

Conceptualizing the nexus between Disaster Risk Reduction and Climate Change Adaptation and Mitigation in Governance

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ABSTRACT

Since climate change is a multi-dimensional phenomenon, policy and regulatory aspects of the new nexus between digitalisation, Disaster Risk Reduction (DRR) and adaptation span across multiple sectors and levels of governance. As such, it stands that a major challenge is to bring together different scales of governance and shareholders to ensure coordination and cooperation in regulating this new nexus. Therefore, this article outlines and discusses the academic literature on DRR and asks how this nexus can be conceptualised from a regulatory perspective and what opportunities and challenges does this new outlook present for climate resilience. As this article demonstrates, despite this emerging nexus between the fields of law, policy, and technology within DRR, they continue to largely work in isolation. However, the development of a methodological framework, integrating law, policy, and technology within a DRR framework provides useful insights in identifying the relevant factors that should be considered when discussing DRR within the context of Climate Change Adaptative-Mitigation

Keywords: *Climate Change, Disaster Risk Reduction, Multi-level Governance, Law, Policy, Technology*

INTRODUCTION

The disaster landscape of the twenty-first century has come to be dominated by extreme weather events, with the number of recorded disasters increasing fivefold over the past 50 years (GAR23, 2023: 20). Just in 2022 alone, South Asia experienced a deadly heatwave, erratic rains, and extreme flooding while hot and dry weather conditions across Europe sparked acute forest fires. Given that stark warning issued by scientists that we are heading in the wrong direction, with greenhouse gas concentrations continuing to rise to record highs and temperatures the warmest on record (IPCC, 2023), the transition to a resilient future has become a top priority on global climate and sustainable development agenda. The adoption of the Sendai Framework for Disaster Risk Reduction 2015–2030, the Paris

Agreement under the UN Framework Convention on Climate Change (UNFCCC)¹, and the Sustainable Development Goals (SDGs) as outlined in the UN Agenda 2030 framework ‘have created an opportunity to build coherence between interrelated policy agendas that have the potential to identify and reduce systematic risks, promote sustainable development and significantly affect the future of humanity’ (Flood et al., 2022: 2). Furthermore, technological innovations provide unprecedented opportunities for building climate resilience. Yet, as this article demonstrates, despite this emerging nexus between the fields of law, policy, and technology within Disaster Risk Reduction (DRR), they continue to largely work in isolation. Therefore, this article asks how this nexus can be conceptualised from a regulatory perspective and what opportunities and challenges does this new outlook present for climate resilience.

Since the 1990s, perceptions and approaches to addressing disasters have changed significantly. The global response has moved away from disaster management, whereby the emphasis was placed on the occurrence of disaster as an event and the response to this event, towards assessing the risk situation and socioeconomic processes that predispose disasters (Gellert de Pinto, 2012: 13). Acknowledging the socially constructive nature of disaster risks, research has shifted away from a biophysical approach to a broader systemic multi-level approach which seeks to address the complex social and environmental vulnerabilities and interdependencies of risks (Frey and Calderón Ramírez, 2019: 426; Folke et al. 2005). Chowdhury and Wessel define multilevel regulation as ‘a term used to characterise a regulatory space, in which the process of rule making, rule implementation or rule enforcement is dispersed across more than one administrative or territorial level amongst several different actors, both public and private. The relationship between the actors is non-hierarchical and maybe independent of each other’ (2012: 346). Furthermore, one of the most important aspects of multi-level regulation is ‘the lack of central ordering of the regulatory lifecycle within the regulatory space’ whereby the process of regulation is decentralised from the state apparatus. Instead, state or public actors are among the various diverse regulatory actors that operate within the space, through formal and informal networks and across different levels, to influence and shape regulation and regulation outcomes (ibid., 346-347). This definition reflects the changes, driven by globalisation, that processes of regulation have undergone in recent decades, including its decoupling from the state and the internationalisation of regulatory policies. Such an approach allows DRR to be approached from a collaborative, multi-party, and multi-level perspective.

Reducing disaster risk and the adverse impacts of natural hazards is fundamental to addressing the rise of climate-related disasters and their devastating physical and socio-economic impacts, as well as to achieving the targets of both the Paris Agreement and the SDGs. However, while adaptation planning and implementation have progressed across all sectors and regions in recent years to various degrees and effectiveness, and public and

1 Paris Agreement, Adopted 12 Dec. 2015 entered into force 16 Nov. 2016 FCCC/2015/L9/Rev.1.

political awareness of the impact and risks of climate change have increased, responses remain ‘fragmented, incremental, sector-specific, and unequally distributed across regions’ (IPCC, 2023: 8). Although there is increasing political commitment, with 126 countries formulating DRR strategies and 97 countries implementing early-warning systems, gaps remain both in terms of investment as well as coverage (GAR23, 2023: 22). Furthermore, while effective adaptation measures have been observed, there has also been an increase in maladaptation in various sectors and regions such as the use of high-cost irrigation in agriculture, disproportionately affecting marginalised and vulnerable groups adversely through the reinforcement and entrenchment of existing inequalities (IPCC, 2023: 8).

Since climate change is a multi-dimensional phenomenon, policy and regulatory aspects of the new nexus between digitalisation, DRR, and adaptation span across multiple sectors and levels of governance, such as global, regional, national, and sub-national. Therefore, it stands that a major challenge is to bring together different scales of governance and shareholders to ensure coordination and cooperation in regulating this new nexus. Digital data and methods that bring information together are crucial to the elaboration of digital supportive infrastructures and capacity building and for planning and implementation of DRR. Furthermore, from a multi-regulatory perspective, DRR also requires a coordinated policy response. As this article demonstrates, although a growing body of research has highlighted the significance of digitalisation for climate change adaptive-mitigation, a comprehensive evaluation of the law, policy, and regulation of digitalisation as an enabler of climate change resilience remains absent despite its huge potential (Balogun et al., 2020; Sivaram, 2018). Therefore, this article aims to address this gap by documenting and exploring the challenges and opportunities of digitalisation of climate change adaptation in DRR. The first section of the article analyses the role of law and policy at international and regional levels in the nexus between disaster law, climate change, digitalisation, and emergency warning systems. The second section discusses the rescaling of DRR processes and the role of multi-stakeholder platforms before moving on to the third section, which focuses on DRR and digital transformation during three phases: pre-disaster, disaster response and post-disaster. The article concludes by discussing the challenges of implementing this new nexus across the fields of law, policy and technology.

THE ROLE OF LAW AND POLICY AT INTERNATIONAL AND REGIONAL LEVELS IN THE NEXUS BETWEEN DISASTER LAW, CLIMATE CHANGE, DIGITALISATION, AND EMERGENCY WARNING SYSTEMS

The international legal regimes that currently exist to address the nexus between natural disasters² and climate change, including Climate Change Adaptation (CCA) are not easy

2 Disaster implies disruption or “a serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses and impacts, which exceeds the ability of the affected community or society to cope using its own resources”;

to grapple with as they are often dealt with separately because natural disasters are usually the object of disaster law, while environmental law deals with climate change. Even environmental law suffers from a similar problem, and both fields lack a “clear treaty” that anchors the key legal principles. Disasters are amplified by climate change and cause the deaths of thousands of people, or even more, and cost billions in reparations and repairs. The nexus between climate change, disaster law and digitalisation will become imperative in impeding climate events and even more so, should this nexus integrate digitalisation and emergency warning systems (EWS) not only ex-ante climatic disastrous events occurrences, but also in the ex-post rebuilding phase. While recent research on DRR acknowledges the important role of law and policy on DRR, it also recognises that it ‘is currently in a significant, formative period of development’ (Samuel et al., 2022: 3).

The role of law and policy in implementing DRR started with the Hyogo Framework for Action 2005-2015: Building the Resilience of Nations and Communities to Disasters (HFA) (UNISDR, 2005), which is the main instrument for building resilience to disasters and engaging Disaster Risk Reduction (DRR) and has now been replaced by the more ambitious Sendai Framework for Disaster Risk Reduction 2015-2030 which seeks to both manage and mitigate disaster risk (UNDRR, 2015). While both agreements emphasise multi-level governance and multi-stakeholder and sector participation, the Sendai Framework is far more reaching through the inclusion of social and health-related issues and the adoption of a more people-centred approach than the Hyogo Framework, which laid out the underlying risk factors of disasters. However, one key outcome of the Hyogo Framework was a global shift in the approach to DRR, moving from emergency response measures to a more comprehensive and systemic approach aimed at enhancing international and regional cooperation. Furthermore, the Hyogo framework has been a key instrument in raising public and institutional awareness of DRR and generating political commitment, cooperation, and action among a wide range of stakeholders and across all levels.

