Special report on the use of

Technology for Disaster Risk Reduction

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FOR DISASTER RISK REDUCTION 2015-2030

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Preface

As the frequency and costs of disasters continue to rise, and with the final years of the Sendai Framework for Disaster Risk Reduction 2015–2030 approaching, it is critical that we support developing countries in making the most of every available resource to accelerate progress. In this regard, advancements in technology offer a clear opportunity to help countries leapfrog progress.

In recent years, rapid progress in areas such as Earth observation, geospatial analysis and artificial intelligence has significantly enhanced our ability to collect, process, and interpret data efficiently. These innovations are greatly improving our understanding of current and projected climate and disaster risks, and have the potential to transform how countries design and implement disaster risk reduction measures, not to mention guide investments in the public and private sectors so that they are risk-informed.

However, adoption of these technologies has been uneven, with many developing countries lagging behind due to factors such as affordability and applicability. This disparity is evident globally but is particularly pronounced in the Americas and the Caribbean.

This special report on Technology for Disaster Risk Reduction (Tech4DRR) aims to bridge the gap between technological progress and its application by highlighting practical use cases. It explores how emerging tools can facilitate real-time monitoring, improve risk modelling, and support data-driven decision-making—all with the overarching goal of reversing the rising trend of disaster impacts.

Acknowledging that technology alone cannot address the complexities of disaster risk, the report calls for a balanced approach—one that combines technological innovation with capacity-building, knowledge-sharing, inclusive policymaking, and a demand-driven approach to developing and applying technology.

I commend the UNDRR Regional Scientific and Technical Advisory Group for Americas and the Caribbean, ARISE USA, and the United States' National Aeronautics and Space Administration (NASA) for collaborating on this innovative report, which not only supports the implementation of the Sendai Framework but also the Global Digital Compact.

By harnessing the power of technology, we can build a future where resilience is not just a possibility but a reality. This report is a solid contribution towards that future.

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Special Representative of the United Nations Secretary-General for Disaster Risk Reduction,
and Head of the United Nations Office for Disaster Risk Reduction (UNDRR)

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Introduction

The components for assessing and understanding disaster risk, namely hazard, exposure and vulnerability, have been conceptually defined since 1980 by the United Nations Disaster Relief Organisation (UNDRO). However, the information required to accurately model and represent each of these components has historically been scarce.

The lack of information has been one of the greatest obstacles to achieving significant progress in generating high-quality risk information, which in turn can support decision-making processes in key areas such as designing and implementing multi-hazard early warning systems (MHEWS), boosting disaster risk reduction (DRR) financing, implementing the resilient infrastructure principles and avoiding the reconstruction of vulnerability after a disaster through resilient recovery and building back better.

The increasing intensity and/or frequency of certain climate-related disasters, such as droughts and floods, provide strong motivation to emphasize the transformative potential of technology (particularly digital technology) in supporting DRR efforts. We are living in the "smart age", witnessing rapid advances in artificial intelligence (AI), quantum computing and blockchain, which are transforming everything, everywhere, simultaneously. DRR is no exception to these advances, and there is growing potential for generating information that can support various decision-making processes.

For instance, the development of new technologies in recent years has significantly increased the availability of tools for monitoring key variables that help understand the processes of hazard formation and/or occurrence. They can also help in identifying and characterizing populations and elements exposed to one or more hazards (e.g. using the Internet of Things to develop proxies), quantifying different dimensions of vulnerability (e.g. through real-time monitoring and diagnostics of critical infrastructure) and using high-resolution satellite imagery to rapidly estimate disaster damages. These advances and the availability of information facilitated by new technologies can also expedite the validation and calibration of various components of any risk model.

While the number of available tools and technologies is a good indicator of progress, it is also important to acknowledge significant advances in their robustness. However, a major setback remains, particularly in Latin America and the Caribbean, related to the adoption, use and adaptation of these technologies in resource-limited environments (e.g. the cost of licences or equipment) or within fragile and conflict-affected settings (e.g. limitations in access to, and maintenance of, monitoring equipment).

A shift in the approach to technology development is therefore required. Currently, most countries in the region must navigate the existing market to find the tools that best fit their needs, with little, if any, interaction with technology developers. The adoption and development costs of many technologies have the potential to increase and decrease, respectively, if a transition is made towards demand-driven development processes.

Despite the availability of more risk data and risk models for almost all countries in the Americas and the Caribbean, their use in decision-making processes (particularly those related to sustainable development) remains limited. This indicates that high-quality risk models and information alone are not sufficient. With this in mind, this special report aims to contribute to the debate on the development and use of cutting-edge technologies for DRR while maintaining a balance between technological progress and the democratization of access to, and use of, science. A clear example of this is found in the field of AI and machine learning (ML), where it is necessary not only to identify and renounce biases inherent in the data used for algorithm training but also to consider how up to date the data are. Computers trained on historical data reflecting past patterns may become outdated or inappropriate for current contexts, since AI and ML technologies are always based on past knowledge, which can hinder the ability to understand future trends. A key example of this are the adverse effects of climate change, which are often not adequately captured in historical data, thereby limiting the robustness of projections required for 10, 20 or even 50 years into the future.

It is well known that early warning systems (EWS) are among the most cost-effective tools for saving lives. Precisely for this reason, in 2022, the United Nations Secretary-General launched the Early Warnings for All (EW4All) initiative, led by UNDRR and the World Meteorological Organization (WMO). In this field, technology has not only made highly relevant recent contributions but also holds additional potential for improvement, particularly in impact-based forecasting. Enhancing monitoring capabilities and identifying new variables that can be monitored, forecasted and more strongly correlated with expected impacts will be crucial. Such forecasts can also be expanded to adopt a more systemic approach by, for example, incorporating considerations related to food security.

The application of technology in DRR also holds great potential for refining, validating and analysing historical disaster event databases (e.g. trend analysis and changes in disaster occurrence patterns). This can be achieved through near-real-time content analysis of social media and online publications, such as identifying fake news and improving public alerts, or by making high-resolution estimations of the location of populations at risk. Significant progress has been made in these areas in recent years, particularly in industrialized countries, from which data are primarily sourced. This highlights that the main challenge at present lies not necessarily in the development of new technologies but rather in the difficulties faced by many governments in developing nations, both at national and local levels, in accessing them, as well as in evaluating their robustness in specific contexts due to biases in their development.

Technology has also a critical role to play in assisting the proper communication of messages to the general public before, during and in the aftermath of disasters. In times where social media channels are widely used by most of the population to obtain near-real-time information, there is a risk of not only false alerts but also fake news. ML techniques have the potential to rapidly counteract these by identifying them and sending offset messages.

When considering technology to assist DRR efforts, we should not only focus on cutting-edge and high-end approaches. The role of “low-tech” solutions in supporting local implementation of DRR has been widely overlooked. Therefore, the adoption of inclusive approaches for their development, including but not limited to Indigenous and traditional knowledge, is much needed.

Regarding AI, while a significant number of people are sceptical about its contributions, an even larger number are using it in increasingly routine activities. It is therefore necessary to continue scaling up AI applications to achieve not only short-term positive impacts but also long-term sustainability. It is also crucial to remember that every model is a simplification of a complex phenomenon, and none can be better than the data from which it was developed. If investment in these two areas (i.e. development and adoption) is not balanced, there is a high risk that, while models and algorithms may generate information for decision makers, it may be difficult to interpret and might lead to over-reliance on results at the expense of existing capabilities.

> Technology for DRR not only has the potential to improve understanding of the subject rapidly and efficiently among both decision makers and the general public, but also to support the use of results in disaster risk financing activities.

Technology for DRR not only has the potential to improve understanding of the subject rapidly and efficiently among both decision makers and the general public, but also to support the use of results in disaster risk financing activities. Perhaps the most tangible example is the development of parametric risk transfer instruments, where technology has proven essential in generating the information required for instrument design. This has, in many cases, enabled insurance coverage for risks that previously had prohibitively high annual premiums, as well as the necessary monitoring mechanisms for rapid compensation (between 2 and 14 days).

The key message of this special report is that technology, regardless of how advanced and robust it may be, cannot solve DRR challenges on its own. For instance, it is evident that the existing challenges go beyond merely increasing investment in technology development and adoption; they also encompass capacity-building efforts and pedagogical shifts that should extend even to primary education. Technology itself can support capacity-building processes, for example, through the use of virtual learning tools.

As we approach the final stretch for implementing the Sendai Framework for Disaster Risk Reduction 2015–2030 (Sendai Framework), it is highly relevant to reflect on the benefits of adopting technologies to support DRR efforts. This reflection should extend beyond technology adoption to include efforts aimed at democratizing high-quality risk information, empowering communities and significantly improving disaster risk management and reduction capacities. In this regard, technology has the potential to explicitly and directly support the four priorities of the Sendai Framework: understanding disaster risk (which evidently requires a thorough risk assessment), strengthening disaster risk governance, increasing DRR financing (including investment in technology development, adoption and training) and enhancing preparedness for emergency response and resilient recovery.

This special report consists of a series of independent chapters organized as follows: chapter 1 introduces the role of technology in DRR, emphasizing the need to explicitly consider the context and discussing the close relationship between technological innovation and risk assessment methods. Chapter 2 presents the role of AI and ML in DRR, describing their benefits and limitations through a series of case studies from Latin America and the Caribbean. Chapter 3 discusses the need to adopt an inclusive approach when developing and training technologies in order to increase their adoption and ensure they are responsive to the local needs. Chapter 4 highlights the benefits of adopting technologies in activities related to MHEWS, by for instance indicating that the introduction and adoption of relatively simple technologies based on Indigenous and local knowledge can yield high life-saving benefits. Finally, chapter 5 explores how certain communication systems, such as social media, have contributed to reducing disaster risk. It also examines the challenges regarding the accuracy and validity of information during and in the aftermath of a disaster that AI and ML can help to solve. Some chapters include a series of case studies that highlight the power of digital tools. In most cases, benefits have been identified at the local level (where DRR must be implemented), but it is also essential to recognize that fostering cooperation, information exchange and the sharing of best practices can maximize the benefits of these tools.

The chapters have been structured independently, allowing readers to focus on those of particular interest. However, we have carefully curated the content and terminology to ensure consistency in the definitions and applications presented. We invite readers to engage with this special report from a critical perspective, so that they not only focus on the regional advancements in technology for DRR but also consider the challenges that lie ahead in improving aspects related to accessibility, applicability and adaptability.

01

A systems approach for identifying and evaluating context-specific technologies for disaster risk reduction

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1. Introduction

The Sendai Framework for Disaster Risk Reduction 2015–2030 (UNDRR, 2015) underscores the indispensable role of technology in mitigating disaster risks and enhancing community resilience. The Sendai Framework calls for leveraging advanced technologies to improve multi-hazard early warning systems, disaster response mechanisms and comprehensive risk assessments. These technological advancements are critical to achieving the framework's goals, which include reducing disaster impacts on livelihoods, health and well-being, as well as damage to critical infrastructure and services.

The development, adoption and implementation of these technologies are more likely to succeed when they are tailored to local contexts and informed by those directly impacted by their use. This involves considering multiple factors including existing infrastructure, local capacities for technological adoption, the specific technological capabilities of the area, community knowledge and involvement, and an enabling policy environment. These considerations are crucial to evaluating the suitability and potential impact of various technologies in different regions and communities. For instance, a technology that proves effective in an urban area with a tech-enabled infrastructure may not be suitable for a rural community that relies on Indigenous knowledge or low-tech systems and solutions.

Despite the rapid proliferation of technologies and innovations to support disaster risk reduction (DRR), there is a lack of standardized criteria and tools for developing and assessing their suitability across diverse contexts and timescales. This often results in shortfalls in tech solutions and the misapplication of technologies, leading to suboptimal outcomes and, at times, exacerbating the vulnerabilities they aim to mitigate. For example, the use of digital technologies in lower-income regions during the COVID-19 pandemic illustrates this issue. Governments and local bodies quickly introduced digital tools, such as smartphone apps, to track the spread of the virus (Gangadharan, 2021). However, their effectiveness was limited by the "digital divide", as many people lacked reliable Internet access or the digital literacy to utilize these technologies effectively. This divide was evident in education, where online learning platforms could not be uniformly accessed across socioeconomic groups, deepening educational inequalities (Unni, 2023).

This chapter will: (1) highlight the role that technology and innovation play in DRR and in achieving the objectives of the Sendai Framework; (2) identify and discuss the key criteria and conditions that need to be considered when evaluating the suitability of different technologies; and (3) provide illustrative regional and global examples of DRR technologies across contexts, emphasizing the necessity of robust and adaptable technology assessment criteria and tools. Through this exploration, the chapter aims to contribute to a more nuanced understanding of how to effectively integrate technology into DRR strategies, ensuring that technological interventions and solutions are human-centric, contextually appropriate and impactful.

2. Role of technology and innovations in DRR

The Latin American and the Caribbean (LAC) region is vulnerable to multiple types of disasters, including hurricanes, earthquakes and floods. Over the past two decades, these events have had severe and widespread impact, affecting more than 190 million people in LAC. The region's vulnerability is constantly tested by compounding risks such as climate change, dense urban populations, economic instability and limited resources. The

2010 Haiti earthquake resulted in over 222,500 deaths, making it one of the deadliest disasters in human history (OCHA and UNDRR, 2023). Hurricanes Eta and Iota hit Central America less than two weeks apart in 2020 at the height of the COVID-19 pandemic, affecting nearly 9 million people and causing widespread destruction (OCHA and UNDRR, 2023).

Disasters in the LAC region are characterized by their complexity and multiplicity, with cascading effects that draw on existing vulnerabilities (UNDRR, 2023b). Climate change has increased the frequency and intensity of severe weather events, leading to recurring and more-intense hurricanes and floods. The region's high population density, particularly in urban areas, and its reliance on climate-sensitive sectors such as tourism and agriculture further heighten its vulnerability to natural hazards. Technology, defined as the application of scientific knowledge for practical purposes, has emerged as an important tool for enhancing DRR efforts. Technologies are often associated with physical devices such as computers, machinery and equipment. However, in the context of DRR, technology takes on a broader meaning that encompasses more than just hardware; rather, it includes "ways of doing things" that can include both hard and soft approaches and aspects related to the environment (Srinivas, 2023).

Various technologies help build the knowledge and understanding needed to manage all risk components (i.e. exposure, vulnerability and hazard). They provide tools to carry out robust risk assessments, improve forecasting capabilities and facilitate efficient early warning systems. For example, Artificial Intelligence (AI) combined with satellite imagery and Geographic Information Systems (GIS) technology can automate the near-real-time updating of disaster risk maps in order to provide more-accurate data support for emergency evacuations, as well as equipment and resource allocation. These technologies can also optimize evacuation route planning, ensuring people in hazardous areas can evacuate quickly.

Many countries in LAC have made great advancements in using technology to identify the susceptibility of geographic locations and infrastructure to damage from severe hazards. AI-powered drone technology can capture post-disaster damage quickly and accurately. For example, the use of drones in both Sint Maarten and Dominica was critical in collecting information after Hurricanes Irma and Maria, respectively, as they were used to assess structural damage to homes and road collapses. These data then translated into more-efficient deployment of resources and aid (Runde, Sandin and Kohan, 2021). Another example is the use of technology in humanitarian assistance after the 2016 Ecuador earthquake, where drones were used to quickly measure the extent of the catastrophe, with more than 7,000 buildings destroyed (Prado, 2016). Such data help authorities allocate relief resources more efficiently and develop more-comprehensive recovery plans for future disasters.

Existing technologies that employ satellite imagery were used to manually tag and categorize rooftops in India based on the materials used for their construction. The roofing materials act as a proxy for the house's socioeconomic condition, indicating the level of its inhabitants' socioeconomic vulnerability to a typhoon. These data were translated into easily shared and understood early warning information, delivered through readily available means to alert people – particularly the most vulnerable – to secure their belongings and shops and evacuate ahead of a typhoon. During this system's use in 2020–2021, 1,100 families were evacuated on time using the advisories generated by the model (Ajmal, 2021).

These and many other DRR technologies are transferable to other countries and can easily be adapted through stakeholder input and guidance to best meet the cultural, social, economic and governance needs of the community and region. Geospatial technologies, often combined with sensor, crowdsourced data analysis, can significantly enhance post-disaster recovery efficiency. Multispectral imaging, which captures data from several distinct segments (bands) of the light spectrum, is widely used for assessing vegetation health, land-cover changes and structural damage (Izumi et al., 2019; Space Voyage Ventures Team, 2024). Hyperspectral imaging, on the other hand, gathers data from hundreds of very fine, closely spaced segments of the light spectrum, allowing for more precise detection of different materials or conditions (for example, distinguishing between different roof types or flood-damaged areas) (Schwandner, 2018). These technologies provide accurate damage assessments, offering specific data to support insurance claims and accelerate recovery. Their use is essential for reducing risks from cascading events, enhancing preparedness and adaptation, building back better and building resilient communities.

"Exposure" refers to the situation of people, infrastructure, housing, production capacities and other tangible human assets located in hazard-prone areas (UNDRR, 2017). Technological advancements, such as earth observation imagery and GIS, have significantly improved our ability to map and monitor these components. For example, space-based earth observation imagery provides high-resolution data that can map the built and natural environments, including buildings and infrastructure. These data can be integrated into population distribution estimates to provide an overview of exposure in different regions. In LAC, GIS has been used to map areas exposed to natural hazards, such as earthquake-prone zones in Haiti, in order to guide reconstruction efforts and urban planning that reduces exposure (Fontes de Meira and Bello, 2020).

3. DRR through an exposure, vulnerability and hazard lens

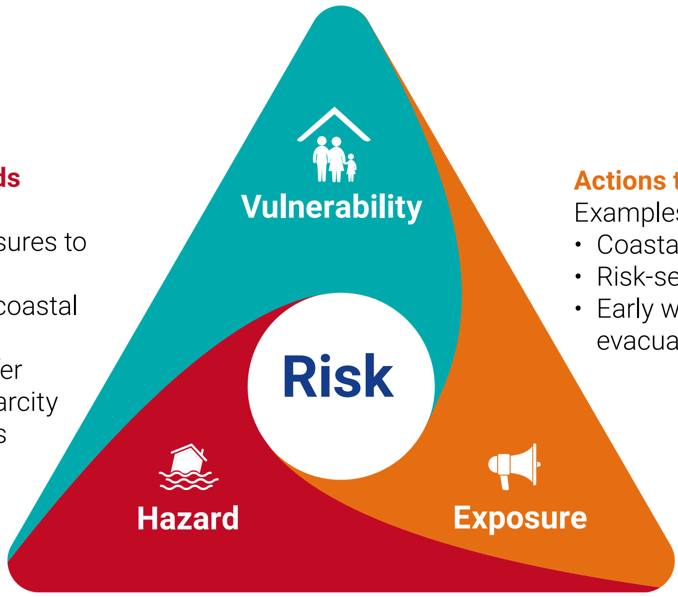
Understanding DRR through a lens that considers all components of the risk equation, namely exposure, vulnerability and hazard, is foundational to effective DRR (Figure 1). Technologies can improve our understanding of the complexities and meaning behind each of these factors at the individual, local and national levels. The *UNDRR Data Strategy and Roadmap 2023–2027* (UNDRR, 2023a) underscores the importance and value of data and technology in strengthening and implementing DRR efforts.

Figure 1. Risk framework illustrating the interconnection between exposure, vulnerability and hazard for disaster risk reduction

Limits to adaptation
E.g., physical, ecological, technological, economic, political, institutional, psychological, and/or sociocultural

Actions to reduce vulnerability
Examples include:
- Social protection
- Livelihood diversification
- Insurance solutions
- Hazard-proof housing and infrastructure

Actions to reduce hazards
Examples include:
- Ecosystem-based measures to reduce coastal flooding
- Mangroves to alleviate coastal storm energy
- Water reservoirs to buffer low-flows and water scarcity
- Reduce greenhouse gas emissions



Actions to reduce exposure
Examples include:
- Coastal retreat and resettlement
- Risk-sensitive land-use planning
- Early warning systems and evacuations

Source: Adapted from the Intergovernmental Panel on Climate Change (IPCC, 2019) *Special Report on Climate Change and Disaster Risk Management*

Vulnerability refers to the conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards (UNDRR, 2017). Technology aids in assessing and addressing these vulnerabilities through accurate data collection and analysis. For instance, big data analytics using AI integrates remote sensing and multispectral data to provide near-real-time disaster forecasts, allowing authorities to identify high-risk areas and take pre-emptive actions more accurately. This technology is particularly crucial for reducing the exposure of populations to storm risks and minimizing human and economic losses. In LAC, big data analytics has been used to assess the impact of previous hurricanes and predict which areas might be most affected by future storms (ITU, 2020). Advances in remote sensing and satellite imagery provide real-time data on weather conditions, enabling accurate forecasting and early warnings for events such as hurricanes and floods, thereby allowing timely evacuations and preparations that reduce vulnerability (NASA, 2024; Google Research, 2024).

Any 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 is a hazard (UNDRR). Disaster risk pertains to the probability of occurrence of a potentially damaging physical event and the potential impact it could have on exposed population and assets. Technological solutions and innovations have greatly enhanced our capacity to understand

and mitigate these risks. The development of probabilistic risk assessments, which use both historical and hypothetical event data to estimate potential losses, has become more robust as computational modelling techniques have advanced. Such modelling enables decision makers to predict potential losses and develop specific response strategies for different scenarios. For example, in Trinidad and Tobago, smart flood management systems use sensors, Internet of Things (IoT) devices and advanced software to monitor water levels, predict flooding and manage water flow through dams and levees to help control hazards (Trinidad and Tobago Meteorological Service, n.d.). The Mayor's Office of Manizales (Colombia), with the support of the National University of Colombia – Manizales headquarters, designed a catastrophic risk assessment for earthquakes and landslides in the city. Based on this study, the city developed and implemented a voluntary collective insurance policy to cover the poorest strata of the population (Salgado-Gálvez et al., 2017; Bernal et al., 2017).

Technology is useful in understanding and managing hazards, exposure, vulnerability and disaster risk. It enables advanced tools for data collection, analysis and communication that help make informed decisions. Technology not only improves the robustness of early warnings and risk assessments, but also facilitates effective planning and response strategies, ultimately reducing the overall impact of disasters on communities. However, it is important to acknowledge that the collection and use of data, while beneficial, can also introduce new risks. In the wrong hands, sensitive information may be exploited to cause harm or to exacerbate vulnerabilities. Therefore, ethical management and protection of data are crucial to ensuring that the benefits of technology in DRR are not overshadowed by potential threats.

3.1 Relationship between technology innovation and risk assessment

The relationship between technology and risk assessment, particularly probabilistic risk assessment (PRA), is integral and multifaceted. PRA provides a robust mathematical framework for estimating the consequences of future disasters by considering the random nature of hazards, vulnerabilities and exposure and by rationally incorporating that uncertainty into the outcomes. This framework offers a set of metrics that fully represent the loss occurrence process, allowing risk management strategies, background trends and modelling under deep uncertainty to be integrated into a solid mathematical framework, making it a versatile decision-making tool (Bernal et al., 2024).

The tremendous computing power and speed of modern technology enable the simulation of multiple risk scenarios and the adjustment of strategic models in near-real-time under different conditions. This technology allows decision makers to quickly assess the effectiveness of solutions and provides stronger data support for resource allocation and response strategies. This capability not only enhances the analysis of potential disaster outcomes but also allows for the modelling and testing of various solutions and pathways, providing a more robust foundation for decision-making. Technology and innovation play a crucial role in DRR by enhancing preparedness, response, recovery, adaptation and resilience. Technology makes PRA significantly more effective, accurate, efficient, comprehensive and reliable and supports better risk management, decision-making and funding through:

1. *Data collection and analysis:* Advanced sensors, data acquisition systems and big data analytics enable the gathering and processing of large data sets, which are essential for identifying and understanding potential risks (i.e. their impacts and occurrence frequency). These technologies can be applied to real-time monitoring and early warning, providing

communities and authorities with accurate risk assessments and response plans. Examples: satellite technology, sensors and IoT, drones and robotics.

2. *Modelling and simulation:* Utilizing high-performance computing (HPC) and sophisticated software tools allows for detailed simulations and modelling, critical for accurate PRA. These technologies assist authorities in planning more-accurate response measures and ensuring efficient resource allocation. Examples: climate models, seismic activity simulations.

3. *Automation and efficiency:* Automation tools and AI enhance the efficiency and accuracy of PRA processes by not only processing input data, such as exposure, vulnerability and hazard parameters, but also directly contributing to risk assessment and decision-making. AI-driven models automate complex risk calculations, optimize iterative simulations and reduce human error, thereby improving the reliability of PRA assessments. For example, AI-driven risk analysis tools can dynamically update models based on real-time data, thereby improving predictive accuracy and supporting adaptive risk assessment. Similarly, machine learning models improve scenario analysis by continuously identifying patterns and correlations within large data sets, enabling scenario forecasting and near real-time risk updates. Examples: AI-driven risk analysis tools for real-time scenario modelling, machine learning models for dynamic hazard forecasting, and automated decision support systems for optimizing resource allocation in disaster response.

4. *Visualization and communication:* Visualization tools and interactive dashboards effectively present complex risk data, making it accessible and understandable to stakeholders and facilitating better decision-making. Examples: GIS, mobile networks, social media.

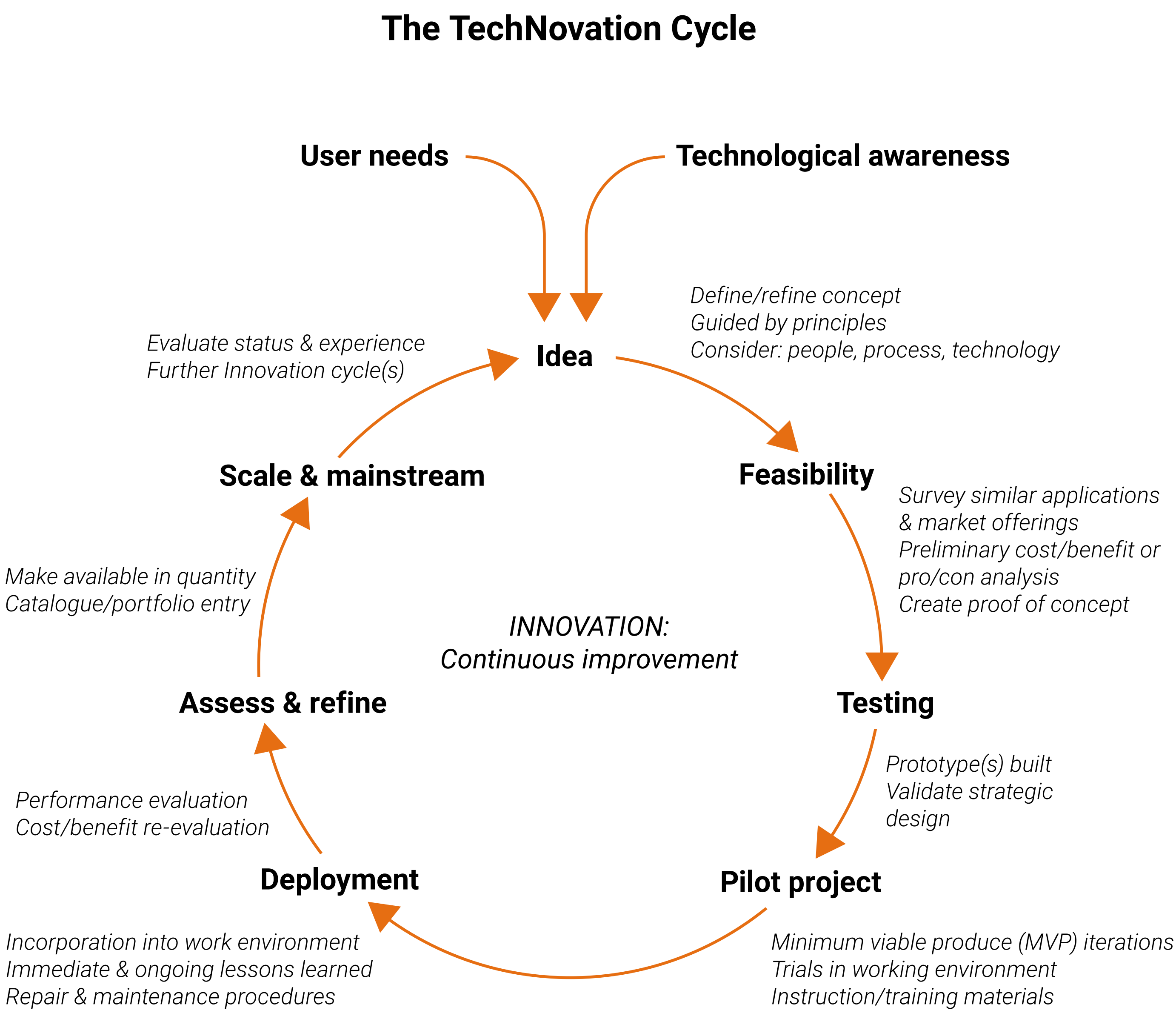
5. *Real-time monitoring and predictive analytics:* IoT devices and predictive analytics enable real-time monitoring and forecasting, which are integral to dynamic risk assessment updates, timely alerts and proactive management. Such real-time prediction systems can detect extreme weather changes or sudden disasters, such as flash floods or volcanic eruptions, giving emergency teams more time to act. Examples: sensors and IoT, early warning systems, predictive analysis, real-time data dashboards.

6. *Interdisciplinary integration:* Integrated software platforms and collaborative tools promote cooperation across various domains (e.g. engineering, finance, healthcare), which is essential for seamlessly integrating diverse expertise into PRA. Examples: smart cities, collaborative platforms.

Furthermore, effective public policies in DRR and sustainable development – ranging from financial protection and knowledge-based public investment to resilient infrastructure, territorial planning and impact-based early warning – can all benefit from estimates and appropriate risk layering obtained through PRA (Bernal et al., 2024). One example of a tool for visualizing risk layering is the Loss Exceedance Curve (LEC), which demonstrates the probability of exceeding different loss thresholds over time. Bernal et al. (2017) provide examples of such a curve, highlighting how different risk layers, ranging from frequent but low-severity losses to rare but catastrophic events, can inform risk retention, transfer and mitigation strategies. Technology can further assist governments and policymakers with performing detailed risk layering for different regions and analysing long-term climate trends based on historical and real-time data. These technologies not only support the planning of resilient infrastructure but also reduce the economic losses caused by disasters through early warning systems while promoting the implementation of sustainable development policies.

The United Nations TechNovation Cycle is an exemplary model for conceptualizing and guiding technological innovation projects in DRR (Dorn, 2021). This structured process spans from initial ideation to full implementation, including feasibility studies, testing, pilot projects, deployment, assessment, refinement, scaling and mainstreaming (Figure 2). It emphasizes learning from both successes and failures, integrating use cases, prototyping and developing minimum viable products.

Figure 2. The TechNovation Cycle: A structured approach to sustainable technology innovation



Source: Dorn, 2021

The TechNovation Cycle emphasizes combining users' experiences, needs and local knowledge with technological awareness to develop the needed innovation(s). Communities that take this human-centric and holistic approach build capacity and understanding, making them more likely to adopt, maintain and expand the technologies that best suit their needs. They can also avoid technologies that, while attractively funded, may be ill-suited to their needs and implementation abilities.

3.2 Reducing vulnerability through technological interventions

Actions to reduce vulnerability through technology can be categorized into several areas, including early warning systems, data collection and analysis, communication, infrastructure resilience and community engagement. Early warning systems provide timely and accurate information about impending hazards, enabling communities and authorities to take preventive measures and evacuate and/or take shelter as needed. Automated weather stations and satellite technology provide real-time data on weather conditions, enabling accurate forecasting and early warnings for events such as hurricanes and floods (World Bank Group, 2019). Several cities in the LAC region use satellite-based systems to monitor and predict hurricane paths, allowing for timely evacuations and preparations (UNDRR, 2023b). The Community Early Warning System (SIATA, 2022), a joint initiative between the city of Medellín (Colombia) and EAFIT University, uses cutting-edge technology, drones, hydrometeorological monitoring equipment and radars, among other tools, to maintain an alert system that activates a chain of calls through community leaders spread more than 17 km along the watershed and throughout marginal neighbourhoods (SIATA, 2022).

Accurate data collection and analysis are fundamental to understanding risks and making informed decisions. GIS technology is used to create detailed maps that highlight areas prone to natural hazards. These maps are essential for urban planning, ensuring that physical infrastructure is not built in high-risk areas. For example, GIS has been used in Haiti to map earthquake-prone zones and guide reconstruction efforts following the 2010 earthquake (Fontes de Meira and Bello, 2020). Additionally, big data analytics help in predicting disaster trends and assessing vulnerabilities. By analysing large data sets, authorities can identify patterns and potential risk factors. Big data analytics can be used to assess the impact of previous hurricanes in the LAC region and predict which areas might be most affected by future storms (GFDRR, 2024). This helps authorities in precise urban and rural planning and enables pre-emptive evacuation strategies, reducing risks from poorly planned infrastructure development.

Technological advancements also support land-use planning and DRR by integrating PRA into decision-making. In Manizales, Colombia, PRA helps city planners and policymakers understand potential disaster impacts and guide development. Using Loss Exceedance Curves (LEC) and Average Annual Loss (AAL) estimations, authorities can identify which areas are too risky for construction and where mitigation measures are needed (Bernal et al., 2017). The city applies seismic "microzonation" (the process of dividing a region into smaller zones based on local geological and seismic conditions to assess earthquake risk more precisely) and hazard mapping to plan safer urban expansion and prioritize infrastructure investments that reduce disaster risk. These tools enhance the accuracy of risk assessments, support resilient infrastructure investments and reduce vulnerabilities by ensuring that urban growth aligns with scientific risk evaluations.

Effective communication technologies ensure that critical information reaches the right people at the right time, thereby reducing the risk of harm. Mobile apps and social media platforms are increasingly used for disaster communication and can provide real-time updates, emergency alerts and information on safe evacuation routes.

During Hurricane Maria, social media played a key role in disseminating information and coordinating relief efforts in Puerto Rico (Pérez-Figueroa, Ulibarrí and Hopfer, 2025). Similarly, AI can analyse multispectral data from drones and satellites in real-time and disseminate disaster warnings through multilingual digital platforms to residents from diverse backgrounds. This allows even vulnerable communities to receive real-time and timely alerts and take actions to reduce losses. In Mexico, SASMEX disseminates early warnings for coastal earthquakes up to one minute before the arrival of strong motion in Mexico City, via electronic messaging using dedicated receivers, public loudspeakers, multi-hazard radios and participating TV and radio stations. This is useful in schools and low-rise buildings, which may have short-column issues, so that people are aware they should evacuate rapidly at the sound of the alert (Suárez, 2022).

Technological innovations in construction and infrastructure design can help reduce vulnerability by providing guidance on constructing buildings and infrastructure that are more resilient to disasters. Advances in building materials and engineering practices, as well as building-code enforcement, have led to the development of earthquake-resistant buildings. In regions such as LAC, adopting these techniques helps minimize damage during seismic events. For example, retrofitting schools and hospitals with earthquake-resistant designs has been a focus in the Dominican Republic (UNDRR, 2007).

Engaging communities in the right technological tools enables them to participate in DRR efforts. For example, technology that enables community members to monitor hazards and environmental changes increases local engagement and awareness, thus saving lives. For instance, community-based flood monitoring systems, where residents use mobile phones to report water levels, help authorities respond more quickly to potential flooding (UNFCCC, n.d.).

3.3 Reducing exposure through technological solutions

Reducing exposure to hazards through technological solutions involves enhancing monitoring and prediction capabilities, optimizing land-use and urban planning, improving infrastructure design and improving communication and coordination. These actions are important in mitigating the impact of disasters and protecting vulnerable communities.

Advanced monitoring and prediction technologies play a pivotal role in anticipating hazardous events, which allows communities and authorities to take protective measures. For example, remote sensing and satellite imagery are essential tools for monitoring environmental changes (stressors) and detecting early signs of potential hazards such as volcanic activity, deforestation or rising sea levels. In LAC, satellite data have been instrumental in tracking hurricane development and progress, enabling preparations, evacuations and adaptations that significantly reduce exposure to these powerful storms.

The World Economic Forum points out that it is crucial to focus on climate adaptation at scale, as well as climate mitigation. We must strengthen our ability to adapt to current and expected climate events, using actionable climate insights to inform decisions. The use of AI for its climate modelling capabilities is fundamental to this, yet we see significantly more AI innovation focused on climate mitigation such as leveraging AI to measure and reduce emissions, than on adaptation. This innovation gap needs to be addressed, and the development of responsible AI must be accelerated to acquire actionable climate insights (Van den Bergh, 2022).

