public considers drones as a technology that poses a threat to their privacy.

Satellite imaging is a form of remote sensing that can be used during mitigation, preparedness, response, and recovery. Satellite images can be acquired free of charge from the International Charter Space & Major Disasters or the Copernicus. Key benefits include improvements in risk awareness and preparedness. Future satellite imaging is likely to enjoy improvements in availability, quality, and analysis software. Some risks exist, namely issues related to the timeliness of data; malfunctioning equipment in space; and legislative risks.

From the cost-benefit ratios, we discover that drones present the best investment option to increase risk awareness and disaster preparedness. Social media crowdsourcing is a better investment option if looking to increase social capital. While strongly supporting preparedness and risk awareness, mobile positioning is an expensive option when compared to the three other alternatives. Satellite imaging is a good alternative if looking to increase risk awareness and preparedness, which comes free of charge.

However, no general conclusions can be drawn. Investment strategies must reflect context-specific needs generated from disaster exposure and social conditions. Instead, we recommend that policymakers use our approach to easily compare benefits and costs of certain investments. Following the example we produced here on four of the technologies considered in BuildERS, we provide policymakers with a tool to support their investment decisions.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Table of contents

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

List of acronyms

AI	Artificial Intelligence
AR	Augmented Reality
BuildERS	Building European Communities Resilience and Social Capital Project
D	Deliverable
IoT	Internet of Things
LCC	Life Cycle Costs
UASs	Unmanned aerial systems
UAVs	Unmanned aerial vehicles
VR	Virtual Reality
WP	Work Package

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

List of figures

List of tables

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Glossary

- **Disaster**

"A serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts" (UNISDR, 2019).

- **Disaster risk management**

"Disaster risk management is the application of disaster risk reduction policies and strategies to prevent new disaster risk, reduce existing disaster risk and manage residual risk, contributing to the strengthening of resilience and reduction of disaster losses" (UNISDR, 2019).

- **Hazard**

"A process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation. Hazards may be natural, anthropogenic or socio-natural in origin" (UNISDR, 2019).

- **Resilience**

Processes of proactive and/or reactive patterned adjustment and adaptation and change enacted in everyday life, but, in particular, in the face of risks, crises and disasters (Morsut et al., 2020, Morsut et al., 2021).

- **Risk**

Risk results from the interaction of hazard(s), exposure and vulnerability (Morsut et al., 2020).

- **Risk assessment**

"Risk assessment (…) is part of the broader risk management process. Risk assessment in turn consist of three tasks: risk identification, risk analysis, and risk evaluation. Risk identification is the initial process of finding, recognising and recording risks. Risk analysis is about developing an understanding of the risk by developing the consequences and their probabilities for the identified risks. Risk evaluation delineates the significance of the level and type of risk" (Pursiainen, 2017).

- **Risk awareness**

Collective (groups and communities) acknowledgment about a risk and potential risk preventing and mitigating actions, fostered by risk communication (Morsut et al., 2020, Morsut et al., 2021).

- **Risk communication**

"Risk communication is the process of exchanging or sharing risk-related data, information and knowledge between and among different groups such as scientists, regulators, industry, consumers or the general public" (Florin and Bürkler, 2018).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

- **Social capital**

Networks, norms, values and trust that entities (individuals, groups, society) have available and which may offer resources for mutual advantage and support facilitating coordination and cooperation in case of crisis and disasters (Morsut et al., 2020, Morsut et al., 2021a, Morsut et al., 2021b).

- **Vulnerability**

Dynamic characteristic of entities (individuals, groups, society) of being susceptible to harm or loss, which manifests as situational inability (or weakness) to access adequate resources and means of protection to anticipate, cope with, recover and learn from the impact of natural or man-made hazards (Morsut et al., 2020, Morsut et al., 2021).

- **Vulnerable groups**

Groups of people sharing characteristics making them individually and, as a group, vulnerable in that they are susceptible to harm or loss. This manifests as situational inability (or weakness) to access adequate resources and means of protection to anticipate, cope with, recover and learn from the impact of natural or man-made risks (Morsut et al., 2020).

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No. 833496

1. Introduction

BuildERS aims to increase societal resilience of European communities against natural- and man-made hazards, by enhancing social capital, risk awareness, and preparedness among the most vulnerable segments of the population. To meet this objective, BuildERS seeks to transform its scientific outputs into actionable recommendations for decision-makers, first-responders, and civil society organizations. This deliverable complements the policy- and practitioner recommendations that are presented in *D5.1 Resilience policy recommendations.*

This report *D5.4 Recommendations on resource allocation for addressing risks* seeks to provide advice on how new financial investments can be decided, in accordance with Task T5.2. Given the scope in BuildERS, these recommendations are designed with European communities in mind. However, as demonstrated in previous BuildERS deliverables *(D1.2 Final report of the unified theoretical framework on the concepts of risk awareness, social capital, vulnerability, resilience and their interdependencies),* societal resilience and disaster risk both depend on local conditions making it difficult to draw generic conclusions applicable to the whole region. We therefore develop a framework to investigate how different emerging technologies and tools can strengthen social capital, risk awareness, disaster preparedness, and in the long run societal resilience. Decision-makers, first-responders, and civil society organizations can thereafter apply the tool to their contexts to explore different investment options.

Deliverable *D2.4 Catalogue of tools, technologies, and media opportunities in disaster risk management*, discussed the following emerging technologies: mobile positioning, social media crowdsourcing, satellite imaging, Internet of Things (IoT), drones, 5G, Artificial Intelligence (AI), machine learning, and blockchain. However, here we apply the tool to the four following technologies suggested in BuildERS:

- Location-based services using mobile positioning data
- Social media crowdsourcing data using AI or machine learning
- Drones and other unmanned aerial vehicles
- Satellite imaging

Thus, no recommendations are provided for 5G, IoT and blockchain. These technologies are instead considered as overarching technological enablers. In many cases, 5G and IoT are essential for effectively using mobile positioning data, social media crowdsourcing, drones, and satellite imaging. Both enable real-time communication between interconnected devices and data collection. For instance, Han et al. (2021) investigated the use of 5G in disaster risk management by concluding that its main advantage regards an improved transmission rate. Shafique et al. (2020) also touched upon the numerous improvements that IoT and 5G can bring in the use of other technologies. In particular, the authors find there is scope for improvement in big data storage and management, benefiting the AI models that are often extremely data hungry. These examples outline where IoT and 5G could bring substantial contribution, but it is evident that they cannot function as technological tools per se in disaster risk management.

Similar conclusions are reached in Deliverable *D2.4 Catalogue of tools, technologies and media opportunities for disaster management*: "From the technological capabilities perspective, 5G

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No. 833496

technology has higher capacity, is faster and has lower latency compared with previous generations. Therefore, it seems to be [*sic*] essential *enabler* for the more real-time communications with mobile assets such as vehicles, robots, drones, cameras and other sensors etc." (p.46, emphasis added). The same reasoning can be easily applied to blockchain: "The Blockchain distributed ledger system and chain of verified information records could play a significant role in improving control of information sources/validity", as concluded in Deliverable *D2.4 Catalogue of tools, technologies and media opportunities for disaster management* (p.48). Blockchain can improve the reliability of the information flow, but it is not a technology to be specifically used in any of the phases of the disaster risk management cycle.

There is a broad agreement in academia that the technologies investigated here constitute examples of emerging technological innovations to be applied in disaster risk management. Munawar et al. (2022) provides an analysis of the state-of-the-art technologies that are frequently used in disaster risk management: geospatial remote sensing (through the use of UAVs, satellites and drones), mobile applications, and AI for the automated analysis of information. Izumi et al. (2019) places GIS and remote sensing, drones, Social Networking Services (SNS) and crowdsourcing among the Top-10 "DRR innovations […] considered the most effective among specialists based on their experience of them" (p. 4). Vermiglio et al. (2021) lists AI, big data analytics, remote sensing (through satellites, UASs, UAVs and drones), geospatial data and social media among the "main applications discussed in the academic literature" (p. 4). Shaw (2020) states that drones, AI, VR (Virtual Reality) and AR (Augmented Reality) are the new technologies that have emerged in the last few years.

This report is structured as follows: Section 2 presents the BuildERS conceptual framework, clarifying the links between social capital, risk awareness, and disaster preparedness. Section 3 introduces our suggested tool for deciding on resource allocation in disaster risk management. Section 4 applies the tool to four investment options, namely mobile positioning data, social media crowdsourcing, drones, and satellite imaging. Section 5 discusses the cost-benefit ratios and provides some recommendations on resource allocation. Section 6 presents the conclusion.

2. BuildERS conceptual framework

The deliverable draws upon the BuildERS framework developed in *D1.2 Final report of the unified theoretical framework on the concepts of risk awareness, social capital, vulnerability, resilience and their interdependencies*. Four concepts are considered:

- **Resilience** - "processes of proactive and/or reactive patterned adjustment, adaptation and change enacted in everyday life but, particularly, in the face of risks and crises".
- **Vulnerability** - "entities' (individuals, groups, society) dynamic characteristic of being susceptible to harm or loss, which manifests as situational inability to access adequate resources and means of protection to anticipate, cope with, recover and learn from the impact of natural or man-made crises".
- **Social capital** - "norms, values, trust and networks, embedded in societies and their inequalities, that entities (individuals, groups, society) may have available and which may offer resources for mutual support and for facilitating coordination and cooperation in the face of risks and crises".
- **Risk awareness** - "collective acknowledgement about a risk and potential risk prevention and mitigation actions, fostered by risk communication".

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

The relations and interlinkages connecting the concepts are shown in **Figure 1**. Resilience and vulnerability are not mutually exclusive but coexist and complement each other. Risk awareness can foster resilience, as it determines how an entity perceives risk and thus behaves in light of a crisis. Low risk awareness can in turn exacerbate vulnerability. Social capital is a key throughout the disaster risk management cycle, and can strengthen societal resilience by facilitating coordinated actions, building trust, and strengthening social networks. Social capital can also improve risk awareness, however, there is less research conducted on how risk awareness may affect social capital.

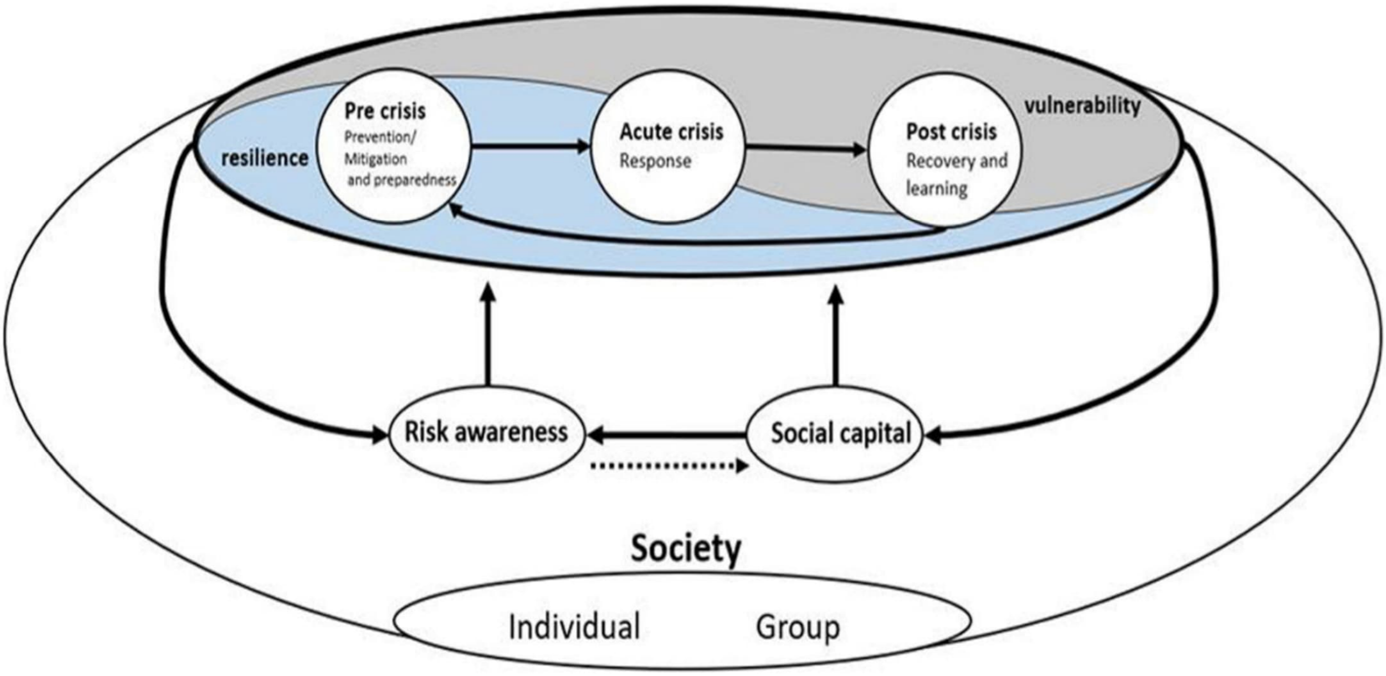

Figure 1: *BuildERS framework adopted from D1.2 Final report of the unified theoretical framework on the concepts of risk awareness, social capital, vulnerability, resilience and their interdependencies*

In addition, disatser preparedness plays a key role in BuildERS *(see D1.2 Final report of the unified tehoretical framework on the concepts of risk awareness, social capital, vulnerability, resilence and their interedependencies).* High levels of social capital contribute to high levels of prepapredness (e.g. Cutter et al., 2008; Dynes, 2006; Johansson and Linnell, 2012; Kapucu, 2008; Kim and Kang, 2010; McEntire and Myers, 2004; Paton, 2007). Disaster preparedness can in turn raise new social capital through volunteerism, and build mutual trust between organizations involved in preparedness activities (Koh and Cadigan, 2008; Reininger et al., 2013). Some scholars argued that high risk awareness leads to improved disaster preparedness (Lupton, 2013). In addition, both social capital and risk awareness must be strengthened during the pre-crisis phase to ensure that affected populations know how to behave in the case of a crisis and what social networks to tap into.

3. Tool guide: Cost-benefit analysis

This section seeks to provide decision-makers and practitioners with an approach for deciding new resource allocations. It draws inspiration from the cost-benefit analysis. However, traditional cost-benefit analyses tend to underestimate intangible benefits and costs. Methods for performing social cost-benefit analyses exist, but these usually assign monetary values to benefits in order to make them comparable to potential costs. Some impacts may not be quantifiable and are therefore neglected in such an assessment (Kind et al. 2017, Mouter et al. 2020; Beria et al. 2012). In the context of disaster risk management, assigning a monetary value to human lives might be questionable both from an economic and ethical point of view (Mechler 2008). We therefore only assign monetary values to costs, whereas benefits are assessed against a number of criteria outlining the key aspects found in the BuildERS framework. In other words, we our suggested tool combines a monetary cost analysis with a qualitative analysis of potential social benefits that may arise from when applying the technologies in disaster risk management.

An overview is presented in **Figure 2**. The tool takes a bottom-up approach and is designed to fit many different contexts. Intended users include anyone involved in disaster risk management regardless of their background and expertise. This includes decision-makers, researchers, project stakeholders, funders, and so on.

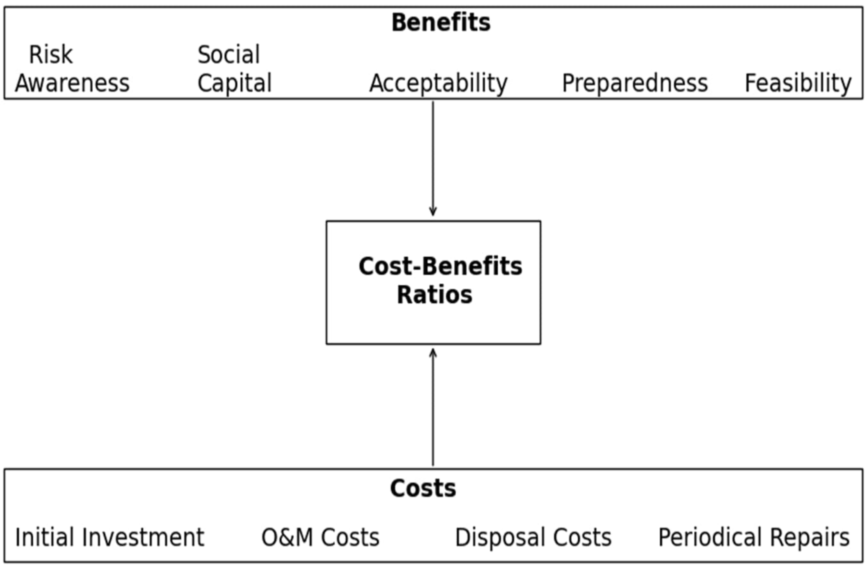

Figure 2: *Cost-benefit assessment method*

We complement cost-benefit analysis with some additional investigations, in order to make the recommendations more feasible in practice. We argue that it is important to consider the following: 1) when the investment options can be applied in disaster risk management, 2) potential financial risks that can alter the costs and benefits, and 3) technological forecasts to ensure what is considered feasible today remains so in the future.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

The guide therefore covers seven themes:

1. **Usage**: Where along the disaster risk management cycle can the technology be applied?
2. **Costs**: What is the cost of investing in the technology for disaster risk management?
3. **Benefits**: What benefits can the technology yield in disaster risk management?
4. **Cost-benefit ratios**: What is the overall monetary value of the different investment options?
5. **Risks**: Are there any risks in using the technology for disaster risk management?
6. **Forecast**: How is the technology likely to develop in the near future?
7. **Provision**: Who is providing the technology?

Notably, we do not quantitatively assess the distribution of costs and benefits. Some socioeconomic groups might bear a higher burden than others. We do, however, consider potential negative impacts upon vulnerable groups when investigating risks associated with the technologies. In addition, cost-benefit analyses tend to favor short-term gains over long-term benefits (Goodland & Ledec, 1987), raising issues regarding intergenerational equity. We recommend that intertemporal equity is qualitatively considered in the decision-making process.

3.1 Usage

First, usage of technologies needs to be assessed. Usage refers to how the investment options can be applied in disaster risk management. Focus lies on the disaster risk management cycle and its four phases: mitigation, preparedness, response, and recovery (Alexander, 2018; Berawi et al., 2019; Pursiainen, 2017; Sawalha, 2020). We recommend assessing usage by looking at the BuildERS deliverable "*D2.4 Catalogue of Tools, Technologies and Media Opportunities for Disaster Management*", which provides a comprehensive overview of how different technologies can be applied in the context of disaster risk management.