Although the Hyogo framework recognised the potential role of digitalisation by prioritising the identification, assessment and monitoring of disasters risks, the enhancement of early warning systems, the use and application of space-based technology, and the need to record, analyse, summarise and disseminate statistical information on disaster occurrence, impacts and losses, it failed to go beyond recommending the establishment of institutional capacities, training and infrastructure to integrate technologies into policy, decision-making and emergency management systems (UNISDR, 2005). Similarly, the Sendai framework acknowledges digitalisation as a key target, highlighting the need to increase the availability of and access to multi-hazard early warning systems, emergency communications mechanisms, social technologies, hazard-monitoring telecommunications systems and DRR information and assessments by 2030. Sendai identifies four key policy United Nations International Strategy for Disaster Reduction (UNISDR), 2009 UNISDR Terminology on Disaster Risk Reduction (Geneva, United Nations Press, 2009)

priorities to address disaster risk management and reduce existing vulnerabilities while preventing the creation of new risks. These include (1) understanding disaster risk, (2) strengthening DRR governance, (3) investing in DRR for resilience, and (4) enhancing disaster preparedness for effective response and “Build Back Better” initiatives during post-disaster and reconstruction. Among these four priorities, digitalisation plays an important role in the collection, analysis, and management of relevant data and statistics for the purpose of pre-disaster risk assessment, prevention, and mitigation as well as for the development and implementation of preparedness and effective responses (UNISDR, 2005). Importantly, the development, maintenance and strengthening of digitalisation are considered in relation to socio-cultural requirements such as gender and the need to promote simple and low-cost equipment and facilities. However, as Venier and Capone note, ‘a sensitive legal issue related to the Sendai Framework Target G on Multi-Hazard Early Warning Systems (MH-EWS) is to determine who bears the ultimate responsibility for producing and distributing accurate and timely emergency warnings (2022: 150). While the Sendai framework encourages global and national actors to strengthen and broaden the use of digitalisation channels like EWS, the language is vague and lacks any comprehensive details regarding the most effective approach or procedures for undertaking such a task nor how to mitigate any potential conflicts between the private and public sectors given that their different scopes and objectives.

The role of law in implementing DRR evolved with the 2014 International Federation of Red Cross and Red Crescent Societies and United Nations Development Programme (UNDP) entitled *Effective Law and Regulation for Disaster Risk Reduction: A Multi-country Report (the Multi-country Report)* (UNDP, 2015). Relevant for the ex-post rebuilding phase, the report finds a significant lack of integration between environmental planning and disaster management laws and recommends greater use of Environmental Impact Assessment (EIA) and DRR tools to assess new situations. In addition, many international multi-lateral environmental agreements (MEAs) also address disaster risk, such as, for example, the 1994 UN Convention to Combat Desertification in Those Countries Experiencing Serious Drought and/or Desertification particularly in Africa (UNCCD, 1994), and specifically targeting sand, dust storms and water scarcity. Many MEAs relevant to disaster management focus also on human rights.

The role of law implementing the nexus between climate change and natural disasters can be traced from its inception with the United Nations Framework Convention on Climate Change (UNCCC), which acknowledged the need for adaptation strategies, but is also short in detail although it does require parties to “cooperate in preparing for adaptation to the impacts of climate change. In addition, the Cancun Adaptation Framework contains four important peculiarities: 1) an adaptation committee to coordinate international efforts; 2) a program for national adaptation plans to encourage long-term planning in developing countries, and 3) a program on “loss and damage”, now called “Warsaw International

Mechanism for Loss and Damage” (UNDRR, 2010). The Warsaw Mechanism aims to address loss and damage associated with the impacts of climate change, including both extreme events and slow onset events, in developing countries that are particularly vulnerable to the adverse effects of climate change. The Warsaw Mechanism also aims to enhance risk management approaches and stronger coordination among stakeholders, but most significantly, “action and support”, including finance, technology, and capacity-building, which might entail including digitalisation and emergency warning technologies in the future.

The management, conservation and restoration of ecosystems can be included and monitored as part of the National Determined Contributions (NDCs) and national adaptation plans under the Paris Agreement of 2016 that represents an opportunity for the role of digitalisation and technology to be incorporated in the law. The capacity at various levels of government and the legal implementation of communities that can respond during an extreme weather event also depends on emergency preparedness, which includes early warning systems and digitalisation. Even a slow onset event will depend on emergency preparedness and emergency warning (EWS), and risk mapping, which are included in the HFA. EWS requires legal and institutional frameworks that make DRR a national priority (Priority Action 1). It requires the integration of scientific knowledge and innovation (Priority for Action 3), and that they substantially contribute to strengthening disaster preparedness (Priority Action 5). EWS can include sirens, radio, television, phone calls, SMS text messages, and e-mails. Digitalisation interlinked with media is also important in emergency preparedness if we consider social network platforms such as Facebook, Twitter, and WhatsApp that might document in real time when climate extreme events are hitting an area and alert the population to be safe. In that sense, regional cooperation on EWS programs and media digitalisation could easily prove to be particularly effective since natural disasters and climate extreme events sometimes affect many countries simultaneously. EWS and digitalisation can also be improved with legislation by mandating international cooperation, incorporating it in treaties and making data and digital tools an important component in tackling climate change impacts and reducing disasters. This legislation is currently missing.

At a regional level, an interesting example of existing regional soft law mechanism of regional integration of disaster prevention in coping with climate change impacts is the Union Council Protection Mechanisms, adopted by the European Council in December 2013 (see European Commission, 2023). This mechanism outlines the role of international cooperation between the EU and its Member States and not only covers mainstream society but also the environment and indigenous people. The European Commission describes how fast the fast-developing technology and the increasing interconnections with various digital tools connecting people affords possibilities in mitigating disaster risks but notes that these same changes are also prone to create new threats and bring challenges in cyber security

(see European Commission, 2020). Intertwined areas of law (DRR law, climate law and digital technological law) are not as clearly defined as one could hope. Even though the nexus between these different areas of law is evident, the regulatory apparatus is not yet ready to officially include and factor in law digitalisation as a tool for climate change adaptation, and there is a clear lack of procedural law applicable to the nexus.

THE RESCALING OF DISASTER RISK REDUCTION PROCESSES

Reflecting the rescaling of regulatory processes, the importance of stakeholder involvement (Jones and Faas, 2017; Boyer-Villemare et al. 2014; Djalante, 2012; Pelling, 2011; Warner, 2008) and social capital (Adger, 2003; Folke et al., Frey and Calderón Ramírez, 2019) in disaster governance has become increasingly recognised. Moreover, multi-stakeholder platforms for Global Platform for Disaster Risk Reduction are widely promoted and supported on the international level by organisations like the United Nations to provide concerted action through coordinated and participatory processes across sectors and at a variety of scales and to help countries cope with the long-term social, economic, and political challenges of disaster risk. Substantive regional DRR systems and approaches have also been established, with regions taking different approaches to reflect their purposes. For instance, the South Pacific has adopted the soft-law regional instrument, The Framework for Resilient Development in the Pacific, which in line with the global Sendai Framework for Disaster Risk Reduction 2015-2030, focuses on domestic implementation of policies whereas the EU approach has focused on value-added DRR through regional preparation and response which is underpinned by strong regional institutions and formal agreements (Hopkins, 2019: 220). The Association of Southeast Asian Nations (ASEAN) model, laid out in the Agreement on Disaster Management and Emergency Response, on the other hand, adopts both a governance structure for managing DRR in the region and binding commitments set out in both its general obligations and specific requirements (Ibid., 229). For some observers, these coordinated regional frameworks hold the most potential with regards to advancing the objects of Sendai, offering binding commitments and robust structures, and ‘serving as a bridge between domestic and global aspirations’, with many taking the lead on concrete actions like early-warning mechanism (Cubie, 2019: 255). Moreover, there is evidence that collaboration between regional platforms leads to cross-border cooperation, facilitating the transfer adaptation strategies and tools, including digital tools (Jerez Columbie, 2022). More recently, other mechanisms such as risk pooling schemes have emerged as a means for building societal resilience towards natural hazards whereby country-specific risks are pooled within a regional portfolio to generate risk diversification benefits and reduce the aggregated costs of coverage (Broberg and Hovani, 2022: 259).