Technology can help reduce exposure to hazards through strategic initiatives such as coastal retreat, risk-sensitive land-use planning, nature-based solutions and early warning systems. Coastal retreat involves relocating communities and infrastructure away from high-risk coastal areas to safer locations. This approach, combined with technology-driven urban planning tools, helps design cities and communities in ways that minimize exposure to hazards. Risk-sensitive land-use planning integrates hazard information into urban planning and development decisions, such that physical infrastructure is not built in high-risk areas. In Saint Lucia, for instance, GIS mapping has guided urban planning efforts to avoid construction in flood-prone areas, thereby reducing the population's exposure to flood risks (CDEMA, 2015; One Saint Lucia, 2022).

Innovative infrastructure design technologies help reduce exposure by physically separating structures from hazards, thus preventing direct impact. In flood-prone regions, for example, technology enables the design and construction of elevated buildings and infrastructure. In coastal areas of the LAC region, elevated construction techniques raise buildings and infrastructure above expected flood levels, keeping them out of harm's way. In coastal areas of the LAC region, homes, hospitals and emergency shelters are built on stilts, raised platforms or elevated foundations to avoid floodwaters rather than merely resisting their impact (Sustainable Buildings Initiative, n.d.; World Construction Today, 2024). Similarly, in earthquake-prone areas, land-use planning and zoning regulations help relocate critical infrastructure away from high-risk zones, reducing direct exposure to hazards.

Additionally, the use of modular and repurposable building materials allows for rapid deployment and reconstruction after disasters, helping communities quickly restore essential infrastructure. These materials – often derived from locally available waste or recycled products such as recycled plastics, compressed earth blocks, bamboo and modular concrete panels – enable faster recovery by lowering the costs and reducing dependence on traditional supply chains. For instance, recycled plastic bricks have been used in post-disaster housing projects in Colombia (Valencia, 2011) and Indonesia (Morton, 2021), while bamboo-reinforced concrete provides a lightweight yet durable option for the rapid restoration of community shelters, as seen in post-earthquake rebuilding efforts in Nepal (Friedrich, 2016) and Ecuador (Van Drunen et al., 2015). This approach not only reduces exposure by enabling rapid reconstruction in safer areas but also promotes sustainable building practices by utilizing easy-to-produce, environmentally friendly resources.

Effective communication technologies are essential for the timely dissemination of information and coordination during disasters to reduce the exposure of populations to hazards. Early warning systems in Trinidad and Tobago, for example, send alerts to residents' mobile phones about approaching storms, allowing them to take action to reduce their exposure to impending hazards (WMO, n.d.b). These interventions highlight the role of technology in mitigating the impact of disasters by decreasing exposure to hazards. On a global scale, UNESCO's Global Tsunami Early Warning and Mitigation Programme, coordinated by IOC-UNESCO, is a critical system for protecting lives from tsunamis. The programme's role has evolved to include more than just issuing warnings; it also assists Member States in assessing risk, implementing early warning systems, educating communities and developing tracking and detection technologies (UNESCO, 2024).

Technological innovations in construction and materials have significantly contributed to the development of disaster-resilient infrastructure, particularly in coastal areas prone to flooding and sea level rise. For instance, advanced engineering techniques such as seismic isolation systems are increasingly being used to enhance the earthquake resilience of critical structures. A key example is the Adana City Hospital in Türkiye, which remained fully operational during the February 2023 earthquakes due to its base isolation system, which reduced seismic impact by 75 per cent while surrounding buildings suffered extensive damage (Osman Ozbulut, 2023). Similarly, flexible and shock-absorbing foundation systems, such as base isolators and seismic dampers, help buildings withstand earthquakes by minimizing ground motion transfer. Despite the proven effectiveness of these technologies in past earthquakes, they have only been implemented in a fraction of the locations where they could provide significant benefits in Türkiye (Osman Ozbulut, 2023). These technologies have been widely implemented in earthquake-prone regions globally to minimize structural damage and ensure the safety of occupants. For example, after experiencing significant damage during the 2004 earthquake, several hospitals in Colombia have been reconstructed with base isolation systems to ensure functionality during seismic events (Eriksen, Mohammed and Coria, 2018). Additionally, flood-resistant materials such as waterproof concrete and corrosion-resistant metals are increasingly used in construction to make critical infrastructure such as hospitals and emergency shelters more resilient (Ulm and Manav, n.d.; Taha et al., 2021).

Technology for environmental management helps maintain natural buffers against hazards and reduce exposure. Drones equipped with seed dispersal technology, for example, are used to reforest areas affected by deforestation, thereby restoring natural barriers that reduce exposure to landslides and floods. In Haiti, drone-based reforestation projects have helped rebuild mangrove forests that protect coastal areas from storm surges, illustrating the role of environmental technologies in DRR (NCBA CLUSA, n.d.).

3.4 Reducing hazards through technological innovation

Technology plays a significant role in reducing disaster risks by not only addressing vulnerabilities and exposure but also by actively mitigating the hazards themselves when this is possible. Actions to reduce hazards through technology include modifying the environment, controlling potential triggers and utilizing innovative solutions to minimize hazard impacts. For instance, ecosystem-based measures leverage natural systems to mitigate hazards (UNDRR, 2020). Mangroves and coral reefs act as natural barriers against storm surges and coastal erosion. Coastal restoration projects use advanced techniques to rebuild these natural buffers, significantly reducing the impact of hurricanes and coastal erosion.

Technological interventions can inform environmental modifications to mitigate natural hazards and reduce their potential impact. AI-supported technology can analyse multispectral data captured by drones and satellites to identify high-risk areas for wildfires or other natural hazards. For example, coastal restoration projects use geoengineering to rebuild natural barriers such as mangroves and coral reefs. In Belize, these projects have successfully helped rebuild mangrove forests, significantly reducing the impact of hurricanes and coastal erosion (The Pew Charitable Trusts, 2022). In wildfire-prone areas, controlled burns and advanced forest management techniques are employed to reduce the amount of combustible material. Satellite imagery and drones monitor forest conditions and plan for strategic controlled burns (NASA, Landsat Science, 2021; NASA, Earth Observatory, 2023). In Dominica, such practices have been adopted to manage wildfire risks, significantly reducing the likelihood of large-scale disasters. Using technologies to understand and identify which products and approaches are best suited to a community should not be overlooked.

Innovative water management technologies can control hazards related to water, such as floods and droughts. Smart flood management systems use sensors, IoT devices, and advanced software to monitor water levels, predict flooding and manage water flow through dams and levees. In many regions, these systems have been deployed to monitor rivers and reservoirs, allowing for proactive measures to prevent flooding and manage water resources efficiently (National Drought Mitigation

Center, n.d.). Similarly, technologies for containing and managing hazardous materials can prevent environmental hazards and reduce disaster risks. Advanced wastewater treatment technologies, for example, prevent the release of hazardous chemicals and pollutants into the environment. In industrial regions of LAC, modern wastewater treatment plants use membrane bioreactors and other advanced filtration methods to reduce the risk of waterborne hazards (United States Environmental Protection Agency, 2007). Brazil has developed a territorial intelligence model, a near-real-time fire-spread prediction system for the Brazilian Cerrado, the biome most affected by wildfires in South America. The system automatically uploads hot pixel and satellite data to generate maps of fuel loads, vegetation moisture and probability of burning, which are used to simulate fire spread. The model's results are available on an interactive web platform to help prevent and promptly combat wildfires (Oliveira et al., 2023).

Infrastructure improvements also play a crucial role in mitigating hazards. Advanced engineering techniques and construction materials are used to retrofit buildings and infrastructure to withstand earthquakes. Seismic sensors, along with building technologies designed to absorb and dissipate seismic energy, can significantly reduce the risk posed by earthquakes. In the Dominican Republic, seismic retrofitting of schools and hospitals has been implemented to minimize damage during earthquakes, reducing the hazard's impact (Rojas-Mercedes et al., 2020).

Climate engineering technologies aim to reduce the hazards associated with climate change by directly intervening in the climate system. For example, cloud seeding technologies use aircraft or ground-based generators to disperse substances into the atmosphere that encourage cloud formation and precipitation, reducing the risk of drought. Some Caribbean islands have explored cloud seeding to address water scarcity during prolonged dry spells, thereby mitigating drought-related hazards (WMO, n.d.a).

In summary, technology reduces disaster risks by actively mitigating hazards through environmental modification, hazard control, infrastructure improvements, water management systems, containment of hazardous materials, and climate engineering. Additionally, the use of repurposable materials, sourced from local waste and integrated into flexible supply chains, further increases the resilience of communities and ecosystems. These materials enable quick recovery and repair of critical infrastructure, reducing dependence on external resources. By combining these sustainable practices with technological interventions, we can diminish the severity of impacts of natural hazards while enhancing the adaptive capacity of both communities and ecosystems against potential disasters.

The LAC region's high vulnerability to disasters is compounded by complex and interconnected risks. Whether in Belize, Dominica, Puerto Rico, Saint Croix or Honduras, each area differs in environmental, social, cultural, economic and developmental aspects, meaning no two countries will have the same vulnerability to hazards and/or exposure conditions. As more technologies are developed to be agnostic, flexible and customizable, they will become increasingly accessible and interoperable. This is particularly beneficial for smaller communities that share borders, as they will be able to partner to share the costs of acquiring these technologies, share data and develop the capacities needed to implement, operate and maintain them.

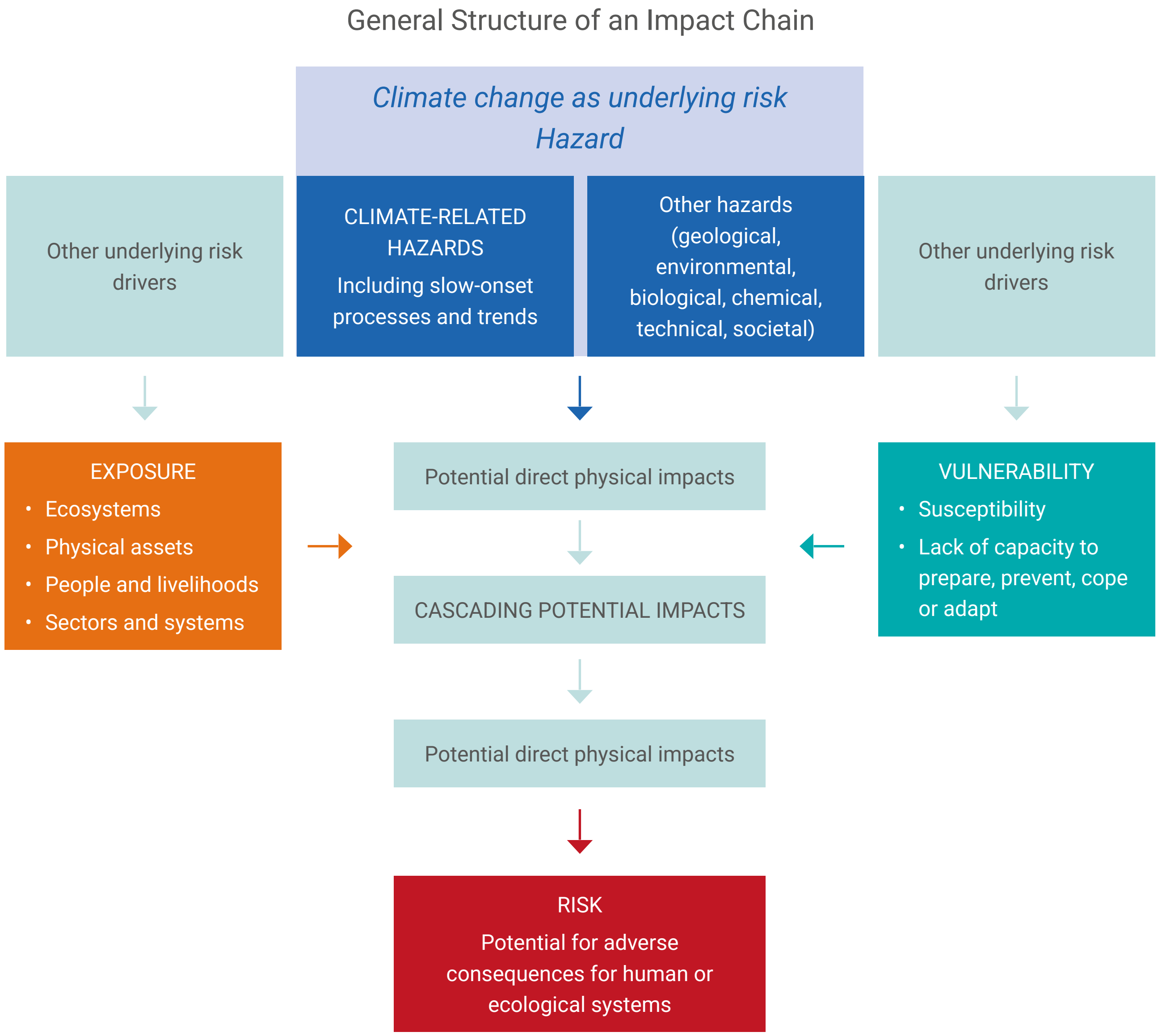
4. Criteria for evaluating the suitability of technologies and innovations in DRR: Essential elements for successful adoption and implementation

As outlined in the previous sections, technologies can be evaluated for their ability to sense, monitor, capture, analyse, manage and communicate vast amounts of valuable information, facts and data. However, we must avoid falling into a technology-driven bias, where technology becomes an end in itself. It is critical to first define the problem and its causes with those most at risk such that the identified technology will contribute to solving it. The first step for a community evaluating technology for DRR is to begin with a clear understanding of the entire community's exposure, vulnerability and hazard characteristics, presented in this chapter in terms of an impact chain (Figure 3).

Successfully pairing any technology (or set of technologies) to address these challenges hinges on stakeholders' understanding of and connection with the technology – or, in most cases, a suite of interconnected technologies – and its value to them. Achieving comprehensive community acceptance, engagement, trust, use and promotion of technology will ensure outcomes are aligned with community-defined goals.

Like any solution, the success of these technologies will be measured by the number of lives saved, the effectiveness of warnings and responses, the speed and ease of recovery and adaptation, the protection of livelihoods, the enhancement of resilience, the knowledge gained and the level of losses and damages that must be absorbed by affected individuals, communities and governments or transferred to external entities such as insurers, aid organizations or risk-sharing mechanisms.

Figure 3. Impact chain framework illustrating how climate-related hazards, exposure and vulnerability contribute to disaster risk



4.1 Accepting and adopting technologies for DRR

Standard technology acceptance models (TAMs) highlight four interconnected factors critical for the acceptance and use of new technologies. These are: perceived usefulness, perceived ease of use, behavioural norms and behavioural intention. In the context of DRR, these factors are shaped by several key influences. Community awareness and understanding play a crucial role in improving knowledge of local hazards and risks over time. The relevance and capability of technology are also vital factors, as they determine how well a technology can address and mitigate these identified risks. Finally, individual and community experiences and perceptions related to these risks influence behavioural norms and intentions, affecting the overall acceptance and effective utilization of DRR technologies.

4.2 Evaluating technological and infrastructural readiness

Successful adoption of DRR technologies not only requires assessing social and behavioural aspects but also evaluating technological readiness and infrastructural support. This comprehensive approach includes assessing technological maturity, which involves understanding the level of DRR awareness in local contexts to ensure technologies are adopted effectively. Additionally, infrastructural compatibility must be considered, taking into account whether the existing infrastructure can adequately support the technology in question, paying specific attention to energy requirements, interoperability and maintenance capabilities. Together, these elements contribute to a holistic assessment framework that is critical for the successful implementation of DRR technologies.

4.3 Scalability of DRR technologies

Scalability means ensuring that DRR technologies can be adapted from local to regional levels without diminishing their effectiveness. An evaluation covers both the adjustability of these technologies to function optimally at various scales and their cost-effectiveness, assessing whether the investments required to scale up are justified by the benefits they provide. This balance is crucial for the broader implementation and sustainability of technology solutions in DRR.

4.4 Enabling policy environment

An enabling policy environment facilitates the acceptance and implementation of DRR technologies by ensuring that knowledge is accessible and leads to actionable steps. The transdisciplinary nature of risk science and knowledge, bridging sectors and stakeholders, may be central to finding solutions (ISC, IRDR and UNDRR, 2021). Supportive policies can facilitate innovation by providing funding, resources and regulatory support and establishing standards to guide the development and deployment of technologies.

4.5 Reliability and trust

The reliability of technology is crucial for its acceptance in any application, including DRR. Reliability encompasses both the consistency and dependability of technology – it must perform reliably under a variety of conditions in order to build trust. Additionally, the accuracy of the information provided by technology is vital; it must deliver precise data that stakeholders can use to make informed decisions. Together, these elements of reliability ensure that technology is not only trusted but also effective in practical scenarios.

4.6 Visualization, communication and (near) real-time analytics

Effective visualization and communication tools are crucial for simplifying complex risk information to make it comprehensible and actionable for stakeholders. These tools help break down intricate risk assessments to facilitate informed decision-making. Complementing these, the integration of IoT devices and predictive analytics into disaster risk management systems enables real-time monitoring and forecasting. This proactive approach not only provides timely updates and alerts but also enhances the overall responsiveness to potential hazards, ensuring that risk management is both dynamic and adaptive to changing conditions. Together, these technologies form a robust framework for managing disaster risks more effectively.

4.7 Interdisciplinary integration

DRR requires inputs from various domains, integrating expertise from engineering, finance, healthcare and more to address the multifaceted challenges of disasters. Technology should facilitate the integration of diverse disciplines through enhanced communication and data-sharing tools such as GIS, which synthesize diverse data to improve decision-making and implementation of DRR strategies.

4.8 Including Indigenous knowledge

Recognizing Indigenous knowledge as a system within DRR enriches traditional and modern approaches to disaster mitigation and preparedness. Initially acknowledged in the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) and later accepted by the IPCC as an alternate approach towards disaster mitigation and community-based preparedness (Panda, Chatterjee and Panda, 2023), Indigenous knowledge provides time-tested, accessible "soft tech" approaches to managing disaster risk. It can also inform and be combined with crowdsourcing and other technologies to strengthen, accelerate and scale innovative solutions for DRR.

4.9 Governance and leadership support

Effective governance and leadership are crucial for fostering a supportive environment for DRR technologies. TAM behavioural norms and behavioural intention relative to DRR tech are shaped by experience, and social, cultural and legal expectations. Trust, consistency and fairness are fundamental to these processes – sometimes framed by principles and morals, and other times by laws and regulations. When these elements are missing, unclear or vague, gaps can emerge in capacity-building, consensus-reaching and engagement with, and utilization of, technologies. In situations where governments or other authorities lack the political will to fulfil their commitments to DRR and the Sustainable Development Goals (SDGs), or where corruption is present, stakeholders' behavioural intentions will weaken. Challenges such as lack of political will and corruption can undermine community engagement and trust, reducing incentives to adopt technological improvements.

Understanding disaster risk in all its dimensions – vulnerability, capacity, exposure of people and assets, hazard characteristics and the environment – must be the basis for more-effective disaster risk management in the future. Paradoxically, while our knowledge of the physical aspects of hazards is increasing, much of that knowledge is not being used effectively or at a scale to ensure robust decision-making beyond emergency responses. Countries still lack multi-hazard risk data on differential vulnerabilities at the required resolutions, and cross-domain interoperability issues are hindering proper risk assessment, model characterization, classification and description (e.g. prospective loss estimate models) (ISC, 2023).

5. Systems thinking in technology for DRR

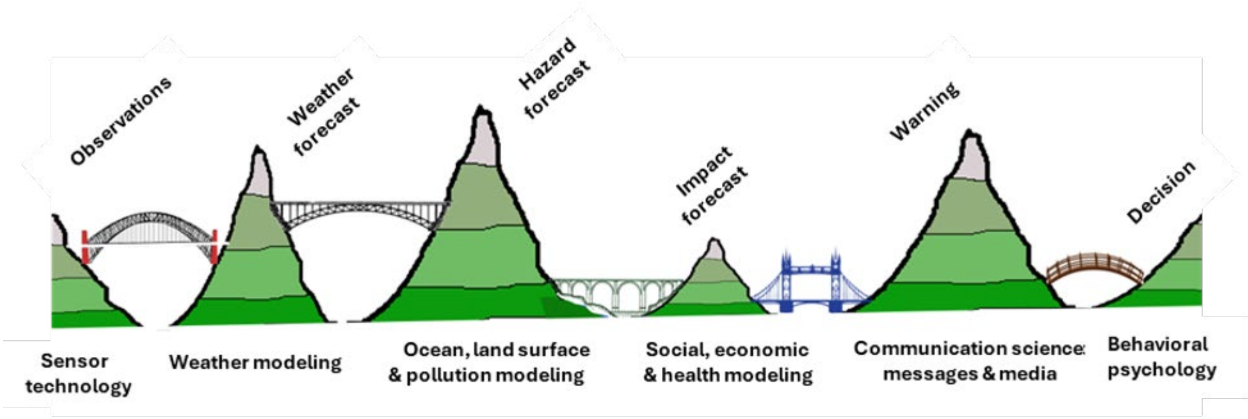
The most comprehensive criteria for assessing and adopting technologies for DRR follow a systems approach. This method is essential for understanding the increasingly interconnected and complex socioecological systems within which risks manifest (see the *Global Assessment Report on Disaster Risk Reduction*, UNDRR, 2019). Traditional risk frameworks often overlook the temporal and spatial interactions of different hazards or the combination of extreme events with slow-onset events or prolonged crises (Keys et al., 2019). Anthropogenic changes and globalization further exacerbate these risks. Concepts such as compound risk, systemic risk, cascading risk, NATECH (natural hazards triggering technological disasters) risk and Anthropocene risk have emerged as alternative frameworks that attempt to capture the dynamic nature of risks in modern systems (ISC, IRDR and UNDRR, 2021).

The adoption of a systems approach in evaluating DRR technologies acknowledges the intricacies of modern risks, including compounding, systemic, cascading and NATECH risks. These risks illustrate the interconnected nature of natural and technological hazards, exacerbated by human activities and global interconnectedness. By embracing systems thinking, stakeholders can better anticipate and mitigate the multifaceted impacts of disasters, ensuring more-robust response mechanisms.

A systems approach to DRR inherently promotes the engagement of a broad array of stakeholders across disciplinary, sectoral and geographical lines. This engagement is critical for fostering mutual understanding and collaboration, which are essential for the nuanced application of technology in diverse contexts. For example, combining insights from Indigenous and local communities with scientific and technological advancements enhances the applicability and effectiveness of DRR strategies, promoting culturally appropriate and widely accepted solutions.

Systems thinking also addresses operational challenges, such as the accessibility of satellite data or the integration of early warning systems. The value chain framework, for example, provides an approach to characterize the warning chain in terms of its processes, inputs and outputs, relationships, contributions and operational contexts. The value chain approach allows us to understand the non-linear relationships that occur in a warning chain where different stakeholders intervene and contribute until reaching a final product. Figure 4, from Golding et al., 2019, illustrates the value chain for high-impact weather warnings by showing the capabilities and outcomes ("green mountains") and the information exchanges ("bridges") that link the capabilities and their associated communities.

Figure 4. Value chain framework in systems thinking for technology evaluation and adoption in disaster risk reduction



Source: Adapted from Golding et al., 2019

By considering the entire value chain of DRR – from data collection and processing to actionable insights and interventions – technology adoption can be optimized for greater impact. Collaborative platforms enabled by technology foster cross-boundary partnerships that enhance resource sharing, knowledge exchange and collective action, crucial for overcoming logistical and operational barriers in DRR.

The private sector plays a crucial role in DRR, utilizing technologies such as GIS, PRA and advanced infrastructure management tools to safeguard businesses' people, assets, operations and reputations. These technologies enable businesses to assess and mitigate risks, ensuring continuity and resilience in the face of potential disasters. The private sector's significant presence in most communities means that it often has access to valuable data and insights that can be shared with public sector efforts, enhancing overall disaster preparedness, response and adaptation strategies. By leveraging these technologies, organizations not only protect their interests but also contribute to the broader safety and resilience of the communities in which they operate.

Adopting a systems approach in the implementation of DRR technologies is more than a strategic choice; it is a necessity in the face of evolving global risks. This approach not only enhances the efficacy and reach of technological solutions but also ensures that these solutions are sustainable, inclusive and adaptable to the changing dynamics of risk and human societies. The concept of resilience in DRR is significantly amplified through systems thinking, while encouraging the exploration of synergies between various frameworks and agendas, such as the SDGs and climate adaptation and mitigation. By aligning DRR technologies with broader developmental objectives, systems thinking helps craft solutions that are not only effective in disaster risk reduction but also beneficial in promoting long-term sustainability and resilience.

02

Artificial intelligence, machine learning and disaster risk reduction

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Executive summary

Artificial intelligence (AI) and machine learning (ML) are transforming disaster risk reduction (DRR) by providing advanced tools for risk analysis, event prediction and emergency response. The advent of generative AI (GAI) and agentic AI (AAI) may continue this progression.[1] This document explores the application of AI technologies in the DRR field, detailing their definitions, benefits, use cases and associated challenges.

AI involves a range of techniques that simulate human intelligence, while ML, a subfield of AI, enables computers to learn from data. GAI extends to enabling computers to generate entirely new content patterned on the data that have been used to train them, while AAI generates actions and processes. These technologies are proving invaluable in various DRR applications, such as predicting seasonal or extreme weather events, developing hazard maps, supporting real-time disaster monitoring and detection, optimizing resource allocation during emergencies, and assisting post-event triage.

However, while AI technologies offer great promise for DRR, their deployment is challenging. Issues such as system failures, cyberattacks, equity of access, and biases in AI models require careful attention. GAI and AAI may “hallucinate”, inventing seemingly authoritative content or taking actions that have no basis in fact at all. Overcoming these challenges demands caution, robust infrastructure, rigorous testing and continuous monitoring.

Furthermore, ethical concerns – such as ensuring fairness and avoiding the perpetuation of existing biases – are crucial for the responsible use of these technologies and require a strong policy and social framework within which to deploy them. Equally important is the need for AI technologies to be developed and implemented in a demand-driven manner, ensuring they address the specific needs of communities, decision makers and emergency responders. AI solutions designed without considering local contexts and user requirements risk becoming ineffective or misaligned with real-world challenges. By engaging stakeholders early on in the development process and fostering interdisciplinary collaboration, AI-driven DRR innovations can be more impactful, adaptable and widely adopted.

The document also highlights the importance of explainable AI (XAI) in enhancing transparency and trust in AI systems. By making AI decision-making processes understandable, XAI can help mitigate the risks associated with “black-box” models, where the rationale behind AI predictions and generated content is opaque.

In conclusion, AI technologies bring substantial benefits to DRR, facilitating more-accurate predictions, more-efficient resource allocation and improved emergency response. However, if they are to be successfully implemented, technical, ethical, social and operational challenges must be addressed. By doing so, organizations can leverage the power of AI and ML to build more-resilient communities and mitigate the impact of disasters.

1 In this document, for convenience, AI, ML and GAI/AAI are referred to collectively as “AI technologies”.

1. Introduction

Disaster risk reduction (DRR) is a critical field that utilizes technological advancements to mitigate and manage the impacts of disasters triggered by natural and human causes. Among these advancements, artificial intelligence (AI), machine learning (ML) and, most recently, generative AI (GAI) have emerged as transformative tools.

As catalysts, these technologies offer unparalleled capabilities in understanding, predicting and responding to disaster risks. AI technologies enable the analysis of vast amounts of data, uncovering patterns and insights beyond human capacity. Below are some aspects through which we can understand how implementing these two technological tools has impacted DRR, and how they have become integral catalysts.

- *Data detection and searches:* AI plays a critical role in identifying and characterizing risk hazards, exposure and vulnerabilities. By analysing data to detect patterns and anomalies beyond human perception, AI enhances our ability to anticipate events and mitigate potential negative impacts.

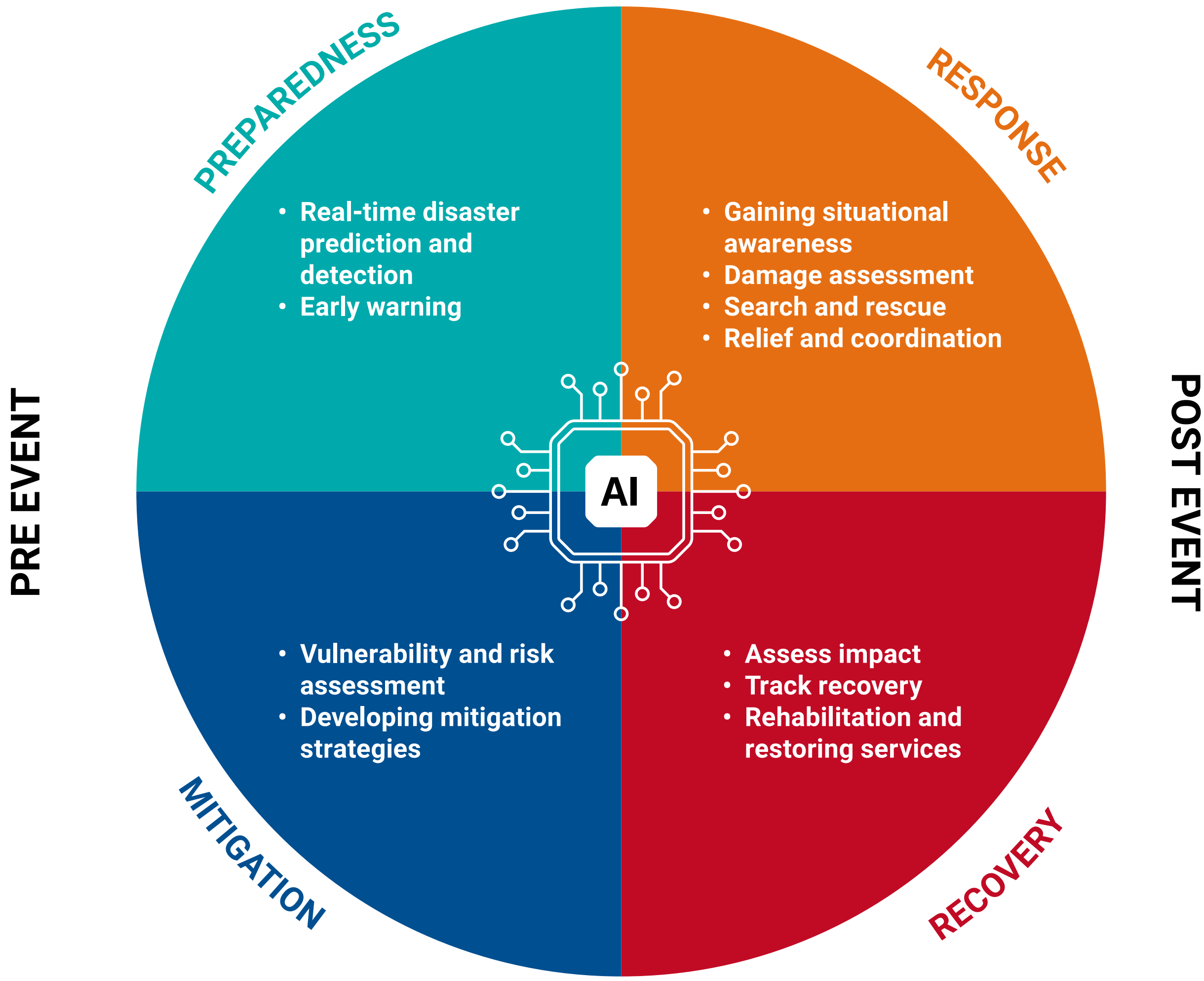
- *Real-time data processing:* The ability of AI to extract meaning from large volumes of data in near-real-time is indispensable for maintaining an up-to-date understanding of conditions on the ground. This enables rapid and effective response in critical situations, thus improving monitoring, forecasts and emergency management.

- *Simulations and risk modelling:* AI simulations provide “what-if” scenarios that help assess potential damage, losses and impacts to population and the natural and physical built environment and then plan prevention measures. Modelling risks and their factors (hazards and vulnerabilities of exposed elements and/or systems) and generating graphical representations, powered by ML algorithms, facilitates the graphical representation of risks. This improves communications and helps contextualize the critical areas identified.

- *Forecasting and preparedness:* AI and ML are critical for forecasting extreme events. By analysing historical and current data, these models can provide timely warnings, which are vital for emergency and/or disaster preparedness and response. GAI could be used to develop realistic training use cases to assist in preparedness.

- *Resource optimization and automated response:* Efficient resource allocation during risk and disaster management is made possible by AI optimization algorithms. In addition, AI-based automated response systems, such as chatbots, can guide people in situations of imminent risk, saving human and non-human lives, providing life support, ensuring business and/or service continuity, supporting environmental services and minimizing damages.

Figure 1. Examples of applications of AI in DRR



In the following sections, we will delve deeper into several key areas. We will start by defining essential terms such as artificial intelligence and machine learning, establishing a clear understanding of their roles and capabilities. Next, we will discuss the numerous benefits of these technologies in the context of DRR, including examples of their successful applications. We will also address the issues and uncertainties associated with AI and ML, such as biases that may replicate existing inequities or favour suboptimal actions, and ethical concerns; we propose solutions to mitigate these challenges. Finally, we will explore the concept of explainable AI and its importance in ensuring transparency and trust in AI systems. Through this comprehensive examination, we aim to provide a thorough understanding of how AI and ML can revolutionize DRR and how the challenges it presents can be avoided.

1.1 Important definitions

There is no single definition of AI, but in general:

> Artificial intelligence is a set of computerized analytic techniques that enable computer systems to simulate human intelligence and problem-solving capabilities,[2] but with far larger quantities than any human could handle, and improve their own performance (accuracy, granularity, range etc.) over time.

AI systems should be designed to align with human values and objectives, ensuring they act in ways that are beneficial to humanity and enhance human well-being. This means that beyond merely replicating human intelligence, AI must operate in ways that are compatible with ethical principles and societal goals.

AI is not a new tool, but its growing use has been enabled primarily by the availability of data from millions of networked sensors (the "Internet of Things" [IoT][3]) and searchable accumulations and archives and by access to computing power in the enormous quantities required to train and operate AI algorithms to generate more meaningful conclusions from those data. Secondarily, there have been developments that increase the range and sophistication of those algorithms, and so broaden the field of potential applications. These trends apply to DRR as much as they do in any other field, resulting in many potentially beneficial use cases.

> *Machine learning (ML)* is a computational method that is a subfield of artificial intelligence. It uses data and algorithms to gradually improve the performance of a computer system at predicting outcomes by correcting in the light of observed errors without being explicitly programmed.

In essence, ML trains machines to learn from data and improve with experience rather than being explicitly programmed for specific tasks. ML algorithms can classify data or make predictions based on analysis of previous data. *Deep learning (DL)* utilizes various neural network architectures to develop models that can automatically learn and represent complex patterns in data, enabling advanced predictive capabilities and decision-making.

> *Generative AI (GAI)* generates original content from the data with which it has been fed. Content may include text, images, speech, computer code or even music.

GAI is the most powerful extension to date of ML and DL (together with other AI technologies such as *natural language processing [NLP]*). GAI tools often derive from large language models (LLMs): ChatGPT, Llama and Bard are well-known examples. However, AI vendors are increasingly also looking at applying GAI technology in the form of smaller models trained on data from within specific fields, such as water management or various medical disciplines.[4]

2 See, for example, https://www.ibm.com/topics/artificial-intelligence.

3 The Internet of Things is generally held to consist of networked specific-to-purpose sensors, whether satellite-based observational capabilities or terrestrial sensors (the latter include cameras and meters); sensing devices mounted to other equipment; and personal devices such as smart phones with sensing capacities. One estimate suggests that there were 17.08 billion IOT devices in use in 2024, rising to 29.4 billion by 2030.

4 See, for example, https://unite.un.org/sites/unite.un.org/files/generative_ai_primer.pdf.

Agentic AI (AAI) builds on the same family of AI techniques as described for GAI. Rather than generating content, however, AAI automates complex workflows to generate independent actions or decisions in pursuit of specific goals. Like GAI, it learns and improves over time.