3.2 Costs

We recommend assessing the costs by using a Life-Cycle Cost (LCC) analysis, by which the total expected lifetime cost is calculated for each alternative (De Risi et al., 2018). The LCC approach has been developed to allow policymakers to rank investment options. It takes into account all the significant and relevant costs that will arise during an asset's life (Beecroft et al., 2017; Gluch & Baumann, 2004; Hoar, 1988; Wiboonrat, 2014)

Assumptions are needed in order to proceed with the analysis. In this study, the investment period is set to ten years. However, the relevant time depends on the technology being assessed. Different time periods are relevant for different technologies (e.g., the time for assessing the LCC of a wastewater treatment is 40 years). Setting a common investment period across all investment options is a necessity to make the results comparable. Future costs are then appropriately discounted and summed up, following the standard procedure of LCC (De Risi et al., 2018). The necessity to do so represents a standard in the economics literature, as the constant increase in the value of money hinders the possibility to compare cash flows that are generated at different points in time. Discounting resolves this problem by reducing future monetary value using a discount factor. The timeframe of ten years is in line with the recommendations provided by the European Commission (2015), that

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

introduced the common guidelines to perform risk-benefit analysis. Therefore, results from different alternatives can be easily comparable. Disposal costs are considered if needed. For example, if the technology is acquired through a Private-Public Partnerships (PPPs) or leasing contract, disaster risk management actors do not hold responsibility for the disposal phase. It can be argued that the disposal costs would represent a cost for the society anyway, both in monetary and environmental terms. We recognize that, but the environmental costs are not considered in this assessment and it reasonable to expect the marginal cost increase generated by the necessity to dispose of the new tools will be small if not negligible. At the end of the lifetime of the technologies and tools considered; the owner will have to dispose of them according to the law. Because the authorities will not figure as the actual owners of these, they will not have to allocate resources to the disposal.

We suggest gathering costs through a literature review or through expert consultation. Multiple cost estimations from several sources should be gathered for each alternative. An average cost value, or a median cost value, can thereafter be calculated, correcting for extreme values that may emerge if data were collected from a single source.

3.3 Benefits

We recomened assessing benefits using a multi-criteria decision analysis. In short, the multi-criteria decision analysis compares different investment options against a number of criteria instead of assigning them a monetary value (Macharis and Bernardini 2015; Tudela et al. 2006; Tsamboulas et al. 1999). The multi criteria decision analysis is designed to help groups to balance conflicting objectives when choosing between different decision alternatives (Gregory & Keeney, 1994). The multi criteria decision analysis can include intangible benefits, thus capturing those values that need to be considered in decision making but are difficult to represent in monetary terms. This makes it especially fit in this context, as many benefits of importance to BuildERS are intangible. Other benefits analysis include enhancing transparency, legitimacy, and credibility; incorporating stakeholder values and perspectives; capturing trade-offs; fitting for complex settings; and supporting learning (Salo & Hämäläinen, 2010).

Given the focus in BuildERS, we suggest applying the key thematic areas to be addressed in the project: risk awareness, social capital, and preparedness. It is assumed that these can strengthen resilience whilst reducing vulnerability. In addition, we suggest two other thematic areas to capture potential practical barriers: feasibility and acceptability. The criteria are presented in **Table 1**, in accordance with BuildERS framework. Notably, criteria can be adapted to fit contextual needs and priorities.

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No. 833496

Table 1: Criteria

Concept	Criterion
Risk awareness	It can strengthen risk and vulnerability assessments.
	It can improve access to crisis information.
	It can improve the quality of crisis information by making it more accurate, timely, or relevant.
Social capital	It can minimize the risk of silo working by strengthening trust and coordination between different organizations.
	It can support citizen engagement in disaster risk management.
	It can enable collaboration and coordination of volunteers.
Preparedness	It can improve data-collection, procedures, methods and sharing.
	It can contribute to the development of plans and strategies to manage crises.
	It can improve emergency management exercises.
Feasibility	It can be viewed as financially viable considering costs and revenues.
	It is likely that there is an access to necessary human, infrastructure, knowledge, and technical resources for implementing and maintaining the service.
	It is likely to be supported by regulatory frameworks
Acceptability	It can meet local expectations in relation to the stated aims and services provided.
	It receives local support from civil society and groups
	The perception of gains/needs are likely to outweigh perceptions of risk/threats

We recommend collecting data by sharing a survey that targets a broad range of stakeholders. This is a time-efficient option, as it allows to quickly involve a vast number of stakeholders with different expertise, experience, and values. These stakeholders should cover different perspectives and expertise, and represent different stakeholder groups including academia, public sector, private enterprises, and civil society organizations. The survey provides a snapshot of attitudes towards different investment options and allows all stakeholders to remain anonymous. Other data collection methods may also be applicable, like workshops, interviews, and focus group discussions, although these are in this case considered less efficient.

Stakeholders are asked to assign a numerical score to indicate to what extent the criteria are fulfilled in the case of the different technologies. The possible answers, “I don’t know”, “Strongly disagree”, “Disagree”, “Agree” and “Strongly agree” are then mapped to numerical values to produce summary statistics. The “I don’t know” replies are excluded from the analysis as they cannot provide any opinion from the stakeholders. The other replies represent increasing scores from 1 to 4, from “Strongly disagree” to “Strongly agree”. This creates a range of possible mean scores from 1 to 4. A higher score indicates higher agreement with the statements proposed in **Table 1**

3.4 Cost-benefit ratios

We recommend generating cost-benefit ratios to make the different investment options comparable. Cost-benefits ratios represent standard tools in the evaluation of investment options. Thanks to the easiness with which they can be produced and interpreted, this analysis is applied in several studies (Fagnant and Kockelman, 2012; Kull et al., 2013; Mechler, 2016; Mechler et al., 2014; Cellini and Kee, 2015; Shreve and Kelman, 2014; Ward et al., 2017). The approach is to make the alternatives comparable by producing ratios between costs and benefits, so that the final decision may be guided by considerations that involve both costs and benefits. This implies that expensive alternatives that bring few or no benefits, and hence produce high cost-benefit ratios, will be discarded in favour of alternatives that require smaller investment and that can return higher benefits, i.e., alternatives with lower cost-benefits ratios. This approach does not limit the possibility to carry out a sensitivity analysis to better assess how different assumptions might impact the results. High uncertainties might be

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No. 833496

related to the costs figures. Varying these within a reasonable range (say, for example, 10%) makes the results more robust to possible flaws in the methodology.

We suggest dividing the investments by the points that are awarded to each technology in the multi-criteria decision analysis. The results can be interpreted as the per-point LCC of each technology in the given field.

3.5 Risk assessment and technology forecast

We also recommend performing a risk assessment and technology forecast to identify potential hidden costs and barriers. Both the risk assessment and technology forecast should pay special attention to how vulnerable groups might endure adverse impacts, thus qualitatively capturing the distribution of costs and benefits. Here it is important to note that emphasis lies on understanding the risks and future technological advancements that may impact the investment and its cost effectiveness. There is less focus on the risks that can be triggered by the technologies.

The same methods are recommended for both the risk assessment and technology forecast. First, we recommend looking at secondary sources through a literature search. Some examples are highlighted in BuildERS deliverable *D2.4 Catalogue of Tools, Technologies and Media Opportunities for Disaster Management*. If insufficient, we suggest contacting experts to discuss future technological development, future costs and benefits, future areas of application, key risks, and current challenges.

3.6 Provision

Provision refers to the act of supplying or providing a good or a service. We recommend exploring how the technology can be provided. Many forms of provisions exist, including public-private partnerships, leasing, fixed-asset investment, etc. We suggest looking at previous forms of partnerships through a literature review. Some examples are provided by BuildERS such as:

- BuildERS D4.3 Practice & product innovation “Applying mobile positioning data for more precise rescue planning and emergency management under cyber-hazard in Estonia”
- BuildERS D4.7 Indonesian Case “Using Mobile Operators’ Data to Locate, Protect and Evacuate Tourists and Other Vulnerable Groups in Disasters”
- BuildERS D2.4 Catalogue of Tools, Technologies and Media Opportunities for Disaster Management

In addition, Merrill (2020) provides a good overview of the advantages and disadvantages of making use of a leasing contract.

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No. 833496

4. Tool in practice: Mobile positioning data, social media crowdsourcing, drones, and satellite imaging

In this section, we apply our tool to four technologies: 1) mobile positioning, 2) social media crowdsourcing, 3) drones, and 4) satellite imaging. We explain how we applied the tool in the textbox, providing details on the case-specific methodology. This can serve as an inspiration for policymakers and practitioners when applying the tool.

We followed the steps outlined in Section 3. We started with an extensive literature review. We screened 70 documents for information about costs, risks, future technological development, and provision in a European context. Documents were selected using Boolean searches on search engines like Google Scholar, Scopus, and Web of Science. Key search terms included mobile positioning data, location-based services, social media crowdsourcing, drones, satellite imaging, remote sensing, forecast, backcast, future, risk, risk assessment, and cost assessment.

To assess the benefits, we shared an online survey asking a group of experts to assign a numerical score to indicate to what extent the criteria were fulfilled in the case of the different technologies. The survey was made available to potential responders via Microsoft Forms during a 17-days period between October 5th and October 21st. One reminder was sent during this period to encourage more replies. In total, 118 replies were collected, 116 of which were used in the analysis as two respondents failed to complete the survey. The respondents represented different geographical regions, including Europe (60%), Asia (15%), and North America (5%). The geographical representation can be partly explained by the language used in the survey (English) and partly by the spread of case studies in the BuildERS project. The respondents also represented 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).

Thereafter, we carried out expert interviews to validate previous findings and collect any missing information. We interviewed 10 experts. 8 participated in an online interview whereas 2 answered the questions over email. Interviews were carried out by two persons in English. The questions were sent beforehand to the informants. Notes were taken during the interviews, which later served as the unit of analysis. The notes were coded using an inductive approach, noting down themes and patterns as they emerged.

This section is structured as follows: Each investment bundle starts with a brief overview of the findings, followed by an in-depth discussion about how the technologies can be applied in disaster risk management, costs and benefit analysis, future technological advancements, potential financial risks assessment, and by whom and how the service is best provided.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

4.1 Mobile positioning data

***Table 2**: Overview - Mobile positioning Data*

Usage	Cost	Benefit	Forecast	Risk	Provision
Mitigation, preparedness, and recovery.	Per-inhabitant costs 0,049€ per month	Key benefits in risk awareness and preparedness.	Increases in demand which will create a more competitive market. Future mobile positioning data will most likely support personalized services.	1. Malfunctioning during infrastructure disruptions 2. Limited data access 3. Data inaccuracy 4. Struggles to identifying the most vulnerable 5. Vulnerable to legislative changes 6. Privacy and confidentiality concerns	Public-private partnership

Mobile positioning is a form of location-based services that provides information on the location of a mobile device and its user (Raper et al., 2007). Mobile positioning can be active, if the system operator constantly tracks the mobile devices, or passive, in which the system operator only tracks the mobile devices when being used. Mobile positioning is, in theory, applicable throughout the entire disaster risk management cycle, and can help authorities, organizations, and first responders to locate the population at risk (Latvakoski et al., 2020; Sari et al., 2021; Tominga et al., 2021). However, mobile positioning data cannot always be used to support rapid response efforts as privacy concerns inhibits the access to real-time data for telecom providers while collecting large datasets. Individual calls from those in need is beyond the scope of this report.

Costs

Mobile positioning data can be acquired through a monthly subscription, costing 0,049€ per inhabitant per month, as evidenced by the interview we conducted with actors in the field. A city of 2 million people, such as Wien or Hamburg, would pay about 98850€ per month for mobile positioning data. Data on the costs come from a representative of one of the largest telecom service providers in Scandinavia, which offers municipalities and other governmental institutions mobile poisoning data to track tourism, manage large crowds during events and for other purposes. Unfortunately, we are not able to break down the costs to the single component (e.g., hardware costs, data processing costs, etc.). We are therefore unable to understand which operation in the process is contributing the largest share to the final cost.

This cost is validated by other figures from telecom providers across Europe. The Austrian market leader A1 offers a vast range of different location services that are designed to match the needs of the customers. Event Insights and Location Insights provide information on attendances to an event

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

and long-term trends at precise locations with the possibility to also look in the past and construct time series. The Location Insights service is provided at fixed monthly rate of €1600 (plus VAT) per month for applications in venues such as shopping centres, shopping streets, leisure places, ski resorts and town centres and is capable of returning a 12-month analysis (A1, 2021). Given that the company itself mentions applications to city centres and shopping streets, it is very likely that upscaling such an approach to an entire city will increase the costs. The figures provided by our interviewee in Northern Europe and the ones provide by A1 makes the two services similar in terms of costs in a city of about 40000 people.

In addition, the European Commission, in partnership with Eurostat (2014), produced a LCC-analysis of an application of mobile positioning data for touristic purposes which indicates what operation in the process that contributes the most to the final cost. About 10 million domestic subscribers are considered with a delay of 15 days. However, these costs only include tourists within the area. Thus, the actual cost is expected to be higher if considering the whole population. Furthermore, the study dates to 2014. Two cost scenarios are included in the analysis: the "*Max*" scenario pertains the case in which the mobile network operator carries out the full processing of the dataset and the "*Min*" scenario pertains the case in which the mobile network operator only extracts, formats and delivers the data. No cost is attributed to the estimation and analysis of the results' phases in the latter scenario. An overview is presented in **Table 3**. The figure presented at the end is computed considering the costs faced during the pilot phase, the costs incurred when automating data extraction and processing, and the yearly maintenance costs of the system for 10 years. These last costs are discounted using the suggested 4% interest rate (European Commission, 2015).

***Table 3**: LCC for mobile positioning data (European Commission and Eurostat, 2014)*

Pilot Phase	**Max (€)**	**Min (€)**
Internal legal expertise	15000	15000
Data extraction and preparation for following processes	30000	30000
Hardware cost for one-time process (12 months of pilot data)	25000	12000
Applying methodology on pilot data (manual process, no automation)	35000	0
Estimation	8500	0
Analysis of the results (coherence, quality, issues)	8000	0
Project management	13500	6000
TOTAL	135000	63000
Implementation of automatic data extraction and processing		
Automation of data extraction and preparation for following processes	20000	15000
Data storage hardware	100000	48000
Processing hardware	100000	0
Developing automated processes according to accepted methodology	250000	0
Exporting data automation	15000	20000
Quality control processes, including central system monitoring	20000	15000
Project management	46000	7500
TOTAL	551000	105500
Maintenance of the system (yearly costs)		
Quality manager	40000	25000
System maintenance	111000	22000
Project management	7000	4000
TOTAL	158000	51000
LCC (10 YEARS)	2018782,4	598701,91

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Another aspect to consider is that the providers of these services in the EU must all operate under the same rules as stipulated in GDPR (General Data Protection Regulation) and that the underlying technology employed should not really differ from country to country. The size of the customers' pools can affect the cost, with largest companies being able to exploit the advantages of an economy of scale. Population size also influences the cost. The larger the dataset to be collected, the more resources will be needed to manage large amounts of data. Another influential factor is the timeliness of the data, the time expectation of accessibility and availability of information (Loshin, 2009). The smaller the delay is, the larger the cost will be. Differences in salary remunerations across the EU are of course to be kept in mind as well. The study from the European Commission, from which costs in Table 3 were collected, does not necessarily limit the use of the data to touristic purposes: once positions have been gathered this information can be used to make informed decision in every aspect of the administration that might benefit from it.

The data we have been able to collect from private actors in the field are more recent than the ones produced by the European Commissions and require less assumptions to formulate the costs for the final figure. We therefore decide to produce with these but present additional data to provide a complete perspective of the market.

Benefits

Mobile positioning data can yield many benefits, as outlined in **Figure 3**. The core benefit of mobile positioning data is that it improves data collection. The data can thereafter be used for different purposes, with the need to guarantee privacy and protection, which in turn can generate additional co-benefits. This can be achieved, for example, through data anonymization (Bayardo & Agrawal, 2005; Lasko & Vinterbo, 2010; Terrovitis et al., 2008; Vokinger et al., 2020; Yoon et al., 2020).

A key benefit of mobile positioning data is improved risk awareness, as supported by previous findings (Dujardin et al., 2020; Leelawat et al., 2017). These findings correspond to what was found in the expert interviews. Mobile positioning data can improve the quality of crisis information as it allows for location-based information. Crisis information can thus be tailored to specific locations. Likewise, mobile-poisoning data can improve access to crisis information by supporting location-based alerting. Crisis information can be sent from disaster risk management actors to the population at risk, based on the location data provided by mobile positioning services. The crisis information is communicated through an SMS.

As also noted during the expert interviews, another benefit is that mobile positioning data can feed into risk and vulnerability assessments, and thus improve their overall robustness. It can provide an estimate of how many people are located in a specific area at a specific point in time and can increase the understanding of the consequences from potential disturbances. This can in turn strengthen preparedness efforts. The risk and vulnerability assessment can support the development of plans and strategies. It will clarify what to prepare for to make plans accordingly. Thereafter, the mobile positioning data can be used to improve emergency exercises by increasing the accuracy of the scenarios. Berawi et al. (2019) shows how accessing data on population density can be achieved through mobile positioning data, and how this can provide input variables to be used in machine learning models to estimate the number of first responders to be deployed in the area.

According to the survey findings, mobile positioning data can also support the coordination and collaboration of volunteers. However, we did not find any sources supporting these claims.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

While, financially, mobile positioning data is considered viable, and the gains are outweighing the risks, this technology scores low on feasibility and acceptability, indicating that there might be some practical barriers in using mobile positioning data in disaster risk management. This is probably connected to issues of privacy and confidentiality (Keusch et al., 2019; Kim and Kwan, 2021; Wenz et al., 2019), as mobile positioning data can be used for surveillance and thus cause privacy breaches. Additional barriers include the lack of capacity in terms of personnel and infrastructure. Mobile positioning data generates large datasets, which require complex analytical models. This capacity can in many instances be lacking. There are also regulatory issues due to GDPR. In addition, mobile positioning data does not prevent silo-working. Thus, this technology is mainly used for disaster risk management rather than supporting internal communication systems for exchanging knowledge or information.

Forecast

Mobile positioning data lies at the intersection of mobile units, mobile networks, and internet. Globally, mobile subscriptions continue to increase from around 8 billion in 2020 to 8.8 billion in 2026. Meanwhile, internet connections are improving across the globe. A shift from 4G to 5G is also expected, increasing transmission rates and connectivity (Jonsson et al., 2021). The number of people generating a mobile footprint is thus likely to increase, ultimately improving mobile positioning services.

Our interview findings show that the Covid-19 pandemic accelerated the use of mobile positioning data, in which the data was used for mapping infections and mobility, as evidenced by previous literature (Ekong et al., 2020; Grantz et al., 2020; Ienca and Vayena, 2020; Santamaria et al., 2020). New areas of application are likely in, e.g., public transport, traffic management, disaster risk management, energy systems. We expect new models combining mobile positioning data with other data sources, and this is likely to further trigger its mainstreaming across societal functions. This increase in demand may result in a more competitive market, ultimately pushing down prices.