Although DRR platforms can be government-led or not, Frey and Calderón Ramírez

(2019) showed that institutional design plays a critical role in the ability of the state to improve its capacity for action through laws, policies, and regulatory incentives. The effectiveness of multi-level DRR is linked to the protagonist role of local governments and their abilities to work across vertical and horizontal dimensions of governance and different territorial scales, involving local communities and citizens while constantly engaging with higher-level authorities (Ibid.). While much research on DRR has focused on the importance of flexible and good governance structures (Van Niekerek, 2015; Pilli-Sihvola and Vaatainen-Chimpuku, 2016), little is known about how governance structures and multi-level regulation can generate and support transformative digital capabilities in DRR as well as how to introduce advanced technology into already existing tools and policies and to reach different stakeholders (Munang et al., 2013; Balogun et al., 2020). However, an increasing number of studies do highlight the potential of digitalisation to enable and accelerate climate change adaptation across different scales through its ability to identify, analyse and share data faster as well as facilitate citizen engagement and participatory adaptation measures during all stages of the Disaster Risk Reduction (DRR cycle), with it being at the centre of risk preparedness, communication, and awareness (Sun et al., 2020).

Discussing the enhancement of cooperation between different stakeholders, Balogun et al. argue that ‘the integration of ICT digitalisation concepts, particularly mobile devices and social media big data analytics, with conventional EWS mechanism has the potential to overcome this challenge by facilitating the communication of time sensitive disaster information to a large number of people, thereby improving response time and actions as seen in the early warning applications’ (2020: 101888). Furthermore, web-based systems can increase stakeholder interaction and co-production for planning and decision-making that integrate hazard and risk knowledge in all stages of the DRR cycle (Jørgen Henriksen et al., 2018) as well as connect citizens and communities with relevant information and services through e-government (Roztockki et a., 2023). Digital technologies such as artificial intelligence have become central to supporting effective decision-making in disaster management due to its ability to extract and analyse the large amounts of data generated (Sun et al., 2020: 2632; Eskandarpour and Khodaei 2017; Velev et al. 2018; Yu et al. 2018; Wang et al. 2018; Barabadi and Ayele 2018). Such is the importance of digital technologies that the UN Secretary-General launched at COP27 an Executive Action Plan to Implement the Early Warning for All Initiative, which calls for every person around the world to be protected by early warning systems by 2027. Under the action plan, a multi-stakeholder platform has been set up to implement the four pillars that make up the early warning chain: Pillar 1, disaster risk knowledge, is led by UNDRR; Pillar 2, detection, observations, monitoring, analysis and forecasting of hazards is led by WMO; Pillar 3, warning dissemination and communication is led by the International Telecommunication Union (ITU) and Pillar 4, preparedness to respond, is led by the International Federation of Red Cross and Red Crescent Societies. However, for the initiative to succeed a multi-level regulatory approach is essential given that the platform needs to work across scales, in

terms of mobilising financial resources (global level), strengthening regional coordination and collaboration around EWS (regional) and building political momentum (national and local level), and across sectors to bringing together relevant government bodies and representatives from all of society (UNDRR, 2023). Yet, while major policy platforms ‘call for “whole-of-government” or “whole-of-society” approaches, disaster-oriented adjustments to social and economic policy at a systemic level are rare’ (Dover, 2022: 30). Although disaster impacts are costly, they are not always top of the agenda of non-disaster policy sectors and for other policy sectors different in degree, impacting the amount of attention given to DRR. Moreover, with regard to cross-cutting issues like digitalisation and DRR, despite many mechanisms being in place, such as DRR strategies, committees and inter-agency collaborative procedures, the compartmentalised structure of government makes policy integration very difficult. As Dover comments, ‘many aspects of DRR create particular challenges, as they are at once every department’s potential concern and no one agency’s sole responsibility’ (Ibid., 31).

While technological innovations undoubtedly have an important role to play in DRR, helping to build resilience and deepen connectivity, technology has advanced at a much faster rate than discussions regarding the politics, governance and policy surrounding technologies such as artificial intelligence. Only recently has research began to focus on issues such as ethics, economics, and regulation (Ulnicane, 2023: 612; Floridi et al., 2018; Jobin et al., 2019; Djeffal et al., 2022; Justo-Hanani, 2022; Larsson, 2020, Radu, 2021). The social, political and cultural implications of such digital technologies represent one of the largest governance challenges for policymakers today, especially regarding the role the state assumes with regard to governing technology (Djeffal et al., 2022). As a recent study by Djeffal et al., demonstrated, just in relation to AI, there is considerable variation in how governments approach its governance, ranging from self-regulation-promoting and market-based approaches, and a combination of entrepreneurial and regulatory governance approaches (Djeffal et al., 2022: 1799). Therefore, one of the key challenges for the public sector remains not only how to regulate the impact of digital technologies across different sectors but how to do this at the intersection of climate change and design an effective governance system with robust institutional arrangements to ensure sustainable digital transformation of disaster risk.

DISASTER RISK REDUCTION AND THE DIGITAL TRANSFORMATION

Technology and digitalisation have the potential to serve as powerful tools in our efforts to tackle the complexities of climate change and disaster risk. Remote sensing, data analytics, and communication technologies offer new opportunities to enhance resilience, improve early warning systems, and enable effective response strategies (Chamola et al., 2021; Munawar et al., 2022). Digitalisation enables data collection, analysis, and

sharing, facilitating evidence-based decision-making and enhancing understanding of climate change impacts and disaster risks. In addition, Artificial Intelligence can efficiently analyse data, employ learning algorithms, and utilise sensing devices to assess, predict, and mitigate the risks associated with climate change (Leal Filho et al., 2022; Munawar et al., 2022). While AI has predominantly been utilised in climate change modelling, impact assessment, and mitigation strategies (Huntingford et al., 2019; Jones, 2017; Rolnick et al., 2022), its potential in climate change adaptation has received comparatively less focus and exploration (Cheong et al., 2022).

In their recent literature review, Sarker et al. (2020) identified that the majority of research focuses on the four main phases of the disaster management cycle: preparedness, mitigation, response, and recovery (Coppola, 2006). The preparedness and mitigation phases encompass activities that occur before a disaster. The response phase involves actions during the disaster, while the recovery phase involves post-disaster activities (Lamsal & Kumar, 2020). In recent years, significant technological advancements have been made, aiming to contribute to all phases of the disaster management cycle as well as regarding climate change adaptation (Chamola et al., 2021; Erdelj & Natalizio, 2016; Leal Filho et al., 2022; Marchezini et al., 2018; McCallum et al., 2016). The following subsections briefly overview technological developments and applications for each phase, starting from pre-disaster activities.

PRE-DISASTER

Pre-disaster activities encompass mitigation, preparedness, and adaptation, with prediction as their core foundation. Traditional methods, such as field monitoring, physics-based models, expert surveys, and multi-criteria decision-making methods, are commonly employed to identify hazards and assess risk factors (Sun et al., 2020). However, these methods can be labour-intensive and computationally costly (Bellaire et al., 2017). In contrast, AI techniques offer the ability to rapidly analyse vast amounts of data, enabling timely hazard risk assessments (Pradhan, 2010; Sun et al., 2020; Yilmaz, 2010). The increasing adoption of AI and machine learning applications in disaster prediction (Sun et al., 2020) is made possible by the availability of large datasets of climate-related data. The collection of high-resolution spatial datasets has been made possible by recent improvements in various related technologies, such as interconnected sensor arrays, IoT devices, satellites for remote sensing, UAVs and drones, simulation data, spatial data and social media (Sarker et al., 2020). These data sources require robust infrastructure, proper management, and institutional commitments for collection, storage, and maintenance. When all these technologies are effectively deployed and managed, accurate and prompt disaster predictions and identification of community vulnerabilities become achievable. This creates numerous opportunities to leverage the power of AI in disaster prediction to

support disaster preparedness, mitigation, and adaptation efforts.

Historically, predictions about weather and extreme events were primarily based on physics-driven numerical models, which solve mathematical equations to simulate the dynamics and physics of the atmosphere, aiming to create an array of realistic forecasts (Ravuri et al., 2021). Over the last decades, numerical weather prediction (NWP) methods have significantly increased their prediction accuracy and resolution due to advancements in high-performance computing and satellite Earth observations (Bauer et al., 2015; Huntingford et al., 2019; Yano et al., 2018). An instance of this is the comparison between the prediction of Hurricane Andrew in 1992, which was forecasted 24 hours before it hit land, and Hurricane Sandy in 2012, where a warning was issued five days in advance due to advancements in NWP modelling combined with assimilated meteorological satellite data (Zeng, 2018). Despite still being the most accurate forecast method, NWP can be laborious and computationally intensive, with a ten-day forecast simulation taking hours of supercomputer computation time, often rendering them too slow and costly for immediate needs (Bi et al., 2023).