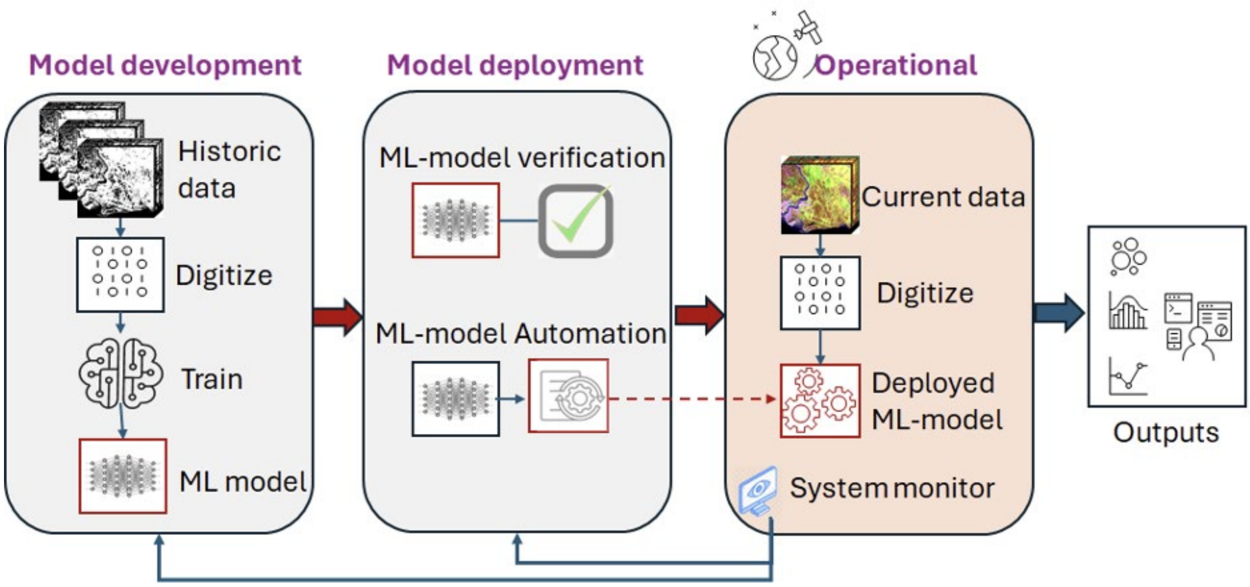
The major uses of AAI look likely to be in business operations (supply chain optimization, as one example) and healthcare. It is so far not known to have been used in the DRR field, but there are potential applications in emergency management, infrastructure operations and other complex decision environments.

1.2 Working with AI technologies

The journey of an ML model (and, by extension, other AI technologies as well) involves three key phases: model development, model deployment and operational management (Figure 2). Each phase ensures the model's effectiveness, scalability and adaptability to real-world applications. In the model development phase, the ML model's foundation is laid through problem definition, data collection, cleaning, feature engineering, model selection, training and evaluation. Once a robust model has been developed, the next phase is deployment, which involves model packaging, infrastructure set-up, integration, testing and deployment to the production environment. The operational phase includes continuous monitoring, maintenance, logging, alerts, retraining, updating, versioning, documentation and reporting to ensure the model's ongoing effectiveness.

However, the adoption of AI technologies is often challenged by top-down approaches, where centralized decision-making slows implementation and creates a disconnect from real-world needs. A more proactive, demand-driven perspective is necessary to ensure that AI solutions are developed in close collaboration with end users and stakeholders. By shifting towards a client-centric model, AI adoption can become more effective, addressing the specific challenges faced by organizations and communities while fostering greater trust and engagement.

Figure 2. Key phases of a machine learning model



1.3 Categories of ML (summarized from Bishop, 2006)

Understanding the different categories of ML is crucial, particularly in fields like DRR. ML, with its various types, such as supervised, unsupervised, semi-supervised and reinforcement learning, plays a crucial role in analysing data and making predictions, making it a cornerstone of AI.

Supervised learning uses a labelled data set to train the model. Each training example has an input and a desired output, and the model learns to map inputs to outputs, enabling it to make predictions on new data. In the context of DRR, supervised learning can be used to predict the impacts of disasters. Historical data on past disasters, including weather conditions, geographical location, exposure and vulnerability development, and response times, can be used to train a model to predict the potential severity of future disasters.

On the other hand, *unsupervised learning* deals with unlabelled data. The model infers natural structure within the data to discover hidden patterns or structures. For DRR, unsupervised learning can be employed; for example, to cluster regions based on their vulnerability to different types of disasters, aiding in resource allocation and risk mitigation efforts.

Semi-supervised learning uses a combination of labelled and unlabelled data to improve learning accuracy, even with limited labelled data available. This approach can enhance prediction models in DRR scenarios. Finally, *reinforcement learning* involves an agent learning to make decisions by interacting with its environment and receiving feedback through rewards or penalties. This can be beneficial for optimizing response strategies in DRR.

In real-life problems, there are many kinds of ML: a summary is set out in appendix 1,[5] together with examples of the data sets and uses that might apply in DRR. It may be inferred from appendix 1 that, beginning with relatively basic ML methods, the various methods – many of which are based on different forms of regression analysis – represent a progression of steps (some incremental, some very large) from one another.

Understanding and leveraging these types of ML can aid in addressing complex challenges in DRR, enabling robust predictions, uncovering hidden patterns, enhancing models with limited labelled data and optimizing decision-making through interaction with dynamic environments.

Examples of ML algorithms currently in use:

- Neural networks are algorithms inspired by the human brain. They interpret data and recognize patterns through interconnected nodes or layers.

- Deep learning (DL) is a subset of machine learning (ML) that uses neural networks with many layers (deep neural networks). It excels at processing large amounts of data to identify complex patterns. In fact, NNs are a crucial part of DL, including various types tailored to different data and learning tasks. For example, feed-forward neural networks, the simplest form of artificial neural networks, are commonly used in basic classification tasks. When they have multiple hidden layers,

5 Appendix 1 focuses on actual AI methods that might be encountered in the DRR field, rather than on the more “meta” classifications that readers may have encountered, such as generative vs predictive, or reactive/limited memory/theory of mind/self-aware, or narrow/general or strong/super AI, and others. These classifications are used within the AI industry rather than by users and some categories such as theory of mind and self-aware, or strong and super AI, do not yet exist and so are not useful for DRR today.

they are considered DL networks, according to Goodfellow, Bengio and Courville (2016).

- Convolutional neural networks (CNNs) are specialized in processing grid-like data, such as images. They are exceptionally effective at recognizing patterns within images and find extensive application in object detection, facial recognition and medical image analysis, making them a crucial component of DL (LeCun, Bengio and Hinton, 2015). Beyond these applications, CNNs play a significant role in developing exposure models for the built environment (i.e. representations of physical assets, such as buildings and infrastructure, that quantify their characteristics, spatial distribution and vulnerability to hazards). CNNs can automatically classify buildings, infrastructure and land-use patterns by analysing satellite imagery, aerial photographs and street-level views. This capability enhances risk assessment frameworks by providing accurate and scalable exposure data, essential for DRR, urban planning and resilience modelling.

- Recurrent neural networks (RNNs) excel in handling sequential data, such as time series or language modelling. When structured with multiple layers, RNNs can also be utilized in deep-learning tasks, as stated by Goodfellow, Bengio and Courville (2016).

- Long Short-Term Memory Networks (LSTMs), a type of RNN, are proficient in learning long-term dependencies. They are often employed in language modelling and time-series prediction tasks and can be applied to both grid-like data, like video frames, and other sequential data (Goodfellow, Bengio and Courville, 2016).

Other important concepts:

- Natural language processing (NLP): NLP focuses on the interaction between computers and human languages. It enables machines to understand, interpret and generate human language. Some examples of applications include chatbots, which provide customer service or personal assistance; language translation, which involves converting text from one language to another; and sentiment analysis, which involves determining the sentiment expressed in a text (Vaswani et al., 2017).

- Transfer learning: Transfer learning involves applying knowledge gained from one domain to another. It is beneficial when there are limited data available for a specific task. Pre-trained models can be fine-tuned to perform new tasks efficiently, often using deep-learning models as a starting point (Goodfellow, Bengio and Courville, 2016).

- Large language models (LLMs): LLMs such as GPT-3 represent a significant advancement in ML and NLP, and are the foundation of GAI. These models have a vast number of parameters and can produce text that is similar to human-generated content and understands context. Some applications of LLMs include (Vaswani et al., 2017):

    - text generation: creating coherent and contextually relevant text

    - conversation agents: engaging in natural conversations with users

In conclusion, by understanding and utilizing the different categories and subfields of AI technologies, we can tackle complex challenges such as DRR. These technologies allow for accurate predictions, identification of hidden patterns, improvement of models with limited labelled data, and enhancement of decision-making by interacting with dynamic environments.

1.4 Benefits of AI technologies in the DRR domain

AI technologies are crucial in DRR, offering a wide array of benefits that greatly enhance the efficiency and effectiveness of disaster management. These technologies enable the development of advanced early warning systems, near-real-time data processing, and predictive models for extreme weather events, which in turn facilitate proactive measures and optimized resource allocation. For instance, AI and ML can more efficiently deploy resources such as emergency responders, medical supplies and relief materials. Additionally, they can enhance disaster management through real-time traffic management, smart infrastructure monitoring and crowdsourced data utilization, ensuring a more responsive and effective approach to mitigating the impacts of disasters.

Furthermore, AI and ML play a key role in risk assessment, hazard mapping and decision-making support during and after emergencies, leading to better outcomes in terms of saving lives and reducing economic losses in the face of different types of disasters. The following section presents some current use cases.

2. Case studies of AI technologies in DRR

Case studies are essential for understanding AI technologies' real-world applications and benefits in terms of DRR. The following sections will provide specific examples of how these technologies can be effectively applied, showcasing their potential to transform disaster preparedness, response and recovery. By illustrating practical implementations, case studies go beyond theoretical concepts and highlight the tangible advantages of AI technologies over traditional methods. This comparative analysis helps the DRR community understand the added value that these technologies bring, particularly in terms of speed, accuracy and efficiency.

Our goal is to demonstrate that case studies serve as proof of concept, validating the effectiveness of AI technologies in DRR and providing quantitative evidence that can convince the user community, from policymakers to practitioners. Furthermore, they highlight best practices and lessons learned, offering insights into challenges faced during deployment and adoption. Beyond technical hurdles, adoption challenges may arise due to institutional resistance, lack of technical expertise, data accessibility issues and the need for regulatory alignment. For instance, organizations may struggle to integrate AI-driven solutions due to legacy systems that are incompatible with modern technologies. At the same time, policymakers may hesitate due to uncertainties about AI's reliability and ethical implications.

Additionally, limited funding for AI initiatives and end-user scepticism can slow adoption. Addressing these barriers is critical to successfully integrating AI technologies into DRR practices. This knowledge is invaluable for refining strategies and improving future implementations.

Further, by detailing applications, significance and future outlooks, case studies offer a road map for leveraging AI technologies in DRR, encouraging continuous innovation and improvement in disaster risk management.

USE CASE: Application of ML for the preparation of mass movement susceptibility maps through discriminant analysis: the Popayán to Mazamorras River Road, Colombia

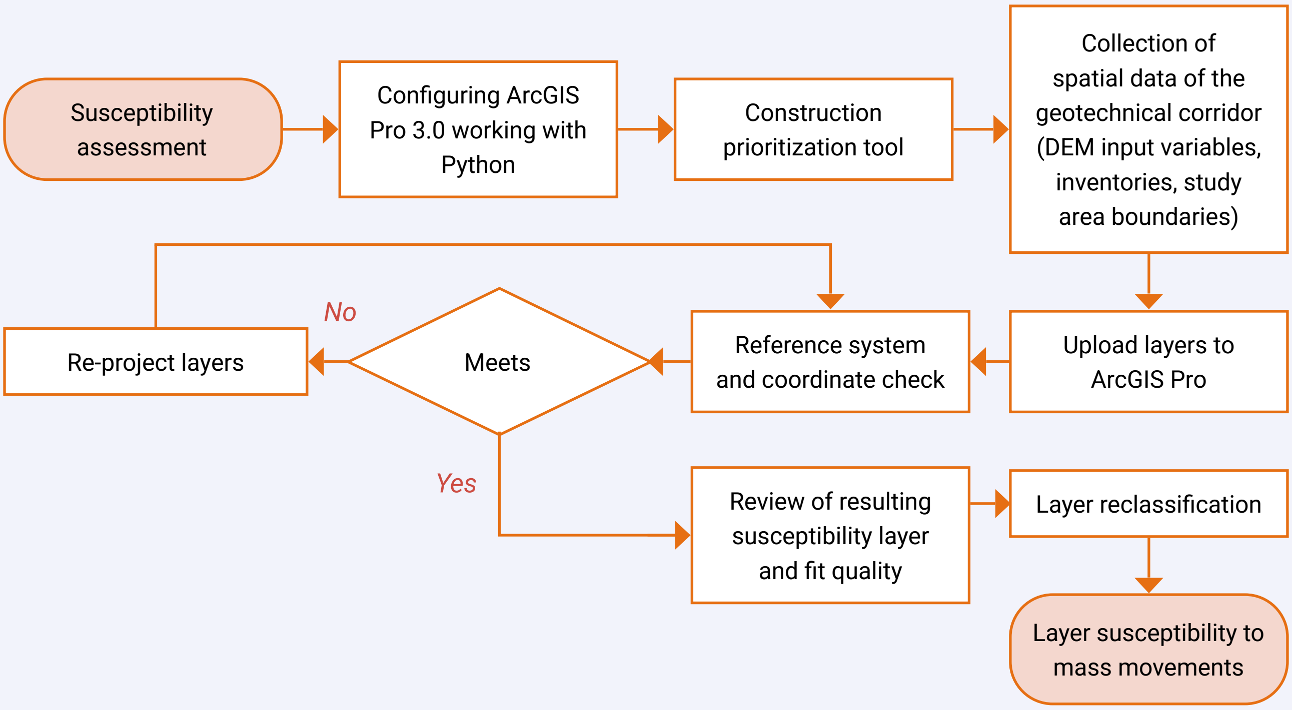
Alejandro Blandón-Santana, Carlos Arturo García-Ocampo and Pedro León García-Reinoso, Universidad del Quindío, Armenia, Colombia

Project overview: The Popayán to Mazamorras River road is vulnerable to landslides and mass movements due to its geological and topographical conditions. This project aims to develop an ML-based methodology to assess and map susceptibility to mass movements along the corridor using geographic information systems (GIS) and discriminant analysis. Traditional susceptibility assessments often rely on expert judgment, which introduces subjectivity. The use of ML techniques automates and enhances the accuracy of risk assessment by reducing human bias and ensuring data-driven classification. By incorporating topographical, geological, vegetation and infrastructure variables, the model objectively identifies unstable zones and generates susceptibility maps. The project leverages ArcGIS Pro for geospatial processing and Python-based ML algorithms for classification, assigning areas into low-, medium- or high-risk categories. This methodological shift improves risk assessment consistency, enabling more reliable decision-making for disaster prevention and road infrastructure management (Smith, Goodchild and Longley, 2018).

Description: A workflow (Figure 3) and tool programmed in Python, developed within the ArcGIS Pro environment, employs linear discriminant analysis (LDA) to classify terrain susceptibility to mass movements. The tool improves upon traditional methods by integrating geospatial data and ML techniques for a data-driven, automated risk assessment approach.

Unlike traditional GIS-based assessments, which often involve manual weight assignments, this ML-based approach objectively analyses multiple environmental factors including: a) topographical factors: slope, curvature and orientation; b) geological conditions: rock type and fault proximity; c) vegetation coverage; d) infrastructure influences: roads and drainage networks. By automating the classification process, the model minimizes subjective judgment, ensuring a consistent, repeatable evaluation of mass movement susceptibility. Additionally, automation reduces processing time, allowing for more-frequent updates and improved scalability across different road corridors.

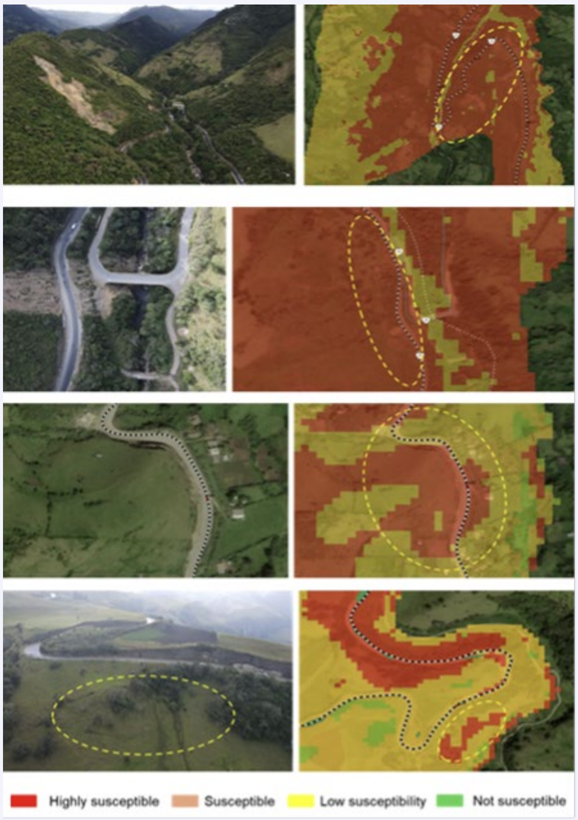
Figure 3. Flow diagram of the implementation of the methodology using the script



Perspective: This methodology represents one of the first ML-based landslide susceptibility mapping efforts in the region, offering valuable insights for infrastructure planning. By automating the risk assessment process, the tool enables more-accurate identification of high-risk zones, ensuring that vulnerable areas are properly recognized and addressed. It also facilitates the efficient allocation of resources for disaster risk mitigation, allowing the authorities to prioritize interventions where they are most needed (França, 2012). Additionally, the methodology has the potential for broader application in similar road corridors across Colombia, contributing to a more comprehensive approach to landslide prevention and management. The Python-automated framework allows for future enhancements, including the incorporation of more advanced ML models and real-time geospatial data updates to further improve the accuracy and responsiveness of risk assessments.

Type of AI/ML used: The project employs LDA, a supervised ML technique used for classification. This method is implemented using scikit-learn within Python and integrated into ArcGIS Pro for spatial analysis. LDA was selected for its ability to separate stable and unstable areas based on multiple predictor variables, including slope (PEND), curvature (CURV), orientation (ORIE), flow accumulation (ACUM), geology (GEOL), geomorphology (GEOMR), vegetation coverage (COBERR), and proximity to faults (DFAL), roads (DVIA), and drainage networks (DDRE), ensuring a data-driven classification approach. Unlike heuristic methods that rely on expert weight assignments, LDA systematically evaluates relationships between these terrain attributes and susceptibility, providing a more objective and reproducible risk assessment framework. Additionally, LDA provides clear interpretability, allowing researchers and decision makers to understand which factors contribute most to mass movement risk. The integration of Python libraries streamlines the model's execution, enhancing reproducibility and efficiency in geospatial analysis (Baeza and Corominas, 2001).

Figure 4. Field verification of areas susceptible to mass movements



Best practices:

- Institutional consideration: The National Roads Institute (INVIAS) follows a structured risk management framework. This project aligns with its efforts to transition from a reactive to a proactive disaster management approach (Law 1523 of 2012).

- Advancing risk knowledge: Previously, risk assessment relied on manual GIS workflows with limited automation. The integration of ML into GIS-based susceptibility mapping improves decision-making, reduces processing time and increases reliability.

- Standardized classification methodology: Areas were classified as having low, medium or high susceptibility based on: a) statistical thresholds derived from the discriminant analysis results; b) field verification and comparison with historical landslide occurrences; c) expert validation from geotechnical specialists. This classification ensures that susceptibility levels are data-driven rather than subjectively assigned (Aristizábal-Giraldo, Vásquez Guarin and Ruíz, 2019).

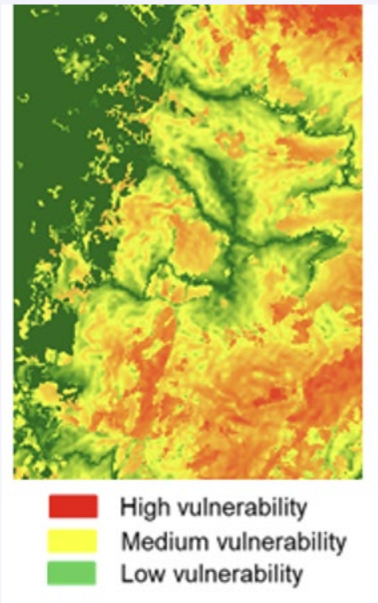
Lessons learned: The adoption of ML-based methods for landslide susceptibility mapping introduced both advantages and challenges. One of the primary challenges was ensuring the availability and accuracy of topographical, geological and infrastructure data, as inconsistencies in input data directly affected the model's predictive performance. Despite these limitations, transitioning from manual GIS modelling to a Python-automated process significantly improved efficiency, reducing human intervention and subjectivity in weight assignment. This automation allowed for faster and more-standardized assessments, making it easier to replicate the methodology across different road corridors. Model validation was another key challenge, as field verification remains essential for confirming predictions. The tool's results were cross-referenced with real-world observations and INVIAS road administrators' reports, demonstrating that 96 per cent of identified high-risk zones corresponded to known critical sections. However, the model's validation accuracy reached only 61 per cent, highlighting the need for improvements in data quality and potentially the incorporation of additional ML techniques such as ensemble models or hybrid approaches to refine predictions (Smith, Goodchild and Longley, 2018). A key lesson from this case study is that ML-based risk assessments require both robust data and institutional adaptation. While the use of Python and ArcGIS Pro facilitated automation, the full integration of ML into risk management workflows requires further capacity-building, training and policy alignment within agencies such as INVIAS. Future improvements should focus on expanding data sets, improving model interpretability and integrating real-time geospatial data to enhance predictive accuracy and adoption in infrastructure planning.

USE CASE: Zoning of vulnerability to wildfires based on fuzzy logic and AI. Procalculo Research and Development Group

Martha Patricia Valbuena Gaona MSc.

Project overview: The Colombian Institute of Hydrology, Meteorology and Environmental Studies (IDEAM) has developed a methodology for zoning the risk related to the occurrence of wildfires for a national analysis (IDEAM, 2015). When developing this methodological proposal, páramo ecosystems[6] and areas such as the Eastern Hills of Bogotá showed low vulnerability to wildfires due to their meteorological, altitudinal and ecosystem conditions.

Figure 5. Vulnerability zoning in the eastern area of Bogotá



However, extreme meteorological phenomena such as the El Niño season and human intervention meant that by the first quarter of 2024, thousands of hectares of these ecosystems were affected by wildfires, affecting the flora, fauna and populations near these areas (Cai et al., 2020).

Considering this context, a methodology based on the IDEAM methodological approach is proposed for local analysis of the zoning of vulnerability around fire occurrences.

Description: Fuzzy logic brings the computational decision process closer to human decision-making,

6 Regions above the continuous forest line, yet below the permanent snowline.

making machines more capable of handling complex problems (Novák, 2012). Fuzzy logic can be a mathematical basis for many ambiguous and inexact variables and systems. It can also provide the basis for reasoning, interpretation, control and making decisions under conditions of uncertainty (Àgueda et al., 2023). For local risk management, this methodology is ideal as it allows the modelling of multi-criteria variables, taking into account their direct influence on the phenomenon studied, on a more detailed scale, offering a higher precision (Juvanhol et al., 2021).

Why it is important: This methodology allows the study of natural phenomena at the local level so that municipal and departmental governments can take action to prevent, address and manage the risk associated with said phenomena.

Perspective: There are plans for this methodology to be extrapolated to other types of disasters, such as landslides and floods, that occur in Colombia during the La Niña phenomenon seasons.

Type of AI/ML used: ML is useful for classifying land cover, which is the main input for plant fuel analysis. In this case, three classes were obtained: grasslands, forests and bare soil. The second variable corresponds to the temperature of the Earth's surface, for which a Landsat 8 image was used. The image bands were downloaded from the USGS EarthExplorer, and the brightness temperature and emissivity were calculated (Andrés-Anaya, 2019).

The topographic analysis was developed using a digital elevation model (DEM), provided by the Alaska Satellite Facility (ASF). With this DEM, a slope raster was calculated for the third variable. DEMs are commonly used in hydrological and geomorphological analyses, but the impact of terrain height in assessing wildfire vulnerability has also been highlighted (Kanga Tripathi, and Singh, 2017).

The CNN, based on deep-learning methods, has produced advances in extracting information from various data sources that can be represented and structured as satellite images (Maxwell et al., 2023). Taking advantage of Planet's high-resolution imagery, using deep-learning models allowed the extraction of paths for multi-criteria analysis.

The fourth variable was related to road accessibility, thus including the impact of human presence on the occurrence of wildfires. Latin samples were used to train the deep-learning algorithm for road extraction. This model is based on a scheme that can encode the road network graph into a three-dimensional tensor. This scheme enables a simple neural network model to be trained to map satellite images onto the road network graph. The construction of the graphs is focused on segmentation with CNN and detecting edges and vertices (He et al., 2020).

Figure 6. Historical FIRMS fires, Bogotá

Best practices: The high-resolution imagery selected was Planet Scope. With three metres of spatial resolution, eight bands in the electromagnetic spectrum and daily temporal resolution, this type of image allows constant monitoring of the territory on a detailed scale and with the possibility of generating a deep spectral analysis.

Regarding the algorithms, support vector machines are proposed, corresponding to a supervised classifier known as one of the main ML classifiers that have achieved outstanding classification results (Ashiagbor et al., 2020). Seventy per cent of the samples were used for model training and 30 per cent were used for validation. Based on the classification, each cover type was classified into a threat category to generate the plant fuel variable.

Lessons learned: The vulnerability zoning results are compared with historical wildfire data information in the resource management system (NASA FIRMS). It is concluded that there is a 91 per cent spatial correlation between the areas of greatest vulnerability and the greatest occurrence of fires in the study area (the Eastern Hills of Bogotá).

USE CASE: Management of water resources in El Niño and La Niña phenomena based on multi-temporal analysis of satellite images

Martha Patricia Valbuena Gaona MSc.

Project overview: La Niña and El Niño are cyclical phenomena that periodically affect Latin America and generate abrupt consequences on the state of water bodies. Floods and droughts are increasing due to global warming, which exacerbates the effects of these natural meteorological phenomena (Cordero et al., 2024). With warmer climatic conditions, projections suggest that changes in the different components of the water cycle will continue, although there are uncertainties about the occurrence of droughts and floods (Moreno Rodríguez, 2020).

Remote sensing offers a wide set of data related to the state of water bodies. By combining this information with meteorological data, it is possible to develop models that allow national and local governments to predict the behaviour of water bodies during each of the seasonal phenomena (Niño and Niña).

Description: Neural networks are a type of AI model designed to recognize complex relationships between variables and make predictions based on patterns in data (Vega, Barco and Hidalgo, 2024). In this project, neural networks are employed to analyse meteorological and seasonal variables alongside remote sensing data to predict changes in the San Rafael Reservoir area. The reservoir, located near Bogotá, Colombia, is a key component of the Chingaza water supply system, which provides approximately 80 per cent of Bogotá's potable water. It plays a crucial role in ensuring water availability, especially during maintenance periods or emergencies when other sources may be compromised.

To model these fluctuations, the water mirror area was extracted using satellite images and ML techniques for coverage classification. This approach ensures an accurate representation of the reservoir's dynamics, allowing authorities to anticipate water shortages and manage resources proactively.

Perspective: This methodology will be extrapolated to other bodies of water, both lentic and lotic, to manage, address and prevent the occurrence of disasters such as floods and droughts.

Type of AI/ML used: The San Rafael Reservoir is located near Bogotá, Colombia, and plays a vital role in the city's water supply system. It is crucial for providing water during maintenance periods and emergencies, although it has faced challenges with low water levels in recent years. The reservoir is part of the Chingaza system and supports the surrounding ecosystem. Its natural beauty also makes it a notable recreational area.

Deep neural networks learn predictive relationships by using a series of non-linear layers to construct intermediate feature representations (Lim and Zohren, 2021). In this study, neural networks allow meteorological variables such as precipitation, temperature, seasonal phenomena (Niño or Niña) and date to be associated with the area of water bodies.

On the other hand, to calculate the area of water bodies, the Object-Based Image Analysis (OBIA) approach to classification was implemented, which provides advantages over pixel-based techniques, such as greater precision in the classification of coverage. The OBIA approach consists of two phases, segmentation and classification, which are carried out to obtain the most significant objects in the image and to be able to categorize the elements into the previously defined classes (Ettehadi Osgouei, Sertel and Kabadayı, 2022). This classification takes into account the objects' spectral response and adds variables such as size, shape and homogeneity to the analysis.

Best practices: Near-infrared spectral information is required for the extraction of water bodies since this spectrum presents the greatest differential response in multispectral images. Information is extracted from the NASA Prediction Of Worldwide Energy Resources (POWER) project and derived from satellites such as Climate Hazards InfraRed Precipitation with Station (CHIRPS) for the meteorological data that are part of the independent variables. The CHIRPS data set is a long-term precipitation record developed for trend analysis and seasonal monitoring of rainfall and drought. The data set was validated in several regions in a global-scale analysis and provided satisfactory monthly, seasonal and annual precipitation variability (Ocampo-Marulanda et al., 2022). These data have global coverage, and when comparing temperature data with the IDEAM meteorological stations, there is a correlation of 85 per cent.

Lessons learned: By integrating remote sensing and AI techniques, it is possible to model up to 87 per cent of the behaviour of water resources. This type of model implemented by the national and local governments allows water resource management for the prevention, attention and management of phenomena such as droughts and floods that are a product of climate change and their effects on seasonal phenomena (e.g. La Niña and El Niño).

Figure 7. Water body area in February 2023

Source: Colombia, Cundinamarca 2024. Planet Labs PBC. All rights reserved. 2024.

Figure 8. Water body area in March 2024

Source: Colombia, Cundinamarca (2024). Planet Labs PBC. All rights reserved. 2024.

USE CASE: Leveraging AI/ML in Google Earth Engine for soil use classification and risk monitoring in Bolivia

Fernando Arturo Ledezma Perizza[7]

This document, along with its code methodology and results, establishes a robust framework for employing AI/ML in environmental monitoring, promoting sustainable land-use practices and enhancing resilience against natural hazards in Bolivia.

Description: This document explores the application of AI and ML techniques within Google Earth Engine to classify soil use types in Bolivia. The approach utilizes Landsat 8 satellite imagery processed through Google Earth Engine, applying a “Random Forest” classifier to categorize land-cover types such as urban areas, vegetation, water bodies and grasslands.

Why it matters: Accurate land-cover classification is crucial for monitoring risks such as wildfires, deforestation and the environmental impacts of urban expansion. In Bolivia, where diverse ecosystems are vulnerable to climate change and human activities, precise monitoring using AI/ML can support timely intervention and sustainable resource management.

Outlook: The integration of AI/ML with Google Earth Engine offers scalable and efficient tools for environmental monitoring and risk management. Future advancements could enhance classification accuracy and expand the scope of applications in biodiversity conservation and disaster response.

Type of AI/ML used: The project employs supervised learning, specifically the Random Forest algorithm, for land-cover classification. This method has been chosen for its robustness in handling multispectral satellite data and its ability to classify complex landscapes with high accuracy.

Best practices:

- “Feature Collection” fusion: Combine urban, vegetation, water and grassland feature collections into a unified data set for classifier training.
- Quality assessment: Employ error matrices and accuracy assessments to validate classification results and refine model performance.
- Temporal analysis: Incorporate multi-temporal satellite imagery to dynamically monitor land-cover changes over time.

Lessons learned:

- Data pre-processing: Effective pre-processing, including image masking and band scaling, is critical for enhancing classification quality.
- Model tuning: Iterative adjustment of classifier parameters and band selection can

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significantly improve accuracy and reduce overfitting.

- Community engagement: Collaborative efforts with local stakeholders ensure AI-driven solutions are contextually relevant and applicable.

Methodology: The methodology follows a structured workflow for land-cover classification using Landsat 8 imagery and a Random Forest classifier. It begins with pre-processing, including masking, calculating median composite and defining feature sets and bands for classification. Training data are then generated to develop the model, followed by training the Random Forest classifier and classifying the composite image. Finally, the classified image is displayed, and accuracy is assessed through evaluation metrics, including a confusion matrix, to ensure the classification results are reliable.

Figure 9. Step-by-step workflow of the AI/ML-based land-cover classification methodology in Google Earth Engine

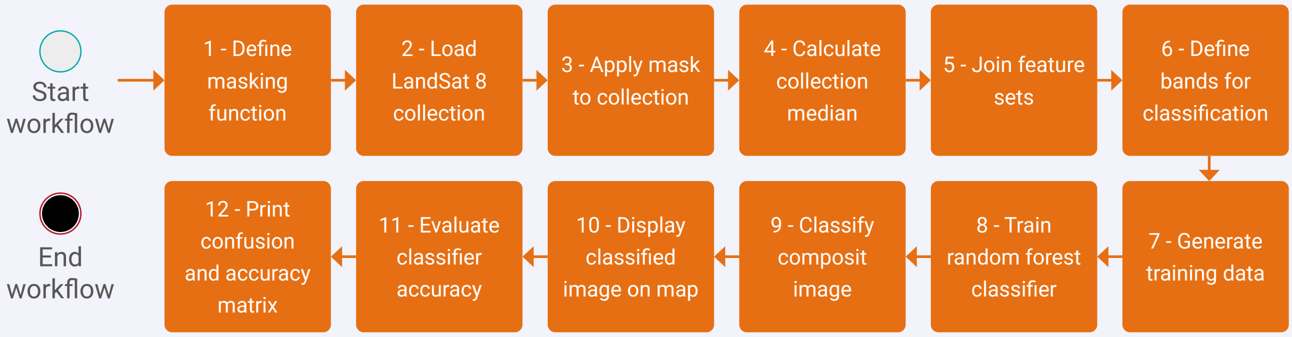
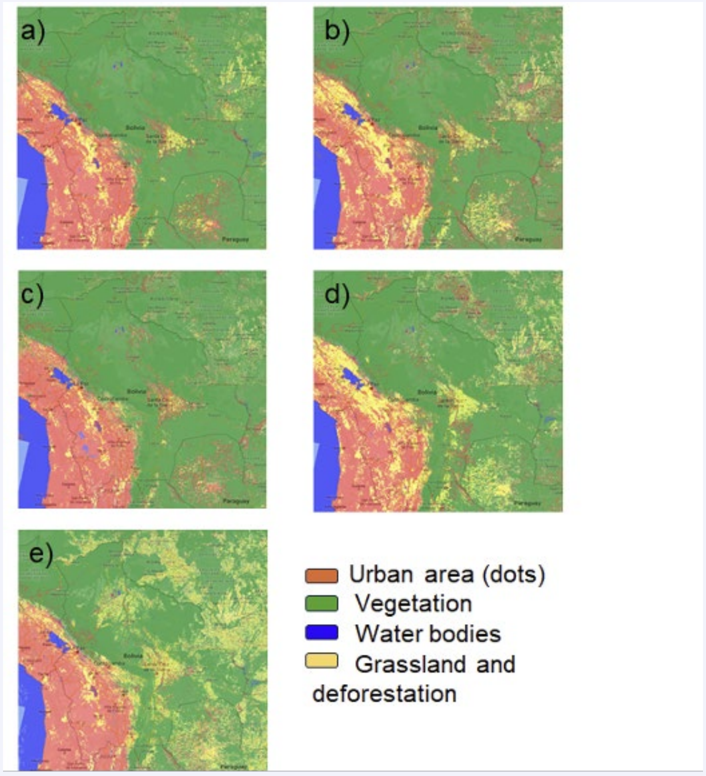


Figure 10. Inter-annual soil use classification results 2019–2023 for Bolivia



Source: Google Earth Engine

Figure 10 presents the annual classification results of soil use in Bolivia from 2019 to 2024, categorized into four primary land-cover types: urban areas, vegetation, water bodies and grasslands.

- Subfigure 10 a (2019): Illustrates the soil use classification for the year 2019, showing the distribution of urban areas, vegetation, water bodies and grasslands and deforestation.

- Subfigure 10 b (2020): Displays the classification for the year 2020, highlighting changes and trends in land cover compared with the previous year.

- Subfigure 10 c (2021): Represents the classification results for 2021, indicating further developments in land-use patterns.

- Subfigure 10 d (2022): Shows the classification for 2022, reflecting ongoing shifts and modifications in the land-cover types.