Future mobile positioning data will most likely support personalized services. Examples include restaurant recommendations, route and conditions, and tourist information (Tung and Soo, 2004). Personalized services within disaster risk management are underdeveloped. There is a high potential in this field. Being able to access people's position represents one of the building blocks of the provision of personalized services (Jung and Chung, 2015). Therefore, more precise and larger positional dataset will enable the supply of personalized services in disaster risk management. However, there is currently a trade-off between personalized services and privacy: the more a service is personalized , the less privacy can be granted. Evidence from surveys, for instance, suggests that privacy guarantees constitute the conditio sine qua non for the transferring of data (Aleksieva-Petrova & Petrov, 2020; Binjubeir et al., 2020; Habibzadeh et al., 2019). Nonetheless, future innovations in this area could address this trade-off. For example, advancements in synthetic data and AI can improve the understanding of mobility patterns whilst guaranteeing privacy.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

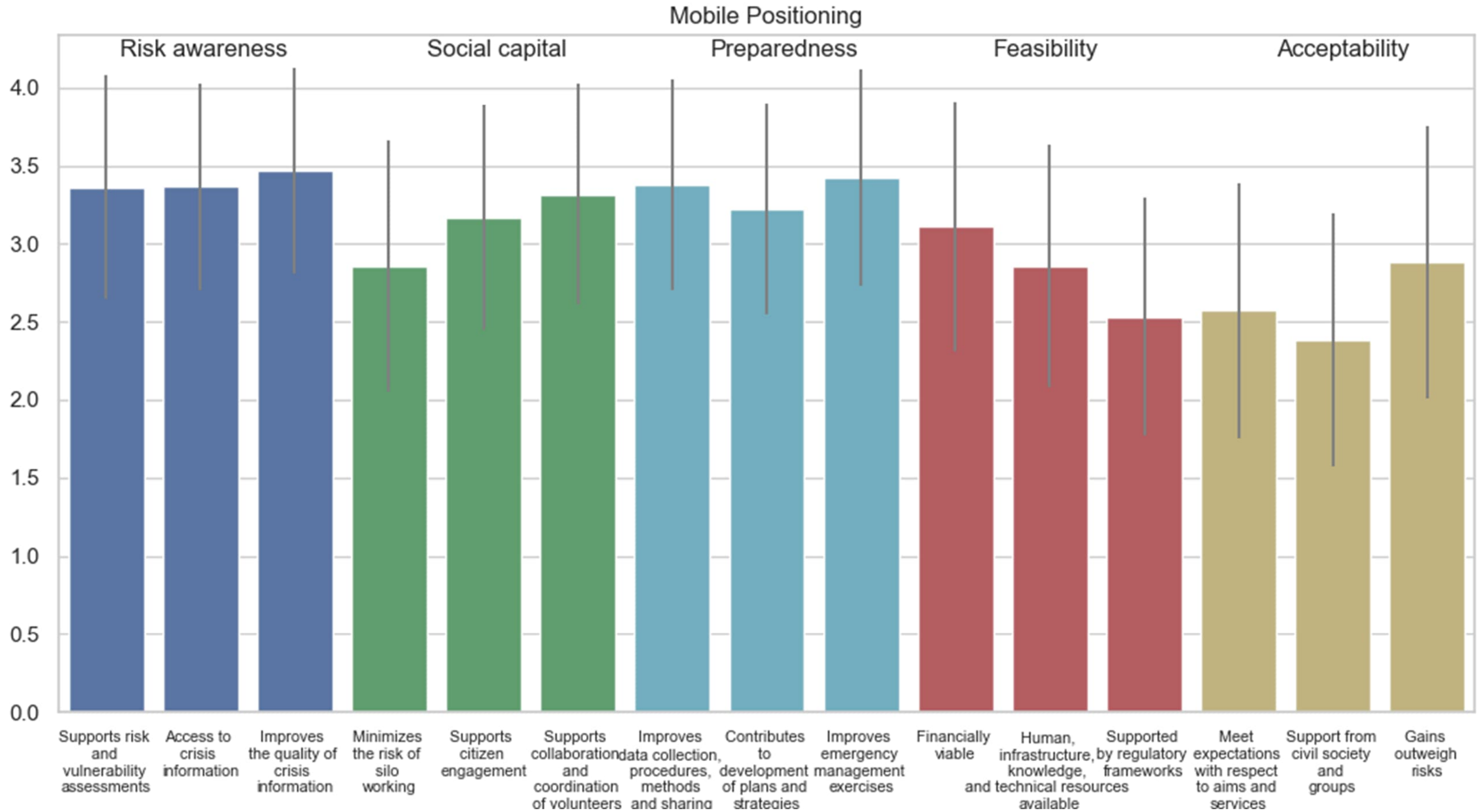

Figure 3*: Benefit analysis of mobile positioning data (means and unitary standard deviations)*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Risks

There are some operational risks that might impede the effectiveness of mobile positioning. During the recovery phase, mobile positioning may malfunction in the event of an infrastructure failure like power outage, loss of internet connection, or disruption to the mobile communication network. Given that disasters per definition are disruptive events, insofar most mobile positioning are inoperable amid disasters (Latvakoski et al., 2020; Sari, et al., 2021; Tominga et al., 2021). Second, it is likely that actors engaged in disaster risk management only have partial access to the mobile positioning data. This, as data is scattered between many different mobile network operators. It may be challenging to establish a partnership with all the mobile network operators active within a geographical location (Võik et al., 2021). Third, the accuracy of the mobile positioning data may be questionable, especially if using historical data. Generally, historical data is reliable concerning population counts and movement patterns. However, there are limitations to what extent historical data can accurately portray the present. Movement patterns may rapidly change in light of disruptive events, as in the case of the Covid-19 pandemic in which people started to stay at home to a much larger extent. Fourth, mobile positioning data has a huge potential for biases. Many countries have in the past cancelled their mobile positioning data programs because their analytical models were inadequate, and thus merely reinforced biases. It is therefore vital to ensure that the analysis captures the complexity of the data. Fifth, some operational risks arise when considering the vulnerable segments of the population. Mobile positioning assumes individuals to own a physical asset like a smartphone or an IoT device. Some vulnerable groups may, however, not have the means or capabilities to own, operate such a device, or connect it to a network, including people with limited economic capabilities, children, elderly, people with certain types of impairments, homeless, or less accessible areas (Latvakoski et al., 2020). There is also the risk that the mobile positioning data is used for discriminatory purposes, thus increasing vulnerabilities. Sixth, as one of our interviewees pointed out, telecom operators are often subjects to a stricter regulation compared to the one that is applied to other actors that acquire positioning data through other means. The ePrivacy regulation imposes larger sanctions on telecom operators, therefore forcing them to face increased insurance costs, resulting in higher prices being charged for the final end-user.

The EU recently introduced the GDPR to harmonize data privacy laws across Europe, whilst reinforcing the individual's right to privacy. GDPR classifies location-based data as personal identifiable information. Consequently, mobile positioning must comply with the requirements outlined in GDPR. While the law mitigates privacy-related issues that emerge when employing mobile positioning data, it also generates new challenges like lack of guidelines, compliance issues, and technical constraints (Ataei et al., 2018). However, insufficient agreements regarding privacy laws continue to persist despite GDPR (Latvakoski et al., 2020). Different countries continue to have different regulations regarding the use of mobile positioning (Võik et al., 2021; Võik et al., 2021), impeding international cooperation in the case of a cross-border disaster (Latvakoski et al., 2020). The regulations are often subject to change, thus imposing a legislative risk in which the future access to mobile positioning data is highly uncertain (Võik et al., 2021; Võik et al., 2021). For example, there might be a legislative shift at both a national and EU-level toward forcing telecom operators to share their raw data with governments free of charge, which according, to some of our interviewees, may undermine efforts from the private sector. Once the authorities have access to data for free, they might be incentivized to develop their own analysis systems and abandon partnerships with the private sector. However, our interview partners highlight the many difficulties with developing an analysis system. This can cause bias and in the worst case discrimination. In addition, telecom companies might stop collecting the mobile positioning data if not motivated by profits.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Having been adopted because of growing concerns over privacy issues, GDPR can potentially give rise to some operational risks. The violation of its rules would also constitute a financial risk for the data administrator as the authority would have to pay fees. GDPR does not allow the use of real-time data in most of the cases, disaster events been included, thus limiting the use of mobile positioning data to the mitigation, preparedness, and recovery phase. Mobile positioning data is at the moment usually provided with a minimum of 24-hour delay due to current European legislation, also guaranteeing the anonymity of the mobile device users. The data is also anonymized, meaning that it is not possible to identify who is in the affected area nor their potential vulnerabilities. Yet it is worth noting that many mobile positioning data analysts can produce a proxy constructed from a long string of time series data that allows for the construction of a model that provides an approximation of the number of people in a location at a given time. The prediction ability of the model increases with the number of observations. Junqué de Fortuny et al., (2013) concludes that employing sparse, fine-grained dataset (the authors mention the example of human behavior) leads to increasing predictive performance as this grows to a massive size. For the purpose of an application in disaster risk management, this would imply that predictive models based on location data should get better as new information flows in. Mobile positioning data can also be used in the response to slow onset disasters as demonstrated during the Covid-19 pandemic.

Provision

We recommend a public-private partnership for applying mobile positioning in disaster risk management. This recommendation is based upon evidence from the two twinning BuildERS case studies "*D4.3: Applying mobile positioning data for more precise rescue planning and emergency management under cyber-hazard in Estonia*" and "*D4.7: Using Mobile Operators' Data to Locate, Protect and Evacuate Tourists and Other Vulnerable Groups in Disasters*".

A public-private partnership grants public authorities the access to the mobile positioning data, as well as analytical capacities that may take several years to develop independently. The structure for data collection and analysis is likely to be more feasible, both financially and technically, for the operators that have already operated in the sector for several years than for public authorities. These can then simply devote their time to applying the data to strengthen their disaster risk management efforts.

It is however important to note that the strategy to develop a partnership is likely to influence the cost of the operation. Being able to reach an advantageous agreement, in economic terms, for the authorities represent a necessity to justify outsourcing these operations to the private sector. This can potentially become difficult in the case in which the mobile network market functions as a monopoly, where the presence of a single operator might increase the costs of the public-private partnership and reduce the authority's bargaining power. Public authorities might decide to access the necessary hardware technologies through a leasing contract with the wholesalers. Authorities will always have access to the latest technology as the contract expires every few years. On the other hand, the legal nature of the leasing does not grant the authority a full power of disposition on the equipment. However, accessing a subscription-based service would save the authority the time to develop its own system and would grant access to the experience of those that have been using these tools for several years. This solution seems to be the most advantageous.

The possibility of a law, mentioned above, that would force data sharing free charge being put in place will probably reshape the bargaining power of the two sides, bringing new provision tools to life.

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No. 833496

4.2 Social media crowdsourcing

***Table 4**: Overview - Social Media Crowdsourcing*

Usage	Cost	Benefit	Forecast	Risk	Provision
Preparedness, response, recovery and mitigation	LCC approach (10 years) Total costs: €3,5M - €5,6 million	Key benefits in social capital.	Social media platforms might change. Crowdsourcing is likely to become more difficult. Analysis software is likely to improve.	1. Messy datasets. 2. Inaccurate data 3. Excludes the most vulnerable 4. Data protection and privacy concerns 5. Biased and discriminatory AI 7.Mulfunctioning infrastructure 8. Misleading information	Integrate into existing structures.

Social media crowdsourcing entails asking the broad masses of social media users to co-create information regarding a particular event, by sharing content, photos, videos, and other forms of data (Latvakoski et al., 2020). It can be active, in which users actively share information during a disaster risk management initiative, or passive, in which information is shared independently from a disaster risk management initiative (Besaleva and Weaver, 2016). Social media crowdsourcing generates large datasets that are best analysed with a high-level natural language processing software. Pre-trained software using AI, machine learning, or blockchain technology have previously proven to be effective (Latvakoski et al., 2020). Recently, there has been an increase in the use of social media crowdsourcing for disaster risk management (Besaleva and Weaver, 2016). Notable examples include: 2010 Haiti Earthquake, 2014 North Stradbroke Island Bushfires (Australia), and 2015 Houston Flooding (USA) (Kankanamge et al., 2019). Social media crowdsourcing can be applied at any stage of the disaster risk management cycle (Latvakoski et al., 2020).

Costs

State of the art literature on the possibility to use social media crowdsourcing in disaster risk management has mainly focused on obtaining the best possible accuracy level (Li et al., 2021; Yu et al., 2019; Yuan and Liu, 2019). Most of these applications have only been developed for academic purposes. For these reasons, literature on the costs of implementing such a tool is scarce. Costs are therefore consolidated from different sources to get an overview of what expenses may emerge from the pilot phase, implementation of automatic data extraction and processing, and maintenance of the system. The findings are presented in Given the nature of social media crowdsourcing, the analysis carried out by the European Commission on mobile data constitute a good starting point. A pilot phase must be planned, where legal expertise is to be sought and data is collected and processed. The automated model to be implemented could potentially follow the one suggested by Hernandez-Suarez et al., (2019), i.e., a variation of a classic Recurrent Neural Network which carries out an analysis of the words contained in social media messages to design a heatmap, through Google Maps, of the

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

most severely hit areas. Such an approach necessarily requires access to Twitter API (application programming interface), the social media used in the original paper, and Google Maps API. These necessities impose additional costs. Once the model has been trained and validated in the pilot phase the proper implementation phase follows, where the whole process is automatised. The maintenance of this tool must account for the fact that the licenses have to be renewed periodically. One of the major challenges in estimating the cost of such a structure is to understand how many people use social networks every day and how many share pictures, geographical positions and comments in the event of a disaster. Several factors play a role in determining these figures: demographic characteristics of the population (e.g., age distribution, the rate of Internet literacy and the population size), socioeconomic characteristics of the population (e.g., social networks may be less accessible in the context of a developing country) and characteristics of the supply of Internet connection (e.g., how many people have access to the network and at what speed). In order to estimate the necessary capacity that is needed, we review 50 datasets of Tweets that were produced during disasters and that constitute training and testing datasets which commonly used in the literature (Alam 2018a, 2018b; Alam 2018; Alam et al., 2018; Imran et al., 2013a, 2013b, 2016; D. T. Nguyen et al., 2017; T. Nguyen et al., 2017; Waqas and Imran, 2019) (the social media used in the original paper) and Google Maps API. These necessities impose additional costs.

Once the model has been trained and validated in the pilot phase the proper implementation phase follows, where the whole process is automatised. The maintenance of this tool must account for the fact that the licenses have to be renewed periodically. One of the major challenges in estimating the cost of such a structure is to understand how many people use social networks every day and how many share pictures, geographical positions and comments in the event of a disaster. Several factors play a role in determining these figures: demographic characteristics of the population (e.g., age distribution, the rate of Internet literacy and the population size), socioeconomic characteristics of the population (e.g., social networks may be less accessible in the context of a developing country) and characteristics of the supply of Internet connection (e.g., how many people have access to the network and at what speed). In order to estimate the necessary capacity that is needed, we review 50 datasets of Tweets that were produced during disasters and that constitute training and testing datasets that which commonly used in the literature (Alam et al., 2018a, 2018b, 2018c, 2018d; Imran et al., 2013a, 2013b, 2016; D. T. Nguyen et al., 2017; Waqas & and Imran, 2019). The results indicate that a monitoring system based on social media should be able to handle, on average, 2580000 data points. We use this figure to estimate the cost of building a system with that capacity below.

Given the nature of social media crowdsourcing, the analysis carried out by the European Commission on mobile data constitute a good starting point. A pilot phase must be planned, where legal expertise is to be sought and data is collected and processed. The automated model to be implemented could potentially follow the one suggested by Hernandez-Suarez et al., (2019), i.e., a variation of a classic Recurrent Neural Network which carries out an analysis of the words contained in social media messages to design a heatmap, through Google Maps, of the most severely hit areas. Such an approach necessarily requires access to Twitter API (application programming interface), the social media used in the original paper, and Google Maps API. These necessities impose additional costs. Once the model has been trained and validated in the pilot phase the proper implementation phase follows, where the whole process is automatised. The maintenance of this tool must account for the fact that the licenses have to be renewed periodically. One of the major challenges in estimating the cost of such a structure is to understand how many people use social networks every day and how many share pictures, geographical positions and comments in the event of a disaster. Several factors play a role in determining these figures: demographic characteristics of the population (e.g., age distribution, the rate of Internet literacy and the population size), socioeconomic characteristics of the population (e.g., social networks may be less accessible in the context of a developing country) and characteristics of the supply of Internet connection (e.g., how many people have access to the network and at what speed). In order to estimate the necessary capacity that is needed, we review 50 datasets of Tweets that were produced during disasters and that constitute training and testing datasets which commonly used in the literature (Alam 2018a, 2018b; Alam 2018; Alam et al., 2018; Imran et al., 2013a, 2013b, 2016; D. T. Nguyen et al., 2017; T. Nguyen et al., 2017; Waqas and Imran, 2019) (the social media used in the original paper) and Google Maps API. These necessities impose additional costs.