The constant influx of high-resolution, real-time weather and climate data from diverse sources, including weather stations, aircraft measurements, satellites, and radar, often exceeds traditional numerical models' processing capabilities, leading to data utilisation delays (Karstens et al., 2015; Rolnick et al., 2022). As a result, there is an increasing inclination towards integrating AI and ML techniques to address these challenges. In addition to being less expensive and more efficient, AI and ML techniques uncover hidden relationships among climate data, which are often unattainable through physical models (Dewitte et al., 2021). While the accuracy of AI prediction methods currently falls short of traditional numerical models and cannot completely supplant them, we are continually witnessing leaps and breakthroughs that reveal the potential of hybrid and purely AI-based methods. For instance, AI-driven methods have already demonstrated superiority over numerical models in nowcasts - very short-term forecasts (up to two hours) (Dewitte et al., 2021; D.-K. Kim et al., 2021; Ravuri et al., 2021) and mid-term forecasts (up to seven days) (Bi et al., 2023). Improvements in nowcast predictions have been achieved using generative adversarial networks based on radar data of cloud formation, providing more accurate and practical results compared to alternative methods (Ravuri et al., 2021). Other types of extreme weather prediction in which AI is accelerating developments are floods (D. Kim et al., 2023; Torkey et al., 2023), drought (Gyaneshwar et al., 2023; Z. Wu et al., 2022; Zellou et al., 2023), extreme heat (Krzywanski et al., 2023; Lopez-Gomez et al., 2023), and hurricanes (Ayyad et al., 2022; T. Kim et al., 2022). In addition to employing weather and climate data for predicting imminent hazards, there has been an exploration of leveraging artificial intelligence to scrutinise data from social media and crowdsourcing for the purpose of disaster prediction (Fitriany et al., 2021; Granell & Ostermann, 2016; Owen, 2020; D. Wu & Cui, 2018).

The ability to predict and detect climate-related disasters is crucial but insufficient on its own to avert human loss and mitigate economic damage (Kelman & Glantz, 2014). Technology by itself cannot provide a comprehensive solution to the complexities of DRR. The integration of human resources with innovative technologies is the only viable approach towards achieving disaster resilience (Lamanna et al., 2012). The UN's International Strategy for Disaster Reduction (ISDR) asserts that effective EWS should not only facilitate timely predictions of impending extreme events but also offer risk assessments to empower communities in setting mitigation and prevention priorities, provide reliable and simple warning messages to authorities and the public, and aid in coordinating the response (UN 2005). An EWS can only have a positive impact if all these criteria are fulfilled. Thus, an EWS extends beyond the technology utilised to detect and monitor climate events and should be considered more broadly as a social process aiming to prevent harm due to hazards (Lewis, 1999; Wisner, 2012, Zommers 2014). The EWS should encompass the decision-making authorities, their processes, and numerous other social aspects preceding and following a hazard event (Zommers 2014).

Another important aspect of EWS after an upcoming hazard has been detected is how the EWS information is communicated to decision makers and the general public (Sarker et al., 2020). Effective EWS need to consider various factors beyond mere prediction accuracy such as determining the target recipients of warnings, the timing of alerts, the content of the messages, and the delivery methods (Glantz, 2004; Grasso, 2023; Kelman & Glantz, 2014). The warning message should be concise, clear, and easily understood by recipients. It should avoid technical jargon, specify affected areas, explain potential losses and their likelihood within a timeframe, and provide instructions for response actions (UNDRR, 2006). Recent advances in ICT and mobile phones give more possibilities to transfer warning messages even to remote areas that traditionally relied on radio or satellite phones for immediate communication (Kelman & Glantz, 2014). The proliferation of mobile phones allows for text, audio, or video warnings, especially for less literate populations. Moreover, applications have been developed that can identify mobile phones in an area and send location-specific alerts (Albalooshi et al., 2023; Bonilauri et al., 2021). While these developments are significant, challenges remain, including affordability, lack of coverage, and unreliable infrastructure in certain areas. It's crucial to remember that the latest technology may not be universally available, reliable, accessible, or affordable (Grasso, 2023).

The same mechanisms and technologies that allow for better and faster prediction and detection of climate-related disasters can be leveraged to develop mitigation and adaptation strategies to build societal disaster resilience. Machine learning offers the potential to prioritise areas of high risk, thereby alerting citizens to imminent dangers (Rolnick et al., 2019). Furthermore, AI's capability to monitor live ecosystems, track biodiversity, and classify species through image-based sensors provides conservationists with invaluable

data to determine priority areas (Rolnick et al., 2019). In the energy sector, addressing the global energy crisis through AI can facilitate the reduction of fossil fuels, paving the way for more sustainable practices and mitigating climate change impacts (Walsh et al., 2020; Elkin and Witherspoon, 2019). Moreover, the integration of AI in infrastructure planning, particularly with the use of risk-related data, promotes the construction of disaster-resilient communities, which not only safeguards against current threats but also equips future generations to tackle unforeseen challenges (Syifa et al., 2019; Ybañez et al., 2021).

DISASTER RESPONSE

The ability to perform quick and efficient search and rescue operations is crucial during the disaster response phase. However, poor communication and limited situational awareness in rapidly changing conditions often hinder these efforts (Erdelj & Natalizio, 2016; Yu et al., 2018). The role of technology during disaster response is becoming increasingly important, as evidenced by the variety of technologies that have been tried and have proven valuable during the disaster response phase, such as UAVs, sensor web and Internet of Things (IoT), spatial data, crowdsourcing, social media, and mobile GPS and Call Data Records (CDR) (Munawar et al., 2022; Sarker et al., 2020; Yu et al., 2018). Aerial technologies like UAVs and satellite remote sensing provide invaluable high-resolution imagery and real-time situational awareness. These technologies are crucial for assessing the severity of disasters, understanding the extent of damage, and locating victims (Esposito & Rizzo, 2022; Rottondi et al., 2021; Ybañez et al., 2021; Yu et al., 2018). On the ground, technologies such as the Internet of Things (IoT), Wireless Sensor Networks (WSN), and mobile GPS and Call Data Records (CDR) are instrumental in facilitating critical communication and data collection (Cumbane, 2022; Khalil et al., 2014). For example, GPS-based geofencing methods have been used to identify the location of mobile phone users within a specific geographical area (Munawar et al., 2022), while WSN can be used to form ad hoc networks to facilitate communication in scenarios when traditional communication networks are unavailable or compromised (Erdelj et al., 2017; Marinho et al., 2013). In addition, robots have been developed for rescue missions and hazardous material removal where human access is not possible or considered risky (Ghassemi & Chowdhury, 2022; Park et al., 2017; Tadokoro, 2005).

Software technologies like crowdsourcing and social media platforms add another layer to disaster management capabilities. Platforms like Twitter, YouTube, and Foursquare facilitate multidirectional flows of information, making response and recovery efforts more efficient (Granell & Ostermann, 2016). They enable real-time communication, public sentiment analysis, and even predictive capabilities that can aid in both the immediate and post-disaster stages. NGOs and government agencies increasingly leverage social media for disaster management to assess public sentiment and reactions (Yu et al., 2018).

Multidirectional communication enabled by crisis crowdsourcing platforms enhances efficiency in response and recovery (Roche et al., 2013). Social media data for disaster response can be utilised in various ways, from data gathering and analysis to narrative construction, disaster-relevant information extraction, geolocation pattern/text/image analytics and information dissemination, making it a versatile tool in disaster scenarios (Carley et al., 2016). However, data from social media platforms like Twitter tends to be more useful for early detection and forecasting rather than in recovery and response activities (Granell & Ostermann, 2016).

Many of those technologies are particularly beneficial in developing countries where traditional infrastructures may be lacking or vulnerable. For example, IoT-enabled devices offer alternative means of communication and data network resilience during disaster situations, helping to bridge the infrastructural gap (Yu et al., 2018). Mobile technology can also disseminate pre- and post-disaster information and alerts, offering insights into relief aid and health hazards, thereby enhancing disaster management efforts (Bossu et al., 2015; Goncalves et al., 2014). However, the utilisation of these technologies comes with limitations. For instance, mobile apps often require an active network for operation, and their efficacy can be compromised in the absence of network connectivity (Mokryn et al., 2012). Similarly, aerial technologies like UAVs face challenges related to battery life, weather conditions, and maximum physical load (Munawar et al., 2022). Despite these challenges, the integrated use of hardware and software technologies holds substantial promise for enhancing the effectiveness and efficiency of disaster response operations.