- Subfigure 10 e (2023): Depicts the classification for 2023, demonstrating the continued evolution of soil use in Bolivia.

Each subfigure includes all the land-cover types (urban areas, vegetation, water bodies and grasslands), providing a comprehensive view of how soil use has changed annually. The high classification accuracy, consistently above 0.998, underscores the reliability of the Random Forest classifier utilized in this study.

These visualizations are crucial for understanding the dynamic changes in Bolivia's land cover and aiding in environmental monitoring, resource management and strategic planning for sustainable development.

Conclusion: This methodology using AI/ML in Google Earth Engine critically supports monitoring risks in Bolivia by accurately classifying soil use types and detecting land-cover changes. It enables early detection and response to natural hazards, assesses environmental impacts, aids in climate change adaptation and supports sustainable resource management. The insights generated empower decision makers with timely information for policy formulation and disaster preparedness, while also engaging local communities in monitoring efforts to enhance resilience and awareness. Overall, this approach contributes to proactive environmental management and effective risk reduction strategies in Bolivia.

USE CASE: Large-scale building damage assessment using a novel hierarchical transformer architecture on satellite images

Dr. Ali Mostafavi

Project overview: The building damage assessment project presents DAHiTrA, a novel deep-learning model using hierarchical transformer architecture to classify building damage extent from satellite imagery in the aftermath of disasters. Utilizing hierarchical transformers, this innovative approach extracts spatial features of multiple resolutions and captures temporal differences to achieve state-of-the-art performance in building damage classification. The project introduces the Ida-BD data set, related to the 2021 Hurricane Ida, to demonstrate model adaptability with limited fine-tuning, enabling effective damage assessment in data-scarce scenarios. DAHiTrA's primary focus is on supporting rapid and accurate post-disaster assessments to assist efficient emergency response.

Description: This project aims to enhance the accuracy and efficiency of post-disaster building damage assessment using satellite imagery. The proposed method addresses the complexity of directly concatenating features for damage localization by focusing on the differences between pre- and post-disaster images. To achieve meaningful and unbiased assessments, the method employs difference blocks to map features onto a common domain, accommodating variations in lighting and weather conditions. Utilizing a hierarchical U-Net-based structure, the network captures features at multiple resolutions, forming a detailed hierarchy to accurately classify and localize damage. The proposed network achieves state-of-the-art performance on a large-scale disaster damage data set (xBD) for building localization and damage classification, as well as on the LEVIR-CD data set for change detection tasks. In addition, the project introduces the Ida-BD data set, containing high-resolution images from Hurricane Ida, to test and refine the model's adaptability to new disaster scenarios. This work demonstrates the effectiveness of the proposed method through transfer learning. Figure 11 shows the building damage assessment results of the proposed method on the Ida-BD data set.

Figure 11. Building damage assessment results on the Ida-BD data set

Why it matters: This project is significant for its potential to optimize emergency response efforts following disasters. Accurate and rapid damage assessment is critical for efficient resource allocation and timely humanitarian aid. By leveraging advanced deep-learning techniques and high-resolution satellite imagery, the outcome of this project can significantly improve the resilience and preparedness of affected regions, ultimately saving lives and reducing economic losses. For stakeholders, including government agencies, NGOs and disaster response teams, DAHiTrA offers a powerful tool to inform and streamline their operations, ensuring a more effective and coordinated response to natural disasters.

Outlook: In future work, the architecture's applications could be extended to other civil infrastructure assessments, such as road damage classification, structure change detection and urban land-cover change classification. Sustainability efforts will focus on continuous model improvement and data set updates to address emerging disaster patterns and infrastructure needs.

Type of AI/ML used: The DAHiTrA model utilizes a combination of vision transformers (ViTs) and U-Net architectures for change detection in satellite images. ViTs capture global context and long-range dependencies in pre- and post-disaster images using self-attention mechanisms, while U-Net excels in multiresolution feature extraction and precise image segmentation through its encoder-decoder structure with skip connections. This synergy enables the model to accurately classify and localize building damages.

Best practices: Ensuring consistent pre-processing of satellite images, including normalization and alignment, is crucial to mitigate variations caused by different lighting, weather conditions and imaging sources. The model training process should begin with a large data set, followed by the application of transfer learning techniques and fine-tuning with targeted data sets to enhance adaptability and performance in new disaster scenarios.

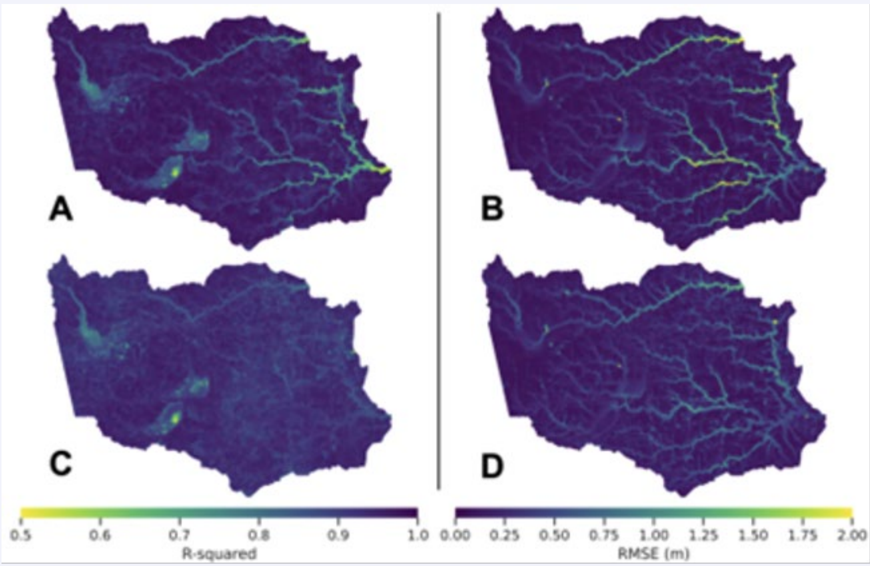
Lessons learned: For building damage extent assessment, model accuracy differs among different damage extents because of imbalanced data or difficulty in detecting differences. Serious unaligned data also cause decreases in performance. Nevertheless, the model is expected to perform fairly well across different regional contexts.

USE CASE: MaxFloodCast: Ensemble machine learning model for predicting peak inundation depth and decoding influencing features

Dr. Ali Mostafavi

Project overview: This project aims to provide accurate and interpretable flood inundation predictions using an innovative ensemble ML approach. It develops the MaxFloodCast model, which integrates physics-based hydrodynamic simulations with ML techniques, particularly XGBoost, to predict peak inundation depths in flood-prone areas. The model is validated against historical flood events, including Hurricane Harvey and Tropical Storm Imelda (see Figure 12), demonstrating its ability to deliver reliable predictions with reduced computational costs.

Figure 12. Test R-squared and RMSE of experiments 1 - A,B and 2- C,D



Description: The primary goal of this project is to predict peak inundation depths accurately while providing interpretable insights into the factors influencing flood risks. By incorporating rainfall data and leveraging a grid-based representation of the study area in Harris County, Texas, the project addresses the challenge of computational inefficiency associated with traditional hydrodynamic models. The validation process involves comparing model predictions against historical flood events to assess performance. The project's innovative approach lies in its ability to reduce computational costs significantly, enabling near-real-time predictions that can inform emergency response and floodplain management strategies while maintaining model interpretability and adaptability across different regions.

Why it matters: The significance of this project lies in its ability to address the critical need for timely, accurate and interpretable flood predictions, which are essential for effective emergency response and flood risk management. By significantly reducing the computational cost and time required for flood modelling, the project enhances the capabilities of stakeholders in anticipating and mitigating flood impacts. The broader implications for stakeholders include improved floodplain management, enhanced resource allocation during emergencies and the potential for adapting the model to other flood-prone regions, thereby contributing to more-resilient and better-informed communities.

Outlook: The long-term benefits include the potential for widespread adoption of the model by municipalities and regions prone to flooding, facilitating proactive and data-driven flood management strategies. Sustainability efforts will focus on ensuring the model remains adaptable to changing environmental conditions and urban developments, which can alter flood dynamics. However, potential challenges include the need for continuous data updates. Despite these challenges, this project holds significant potential for enhancing resilience and supporting sustainable urban planning and disaster preparedness.

Type of AI/ML used: This project employs a combination of AI and ML techniques, specifically utilizing the XGBoost algorithm, which is known for its robustness and efficiency in handling large data sets. XGBoost is a gradient-boosting framework that constructs predictive models by combining the strengths of multiple decision trees to improve accuracy and reduce overfitting . The input features include rainfall data, as well as topographic and hydrological features (such as imperviousness and height above nearest drainage). This technique is particularly well-suited for the MaxFloodCast project as it enables the model to capture intricate relationships between various environmental features, such as peak and cumulative precipitation, and their impact on flood inundation.

Best practices: In model training, employing a large and diverse set of simulation events and features, including peak and cumulative precipitation data, is crucial for capturing the complexity of flood dynamics. Engaging users, such as emergency managers and urban planners, early on in the development process is vital to tailor the model's outputs to their specific needs and ensure its practical applicability. Additionally, developing intuitive tools that present model results in an interpretable format fosters greater trust and adoption among stakeholders, enabling more informed decision-making in flood risk management.

Lessons learned: One major takeaway is the importance of high-quality, high-resolution data in achieving accurate flood predictions; the use of physics-based hydrodynamic simulations combined with ML significantly enhances the model's precision. Another important lesson is the necessity of continuous user training and engagement to ensure that stakeholders can effectively interpret and utilize the model's outputs in real-time decision-making. Adopting this model in other regions would require some baseline models (H&H models) for evaluating the model's performance in a new context.

USE CASE: Proactive disaster risk mitigation using year-ahead alerts with actionable analytics

Subarna Bhattacharyya

Description: Climformatics is an early warning system decision support tool that provides year-ahead alerts with actionable analytics built using ML to make highly accurate climate predictions at the 2–3 km^2 scale covering the coming 6–12 months. These tools span the interface between weather and climate, and can be as accurate for any given day many months ahead as the traditional nightly weather forecast for that day.

- Technology bridges the gap between weather and climate: This predictive tool offers localized climate and weather forecasts with high accuracy, covering time frames ranging from near-term to long-term and scales as fine as <30 km. By leveraging cutting-edge technology (Bhattacharyya and Ivanova, 2017), it applies data science and ML methods to large-scale physics-based climate model data sets. It addresses gaps in subgrid scale processes that are not yet captured by traditional weather and climate models. This system provides highly localized climate predictions on various timescales, from hourly to seasonal and even up to one year in advance, for applications such as solar power, net load, fire weather, heatwaves and localized climate trends.

- This solution enables energy and utility companies to model capacity with precision, anticipate climate-related disasters, proactively mitigate risks and improve long-term sustainability and profitability. The technology is globally scalable across various sectors, including agriculture, renewable energy and water resources management.

- These data products include an early warning system to support utility companies' decision-making, hourly solar power forecasts for modelling reductions in load due to behind-the-meter solar production, and actionable climate-smart insights for proactive risk resilience and energy efficiency. CTOs could utilize these products to optimize operations and support informed decisions. By forecasting extreme weather events at regional and hyperlocal levels, this tool complements existing energy and disaster preparedness market technologies, and there are plans for future integration that will not disrupt business operations.

Why it matters: Current operational weather and climate forecasts, as well as future climate projections modelled on future greenhouse gas emissions, have limitations in accuracy and predictive ability. Moreover, these forecasts are more general and cannot be used to make actionable decisions on the anticipated nature, location and time of occurrence of the natural climate disaster sufficiently in advance. A modern, more forward-looking model is needed for proactively mitigating the risks of natural climate hazards. AI will allow a much more accurate appraisal for the coming year of seasonal factors such as rainfall and heat (driving drought, wind, flood and wildfire risk, and heat stress on people, livestock and the energy grid), and also seasonal food supply. This will enable months of advanced warning and preparation, for example in stockpiling supplies and pruning vegetation near power lines in high-risk locales, that could well attenuate what would otherwise have been a bigger disaster.

Benefits: These tools have a strategic focus on "holonomic" solutions, which tackle critical challenges in sustainable energy, water management, food resilience and food security. Such advanced climate prediction tools empower communities and industries to thrive by offering "climatization" solutions for proactive risk mitigation, improved resource management, and sustainability, leading to broader societal benefits. Specifically, these solutions offer three primary benefits:

- Disaster mitigation and improved efficiency: This tool enhances efficiency across multiple sectors and dimensions by providing unique insights into the future, enabling more-precise investments and optimized operations. This reduces redundancies and costs, improves supply chain management and lowers emissions, leading to cost savings in energy generation and optimized agricultural productivity.

- Emission reduction: By facilitating greater penetration of solar and green energy, the tool contributes to lower electricity/energy prices, benefiting economically disadvantaged communities.

- Sustainability: Climformatics is committed to enabling customers achieve the three pillars of sustainability: economic growth, environmental protection and social equity.

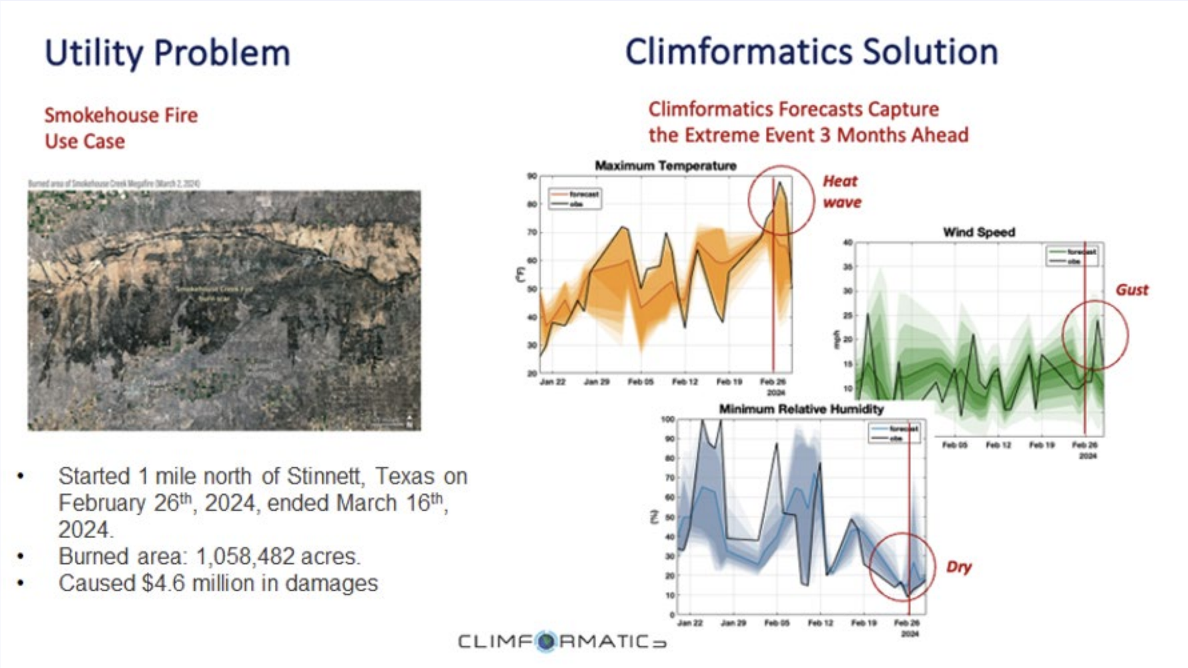
Outlook: We need a forecast tool with increased spatial granularity and temporal range (for improved accuracy for any given locale or day) and increased integration with background data (for example, soil saturation to help assess run-off, or vegetation types and levels to help assess wildfire risks) to predict the possible localized consequences of the weather in question. With such a tool, we could have alerted authorities well in advance about the risk of a hurricane over Maui, considering the potential fire weather conditions, to mitigate the risk and prevent the loss of lives, trauma and devastation similar to the 2018 Camp Fire that devastated Paradise, California, as well as the 2025 Los Angeles fire in Eaton, California. This tool is now available. We can warn communities and governments about upcoming extreme climate events including heatwave, fire weather, drought or severe rainfall coming their way at their business and community locations, not days but months, seasons or a year in advance. This will enable proactive measures to "climatize" operations, protect businesses and communities against interruptions and prevent loss of lives, livelihoods and properties.

Type(s) of AI/ML used: Several applied mathematical and statistical tools together with machine and deep-learning tools such as artificial neural networks have been used.

- *Use case validation of these models:*

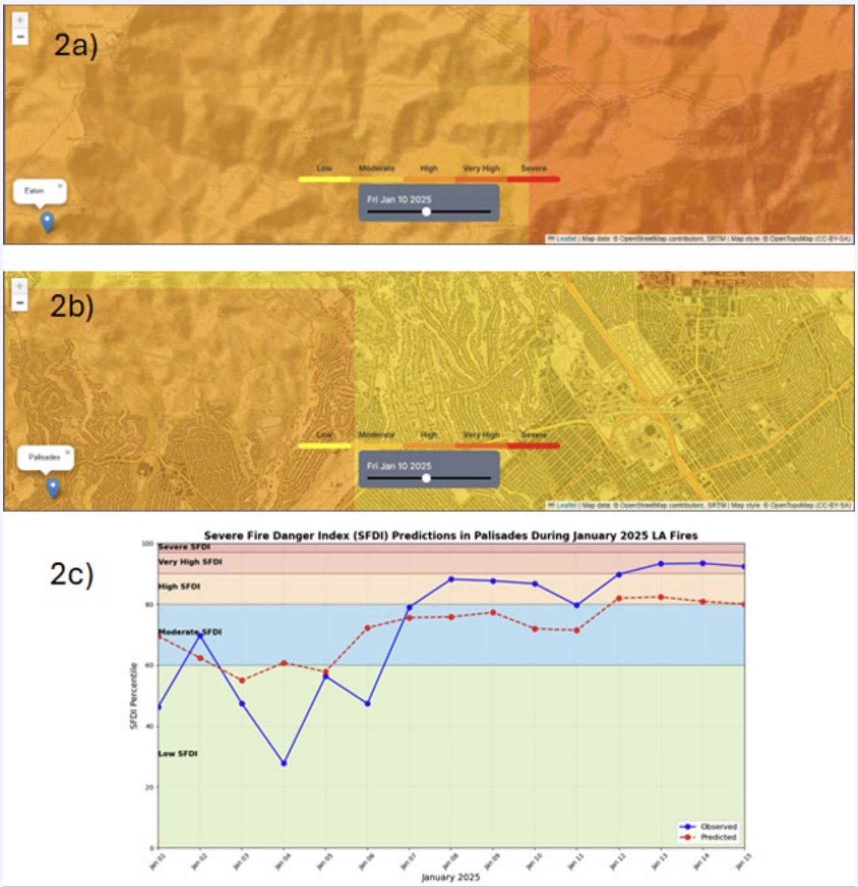
2024 Texas Smokehouse Creek Fire: At the request of one of our Climformatics partners, we validated our technology solution in a case study of the largest fire in the history of Texas – the Smokehouse Creek megafire. It began on 26 February 2024, near Stinnett, Texas, and was contained on 16 March 2024, after burning 1,058,482 acres and causing $4.6 million in damages and over $200 million in lawsuits. We produced three-month probabilistic forecasts of daily fire weather variables, including temperature, relative humidity, wind speed and the Fosberg Fire Weather Index (FFWI) for four locations in the vicinity of the Smokehouse Fire: Stinnett, Pampa, Canadian and Seiling, Texas. The figure demonstrates that Climformatics forecasts were able to capture the extreme weather event at the time of the Smokehouse Fire incident three months in advance. Our analysis shows that there was a four-day (25–29 Feb 2024) heatwave with anomalously high temperatures for the season in the range of 75–90°F. The relative humidity dropped to ~20 per cent. These, combined with gusts of over 20mph, created conditions of extreme fire danger. Climformatics forecasted both the heatwave and the extreme fire danger (see Figure 13).

Figure 13. Climformatics Early Alert System Technology could have predicted the Texas Smokehouse megafire in 2024 at least three months ahead



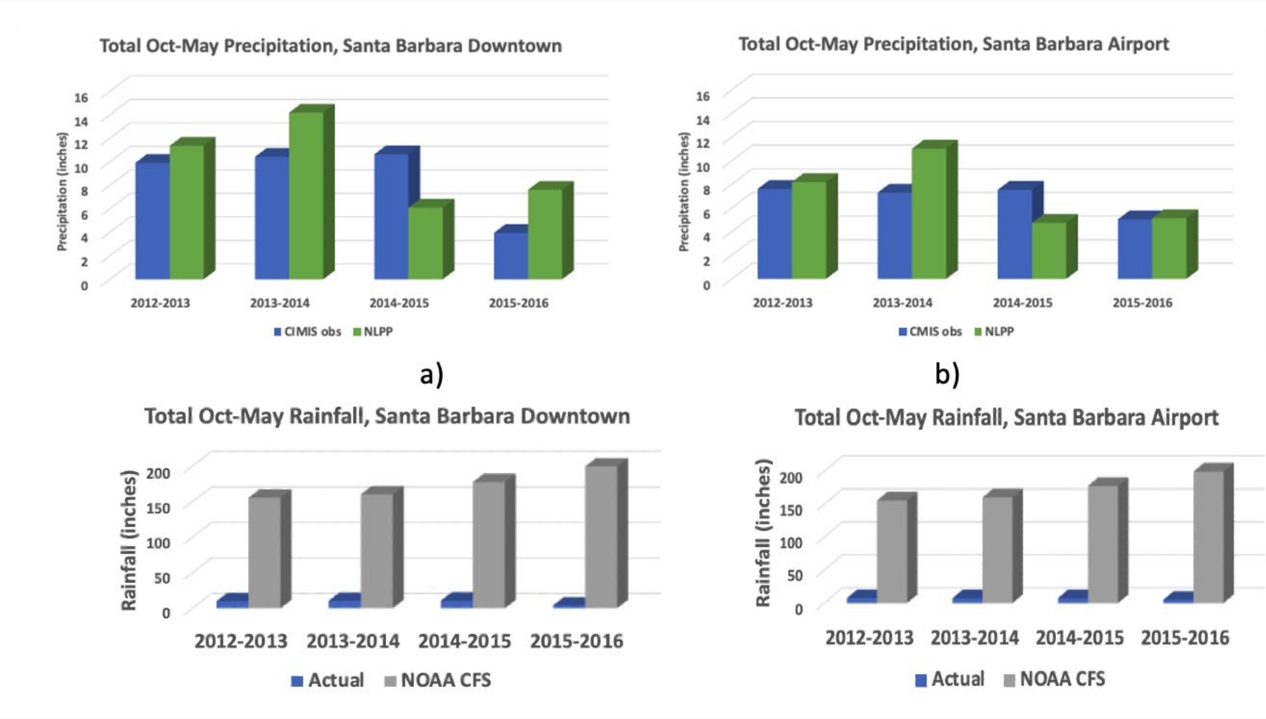
2025 Los Angeles Fires: The 2025 Southern California Wildfires started on 7 January 2025 and were contained on 31 January 2025. The fires covered the areas of Palisades and Eaton, California, resulting in 29 casualties (17 in Eaton and 12 in Palisades). The Palisades fire covered 23,707 acres, destroying 6,837 structures and damaging an additional 1,017. The Eaton fire burned 14,021 acres, destroying 9,418 structures and damaging 1,073. Economic losses totalled around $250 billion, with an estimated $35–45 billion in insurance payouts. The Climformatics tool could have predicted such high fire risk at least a month ahead in this case with great actionable accuracy. (See Figure 14)

Figure 14. The Climformatics Fire Weather Prediction tool could have forecasted the High Fire Weather Index on 10 January 2025 for Eaton (see map in 2(a)) and Palisades (see map in 2 (b)). Figure 14 (c) shows the forecasted Severe Fire Danger Index for Palisades for 10 January 2025 as compared to observations.



- Precipitation prediction validation: This technology was extensively tested and validated with monthly frequency time series of precipitation and temperature for 2011–2016 in 300 ZIP Codes across California's agricultural areas. A comparison in Figure 14 demonstrates the accuracy of NLPP (Near-to-long-term Precipitation Prediction) compared with CIMIS (California Irrigation Management Information Systems) observations and retrospectively National Oceanic and Atmospheric Administration (NOAA) nine-month forecasts for seasonal rainfall in two locations 8.4 miles apart in Santa Barbara, CA. This example demonstrates that the current NOAA CFSv2 predictions are not capable of resolving the variety of microclimates, i.e. NOAA's forecasted rainfall amount for the two locations in Santa Barbara was the same, and it also considerably overestimated the actual rainfall by about 170 inches/season. Climformatics' predictions for the same locations are dramatically improved, with errors of about 4 inches/season.

Figure 15. Comparison of seasonal (Oct–May) total precipitation (inches) between CIMIS observations/actuals (blue), NLPP forecast (green) in: a) Santa Barbara, CA – downtown; b) Santa Barbara, CA – airport; c) same as a); d) same as b) but for CIMIS (blue) and NOAA-CFS forecast (grey) [Note the scale difference].



Best practices: Current catastrophe risk modelling applied to disaster preparedness is backward-looking since it is often based on legacy risk models that use long-term historical data. Best practice will increasingly be a forward-looking emerging catastrophe risk model that can additionally capture the physics of the ever-changing weather and climate conditions.

Lessons learned:

- AI and physics-based models can be especially powerful.
- Such efforts require large-scale computational resources in order to scale from smaller regions to global locations and may become computationally expensive.
- There are many potential data sources, but data need to be sourced with care. Quality and veracity, even of government data sets, is subject to variation.
- Tools such as this may need to be substantially tailored for each use case and customized further for each customer.
- These tools will also need to be easy to use and easily adaptable for feeding into any existing business decision support tool that the customer may be using.
- The use of AI in no way replaces forecasting expertise – skill and experience is still required to assess the outputs and frame the requisite actions as a result.
- With climate-driven catastrophes on the rise across different parts of our planet, communities and businesses may be more amenable to using such a proactive risk mitigation tool.

USE CASE: Building attribute prediction in hazard modelling: Using machine learning to classify residential buildings for hazard mitigation and disaster response

Mike DePue

Ricky Passarelli

Description: AtkinsRéalis developed an ML approach using aerial photography to classify building attributes for residential structures in Puerto Rico and the US Virgin Islands. This initiative supports the Federal Emergency Management Agency (FEMA) in creating a detailed building inventory to be used in Hazus, a software for hazard mitigation planning and disaster response analytics. The project employed two methodologies: a boosted regression tree model (BRTM) and a convolutional neural network (CNN), which were trained using remotely gathered aerial imagery and building-footprint data.

Why it matters: This innovative approach allows FEMA to maintain a highly accurate and scalable building inventory that is essential for hazard modelling and disaster planning. By achieving accuracy levels comparable to manual surveys (80–90 per cent), the ML model saves significant time and resources, making it possible to assess entire building inventories efficiently. This scalable solution enables better disaster preparedness and more-accurate risk assessments, ultimately helping protect lives and property during disasters.

Outlook: With the success of this model in Puerto Rico and the US Virgin Islands, FEMA can expand the technology to other regions, including the mainland US. The ML model's scalability and accuracy demonstrate potential for broader use in hazard mitigation efforts. Future advancements in the methodology, along with improved data sources, will continue to enhance FEMA's ability to plan for and respond to disasters.

Best practices:

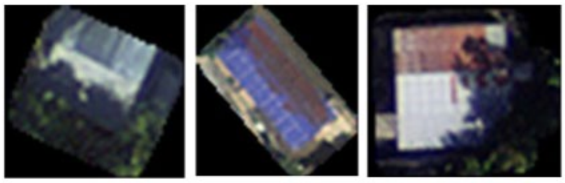
- Model selection: Combining different ML techniques like BRTM and CNN improves model accuracy and flexibility, depending on the type of data and the desired outcome.

- Remote data gathering: Using aerial imagery for data collection is both cost-effective and scalable, allowing large areas to be assessed without requiring manual surveys.

- Integration with existing systems: Integrating the ML model's output with FEMA's Hazus software ensures that the results are immediately applicable to hazard planning and response analytics.

Figure 16. Roof type predictions in Puerto Rico

Example of correct and incorrect predictions of roof type in Mayaguez, Puerto Rico



Examples of correct metal roof predictions in Puerto Rico

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Lessons learned:

Scalability: ML models can match human accuracy while being far more scalable, allowing for rapid assessments of large building inventories without manual labour.

Versatility of ML: Different ML approaches, such as BRTM and CNN, can be combined to improve the accuracy and robustness of predictions.

Support for expansion: The methodology is adaptable and can be expanded beyond Puerto Rico and the US Virgin Islands, offering FEMA the opportunity to implement similar strategies across the mainland US.

USE CASE: Assessing hurricane damage with machine learning: Predicting damage in flood zones to optimize hurricane response and aid

Mike DePue

Ricky Passarelli

Description: Substantial Damage Estimates (SDEs) help FEMA assess post-hurricane damage and coordinate recovery efforts. Traditionally, SDEs required door-to-door inspections, making the process slow and labour-intensive. The AtkinsRéalis team developed an ML model to automate SDE generation by predicting which structures in flood zones were likely to be substantially damaged. This model used a small sample of data from analytics, remote sensing and field reconnaissance to make predictions across larger areas, streamlining FEMA's recovery process.

Why it matters: This automated system drastically reduced the need for manual inspections, improving response times and focusing FEMA's resources on the most affected areas. By cutting down manual inspections to one-fifth of the total, FEMA could direct recovery teams more efficiently to help impacted communities rebuild faster. Moreover, the model provided valuable insights into the relationship between environmental factors such as flooding and wind damage, informing future disaster response strategies.

Outlook: The success of the ML model in Puerto Rico and the US Virgin Islands during Hurricanes Irma and Maria suggests that this technology can be scaled to other disaster-prone areas. As ML and data analytics continue to evolve, this approach can be refined for greater accuracy and efficiency, further reducing the burden of manual inspections. There is also potential to expand its application to other types of disasters, such as wildfires or earthquakes.

Best practices:

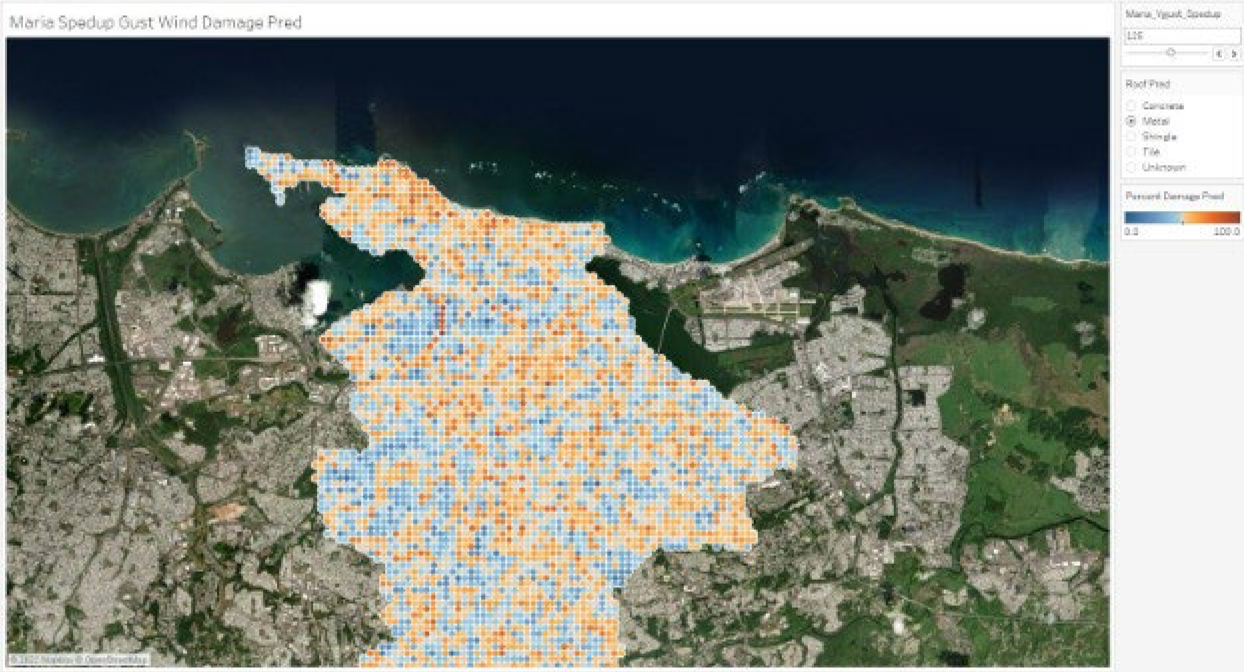
- *Data fusion:* Combining remote sensing, field data and analytics to train ML models creates robust predictions. This approach leverages multiple data types for greater accuracy.
- *Selective inspections:* Reducing the number of on-the-ground inspections by focusing only on high-risk areas saves time and resources, allowing teams to respond faster.
- *Collaboration:* Close collaboration between AI/ML experts and disaster response agencies (e.g. FEMA) ensures that the technology is aligned with real-world recovery needs.

Lessons learned:

- *Efficiency gains:* Automating damage estimates can drastically cut down on manual labour and associated costs, as seen by FEMA saving around $10 million in resources.
- *Targeted resource allocation:* Predictive modelling helps agencies prioritize where to deploy resources most effectively during recovery efforts.
- *Scalability:* While highly effective for hurricanes, the model can be adapted for other disaster

scenarios, suggesting that AI/ML is a versatile tool for future emergency management.

Figure 17. Dashboard of percentage damage predictions in San Juan, PR, using a version of the ML model (125mph shown)



Source: People Data Technology

3. Threats and challenges of AI and ML for DRR

The integration of AI technologies into DRR offers significant advancements in risk and disaster management. However, this integration also brings forth critical challenges that need to be addressed. One major concern is the lack of transparency in decision-making processes, as many AI models function as opaque "black boxes", thus hindering validation and explanation of results. Additionally, ethical issues surrounding biases or obsolescence in training data and over-reliance on technology are key considerations.

As over-dependence on AI technologies could lead to significant risks, traditional DRR methods must be integrated with technological solutions to avoid exclusively AI-driven strategies. Moreover, there are environmental impacts to consider, as the energy-intensive infrastructure required for AI technologies (especially GAI) contributes significantly to carbon footprints and climate change. This calls for sustainable implementation strategies to mitigate environmental effects. Addressing underrepresentation in AI models and safeguarding personal data against leakage are also vital considerations. Lastly, the ethical deployment of AI technologies, while being mindful of cybersecurity risks, is imperative to ensure equitable outcomes and minimize potential harm to vulnerable communities. Overall, the successful integration of AI technologies into DRR requires careful navigation of ethical, technical and societal implications to maximize benefits and minimize risks.

3.1 Understanding the black-box and white-box concepts

Castelvecchi (2016) highlighted the role of DL in future radio astronomy observatories, noting that these systems will be crucial in sifting through vast amounts of data to identify meaningful signals. He raised pertinent questions: How exactly does the machine identify these signals? How can we ensure the accuracy of its findings? These inquiries underscore the importance of understanding and trusting deep-learning processes in handling complex data tasks.

Keeping these questions in mind, AI encompasses two main model types: black-box and white-box models. A black-box model's internal workings are not readily understandable. In contrast, a white-box model, also called an interpretable model, provides clear insights into its decision-making process, making it easily understandable for the user.

Explainability: One of the issues with AI is that, as it becomes more advanced and larger-scale, perhaps incorporating billions of separate regression analyses in the case of an LLM, humans struggle to explain the output – exactly why the algorithm has produced a particular result. This "black-box" quality makes it hard to check for accuracy and freedom from bias or hallucination and ensure consistency and appropriateness in its output; it reduces accountability and impacts audibility, for example, to verify regulatory compliance. Consequently, it imposes major limitations on the extent to which AI can or should be trusted.

The set of techniques designed to address this issue is referred to as explainable AI (XAI).[8,9] They consist of:

- Checks for prediction accuracy: Checking to see how well, given the data, the AI would have explained known past events or trends (part of the implementation process), and then continuously checking for fit with actual outcomes over time to detect drift or bias, or emergent issues, for example when using the AI in novel circumstances. One technique for this is local interpretable model-agnostic explanations (LIME),[10] which show human users which features (variables) in the AI had the biggest impact on any specific conclusion.
- Traceability: With neural networks, tracing the links between each neuron and scoring its contribution to the final output. A technique for this is Deep Learning Important FeaTures (DeepLIFT).[11] This approach becomes more and more resource intensive as neural nets grow in size, and it can only be implemented retrospectively – by which time the AI may already have induced critical errors on the part of disaster managers.
- Careful scrutiny and review of the data used to train the AI: Are the data representative of the populations affected, the problems being addressed and the circumstances likely to be encountered? Are the data current? And so on. Reviewing test outcomes with affected populations for factors including completeness and acceptability.
- Education: For the team working with the AI so that its strengths and potential weaknesses are fully understood.