Once the model has been trained and validated in the pilot phase the proper implementation phase follows, where the whole process is automatised. The maintenance of this tool must account for the fact that the licenses have to be renewed periodically. One of the major challenges in estimating the cost of such a structure is to understand how many people use social networks every day and how many share pictures, geographical positions and comments in the event of a disaster. Several factors play a role in determining these figures: demographic characteristics of the population (e.g., age distribution, the rate of Internet literacy and the population size), socioeconomic characteristics of the population (e.g., social networks may be less accessible in the context of a developing country) and characteristics of the supply of Internet connection (e.g., how many people have access to the network and at what speed). In order to estimate the necessary capacity that is needed, we review 50 datasets of Tweets that were produced during disasters and that constitute training and testing datasets that which commonly used in the literature (Alam et al., 2018a, 2018b, 2018c, 2018d; Imran et al., 2013a, 2013b, 2016; D. T. Nguyen et al., 2017; Waqas & and Imran, 2019). The results indicate that a monitoring system based on social media should be able to handle, on average, 2580000 data points. We use this figure to estimate the cost of building a system with that capacity

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Table 5: LCC for social media crowdsourcing

Pilot Phase	**Cost (€)**
Internal legal expertise	15000
Data extraction and preparation for following processes	30000
Hardware cost for one-time process (12 months of pilot data)	25000
Applying methodology on pilot data (no automation)	35000
Estimation	8500
Analysis of the results (coherence, quality, issues)	8000
Project management	13500
License to Google API	66 per 1000 requests
License to Twitter API	2110 per month
TOTAL	881195
Implementation of automatic data extraction and processing	
Automation of data extraction and preparation for following processes	20000
Data storage hardware	100000
Processing hardware	100000
Developing automated processes according to accepted methodology	250000
Exporting data automation	15000
Quality control processes, including central system monitoring	20000
Project management	46000
TOTAL	551000
Maintenance of the system (yearly costs)	
Quality manager	40000
System maintenance	111000
Project management	7000
License to Google API	66 per 1000 requests
License to Twitter API	2110 per month
TOTAL	353195
LCC (TEN YEARS)	3507316,97

Several factors can potentially contribute to influence both the costs and the timing of the implementation. First of all, programming languages nowadays offer packages that provide the backbone of several machine learning models and the users only have to tune the parameters to their purpose. For example, Python has many of such libraries: TensorFlow, PyTorch, NeuroLab and Scikit Proceeding this way would save both time and money as there is no need to generate a model from scratch. However, it is sometimes necessary to create one's own model when those already available do not match the needs of the application. Nonetheless, on the opposite spectrum of possibilities, creating the model from scratch might turn out to be extremely expensive and time consuming. Outsourcing the creation of the model to a data analytics company has the potential to reduce time but increase the costs and expose the authority to the risk of data misamanegment under current European laws on data and privacy protection. Unfortunately, an aspect that the user cannot control but that has the potential to impact costs and time is the quality of the data. It is true that common spelling mistakes in social media messages can be easily dealt with but at the cost of more time being invested in programming a more sensible model.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Additional figures on the costs were collected by looking at the tools and the technologies that the European Union developed under the Horizon2020 program. In particular, during November 2016 and April 2019, €1.8 million were devoted to the E2mC project[1], with the aim of proving *"the technical and operational feasibility of the integration of social media analysis and crowdsourced information within the Mapping and Early Warning components of Copernicus Emergency Management Services.*" Using the same reference period, 10 years, the 4% interest rate and assuming a yearly maintenance cost that is about 25% of the implementation cost (as suggested by one of our interviewees), we came up with a LCC value that is about €5.6 million. We suggest using this figure as it comes from a more recent project designed to involve social media crowdsourcing in disaster risk management.

Benefits

Social media crowdsourcing generates many benefits, as shown in **Table 5**. Key benefits are associated with social capital. By definition, social media crowdsourcing engages citizens by giving them a voice. It makes disaster risk management more participatory, which can strengthen social capital. This in turn supports the collaboration and coordination of volunteers, as it provides citizens with an opportunity to voluntarily share information and thus support disaster management efforts.

Social media crowdsourcing can also improve access to information, as it allows disaster risk management operators to gather data from multiple sources about zones that may be difficult to reach. It can increase the volume of data. However, information quality might be questionable. Citizens can share misleading information, both intentionally and unintentionally and the use of bots might generate additional difficulties in providing the necessary assistance.

As shown in **Figure 4**, social media crowdsourcing scores rather low on preparedness. This has been observed since social media crowdsourcing in practice is used in the reactive phase of disaster risk management. For instance, Academic literature, risk maps can be constructed during the mitigation phase through the involvement of private citizens. During the preparedness phase the public can be trained through social media campaign, supporting the co-creation of social capital. However, it scores low in feasibility and acceptability indicating that there are some barriers to applying social media crowdsourcing in practice. Social media crowdsourcing is considered financially viable but struggles with regulations, human and technical capacity, and social acceptance. These barriers are further discussed in relation to operational risks.

[1] https://cordis.europa.eu/project/id/730082

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

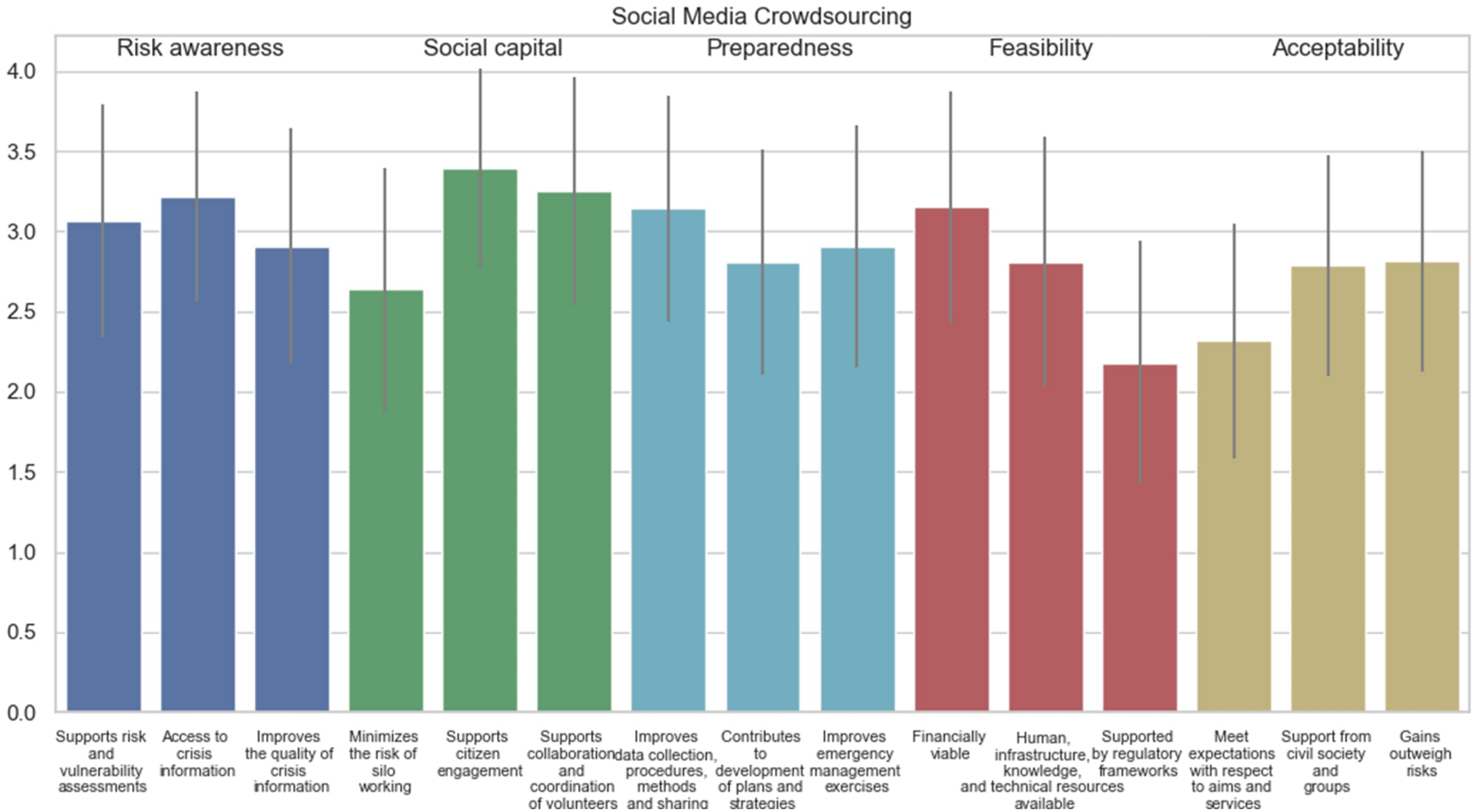

Figure 4*: Benefits analysis of social media crowdsourcing (means and unitary standard deviations)*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Forecast

Globally, social media users have more than doubled from around 2 billion in 2015 to 4.5 billion in 2021 (Dean, 2020). Given these past rapid advancements, social media and crowdsourcing are respectively likely to continue to grow in the near future. This trend has been confirmed by another BuildERS deliverable, *D1.4 Communication behaviour in Europe and vulnerabilities*, where the authors state “Our research indicated that while traditional information sources remain relevant during certain crisis cases and for certain publics, the landscape of crisis communication is being transformed by the increasing use of social media” (p.5). Innovative methods and strategies improving the efficiency of social media crowdsourcing are likely to emerge. Nonetheless, it is becoming more challenging to crowdsource data. Engagement is decreasing and crowdsourcing is gaining a poor public perception, especially following the Facebook-Cambridge Analytica scandal, in which data from millions of Facebook users was harvested and thereafter misused in the American 2016 presidential campaign. Unfortunately, this trend is likely to continue in the future in the long run making it increasingly difficult to gather a sufficient amount of data for analysis

The future is likely to witness a shift in what social media platforms are used in crowdsourcing initiatives. At the moment, Facebook and Twitter are widely used for crowdsourcing information. However, the social media landscape is different when looking at what platforms are the most popular among users. Currently, Facebook is the leading social network with 2.9 billion active users, followed by Youtube, WhatsApp, Facebook Messenger, and WeChat (Dean, 2020). Considering these trends, future social media crowdsourcing is likely to make a shift to messenger-based platforms.

New data analysis methods and techniques are likely, predominantly emerging from advancements in AI and machine learning. These advancements can improve data processing and make it easier to analyse large quantities of data, ultimately introducing the possibility to combine the crowdsourced data with other data sources.

Looking at the social media market in general, this is extremely volatile to changes in the dominating big tech companies. Regulations have forced these big tech companies to rethink their revenue models, ultimately transforming how social media crowdsourcing is carried out. A recent example is the Apple iOS update in 2021 to notify users if their data is tracked, potentially making it more challenging for social media platforms to harvest user-data. In light of this update, Facebook has been forced to develop new revenue streams. Looking forward, future disruptions are likely to emerge as Google enters the social media industry as, despite being a key big tech company, it currently does not own any social media platforms except YouTube.

Risks

Operational risks do exist in the case of social media crowdsourcing, of which unmanageable datasets are considered a stark example. Messy datasets can make social media crowdsourcing ineffective (Bott et al., 2014). In its very nature, social media crowdsourcing generates large, messy, and unorganized datasets (Latvakoski et al., 2020). This, as social media posts vary in terms of language, slang, hashtag, and content. In addition, few posts include a geographical location tag (Besaleva and Weaver, 2016). Also, content can be published on many different platforms. Nonetheless, this risk can be mitigated by investing in a pre-trained software that use AI, machine learning, or blockchain technology. Examples of such pre-trained models include: Google AI’s BERT, Allen AI’s ELMo, Open AI’s GPT-2, and Fast-AI’s ULMFiT (Latvakoski et al., 2020). There are however some significant operational risks associated with AI, machine learning, and blockchain. Such technologies rely on

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No. 833496

algorithms that may produce inaccurate information due to system complexity, ethical dilemmas, contextual changes, biases, and measurement error (Babic et al., 2021; Leslie, 2019). There is also a risk that AI, machine learning, and blockchain mimic their designer's preconceptions and biases, thereby reinforcing existing patterns of marginalization (Leslie, 2019).

Another operational risk regards the accuracy of data. The inaccuracies may arise from limited access to crowdsourced data, due to:

- Restrictions imposed by the service provider, who ultimately controls what data can be extracted (Latvakoski et al., 2020).
- Information being shared in closed networks inaccessible to actors engaged in disaster risk management (Denzer et al., 2015).
- Low trust towards disaster risk management operators makes the public reluctant to share information (Latvakoski et al., 2020).
- The crowd shares little or no information (Bott et al., 2014), which may be the case if people are required to download separate apps for crowdsourcing (Latvakoski et al., 2020).

Another yet so alarming source of data inaccuracy is the risk of misleading information. Key characteristics of disaster response like urgency, sensitivity, and fragmentation can create a breeding ground for misinformation or disinformation (Besaleva and Weaver, 2016). This point has been raised in Deliverable D2.3 *Social media campaign analysis and governments' responses to disinformation*: "It is not possible to eliminate all unintentional misinformation spread by the officials or by the members of the public. Thus, it is advised to invest in media and information literacy training and information awareness campaign" (p. 85). Misinformation can be the result of an incorrect or incomplete understanding of the situation, whereas disinformation is the deliberate spread of false or misleading information (Denzer et al., 2015). In addition, there is a risk that online bots deliberately spread disinformation. Deliverable D1.4 *Communication behaviour in Europe and vulnerabilities* concludes that people who are less experienced in the use of social media have more difficulties in assessing and processing the information and are thus more vulnerable to false and harmful information. Disaster risk management operators may lower trust in the crowdsourced data, and thus not use it to its full potential. Here blockchain can come in handy (K. Wang et al., 2019), by making the data safer from manipulation and the social media users more accountable for the quality and the accuracy of the content that they share. Nonetheless, some authors emphasize that several major challenges may arise from an application of blockchain (Golosova and Romanovs, 2018). Another possible risk mitigation method is data triangulation, in which the dataset is checked and validated against others coming from alternative sources.

Given its public availability, the risk that crowdsourced data fall into the hands of users with bad intentions is always present. This risk can be mitigated by dividing the larger task into smaller ones, thus only allowing users to have partial access to the information at hand.

Disasters are sporadic, and thus generate an ad-hoc demand for crowdsourced data. Unfortunately, this may result in another operational risk. It can be challenging for local disaster risk management operators to maintain the formal institutions, capacities, and resources that are needed for social media crowdsourcing. Some areas might only encounter a crowdsourcing-relevant event every few years. In addition, social media evolves rapidly. Crowdsourcing initiatives must keep up with these

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

technological shifts and advancements to maintain their effectiveness, and hence avoid becoming obsolete. Regular capacity development may mitigate this risk, although it demands additional costs.

Returning to the overarching objective in BuildERS, there is a question regarding the effectiveness of social media crowdsourcing in reaching the most vulnerable citizens in European societies. A prerequisite for social media crowdsourcing is access to a physical device such as a smartphone, tablet, or computer (Bott et al., 2014) and to an Internet connection. Access to technology is however far from universal, as the most vulnerable groups in society tend to lack the means or capabilities to operate the required devices. This includes people with limited economic capabilities, children, elderly, people with certain types of impairments, and people experiencing homelessness (Latvakoski et al., 2020). Consequently, the most vulnerable parts of the population may be excluded from participation, ultimately causing biases in the crowdsourced data.

Legislation like GDPRhas been adopted by European authorities with the aim of providing a legal framework against uncontrolled data sharing and usage. Privacy concerns are prioritized over free discolure of personal data. This implies that collecting, managing, and storing data might become more difficult and more expensive. Registering data about location, name, and pictures is only permitted within the limitations designed by GDPR. Sharing this data requires additional compliance to the rules. States are furthermore likely to implement new regulatory frameworks to keep up with the advancements in social media, thus imposing a legislative risk in which the future access to crowdsourced data is highly uncertain.

Provision

We recommend that organizations engaged in disaster risk management invest in in-house capacity. This recommendation is provided here since the assumption is that most organizations already have communication officers working with outreach tools and social media. These can be further trained to master social media crowdsourcing, thus building on their existing knowledge and skills in social media management. This is a cost-effective option as it makes advantage of available personnel.

The possibility to outsource the whole process to an external platform provider is limited in the field of social media crowdsourcing for disaster risk management. Several platforms exist but they mainly target private businesses that look for customers' reviews to improve their customer services. These platforms cannot be easily adapted to disaster risk management as geo-positioning is not an essential part of business-related applications. Among the external platform providers in disaster risk management, we highlight Ushahidi (Hirata et al., 2018; Pánek et al., 2017), which offers monthly basic subscription for $49 and a business-tailored solution starting from $5000.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

4.3 Drones

***Table 6**: Overview - Drones*

Usage	Cost	Benefit	Forecast	Risk	Provision
Preparedness, response, and recovery	€ 5.7 million	Key benefits in risk awareness and preparedness.	The market for drones is likely to grow. The technology is also rapidly evolving.	1. Cannot operate in certain environments 2. Legislative changes 3. Negative public perceptions 4. Hacking and images leak	Public procurement

Unmanned aerial vehicles, here referred to as drones, are aircrafts operating without a human pilot onboard (Nikhil et al., 2020). Drones come in many sizes, in which wingspans can vary from 60 meter to three centimeter (Aydin, 2019). Lately, drones have been employed in disaster risk management. Drones can support preparedness, response, and recovery efforts, and can operate in situations when more conventional methods fall short. Foremost, drones can access, and monitor locations previously considered inaccessible. Areas of application include rapid impact assessments, early warning systems, search and rescue missions, hazard monitoring, supply deliveries, and many more (Latvakoski et al., 2020).

Costs

Previous research suggests that the technology and the services that are required to obtain data from a territory using drones is constant throughout a range of fields. Thus, it can be reasonable to assume that territorial observations for agricultural purposes are carried out in ways that are similar to those found in the field of disaster risk management (Nhamo et al., 2020; Řezník et al., 2017). The market for these services is much larger in the agricultural sector than in disaster risk management, thus simplifying our data collection about costs. As a case in point, the Food and Agriculture Organization of the United Nations (FAO) has used UAVs observations to identify the villages mostly affected by droughts in Myanmar (FAO, 2018). While this represents an application that is strictly related to agricultural issues, it is clear that once mapping operations have been carried out, many other assessments can follow, such as those related to disaster risk management (FAO, 2018).

Different cost estimates are presented in **Table 7**. Matese et al. (2015) reports decreasing costs per-hectare compared to other mapping alternatives when using drones. Similarly, Borgogno Mondino and Gajetti (2017) present costs curves that are highly influenced by the size of the imaging area and the height of the drone's flight. Both in the case of a rotating wings drones (R-UAV) and in the case of fixed wing drones (F-UAV), the larger the mapped areas are, the smaller the costs per-hectare. In addition, the higher the flight height, the smaller the price. These results are driven by the large relevance of fixed costs, which are then distributed to a larger area when the size of surveyed land is increased. In addition, F-UAVs seem to be cheaper, even though only to a small extent than R-UAV; but this difference fades away as the size of the mapping area increases. Mondino and Gajetti (2017)

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

reports the cost-area function under different settings and its shape suggests that a minimum marginal cost per hectare can be reached, meaning that additional pieces of land can be investigated with no significant increase in the cost. In comparison, Stahl et al. (2020) reports a cost of €2.5 per hectare with a survey area of 100ha. The cost might, of course, be influenced by the cost of labor, with expert pilots being more expensive than amateurs. For example, UK's Approved Network of Commercial Drone Operators suggests that the costs of drone aerial photography might hover between £50-£100 and £150-£500 depending on the willingness of the customer to turn to an amateur or to professional pilot approved by the Civil Aviation Authority (Drone Safe, 2018). Similar prices seem to be the ones found in the Swedish market for the same type of services[2].