POST-DISASTER

The incorporation of various technologies in the field of disaster recovery has led to marked improvements in both the efficiency and effectiveness of restoration efforts (Chamola et al., 2021; Munawar et al., 2022; Sarker et al., 2020; Yu et al., 2018). Automated inspection technologies, driven by computer vision and image processing techniques such as image segmentation and deep learning, offer a robust alternative to traditional manual methods for assessing infrastructure damage (Pantoja-Rosero et al., 2023; Torok et al., 2014). This shift is particularly significant for maintaining the structural integrity of buildings, roads, and bridges, where manual inspections may miss subtle but crucial signs of damage (Liu & Liu, 2013). Big data analytics also play a crucial role in enhancing post-disaster operations. For instance, real-time information derived from social media platforms like Twitter has been utilised for disaster mapping, providing invaluable updates that fill existing gaps in rescue operation coordination (Yusoff et al., 2015).

Furthering these advancements, predictive analytics and remote sensing technologies offer another layer of sophistication to disaster management protocols. Cloud platforms powered by artificial intelligence can expedite the restoration of community and business

infrastructure, enabling quicker resumption of operations and better preparedness for future incidents (Ahmad & Ma, 2020; Cao et al., 2021; Gupta et al., 2022). Satellite remote sensing technology enhances these capabilities by providing high-resolution, multidimensional data that can be used for a variety of functions, such as post-disaster damage assessment and operational assistance (Carani & Pingel, 2023; Plank, 2014; Yamazaki & Liu, 2016). More specifically, these high-resolution images are crucial for assessing structural deformations in land areas, changes in water bodies, and the extent of building damage in disaster-struck areas (Ehrlich et al., 2013; Liou et al., 2010). Active sensors like synthetic aperture radar (SAR) offer solutions to limitations posed by optical satellite imagery, such as cloud cover and night-time conditions, thereby extending the observational capabilities during adverse situations (Chini et al., 2013; Pradhan, 2010). Big data, including satellite imagery, enhances adaptive optimisation for disaster recovery and effectively manages limited resources (Horita et al., 2017). Remote sensing data is crucial for detecting climate change impacts and evaluating recovery efforts (Sarker et al., 2020).

CONCLUSION

In conclusion, from a regulatory perspective, the existing different sources of law and policy covering the nexus do not incorporate digital data and EWS as they should. Legal regimes governing DRR, climate change adaptation and digitalisation are yet to be developed. We have yet to understand how to integrate all the components of this nexus into the law and understand who is responsible for implementing and coordinating, institutionally. A treaty specifically dedicated to this nexus and expressly dedicated to climate change, disaster risks, digitalisation and incorporating EWS is what is needed now. Regional cooperation's regulations are also recommended, given that climate change's impacts might simultaneously affect several countries. At the national level, most countries already have laws governing disaster management and adaptation plans, but they do so separately and without incorporating the technological and digital components simultaneously, which means that there is not yet institutional integration among these three components. Integrating in a cross-sectorial and multi-level collaboration is key to attempts to implement regulations integrating climate change adaptation, disaster risk reduction and digitalisation simultaneously.

On the global level, the Sendai framework acts as both a strategic plan and guiding principles for addressing disaster risk management and development in all countries. However, while the Sendai framework has enhanced coherence with other key global frameworks, including the Paris Agreement and Agenda 230 for sustainable development, its alignment with and integration of digital technologies into institutional arrangements and policy remains limited, affecting the effectiveness of DRR. Furthermore, although the Sendai framework has served as an important instrument in fostering political commitment

and high-level authority for public policy for DRR which has been most notable in the vertical alignments of global and regional decision-making bodies that have supported the development of high-level strategic initiatives, on the national and sub-national levels there remains a lack of coordination among institutions at various levels, agencies and sectors to integrate and coordinate digital technologies into DRR policies and strategies. Digital technologies are playing an increasingly important role in disaster preparedness and protection, enhancing our knowledge of the occurrence of disasters and risks and their potential impact on societies through enhanced monitoring and observational systems. However, the decision to act upon this information requires both political will and a coordinated multi-level governance response. This involves, on the one hand, the decentralisation of the decision-making process and responsibilities for resilience building and disaster management practice in society through established networks that bring together relevant government bodies and representatives from all of society as well as the enhancement of the role of local governments and communities. On the other hand, a cross-institutional approach is required to embed digital technologies as well as associated discussions regarding the ethics, economics, and regulation of such technology in all government strategies and policies that are directed towards any planned DRR intervention.

Continuous improvements in computational power and the increased volume of data from space-based observation have allowed for the development of a high spatial and temporal resolution Earth System model (ESM) (Huntingford, 2019). These high-resolution models have enhanced the predictability of extreme climate events, providing timely warnings and formulating more precise mitigation strategies (Avila-Diaz et al., 2023; Huntingford et al., 2019). In addition, AI has emerged as a transformative tool to augment global climate change DRR and adaptation efforts by helping identify patterns and make predictions that can be essential for long-term climate adaptation strategies at the global level (Bi et al., 2023; Dewitte et al., 2021; Kim et al., 2021; Ravuri et al., 2021; Reichstein et al., 2019). Furthermore, given the disparity in digital access among nations, numerous initiatives and international platforms have been established to promote climate technology transfer (Oh, 2022). Likewise, for transmitting climate data, services like the Copernicus Climate Change Service offer reliable and free data about the atmosphere, terrestrial areas, oceans, and ice, available in real-time for the advantage of all countries (Buontempo et al., 2022). However, the transfer of climate data is not without challenges. Data quality and standardisation discrepancies can lead to interpretative difficulties (Liu et al., 2015). Infrastructural inadequacies, particularly in developing nations, constrain extensive climate datasets' efficient storage and processing (Shiferaw et al., 2014). Addressing these barriers requires comprehensive international policies and agreements that standardise data quality and formats and strong legal frameworks that safeguard security while promoting open data access for the global community. Technological opportunities for DRR on a national level are mainly guided by the ability to develop more effective localised monitoring to forecast local climate events, allowing for timely interventions and planning. Data collection can

become more fine-grained as advanced technologies enable countries to tailor data collection methods to their needs. For example, drones, sensors and IoT devices can monitor local climate variations, helping countries gain granular insights into changes and potential threats within their borders (Mois et al., 2017). Technological advancements in sensor networks are reshaping climate responsiveness by capturing data from topographically intricate regions, previously difficult to monitor, facilitating more accurate predictions of events like flash floods and avalanches (Thüring et al., 2015; Yoshikane et al., 2021). Emerging technologies like UAVs have begun addressing accessibility issues in data collection, offering a solution for regions challenging to reach due to human or logistic constraints (Chamola et al., 2021; Newman, 2007). Simultaneously, transfer learning allows foundational models developed in data-rich regions to be adapted to different contexts. Google's flood risk system and Deines et al.'s crop yield model exemplify this, trained in specific locales but adaptable globally, making them valuable, especially in areas with limited institutional record-keeping (Deines et al., 2021; Nevo et al., 2020). Developing countries grapple with a dearth of digital data on local climate projections, a hindrance to implementing optimal agricultural practices (Balogun et al., 2020; Leal Filho et al., 2022). There is a need for high-quality, homogenous data series to improve projections and ensure the accuracy of downscaled global climate models (Brunet & Jones, 2011; Munang et al., 2013). As the network grows increasingly autonomous with the onset of IoT and satellite-based technology, ensuring equitable access and applicability to these technologies is imperative for nations to combat climate change challenges effectively (Chamola et al., 2021).

While the technological innovations for climate adaptation provide opportunities, they also come with inherent challenges that policymakers must address. For many regions, the availability of digital climate data is constrained primarily to recent decades, despite international efforts to enhance data accessibility (Brunet & Jones, 2011). The lack of localised data on the impacts of future extreme events impedes the formation of tailored adaptation and DRR strategies, highlighting the pressing need for targeted investments in data collection and analysis (Birkmann & von Teichman, 2010). Additionally, the deployment of advanced tools such as UAVs, though potent in solving accessibility issues, remains economically prohibitive for many developing nations (Chamola et al., 2021). For policymakers, these challenges underline the need for equitable distribution of technology, resources, and knowledge. Laws and policies should promote public-private partnerships, fostering innovation while ensuring that benefits are accessible to all, especially the most vulnerable. Moreover, international collaboration becomes vital, not just for technology transfer, but for developing legal frameworks that standardise data quality and ensure security while encouraging open data access. In this interconnected world, only a harmonised legal and policy approach can truly harness the potential of these technological advancements for global climate adaptation.