For now, it may be necessary to place limits on the deployment of AI technologies, especially GAI and AAI, in situations where rapid decisions are being made for instant action. Given the propensity of some AI technologies to hallucinate (see below), it would be prudent (for now) to use them in situations where there will be time to review their output before it is acted upon. Examples of safer use cases include the generation of training scenarios or inputs to logistics planning in advance of, say, a hurricane or wildfire season.

Privacy: AI will often be designed to enable connections between different data sets and items of data within them. For this reason, AI-powered marketing tools, for example, may be seen by some as an invasion of privacy. They allow detailed pieces of personally identifiable information (PII) about an individual – including aspects of their life they might prefer to keep private – to be linked together, forming a profile that could be used for purposes without the individual's consent. This has always been a problem with IT systems, but through its power, AI exacerbates it significantly.

AI for DRR is no different. For example, if we take the hypothetical example of an AI designed to assemble data on survivors of a disaster for the purpose of assessing who may need which kind of help, this may require data on their age, address, job, family, marital and welfare status, health, financial resources, and so on. As well-intentioned as the tool might be, all of these data items present significant privacy items in isolation, and together,

8 Not to be confused with the private company of the same name.

9 A good overview of XAI can be found at https://www.ibm.com/topics/explainable-ai#:~:text=Resources-,Take%20the%20next%20step,created%20by%20machine%20learning%20algorithms.

10 See, for example https://c3.ai/glossary/data-science/lime-local-interpretable-model-agnostic-explanations/.

11 See, for example https://arxiv.org/abs/1704.02685.

they compound one another. The AI might then be rejected by the population it is intended to help.

The underlying problem goes well beyond AI, however. Effective DRR and privacy may be fundamentally at odds with each other. DRR may require specific knowledge of individuals in a specific area, to enable priorities to be determined, or resources to be allocated. Privacy, by definition, requires the opposite –that those individuals should be able to remain anonymous, and their circumstances known only to whom they choose. Resolving this tension requires a societal view in each country of where the boundaries should lie and, quite possibly, legislation to instantiate this view, which AI cannot hope to provide.

However, once these boundaries are clear, those developing AI for DRR need to take a number of steps to ensure the tools stay within those boundaries:

- Carefully review all definitions of the data items, individually and collectively, that the system will use for privacy (and legal) implications.
- Consider alternatives to personally identifiable information; will anonymized data suffice?
- At a minimum, consult with stakeholders to explain the intended usage and demonstrating the value of having the data in question.
- Create credible safeguards against those data being used for unauthorized purposes.
- Have a plan B: In the event that the plans would overstep the boundary of social or legal acceptability, how can the tool deliver the required benefits another way?

3.2 System failures

As with any IT (or other) system, sensing, communications or processing equipment in AI systems may fail, causing a loss of service. This could be particularly problematic when the AI is being used in responding to an actual disaster, and when rapid decision support is required. In many cases, this undesirable outcome will be obvious to the user, who can then switch to whatever back-up system exists. However, in some cases, such as when an input data source fails – such as a data stream from a sensor – the system may continue to operate as if everything is normal, while actually producing distorted results.

The solutions to this issue are the same as for other IT systems:

- Redundant systems and AI-independent backups: Ensure duplicated processors, data sources and communication links for continuous operation. Back-up systems should be physically remote to prevent simultaneous failures, and contingency plans should allow manual decision-making and conventional forecasting methods when AI is unavailable.
- Specify service levels required from vendors and incorporating proof of these into procurement processes.
- For highly critical systems, perhaps borrow from the approach for high-assurance systems such as air traffic control, incorporating a Failure Modes, Effects and Criticality Analysis (FMECA) stage into the design process, systematically identifying and designing to eliminate the risk of high criticality failures. These risks will include those inherent in the AI itself (see below).
- “Human-in-the-loop” disaster response and alternative protocols: Establish manual override mechanisms, human decision checkpoints, and training programmes to ensure emergency teams can effectively

operate without AI assistance when necessary. AI should enhance, not replace, human expertise in disaster scenarios.

3.3 Cyberattacks

Cyberattacks include tampering designed to steal data, distort the system's output in some way, deny access or cause physical damage to it and any assets to which it may be linked. They may be carried out by "hobbyists", criminal gangs or state actors. With AI, there may also be scope to manipulate input data, causing the AI to respond erroneously in some way.

As with system failures, the solutions to cyberattacks are the same as for other forms of IT:

- Effective management of passwords, vigilance for phishing attacks.
- An effective "skin" – firewalls, frequent penetration testing.
- An effective "immune system" – tools (themselves often AI-powered) that can detect anomalies in any part of the system and rapidly isolate that part. These tools can also detect anomalies that indicate failing equipment or human errors, such as an operator misconfiguring a control or a technician failing to register a new device connected to the network.
- Systematic deployment of all updates issued by vendors.

3.4 Bias

AI has unfortunately gained notoriety due to instances of bias, whereby it generates inaccurate answers or predictions when applied to specific situations or produces skewed outcomes. Some recent examples, many related to race and gender bias, include:

- mortgage algorithms that perpetuate racial bias in lending[12]
- recruitment algorithms that exacerbate bias against women[13]
- an application to predict clinical risk that was shown to perpetuate certain racial myths and biases in medicine.[14]

The review titled "Common pitfalls and recommendations for using machine learning to detect and prognosticate for Covid-19 using chest radiographs and CT scans" by Roberts et al. (2021) evaluated 62 studies. It found that both small and large data sets used in ML for COVID-19 detection have biases that can make the models unreliable and lead to unequal healthcare outcomes. For example, one major bias is found in small data sets, which often fail to capture the full variability of the target population, leading to models that do not generalize well. This results in biased predictions that reflect the limited scope of the training data rather than the broader population. The study also noted biases in the selection and measurement of features and outcomes used by the models, making them inaccurate. A further source of bias may simply be the accidental use of obsolete data. Many studies have yet to externally validate their models, which can make them less reliable in real-world scenarios, especially for high-stakes situations such as COVID-19 detection and prognosis.

12 See https://news.berkeley.edu/2018/11/13/mortgage-algorithms-perpetuate-racial-bias-in-lending-study-finds.

13 See https://thenextweb.com/news/study-shows-how-ai-exacerbates-recruitment-bias-against-women.

14 See https://www.nejm.org/doi/pdf/10.1056/NEJMms2004740.

The impact of bias in AI goes beyond fairness and equity; it can also result in significant technical failures. A notable example is Zillo,[15,16] an online real estate marketplace that suffered major losses due to its AI algorithms overestimating the future value of properties. The algorithms failed to consider the impact of the cooling housing market during the COVID-19 pandemic and the increased time needed to renovate and "flip" properties due to a shortage of contractors. This bias, which stemmed from the assumption that past trends would continue and illustrated systemic bias in its predictive models, came close to destroying the company.

In the DRR environment, bias can significantly impact risk assessments, disaster response strategies and recovery planning. One critical concern is the use of ML models trained on data sets primarily from data-rich regions, such as developed countries, which may not generalize well to data-scarce regions. Damage detection models, for instance, often rely on high-resolution satellite imagery and extensive post-disaster data sets that are more readily available in certain countries. When these models are applied to regions with different building typologies, construction materials or urban layouts, they may fail to detect damage accurately, leading to misallocation of resources and ineffective response efforts.

Similarly, bias can emerge in the development of exposure models, where training data may disproportionately represent urban, well-mapped environments while underrepresenting rural or informal settlements. This skews disaster risk assessments, making them less effective for vulnerable populations. Building typologies are another source of potential bias, as ML models trained on structural data from earthquake-prone, high-income regions may not properly assess the vulnerabilities of buildings in lower-income, tropical or flood-prone regions. If not accounted for, such biases could lead to underestimation or overestimation of risk, ultimately affecting preparedness and mitigation efforts.

Ensuring unbiased and contextually relevant AI models in DRR requires diverse, representative data sets, continual validation, and collaboration with local stakeholders to capture regional differences. Addressing these biases will improve disaster response equity, resource allocation, and the overall effectiveness of AI-driven DRR strategies.

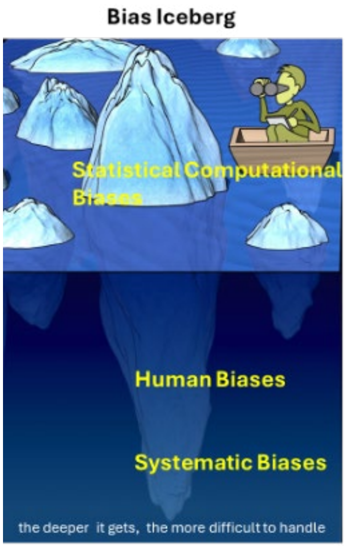
Good bias versus bad bias: Oliveira et al. (2021) researched biased resampling strategies for imbalanced spatio-temporal forecasting tasks. They focused on predicting extreme and rare events, such as abnormal weather conditions and pollution spikes, and tested their algorithms using: a) multivariate adaptive regression splines; b) Random Forest; and c) regression tree algorithms. The study's results showed that standard random resampling methods without accounting for biases often led to inaccurate predictions. This resulted in underestimating or overestimating the frequency and intensity of extreme events, which could cause severe technical failures, such as inadequate disaster preparedness or misallocating resources in response to "false positives".

By introducing biased resampling strategies, the researchers were able to address these issues. The biased methods prioritized data points that were more relevant for forecasting rare occurrences, enhancing the model's ability to predict extreme values accurately. This improvement in predictive performance ensured that forecasts were more reliable, reducing the risk of significant errors and improving overall disaster response and management strategies.

15 See https://kesq.com/money/cnn-social-media-technology/2021/11/09/zillows-home-buying-debacle-shows-how-hard-it-is-to-use-ai-to-value-real-estate-2/.

16 See https://www.deeplearning.ai/the-batch/price-prediction-turns-perilous/

Understanding biases in depth: Biases in AI can be categorized into systemic, human and statistical computational biases. Systemic bias arises when the underlying assumptions and frameworks of the AI model perpetuate existing inequalities or inaccuracies in the system. Zillow's systemic bias was due to its reliance on historical data trends without considering the dynamic nature of the housing market. Data obsolescence is also a systemic bias.



Human bias is introduced by the designers, trainers and implementers of AI systems. This occurs when training data reflect unconscious assumptions or prejudices, leading to skewed learning and biased outcomes. For example, if a disaster prediction model is trained mainly on data from wealthier urban areas, it may fail to account for vulnerabilities in informal settlements, where construction quality and infrastructure differ significantly. The building damage assessment using a hierarchical transformer architecture (DAHiTrA) for Hurricane Ida illustrates this challenge. The model was trained using high-resolution satellite images from well-mapped urban regions but may have underperformed in low-income, informal settlements due to less-detailed training data. This highlights a common human bias in AI for DRR, where models built in data-rich environments do not generalize well to data-poor regions. Addressing this bias requires incorporating diverse data sets, collaborating with local experts and continuously refining training data to capture a broader range of disaster impacts.

Similarly, the zoning of vulnerability to wildfires using fuzzy logic in Colombia faced challenges related to human bias in model design. The classification of wildfire-prone areas prioritized vegetation type and land cover but underestimated the impact of human activities such as illegal land clearing or agricultural burning. This bias resulted from the model designers' implicit assumptions about which factors drive wildfires, reinforcing a biased interpretation of risk. Future iterations should incorporate data on human interventions, such as land management practices, to improve prediction accuracy.

Statistical computational bias arises when AI models are trained on limited data sets or when the methods used for data processing introduce errors. This can occur if training data sets fail to cover all possible scenarios, leading to overfitting, whereby an AI model performs well on training data but poorly in real-world situations. Zillow's failure to predict housing market shifts is an example of this issue, as its AI over-relied on past patterns that did not account for emerging market conditions.

A similar challenge exists in AI-driven flood prediction models, such as MaxFloodCast, which integrates physics-based hydrodynamic simulations with ML. While the model achieved high accuracy in Harris County, Texas, its applicability to Latin American regions with different hydrological conditions remains uncertain. If the training data set primarily included flood scenarios from North America, the model might struggle with flooding patterns in tropical or mountainous regions. To reduce statistical bias, AI models should incorporate diverse environmental data, allowing for greater adaptability across geographical contexts.

In addition, biases can also arise in how data are visualized to inform decision-making. If certain facts are highlighted while others are downplayed or excluded, it can skew conclusions and lead to erroneous decisions. These issues highlight the importance of addressing all three types of bias to develop fair and reliable AI systems for DRR.

By understanding and mitigating systemic, human and statistical computational biases, AI technology experts can create more robust, accurate and equitable models, preventing the kinds of technical and economic failures experienced by Zillow. Some methods for doing this are outlined below.

In conclusion, the responsible adoption of AI and ML in DRR requires a constant assessment of risks and the implementation of adequate safeguards. If we manage to address and mitigate these challenges, these technologies can be powerful allies in protecting lives and reducing the impact of disasters associated with the natural physical and the built physical.

Best practices for handling AI biases in the DRR domain: Solving bias issues in AI used for DRR may not only rectify the immediate problem, but may also potentially reverse the effects of unconscious social/historical biases that would have led to it in the first place. Techniques for doing this include the following:[17]

- Using existing technical tools and methods, such as Red team reviews or audits.
- Rigorous testing of each system module in isolation and then together.
- Using multiple metrics: user surveys, false positives, false negatives, and so on.
- Rigorous characterization of, and quality assurance (QA) on, the data used for training, such as confirmation of the data's age, provenance, limitations etc.
- Sampling the raw data and training data for missing values, any evident skews by age, sex, ethnicity, region, ecotone, risk, disaster type, etc.
- Continually monitoring any difference between training data outcomes and in-use outcomes.
- For supervised learning, reviewing the neutrality of the labels used to classify data.
- Communicating the limitations of the training data to users: what was/was not included?
- Testing the AI with counterfactual examples[18] to assess fairness according to whether results affecting one population would be the same if another population were in the same situation.
- Imagining that AI tool outputs were a piece of proposed legislation and asking: who would object to it and why? Should the tool's conclusions, therefore, be adjusted in some way?
- Addressing the explainability of the AI's output (see below), as XAI technology increasingly allows, so that it does not appear arbitrary and does not cause unnecessary surprises.
- Comparing AI outputs alongside those a human has generated.
- Continuous monitoring after deployment, especially if subsequent learning is expected; in effect, the testing phase should never stop.
- Ensuring there is a "human in the loop" before activating a process or asset as a result of the AI's operation.

3.5 Hallucinations

AI hallucinations are errors that occur in LLMs and, thus, in GAI/AAI. These errors cause the AI

17 This list has been assembled from https://ai.google/responsibility/responsible-ai-practices/ and https://hbr.org/2019/10/what-do-we-do-about-the-biases-in-ai

18 See https://papers.nips.cc/paper_files/paper/2017/hash/a486cd07e4ac3d270571622f4f316ec5-Abstract.html.

to perceive patterns that do not exist, leading it to produce an output that may appear realistic but contains factual errors or complete nonsense (GAI); or to take actions that may be counterproductive or even dangerous (AAI). While AI hallucinations can sometimes be seen as a source of creativity in fields such as art and design, they are not desirable in the context of DRR (Bender et al., 2021; Marcus and Davis, 2019).

In the domain of DRR, the importance of addressing AI hallucinations cannot be overstated. AI systems are increasingly leveraged for predicting natural disasters, assessing risks and coordinating response efforts. However, AI hallucinations pose significant dangers in this context. They can lead to the generation of false information about disaster scenarios, resulting in incorrect decisions by emergency responders and causing delays and misallocation of resources, thereby exacerbating the situation (Vinuesa et al., 2020). Moreover, erroneous patterns identified by AI can trigger false alarms or missed warnings, which can either induce unnecessary panic or leave communities unprepared for impending disasters (Amodei et al., 2016). Additionally, frequent AI hallucinations can erode trust in AI systems among stakeholders, including government agencies, first responders and the public. This erosion of trust undermines the effective implementation of AI-driven DRR strategies, highlighting the critical need for robust measures to mitigate AI hallucinations (Taddeo and Floridi, 2018).

Hallucinations arise from the same sources as bias – skewed or obsolete input data, overfitting to training data and, increasingly, from the sheer complexity of LLMs (see appendix 1). The solutions are similar to those for dealing with bias, notably using appropriate and complete training data, continuous testing and human oversight (Mitchell et al., 2019). As stated, using GAI and AAI in situations where there cannot be a human in the loop should be avoided. It may also make sense to define constraints that limit the content or actions that the AI may generate as output, similar to how publicly available LLMs such as ChatGPT are constrained from reproducing profanity or offensive images (OpenAI, 2023).

Note: It is important to emphasize that hallucinations primarily occur in GAI under DL, affecting text and image generation (Bender et al., 2021). This issue does not apply to all AI systems, and understanding this distinction is crucial for effectively managing and mitigating the risks associated with AI hallucinations in various applications (Marcus and Davis, 2019).

4. Summary and conclusion

In this paper, we emphasized the potential of AI technologies in disaster risk reduction (DRR), highlighting the importance of high-quality data and pre-processing. We stressed the significance of community engagement for successful implementation, as it fosters trust and acceptance. We also discussed the need for explainable AI (XAI) to improve transparency and trust in AI systems and emphasized the importance of ensuring system reliability.

However, AI deployment in DRR remains challenging, particularly in the Americas and the Caribbean. Climate-induced disasters such as hurricanes, floods and wildfires continue to intensify, making real-time AI-driven insights crucial. Nevertheless, uneven technological access, data scarcity and the high cost of AI implementation hinder widespread adoption in many developing nations. Additionally, biases in AI models could disproportionately affect vulnerable communities, leading to misinformed decision-making. For example, the application of ML for mass movement susceptibility mapping in Colombia highlighted the importance of local data availability for AI-driven landslide risk assessment, and also revealed significant gaps in historical event records that limit predictive accuracy.

Similarly, the zoning of vulnerability to wildfires using fuzzy logic and AI in Colombia demonstrated that while high-resolution satellite imagery can improve risk mapping, limited access to computational resources and cloud-based AI tools in some areas remains a barrier to implementation. In Bolivia, the use of Google Earth Engine and Random Forest for land-cover classification showcased the potential of AI for environmental monitoring, yet emphasized how the lack of consistent, region-specific training data sets can reduce model accuracy when applied to different ecosystems. These cases underline the broader issue of AI models trained on data sets from high-income regions failing to generalize effectively in Latin America.

To address these challenges, future research should focus on developing localized AI models tailored to regional hazards and socioeconomic conditions, while ensuring that AI solutions are accessible and interpretable for policymakers and emergency responders. Expanding regional data-sharing frameworks, improving computational infrastructure and fostering cross-border collaboration between research institutions can enhance the effectiveness of AI in DRR. Furthermore, strengthening explainable AI (XAI) efforts will be crucial to ensuring that decision makers in Latin America trust and act upon AI-driven recommendations, avoiding misapplications that could worsen disaster outcomes. By proactively tackling these barriers, AI-driven DRR initiatives can become more inclusive, adaptive and impactful, ultimately strengthening the resilience of communities across the Americas and the Caribbean.

Appendix 1: AI methods[19]

AI method	*Description*	*Learning method*	*Example data sets*	*Examples of use in DRR*
Machine learning (ML)	Uses data and algorithms to gradually improve performance of a computer system at predicting outcomes by correcting in the light of observed errors without being explicitly programmed. Some ML methods that may be encountered include:		• Sensor data	• Flood prediction • Earthquake magnitude estimation • Required actions
	Linear regression: Finds the best fit between variables and predicts values based on the fit identified.	Supervised (uses manually labelled data)		
	Bayesian inference: Continuously updates assessed probabilities of events or parameters in light of new evidence.	Supervised or unsupervised (can use unlabelled data and discover for itself)		
	Decision tree: For classification of data types and/or regression/prediction.	Supervised		
	Random Forest: Combines the output of multiple decision trees that may focus on different areas of the data.	Supervised		
	Support vector machines (SVMs): Complex classifications through finding the largest gaps between data points in multiple data sets.	Supervised		
	Clustering: Infers similarity from features and attributes, and groups instances or items with those similar features.	Unsupervised		

19 This appendix draws heavily on Cheng-Chun Lee, and others (2022). Roadmap towards responsible AI in crisis resilience management. Available at arXiv:2207.09648v2 [cs.SI] 8 Sep 2022. Grateful thanks to the authors.

AI method	*Description*	*Learning method*	*Example data sets*	*Examples of use in DRR*
Artificial neural networks (ANN)	A form of ML inspired by the human brain, where "neurons" are processing nodes, each with their own weightings that function like separate regression models. Nodes are arranged in layers: an input layer and perhaps a "hidden" layer, each partially processing the problem before being combined by the output layer. "Learning" happens as weights are changed in response to observed performance. ANN is often used as the foundation for natural language processing and computer vision (see below). There are three broad types:		• Mobile phone activity data • Digital trace data	• Risk assessment • Damage monitoring • Crowd and migration monitoring • Location mapping • Mobility evaluation • Activity and recovery evaluation
	Feed-forward (sometimes called multilayer perceptrons): The "classic" ANN.	Supervised		
	Convolutional: These use matrix multiplication, for example to identify patterns within an image or stream of data, and thus what the image itself might be or what the stream of data is telling us.	Supervised		
	Recurrent: Embody feedback loops – often used for time series predictions.	Either supervised or semi-supervised (some data are labelled but not all)		
Deep learning (DL)	Neural networks using more than one hidden layer (and as many as hundreds) to ingest structured or unstructured data (images, text) and derive conclusions and predictions. May include any of the three types of neural network described above.	Usually supervised	• As above – at larger scale	• As above – at larger scale

AI method	*Description*	*Learning method*	*Example data sets*	*Examples of use in DRR*
Natural language processing (NLP)	Gives computers the ability to understand and respond to text or spoken words. Usually based on DL, and convolutional neural networks in particular, combined with ML classification techniques such as SVMs.	Supervised, semi-supervised and unsupervised, depending on the specific component – NLP requires a family of techniques	• Social media • Operating instructions	• Early warning (text- or speech-based • Situational awareness • Infrastructure operation • Damage monitoring • Sentiment analysis: social impact detection, recovery evaluation • Fake news detection
Computer vision	Gives computers the ability to derive useful information from images, including pictures and videos. As noted above, it is usually powered by DL convolutional neural networks.	Supervised, semi-supervised and unsupervised, depending on the specific component. Computer vision requires a family of techniques.	• Satellite and aerial images • CCTV • Conventional photography	• Vegetation management • Risk, exposure and vulnerability assessment • Damage assessment • Recovery evaluation

AI method	Description	Learning method	Example data sets	Examples of use in DRR
Large language models (LLMs) and generative AI (GAI)	Very large DL recurrent neural networks that analyse massive accumulations of data to "predict" what each next word should be. (ChatGPT-4, a well-known LLM, was trained on 45 gigabytes of data, for example, and its eight linked neural networks with over 120 layers collectively have a reported 1.76 trillion weights). LLMs have moved beyond traditional AI, which makes predictions based on analysis of historical data, to become *generative* AI, i.e. producing brand new outputs (text, images, speech) that can be difficult to distinguish from human-created material.	Supervised, semi-supervised and unsupervised, depending on the specific component	• LLMs could be created for regions, tasks or industry sectors.	• Research • Generation of training scenarios • Expert advice on strategy and priorities
Agentic AI (AAI)	As for GAI but producing recommendations or actions. Capable (if allowed) of autonomous operation of complex processes.	As above	• As above	• Supply chain planning • Triage recommendations
Time series AI	A family of ML and neural network techniques that analyse historical or streaming (i.e. contemporaneous) time series data to forecast, detect anomalies, recognize temporal patterns and create classifications based on these.	Unsupervised, supervised (e.g. to weed out profanity or abusive material), semi-supervised and reinforcement. Reinforcement learning mimics trial and error as the machine seeks to optimize results.	• Weather data • River flow data	• Forthcoming weather or river flow impacts – early warning • Required next actions

03

Inclusive technology: Bridging cultures and climate resilience

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Concept and keywords

Technology availability, affordability and accessibility, and data representation are critical aspects of disaster risk reduction (DRR). Ensuring data are properly represented and technology is realistically available and accessible is essential to reducing vulnerability in its multiple forms. Often, those who collect and analyse data are not part of the affected groups, which can lead to biased results that indirectly hinder the main objective of reducing vulnerabilities. Therefore, it is crucial to address this issue by ensuring that diverse groups are involved in data collection and analysis processes. This will help ensure accurate data representation and reduce vulnerabilities.

As a concept, “technology” will be defined differently depending on generations, geographies, demographics and access conditions. It is important to be expansive in how technology is designed and contextualized. Regardless of the type or design, technology can only effectively reduce risk when there is a focus on its context and usability.

1. Introduction

Addressing disaster risk reduction (DRR) requires a nuanced exploration of technology access and data representation. This chapter embarks on an intellectual journey, embracing diverse perspectives on technology and recognizing that different definitions foster inclusivity. For instance, an expansive conceptualization of technology that includes Indigenous technologies, which may differ from Internet- or data-dependent technologies, can broaden our understanding and approaches.

The chapter considers how context and usability can emerge as guiding principles in DRR, underlining that effectiveness of technology in DRR depends on its alignment with specific needs and circumstances. This understanding becomes crucial in crafting adaptive and sustainable solutions tailored to the unique challenges faced by communities in the Americas and the Caribbean. Through this comprehensive exploration, the authors aim to contribute to the ongoing discussion within the DRR community and engage a broader audience interested in the intersection of technology, inclusion and DRR.

2. Inclusion and the technology spectrum

The response to disasters and also to risk reduction lies at the intersection of technology and humanity. To achieve a true and tangible impact, it is imperative to recognize the importance of inclusion. The technologies employed in these critical fields range from simple to sophisticated, bridging gaps between different age groups, cultures and levels of access to technology. Understanding this spectrum is not just about technological progress; it ensures that each community, regardless of its unique characteristics, can benefit from effective DRR strategies. Inclusion must therefore be understood as a combination of efforts to make the processes of designing and validating proposed technologies participatory to ensure they are socioculturally relevant and adapted to diverse needs.

2.1 Non-technical solutions: resilience through simplicity

Non-technical solutions, mostly based on simplicity and traditional practices, are inherently inclusive. They leverage local knowledge and community networks, transcending generational and cultural boundaries. The use of oral communication and traditional construction techniques are accessible to diverse communities, fostering resilience across all age groups and cultural contexts. Recognizing these systems as forms of technology is important in emergencies, as they function continuously, regardless of access to electricity or other infrastructure requirements (Rea, 2022). For Indigenous and local social groups, these systems must be based on their fundamental institutional entities, such as the collective (Esteva, 2012) and their world view. This includes considering their knowledge systems and ontological dimensions (Viveiros de Castro 1998; Inglod, 2000).

For instance, learnings from the Indigenous communities of the Americas and the Caribbean have yielded important reflections on the role that human beings play in relation to the Earth. A large part of the planet's biodiversity that is well preserved or conserved is located on Indigenous lands, whether or not they are demarcated as such. Knowledge related to these lands and territories results in a variety and diversity of fauna and flora, at low financial cost, thus establishing a unique socioenvironmental sustainability process.

2.2 Low-tech solutions: practical and accessible

Low-tech approaches are practical and accessible to a wide range of users. Hand-crank radios, solar chargers and manual water filtration systems serve communities with varying levels of technological sophistication. They provide everything from early warnings to potable water during and after emergencies. Information itself can be a low-tech solution. For example, a lesson learned from the Great Japan Earthquake of March 2011 was that both communities and emergency services needed good information about shelter needs and the availability of facilities (Murayama, Scholl and Velev, 2021). These low-tech solutions are designed to empower people of all ages, backgrounds and abilities, ensuring disaster preparedness is not limited by technological disparities. The principles of equity, reciprocity and pluriversal complementarity (Escobar, 2018) should guide access to, and the creation of, new technologies.

2.3 High-tech solutions: robustness and efficiency

When high-tech solutions such as satellite imagery, drones, early warning systems (EWS) and artificial intelligence (AI) are integrated into disaster response, they have the potential to accelerate positive outcomes. The use of these and other technologies in emergencies has led to improvements in wildfire prediction, efficiency in resource allocation, event monitoring and the ability to anticipate recovery costs (Vermiglio et al., 2022). However, while technological advancements have revolutionized disaster risk management, their effectiveness depends on inclusivity, accessibility and affordability – particularly in developing regions where digital divides persist (Enigma Advisory, 2024). Ensuring that disaster technologies are designed with the needs of diverse communities in mind is essential to fostering equitable resilience. Many at-risk communities face barriers such as digital illiteracy, inadequate infrastructure and high costs, which hinder the widespread adoption of disaster management tools (Cawley and McEntire, 2024). To bridge these gaps, disaster technologies must be co-developed with end users, ensuring that their perspectives shape design and implementation.

Both technological advancements and local resilience strategies should be incorporated into this co-design to ensure accessibility. Many communities have developed risk knowledge systems based on lived experience, using adaptive responses to climate events for centuries (Sillitoe, 2017). Recognizing and incorporating these systems into modern technologies ensures that disaster preparedness is not only data-driven but also culturally and socially relevant. An example of this is a scenario that incorporates traditional EWS alongside AI-driven models to create hybrid approaches that reflect local realities (Sillitoe, 2017).

A final challenge to address relates to affordability. Advanced and cutting-edge technologies are often prohibitively expensive, restricting their use to well-resourced organizations and leaving marginalized communities behind (Brown, Smith and Lee, 2024). Governments, humanitarian organizations and private sector partners must work towards cost-effective solutions that enable broad adoption. Open-source platforms, mobile-based alerts and simplified digital tools are examples of solutions that can help extend access to high-tech approaches while reducing financial burdens on resource-limited communities (Enigma Advisory, 2024).

2.4 Intergenerational use, opportunities, and deficits in access

Technology utilization also varies significantly across generations, reflecting divergent approaches, priorities and resource access. At the forefront of this discussion is the evolution of digital platforms and communication channels. From the older generation's early adoption of online forums to millennials and Gen Z's seamless integration of social media platforms such as Facebook and X, generational gaps in technological engagement echo throughout DRR. While some people rely on traditional communication methods during and after disasters, others harness the real-time dissemination capabilities of social media and messaging apps to coordinate relief efforts and disseminate critical information in near-real-time. Exploring generational differences in technology use for DRR requires reviewing the concept of resilience, where age, culture and socioeconomic factors shape the collective response to natural hazards.

For those who take on the task of reflecting on DRR actions and projects, developing a conceptualization that is appropriate to the context, or intended object, is one of today's biggest challenges. Doing so implies not only reflecting on methods and processes for conceptual construction in the scientific, technological and communicational domains, but also often reconstructing analysed concepts. A critical content analysis always points out issues that generate instability in established systems; proposing conceptual or systemic solutions for them will always require a lot of effort (combined with specialized skills) from the analyst. DRR is a socially constructed concept that examines the relationship established between subjects, and between subjects and objects, in a given context to achieve real and concrete resilience.

3. Holistic integration: the power of synergy

Holistic integration, combining non-technical, low-tech and high-tech solutions, embodies the spirit of inclusion in technology and DRR. Understanding and adopting this spectrum ensures disaster response and risk reduction strategies meet the diverse needs of communities worldwide.

Understanding the importance of age, culture and accessibility is an important component of building resilient communities, regardless of the technological landscape surrounding them. Inclusion becomes not just an objective but a fundamental principle that guides our approach to safeguarding lives and enhancing community resilience during crises.

3.1 Indigenous knowledge or technology?

To examine the relationship between culture and technology, we must first articulate the differences between them. Cultural models cannot be analysed in the same way as technological characteristics. Culture is superstructural, whereas technology is based on a set of organic and inorganic mechanical elements to achieve an objective. It is imperative to analyse where culture and technology intersect in order to help understand the instrumental use of technology. This can be understood as a kind of ontological invention, based on the development of new technologies such as AI. This suggests paying attention to the ways of thinking that have maintained the forms of socialization between culture and nature over time and space, in order to understand their behaviours. It is about defining meanings to find interpretive patterns in the culture–nature relationship or, more concretely, the relationship between technology and climate phenomena. The problem lies in the biases of science regarding the Indigenous perspective of knowledge in its interpretive models. For example, Western science does not accept that the world of humans and non-humans, as well as the natural and the supernatural, coexist interdependently.

From the Indigenous perspective, technology is key to recalibrating the balance between culture and nature. In the Western world, culture and nature are two separate elements, but in the Indigenous world they are united. The Indigenous position prioritizes that all new technology must be truly inclusive and participatory. Indigenous communities expect that new technology will not only contribute to developing resilient mechanisms to improve DRR but will also help restore balance in the human–nature relationship. The new technology should go beyond dualistic analyses, eliminating the opposition between modernity/tradition, science/belief and so forth to recognize a culturally diverse world (Ashish et al., eds., 2019).

The current scientific method has shown limitations in understanding Indigenous knowledge, but should not ignore it. Indigenous knowledge about the territories has allowed Indigenous communities to develop and accumulate true and legitimate learnings that have enabled them to keep their territories in balance through creative processes. These processes are the repository of non-systematized Indigenous technologies used to reduce the risks and disasters of climate change that now threaten Indigenous territories.

Three hundred years before the arrival of the Europeans to the Americas, one of the largest civilizations in the world, the Incas, was formed in the Andean mountains. Living at over 3,000 metres of altitude, the Incas cultivated their crops on these lands. According to palaeoecological studies, there was a period of global warming (Chepstow-Lusty et al., 2009) from around 1,100 A.D. that lasted about four centuries. During this period, the populations of the Andes moved up the mountains in search of lower temperatures and developed a sophisticated agricultural production system using meltwater managed by irrigation systems to cultivate terraced lands. Combined with tree plantations and forest conservation, this formed a traditional knowledge system that has been transmitted from generation to generation. This knowledge is now being reused in a mitigation and resilience plan for climate events affecting the Andean mountain range that have increased in frequency and/or intensity due to the effects of climate change, in an area where glacier coverage has retreated to 51 per cent of its original area.

At the foot of the glaciers of the Sacred Valley of the Incas live Quechua Indigenous communities. Their ancestral knowledge is being drawn upon, with the same technology applied over 400 years ago being put to use today. Large-scale reforestation with native trees – such as Q'euñas (polylepis), which are now nearly extinct in the area – is understood as a crucial strategy for human survival as they capture and store water. Indigenous communities regard the cultivation of these communal forests as a guarantee for their future water and fuel needs and hope they will restore the socioenvironmental balance.

Rather than treating Indigenous and traditional knowledge as separate and subordinate, it is imperative to examine its intersection with the systemic whole. This perspective allows for an understanding of the instrumental use of technology, particularly emerging fields such as AI. Within the broader cultural context, AI offers an opportunity to integrate Indigenous knowledge systems by recognizing the ways of thinking that have sustained the relationship between human communities and natural ecosystems over time. For instance, Indigenous fire management practices, which emphasize the use of controlled burns to prevent larger wildfires, can inform AI models that aim to assess wildfire risk and guide DRR strategies.

New technology must be designed with an understanding of traditional knowledge and incorporate it into the information management system equitably and inclusively. A pluriversal and holistic perspective is fundamental. Both science-based and ancestral knowledge can contribute to innovation by integrating into new formulas for technology development, which will be truly inclusive as long as it is participatory in both theory and practice. Understanding the forms of environmental adaptability in various global scenarios characterized by particular and differentiated cultural processes should lead to identifying patterns of similarity that can be universally adapted. A new way of thinking in science is evident: a post-normal science (Funtowicz and Ravetz, 2018). The combination of these approaches should open the door to accounting for non-traditional data sets – such as oral histories, community narratives and ecological signals – alongside conventional scientific data. This requires developing data structures that can encode qualitative insights and cultural epistemologies while ensuring that the technology remains accountable to the communities it seeks to serve.

3.2 Who's at the (tech) table?

As climate change highlights the need for comprehensive disaster response plans, discussions of which technologies are included, and their origins, become increasingly important. Indigenous technologies, often deprioritized by policymakers despite their histories of effectiveness, must be deliberately included to ensure equity in emergency management policy and maximize potential environmental and community benefits (Takako et al., 2019).