***Table 7**: Drones costs*

Reference	Cost
Matese et al. (2015)	**Cost for drone mapping 5 ha** - Acquisition cost: €1500 - Georeferencing and orthorectifying: €500 - Image processing: €200 - TOTAL: €2200 **Cost for drone mapping 20 ha** - Acquisition cost: €4000 - Georeferencing and orthorectifying: €1000 - Image processing: €300 - TOTAL: €5300
Stahl et al. (2020)	€2.5 per hectare with a survey area of 100ha
Mondino and Gajetti, 2017	Between €125.76-129.63 per hour
Drone Safe, 2018	Hobbyist: €60 - €120 Professional pilot: €180 - €590

Using the data that are made available by drone producers and the cost estimates that are used in academic publications, it is possible to produce an independent estimation of the LCC of a fleet of drones that is purchased and autonomously managed by a national authority. An independent drone flee is preferred due to privacy concerns, which is further discussed in Provision section.

An overview of the LCC results is presented in **Table 8**. The cost estimations and assumptions for a whole drone fleet are obtained from the Swedish police force, which operates one of the largest drone fleets in Europe with about 300 drones and over 200 operators (DJI, 2021). The Swedish police force uses the drone DJI (Da Jiang Innovations) Mavic 2 Enterprise. Estimating the life expectancy of drones is difficult as it is affected by several factors such as the field of application, the type of drones, the ability of the operator and so on. There are few studies which proposed values for the life expectancy, (Figliozzi, 2017; Yowtak et al., 2020), and assumed a three and two years drone life respectively. Figliozzi (2017) also investigates the alternative of five years. We argue for employing a three years life-span, considering that the lifetime can be expanded over two years through insurance agreement with the producers, that would guarantee spare parts, and that the continued training and exposure to extreme conditions make the 5-years lifespan options seem unlikely. In a 10 years' time frame, drone fleet need to be renewed three times. This also guarantees that authorities have access to best available technology and protects it against obsolescence. Given that drones operators will be employed as regular employees by the authority, we are only considering the cost

[2] https://www.highshot.se/pricing

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

of obtaining a license in our analysis. A case in point is the approach of the Swedish police that trained 200 of its police officers to obtain a drone license rather than relying on external resources[3,4,5]. We assume that this has led to no further increase in personnel cost other than the one pertaining the pilot license. The Swedish Transport Agency (Transport Styrelsen, 2021) provides the data on the costs for obtaining a pilot license and registering a drone (Transport Styrelsen, 2021). These costs are 50 SEK (about €5) per year per operator and a lump sum payment per drone which is 130 SEK (about €13). In addition, electricity price must be considered. Electricity price in Sweden for the first semester of 2021 for non-household consumption was about 0.1 €/kWh, taxes and levies included (Eurostat, 2021). DJI, as the producer of drones indicated in Table 8, offers a comprehensive protection service for their purchased drones. We assume that the DJI Care Enterprise Basic is purchased with each drone and then renewed every year. Note that this service has different prices depending on the type of drone for which it is purchased. For large and expensive drones, a 1-year warranty is included in the product, and additional warranty is purchased for the second and the third year only. The service covers damages from accidents like crashing, water damage, or signal interference. With such a measure we solve the problem of modelling the need for reparation and maintenance services. Insurance for drone operators in Sweden can be purchased at an annual cost of about SEK 1600 (€160) with the additional advantage that some of the insurance companies also offer spare parts replacement for a value of up to 1000€ Such a replacement service would then help compensate the maintenance and replacement costs of parts that are not covered by the service provider(Försäkring, 2021). Following the approach of Stahl et al. (2020), we employ a 0.833 €/Wh cost rate for the disposal of the battery. Given its components, this is the part of the drones that will probably require the most in terms of expenditure during the disposal phase. It should be noted that the sensitivity of the data that are acquired during the operational life, makes it impossible to envisage the possibility to sell the drones as a secondhand product to reduce its costs. Table 8 reports the results of the LCC analysis per drone.

Table 8*: LCC for drones*

Drone	Application	10 years LCC result (€)
DJI Phantom 4	Crowds monitoring, Search & Rescue	8600
DJI Matrice 300 RTK (Zenmuse P1 camera)	Mapping, Search & Rescue	77000
DJI Mavic 2 Advanced	Search & Rescue	25600
DJI Mavic 2 Enterprise	Search & Rescue, Crowds monitoring	12750
DJI Inspire 2 X5S Standard	Mapping, Search & Rescue	22450
DJI Inspire 2 X7 Standard	Mapping, Search & Rescue	30570
DJI Phantom 4 RTK	Mapping, Search & Rescue	27125

Constructing a drone fleet that is optimal under every circumstance is impossible. The composition, as different drones perform different tasks with different degrees of precision, is designed so as to meet the needs of the authorities and the characteristics of the territory over which the flee will be

[3] https://www.mynewsdesk.com/uk/dji/news/top-public-safety-drone-programs-in-europe-how-rescue-teams-firefighters-and-the-police-use-drones-to-propel-their-operations-436287?utm_campaign=widget&utm_medium=widget&utm_source=www.24timmar.se
[4] https://spheredrones.com.au/blogs/news/swedish-police-have-around-350-drones-in-service-creating-europe-s-largest-drone-program
[5] https://enterprise-insights.dji.com/user-stories/how-swedish-police-started-case-study

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

deployed. The point of showing the LCC result for alternative drones is to encompass the great variety of prices and functionalities that are found on the drone market. Focusing exclusively on DJI products is far from being reductive, considering the large market share that the company retains (Bloomberg, 2020). The size of the drone fleet is also extremely influenced by the dimension of the authority that is deploying it. For instance, the drone department of the Croatian Mountain Rescue Service (HGSS) consists of only 49 pilots and 40 drones. We will proceed considering a drone fleet with the size of that deployed by the Swedish police force. The capacity of 300 drones is filled with the alternatives presented in Table 8 making sure to provide a coverage of the possible needs those drones can meet and avoid to rely on the most expensive or the cheapest ones. This would, ideally, prevent a result that is skewed towards any of the extreme, i.e., avoid returning a result that is too expensive or too cheap. The composition employed here is purely speculative and Table 8 allows the reader to compose her own fleet according to her knowledge. 15 mapping drones per each possible alternative are purchased to guarantee a sufficient mapping capacity (DJI Matrice 300 RTK, DJI Inspire 2 X5S, DJI Inspire 2 X7 and DJI Phantom 4 RTK); 30 DJI Mavic 2 Advanced drones are purchased to provide a sufficient number of thermal cameras for search and rescue activities. The rest is evenly distributed between DJI Phantom 4 and DJI Mavic 2 Enterprise, multi-purpose drones that can be deployed in several settings, even if with a lower degree of accuracy and precision. This returns a cost of about €5370000 in drones and €280000 for operators. The latter is independent of the drones used in the fleet, with a software cost of about €50800. It also suggests 10 data analysts working with the DJI Terra Pro software, which enables 2D/3D real-time mapping and 2D/3D mission planning for DJI drones. In total, the deployment of such a drone fleet for 10 years, with the assumptions we have made, will cost €5.7 million. Given the difficulty to predict what future costs on the drone market will look like, the way we proceeded was to assume that no major change will occur. Additionally, we cannot rule out the possibility that thanks to technological progress, new drones in the future will be able to carry out new tasks in the field of disaster risk management consequently affecting the composition of the drone fleet.

Benefits

Drones can yield many benefits, as shown in **Figure 5**. At the very core, drones improve data collection which in turn creates additional benefits. The data can be used for many purposes in order to strengthen risk awareness and disaster preparedness, ultimately improving disaster risk management.

A key benefit concerns provision of crisis information. Drones can collect data which can improve crisis information and strengthen the overall situational awareness amid crisis, and consequently improve the quality of crisis information. Drones also offer the possibility to broadcast information to other operators on the ground, allowing a larger audience to access the crisis information.

Drones can also collect data to increase the robustness of risk and vulnerability assessments. Using drones, operators are able to map hazards and infrastructures, thus generating a better understanding of hazard frequencies, vulnerabilities, and impacts, ultimately improving preparedness and mitigation efforts. This can in turn support disaster preparedness efforts. The risk and vulnerability assessment can feed into plans and strategies, ultimately increasing their accuracy. Drones can also provide input to emergency exercises, anchoring the simulation to real-life data.

As shown in **Figure 5**, drones score low in feasibility, social capital and acceptability indicating that some barriers seem to exist in implementing drones in practice. It is worth noting that the gains, however, are considered to outweigh the risks. The following barriers seem to exist:

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

- Lack of available resources in terms of labor, infrastructure, knowledge, and technology.
- Lack of regulatory framework.
- Social acceptance is low because of associated ethical risks.

According to the survey responses, drones cannot improve social capital and cannot be used to minimize silo-working, support citizens engagement, or coordinate volunteers. The low score in the citizen engagement category is the result of authorities' restrictions on private drones' usage during emergency operations (CASA, 2021; FAA, 2020). Nonetheless, we believe that this score might be biased as previous experiences using drones in disaster risk management indicates that it can limit silo-working. This needs to be further investigated.

Forecast

Drones were initially developed for military purposes. Today, drones are also available for commercial use (Aydin, 2019). Civilian drones are mostly used for recreational purposes (Altawy and Youssef, 2017), but future applications are likely to include delivery of goods and services, agriculture, underwater missions, infrastructure monitoring, and many more (Aydin, 2019). Drones are likely to become easier to use. Also, current trends show a decrease in cost for customized drones which is likely to further stimulate the market (Insider Intelligence, 2021). For the American market, the number of licensed remote pilots is expected to rise from 29,000 in 2016 to 422,000 remote pilots by 2021 (Aydin, 2019). This market growth creates an economy of scale, which in turn pushes down prices.

In addition, drone technology is rapidly evolving. Improvements in payload capacity, flight time, collision avoidance, and signal range are underway (Aydin, 2019). Other future features include full autonomy, built in safety mechanisms, airspace awareness, self-monitoring system, and auto action (Insider Intelligence, 2021). These developments are likely to be stimulated by advancements in AI and machine learning. Furthermore, drones are likely to start carrying new types of sensors. Consequently, datasets are likely to improve in terms of size, precision, and accessibility.

There are also likely improvements in analysis software. For example, cloud services have recently improved data management. Moreover, software has been streamlined which allows for more efficient data processing. Advancements in AI and machine learning are likely to further improve capabilities to analyze data obtained from drones.

Drone operations depend on wireless connectivity for communication, and consequently benefit from the introduction of 5G networks. The improved capabilities of 5G networks can yield the following future benefits:

- Improved radio coverage due to less interferences, cell coverage irregularities, and complex neighbor cell relationship.
- Optimized drone traffic though network slicing.
- Better identification and tracking of drones (Yang et al., 2018).

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No. 833496

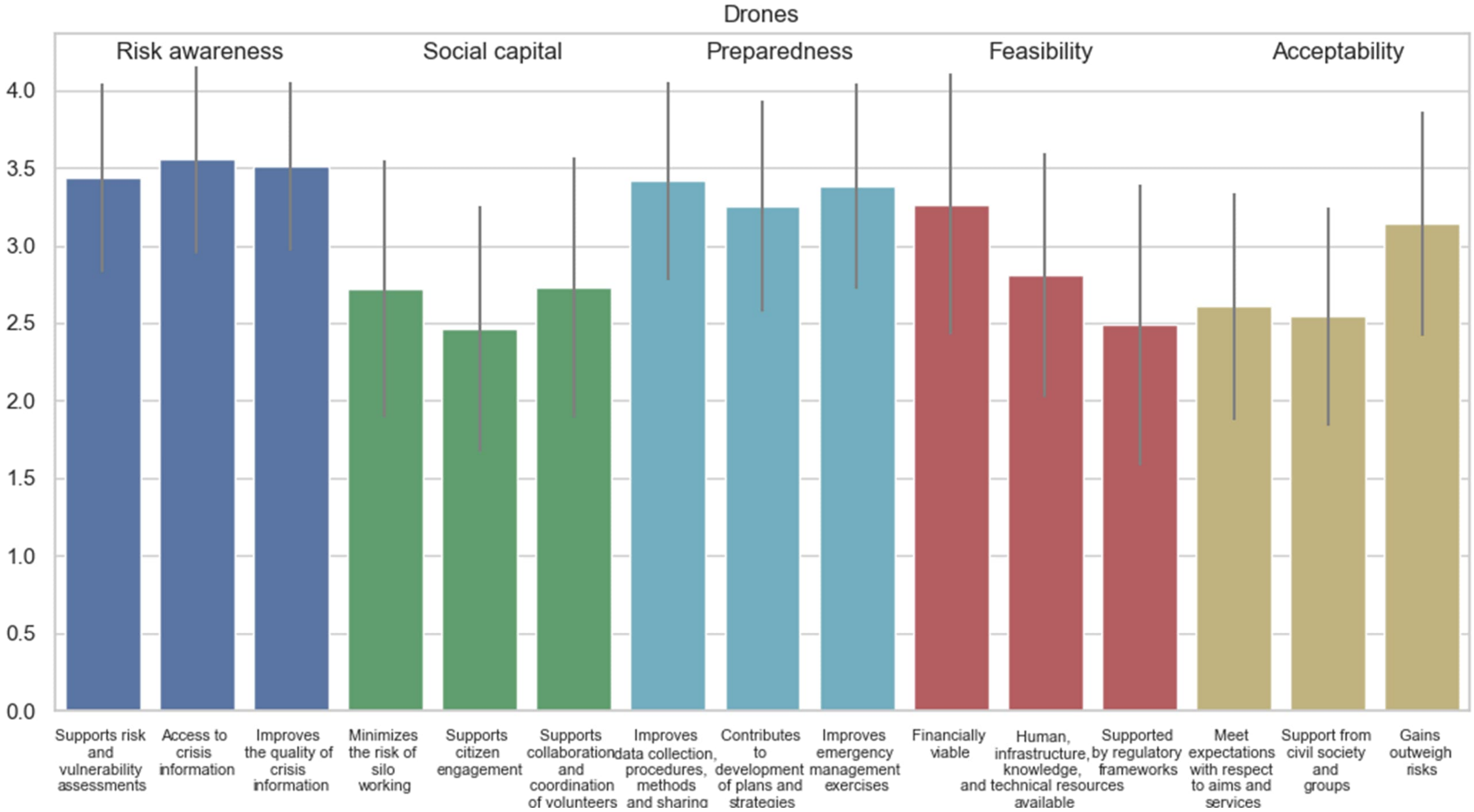

Figure 5*: Benefits analysis of drones (means and unitary standard deviations)*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Significant improvements are currently being achieved regarding the possibility to train drone operators in a safe and controlled environment. An increased preparation and a better understanding of the technology will enable operators to achieve a significant reduction in some of the risks outlined further. In particular, Augmented Reality (AR), Virtual Reality (VR) and mixed reality are already making safe and secure training sessions a reality (Liu et al., 2018; Nguyen et al., 2019; Ribeiro et al., 2021; Zhu and Li, 2021). The possibility to train operators through AR/VR solves the ethical constrains to creating a disaster scene in real life. By controlling all the factors in a computer-generated scenario, it is possible to understand which factors affect the efficiency and the success of the operations. By now, AR/VR simulations have been run in both urban and rural settings, therefore exposing the operators to the different environments while operating them. Disaster preparation, evacuation, and search and rescue represent situations that can be easily simulated by modern software (Zhu and Li, 2021).

Risks

The use of drones in disaster risk management involves some operational risks. Environmental factors can compromise the effectiveness of drones, many of which are especially problematic in the case of disaster risk management considering the disruptiveness that characterizes disasters. Drones are often designed to operate in intact environments, whereas in a disaster situation they are forced to handle much rougher terrain. Most commercially available drones cannot operate in adverse weather conditions like heavy rain, strong winds, or snowstorms. Drone operations are particularly difficult in mountainous or forested terrain (Hildmann & Kovacs, 2019). In addition, the communication between a drone and its pilot can be obstructed by for example nearby buildings, radio interference, and metal objects (American Red Cross, n.d.). Regulatory frameworks in some cases prevent drones from flying close to buildings and populated areas.

Other key operational risks include the following:

- Collisions between drones and other objects.
- Drone accidents can start fires if the batteries break.
- Drones can fall and injury people on the ground.

Such risks are likely to decrease as the technology matures, as key components improve.

Drones are subject to legislative risk. The rapid advancements in drone technology have outpaced the legal ability to adapt (Hildmann & Kovacs, 2019). As a result, there is currently no regulatory framework for drones in EU and it varies among its member states (European Commision, 2016). National authorities often impose regulations that keep the airspace closed for drones. The near future is however likely to witness many countries to impose or amend regulatory frameworks regarding the use of drones (Hildmann & Kovacs, 2019). As a recent step towards standardization, it is as of July 2020 mandatory to have a drone flight license in all EU member states (Latvakoski et al., 2020). Despite that such efforts towards standardizations are welcomed, it shows that the future of regulatory frameworks for the use of drones remains paved with uncertainty. Changes in regulations can adversely affect the use of drones in disaster risk management, ultimately challenging its future effectiveness.

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No. 833496

The use of drones imposes some ethical risks. Drones are capable of performing advanced forms of surveillance, and thus pose a significant threat to privacy and personal data protection. Images might be misused (Pauner et al., 2015). The public considers drones as a technology that poses a threat to their privacy (Aydin, 2019), but they do however consider some areas of application acceptable of which disaster risk management is one example (e.g. Herron et al., 2014; Reddy & DeLaurentis, 2016). Previous research however indicates that the public opinion regarding drones is at a formative stage, and thus likely to change in the near future (Aydin, 2019). It is therefore important that the use of drones is approached with caution, to avoid any negative public perceptions. This, as surveillance can damage social capital ultimately causing distrust towards authorities.

Provision

Drawing from our interview findings, we recommend that public authorities purchase and operate their own drone fleet. Civil protection agencies and policies bodies tend to prefer having their own drones and perform their own data analysis rather than having to rely on services provided by third parties. This, as drones collect sensitive information about private citizens. Arguably, such data should not be made easily accessible to other than national authorities. Hence, it is not reasonable to promote collaboration with third party providers. Drones would be more easily accepted by the population with a guarantee that the information collected will be kept within the control of the national authority that has collected them. Anonymization could potentially be a solution that would make PPPs more acceptable, but it would also imply increased costs for the service providers for the treatment of the data and for the actions that are necessary in order to comply with GDPR. Moreover, little prevents these providers from charging higher prices to the authorities because of the increased costs that they face.