The evolving technological landscape has ushered in unprecedented opportunities for

building climate resilience at the city or local level. The advent of 3D city modelling, early warning systems, and digital twins has revolutionised urban planning and design (Balogun et al., 2020; Pantoja-Rosero et al., 2023). An exemplary case is the city of Lisbon, which has harnessed a digital twin to simulate myriad scenarios, aiding in the formulation of mitigation strategies across diverse return periods (Riaz et al., 2023). These tools, in tandem with predictive and prescriptive analysis, bolster the construction of disaster-resilient infrastructure (Syifa et al., 2019). Internet-based platforms armed with AI components, like the one established for flood predictions in Europe, leverage data from physical sensors and social networks to discern erratic behaviours and assess vulnerabilities in communities and critical structures (Fang et al., 2015; Munawar et al., 2022). These advances, complemented by machine learning and cognitive computing, have the potential to revolutionise energy management and optimisation in urban areas (Leal Filho et al., 2022; Şerban & Lytras, 2020). However, the integration of these innovative tools is not without challenges. Big cities typically possess comprehensive data, rendering AI predictions accurate. Yet, this might not hold for smaller cities or rural areas. The availability, accuracy, and ownership of such data can present obstacles. Furthermore, the high level of expertise required to deploy some of these tools, combined with their dependence on sophisticated software and high-end computers, can deter their adoption in economically disadvantaged areas (Sun et al., 2020). Besides, the intricacies of diverse hazards and socioeconomic backgrounds of communities imply that AI-based decision tools developed for one community might falter in another. This divergence between research findings related to disaster management and the policies adopted by city councils remains a major impediment to establishing a consistent and effective approach to disaster management. Marrying research initiatives with local policies mandates collaborative engagement of governmental bodies in urban planning and development (Munawar et al., 2022). Moreover, the rapid influx of AI applications striving for environmental sustainability grapples with the rebound effects of energy-intensive frameworks, potentially derailing carbon neutrality goals (Leal Filho et al., 2022). As cities extend into climate-sensitive zones, the vulnerabilities intensify, underscoring the urgency for city-level technological interventions (Balogun et al., 2020; Marks, 2019). Addressing the ethical, transparency, and safety concerns rooted in these challenges warrants regulatory scrutiny and an apt legislative framework to preclude AI's counterproductive impacts (Leal Filho et al., 2022).

REFERENCES

- Adger, N. (2003). Social Capital, Collective Action, and Adaptation to Climate Change. *Economic Geography* 79 (4): 387–404.
- Ahmad, M. I., & Ma, H. (2020). An investigation of the targeting and allocation of post-flood disaster aid for rehabilitation in Punjab, Pakistan. *International Journal of Disaster*

Risk Reduction, 44, 101402. <https://doi.org/10.1016/j.ijdr.2019.101402>

Avila-Diaz, A., Torres, R. R., Zuluaga, C. F., Cerón, W. L., Oliveira, L., Benezoli, V., Rivera, I. A., Marengo, J. A., Wilson, A. B., & Medeiros, F. (2023). Current and Future Climate Extremes Over Latin America and Caribbean: Assessing Earth System Models from High Resolution Model Intercomparison Project (HighResMIP). *Earth Systems and Environment*, 7(1), 99–130. <https://doi.org/10.1007/s41748-022-00337-7>

Ayyad, M., Hajj, M. R., & Marsooli, R. (2022). Artificial intelligence for hurricane storm surge hazard assessment. *Ocean Engineering*, 245, 110435. <https://doi.org/10.1016/j.oceaneng.2021.110435>

Balogun, A.L., Marks, D., Sharma, R., Shekhar, H., Balmes, C., Maheng, D., Arshad, A & Salehi, P. (2020). Assessing the Potentials of Digitalization as a Tool for Climate Change Adaptation and Sustainable Development in Urban Centres, *Sustainable Cities and Society* 53, 101888. <https://doi.org/10.1016/j.scs.2019.101888>

Bauer, P., Thorpe, A., & Brunet, G. (2015). The quiet revolution of numerical weather prediction. *Nature*, 525(7567), Article 7567. <https://doi.org/10.1038/nature14956>

Bellaire, S., van Herwijnen, A., Mitterer, C., & Schweizer, J. (2017). On forecasting wet-snow avalanche activity using simulated snow cover data. *Cold Regions Science and Technology*, 144, 28–38. <https://doi.org/10.1016/j.coldregions.2017.09.013>

Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X., & Tian, Q. (2023). Accurate medium-range global weather forecasting with 3D neural networks. *Nature*, 619(7970), Article 7970. <https://doi.org/10.1038/s41586-023-06185-3>

Birkmann, J., & von Teichman, K. (2010). Integrating disaster risk reduction and climate change adaptation: Key challenges—scales, knowledge, and norms. *Sustainability Science*, 5(2), 171–184. <https://doi.org/10.1007/s11625-010-0108-y>

Bossu, R., Laurin, M., Mazet-Roux, G., Roussel, F., & Steed, R. (2015). The Importance of Smartphones as Public Earthquake-Information Tools and Tools for the Rapid Engagement with Eyewitnesses: A Case Study of the 2015 Nepal Earthquake Sequence. *Seismological Research Letters*, 86(6), 1587–1592. <https://doi.org/10.1785/0220150147>

Boyer-Villemaire, U, Benavente, J., Cooper, J. A. G., & Bernatchez, P. (2014). Analysis of Power Distribution and Participation in Sustainable Natural Hazard Risk Governance: A Call for Active Participation.” *Environmental Hazards-Human and Policy Dimensions* 13 (1): 38-57. doi: 10.1080/17477891.2013.864592.

Broberg, M. & Hovani, E. (2019) Disaster risk reduction through risk pooling: The case of hazard risk pooling schemes. In Samuel, K.L.H., Aronsson-Storrier, M., Nakjavani Bookmiller, K. (eds.) *The Cambridge handbook of disaster risk reduction and*

international law. Cambridge University Press.

- Brunet, M., & Jones, P. (2011). Data rescue initiatives: Bringing historical climate data into the 21st century. *Climate Research*, 47(1–2), 29–40. <https://doi.org/10.3354/cr00960>
- Buontempo, C., Burgess, S. N., Dee, D., Pinty, B., Thépaut, J.-N., Rixen, M., Almond, S., Armstrong, D., Brookshaw, A., Alos, A. L., Bell, B., Bergeron, C., Cagnazzo, C., Comyn-Platt, E., Damasio-Da-Costa, E., Guillory, A., Hersbach, H., Horányi, A., Nicolas, J., ... Marcilla, J. G. de. (2022). The Copernicus Climate Change Service: Climate Science in Action. *Bulletin of the American Meteorological Society*, 103 (12) E2669–E2687. DOI: <https://doi.org/10.1175/BAMS-D-21-0315.1>
- Cao, C., Liu, Y., Tang, O., & Gao, X. (2021). A fuzzy bi-level optimization model for multi-period post-disaster relief distribution in sustainable humanitarian supply chains. *International Journal of Production Economics*, 235, 108081. <https://doi.org/10.1016/j.ijpe.2021.108081>
- Carani, S., & Pingel, T. J. (2023). Detection of Tornado damage in forested regions via convolutional neural networks and uncrewed aerial system photogrammetry. *Natural Hazards*, 119(1), 143–166. <https://doi.org/10.1007/s11069-023-06125-4>
- Carley, K. M., Malik, M., Landwehr, P. M., Pfeffer, J., & Kowalchuck, M. (2016). Crowd sourcing disaster management: The complex nature of Twitter usage in Padang Indonesia. *Safety Science*, 90, 48–61. <https://doi.org/10.1016/j.ssci.2016.04.002>
- Carani, S., & Pingel, T. J. (2023). Detection of Tornado damage in forested regions via convolutional neural networks and uncrewed aerial system photogrammetry. *Natural Hazards*, 119(1), 143–166. <https://doi.org/10.1007/s11069-023-06125-4>
- Carley, K. M., Malik, M., Landwehr, P. M., Pfeffer, J., & Kowalchuck, M. (2016). Crowd sourcing disaster management: The complex nature of Twitter usage in Padang Indonesia. *Safety Science*, 90, 48–61. <https://doi.org/10.1016/j.ssci.2016.04.002>
- Chamola, V., Hassija, V., Gupta, S., Goyal, A., Guizani, M., & Sikdar, B. (2021). Disaster and Pandemic Management Using Machine Learning: A Survey. *IEEE Internet of Things Journal*, 8(21), 16047–16071. <https://doi.org/10.1109/JIOT.2020.3044966>
- Chini, M., Piscini, A., Cinti, F. R., Amici, S., Nappi, R., & DeMartini, P. M. (2013). The 2011 Tohoku (Japan) Tsunami Inundation and Liquefaction Investigated Through Optical, Thermal, and SAR Data. *IEEE Geoscience and Remote Sensing Letters*, 10(2), 347–351. <https://doi.org/10.1109/LGRS.2012.2205661>
- Cheong, S.-M., Sankaran, K., & Bastani, H. (2022). Artificial intelligence for climate change adaptation. *WIREs Data Mining and Knowledge Discovery*, 12(5), e1459. <https://doi.org/10.1002/widm.1459>