One example highlighting the efficacy of a broad definition of technology in disaster resiliency is seen within the Kalinago and Garifuna communities of Dominica and Saint Vincent, where traditional knowledge about hurricane and volcano preparedness is routinely used (Hofman et al., 2021). Adaptive housing practices, EWS and sea level rise mitigation technologies found in these communities exemplify how expanding the policy definition of technology can serve Latin America and the Caribbean. Adopting this traditional knowledge *in future reports and technical assistance projects* can produce comprehensive plans to implement the Sendai Framework for Disaster Risk Reduction 2015–2030 (Sendai Framework).

When this broader definition of technology is achieved and implemented, people throughout Latin America and the Caribbean can participate more actively in building their resilience and contributing to collective disaster preparedness and response efforts. This inclusion allows them to see their histories of technological development reflected in DRR policies, resulting in more inclusive and effective climate change adaptation for the region.

4. Technology for DRR and inclusion of people on the move

Migration has been, and always will be, a strategy for building resilience and coping with shocks, including adapting to environmental change. With the number of international migrants estimated at nearly 281 million globally (IOM, 2024), more people are on the move than ever before. Globally, more than 108 million people are forcibly displaced by conflict, violence, human rights violations and disasters (UNHCR, 2022). An average of 25.3 million new displacements by disasters each year were recorded between 2008 and 2022 (Internal Displacement Monitoring Centre, n.d.), three times higher than those displaced by conflict and violence. Hazardous events, amplified by compound risk factors such as ecosystem degradation, climate change, conflict, epidemics and pandemics, water scarcity, unregulated urbanization, and underlying conditions such as weak governance, corruption and violence (Daher, Pappas and Lavell, 2023), are expected to increase displacement, compelling millions more to migrate within and across borders (IOM, 2023).

Worldwide, migrants, asylum-seekers and refugees are more vulnerable in the face of disasters, facing specific conditions of marginalization. Migrants often fall between the cracks of existing protection mechanisms and are not always considered in crisis preparedness and emergency response frameworks and programmes, despite facing vulnerabilities beyond those faced by citizens of a country experiencing a crisis. Limited access to critical and timely information – due to factors such as limited language proficiency and local knowledge, social and spatial isolation, and the host society's political and cultural stances towards migration and migrants – makes it challenging for migrants to access adequate services, resources and opportunities. They often face attacks and discrimination, restrictions on mobility, irregular immigration status, confiscated or lost identity or travel documents, and other factors hindering their ability to ensure their safety and well-being. These groups may also experience increased vulnerability if their living conditions are below average (i.e. refugee camps and/or marginal settings in dangerous areas) or if they have poor health or low education (IOM, n.d.a). These factors impact their exposure to hazards and access to self-protection and support options, increasing their vulnerability to disasters.

Building on the growing international attention on human mobility and the environment, the Sendai Framework explicitly calls for the inclusion of migrants in DRR policies and practices of their host countries and communities. These efforts support the 2030 Agenda for Sustainable Development Goal of reducing inequality (Goal 10), including facilitating safe, regular and orderly migration through well-managed migration policies (Target 10.7). However, efforts to put this provision into practice have been inconsistent. To strengthen these efforts, the International Organization for Migration (IOM) and the Council of Europe have been working together to implement the 15 Guidelines to Protect Migrants in Countries Experiencing Conflict or Natural Disaster. These guidelines provide practical, non-binding, voluntary guidance for states, private sector actors, international organizations and civil society to raise awareness of the need to include migrants in their work and to equip them with technological tools, relevant skills and knowledge for the preparedness, emergency response and post-crisis phases (IOM, n.d.a). As sudden- and slow-onset disasters are expected to increase displacement, strengthening disaster risk governance and prevention at all levels has become urgent.

4.1 Climate risks, migration and displacement in Latin America

Climate-, weather- and water-related extremes have led to up to 15 times more fatalities than other deadly hazards for people in Latin America (UNDRR and WMO, 2023). Migrants, asylum-seekers and refugees constitute a significant and growing share of the general population of Latin America's vulnerable and least developed countries. These countries are not significant contributors to the climate crisis in terms of their equivalent CO^2 emissions, but disproportionately bear the brunt of its impacts.

In 2023, a total of approximately 2.8 million internal displacements were recorded in the Americas and the Caribbean. Disasters accounted for 2.1 million, a similar figure to that of 2022, whereas conflict and violence accounted for the remaining 637,000 (Internal Displacement Monitoring Centre, n.d.). The region's vulnerability to disasters (including those intensified by the adverse effects of climate change) intensifies other factors, including poverty, inequality and food insecurity. Extreme weather events, such as floods or hurricanes, can destroy homes, infrastructure and agricultural production, serving as the final push to migrate on top of existing vulnerabilities and risk conditions.

A recent joint report from IOM and the World Food Programme (WFP) determined that exposure to natural hazards is significantly associated with recent migration and a desire to migrate permanently to another country, potentially becoming a trigger for migration if disaster risk increases (WFP and IOM, 2022). Food insecurity is a long-standing problem and a large driver of migration, especially in Guatemala, which has high rates of chronic childhood malnutrition. According to a joint report by the Migration Policy Institute, WFP and the Massachusetts Institute of Technology, food-insecure people in Northern Central America are three times more likely to make concrete plans to migrate than those who are not food insecure (Ruiz Soto et al., 2021).

5. Migrant inclusion in disaster management

Migrants often bring unique skills and knowledge from their home countries, such as expertise in disaster-resistant construction methods. Their fluency in other languages can be invaluable for reaching isolated communities and their participation can lead to culturally sensitive approaches, helping design training materials that resonate with their communities or identifying trusted leaders who can effectively communicate risk reduction messages. By involving migrants as volunteers, DRR efforts can foster trust and build bridges between migrant and host communities. Essential parameters in this process include:

- *Data collection:* Conducting tailored risk assessments that consider specific vulnerabilities of migrant populations, such as limited access to transportation, can help develop targeted mitigation strategies (UNISDR, 2014). Data-driven approaches can optimize resource allocation, such as mapping flood-prone areas with high migrant populations or ensuring stockpiles include culturally appropriate food items. Migrants can contribute valuable insights through surveys conducted in their preferred languages. Partnering with migrant organizations can facilitate fit-for-purpose and inclusive data collection.

- *Effective communication*: Disseminating vital information in multiple languages through various channels, such as SMS, radio and outreach through trusted community leaders, ensures everyone receives critical warnings and instructions on time. EWS play a crucial role in this process by delivering clear, targeted messages detailing the specific actions to be taken. For instance, alerts should include precise evacuation routes, shelter locations and safety measures tailored to the needs of different groups, such as childcare options for single parents (WHO, 2017). Ensuring that these messages are accessible and understandable to all, including migrants, makes EWS more effective and helps save lives. Collaboration with migrant communities to develop and test these messages can further improve their relevance and impact.

- *Collaboration*: Collaboration between civil society, research institutions and local authorities allows for joint training programmes on cultural sensitivity and communication for both migrants and DRR personnel (Adly, 2017). Migrant organizations might possess unique resources, such as translators and culturally appropriate supplies, that can be shared with other DRR actors. Collaboration strengthens advocacy for migrant inclusion in policies and funding allocation for DRR efforts.

- *Empowerment:* Training programmes in disaster preparedness, first aid and emergency response skills can empower migrants to protect themselves and their communities (Rosenbaum and Long, 2018). Financial assistance programmes can help migrants improve their housing conditions or invest in disaster preparedness and risk reduction measures. A resilient community ensures everyone has access to essential services such as healthcare and social support.

- *Building trust:* Ongoing collaboration with migrant communities, engagement in community events or social initiatives (Turin et al., 2021), and respecting migrant rights, such as avoiding immigration enforcement during disasters, foster cooperation and provide a sense of security. Culturally sensitive communication using respectful and inclusive language demonstrates respect for migrant communities.

- *Combating stereotypes:* Promoting stories showcasing migrants' contributions to the community can challenge stereotypes and encourage social inclusion. Advocacy campaigns can raise awareness among policymakers and the public about the importance of including migrants in DRR. Collaborating with media outlets to portray migrants as valued community members can promote inclusive messaging and shift public perceptions.

Including migrants in DRR includes activities beyond disaster preparedness. When working together on DRR, migrants and host communities can build stronger relationships and a sense of shared responsibility for safety, by fostering social cohesion and reducing migrant marginalization. This leads to a sense of belonging and benefits everyone, promoting sustainable development and creating a safer environment for all residents. Harnessing migrants' unique skills and knowledge and building trust through inclusive practices can strengthen communities, making them more resilient and prepared for disasters.

5.1 Prospective areas of intervention for DRR technologies and inclusion of people on the move in Latin America

While the previous section highlighted the importance of social and institutional changes for migrant inclusion in DRR, technology can also bridge the gap. Neglecting human mobility in DRR technology creates blind spots, hinders response efforts and leaves entire populations exposed and vulnerable. This section summarizes prospective technological advancements offering the potential for inclusive DRR in Latin America. Addressing the challenges faced by migrants and refugees, these technologies can create a more prepared and resilient society for all.

Multi-hazard early warning systems (MHEWS): Cost-effective and reliable real-time monitoring systems can issue alerts via SMS, radio broadcasts, mobile apps, sirens and loudspeakers, among others, with the aim of protecting lives and livelihoods from different types of hazards, such as floods, heatwaves, storms and tsunamis. The *Global Status of Multi-Hazard Early Warning Systems* – based on the Target G report in the Sendai Framework Monitor (2022) – reveals that countries with substantive-to-comprehensive early warnings coverage have disaster mortality that is eight times lower than countries with limited coverage. According to the Global Commission on Adaptation (2019), giving 24 hours' notice of an impending hazardous event can reduce damages and losses by 30 per cent. Investing US$800 million in such systems in developing countries would prevent annual losses of $3 billion to $16 billion. Despite the urgent need and the clear benefits, only half of countries worldwide report having adequate MHEWS. Even fewer have regulatory frameworks connecting early warnings to emergency and response plans. There are also gaps in the global observing system required to generate forecasts. By providing timely alerts and actionable information to communities, the effectiveness and reliability of EWS can be improved, enabling better preparation and response to hazards.

Earth Observation Systems (EOS) and risk mapping & monitoring: Satellite imagery and aerial photography monitor land-cover changes, provide valuable information for the development of detailed maps of hazard zones, identify exposed and vulnerable areas prone to landslides or flooding, and track weather system development (Mashala et al., 2023). These technologies guide infrastructure development and evacuation planning. Data can identify areas where migrants might be stranded or require specific assistance. LiDAR (light detection and ranging) technology also offers high precision; however, it may be too specific and costly for large-scale assessments. Instead, combining satellite imagery with other cost-effective remote sensing technologies can provide comprehensive risk mapping and monitoring, ensuring efficient resource allocation and timely interventions.

Geographic information systems (GIS): GIS enable digital maps to be created that integrate various data layers such as hazard zones, infrastructure locations, population density and vulnerable areas within communities, empowering migrants to identify and share critical information. The gathering and processing of all these input parameters allow for better risk assessments, evacuation planning and resource allocation. For instance, Ecuador's Ministry of Disaster Risk Management uses GIS to map potential flood zones and evacuation routes in coastal areas (Ahasan et al., 2022).

Mobile phone technology: With nearly 75 per cent of the world's population owning a mobile phone, mobile networks have become powerful communication channels targeting at-risk areas. While mobile broadband networks are widely accessible, with 87 per cent of the population in Latin America within range of a 4G signal, actual usage and penetration rates can vary significantly. Mobile apps, available in multiple languages, can be used to disseminate critical disaster preparedness information, evacuation plans and real-time alerts to migrants. These apps can also be used to report damages and request resources. Ensuring that these technologies are accessible and user-friendly for all, including those with limited broadband access, is crucial for effective DRR.

AI-powered solutions: AI offers a promising avenue for enhancing DRR and promoting the inclusion of people on the move in building more-resilient communities in the face of increasing climate-related challenges. One area where AI can make a significant impact is in predicting the effects of extreme climate events on agriculture (Karanth et al., 2023; Khonina et al., 2024). By combining AI with multispectral technology, it is possible to identify drought or flood risks in food-producing regions in a robust manner, and to enable the timely issuance of multilingual alerts via SMS and mobile apps, providing a cost-effective and real-time EWS (Materia et al., 2024). This information can empower farmers to take proactive measures to reduce crop losses and enhance their resilience to climate change. Another critical application of AI lies in flood risk mapping. By analysing hyperspectral imaging data, AI can more precisely identify high-risk flood areas, especially in regions with concentrated migrant populations (Jones et al., 2024; Khonina et al., 2024). This information is invaluable for disaster response planning, as it enables the optimal allocation of relief resources to areas most in need. AI can also revolutionize EWS. By processing satellite and drone data, AI can generate actionable real-time alerts that can be disseminated through multilingual mobile applications and community radio. This ensures that all community members, including migrants, receive critical safety information promptly.

5.1.1 Social media and interactive platforms for communication, coordination and information-sharing

Social media and online platforms can be leveraged for targeted communication with migrant communities, facilitating information-sharing, search and rescue efforts, and volunteer coordination. They connect migrants with local resources, social-safety networks and disaster preparedness training materials, fostering a sense of community. While these technologies offer significant benefits, migrants and refugees often face challenges in utilizing them effectively:

- *Language barriers:* Information disseminated through MHEWS or public advisories might not be available in languages understood by all migrant populations, especially recent arrivals.

- *Limited access to technology:* While mobile phone ownership and Internet connectivity have significantly increased, disparities still exist. Migrants, especially those who are undocumented or living in informal settlements, may face barriers to accessing mobile phones or reliable Internet connectivity. These barriers can hinder their ability to receive warnings or access resources through technologies such as mobile apps.

- *Lack of awareness*: Newly arrived migrants may not be familiar with local warning systems or evacuation procedures.

- *Digital divide*: Limited Internet access and digital literacy among some migrant populations can be a barrier.
- *Data gaps*: Migrant populations are often transient and undocumented, making data collection about their location and vulnerabilities a difficult task. This hinders targeted interventions.
- *Data privacy concerns*: Migrants, especially undocumented migrants, may be hesitant to register or provide personal information due to privacy concerns. Building trust is crucial.

5.1.2 Inclusive solutions moving forward

To address these technological advancements and challenges, the following strategies are identified for more-inclusive approaches for migrants and refugees:

Tech4DRR for all

MHEWS information needs to be multilingual and disseminated through channels that are accessible to migrants, including community radio and migrant-focused social media groups. Developing multilingual EWS and disseminating alerts and public information through SMS in multiple languages can address gaps and deliver people-centred, end-to-end MHEWS that leave no one behind. For example, Ecuador's Ministry for Disaster Risk Management partnered with the Red Cross to broadcast EWS alerts in Haitian Creole for Haitian migrants located in vulnerable coastal areas. The *Registro Único de Migrantes* (Single Registry for Migrants) helps identify and register migrants, facilitating access to social services and potentially including them in EWS. In Peru, the National Center for Disaster Prevention Studies (CENEPRED) uses an MHEWS that broadcasts alerts in Spanish and Quechua to reach Indigenous and Spanish-speaking populations. Information hotlines with multilingual support can further bridge the gap; one such example is Colombia's *Red Alerts* app, which allows users to register and receive real-time alerts based on their location. This app could benefit geographically dispersed migrant populations and is available in multiple languages.

Community outreach

Collaborating with migrant community leaders and non-governmental organizations (NGOs) to translate vital information and conduct awareness campaigns in native languages ensures information reaches target populations. Fear of detection, detention or deportation may inhibit migrants in irregular immigration situations from accessing available communication channels. Migrant children may become unaccompanied or separated, absorbing information and communicating their needs differently from adults. Elderly migrants in particular may lack host-language capabilities. Migrants with disabilities may require Braille, audio cues and other disability-sensitive interventions.

During emergencies, migrants can provide information about risks, local needs and protection gaps. Stakeholders can communicate and receive information from migrants through social media, places of worship, and family and community connections in their states of origin. Repeat messaging, using multiple channels and mediums (e.g. infographics, audio, print), can expand coverage. Communication efforts should be sensitive to migrants in different circumstances, particularly those with irregular immigration status, in detention or isolated and remote conditions, or lacking access to social networks.

Offline, location-based alerts

Develop location-based EWS to warn individuals, regardless of the language they speak or their mobile network. Implementing low-tech solutions, such as community sirens or loudspeakers to disseminate warnings in areas with limited mobile phone penetration, is an example of this good practice. Establishing people-centred warning techniques based on traditional methods, such as weather forecasts based on animal behaviour or using volunteers to assess situations and inform communities about dangers, are also valuable approaches. For instance, some communities make use of drums and fire signals. During emergencies, stakeholders can develop consistent messaging on risks and status updates, with 24-hour call centres staffed by linguistically diverse and trained personnel offering information and services once a conflict or disaster triggers.

Collaboration

Collaboration between DRR agencies, NGOs working with migrants, and mobile network operators is essential for developing inclusive technology solutions. Working at national and local levels, IOM assisted 16 countries in developing or upgrading EWS and improving radio station infrastructure to enhance public information and warning announcements. This support increased disaster information reach to marginalized regions, increasing lead times before hazards strike. Sharing conflict or disaster analysis among stakeholders, including private sector actors and civil society, facilitates informed decision-making.

Digital literacy training

Investing in digital literacy training programmes for migrant communities can bridge the digital divide. Local civil society actors have first-hand knowledge of incipient conflicts or disasters and their potential impacts on migrants. Health or outreach workers who understand different cultures and languages can effectively deliver information to migrant communities. Using multiple communication channels, including traditional and innovative methods, accommodates diverse ways of absorbing information. Mobile applications and social media provide crisis-related information cost-effectively. Helplines, hotlines and call centres facilitate communication with migrants.

Integrating migrant data collection

Integrating migrant data collection into existing systems, such as EWS and crisis monitoring systems, can ensure that information on migrant presence and conditions is systematically included. Migrants (individually or collectively) can contribute to data collection and analysis, which is useful for risk assessments and preparation (e.g. contingency plans). Earth observation data can identify informal settlements where migrants reside, informing targeted evacuation plans and shelter allocation. Colombia's EWS integration with social media platforms allows wider information dissemination and near-real-time updates, which are particularly useful for younger migrants that have a larger engagement with, and presence on, social media. The *Comprehensive Plan for Attention and Assistance to Victims* mobile app registers internally displaced people and migrants for targeted aid distribution.

Viewed through a DRR lens, the nexus between climate change and human mobility is a potent source of vulnerabilities at both the individual and community levels. Actively involving migrant communities in the design and implementation of technology solutions for DRR ensures that their specific needs and preferences are addressed. This can be achieved through participatory approaches, such as community workshops, focus groups and feedback mechanisms. Engaging migrants in this way is imperative for the leave no one behind strategy, as it not only improves the relevance and effectiveness of the technologies but also fosters a sense of ownership and empowerment. However, the effectiveness of technology relies on:

- *Accessibility and affordability*: Ensuring migrants have access to devices and Internet connectivity is crucial. This can be achieved through partnerships with technology companies, NGOs and government agencies. Initiatives such as the UNHCR Connectivity for Refugees programme work to provide affordable and meaningful Internet access by collaborating with stakeholders such as the International Telecommunication Union (ITU), GSMA and various governments.

- *Digital literacy*: Training programmes help migrants develop skills to effectively utilize these technologies. Universities, training organizations and NGOs can play a pivotal role in this effort. For instance, universities can offer courses and workshops on digital literacy tailored to migrants' needs, while training organizations can provide hands-on sessions and resources. Additionally, organizations such as World Education and Microsoft Philanthropies offer digital literacy resources and training modules specifically designed for refugees and migrants. These programmes can be implemented by local NGOs, community centres and educational institutions to ensure migrants can fully benefit from available technologies.

- *Data privacy*: Data collection must be transparent and secure, respecting migrant privacy concerns. Organizations should implement robust data protection measures and communicate clearly with migrants about how their data will be used and protected. This builds trust and encourages participation in data-driven initiatives.

6. Integrating education and technology into DRR strategies

Effective DRR is an urgent priority for Latin America and the Caribbean as climate change, population growth, urban development in risk-prone locations and other factors are increasing the overall toll of disasters. In this context, integrating education and technology emerges as a key strategy to reduce disaster risks and simultaneously plays a crucial role in preparation and mitigation strategies. The combination of education and technology can strengthen the resilience of vulnerable communities in the face of catastrophic events.

- *Community education as a fundamental basis*: Education empowers communities with the knowledge and skills to prepare for, and face, emergencies. Understanding local geography is essential for identifying risk areas and delivering training on safety protocols. Public and/or community awareness is a fundamental step, as an informed population is more likely to adopt safe behaviours and participate in disaster preparedness and resilience activities.

- *Technology adoption*: Technology offers advanced tools for prediction, monitoring and rapid response. EWS can provide timely notifications to communities about imminent hazards and impacts, ensuring valuable time for evacuations and preparations. Remote sensing and satellite surveillance facilitate environmental change monitoring and risk assessment, contributing to informed decision-making. Implementing relevant technology that communities can adopt is an important challenge that can be developed collectively, involving the community, local governments, academia and other entities.

- *Digital educational platforms adapted to culture and risk context*: Technology offers opportunities for designing educational content adapted to the culture and risk needs of communities, providing relevant information on disaster preparedness, response techniques and mitigation measures. Accessibility to online resources allows education to reach broader audiences, including remote or hard-to-reach areas. Adapting content to different levels of understanding facilitates teaching and inclusion.

- *Satellite and geospatial data*: Satellite and geospatial data collection and analysis provide valuable information to assess and forecast disaster risk. They are also useful in informing the planning of specific interventions in risk-prone areas.

- *Sharing experiences and success stories:* Continuous collaboration between the community, educational and technological sectors, and government organizations is essential to build a safer and more-resilient future. Projects with this approach are being developed in Latin America. One initiative is the Network of Laboratories for Disaster Risk Reduction in Latin America and the Caribbean, a scientific, academic and institutional community addressing gaps and challenges in DRR through research, sharing capabilities and technology development.

This international cooperation initiative involves the NASA Disaster Programme, Red LabOT, the Paraguayan Space Agency, leading private technology companies and Esri Panamá. It includes 23 GeoLabs in universities, colleges and research centres across 17 Latin American countries, using spatial data and developing GEO capabilities to address community needs and challenges. Through the Lab Network and its Earth Observations Education youth programme, more than 500 high school students have been trained to help their communities solve DRR challenges using Earth observations, GIS and remote sensing.

7. Importance of properly representing data for tech deployment

In modern decision-making and policy formulation, data shapes our understanding of complex issues and problems. Proper representation of data is not merely a technical exercise but a moral obligation influencing informed decision-making, transparency, equity and social justice. In disaster response and DRR, accurate, fit-for-purpose and ethical data representation is not just a virtue but a necessity (Hooker, 2021). Understanding data and their impact on communities is crucial for deploying technology to mitigate disaster impacts.

- *Informed decision-making*: Accurate and fit-for-purpose data serve as the foundation for supporting decisions at all levels. Proper representation cannot be overstated, as misrepresentation can lead to flawed conclusions and misguided actions, especially in high-stakes environments such as disaster response. This is where intention and positionality are crucial. When dealing with divested populations, it must be acknowledged that there may be flaws in technology design and data collection that negatively impact these groups. Organizations producing tools and products sometimes have diversity issues that affect the resources they provide. If you are from the Global North, these products are likely produced in your region with accompanying biases. This problem can be mitigated by, for instance, involving local actors in testing, analysis and collection.

- *Transparency and accountability*: Transparent data representation is a cornerstone of trust, which is paramount in DRR and response efforts. Institutions gain credibility when data are accurately portrayed. This means indexing and publishing the data, implementation tools and methods for review and scrutiny. Communicating the data and collection methods clearly and accessibly to various populations enables stakeholders to hold researchers and organizations accountable during crises.

- *Equity and social justice*: Proper data representation ensures marginalized groups are not overlooked in a disaster. It addresses disparities and advocates for equitable solutions, promoting resilience and emphasizing inclusivity in leveraging technology for effective DRR. Integrity and bias in data representation pose a threat to the integrity of our insights. There are lessons to be learned about recognizing and mitigating bias (Schwartz et al., 2022).

- *Biases in data:* Bias is described in scientific terms as "any systematic deviation between the results of a study and the truth" caused by a tendency to favour one person, thing or explanation over another (Science News Learning, n.d.). Different types of bias can be introduced at any stage of the research process, skewing results and negatively affecting the development of solutions. Accurate and comprehensive data collection is essential for formulating effective DRR strategies. Data collection biases can significantly undermine efforts by skewing data, leading to potentially devastating consequences. In disaster-prone areas, where communities are already vulnerable, ensuring unbiased data collection is crucial for an effective response.

Sampling or selection biases occur when the sample used in a study is not representative of the entire population. When the sample is too small, or not randomized, the study can result in misrepresentations of the larger population's actual characteristics or needs. Addressing such biases ensures that the policies developed meet the entire population's needs, encompassing the unique needs of different communities.

It is also important to recognize and rectify the historical underrepresentation of certain groups in creating DRR strategies. Although disasters are universal, they often spotlight long-standing disparities and inequities experienced by racial and ethnic minorities and those with less access to resources, who are less likely to evacuate and more affected by disasters (Bethel, Burke and Britt, 2013). Ensuring these individuals and communities are adequately represented can reduce vulnerabilities and enhance response effectiveness.

In the aftermath of Hurricane Katrina, officials in Louisiana established the Road Home programme with federal funding to help Louisianians rebuild or sell their damaged houses (Hammer, 2022). However, the decision to disburse funds based on appraised home values instead of rebuilding costs left those in poorer neighbourhoods unable to rebuild. Racially discriminatory economic practices like redlining[1] meant homes in Black neighbourhoods were appraised far lower than those in White communities. As of 2021, there were 100,000 fewer Black New Orleanians than before Hurricane Katrina, and the Black population of New Orleans was the only racial group significantly below its 2000 population level (Babb, 2021).

7.1 Diverse data collectors

To reduce bias during data collection, researchers should assemble diverse teams who bring a variety of perspectives, essential for technology-driven disaster responses. This inclusivity ensures data accurately reflect the complexities and varied experiences of different demographic groups,

1 The practice of denying people access to credit because of where they live.

leading to more effective and equitable disaster response strategies.

The Office for the Coordination of Humanitarian Affairs (OCHA) established a global humanitarian data centre in the Netherlands in 2017 to improve data collection and data sharing for disaster relief efforts (The Humanitarian Data Center in the Netherlands, 2016). By leveraging this database, organizations can access comprehensive and reliable data to better understand and respond to dynamic crises.

7.2 Data analysis bias

Bias can also influence researchers when interpreting results and drawing conclusions. This can lead to skewed insights and misinformed decisions, compromising response efforts. Incorporating multiple analytical perspectives and adhering to ethical data practices are essential in technology-driven disaster research to provide comprehensive and equitable data-driven response strategies.

Confirmation bias occurs when researchers seek and interpret information in ways that affirm their pre-existing beliefs or values. Such biases could compromise disaster management strategies. For example, after the Exxon Valdez supertanker spilled 11 million gallons of oil in Alaska's Prince William Sound in 1989, Exxon and other stakeholders minimized the disaster's impact to protect corporate interests. Relying on optimistic predictions led to underestimating the resources needed, delaying response efforts and hindering timely restoration (Brooks et al., 2020). Researchers should clearly define study parameters before analysing data and implement peer review mechanisms to prevent personal biases from influencing research outcomes.

Disaster responses must be culturally sensitive. Analysing data without context can lead to misinformed and potentially harmful decisions. Culture – the shared collective knowledge, beliefs and traditions that allow a group to adapt to their ecological contexts over generations – plays a crucial role in understanding how people experience disasters and develop adaptive strategies (Rahmani, Muzwagi and Pumariega, 2022). Language barriers and low education levels among minority populations were significant impediments to effective disaster relief after Hurricane Katrina (Systems Research Applications International, Inc., 2008). These barriers led to inadequate warnings and assistance, exacerbating the vulnerability of Louisiana's immigrant communities. Understanding and respecting cultural norms and values are essential in interpreting community needs and maximizing disaster response effectiveness, especially regarding mental health responses and humanitarian relief efforts.

7.3 Intersectional analysis

Recognizing that individuals belong to multiple identity groups is crucial to understanding experiences during and after disasters. Intersectionality provides a lens to see how various forms of inequality operate together and exacerbate each other, making it important to analyse since those facing more inequalities experience higher risks during and after disasters (Steinmetz, 2020). Researchers who take an intersectional approach can better reflect on the complexities of power structures at play in climate and disaster risk, preventing the simplification of local realities that may misinform policies (Chaplin, Twigg and Lovell, 2019). Intersectional approaches can provide more nuanced and equitable solutions, ensuring no one is left behind.

After Hurricane Irma struck Antigua and Barbuda in September 2017, government stakeholders, such as the National Office of Disaster Services (NODS), the Directorate of Gender Affairs (DoGA), and Disaster District Coordinators (DDCs), implemented programmes responding to various intersectional vulnerabilities (Kotsinas, 2020). Dignity kits (including toothpaste, soap and menstrual products) were distributed to women, and psychosocial support services were provided to create safe spaces to discuss toxic masculinity and gender-based violence. The Government's approach made visible the social categories of sexuality and gender identity, which are commonly neglected in disaster management.

7.4 Ethical data practices

Ethical data practices ensure that the autonomy and privacy of disaster survivors are respected. Safeguards that ensure participants give their informed consent and that protect their privacy through data anonymization are ethical necessities when deploying technology in disaster-stricken areas (Substance Abuse and Mental Health Services Administration, 2016). Researchers should respect the autonomy and rights of individuals to maintain study integrity, and removing personally identifiable information from data sets prevents the misuse of private data.

Properly representing data is a moral imperative, particularly when technology becomes a critical tool in disaster response and risk reduction. Embracing inclusivity, intersectionality and ethical practices becomes the catalyst for creating a more just and accurate representation of our world in the context of disaster response. The ethical use of technology, rooted in unbiased and inclusive data representation, becomes the linchpin for effective, compassionate and equitable disaster response strategies.

04

Technology and multi-hazard early warning systems (MHEWS)

Authors

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1. Importance of information components for decision-makers

Early warning systems (EWS) have a primary function, which is to alert the population and authorities quickly and accurately, through as many channels as possible, about the occurrence of dangerous phenomena that jeopardize the safety and lives of people, thus enabling them to act promptly. In Latin America and the Caribbean, these systems' characteristics differ depending on the geographical context, the regulatory and organizational framework of each country, and the level of economic, information and technological resources available. However, they all require a robust data and information component to ensure all their components operate effectively.

Components are commonly divided into and connected via: a monitoring system that involves specialized technical departments and agencies that provide data on different hazards; an information system (or risk knowledge system) that enables a logic to be established for adapting, adopting and promoting standards, protocols, processes and technological solutions for the management of information related to disaster risk management at various levels; and a communications system that facilitates the continuous exchange of information between organizations involved in disaster risk reduction and management, in addition to emergency preparedness and response.[1]

Since information is an extremely important factor, it is also important to identify its points of interaction with the human component, especially regarding information that informs management and decision-making in emergencies and that can be supported by technologies that help it to be understood quickly.

According to the World Meteorological Organization (2018),[2] when discussing EWS, it is customary to differentiate between some components associated with:

1. The identification and knowledge of risk, which implies fully understanding all dimensions of disaster risk, including the characteristics of hazards, exposure and vulnerability, and their links with people, communities and organizations at different territorial levels.

2. The systems and processes for detection, monitoring, analysis and forecasting of hazards, and their potential impacts on the exposed population and infrastructure.

3. Dissemination and communication of warnings, which include alert dynamics (related to the organization and flows of information to different actors) for authorities and the population in the event of adverse forecasts and emergencies. These warnings seek to ensure that decision-makers, formal entities with technical and political authority and responsibility to act in emergencies, and local actors with influence in their territories receive timely warnings regarding imminent dangerous events, thereby facilitating national and local coordination, in addition to response actions.

4. Preparedness and response capabilities, which include measures to be taken in response

1 Ideally, this should incorporate the criteria of interoperability, reliability, scalability, portability, resilience and redundancy (protection against losses and failures), among others.

2 For more information, see: https://earlywarningsforall.org/site/early-warnings-all

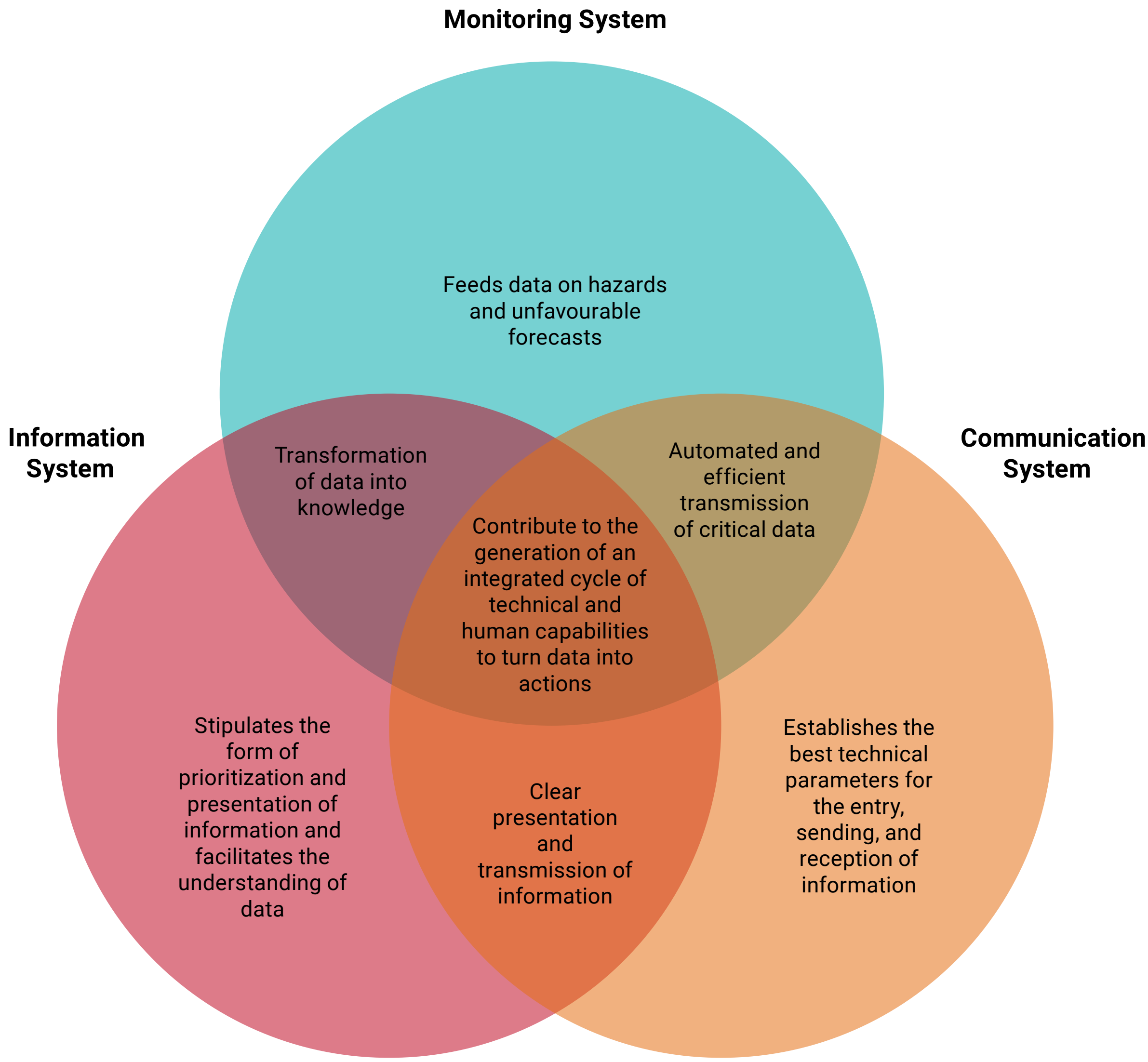
to alerts at both the administrative and community levels, supported by an adequate understanding of risks and effective and efficient communication about the possible impacts of an event.

Each of these elements is important when designing an EWS that functions correctly and promptly in emergency situations. However, focusing on the third point – specifically the work of authorities and decision-makers – some elements critical to the proper functioning of decision-making structures in emergency situations are associated with the information available. These are: a) how information is organized, to prioritize relevant data for fast decision-making during crisis situations; b) the clarity of information, to ensure precision and facilitate the comprehension and reading of information; and c) la the speed of information delivery, to reduce the time between the issuance of crucial data and its reception by the responsible authorities and the population at risk. The first two points are connected to the design criteria and protocols that the information system can establish. The last point is related to the physical and technical aspects that fall within the communication system's framework for action.