4.4 Satellite imaging

Table 9: *Overview - Satellite imaging*

Usage	Cost	Benefit	Forecast	Risk	Provision
Mitigation, preparedness, response, and recovery	Free of charge	Key benefits in risk awareness and preparedness	Improved availability and quality. Improvements in analysis software are also likely	1. Issues related to timeliness. 2. Malfunctioning equipment in space. 3. Legislative risks	Satellite data can be acquired free of charge from the International Charter Space & Major Disasters or the Copernicus

Satellite imaging is a remote sensing tool that collect pictures of the Earth using satellites. The pictures provide an overhead perspective, offering the possibility to detect patterns over large areas rather than independent properties (Campbell and Wynne, 2011). Satellite imaging can be applied at all stages of the disaster risk management cycle, and serves as a great tool for disaster data collection (Latvakoski et al., 2020; Taubenböck et al., 2013). As a case in point, satellite imagining have successfully supported humanitarian impact assessments in, for example, Gaza, South Sudan, and

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No. 833496

Ukraine (Rebois and Alschner, 2015). Previous usage indicates that optical remote sensing images can map floods and wildfires, SAR images can map geologic hazards, and metrological images can map hydrometeorological hazards (Latvakoski et al., 2020).

Costs

In the past satellite imaging has generated costly data (Latvakoski et al., 2020). Many free options have however emerged over the past few years (Taubenböck et al., 2013). Two notable examples include the International Charter Space and Major Disasters and the EU Copernicus, each is further presented below. Other costs would eventually emerge as employees need to be trained and hardware needs to be purchased. Anyway, to our knowledge, most of the authorities in the EU already have put in place the necessary structure to work with satellite images. Therefore, we do not see any additional costs coming on top of the ones that are already being incurred.

The *International Charter Space and Major Disasters* (2021) is a worldwide initiative that make satellite data available for benefit disaster risk management, by mobilising space agencies around the globe to utilize their know-how and satellites through a single access point that operates 24 hours a day, 7 days a week and at no cost to the user. Following a request, users may receive satellite data of affected areas within a matter of hours or days, depending on the type of the disaster and available satellite resources. The satellite data is applicable to cyclones, earthquakes, fires, floods, snowstorms, ocean waves, oil spills, volcanoes, landslides, and others. Authorized users, those who can send requests, fulfil the following requirements: be a national disaster management authority or its delegated agency in that country; have the capacity to download and utilise maps; be able to submit and pursue activation requests in English. As of February 2021, all the EU countries have the direct access to the resources offered by the Charter.

The *Copernicus* (2021) is an EU initiative that aims to strengthen European information services based on satellite Earth observation and in situ data, with a focus on environmental conditions on land, sea, and atmosphere. Information provided by the Copernicus seeks to support mitigation and adaptation strategies, disaster response efforts, and ultimately improve safety for communities and their citizens. The satellite data is provided free-of-charge. Copernicus has also developed services, in which the satellite data is transformed into a user-friendly format: 1) the Copernicus Atmosphere Monitoring Service, 2) the Copernicus Marine Environment Monitoring Service, 3) the Copernicus Land Monitoring Service, 4) the Copernicus Climate Change Service, 5) the Copernicus Emergency Management Service, and 6) the Copernicus Security Service.

Benefits

As shown in **Table 9**, satellite imaging can yield many benefits. Similar to drones, satellite imaging improves data collection which in turn can yield additional benefits. Drones and satellite imaging can collect data at different scales with different degrees of accuracy. The collected data can be used for different purposes, thus improving risk awareness and disaster preparedness.

Satellite imaging yield benefits associated with risk awareness. Satellite imaging can map natural hazards, infrastructure, and disaster impacts. This can be transformed into high-quality crisis information targeting the population at risk. A satellite is however not sufficient in itself but must be presented in a user-friendly format in order to increase access to crisis information among decision-makers and citizens.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Another benefit of satellite imaging is that it supports risk and vulnerability assessments. It can provide data on many natural hazards including, but not limited to, climate extremes, floods, earthquakes, and storms. The data can strengthen the understanding of nature and extent of potential hazards. However, satellite imaging struggles with assessing social vulnerability. These improvements in risk and vulnerability assessment create a cascade of benefits regarding disaster preparedness. The risk and vulnerability assessments inform plans and strategies, which in turn can be tested in emergency exercises.

However, satellite imaging has limitations in terms of feasibility and acceptability which indicates some practical barrier. It is considered financially viable, but some barriers seem to exist regarding human and technical capacity, regulatory frameworks, and social acceptance. The gains, however, are considered to outweigh the risks.

Moreover, satellite imaging does not strengthen social capital. As shown in **Figure 6**, satellite imaging does not minimize the risk of silo-working, strengthen citizen engagement, or support coordination of volunteers. Perhaps this is because satellite imaging entails a technically complicated process and is thus implemented top-down with little citizens engagements and volunteers. However, volunteers can be involved in the analysis. The Humanitarian OpenStreetMap Team is a prominent example, in which volunteers help analyze impact and damage through open mapping (Latvakoski et al., 2020). In addition, the opinions collected by Mazumdar et al. (2017) through engagement with crowdsourcing experts suggest a common shared view that access to technology, increased awareness of technology and citizen science initiatives will collaborate to increase citizens involvement in the activities pertaining satellite imaging.

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No. 833496

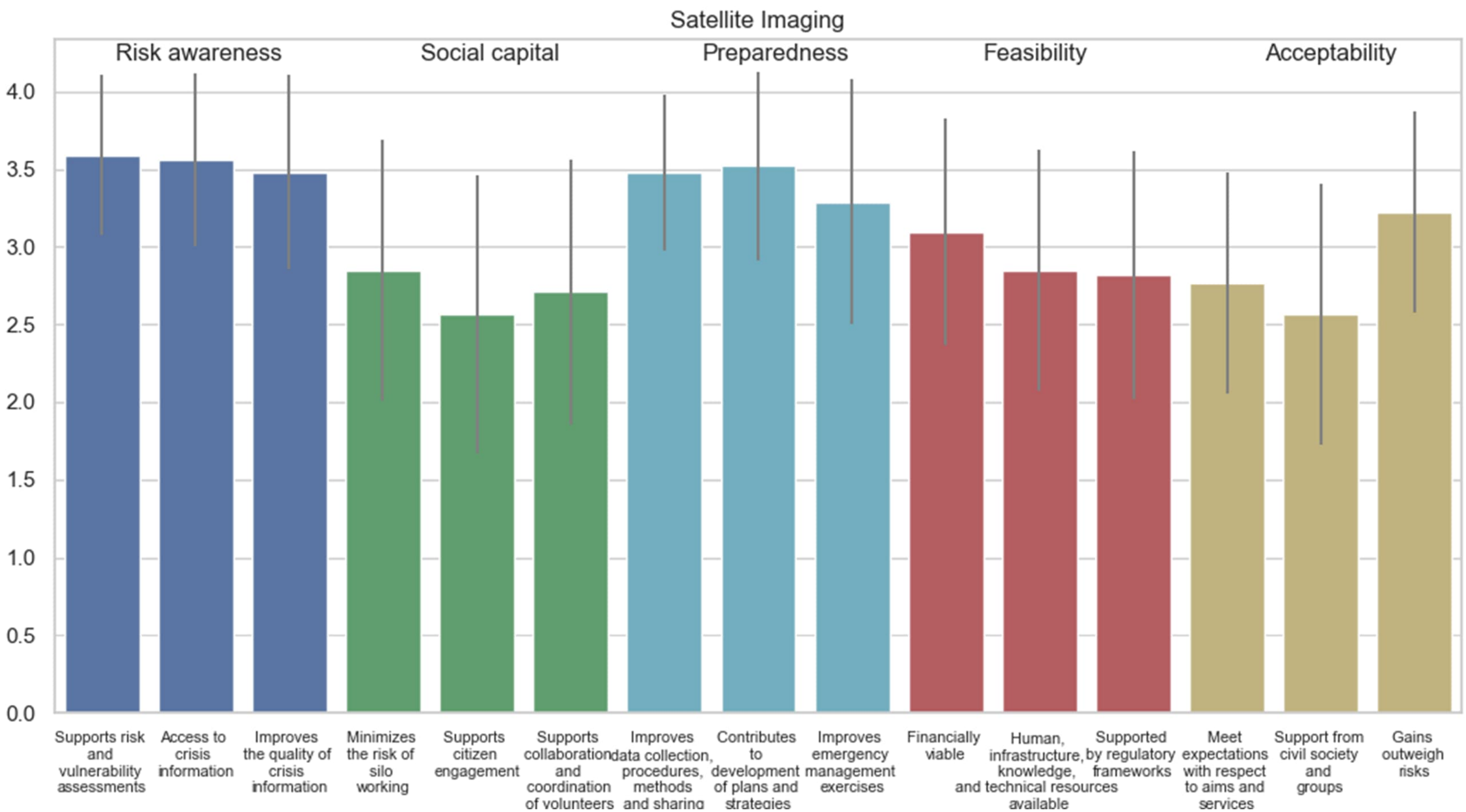

***Figure 6**: Benefits analysis of satellite imaging (means and unitary standard deviations)*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Forecast

There is currently a growing demand for timely and accurate satellite imagery (Santos, 2019). The number of satellites orbiting Earth is constantly increasing, thus improving access to satellite images. In 2020, 2666 operational satellites orbited Earth (UCS, 2021). In the next ten years, it is estimated that an average of 990 satellites will be launched every year resulting in a total of 9935 satellites orbiting Earth by 2028. This indicates an increase of 332% (Euroconsult, 2019). Many small satellites in the low earth orbit are planned to be launched in the upcoming years. Consequently, satellite imagery is expected to improve in terms of timeliness, data availability, observation capabilities, and quality (Santos, 2019).

The future is likely to experience improvements in hyperspectral remote sensing, also known as imaging spectroscopy, that can capture images with a spectral signature constating of thousands of elements in a single pixel. Consequently, satellite datasets are likely to become more detailed and increase in volume. Improvements are likely in analysis software in order to keep up with the increases of data, of which data format conversing, open GIS applications and real-time data processing are critical (Sajjad and Kumar, 2019).

There are recent advancements in technology indicating an increased availability of high-resolution satellite imagery. These advancements are however driven by the satellite industry, thus reinforcing a usability gap between those producing the data, and the end-users who apply the information in practice. Future advancements in usability are likely, in which satellite data is presented in a more user-friendly format.

It is worth noting that drones are increasingly being used to map smaller areas (Sajjad and Kumar, 2019), thus raising the question if satellite imaging is becoming obsolete in the near future. Satellites and drones however collect data at different scales and different degrees of accuracy, meaning that they should be considered as complementary technologies. Satellites offer a grand view of larger areas, whereas drones provide more detailed views of specific areas. The future is likely to experience improvements in how data from drones and satellites can be combined.

Risks

Timeliness is critical in disaster risk management given the urgency that characterizes a crisis, yet it cannot be guaranteed when using satellite imaging, thus posing an operational risk. In the worst case scenario, the satellites may miss the disruptive event. The timeliness mainly depends on the revisit period, i.e., how often a satellite is acquiring an image of the same location. The revisit period in turn depends on the number of satellites, where the more satellites in orbit the shorter revisit period. Collectively, satellite operators have the capacity to map every part of the world on a daily basis. However, the data is seldomly combined, meaning that operators with few satellites may endure longer revisit periods. Operators who have short revisit periods often offer coarser resolution. There is thus a trade-off between timeliness and resolution. Using a constellation of satellites rather than single units may mitigate this risk. Moreover, timeliness also depend on weather conditions as a dense cloud cover reduces visibility and hence inhibits the timely delivery of satellite images. Many methods do, however, exist to solve this problem (Wang et al., 2019).

Malfunctioning satellites is another operational risk. Potential problems that may emerge once the satellite is launched include: incorrect orbits, collisions, space weather, and internal problems. Little can be done from Earth's control stations once the problem emerges. To mitigate this risk, satellites undergo meticulous testing before being launched. The risk can, however, not be fully eliminated.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Legislative risks exist when using satellite imaging. Space imagery complies to a legal framework that evolves as the technology advances. Despite most satellite imagery is not personal; face recognition is possible by aggregating multiple discernable features in an image. Thus, satellite imaging invokes serious privacy and data protection concerns. While GDPR covers some of these, it fails to address issues related to satellites. Hence, new legislation is likely to be designed as satellite imaging continues to advance.

Provision

Acquiring the service from the International Charter Space and Major Disasters or the Copernicus is recommended, as they offer satellite data free-of-charge. Likewise, all the satellite imaging solutions listed in "*D2.4 Catalogue of tools, technologies and media opportunities for disaster management*" come for free, most of them to the general public and all of them to national authorities are involved in disaster risk management operations.

5.Cost-benefits ratios

Cost-benefits ratios represent a standard application in the context of cost-benefits analysis (Botzen et al., 2017; De Risi et al., 2018; Dedeurwaerdere, 1998; Fagnant and Kockelman, 2012; Golub et al., 2021; Kull et al., 2013; Rai et al., 2020; Shreve and Kelman, 2014; Tuan et al., 2015). These figures are easy to construct once the necessary data have been collected. This last process can be carried out by evaluating both the costs and the benefits in monetary terms, with the risks that assigning a monetary value to benefits may entail, or by assigning indexed values to these. We have used the latter approach, assigning monetary values to costs and collecting opinions from stakeholders to construct the benefits indices.

Constructing the ratios requires dividing the costs of each alternative by the benefits they can produce. By doing so, we correct some inconsistencies that may emerge in the evaluation process: some alternatives may be assigned high benefits, but they may turn out to be extremely expensive. By dividing the costs by the benefits, we are producing a result that informs policymakers how expensive it is to produce these benefits. When using monetary values for costs and benefits that returns a result that can be easily interpreted: if the ratio is higher than 1, that means that the costs are higher than the benefits; if the ratio equals 1 benefits and costs are the same; the benefits are larger than the costs if the ratio is smaller than 1. However, when points are assigned to benefits, rather than monetary values, the reasoning is different: in this case what we get is the cost of that alternative per each point of benefits. Meaning that cheaper alternatives, with lower ratios, should be preferred to expensive one, with high ratios, as the formers can produce the benefits at lower unitary costs. The results derived from the mixed approach used here are summarised below and can be interpreted as the cost in Euros per each point of benefits produced. It should be noted that satellite imaging is excluded from this evaluation because there is no cost for emergency agencies in accessing satellite images from international authorities. An overview of the results is provided in **Figure 7**.

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No. 833496

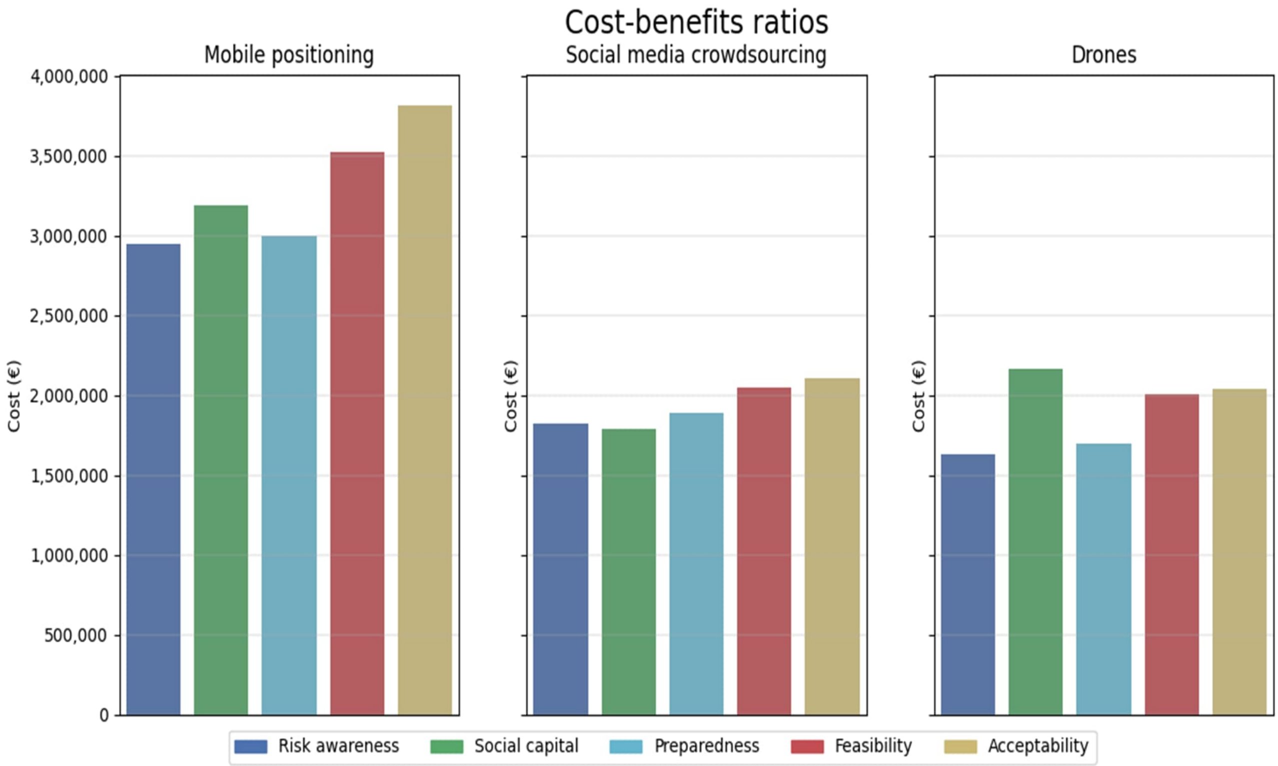

***Figure 7**: Cost-benefits ratios*

For instance, our study suggest that, when it comes to risk awareness, drones represent the cheapest technology to invest in, in terms of benefits they can provide for each Euro invested. Drones have the highest mean score in the three aspects we investiagated about risk awareness ("it can strengthen risk and vulnerability assessments", "it can improve access to crisis information", "it can improve the quality of crisis information by making it more accurate, timely, or relevant"). The second-best option, social media crowdsourcing, cannot produce the same benefits as drones despite being cheaper (in absolute value, without considering the benefits). Mobile positioning is more expensive than the other alternatives and fails to produce the same benefits. Drones is also the option to invest in for the policymakers that prefer to focus on preparedness and feasibility. Because of the restrictions to fly private drones in certain areas and during a disaster, the score for drones pertaining social capital is significantly lower than the one assigned to social media crowdsourcing. Bearing in mind that social media crowdsourcing is also less capital-intensive, this explains why social media crowdsourcing has a better (lower) cost-benefits ratio than drones in social capital: higher benefits at a lower cost. While it scores high in preparedness and risk awareness, mobile positioning is too expensive when compared to the two alternatives.

Drones seem to represent, across all categories, the best alternatives to invest in. However, while the tool can be generally applied in almost any context, the underlying data we used here are too specific to be used for a recommendation that would fit every case. Some caution is therefore necessary. As we have pointed out before, valuation of the possibility to use each of the technologies described in this report is necessary, which is dependent on several conditions that prevents our conclusion from being applicable to every setting. When considering an investment in disaster risk management, policymakers should assess the potential benefits in their specific context. Once the necessary

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

assessments have been carried out, the methodology presented here can be easily replicated in different conditions.