- Chowdhury, N. & Wessel, R. (2012). Conceptualising Multilevel Regulation in the EU: A Legal Translation of Multilevel Governance?. *European Law Journal*, 18(3), 335-357. <https://doi.org/10.1111/j.1468-0386.2012.00603.x>
- Coppola, D. (2006). *Introduction to International Disaster Management*. Elsevier.
- Cubie, D. (2019). Embracing regionalism: Lessons from the UN regional seas programme for UNISDR and the Sendai Framework. In Samuel, K.L.H., Aronsson-Storrier, M., Nakjavani Bookmiller, K. (eds.) *The Cambridge handbook of disaster risk reduction and international law*. Cambridge University Press.
- Cumbane, S. P. (2022). Population Displacement Estimation During Disasters Using Mobile Phone Data. <https://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-312254>
- Deines, J. M., Patel, R., Liang, S.-Z., Dado, W., & Lobell, D. B. (2021). A million kernels of truth: Insights into scalable satellite maize yield mapping and yield gap analysis from an extensive ground dataset in the US Corn Belt. *Remote Sensing of Environment*, 253, 112174. <https://doi.org/10.1016/j.rse.2020.112174>
- Dewitte, S., Cornelis, J. P., Müller, R., & Munteanu, A. (2021). Artificial Intelligence Revolutionises Weather Forecast, Climate Monitoring and Decadal Prediction. *Remote Sensing*, 13(16), Article 16. <https://doi.org/10.3390/rs13163209>
- Djalante, R. (2012). Adaptive Governance and Resilience: The Role of Multi-Stakeholder Platforms in Disaster Risk Reduction. *Natural Hazards and Earth System Sciences* 12(9): 2923–2942. doi: 10.5194/nhess-12-2923-2012.
- Djeffal, C., Siewert, M. B., & Wurster, S. (2022). Role of the state and responsibility in governing artificial intelligence: A comparative analysis of AI strategies. *Journal of European Public Policy*, 29(11), 1799–1821. <https://doi.org/10.1080/13501763.2022.2094987>
- Dover, S. (2022). Policy Learning for Disaster Risk Reduction. In James, H., Shaw, R., Sharma, V., & Lukasiewicz, A (eds) *Disaster Risk Reduction in Asia Pacific Governance, Education and Capacity*, Palgrave Macmillan.
- Ehrlich, D., Kemper, T., Blaes, X., & Soille, P. (2013). Extracting building stock information from optical satellite imagery for mapping earthquake exposure and its vulnerability. *Natural Hazards*, 68(1), 79–95. <https://doi.org/10.1007/s11069-012-0482-0>
- Elkin, C., & Witherspoon, S. (2019). Machine learning can boost the value of wind energy. <https://deepmind.com/blog/article/machine-learning-can-boost-value-wind-energy>.
- Erdelj, M., Król, M., & Natalizio, E. (2017). Wireless Sensor Networks and Multi-UAV systems for natural disaster management. *Computer Networks*, 124, 72–86. <https://doi.org/10.1016/j.comnet.2017.05.021>

- Erdelj, M., & Natalizio, E. (2016). UAV-assisted disaster management: Applications and open issues. 2016 International Conference on Computing, Networking and Communications (ICNC), 1–5. <https://doi.org/10.1109/ICCNC.2016.7440563>
- Esposito, C., & Rizzo, G. (2022). Help From Above: UAV-Empowered Network Resiliency in Post-Disaster Scenarios. 2022 IEEE 19th Annual Consumer Communications & Networking Conference (CCNC), 477–480. <https://doi.org/10.1109/CCNC49033.2022.9700675>
- European Commission. (2020). Overview of natural and man-made disaster risks the European Union might face, available: <https://www.preventionweb.net/publication/overview-natural-and-man-made-disaster-risks-european-union-may-face-2020-edition>
- European Commission. (2023). Union Civil Protection Mechanism, available: https://civil-protection-humanitarian-aid.ec.europa.eu/what/civil-protection/eu-civil-protection-mechanism_en
- Fang, S., Xu, L., Zhu, Y., Liu, Y., Liu, Z., Pei, H., Yan, J., & Zhang, H. (2015). An integrated information system for snowmelt flood early-warning based on internet of things. *Information Systems Frontiers*, 17(2), 321–335. <https://doi.org/10.1007/s10796-013-9466-1>
- Fitriany, A. A., Flatau, P. J., Khoirunurrofik, K., & Riama, N. F. (2021). Assessment on the Use of Meteorological and Social Media Information for Forest Fire Detection and Prediction in Riau, Indonesia. *Sustainability*, 13(20), Article 20. <https://doi.org/10.3390/su132011188>
- Flood, S., Jerez Columbié, Y., Le Tissier, M., O’Dwyer, B. (eds.) (2022). *Creating Resilient Futures Integrating Disaster Risk Reduction, Sustainable Development Goals and Climate Change Adaptation Agendas*. Palgrave MacMillan.
- Floridi, L., Cows, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds & Machines*, 28, 689–707. DOI: 10.1007/s11023-018-9482-5
- Folke, C., T. Hahn, P. Olsson, and J. Norberg. (2005). Adaptive Governance of Social-Ecological Systems. *Annual Review of Environment and Resources* 30: 441–473. doi:10.1146/annurev.energy.30.050504.144511.Frey, K., & Calderón Ramírez, D. R. (2019). Multi-level network governance of disaster risks: the case of the Metropolitan Region of the Aburra Valley (Medellin, Colombia), *Journal of Environmental Planning and Management*, 62(3), 424-445. DOI: 10.1080/09640568.2018.1470968

- Gellert de Pinto, G. (2012). El cambio de paradigma de la gestión de desastres a la gestión del riesgo [The Paradigm Shift from Disaster Management to Risk Management]. *Boletín Científico, Sapiens Research* 2 (1): 13–17.
- Ghassemi, P., & Chowdhury, S. (2022). Multi-robot task allocation in disaster response: Addressing dynamic tasks with deadlines and robots with range and payload constraints. *Robotics and Autonomous Systems*, 147, 103905. <https://doi.org/10.1016/j.robot.2021.103905>
- Goncalves, A., Silva, C., & Morreale, P. (2014). Design of a Mobile Ad Hoc Network Communication App for Disaster Recovery. 2014 28th International Conference on Advanced Information Networking and Applications Workshops, 121–126. <https://doi.org/10.1109/WAINA.2014.26>
- Granell, C., & Ostermann, F. O. (2016). Beyond data collection: Objectives and methods of research using VGI and geo-social media for disaster management. *Computers, Environment and Urban Systems*, 59, 231–243. <https://doi.org/10.1016/j.compenvurbsys.2016.01.006>
- Gupta, S., Modgil, S., Kumar, A., Sivarajah, U., & Irani, Z. (2022). Artificial intelligence and cloud-based Collaborative Platforms for Managing Disaster, extreme weather and emergency operations. *International Journal of Production Economics*, 254, 108642. <https://doi.org/10.1016/j.ijpe.2022.108642>
- Gyaneshwar, A., Mishra, A., Chadha, U., Raj Vincent, P. M. D., Rajinikanth, V., Pattukandan Ganapathy, G., & Srinivasan, K. (2023). A Contemporary Review on Deep Learning Models for Drought Prediction. *Sustainability*, 15(7), Article 7. <https://doi.org/10.3390/su15076160>
- Hopkins, J.W. (2019) Soft obligations and hard realities: Regional disaster risk reduction in Europe and Asia. In Samuel, K.L.H., Aronsson-Storrier, M., Nakjavani Bookmiller, K. (eds.) *The Cambridge handbook of disaster risk reduction and international law*. Cambridge University Press.
- Horita, F. E., de Albuquerque, J. P., Marchezini, V., & Mendiondo, E. M. (2017). Bridging the gap between decision-making and emerging big data sources: An application of a model-based framework to disaster management in Brazil. *Decision Support Systems*, 97, 12-22. DOI: <https://doi.org/10.1016/j.dss.2017.03.001>
- Huntingford, C., Jeffers, E. S., Bonsall, M. B., Christensen, H. M., Lees, T., & Yang, H. (2019). Machine learning and artificial intelligence to aid climate change research and preparedness. *Environmental Research Letters*, 14(12), 124007. <https://doi.org/10.1088/1748-9326/ab4e55>
- IPCC. (2023). *Climate Change Synthesis Report 2023*. Available: <https://www.ipcc.ch/>
-