On one hand, the information system (whose function is to process, analyse and structure data from monitoring and transform them into comprehensible and useful information for various actors, such as government authorities, emergency agencies and the population in general) aims to facilitate the interpretation of possible impacts, thereby helping establish an order of priority for information according to its relevance and urgency. This in turn enables forecasts to be generated and impact scenarios to be developed. Once the information has been processed and organized in order of priority, it is essential that it is successfully delivered to those who must make decisions and act. In this sense, the communication system plays a key role in the dissemination of alerts and recommendations through multiple channels, such as radio, television, mobile phone services, social networks, sirens and official bulletins. Furthermore, the communication system defines the technical parameters and the protocols necessary to ensure that the information is transmitted clearly, accessibly and in the shortest-possible time, to enable authorities and civil society to take preventive or response measures in the face of an imminent event.

In this way, EWS are strongly influenced by the synergy and interaction between: the monitoring system, which provides data on hazards and forecasts; the information system, which determines the way in which to order data according to their priority and relevance, and how to present them to facilitate data comprehension; and the communication system, which is responsible for establishing the best technical parameters for the entry, sending and reception of information. Understanding the points of integration and complementarity of each system, along with their contributions to EWS, is extremely important when evaluating the technical and technological developments that should be deployed in order to achieve key objectives.

Figure 1. Synergies between monitoring, information and communication systems



It is important that this entire complex interaction between systems incorporate elements of adaptability given the diversity of hazards to which a territory is exposed, since in many cases hazards have distinct timelines. For example, in the case of extreme hydrometeorological events such as hurricanes or increases and decreases in temperature, there is more time to detect, monitor, plan and generate information flows. The time between the risk being identified, unfavourable forecasts being made and a phenomenon's occurrence being recorded allows evidence to be provided and guidelines prepared for decision-makers relatively far in advance. In contrast, for events that cannot be detected as far in advance, such as earthquakes and tsunamis under certain conditions (e.g. proximity of the epicentre to the coast), fast reactions are required, since every second counts in reducing material and human losses. This makes the organization of information and the speed of its transmission extremely important, given that the flow of timely data can be overwhelming in light of changing conditions, how events develop and the dynamic impact scenarios that unfold in these situations.

Considering the time factor is therefore not only crucial when comprehensively designing the information flows and transmission and communication systems, but also in addressing the various needs and objectives in terms of the information and its relationship with time. On the one hand, the population needs alerts to be issued as quickly as possible and to access them in the shortest-possible time and through various channels,[3] including low-tech transmission channels, such as sirens and megaphones, in order to reach the largest number of people possible. On the other hand, authorities and decision-makers need more-detailed information with greater possibilities for analysis. This type of information, and its more time-consuming processing, is key to planning for, and adequately managing, emergencies.

Furthermore, it is used in strategic decision-making processes, such as the allocation of resources, the coordination of response teams and the application of risk reduction measures. However, due to its complexity, it is not suitable for the process of issuing alerts, which requires speed, simplicity and precision.

We can therefore appreciate the importance of information, and the times and ways in which it intervenes in different units and systems for disaster risk reduction and alert processes during emergency situations.

Looking at EWS in more detail, we must point out some essential elements that intervene in the flow of information at different levels and that affect how and when decision-makers react. The main elements are:

a. *Data acquisition:* This is the crucial first step in the functioning of an EWS. It involves collecting relevant information from various sources – depending on the hazard being monitored – such as meteorological stations, seismic sensors, satellites and field report@olutions to emerging problems, and they should undergo continuous training and knowledge updating to stay at the forefront of the use of tools, methods and technologies.

b. *Data processing:* Consists of converting raw data into useful information through statistical analysis, algorithms and predictive models. This very important process allows for data to be interpreted and forecasts to be generated that can be used by decision-makers. Some crucial factors are efficient processing (which enables complex information to be interpreted quickly) and the use of advanced predictive models to reduce uncertainty, improve the levels of robustness and accuracy in predictions, and increase confidence in the decisions made.

c. *Information management protocols:* Establish the ways of managing and distributing information within the EWS. These protocols ensure that information is managed in a coherent and standardized manner, and help decision-makers interpret and use it. Ideally, they should be governed by the principles of: consistency, to ensure that the information is robust and comprehensible; efficiency, to reduce response times based on the improvement in data transfer and management; and security, to ensure that sensitive information is not misused and to respect confidentiality requirements as appropriate.

3 According to sources from UNDRR and WMO (2022), global access to the use of communication channels is distributed as follows: 91% of the population use social networks, 87% use television, 81% use the Internet, 91% use radio, 76% use print media, 84% use emails and 72% use mobile phones. These distribution levels allow us to establish an order of priority for channels when sharing alerts and information, and to adapt the technologies and technical requirements to ensure they are used correctly and achieve the objective, which is to inform in a timely manner.

d. *Availability of trained technical personnel:* Personnel should have the necessary training and knowledge to handle complex technologies, interpret data accurately and make evidence-based decisions. Ideally, they should also have technical experience that allows them to find solutions to emerging problems, and they should undergo continuous training and knowledge updating to stay at the forefront of the use of tools, methods and technologies.

e. *Writing and formatting protocols for information delivery:* These must enable standardized ways in which information is organized and presented to decision-makers, ensuring that data are clear, relevant and concise in all types of reports and alerts, prioritizing easy-to-understand and easy-to-use structures, and ensuring uniformity in formats to facilitate data comparison and identification of trends and variations.

f. *Data management technologies:* These are the tools and systems used to communicate, store and manage data on digital platforms or other mechanisms. These technologies must be capable of handling large volumes of information without diminishing its integrity and coherence, while ensuring speed in the availability, transmission and access to data, and maintaining robust security parameters.

g. *Information delivery mechanisms:* These include physical and technical elements such as software (applications, web pages, etc.), communication mechanisms, signal protocols and data packaging, which are vital for successfully sharing information with decision-makers and the general public. Redundancy of communication channels and verification mechanisms is also crucial to ensure that information is communicated in its entirety. These elements must incorporate accessibility criteria, facilitate interaction with and feedback from the system's users, and allow for a rapid flow of information, in terms of both distributing alerts and updating critical information.

h. *Designing information visualization:* This refers to how information is presented, seeking to ensure it is easy to understand, interpret and manage, including the appropriate use of shapes and colours, graphs, maps and dashboards, among others. Good user-oriented (co)design should help make information quick to understand and effectively communicate complex data to varied audiences.

2. Challenges in technological integration

Addressing the various challenges related to technological integration in EWS is fundamental to improving their effectiveness and capacity to respond to disasters. Firstly, regarding the security and privacy of information, the collection and management of large volumes of data require strict security measures to be adopted to protect sensitive information and thus guarantee the privacy of individuals. To achieve this objective, it is important to consider during the planning stage efforts that allow progress in the construction and dissemination of frameworks and protocols that integrate cybersecurity with DRR. For example, the development of advanced encryption protocols and cyber threats mitigation strategies. The implementation of robust authentication systems, state-of-the-art firewalls, and intrusion detection technologies are necessary to achieve this objective. In addition, design guidelines should conform to the rules or regulations promoted by official computer security agencies, such as the Computer Security Incident Response Team (CSIRT) in Chile, the guidelines indicated in the CONPES Cybersecurity and Cyber-defence Policy Guidelines of Colombia, or international data protection parameters, such as the General Data Protection Regulation of the European Union, among others.[4]

Furthermore, we must keep in mind the set of development efforts and diverse platforms that various participants have implemented as part of their contributions through the set of initiatives and actions dedicated to disaster resilience. However, regarding interoperability between these systems and platforms, the differences between standards and technical elements established by the various service providers must be considered. These differences can hinder the fluid and efficient integration of information both in terms of technical aspects and the cost of integrating functions and flows.[5] It is therefore vital to develop interoperability models that facilitate communication and data exchange between heterogeneous systems, and to promote the generation of processes for standardizing protocols and data formats with a view to future adaptation. To this end, the implementation of open APIs and the use of communication standards such as RESTful and MQTT[6] can represent a viable solution for multiple sectors at varying levels of development, helping to improve interoperability. Furthermore, the complementary adoption of microservices-based architectures can facilitate the modular integration of different technological components.

It is also important to address the potential difficulties regarding scalability and adaptability to different geographic, demographic and technological contexts and to multiple hazards, since this requires a flexible and scalable technological infrastructure. To achieve this, it is essential to promote research development that analyses scalable system alternatives capable of dynamically adjusting to environmental changes and alert needs, using principles of adaptive design and fault recovery capacity. These efforts should be accompanied by the adoption of cloud solutions and containers such as Docker or Kubernetes; this will allow resources to be increased or decreased according to demand.[7] Additionally, implementing machine learning algorithms that adapt to new data patterns can help improve system flexibility.

Similarly, mass data collection requires advanced storage, processing and analysis capabilities to extract useful and accurate information. Progress must be made in establishing efficient big data methods and data cleaning and validation techniques to ensure the quality and relevance of the information used in EWS. The implementation of open-source big data solutions such as

4 For more information, see: https://eur-lex.europa.eu/legal-content/ES/TXT/?uri=celex%3A32016R0679.

5 It would be interesting to address elsewhere the scope and level of involvement of communication service providers regarding the technical, development and responsibility requirements in disaster situations, along with their role in establishing regulations, protocols and rules to improve resilience in different territories.

6 RESTful is the implementation of the REST (Representational State Transfer) software architecture style, which is used to perform communications between the client and the server, and which relies on the HTTP protocol for communication with the server. MQTT (Message Queuing Telemetry Transport) is a lightweight messaging protocol used with clients who need a small code footprint, are connected to unreliable networks or have limited bandwidth resources. It is mainly used for machine-to-machine (M2M) communications or Internet of Things (IoT) type connections. For more information, see: Richardson et al. (2019).

7 Docker is a container runtime technology that enables software to be packaged into standardized units called “containers” (understood as isolated and lightweight environments that allow applications to run consistently and efficiently, encapsulating the code, dependencies and configuration that are necessary for its execution). Kubernetes, on the other hand, is a container organization tool that enables system scaling to manage, coordinate and program containers on a large scale. For more information, see: Shah and Dubaria (2019).

Hadoop and Spark,[8] along with non-relational databases (NoSQL), facilitates the handling of large data volumes and provides a viable option to efficiently address this issue, considering the costs associated with implementing such systems. Furthermore, using automated data processing flows (for data routing and practical transformation) improves the consistency and accuracy of information by ensuring smooth data collection. This optimizes information use, allows for a focus on behaviours and process efficiency, and reduces the possibility of human errors.

It is also crucial to take a comprehensive approach to inclusion and closing the digital gap among different population groups. Advances in modern technology do not necessarily align with advanced levels of education, knowledge, access to and adoption of various developments and applications of these technological solutions. This presents unique challenges, including how to provide inclusive and effective communication before, during and after disasters. In Latin America and the Caribbean, we often have a range of competing communication channels, service providers and different coverage levels. This creates a very disparate landscape that hinders information integration, data flow channels and synchronization of messages that would ensure consistent and accessible information in real-time. In this context, exploring initiatives to unify platforms through systems that integrate multiple channels into a single centralized ecosystem — such as simultaneous alerts via SMS, social media and radio stations, for instance – could have significant positive impacts and set a precedent for further developments with broader coverage and adoption among diverse populations.

To continue making progress towards ensuring that different communities, especially the most vulnerable (including rural communities), have access to and can benefit from EWS-integrated technologies, we should look into digital inclusion strategies that may eliminate inequalities in technology access, considering socioeconomic, educational and geographic factors, as well as accessibility elements for people with different types of disabilities. Designing low-cost, easy-to-implement solutions — such as lightweight mobile applications and alert systems based on mobile phone messaging – that operate within limited communication infrastructures is key to improving coverage in remote areas or places with digital infrastructure constraints.

An additional challenge is involving local communities in designing, implementing and/or operating EWS through this type of technology. The use of applications that allow people to report adverse events can enhance hazards awareness and strengthen community capacity to detect them through community monitoring. One such example is the Red de Informantes Mercalli [Mercalli Informants Network], used by the National Service for Disaster Prevention and Response (SENAPRED, by its Spanish acronym) of Chile. SENAPRED establishes a training protocol for informants located in different territories. After an earthquake, these informants report their perception of the intensity and damage to authorities through official channels using standardized information. Such initiatives can be implemented through communication systems with low connectivity and technological requirements but that are able to reach much of the population, such as walkie-talkies and mobile phones.

8 In the field of Big Data, Hadoop (Apache) is an open-source software framework that enables the programming of distributed applications that are capable of working with massive amounts of data and network nodes. This streamlines workloads, enhances scalability and ensures fault tolerance. On the other hand, Spark (also by Apache) is an open-source big data project that offers high-level programming models. It can operate with SQL and real-time data processing APIs to apply distributed machine learning and graph processing, among other functionalities. For more information, see: Benbrahim, Hachimi, and Amine (2019).

Another interesting example is the case of Mexico and the design of the guide to developing community-based EWS, embedded within the project "Early Warning Systems and Risk Reduction for Slope Instability Associated with Deforestation and Degradation in Climate Change Contexts" (WRI, UNDP, SEMARNAT and INECC, 2021). This inter-institutional effort involves organizations such as the Secretariat of Environment and Natural Resources (SEMARNAT, by its acronym in Spanish), the National Institute of Ecology and Climate Change (INECC, by its acronym in Spanish), the World Resources Institute (WRI), and the United Nations Development Programme (UNDP) in Mexico. Through this partnership, they have created this instrument with the objective of strengthening the adaptive and response capacities of the population to hydrometeorological phenomena and climate change impacts, primarily in rural and Indigenous regions, as an adaptation and disaster risk reduction strategy (WRI, UNDP, SEMARNAT, INECC, 2021, p.9). This initiative enables communities to participate in the creation of EWS, in which technology integration plays a privileged role in developing solutions tailored to local social, geographic contexts and demographic contexts.

An important element is also addressing the challenge of sustainability and long-term maintenance of these technological systems. It is crucial to consider the socioeconomic conditions of territories, communities and governments, as well as their capacity to continuously maintain and update the enabled technological infrastructures. For that reason, it is important to study and establish sustainable financing models and preventive maintenance strategies that ensure the continued operation of existing technological systems. In addition, it is important to adopt scalable and adaptable solutions that can facilitate these tasks, and to integrate them into policy instruments and territorial planning frameworks to provide long-term viability. However, if we wanted to resolve a recurring limitation in EWS in Latin America and the Caribbean, it would be useful to observe the disconnect between EWS and territorial planning processes. In various countries in the region, inadequate planning has led to human settlements being built in very exposed and vulnerable areas, significantly increasing disaster-related risks. For instance, in Terrenas, Dominican Republic, unregulated urban growth and wetland removal for tourism infrastructure development have created conditions that hinder effective risk management (Del Granado et al., 2016). Such examples are common across the region, and to overcome these barriers, it is highly recommended that information from EWS be used to inform and update territorial planning instruments, promoting measures that encourage sustainable land use and prevent the construction of settlements in high-risk areas.

This integration helps anticipate disaster scenarios and direct public investments towards projects that reduce structural and social vulnerability. It also presents an opportunity to promote the prevention of key ecosystem degradation. When, for example, mangroves and wetlands are compromised — and in many cases even affected to the point of disappearance —, their natural risk reduction capacity diminishes in many regions of Latin American and the Caribbean.[9] Reforestation and sustainable resource management projects serve as an example of how local communities can actively participate in risk reduction, while strengthening their adaptive capacities and promoting social cohesion. Integrating these actions into educational and awareness-raising

9 In Ecuador, the conversion of mangroves into shrimp farms has increased exposure to seasonal flooding, while in the Dominican Republic, hotel infrastructure has removed natural barriers against hurricanes and storms. Restoring these ecosystems should be made a priority, not only due to their capacity to protect against disasters but also because of their contribution to sustainable development and biodiversity conservation. For more information, see: Del Granado et al. (2016).

programmes presents an opportunity to foster a mindset based on prevention and resilience. This can also serve as a pillar for developing guidelines that enable the collection of data and information from the community level, leveraging local knowledge regarding natural resources, geography and infrastructure in the territory. Additionally, it facilitates the establishment of appropriate usage criteria for decision-making and makes it possible to link this type of information with EWS to enhance timely reporting and monitoring of emergency situations in areas where equipment and personnel are scarce.

In this regard, self-managed EWS developed in local communities represent a valuable foundation for disaster risk management and reduction in rural areas with limited access and low resources. These systems, often based on traditional knowledge and simple tools such as walkie-talkies or community alarms, can enable immediate and contextually relevant responses to emergencies. However, they could be made considerably more efficient through strategic investments that facilitate the integration of some modern technologies. Supporting the development of these systems that use more-accessible technologies, such as mobile applications or low-cost sensors, could improve the reach of alerts by expanding coverage and reducing exclusive dependence on external actors.

We recommend working towards developing action lines that help establish strategic partnerships with the private sector, foster synergies between public and private actors, and forge validation connections with academic institutions. This would enable balanced participation and strong collaboration. A positive example of such a partnership is the Participatory Implementation Plan for the Trinational Early Warning System between Bolivia, Brazil and Peru. This initiative focuses on "the adaptation of municipalities in the Amazonian tri-border area to climate change through an advanced drought and flood forecasting service."[10] This plan is implemented by the Amazon Cooperation Treaty Organization (ACTO, by its acronym in Spanish) under the Strategic Action Program for the Integrated Management of Water Resources in the Amazon Basin. Such initiatives, as well as community-based EWS like the aforementioned guide, promote the participation of public sector representatives and committed community leaders in local spaces and enable the development and strengthening of capacities for designing EWS based on local realities and the effective participation of communities. This serves as an excellent example of opportunities for multiple integration of community participation, technology development and DRR.

3. Best practices and recommendations for optimizing information flow for decision-makers in EWS

Considering the above, some best practices can be established to help improve and facilitate the proper functioning of EWS, particularly in relation to the role of decision-makers who use them. Best practices are also systematically linked to other components of the disaster risk management and reduction ecosystem.

Firstly, one best practice is that the technical agencies responsible for providing forecast data and information on events associated with natural phenomena, as part of the monitoring system,

10 For more information, see: https://aguasamazonicas.otca.org/bolivia-brasil-y-peru-crean-plan-participativo-de-implementacion-del-sistema-de-alerta-temprana-trinacional/

communicate and report information using internationally recognized and well-documented standards. This helps facilitate cooperation and the integration of cross-border support networks in the event of an emergency, while also streamlining the responsible actors in these processes. Additionally, we recommend that staff in EWS departments (or equivalent) should have the knowledge and analytical capacities regarding multiple socio-natural phenomena and that they should participate in periodic training and refresher processes. This helps them determine how urgent information transmission is, ultimately helping to reduce reaction times (UNDRR and WMO, 2022).

Furthermore, it is advisable that communication formats follow criteria for prioritizing information clearly based on the importance and use of the data during and after an adverse event. The prioritization criteria should be presented in a way that simplifies the user experience and facilitates data comprehension, thereby improving decision-making, reducing response times and improving emergency management. It is also essential to develop and implement redundancy and backup systems to ensure that information remains available at all times, even in the event of technical failures, service interruptions or disasters that may affect infrastructures. The continuity of communication and information flows and processes, along with the functionality of the channels that enable emergency response protocols, must be supported by backup mechanisms and alternatives to ensure they can operate in any eventuality.

It is also recommended that the process for adopting technologies integrate the training of personnel working in EWS and incorporate levels of co-creation with them, facilitating the simple and fast adoption of information, actions and measures. In this regard, it is essential to make progress towards building a governance model that guarantees the inclusion of all technical bodies and stakeholders within the multi-hazard early warning systems (MHEWS). This means guaranteeing that no institution is relegated or excluded from decision-making processes and ensuring stakeholder representation is balanced. Additionally, it is crucial to foster investment in technologies that benefit multiple institutions, thereby ensuring effective and equitable collaboration within the system. Furthermore, it is advisable to develop EWS and their associated systems by leveraging, whenever possible, existing and operational technologies, and avoiding the imposition of new technologies that require retraining for their users and operators. Although this principle is particularly relevant for countries lacking the necessary resources to implement and deploy new high-cost infrastructures, it is also applicable to those countries that do possess such resources. It is not so much a matter of resource management as an acknowledgement that digital systems have an impact (such as resistance to change or increased time for adaptation and adoption of new usage methods) on the people who use them, and it is advisable to minimize this impact whenever possible.

Advancing towards certain levels of standardization in both data collection and processing and presentation of information facilitates the creation of international networks with a common language for disaster prevention. This helps shape international partnerships in which the analysis of experiences in the use of technologies for EWS developed in other countries can help identify trends, best practices and innovative solutions that have proven effective in different contexts. Gathering positive elements from successful experiences and enabling processes to incorporate and adapt to regional and local contexts can contribute to developing tools that avoid becoming obsolete quickly in terms of their interoperability.

Finally, we must reiterate the importance of having robust governance among the actors participating in MHEWS, to make these systems more efficient in resource distribution and optimization of measurement instruments. This is a crucial factor in establishing collaboration pillars that enable new forms of development and the adoption of improvement alternatives for current systems.

4. Improving information delivery processes to EWS decision-makers: the case of Chile

With the enactment of Act No. 21.364 in 2022, which created the National Service for Disaster Prevention and Response (SENAPRED, by its Spanish acronym) of Chile, improvements in understanding of risk and in strengthening of research and EWS were observed through capabilities and infrastructure to monitor and analyse hazards, vulnerabilities and emergency impacts (National Congress of Chile, 2021, article 24). This act is supplemented by the National Policy for Disaster Risk Reduction 2020–2030, whose fourth priority pillar aims to strengthen EWS in their phases of monitoring, evacuation and communications. The aim is to ensure timely and accessible information through the development of technological infrastructure to alert authorities and the population (National Emergency Office, 2020, p.99).

In this context and in anticipation of the 2024 wildfire season, SENAPRED identified the need to evaluate existing opportunities for improvement in terms of incorporating modernization elements into the national EWS. To this end, an assessment was conducted that revealed critical areas for improvement, with information flows for decision-makers being one of the most relevant aspects. The assessment took into consideration the wildfires in early 2023, which affected the regions of Maule, Ñuble, Biobío and La Araucanía. This emergency exposed significant opportunities for innovation in how information was entered, transmitted and received, and examined how these elements impacted the capacity and speed of response from risk managers and decision-makers in the public sector.

Continuing to focus on innovation and generation of continuous changes in the EWS, SENAPRED undertook to improve and reduce response times in decision-making during disasters, and to adapt to the new conditions arising from emergencies. To address the standardization of information, records were studied and the Alfa 2 Project was revisited, which utilized earthquake software in systematizing, consolidating and disseminating early warning and emergency reports. This was complemented by the Emergency Operational Management System Experience (2016–2018), which sought to integrate procedures from early warning centres, now called the early warning unit, and mainly focused on consolidating information on earthquakes and tsunamis.

Both initiatives helped the organization understand the need to not only tailor the EWS to the particularities of each disaster but also to consider the needs related to the human components involved in the EWS information supply chain, especially concerning early warning unit operators. These operators deliver detailed information to decision-makers and their work largely determines how easy critical data are to understand when establishing and executing actions during an emergency.

Thus, to meet the objectives set by both Act No. 21.364 and the National Policy for Disaster Risk Reduction, SENAPRED, through the Ministry of the Interior and Public Security, submitted a request to modernize the EWS, focusing its work on opportunities for improvement regarding the work of the early warning unit. Faced with this challenge, the Risk and Emergency Management Unit of the Subsecretariat of the Interior began working in 2022 with the Institute for Disaster Resilience (Itrend) to conduct a series of assessments to prepare for the development of a technological tool aimed at improving information flows for decision-making, capable of systematically and effectively visualizing the information deployed by the early warning unit.

The initial assessment revealed significant shortcomings in previous information flows, such as deficiencies in report drafting protocols and the technological support used for timely data transmission and reception. It also highlighted challenges that operators face in delivering information to the authorities, such as prolonged processing times and a lack of information standardization.

Based on this assessment, work began in 2023 on developing two applications capable of mitigating these shortcomings, reducing report generation times and ensuring information standardization and organization. The first version of each app was developed with a focus on wildfires. As this was an initial phase, it was decided to prioritize this hazard, as it is one of the most recurrent in the country according to SENAPRED data.

The first tool was designed as a data acquisition application for the standardized generation of alerts and for use by the early warning unit technical team, with the aim of reducing report generation times while standardizing and organizing information. Consequently, it was named the "Event, Alert and Emergency Management and Monitoring Tool for the Early Warning Unit."

The initial version was launched in September 2023 and underwent a pilot phase from January to June 2024 at the national early warning unit in the Metropolitan Region. The tool is now being introduced in priority regions such as Valparaíso, O'Higgins, Maule, Ñuble and Biobío, with specific training on its use being run for regional alert unit personnel and SENAPRED regional staff. Being a web application, it does not require additional software installation on users' computers, as it is fully operational on the most widely used web browsers (such as Chrome, Edge and Firefox).

The tool's data model considers three main structures: events, alerts and committees. Events store technical characteristics related to an emergency, such as the area affected by a wildfire, damages, and resources used to tackle the emergency. Alerts correspond to the administrative information of the emergency and indicate type (early preventive, yellow or red), level (municipal, provincial, regional or national) and alert coverage (the specific affected area). Finally, committees are a record of technical meetings such as Disaster Risk Management Committees (COGRID, by its acronym in Spanish)[11] or technical tables conducted in an emergency.

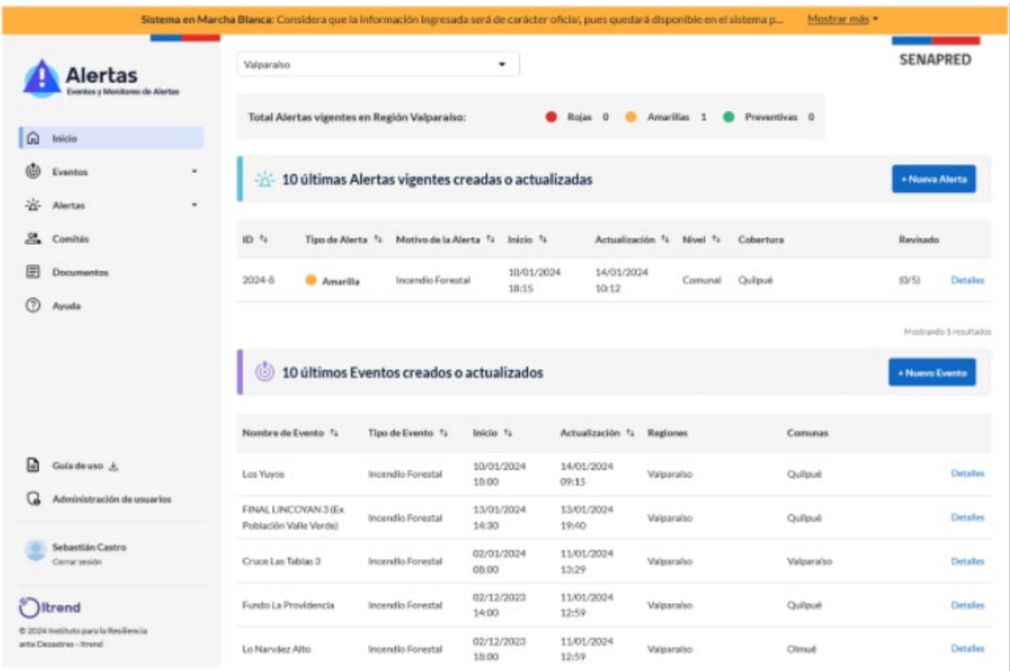
One of the advantages of the implemented model is its capacity to retain the history of events and alerts as the emergency evolves. This is achieved through generating a log of records documenting event updates. Similarly, for an alert, it is possible to record its evolution through the various states that are defined over time. These options ensure that the information for each event and alert is consolidated into a single entry, guaranteeing the traceability of emergency management.

Additionally, to prevent duplicated work and information, the model allows events, alerts and committees to be linked. Thus, an alert can be linked to one or more events, eliminating the need to re-enter technical information that would otherwise warrant the declaration or update of an alert in the system. This functionality is

11 The Disaster Risk Management Committees are a management component within the National Disaster Prevention and Response System. They are activated in the event of an emergency at the municipal, provincial, regional or national level. For more details on Chile's emergency response organization, see Act No. 21.364, which establishes the National Disaster Prevention and Response System, replacing the National Emergency Office with the National Service for Disaster Prevention and Response and adapting the guidelines.

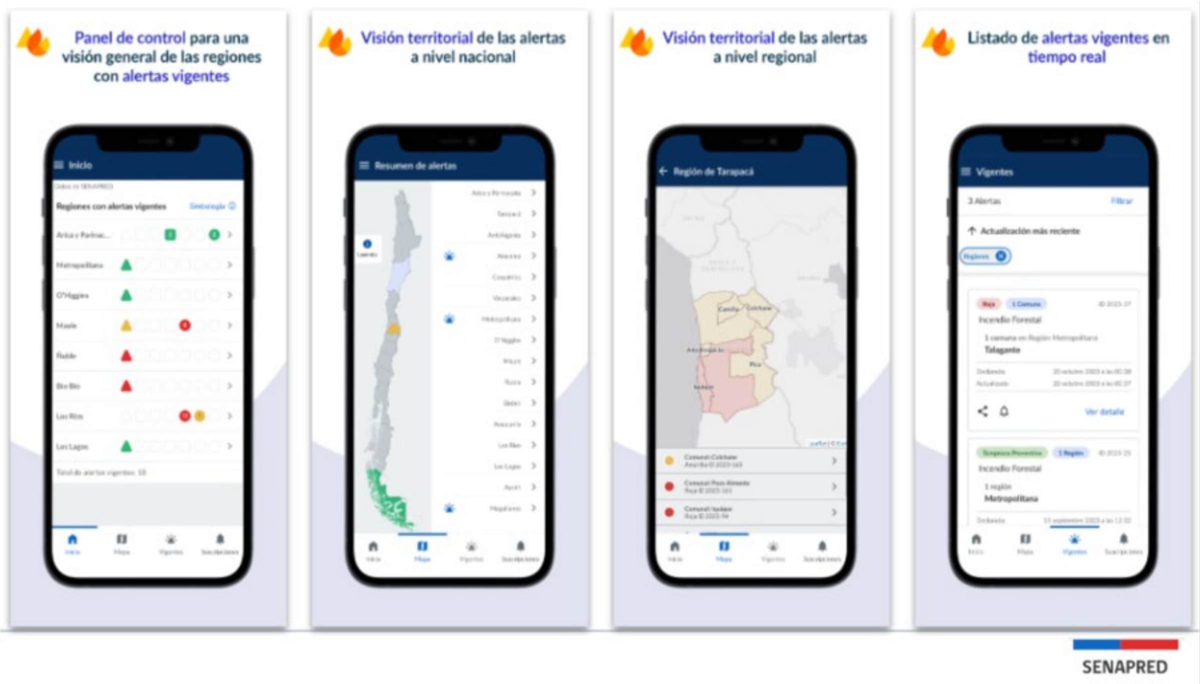
used in the automatic generation of documents that the national and regional early warning units traditionally draft manually. In total, three documents were generated: i) Incident or Emergency Report; ii) Technical Risk Analysis; and iii) National Summary of Wildfires. Finally, each time a user declares an alert or generates a new status for an existing one, the system sends a notification, which is currently being utilized by a second tool: a mobile application developed for authorities, described below.

Example of the home dashboard: "Management and Monitoring Tool for the Early Warning Unit"



The second tool was a mobile application called "Events and Alert Monitoring" (EMA, by its acronym in Spanish), a visualization tool designed for institutions and key stakeholders involved in monitoring events, alerts and emergencies. It was developed to enhance communication and decision-making among institutions in response to various types of emergencies and is compatible with iOS and Android devices. This application, which provides an up-to-date record of alerts declared by the early warning unit for wildfires, allows alerts with behavioural patterns to be detected, and offers detailed information on each issued alert. For each alert, the tool provides information on territorial coverage, affected areas and levels of impact in hectares, resources deployed to address the associated event (wildfire), and historical evolution. Among its features, the application provides access to an updated record of issued alerts, includes search and filtering tools, offers aggregated visualizations that facilitate understanding of the distribution of alerts across the national territory, and enables alert subscription tools for particularly relevant notifications. This allows users to receive notifications when the early warning unit declares or modifies an alert, according to a user-configured notification preference setting.

Example of different interfaces on the "Mobile application for events and alerts visualization for authorities"



Both tools underwent a six-month pilot phase. During this phase, the tool was exclusively used by SENAPRED's national early warning unit.

During the pilot phase, the national early warning unit successfully used both tools and issued all wildfire alerts without significant difficulties. This led to a 40 per cent reduction in the time spent by operators and coordinators on document drafting and review tasks. Similarly, the tools demonstrated their ability to operate continuously, translating into high reliability for a service that must function without interruptions. Visualization, the ease of reading, the prioritization levels of information, search options, timely alert updates and the ability to consult technical information were well received by institutions. These types of improvements, focused on how information interacts within the structures of EWS, allow for a more organized, faster and more efficient decision-making process to respond to an emergency. This type of progress is particularly important in response to rapidly destructive phenomena such as wildfires.

5. Multi-hazard maps: challenges and ways to contribute to EWS

Among the various instruments that can contribute to comprehensive disaster risk management are hazard maps, which aim to provide a geospatial graphical perspective that allows for the identification of areas exposed to the direct and indirect effects of a hazard and the intensities that may be recorded within a given time frame (e.g. maximum ground acceleration for a 500-year return period). These maps are usually focused on a specific hazard, graphically representing information based on the characteristics of a particular socio-natural or anthropogenic phenomenon (Mesías Rosas, 2017). They make a significant contribution by providing relevant information for identifying, understanding and eventually reducing risk, preparing for an emergency, and coordinating actions aimed at saving human lives and reducing material losses (Renda et al., 2017). Their contribution varies depending on their capacity to deliver precise information and accurate estimates regarding hazards and their impact on the territory and to offer valuable insight for decision-making by institutions responsible for disaster prevention and response.

However, maps alone are not necessarily capable of understanding multiple interacting hazards in territories exposed to two or more phenomena. The differences in addressing each hazard, which by their nature require specific observation methods and measurement parameters, complicate the task of integrating and visualizing them within a single map.

One of the major challenges for these tools is integrating multiple hazards into a single map by incorporating metrics, having standardized databases and maintaining appropriate levels of scale homogenization. Efforts in this area aim to develop multi-hazard maps for use in research, planning and comprehensive disaster risk management decision-making, providing a more thorough and precise overview of the dangers faced by a community or region, thereby improving risk understanding. These instruments have the potential to facilitate planning and preparedness by delivering valuable information to those responsible for developing mitigation and response strategies. Additionally, these maps can serve as a useful educational resource to raise awareness among the population about territorial hazards, fostering a culture of preparedness (UNDRR and WMO, 2022).

Among the challenges involved in developing multi-hazard maps, the following stand out:

a. *Standardization of information:* Different hazards are often documented and analysed using diverse formats and methodologies, originating from various sources. These sources may not necessarily share the same data processing methodologies or scales and may exist in incompatible formats (e.g. vector files, raster data), thus posing a challenge for data integration.

b. *Scale homogenization and use of perspectives:* Hazards can be mapped at different scales, making homogenization crucial to ensure consistency in multi-hazard maps. This process is essential to ensure maps are accurate and useful. Different hazards can affect each area unevenly, and it is crucial that maps coherently represent this variation. To achieve this, several strategies can be employed, such as: data standardization, in order to adjust data to a common scale to enable accurate comparisons between different hazards; the integration of multiple perspectives, which allows for the incorporation of information from various disciplines and sources to provide a more thorough and precise overview; and the use of advanced geospatial models, which enables the application of modelling and simulation techniques to harmonize data and represent hazards consistently.

c. *Need for specialized inputs and technologies:* Developing multi-hazard maps requires various inputs and technologies, such as: topographic instruments for territorial data collection, satellite imagery for wide and detailed terrain visualization, databases containing historical and updated hazard information, and drones for real-time aerial data collection. On the technological side, it is necessary to use software such as Geographic Information Systems (GIS), simulation software and predictive modelling.