6.Conclusions

This deliverable aims to provide recommendations on resource allocations for disaster risk management., in accordance with task 5.2. To meet this objective, we developed an approach and investigated how different emerging technologies and tools can strengthen social capital, risk awareness, disaster preparedness, and in the long run societal resilience. We illustrated the approach in four technologies proposed by BuildERS, namely mobile positioning data, social media crowdsourcing, drones, and satellite imaging. This deliverable provides guidance regarding the form of provision for each of these tools, what future development to expect in the coming years, what risks to pay attention to when investing and when deploying them, potential benefits, and cost figures per technology.

The cost-benefit ratios indicate where resources are best spent to increase social capital, risk awareness, and disaster preparedness. However, we refrain from making any general conclusions. BuildERS is broad in terms of its geographical scope, and includes countries across Europe with different risk landscapes, social vulnerabilities, and financial capacities. Looking at the Sendai Framework for disaster risk reduction, priority area one states that “Disaster risk management should be based on an understanding of disaster risk in all its dimensions of vulnerability, capacity, exposure of persons and assets, hazard characteristics and the environment” (UN, 2015). In other words, a cost-benefit assessment must consider these contextual factors to avoid unintended side effects upon different vulnerable groups. What is considered appropriate in one context might not be so in a different one. For example, mobile positioning data is a powerful tool in urban areas but must be replaced by drones in rural settings. Similarly, satellite imaging can collect data on large spatial scale, but cannot operate in cloudy conditions, while drones can do so (Emilien et al., 2021). Cost figures are also very likely to vary across European regions. Averaging multiple results of alternative cases does not produce a usable result to guide practitioners and decision-makers. While many authors have proposed using probability distributions to model the likelihood of a disaster, it is clear that these functions are still dependent on local variables. Thus, investment strategies as well are context-specific depending on spatial characteristics of the study area. As demonstrated in other BuildERS deliverables, vulnerabilities is represented differently depending on context hence requiring different types of disaster risk reduction measures (see for example: *D1.2 Final report of the unified theoretical framework on the concepts of risk awareness, social capital, vulnerability, resilience and their interdependencies, D1.3 Report on segments of vulnerability, country by country basis – inside and outside the official data, D1.6 Vulnerability and vulnerable groups from an intersectionality perspective, and D5.1 Resilience policy recommendation – First report).*

However, there are some limitations with our suggested approach even when refraining from formulating general conclusions. The methodology is influenced by many challenges pertaining to the application of cost-benefit analysis approach for evaluation of investment options in disaster risk management. Key limitations are imposed by the inherent uncertainties that characterize disaster risk management – both regarding hazard frequencies and associated consequences. Similar to the findings of Dedeurwaerdere (1998) and Vorhies and Wilkinson (2016), it is noted that data is lacking thus making it difficult to draw plausible conclusions from time series. The intangible effects associated with social capital, risk awareness, and disaster preparedness are difficult to assign monetary values, serving as an additional obstacle that may undermined the quality of the output.

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No. 833496

Furthermore, our findings do not capture the inequal distribution of risk, cost, and benefits. As shown in BuildERS, risk is not equally distributed within a community meaning that some vulnerable groups may suffer far worse consequences in the case of a disaster. Hence, different individuals might express different preferences toward exposure to risk and make their investments accordingly. Given the above-mentioned limitations, we recommend policymakers and practitioners to consider this deliverable as a source of inspiration. The presented methodology in this study can help better understand where to allocate proper resources considering their costs and benefits but must be tailored to account for local specificities.

To conclude, this deliverable takes a significant step in transforming BuildERS research into actionable recommendations for policymakers and practitioners. Later deliverables will complement our findings through adding policy- and practitioner recommendations on how to improve social capital, risk awareness, disaster preparedness, and in the long run societal resilience.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Bibliography

Alam, F., Joty, S., & Imran, M. (2018a). Graph Based Semi-supervised Learning with Convolution Neural Networks to Classify Crisis Related Tweets. *ArXiv:1805.06289 [Cs]*. http://arxiv.org/abs/1805.06289

Alam, F., Joty, S., & Imran, M. (2018b). Domain Adaptation with Adversarial Training and Graph Embeddings. *ArXiv:1805.05151 [Cs, Stat]*. http://arxiv.org/abs/1805.05151

Alam, F., Ofli, F., & Imran, M. (2018). CrisisMMD: Multimodal Twitter Datasets from Natural Disasters. *ArXiv:1805.00713 [Cs]*. http://arxiv.org/abs/1805.00713

Alam, F., Ofli, F., Imran, M., & Aupetit, M. (2018). A Twitter Tale of Three Hurricanes: Harvey, Irma, and Maria. *ArXiv:1805.05144 [Cs]*. http://arxiv.org/abs/1805.05144

Aleksieva-Petrova, A., & Petrov, M. (2020). Survey on the importance of using personal data for learning analytics and of data privacy. *2020 International Conference Automatics and Informatics (ICAI)*, 1–4. https://doi.org/10.1109/ICAI50593.2020.9311340

Alexander, D. E. (2018). L'Aquila, central Italy, and the "disaster cycle", 2009-2017. *Disaster Prevention and Management: An International Journal*, *28*(4), 419–433. https://doi.org/10.1108/DPM-01-2018-0022

Altawy, R., & Youssef, A. M. (2017). Security, Privacy, and Safety Aspects of Civilian Drones: A Survey. *ACM Transactions on Cyber-Physical Systems*, *1*(2), 1–25. https://doi.org/10.1145/3001836

American Red Cross. (n.d.). *Drones in the RCRC*. Retrieved July 20, 2021, from https://americanredcross.github.io/rcrc-drones/benefits-costs.html

Ataei, M., Degbelo, A., Kray, C., & Santos, V. (2018). Complying with Privacy Legislation: From Legal Text to Implementation of Privacy-Aware Location-Based Services. *ISPRS International Journal of Geo-Information*, *7*(11), 442. https://doi.org/10.3390/ijgi7110442

Aydin, B. (2019). Public acceptance of drones: Knowledge, attitudes, and practice. *Technology in Society*, *59*, 101180. https://doi.org/10.1016/j.techsoc.2019.101180

Babic, B., Cohen, I. G., Evgeniou, T., & Gerke, S. (2021). When Machine Learning Goes Off the Rails. *Harvard Business Review*, *99*(1), 76–84.

Bayardo, R. J., & Agrawal, R. (2005). Data privacy through optimal k-anonymization. *21st International Conference on Data Engineering (ICDE'05)*, 217–228. https://doi.org/10.1109/ICDE.2005.42

Beecroft, A., Peters, E., & Toole, T. (2017). Life-cycle costing of rain and flood events in Queensland—Case studies and network-wide implications. *Road & Transport Research*, *26*(3), 22–35. https://doi.org/10.3316/informit.231376995119790

Berawi, M., Leviakangas, P., Muhammad, F., Sari, M., Gunawan, G., Yatmo, Y. A., & Suryanegara, M. (2019). *Optimizing Search and Rescue Personnel Allocation in Disaster Emergency Response using Fuzzy Logic*. https://doi.org/10.14716/ijtech.v10i7.3709

Besaleva, L. I., & Weaver, A. C. (2016). *Crowdsourcing for Emergency Response*. 6.

Binjubeir, M., Ahmed, A. A., Ismail, M. A. B., Sadiq, A. S., & Khurram Khan, M. (2020). Comprehensive Survey on Big Data Privacy Protection. *IEEE Access*, *8*, 20067–20079. https://doi.org/10.1109/ACCESS.2019.2962368

Bloomberg. (2020, March 26). DJI Won the Drone Wars, and Now It's Paying the Price. *Bloomberg.Com*. https://www.bloomberg.com/news/features/2020-03-26/dji-s-drone-supremacy-comes-at-a-price

Borgogno Mondino, E., & Gajetti, M. (2017). Preliminary considerations about costs and potential market of remote sensing from UAV in the Italian viticulture context. *European Journal of Remote Sensing*, *50*(1), 310–319. https://doi.org/10.1080/22797254.2017.1328269

Bott, M., Gigler, B.-S., & Young, G. (2014). *The Role of Crowdsourcing for Better Governance in Fragile State Contexts*. World Bank.

Botzen, W. J. W., Monteiro, É., Estrada, F., Pesaro, G., & Menoni, S. (2017). Economic Assessment of Mitigating Damage of Flood Events: Cost–Benefit Analysis of Flood-Proofing Commercial Buildings in Umbria, Italy. *The Geneva Papers on Risk and Insurance - Issues and Practice*, *42*(4), 585–608. https://doi.org/10.1057/s41288-017-0065-0

Campbell, J. B., & Wynne, R. H. (2011). *Introduction to remote sensing: Fifth edition* (5th ed.). Guildford Press. https://books.google.se/books?hl=sv&lr=&id=NkLmDjSS8TsC&oi=fnd&pg=PP1&dq=history+of+remote+sensing&ots=s2Hlu-qX2w&sig=ajN5dGt9RC9lyd7mZ4Uh2Te6j68&redir_esc=y#v=onepage&q&f=true

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

CASA. (2021, March 18). *Emergencies and public spaces* [DCMIType]. Civil Aviation Safety Authority; Civil Aviation Safety Authority. https://www.casa.gov.au/drones/drone-rules/emergencies-and-public-spaces

De Risi, R., De Paola, F., Turpie, J., & Kroeger, T. (2018). Life Cycle Cost and Return on Investment as complementary decision variables for urban flood risk management in developing countries. *International Journal of Disaster Risk Reduction*, *28*, 88–106. https://doi.org/10.1016/j.ijdrr.2018.02.026

Dean, B. (2020, August 12). How Many People Use Social Media in 2021? (65+ Statistics). *Backlinko*. https://backlinko.com/social-media-users

Dedeurwaerdere. (1998). *Cost—Benefit analysis for natural disaster management: A case—Study in the Philippines.* http://cidbimena.desastres.hn/docum/crid/Septiembre2007/CD1/pdf/eng/doc10015/doc10015.htm

Denzer, R., Argent, R. M., Schimak, G., & Hřebíček, J. (2015). *Environmental Software Systems. Infrastructures, Services and Applications: 11th IFIP WG 5.11 International Symposium, ISESS 2015, Melbourne, VIC, Australia, March 25-27, 2015, Proceedings*. Springer.

Drone Safe. (2018). *The cost of drone aerial photography*. Drone Safe Register News and Blog. https://dronesaferegister.org.uk/blog/how-much-does-drone-photography-cost

Dujardin, S., Jacques, D., Steele, J., & Linard, C. (2020). Mobile Phone Data for Urban Climate Change Adaptation: Reviewing Applications, Opportunities and Key Challenges. *Sustainability*, *12*(4), 1501. https://doi.org/10.3390/su12041501

Ekong, I., Chukwu, E., & Chukwu, M. (2020). 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 and UHealth*, *8*(4), e19139. https://doi.org/10.2196/19139

Emilien, A.-V., Thomas, C., & Thomas, H. (2021). UAV & satellite synergies for optical remote sensing applications: A literature review. *Science of Remote Sensing*, *3*, 100019. https://doi.org/10.1016/j.srs.2021.100019

EU Copernicus. (2021). *What is Copernicus*. Copernicus EMS - Mapping. https://emergency.copernicus.eu/mapping/ems/what-copernicus

European Commision. (2016, September 22). *Unmanned aircraft (drones)* [Text]. Mobility and Transport - European Commission. https://ec.europa.eu/transport/modes/air/uas_en

European Commission (Ed.). (2015). *Guide to cost-benefit analysis of investment projects: Economic appraisal tool for cohesion policy 2014-2020*. European Union.

European Commission, & Eurostat. (2014). *Feasibility study on the use of mobile positioning data for tourism statistics :consolidated report.* Publications Office. https://data.europa.eu/doi/10.2785/55051

Eurostat. (2021). *Electricity prices for non-household consumers—Bi-annual data (from 2007 onwards)*. https://ec.europa.eu/eurostat/databrowser/view/NRG_PC_205__custom_1551336/default/table?lang=en

FAA. (2020). *Airspace Restrictions* [Template]. https://www.faa.gov/uas/recreational_fliers/where_can_i_fly/airspace_restrictions/

Fagnant, D. J., & Kockelman, K. M. (2012). Outcome of Transportation Projects under Uncertainty: Examination of Benefit–Cost Ratios and Other Impacts. *Transportation Research Record*, *2303*(1), 89–98. https://doi.org/10.3141/2303-10

FAO. (2018). *E-agriculture in action: Drones for agriculture*.

Figliozzi, M. A. (2017). Lifecycle modeling and assessment of unmanned aerial vehicles (Drones) CO2e emissions. *Transportation Research Part D: Transport and Environment*, *57*, 251–261. https://doi.org/10.1016/j.trd.2017.09.011

Florin, M.-V., & Bürkler, M. T. (2018). *Introduction to the IRGC Risk Governance Framework*. https://doi.org/10.5075/EPFL-IRGC-233739

Gluch, P., & Baumann, H. (2004). The life cycle costing (LCC) approach: A conceptual discussion of its usefulness for environmental decision-making. *Building and Environment*, *39*(5), 571–580. https://doi.org/10.1016/j.buildenv.2003.10.008

Golosova, J., & Romanovs, A. (2018). The Advantages and Disadvantages of the Blockchain Technology. *2018 IEEE 6th Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE)*, 1–6. https://doi.org/10.1109/AIEEE.2018.8592253

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Golub, A., Mutenje, M., Wong, B., Chiotha, S., Razvi, S., Billiat, S., & Nyengere, J. (2021, August 17). *A Cost-benefit Analysis of Environmental Management and Disaster Risk Reduction in Malawi—Technical Report*. Africa Portal; African Institute for Development Policy (AFIDEP). https://www.africaportal.org/publications/cost-benefit-analysis-environmental-management-and-disaster-risk-reduction-malawi-technical-report/

Goodland, R., & Ledec, G. (1987). Neoclassical economics and principles of sustainable development. *Ecological Modelling*, *38*(1), 19–46. https://doi.org/10.1016/0304-3800(87)90043-3

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., & Wesolowski, A. (2020). The use of mobile phone data to inform analysis of COVID-19 pandemic epidemiology. *Nature Communications*, *11*(1), 4961. https://doi.org/10.1038/s41467-020-18190-5

Gregory, R., & Keeney, R. L. (1994). Creating Policy Alternatives Using Stakeholder Values. *Management Science*, *40*(8), 1035–1048. https://doi.org/10.1287/mnsc.40.8.1035

Habibzadeh, H., Nussbaum, B. H., Anjomshoa, F., Kantarci, B., & Soyata, T. (2019). A survey on cybersecurity, data privacy, and policy issues in cyber-physical system deployments in smart cities. *Sustainable Cities and Society*, *50*, 101660. https://doi.org/10.1016/j.scs.2019.101660

Han, T., Ribeiro, I. de L., Magaia, N., Preto, J., Segundo, A. H. F. N., de Macêdo, A. R. L., Muhammad, K., & de Albuquerque, V. H. C. (2021). Emerging Drone Trends for Blockchain-Based 5G Networks: Open Issues and Future Perspectives. *IEEE Network*, *35*(1), 38–43. https://doi.org/10.1109/MNET.011.2000151

Hernandez-Suarez, A., Sanchez-Perez, G., Toscano-Medina, K., Perez-Meana, H., Portillo-Portillo, J., And Luis, V. S., & Javier García Villalba, L. (2019). Using Twitter Data to Monitor Natural Disaster Social Dynamics: A Recurrent Neural Network Approach with Word Embeddings and Kernel Density Estimation. *Sensors (Basel, Switzerland)*, *19*(7). https://doi.org/10.3390/s19071746

Herron, K. G., Smith, H. C. J., & Silva, C. L. (2014). *US Public Perspectives on Privacy, Security, and Unmanned Aircraft Systems*. 82.

Hildmann, H., & Kovacs, E. (2019). Review: Using Unmanned Aerial Vehicles (UAVs) as Mobile Sensing Platforms (MSPs) for Disaster Response, Civil Security and Public Safety. *Drones*, *3*(3), 59. https://doi.org/10.3390/drones3030059

Hirata, E., Giannotti, M. a., Larocca, A. p. c., & Quintanilha, J. a. (2018). Flooding and inundation collaborative mapping – use of the Crowdmap/Ushahidi platform in the city of Sao Paulo, Brazil. *Journal of Flood Risk Management*, *11*(S1), S98–S109. https://doi.org/10.1111/jfr3.12181

Hoar, D. W. (1988). AN OVERVIEW OF LIFE-CYCLE COSTING TECHNIQUES. *Property Management*, *6*(2), 92–98. https://doi.org/10.1108/eb006685

Ienca, M., & Vayena, E. (2020). On the responsible use of digital data to tackle the COVID-19 pandemic. *Nature Medicine*, *26*(4), 463–464. https://doi.org/10.1038/s41591-020-0832-5

Imran, M., Elbassuoni, S., Castillo, C., Diaz, F., & Meier, P. (2013a). Extracting information nuggets from disaster- Related messages in social media. *ISCRAM*.

Imran, M., Elbassuoni, S., Castillo, C., Diaz, F., & Meier, P. (2013b). Practical extraction of disaster-relevant information from social media. *Proceedings of the 22nd International Conference on World Wide Web*, 1021–1024. https://doi.org/10.1145/2487788.2488109

Imran, M., Mitra, P., & Castillo, C. (2016). Twitter as a Lifeline: Human-annotated Twitter Corpora for NLP of Crisis-related Messages. *ArXiv:1605.05894 [Cs]*. http://arxiv.org/abs/1605.05894

Insider Intelligence. (2021). Drone technology uses and applications for commercial, industrial and military drones in 2021 and the future. *Business Insider*. https://www.businessinsider.com/drone-technology-uses-applications

Jonsson, Möller, R., Davis, S., Linder, P., Lindberg, P., Ramiro, J., Outes, J., Bhardwaj, A., Muñiz Garcia, C., Baur, H., Alger, J., Krautkremer, T., Chandra, R., Lundborg, T., Belaoucha, B., Burstedt, F., Latta, C., McCrorey, R., & Kuoppamaki, K. (2021). *Ericsson Mobility Report June 2021*. 36.

Jung, H., & Chung, K. (2015). Ontology-driven slope modeling for disaster management service. *Cluster Computing*, *18*(2), 677–692. https://doi.org/10.1007/s10586-015-0424-1

Junqué de Fortuny, E., Martens, D., & Provost, F. (2013). Predictive Modeling With Big Data: Is Bigger Really Better? *Big Data*, *1*(4), 215–226. https://doi.org/10.1089/big.2013.0037

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Kankanamge, N., Yigitcanlar, T., Goonetilleke, A., & Kamruzzaman, M. (2019). Can volunteer crowdsourcing reduce disaster risk? A systematic review of the literature. *International Journal of Disaster Risk Reduction*, *35*, 101097. https://doi.org/10.1016/j.ijdrr.2019.101097

Keusch, F., Struminskaya, B., Antoun, C., Couper, M. P., & Kreuter, F. (2019). Willingness to Participate in Passive Mobile Data Collection. *Public Opinion Quarterly*, *83*(S1), 210–235. https://doi.org/10.1093/poq/nfz007

Kim, J., & Kwan, M.-P. (2021). An Examination of People's Privacy Concerns, Perceptions of Social Benefits, and Acceptance of COVID-19 Mitigation Measures That Harness Location Information: A Comparative Study of the U.S. and South Korea. *ISPRS International Journal of Geo-Information*, *10*(1), 25. https://doi.org/10.3390/ijgi10010025

Koh, H. K., & Cadigan, R. O. (2008). Disaster Preparedness and Social Capital. *Social Capital and Health*, 273–285. https://doi.org/10.1007/978-0-387-71311-3_13

Kull, D., Mechler, R., & Hochrainer-Stigler, S. (2013). Probabilistic cost-benefit analysis of disaster risk management in a development context. *Disasters*, *37*(3), 374–400. https://doi.org/10.1111/disa.12002

Lasko, T. A., & Vinterbo, S. A. (2010). Spectral Anonymization of Data. *IEEE Transactions on Knowledge and Data Engineering*, *22*(3), 437–446. https://doi.org/10.1109/TKDE.2009.88

Latvakoski, J., Bäck, A., Parmes, E., Öörni, R., Ceylan, Ö., Tominga, A., Orru, K., Siim, E., Klaos, M., Galvani, A., Schieffelers, A., Myllylä, M., Jukarainen, P., Berawi, M. A., & Max, M. (2020). *D2.4 catalogue of tools, technologies and media opportunities for disaster management* [BuildERS Deliverable]. https://buildersproject.eu/results

Leelawat, N., Suppasri, A., Latcharote, P., Imamura, F., Abe, Y., & Sugiyasu, K. (2017). Increasing tsunami risk awareness via mobile application. *IOP Conference Series: Earth and Environmental Science*, *56*, 012001. https://doi.org/10.1088/1755-1315/56/1/012001

Leslie, D. (2019). *Understanding Artificial Intelligence Ethics and Safety: A Guide for the Responsible Design and Implementation of AI Systems in the Public Sector* (SSRN Scholarly Paper ID 3403301). Social Science Research Network. https://doi.org/10.2139/ssrn.3403301

Li, L., Bensi, M., Cui, Q., Baecher, G. B., & Huang, Y. (2021). Social media crowdsourcing for rapid damage assessment following a sudden-onset natural hazard event. *International Journal of Information Management*, *60*, 102378. https://doi.org/10.1016/j.ijinfomgt.2021.102378

Liu, H., Bi, Z., Dai, J., Yu, Y., & Shi, Y. (2018). UAV Simulation Flight Training System. *2018 International Conference on Virtual Reality and Visualization (ICVRV)*, 150–151. https://doi.org/10.1109/ICVRV.2018.00052

Loshin, D. (2009). Chapter 5—Data Quality and MDM. In D. Loshin (Ed.), *Master Data Management* (pp. 87–103). Morgan Kaufmann. https://doi.org/10.1016/B978-0-12-374225-4.00005-9

Matese, A., Toscano, P., Di Gennaro, S. F., Genesio, L., Vaccari, F. P., Primicerio, J., Belli, C., Zaldei, A., Bianconi, R., & Gioli, B. (2015). Intercomparison of UAV, Aircraft and Satellite Remote Sensing Platforms for Precision Viticulture. *Remote Sensing*, *7*(3), 2971–2990. https://doi.org/10.3390/rs70302971

Mazumdar, S., Wrigley, S., & Ciravegna, F. (2017). Citizen Science and Crowdsourcing for Earth Observations: An Analysis of Stakeholder Opinions on the Present and Future. *Remote Sensing*, *9*(1), 87. https://doi.org/10.3390/rs9010087

Mechler, R. (2016). Reviewing estimates of the economic efficiency of disaster risk management: Opportunities and limitations of using risk-based cost–benefit analysis. *Natural Hazards*, *81*(3), 2121–2147. https://doi.org/10.1007/s11069-016-2170-y

Mechler, R., Czajkowski, J., Kunreuther, H., Michel-Kerjan, E., Botzen, W., Keating, A., McQuistan, C., Cooper, N., & O'Donnell, I. (2014, September). *Making Communities More Flood Resilient: The Role of Cost Benefit Analysis and Other Decision-support Tools in Disaster Risk Reduction* [Other]. https://pure.iiasa.ac.at/id/eprint/11193/

Merrill, T. W. (2020). The Economics of Leasing. *Journal of Legal Analysis*, *12*, 221–272. https://doi.org/10.1093/jla/laaa003

Morsut, C., Kuran, C. H. A., Kruke, B. I., Nævestad, T.-O., Orru, K., & Hansson, S. (2021). A critical appraisal of individual social capital in crisis response. *24*. https://doi.org/10.1002/rhc3.12236

Morsut, C., Kuran, C., Kruke, B. I., Orru, K., & Hansson, S. (2021). Linking resilience, vulnerability, social capital and risk awareness for crisis and disaster research. *Journal of Contingencies and Crisis Management*, *n/a*(n/a). https://doi.org/10.1111/1468-5973.12375

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Morsut, C., Kuran, C., Kruke, B. I., Schobert, M., Gabel, F., Orru, K., Hansson, S., Nahkur, O., Rhinard, M., Molarius, R., Schmersal, E., Savadori, L., Nævestad, T.-O., & Bairampa, E. (2020). *D1.2 Final report of the unified theoretical framework on the concepts of risk awareness, social, capital, vulnerability, resilience and their interdependencies* [BuildERS Deliverable]. https://buildersproject.eu/assets/content/BuildERS_D1.2.pdf

Nguyen, D. T., Ofli, F., Imran, M., & Mitra, P. (2017). Damage Assessment from Social Media Imagery Data During Disasters. *2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, 569–576.

Nguyen, T., Al-Mannai, K., Joty, S. R., Sajjad, H., Imran, M., & Mitra, P. (2017). Robust Classification of Crisis-Related Data on Social Networks Using Convolutional Neural Networks. *ICWSM*.

Nguyen, V. T., Jung, K., & Dang, T. (2019). DroneVR: A Web Virtual Reality Simulator for Drone Operator. *2019 IEEE International Conference on Artificial Intelligence and Virtual Reality (AIVR)*, 257–2575. https://doi.org/10.1109/AIVR46125.2019.00060

Nhamo, L., Magidi, J., Nyamugama, A., Clulow, A. D., Sibanda, M., Chimonyo, V. G. P., & Mabhaudhi, T. (2020). Prospects of Improving Agricultural and Water Productivity through Unmanned Aerial Vehicles. *Agriculture*, *10*(7), 256. https://doi.org/10.3390/agriculture10070256

Nikhil, N., Shreyas, S. M., Vyshnavi, G., & Yadav, S. (2020). Unmanned Aerial Vehicles (UAV) in Disaster Management Applications. *2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT)*, 140–148. https://doi.org/10.1109/ICSSIT48917.2020.9214241

Pánek, J., Marek, L., Pászto, V., & Valůch, J. (2017). The Crisis Map of the Czech Republic: The nationwide deployment of an Ushahidi application for disasters. *Disasters*, *41*(4), 649–671. https://doi.org/10.1111/disa.12221

Pauner, C., Kamara, I., & Viguri, J. (2015). Drones. Current challenges and standardisation solutions in the field of privacy and data protection. *2015 ITU Kaleidoscope: Trust in the Information Society (K-2015)*, 1–7. https://doi.org/10.1109/Kaleidoscope.2015.7383633

Pursiainen, C. (2017). *The Crisis Management Cycle*. Routledge. https://doi.org/10.4324/9781315629179

Rai, R. K., van den Homberg, M. J. C., Ghimire, G. P., & McQuistan, C. (2020). Cost-benefit analysis of flood early warning system in the Karnali River Basin of Nepal. *International Journal of Disaster Risk Reduction*, *47*, 101534. https://doi.org/10.1016/j.ijdrr.2020.101534

Raper, J., Gartner, G., Karimi, H., & Rizos, C. (2007). Applications of location–based services: A selected review. *Journal of Location Based Services*, *1*(2), 89–111. https://doi.org/10.1080/17489720701862184

Rebois, Y., & Alschner, F. (2015). Use of Satellite Imagery at the ICRC (International Committee of the Red Cross). *GI_Forum*, *1*, 402–405. https://doi.org/10.1553/giscience2015s402

Reddy, L. B., & DeLaurentis, D. (2016). Opinion Survey to Reduce Uncertainty in Public and Stakeholder Perception of Unmanned Aircraft. *Transportation Research Record: Journal of the Transportation Research Board*, *2600*(1), 80–93. https://doi.org/10.3141/2600-09

Reininger, B. M., Rahbar, M. H., Lee, M., Chen, Z., Raja, S. A., Pope, J., & Adams, B. (2013). Social Capital and Disaster Preparedness Among Low Income Mexican Americans in a Disaster Prone Area. *Social Science & Medicine (1982)*, *83*, 50–60. https://doi.org/10.1016/j.socscimed.2013.01.037

Řezník, T., Lukas, V., Charvat, K., jr, K., Křivánek, Z., Kepka, M., Herman, L., & Řezníková, H. (2017). Disaster Risk Reduction in Agriculture through Geospatial (Big) Data Processing. *International Journal of Geo-Information*, *2017*. https://doi.org/10.3390/ijgi6080238

Ribeiro, R., Ramos, J., Safadinho, D., Reis, A., Rabadão, C., Barroso, J., & Pereira, A. (2021). Web AR Solution for UAV Pilot Training and Usability Testing. *Sensors*, *21*(4), 1456. https://doi.org/10.3390/s21041456

Riegg Cellini, S., & Edwin Kee, J. (2015). Cost-Effectiveness and Cost-Benefit Analysis. In *Handbook of Practical Program Evaluation* (pp. 636–672). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119171386.ch24

Sajjad, H., & Kumar, P. (2019). Future Challenges and Perspective of Remote Sensing Technology. In P. Kumar, M. Rani, P. Chandra Pandey, H. Sajjad, & B. S. Chaudhary (Eds.), *Applications and Challenges of Geospatial Technology* (pp. 275–277). Springer International Publishing. https://doi.org/10.1007/978-3-319-99882-4_16

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Salo, A., & Hämäläinen, R. P. (2010). Multicriteria Decision Analysis in Group Decision Processes. In D. M. Kilgour & C. Eden (Eds.), *Handbook of Group Decision and Negotiation* (Vol. 4, pp. 269–283). Springer Netherlands. https://doi.org/10.1007/978-90-481-9097-3_16

Santamaria, C., Sermi, F., Spyratos, S., Iacus, S. M., Annunziato, A., Tarchi, D., & Vespe, M. (2020). Measuring the impact of COVID-19 confinement measures on human mobility using mobile positioning data. A European regional analysis. *Safety Science*, *132*, 104925. https://doi.org/10.1016/j.ssci.2020.104925

Santos, C. (2019). *Satellite Imagery, Very High-Resolution and Processing-Intensive Image Analysis: Potential Risks Under the GDPR* (SSRN Scholarly Paper ID 3413014). Social Science Research Network. https://papers.ssrn.com/abstract=3413014

Sawalha, I. H. (2020). A contemporary perspective on the disaster management cycle. *Foresight*, *22*(4), 469–482. https://doi.org/10.1108/FS-11-2019-0097

Shafique, K., Khawaja, B. A., Sabir, F., Qazi, S., & Mustaqim, M. (2020). Internet of Things (IoT) for Next-Generation Smart Systems: A Review of Current Challenges, Future Trends and Prospects for Emerging 5G-IoT Scenarios. *IEEE Access*, *8*, 23022–23040. https://doi.org/10.1109/ACCESS.2020.2970118

Shreve, C. M., & Kelman, I. (2014). Does mitigation save? Reviewing cost-benefit analyses of disaster risk reduction. *International Journal of Disaster Risk Reduction*, *10*, 213–235. https://doi.org/10.1016/j.ijdrr.2014.08.004

Stahl, P., Roessler, C., & Hornung, M. (2020, January 17). *Performance and Life Cycle Cost Comparison of Optimized Fixed-Wing VTOL UAV Configurations*. https://doi.org/10.25967/490207

Taubenböck, H., Geiß, C., & Klotz, M. (2013). *Present day and future remote sensing data. Report on globally available present-day and future remote sensing data and products.* Framework to integrate Space-based and in-situ sENSing for dynamic vUlnerability and recovery Monitoring. https://elib.dlr.de/93002/1/D2_1_PresentAndFutureDayRemoteSensingData_final.pdf

Terrovitis, M., Mamoulis, N., & Kalnis, P. (2008). Privacy-preserving anonymization of set-valued data. *Proceedings of the VLDB Endowment*, *1*(1), 115–125. https://doi.org/10.14778/1453856.1453874

The International Charter Space and Major Disasters. (2021). *About the Charter—International Disasters Charter*. About the Charter. https://disasterscharter.org/web/guest/about-the-charter;jsessionid=66352701297313549F5A102116C81FB2.APP1

Transport Styrelsen. (2021). *Oväntat få drönarkort i hela landet*. https://www.transportstyrelsen.se/sv/Press/Pressmeddelanden/2021/ovantat-fa-dronarkort-i-hela-landet/

Tuan, T. H., Tran, P., Hawley, K., Khan, F., & Moench, M. (2015). Quantitative cost-benefit analysis for typhoon resilient housing in Danang city, Vietnam. *Urban Climate*, *12*, 85–103. https://doi.org/10.1016/j.uclim.2015.01.002

Tung, H.-W., & Soo, V.-W. (2004). A personalized restaurant recommender agent for mobile e-service. *IEEE International Conference on E-Technology, e-Commerce and e-Service, 2004. EEE '04. 2004*, 259–262. https://doi.org/10.1109/EEE.2004.1287319

UCS. (2021). *Satellite Database | Union of Concerned Scientists*. UCS Satellite Database. https://www.ucsusa.org/resources/satellite-database

UNISDR. (2019). *Terminology*. https://www.unisdr.org/we/inform/terminology (

Võik, E. J., Sari, M., Vania Salim, A., Berawi, M. A., Lusikka, T., & Schobert, M. (2021). *BUILDERS D4.7 Indonesian Case "Using Mobile Operators' Data to Locate, Protect and Evacuate Tourists and Other Vulnerable Groups in Disasters"* [BuildERS Deliverable].

Võik, E. J., Tominga, A., Klaos, M., Silm, S., Orru, K., Lusikka, T., Keränen, J., & Schobert, M. (2021). *BUILDERS D4.3 Practice & product innovation "Applying mobile positioning data for more precise rescue planning and emergency management under cyber-hazard in Estonia"* [BuildERS Deliverable]. https://buildersproject.eu/results

Vokinger, K. N., Stekhoven, D. J., & Krauthammer, M. (2020). Lost in Anonymization—A Data Anonymization Reference Classification Merging Legal and Technical Considerations. *Journal of Law, Medicine & Ethics*, *48*(1), 228–231. https://doi.org/10.1177/1073110520917025

Vorhies, F., & Wilkinson, E. (2016). *Co-Benefits of Disaster Risk Management*. The World Bank. https://doi.org/10.1596/1813-9450-7633

Wang, K., Dong, J., Wang, Y., & Yin, H. (2019). Securing Data With Blockchain and AI. *IEEE Access*, *7*, 77981–77989. https://doi.org/10.1109/ACCESS.2019.2921555

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

Waqas, H., & Imran, M. (2019). #CampFireMissing: An Analysis of Tweets About Missing and Found People From California Wildfires. *ISCRAM*.

Ward, P. J., Jongman, B., Aerts, J. C. J. H., Bates, P. D., Botzen, W. J. W., Diaz Loaiza, A., Hallegatte, S., Kind, J. M., Kwadijk, J., Scussolini, P., & Winsemius, H. C. (2017). A global framework for future costs and benefits of river-flood protection in urban areas. *Nature Climate Change*, *7*(9), 642–646. https://doi.org/10.1038/nclimate3350

Wenz, A., Jäckle, A., & Couper, M. P. (2019). Willingness to use mobile technologies for data collection in a probability household panel. *Survey Research Methods*, *13*(1), 1–22. https://doi.org/10.18148/srm/2019.v1i1.7298

Wiboonrat, M. (2014). Life cycle cost analysis of data center project. *2014 Ninth International Conference on Ecological Vehicles and Renewable Energies (EVER)*, 1–6. https://doi.org/10.1109/EVER.2014.6844139

Yang, G., Lin, X., Li, Y., Cui, H., Xu, M., Wu, D., Rydén, H., & Redhwan, S. B. (2018). *A Telecom Perspective on the Internet of Drones: From LTE-Advanced to 5G*. 8.

Yoon, J., Drumright, L. N., & van der Schaar, M. (2020). Anonymization Through Data Synthesis Using Generative Adversarial Networks (ADS-GAN). *IEEE Journal of Biomedical and Health Informatics*, *24*(8), 2378–2388. https://doi.org/10.1109/JBHI.2020.2980262

Yowtak, K., Imiola, J., Andrews, M., Cardillo, K., & Skerlos, S. (2020). Comparative life cycle assessment of unmanned aerial vehicles, internal combustion engine vehicles and battery electric vehicles for grocery delivery. *Procedia CIRP*, *90*, 244–250. https://doi.org/10.1016/j.procir.2020.02.003

Yu, M., Huang, Q., Qin, H., Scheele, C., & Yang, C. (2019). Deep learning for real-time social media text classification for situation awareness – using Hurricanes Sandy, Harvey, and Irma as case studies. *International Journal of Digital Earth*, *12*(11), 1230–1247. https://doi.org/10.1080/17538947.2019.1574316

Yuan, F., & Liu, R. (2019). *Identifying Damage-Related Social Media Data during Hurricane Matthew: A Machine Learning Approach*. *2*, 207–214. https://ezp.sub.su.se/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=edsbl&AN=CN605405937&site=eds-live&scope=site

Zhu, Y., & Li, N. (2021). Virtual and augmented reality technologies for emergency management in the built environments: A state-of-the-art review. *Journal of Safety Science and Resilience*, *2*(1), 1–10. https://doi.org/10.1016/j.jnlssr.2020.11.004

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496

CONTACT US

www.buildersproject.eu

@BuildERS_EU

https://www.facebook.com/Builders-2762442730463980/

https://www.linkedin.com/company/builders-h2020

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 833496