6. Potential contributions

The benefits of multi-hazard maps relate to their ability to significantly impact disaster risk reduction and management by providing a comprehensive perspective that goes beyond identifying individual hazards. Their value lies in their ability to enhance information parameters and schemes used in planning and emergency management, which enables broad detection of vulnerable areas and supports resource prioritization. This approach aligns with global initiatives such as Early Warnings for All (EW4All), which aims for EWS not only to issue alerts about imminent events, but also to provide useful information for designing effective responses based on the specific conditions of each community. Multi-hazard maps allow for high-risk zones to be identified accurately. This enables investment to be prioritized in resilient infrastructure, community training to be strengthened and more-efficient mitigation measures to be developed. Additionally, they contribute to the design and logistical development of emergency response processes, as they help develop mitigation strategies, can identify the most appropriate and effective measures relevant to each territory, and facilitate the planning of evacuation routes, safe zones and shelters. These elements help build a shared understanding of risk beyond political and administrative boundaries, and in turn, they can support the design and implementation of evacuation drills and exercises.

Multi-hazard maps can also play an important role in risk education and awareness. The availability of clear and comprehensible maps can help communities better understand the hazards to which they are exposed and encourage the adoption of preventive measures within community spaces. The development of family and community evacuation plans can be better supported by accurate maps that provide valuable information about the interaction of various hazards.

One of the key innovations in the development of multi-hazard maps is the integration of data and advanced predictive models. By using technologies such as hazards modelling combined with satellite data and GIS, it is possible not only to visually represent each individual hazard but also to simulate complex scenarios involving multiple hazards that may occur simultaneously or sequentially. This enables their effects to be anticipated and the most vulnerable areas to be more accurately assessed. Furthermore, the incorporation of artificial intelligence and machine learning algorithms into the processing of these data can enhance predictive capabilities and optimize decision-making processes by generating models that continuously adjust as new and better information becomes available. This approach not only improves prediction accuracy, but also facilitates response planning and resource allocation during emergency situations. This element is key, and it supports measuring in the application of various tools such as indexes and risk metrics that consider vulnerability as a central factor (Pelling, 2013). Examples include the Social Vulnerability Index (SoVI), the World Risk Index and the Index for Risk Management initiative for Latin America and the Caribbean (INFORM-LAC).[12]

In addition to technological integration, another critical challenge worth mentioning is community participation in the generation and validation of data. Incorporating local knowledge and risk perceptions from affected communities into

12 The Social Vulnerability Index – SoVI, applied to disaster risk management, is available at: https://datospararesiliencia.cl/dataset.xhtml?persistentId=doi:10.71578/HNIJX9. The World Risk Index 2024, published by Bündnis Entwicklung Hilft, is available at: https://reliefweb.int/report/world/worldriskreport-2024-focus-multiple-crises. The INFORM Risk Index for Latin America and the Caribbean, applied by UNICEF, is available at: https://www.unicef.org/lac/informes/%C3%ADndice-de-gesti%C3%B3n-de-riesgo-para-am%C3%A9rica-latina-y-el-caribe.

map development can make them significantly more useful and applicable. Strategies such as participatory workshops and the use of mobile applications for data collection can strengthen community response capacities and improve the adaptability of disaster risk reduction and management strategies.

Data interoperability is another crucial aspect to consider. As the volume of available information increases and technologies evolve, it is essential to ensure that the various systems and databases are compatible with each other. This involves applying interoperability principles such as FAIR (Findability, Accessibility, Interoperability, and Reuse of digital assets),[13] promoting open data and making information available through standard, well-documented interfaces (APIs). This ensures the accessibility and usability of multi-hazard maps for a wide range of users, from government institutions to NGOs and the private sector, and makes the maps themselves valuable inputs to be integrated into tools such as EWS.

In summary, while hazard maps are powerful tools for disaster risk management, their capacity to integrate multiple hazards and diverse data remains a critical area for development. The combination of advanced technologies, community participation and interoperable data standards is essential for improving preparedness, response and recovery efforts for both natural and human-induced disasters worldwide, and for strengthening the development of EWS capable of effectively integrating multiple hazards.

13 For more information on interoperability principles, see: https://www.go-fair.org/fair-principles/

05

Communication and social networking tools

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1. Introduction

Any website or application that enables people to connect online via social networking are collectively termed “social media”. The rapid expansion of Internet access, improvements in telecommunications and the increasing use of social media have transformed how we understand, manage and reduce disaster risks. Information now spreads faster than ever, allowing people to stay informed, prepare in advance and respond effectively to crises.

Communities today have access to real-time data, expert recommendations and step-by-step guidelines on how to protect themselves and their surroundings. This level of connectivity has fundamentally changed how we approach disaster preparedness and response.

In this digital era, social networks have established themselves as powerful tools in the disaster risk management and reduction fields, playing a fundamental role in information dissemination, response coordination and impact mitigation. For example, anyone with a social media account has the possibility to share real-time information about disasters, including geographic location, photos, videos, messages or a combination thereof. Thus, social media and social networks have become critical to providing real-time access to information. Emergency management and community organizations, among others, have recognized the potential of social media to provide timely information and alert communities about impact warnings, disaster prevention and response.

Journalists play a vital role in disaster risk reduction (DRR) by ensuring that information is accurate, timely and actionable. Their responsibilities extend beyond merely reporting events – they are key actors in fostering resilience, countering misinformation and holding authorities accountable. However, as technology continues to reshape media landscapes, journalists must adapt to new tools and methodologies. By integrating data journalism, satellite imagery, AI-driven analytics and social media verification techniques, they can enhance their ability to report on disasters with precision and depth. At the same time, ethical considerations must remain at the forefront of their work, ensuring that the pursuit of real-time coverage does not compromise accuracy, transparency or inclusivity.

Disaster communication is not just about delivering information; it must empower communities to prepare, respond and recover. To achieve this, journalism must embrace a risk-informed approach, recognizing that disasters, far from being isolated events, are interconnected with broader social, political and environmental factors. Ultimately, the future of disaster reporting lies in leveraging technology responsibly, strengthening community trust and prioritizing the needs of the people most affected.

Social media has transformed the way in which information is disseminated in emergency situations. Unlike traditional media, which can face delays in the transmission of news, platforms such as X (formerly Twitter) and Facebook allow for the instantaneous dissemination of critical alerts and updates. Since “social media provides opportunities for engaging citizens in the emergency management by both disseminating information to the public and accessing information from them” (Simon, Goldberg and Adini, 2015), this immediate communication capability is crucial for real-time decision-making, which can be decisive in minimizing damage and preserving lives. Organizations and institutions in charge of disaster management can rely on social networks and tools such as geolocation to improve their responses and have a direct impact on the people most affected.

In recent years, social networks have proved to be a means of rapidly organizing and coordinating humanitarian relief efforts. During disasters such as earthquakes or hurricanes, the ability to quickly gather human and material resources is vital for effective response and resource management. Platforms such as WhatsApp and Facebook have been used effectively to coordinate rescue logistics and the distribution of supplies, as well as being a channel where specific community needs can be quickly addressed. One such example is the efforts coordinated through social networks after the 2010 earthquake in Haiti, when these networks facilitated the mobilization of volunteers and the collection of donations. This efficient organizational capacity allows for an effective response, although it also faces challenges such as the management of large volumes of information and the need to verify the authenticity of sources. This outreach to the community also works to raise awareness and there is no limit on the number of people who can participate in these channels.

Social networks serve as crucial platforms for disaster prevention education and awareness-raising, and in recent years have been used to provide accessible information. Through educational campaigns, essential knowledge on how to prepare for and mitigate the effects of disasters can be disseminated. Preventive education is a key component in building resilient communities. The #HurricaneStrong initiative, for example, has been used on X (formerly Twitter) to educate the public about hurricane preparedness, demonstrating the power of social networks in disseminating preventive knowledge. However, the effectiveness of these campaigns depends largely on the reach and receptiveness of the target audience, as well as the ability to sustain attention over the long term.

In this chapter, we discuss how social media is not just a tool for staying connected and how it has, in fact, become an essential part of disaster risk management. More than ever, governments, emergency response agencies, community organizations and individuals are using social media to provide and obtain real-time alerts, guide evacuations and share life-saving information.

1.1 Roles and responsibilities of the media and journalists regarding the use of technology in times of disaster

A discussion of the media's role in covering disasters and emergency situations is very much needed. Since the media plays a large role in informing, educating, monitoring and giving voice to affected communities, its contribution to the security, protection and resilience of society in times of crisis has become evident in recent years. However, there is still room for improvement, as discussed below:

- *Reporting with accuracy and truthfulness:* To maintain public trust, journalists must verify their sources and cross-check information before publishing it. The media must only provide accurate and verified information about the disaster, which is essential to preventing the spread of rumours and confusion at critical moments.

- *Encouraging fact-checking and responsible sharing on social media:* In times of crisis, anyone with Internet access can contribute to the information ecosystem. While this democratization of information can be valuable, it also increases the risk of misinformation. Users should verify sources before sharing disaster-related content, prioritize official channels and avoid amplifying unverified claims that may cause panic or confusion. Media outlets and journalists can help by promoting digital literacy and fact-checking tools to support responsible information-sharing.

- *Alerting and educating the population:* If time allows, the media should alert the population to the potential impacts of an upcoming disaster; this includes reporting on warnings, evacuations and safety measures. In addition, the media should educate the public on how to prepare for future disasters and provide practical advice on (or dissemination of) actionable guidelines that can help save lives. All information should be based on official sources (such as country or regional authorities) and guidance around DRR. AI-powered tools can enhance early warning systems by analysing meteorological data, social media trends and historical disaster patterns to predict potential impacts more accurately.

- *Reporting on the disaster response:* The media must be vigilant when reporting on the response to a disaster. This includes monitoring the effectiveness of rescue operations, aid distribution and inter-agency coordination.

- *Promoting resilience and preparedness:* The media can contribute to societal resilience by reporting on risk reduction and disaster preparedness practices. Similarly, publishing inspiring stories of resilient recovery and rebuilding can also motivate communities to remain hopeful and work together towards achieving a common goal. By fostering this discussion, the media can play a crucial role in communicating relevant information throughout the disaster management cycle. Its work involves not only reporting the facts, but also contributing to DRR, building resilience and improving the response of affected communities.

- *Content differentiation:* In disaster situations, media coverage tends to be similar between different outlets, as they all report on the same core events using common sources (including posts by the general public). However, journalists may try to stand out by presenting different ideas and original approaches regarding disaster risk, its metrics (e.g. return periods) and components (e.g. hazard, vulnerability and exposure). To avoid generating confusion among the affected communities, a DRR approach should be adopted when providing a wide range of ideas. Similarly, by consciously setting the agenda rather than passively following it, journalists can offer their audiences a unique and relevant perspective. Natural language processing (NLP) can help identify emerging narratives and trends in disaster reporting, enabling journalists to refine their coverage and avoid repetitive content.

- *Tailoring messages to the target audience:* The needs of audiences vary according to their profile and the arrival of the media for which the journalist works. During a disaster, the general public (including the affected communities) require verified and accurate information about the event, its impact, and rescue and relief efforts; they also need data based on scientific facts to counter panic. National audiences do not need the same level of detail as local audiences, but international organizations, although geographically distant, also require specific information about the actions of other actors and the exact needs.

- *Using social media responsibly:* The proper use of social media is linked to ethical challenges and responsibilities. For this reason, journalists should carefully verify information before its dissemination on different channels, under the premise that “speed should not compromise accuracy”. Similarly, the inclusion of multiple perspectives and voices on social media is critical for equitable and accountable coverage.

- *Embedding a disaster risk perspective in everyday journalism:* Disaster reporting is not just about covering emergencies as they happen; it is about helping audiences understand risk as an ongoing reality. Journalists play a key role in shaping public awareness, and their coverage should not be limited to crisis moments but rather address the factors that influence disaster risk before, during and after an event. Raising risk awareness through journalism means recognizing that disasters are not isolated events but the result of intersecting vulnerabilities, exposure conditions and characteristics of one or multiple hazards.

Media outlets have the power to shift the public mindset from reaction to prevention, influencing both policy and behaviour in ways that can save lives and reduce losses.

- *Building audience trust*: Trust is the foundation of effective disaster communication. In moments of crisis, people turn to the media in search of accurate, timely and actionable information. However, trust is not built overnight since it is only cultivated through consistent, responsible and transparent reporting in everyday coverage.

In summary, the strategies for communicating risk must adapt to the rapid and varying conditions in which disasters evolve. In an era dominated by digital platforms, the responsible use of technology – such as AI-driven data analysis, satellite monitoring, real-time mapping and automated fact-checking – can enhance the accuracy and reach of disaster reporting. Whether through traditional journalism or social media, leveraging these tools ensures that clear, verified and timely information reaches those who need it most. By integrating digital innovations into reporting while prioritizing public awareness and trust, we can strengthen disaster preparedness and build more-resilient communities.

1.1.1 Mental health and disasters in social media

Although social media can be an invaluable tool to keep us connected, informed and supported before, during and after a disaster, it can also become a minefield for our mental health if not properly managed. Hall et al. (2019) studied the association between exposure to disasters and the use of media and post-traumatic stress disorder when social media posts show images or videos of damage to homes, the environment or people who were injured or killed. However, the study found that social media posts that show people in heroic or collaborative situations have little post-traumatic impact and even encourage people to search for more related content and information.

It is important to understand how to care for our emotional well-being as we navigate these digital spaces during crisis situations. Some strategies that are useful in protecting mental health during disasters regarding social media content are outlined below:

1. Set clear boundaries: It is easy to fall into a cycle of excessive consumption of news and social media content during crisis situations. Setting time and frequency limits to avoid overexposure to stressful information, such as by scheduling specific times of the day to check the news and social media, allows the mind to take a break at other times.

2. Double-check the information sources: In times of crisis, fake news and misinformation can spread quickly on social media, with the possibility of increasing anxiety and fear. It is therefore recommended to always verify the source and veracity of information before further sharing it or making decisions based on it. Only official and specialized news sources should be relied upon.

3. Foster a supportive community: Using social media to connect with friends, family and supportive communities who can provide comfort, guidance and solidarity during difficult times helps people engage in constructive, positive conversations that promote mutual care and resilience.

4. Practise self-reflection and self-care: Be aware of how you feel while scrolling through social media during a crisis. If you notice that certain types of content are negatively affecting you, don’t hesitate to step away and prioritize your emotional well-being. Spend time doing activities that help you relax, such as meditation, exercise or reading.

5. Be tolerant of yourself and others: In times of crisis, it is important to remember that we are all dealing with difficult situations in the best way we can. Try to be empathetic and compassionate towards yourself and others in online interactions, for instance by avoiding judging or criticizing others, as a simple act of kindness can make a difference to someone's emotional well-being.

6. Be mindful of algorithmic triggers: Social media platforms use algorithms to prioritize content based on engagement, which means that the more disaster-related content you consume, the more of it you will see. This can create an overwhelming and distressing cycle. To counteract this, it is recommended that you actively engage with positive, educational or uplifting content to balance your social media feed. Additionally, consider muting certain keywords, unfollowing accounts that contribute to your distress, or using features like "See less of this" to limit exposure to triggered content.

1.1.2 Ethics of social media use during disasters

As a tool for sharing information and communication, social media has a wide range of benefits related to DRR. However, its use comes with ethical challenges in disaster contexts, particularly concerning access, equity, misinformation, privacy and psychological impact.

- *Relationships and authoritative voices:* Social media is by its very nature about relationships, with trust levels impacted by a range of factors, such as familiarity and identification with an account/individual/organization and the perceived level of expertise. The rise of influencer culture and the negative impacts this has on perceived expertise or authority is also important to note. The relationship on social media between the population and emergency agencies must be understood as multi-directional. From the population's perspective, the ethical tension lies in prioritizing messages that originate from an authoritative source (e.g. a local emergency authority) and combating rumours and misinformation while at the same time recognizing that organic community communications and sometimes non-expert influencer voices may contribute (positively and negatively) to DRR. Similarly, the upward flow of information or intelligence-gathering may be informed by social media. For instance, how do emergency authorities prioritize voices in the collection of this information and how do existing relationships/perceptions as well as access gaps influence this?

- *Algorithmic bias:* Machine learning algorithms and opaque recommendation systems influence which disaster-related information is prioritized online. This raises several ethical concerns such as the following:

    - Misinformation and viral rumours may be amplified over verified, expert-led content.

    - Crisis response posts may reach certain demographics more than others, leading to disparities in levels of awareness and preparedness.

    - Algorithms may reinforce bias by prioritizing content from dominant languages or regions, thereby excluding marginalized voices.

Emotional manipulation and sensationalism: Social media algorithms tend to prioritize content that generates high engagement, often amplifying emotionally charged and fear-driven narratives. While urgency is necessary in disaster communication, excessive sensationalism can lead to panic, misinformation or crisis fatigue among the public. Journalists, emergency responders and media outlets must ensure that risk is communicated responsibly, maintaining a proper balance between urgency and accuracy. Disaster-related messages should be clear, direct and without exaggerations. Encouraging preparedness rather than panic is essential, as shifting the focus towards proactive measures fosters a sense of empowerment rather than helplessness.

1.2 Challenges in the Americas and the Caribbean

Communication plays a strategic role in coordinating effective responses to mitigate disaster impact. It offers the means to inform users about events that have the potential to negatively impact us all, and the practices that we can implement in response. In this sense, the use of technological tools has significantly improved DRR efforts in the region.

Nevertheless, there are several challenges in the Americas and the Caribbean region, as set out below:

- *Misinformation, rumour spreading and inaccessible information:* During emergencies, individuals are exposed to large quantities of information, often without being aware of its validity or the risk of misinformation. In the aftermath of the Haiti earthquake in 2010 and Hurricane Maria in 2017, misinformation and rumours complicated rescue and humanitarian response efforts. An often-overlooked challenge in Latin America and the Caribbean is its linguistic diversity, as it is home to many linguistic groups, including Indigenous communities and migrant populations, many of whom may not receive emergency messages in a language they fully understand. Additionally, people with disabilities, such as those who are visually or hearing impaired, may struggle to access life-saving information if it is not provided in alternative formats, including sign language interpretation, Braille or audio alerts.

- *Unequal access to technology:* This issue is especially evident in marginalized communities, where it limits their capacity to receive, act upon and share critical information during and after disasters. This also exacerbates post-disaster inequalities, as communities are uncertain about what is happening around them or are unable to access aid and shelter information. This is why it is important to use traditional telecommunications methods in addition to social networks.

- *Lack of political action*: There is a lack of leadership and effective commitment among some governments to implement policies and resources to strengthen emergency communication, despite the fact that disaster resilience is a shared responsibility and everyone's business (Dufty, 2012).

- *Insufficient integration of risk management and disaster communication education in school curricula and educational programmes*: Until this topic is embedded in the curricula, actions and preparedness plans among the general public will be heavily constrained, which will undermine disaster risk management efforts.

- *Lack of community-based solutions*: Grass-roots organizations, community leaders and local emergency networks play a fundamental role in disaster preparedness and response. Empowering communities with decision-making capabilities and providing them with the necessary resources to manage localized risks ensures that disaster communication efforts are not only effective but also culturally relevant and widely accepted.

In light of the above, the following actions are proposed, with the aim of addressing the identified challenges:

- *Strengthening media and digital literacy*: Implement educational programmes that improve people's ability to discern between truthful information and disinformation on digital platforms by developing their critical skills in the evaluation of sources. Also, implement training and information campaigns at all levels, so that the informed population can manage disasters and be active actors when necessary.

- *Developing clear and accessible communication protocols*: Establishing clear guidelines that use clear language is critical at all levels to ensure that emergency information effectively reaches all affected communities.

- *Fostering public–private collaboration*: Facilitating strategic partnerships between governments, non-governmental organizations (NGOs) and private technology companies to improve coordination and disaster response helps foster community-based solutions. Involving all stakeholders facilitates the dissemination of verified information and crisis management.

- *Ongoing training and crisis drills*: Conducting periodic exercises that prepare citizens in how to respond effectively to emergency situations – including practising using emerging technologies and data management during real and simulated crises – will promote a culture of prevention, which is necessary for the population to feel safe in the face of certain events.

- *Promoting transparency and accountability*: Implementing policies that promote transparency in crisis communications and accountability of the actors involved in disaster management will build public confidence and make responses more effective. These policies will help us ensure that our channels are trustworthy, and we will reinforce the institutional framework necessary for risk management.

Effective disaster risk management in Latin America and the Caribbean cannot be achieved in isolation; it requires a collective effort that bridges political action, social engagement and cultural understanding. To create truly inclusive and effective DRR strategies, governments, organizations and communities must work together to develop integrated, context-sensitive solutions that respect local identities, traditions and social structures. Strengthening disaster communication and risk management is not only a technical necessity but also a social responsibility that depends on collaboration, transparency and proactive engagement. Only by fostering stronger coordination between institutions and civil society can we move beyond aspiration and towards a more resilient, better-prepared future for the region.

1.3 Role of journalists and technology in disaster information

It is crucial that we discuss the role of the media in the coverage of disasters and emergency situations since their function goes beyond simply informing; they also have ethical and social responsibilities. Their "watchdog role" involves informing, educating, monitoring and giving voice to affected communities (UNDRR, 2021). In doing so, they contribute to the safety and resilience of society in times of crisis. The following are some key roles they should play (Zitzmann, 2020; Acosta Aguilar, 2022):

- *Accurate and truthful reporting:* As accuracy is critical to maintaining public trust, journalists must verify their sources and cross-check information before publishing it to ensure accurate and verified information about the disaster is provided. Accuracy is essential to avoid the spread of rumours and confusion at critical times.

- *Alert and educate the population:* The media has a responsibility to alert the population of an impending disaster; this includes reporting on warnings, evacuations and safety measures. In addition, journalists should educate the public on how to prepare for future disasters and provide practical advice and guidelines for life-saving action based on official sources from the country's or region's DRR systems.

- *Monitor and evaluate the authorities' response:* The media and its journalists should be "vigilant" in the sense of monitoring how authorities respond to a disaster. This includes assessing the effectiveness of rescue operations, relief distribution and inter-agency coordination. For this purpose, they should be familiar with official disaster response plans.

- *Promoting resilience and preparedness:* Journalists play a crucial role in communicating relevant information during disasters associated with the physical natural and physical built environment. Their work involves not only reporting the facts, but also contributing to DRR and building resilience and improving the response of affected communities. The media can contribute to societal resilience by reporting on risk reduction and disaster preparedness practices. Similarly, publishing inspiring stories of recovery and rebuilding can also motivate communities to maintain hope and work together. (Domínguez-Panamá, 2017; Mayo-Cubero, 2021; Lozano Ascencio, Franz Amaral and Puertas Cristóbal, 2020)

- *Data journalism and AI-driven data*: With the growing availability of big data and AI tools, journalists have access to real-time analytics, predictive modelling and trend analysis, which can enhance disaster coverage. This also comes with ethical concerns about data interpretation, bias and potential misuse of AI-generated information. Journalists must be trained to critically analyse AI-driven reports and ensure they contextualize, rather than blindly rely on, data. Integrating data visualization tools, geographic information systems (GIS) mapping and AI-based trend analysis can strengthen journalistic narratives, making them more informative, accessible and actionable for different audiences.

2. Implementation and technological opportunities in disaster risk management offered by communication channels

This section focuses on improving preparedness and response to catastrophic events by integrating advanced technologies and innovative strategies into communication channels. The integration of advanced technologies establishes a robust framework for addressing crises more effectively, thereby ensuring effective protection of human life and resources at risk, while making affected communities more resilient.

Real-time monitoring and analysis of relevant data (such as water levels and weather conditions) using technologies such as the Internet of Things (IoT), earth observations and GIS provide critical information for assessing risks, planning coordinated emergency responses and developing multi-hazard early warning systems.

This information, if efficiently shared through digital platforms and mobile applications, has the potential to improve communication and coordination between local authorities, response teams and the population at risk. Educational technologies, such as virtual reality simulations and online continuing education, can also play a central role in community disaster preparedness, since these tools not only promote public awareness of safety measures such as first aid and evacuation procedures, but are also fundamental in educating and raising awareness of risk among new generations. It is essential that from an early age, children are aware of how to act in emergencies so that they can become effective communicators of information in their communities, facilitating a rapid and coordinated response from both the population and the authorities. In addition, preparing children in this way contributes significantly to the capacity of communities to adapt and recover by fostering a culture of safety and prevention that mitigates the adverse impacts of disasters on vulnerable populations.

2.1 The role of social media tools in promoting disaster resilience

Nowadays, the use of technologies is no longer seen as just an option in human interaction, but rather as a necessary tool for the evolution and development of current and future generations. In recent years, we have witnessed constantly shifting social components and habits, as we have moved from conversations in public parks to chatting with stickers in messaging applications, and from education in a classroom to on device screens, all of which evidences the presence and relentless march of technological growth and the need to use technology for disaster management.

People tend to seek information on social networks for themselves as “people are natural information seekers, relying primarily on their own social networks. Following a disaster the public initially seeks the most common and familiar channels: phone calls, emails or text messages. If unsuccessful, they turn to alternatives and/or official resources of information” (Stiegler, Tilley and Parveen, 2011). This curiosity translates into the need to know and stay informed, but also into the need for certainty when disasters occur.

The ability of social networks to provide emotional and psychological support in times of crisis should not be underestimated, as social media can help build community resilience, minimize residual risk (such as through coordination tasks, discussions and post-event improvement) and create safer communities through shared responsibilities (Dufty, 2012). This results in the creation of “social capital” for disasters which helps the community to have free access channels where they can feel supported, create donation campaigns and keep the Internet informed about what is happening in real time.

Social media plays a multifaceted role in promoting disaster resilience, facilitating everything from rapid information dissemination to emotional support and aid coordination. Although it presents challenges such as the spread of false information and the management of large volumes of data, its overall positive impact on disaster preparedness and response is undeniable and suits the needs of an ultra-connected population. Strategically integrating these tools into disaster management policies can significantly strengthen the ability of communities to cope with, and recover from, adverse events, and can provide a viable option when traditional communication channels are lost. Reinforcing the use of social media and institutionalizing certain channels has become a necessity to nurture our means of response.

2.2 Youth as disseminators

Crises often bring uncertainty and despair, particularly for young people who are preparing for adult life yet face diminished opportunities and an unpredictable future. The COVID-19 pandemic and post-pandemic context, which varied from country to country, created an uncertain environment for young people trying to start work and develop their life projects. However, crises are also times of change and an opportunity for innovation, requiring new ways of doing and thinking in order to adapt to new realities. A sociological perspective that advocates for a sociocultural approach recognizes that young people are not just an age group, but a key social and political actor, a group that is always present in the processes of societal transformation and that, regarding aspects such as risk management, can contribute to a variety of activities due to their culturally inherent attributes such as: critical thinking, the superior ability to learn and perform in new technologies, and their commitment and energy when they recognize a purpose worthy of struggle.

Therefore, young people's participation in DRR can be relevant in terms of contributing their capabilities and skills in information management and the use of new technologies. There is enormous potential in involving youth, alongside the expertise of organizations and educational centres, in addressing DRR. There should be an understanding that communities are dynamic: people may join for common goals and separate again once these have been achieved (Twigg, 2009; McAslan, 2011). Youth engagement is vital, particularly in regions such as Latin America and the Caribbean that are increasingly exposed to environmental hazards. Through education, technology, advocacy and innovative marketing strategies, young people can become powerful disseminators of hazard information, fostering resilience before, during and after disasters. Additionally, they can create supportive networks to generate community resilience and support, thereby impacting directly on mental health and trauma too.

This collaborative approach ensures that local knowledge, customs and practices are respected. It also empowers communities to take ownership of their resilience-building efforts, fostering a sense of collective responsibility and self-reliance. Furthermore, recognizing the knowledge and expertise of civil society organizations (especially those with youth-led initiatives) will help in the design, implementation and monitoring of programmes to leverage resources more effectively.

Youth networks and organizations can serve as hubs for collaboration and action where knowledge exchange and innovation thrive. Harnessing technology and social media, youth can mobilize their peers on a large scale, amplifying the impact of DRR efforts. This proactive engagement fosters a sense of community ownership and resilience, as young people take charge of their future.

However, successful engagement hinges on trust, which is understood as the confidence that individuals have in the reliability, integrity, governance and fairness of institutions. Establishing trust between youth and authorities is crucial for effective communication and collaboration. Transparency, accountability and inclusivity are essential to building and maintaining trust, ensuring that youth feel valued and empowered in these efforts, and fostering economic development, societal stability and the effective functioning of democracy. Likewise, the participation of young people is linked to society's capacity to involve them in constructing a life project that will overcome the sense of hopelessness arising from the crisis. Allowing young people to become involved in efforts to learn about disaster risk and the measures needed to reduce it also allows them to enter a space of opportunities and alternatives to an otherwise uncertain and distressing situation; it empowers them to take responsibility for the present and a future that is also theirs.

Intergenerational collaboration is essential in bridging knowledge gaps between youth and older generations in disaster preparedness. Proactive strategies, such as participatory decision-making and youth-led initiatives, empower young people to drive change within their communities. By actively involving youth in the planning, implementation and evaluation of DRR programmes, stakeholders ensure that DRR efforts are sustainable, relevant and deeply embedded in community resilience strategies.

3. Innovative ideas and recommendations

Some ways of optimizing social media impact on the DRR cycle are explored below:

- We recommend developing social media use in DRR guidelines to ensure best practice by disaster stakeholder organizations. This acknowledges that social media communications in a disaster are often not driven by people with explicit social media or communications training, and that by its very nature a disaster may subvert usual best practice in social media communication. Social media platforms should develop disaster-specific content moderation policies to detect and reduce misinformation, scams and fear-driven narratives during crises. This could involve AI-powered fact-checking tools, collaboration with emergency authorities and real-time content monitoring to prevent the spread of harmful information.

- We recommend proactively and pre-emptively nurturing a positive relationship with the community, including local social media influencers and with an emphasis on target groups (e.g. youth), to help create trust between the community and the emergency authorities. Those tasked with intelligence-gathering during a disaster should use an equity lens when gathering information via social media pathways and ask whether the voices/experiences of the most vulnerable people are being represented by the social media noise.

- Journalists play a crucial role in ensuring accurate, verified and responsible disaster reporting across digital platforms. Training programmes should be developed to equip journalists with fact-checking skills, digital verification tools and ethical guidelines for reporting in crisis situations. Additionally, media outlets should collaborate with emergency response agencies to disseminate life-saving information, counter misinformation and provide clear, science-based coverage of disaster risks. Empowering journalists with real-time access to authoritative sources, satellite data and AI-driven risk analysis can enhance their ability to report disasters accurately and help communities make informed decisions.

- Efforts to optimize social media as a tool for DRR will ideally include a gap analysis related to both device penetration and Wi-Fi coverage, as well as additional nuances impacting on equity at the local level.

- To ensure inclusive communication, emergency messaging should be available in multiple languages and adapted for accessibility, including audio descriptions, sign language interpretation and easy-read formats. This would help reach marginalized communities, including non-native speakers, individuals with disabilities and people with limited digital literacy.

- The authorizing environment for disaster messaging by emergency authorities would ideally support a flexible and adaptable use of social media during disasters to address access and equity risks.

- Social media platforms may consider engaging with emergency authorities to create a validation process and categorization that social media users can easily recognize as a means of flagging authoritative or endorsed voices in a disaster.

- Open-source and open-data practices are encouraged as a way to improve transparency. Ideally, international standards should be developed to differentiate between credible and non-credible disaster-related social media reports in terms of both AI and misinformation.

- Incorporating social media communication into the post-disaster response debrief and evaluation processes will foster an environment of quality improvement.

Conclusions

This special report, developed through a collaboration between UNDRR, ARISE USA, NASA and the Regional Scientific and Technical Advisory Group (RSTAG) and a wide range of experts, has examined the past, present and future applications of technology in advancing disaster risk reduction (DRR) efforts. By providing detailed explanations, definitions and regional case studies, this report showcases how various technologies have helped bridge critical gaps in data gathering, data processing and disaster risk modelling related to multiple hazards and at different scales in recent years.

Many technological advancements have significantly improved our overall understanding of disaster risk – an essential foundation for designing, planning and implementing effective DRR strategies. Robust and accurate risk assessments enable policymakers to prioritize investments in resilient infrastructure, develop training exercises such as emergency drills and design risk-informed recovery plans aimed at building back better.

However, despite substantial progress in areas such as Earth observation, early warning systems (EWS) and hazard analysis, it is clear that technology alone cannot resolve all DRR challenges. While artificial intelligence (AI) and machine learning (ML) have driven rapid advancements in these domains, their transformative potential depends on the successful integration of technology with socioeconomic, cultural and infrastructural considerations.

The Americas and the Caribbean region presents a complex and diverse landscape of hazards, exposure and vulnerabilities. As such, technologies must be tailored to local contexts and guided by inclusivity principles. This includes adopting demand-driven approaches, promoting community-led data collection, integrating Indigenous and traditional knowledge, and ensuring multilingual and culturally appropriate communication strategies to reach all segments of the population effectively.

AI-based technologies, when deployed in developing countries, often suffer from data bias. These tools are typically trained using data from high-income, data-rich countries with vastly different contextual realities, ranging from building types to socioeconomic conditions. The effectiveness of these tools is therefore heavily influenced by the context in which the training data were gathered. Understanding this is just as important as understanding the technology itself.

While AI is often viewed as a universal solution for a variety of challenges in almost all fields, it is important to recognize its limitations. AI relies on historical data, meaning it may struggle to anticipate emerging trends crucial to DRR such as those driven by climate change and changing exposure characteristics. Human intelligence remains indispensable, especially when navigating future uncertainties and making high-stakes decisions in urgent, complex and uncertain situations.

Though new technologies can accelerate data processing, this does not necessarily make them better tools for risk assessments. Capacity-building remains essential to empower practitioners with the ability to interpret results, understand technological limitations and make sound decisions under these conditions.

This report also emphasizes the importance of fostering demand-driven development for new technologies. Bridging the technological gap in developing countries requires affordable, operable solutions and a systems-thinking approach. This means acknowledging the interconnected, dynamic and multifactorial nature of disaster risk. Technologies must therefore be embedded within a broader understanding of that systemic nature of disaster risk.

Technology use in DRR should go beyond producing data and risk metrics. It must be complemented by well-trained professionals capable of interpreting and validating model outputs. This brings with it a critical need for accountability – from developers who must ensure transparency (avoiding black-box models), to users responsible for making informed decisions during crises.

AI should not be seen merely as an innovation tool. First, it cannot replicate the creativity and foresight of human thinking (i.e. the spark of innovation). Second, successful innovation requires adoption, which in turn hinges on appropriate technological, socioeconomic and infrastructural conditions, from design to deployment.

A practical example of technology use explored in this report is the role of social media in DRR. Far beyond being a mere communication tool, social media now serves as a real-time, interactive platform for raising public awareness and ensuring public safety. Journalists play a crucial role as intermediaries, and equipping them with AI-powered verification tools can enhance the accuracy and reliability of crisis information. AI also offers potential in moderating disaster-specific content and combating misinformation by enabling quick identification and validation of credible sources during emergencies. This facilitates the smooth deployment of preparedness and response activities when available.

Importantly, the report highlights the enduring value of "low-tech" solutions, especially in the context of EWS. These approaches, though not cutting-edge in data processing or analytics, have demonstrated life-saving impacts when adapted to local, often rural, contexts. Incorporating traditional and Indigenous knowledge has not only improved system effectiveness but also fostered community trust and engagement.

Interoperability of data remains a key enabler for DRR technologies. Effective adoption of tools depends on the ability to access and integrate diverse data sets. Encouragingly, efforts to standardize data formats and create open, online repositories have improved the predictive capabilities of risk models.

The use of technology in DRR is still unfolding. Ongoing debates on issues such as model development, intellectual property and accountability must address all the emerging challenges mentioned in this report. For instance, assumptions about the perpetual availability of free training data are becoming increasingly questionable, as access becomes restricted and licensed models – which are often developed with public resources but exploited by private entities or individuals – are becoming the norm. This report seeks to initiate these critical discussions, bringing together voices from academia, policy and practice to explore both achievements and ongoing challenges.

On the complex path ahead, the Sendai Framework for Disaster Risk Reduction 2015–2030 can help shape and create more of the global common goods that are mandatory to accelerate the targets set for its four priorities. The Midterm Review of the Sendai Framework includes several recommendations related to the role of technology in DRR and has recognized technology as a critical enabler of disaster resilience, but only if it is inclusive, people-centred and equitably distributed. Ultimately, the effective use of technology for DRR has the potential to foster and create more-efficient DRR ecosystems. These ecosystems can serve a new generation of disaster risk management experts, safeguarding hard-earned development goals and guiding our societies towards resilient development.

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