report/ar6/syr/downloads/report/IPCC_AR6_SYR_SPM.pdf

- Jerez Columbié, Y. (2022). Adapting to climate change through disaster risk reduction in the Caribbean: Lessons from the global south in tackling the sustainable development goals. In Flood, S., Jerez Columbié, Y., Le Tissier, M., O'Dwyer, B. (eds.) *Creating resilient futures integrating disaster risk reduction, sustainable development goals and climate change adaptation agendas*. Palgrave MacMillian
- Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, 1(2019), 389–399. DOI:10.1038/s42256-019-0088-2
- Jones, N. (2017). How machine learning could help to improve climate forecasts. *Nature*, 548(7668).
- Jones, E. D., & Faas, A. J. (eds.) (2017). *Social Network Analysis of Disaster Response, Recovery, and Adaptation*. Amsterdam: Elsevier.
- Jørgen Henriksen, H., Roberts, M. J., Van der Keura, P., Harjannek, A., Egilsonb, D., & Alfonso, L. (2018). Participatory early warning and monitoring systems: A Nordic framework for web-based flood risk management. *International Journal of Disaster Risk Reduction*, 31, 1295 – 1306. <https://doi.org/10.1016/j.ijdr.2018.01.038>
- Justo-Hanani, R. (2022). The politics of artificial intelligence regulation and governance reform in the European Union. *Policy Sciences*, 55(1), 137–159.
- Karstens, C. D., Stumpf, G., Ling, C., Hua, L., Kingfield, D., Smith, T. M., Correia, J., Calhoun, K., Ortega, K., Melick, C., & Rothfus, L. P. (2015). Evaluation of a Probabilistic Forecasting Methodology for Severe Convective Weather in the 2014 Hazardous Weather Testbed. *Weather and Forecasting*, 30(6), 1551–1570. <https://doi.org/10.1175/WAF-D-14-00163.1>
- Kelman, I., & Glantz, M. H. (2014). Early Warning Systems Defined. In A. Singh & Z. Zommers (Eds.), *Reducing Disaster: Early Warning Systems For Climate Change* (pp. 89–108). Springer Netherlands. https://doi.org/10.1007/978-94-017-8598-3_5
- Khalil, I. M., Khreishah, A., Ahmed, F., & Shuaib, K. (2014). Dependable wireless sensor networks for reliable and secure humanitarian relief applications. *Ad Hoc Networks*, 13, 94–106. <https://doi.org/10.1016/j.adhoc.2012.06.002>
- Kim, D., Park, J., Han, H., Lee, H., Kim, H. S., & Kim, S. (2023). Application of AI-Based Models for Flood Water Level Forecasting and Flood Risk Classification. *KSCE Journal of Civil Engineering*, 27(7), 3163–3174. <https://doi.org/10.1007/s12205-023-2175-5>
- Kim, D.-K., Suezawa, T., Mega, T., Kikuchi, H., Yoshikawa, E., Baron, P., & Ushio, T. (2021). Improving precipitation nowcasting using a three-dimensional convolutional

- neural network model from Multi Parameter Phased Array Weather Radar observations. *Atmospheric Research*, 262, 105774. <https://doi.org/10.1016/j.atmosres.2021.105774>
- Kim, T., Yang, T., Zhang, L., & Hong, Y. (2022). Near real-time hurricane rainfall forecasting using convolutional neural network models with Integrated Multi-satellite Retrievals for GPM (IMERG) product. *Atmospheric Research*, 270, 106037. <https://doi.org/10.1016/j.atmosres.2022.106037>
- Krzywanski, J., Skrobek, D., Zylka, A., Grabowska, K., Kulakowska, A., Sosnowski, M., Nowak, W., & Blanco-Marigorta, A. M. (2023). Heat and mass transfer prediction in fluidized beds of cooling and desalination systems by AI approach. *Applied Thermal Engineering*, 225, 120200. <https://doi.org/10.1016/j.applthermaleng.2023.120200>
- Lamanna, Z., Williams, K. H., & Childers, C. (2012). An Assessment of Resilience: Disaster Management and Recovery for Greater New Orleans' Hotels. *Journal of Human Resources in Hospitality & Tourism*, 11(3), 210–224. <https://doi.org/10.1080/15332845.2012.668653>
- Lamsal, R., & Kumar, T. V. V. (2020). Artificial Intelligence and Early Warning Systems. In T. V. V. Kumar & K. Sud (Eds.), *AI and Robotics in Disaster Studies* (pp. 13–32). Springer Nature. https://doi.org/10.1007/978-981-15-4291-6_2
- Leal Filho, W., Wall, T., Rui Mucova, S. A., Nagy, G. J., Balogun, A.-L., Luetz, J. M., Ng, A. W., Kovaleva, M., Safiul Azam, F. M., Alves, F., Guevara, Z., Matandirotya, N. R., Skouloudis, A., Tzachor, A., Malakar, K., & Gandhi, O. (2022). Deploying artificial intelligence for climate change adaptation. *Technological Forecasting and Social Change*, 180, 121662. <https://doi.org/10.1016/j.techfore.2022.121662>
- Liou, Y.-A., Kar, S. K., & Chang, L. (2010). Use of high-resolution FORMOSAT-2 satellite images for post-earthquake disaster assessment: A study following the 12 May 2008 Wenchuan Earthquake. *International Journal of Remote Sensing*, 31(13), 3355–3368. <https://doi.org/10.1080/01431161003727655>
- Liu, Q., & Liu, Y. (2013). An approach for auto bridge inspection based on climbing robot. 2013 IEEE International Conference on Robotics and Biomimetics (ROBIO), 2581–2586. <https://doi.org/10.1109/ROBIO.2013.6739861>
- Lopez-Gomez, I., McGovern, A., Agrawal, S., & Hickey, J. (2023). Global Extreme Heat Forecasting Using Neural Weather Models. *Artificial Intelligence for the Earth Systems*, 2(1). <https://doi.org/10.1175/AIES-D-22-0035.1>
- Marchezini, V., Horita, F. E. A., Matsuo, P. M., Trajber, R., Trejo-Rangel, M. A., & Olivato, D. (2018). A Review of Studies on Participatory Early Warning Systems (P-EWS): Pathways to Support Citizen Science Initiatives. *Frontiers in Earth Science*, 6. <https://www.frontiersin.org/articles/10.3389/feart.2018.00184>
-

- Marinho, M. A. M., de Freitas, E. P., C. Lustosa da Costa, J. P., F. de Almeida, A. L., & de Sousa, R. T. (2013). Using cooperative MIMO techniques and UAV relay networks to support connectivity in sparse Wireless Sensor Networks. 2013 International Conference on Computing, Management and Telecommunications (ComManTel), 49–54. <https://doi.org/10.1109/ComManTel.2013.6482364>
- Marks, D. (2019). Assembling the 2011 Thailand floods: Protecting farmers and inundating high-value industrial estates in a fragmented hydro-social territory. *Political Geography*, 68, 66–76. <https://doi.org/10.1016/j.polgeo.2018.10.002>
- McCallum, I., Liu, W., See, L., Mechler, R., Keating, A., Hochrainer-Stigler, S., Mochizuki, J., Fritz, S., Dugar, S., Arestegui, M., Szoenyi, M., Bayas, J.-C. L., Burek, P., French, A., & Moorthy, I. (2016). Technologies to Support Community Flood Disaster Risk Reduction. *International Journal of Disaster Risk Science*, 7(2), 198–204. <https://doi.org/10.1007/s13753-016-0086-5>
- Mois, G., Folea, S., & Sanislav, T. (2017). Analysis of Three IoT-Based Wireless Sensors for Environmental Monitoring. *IEEE Transactions on Instrumentation and Measurement*, 66(8), 2056–2064. <https://doi.org/10.1109/TIM.2017.2677619>
- Mokryn, O., Karmi, D., Elkayam, A., & Teller, T. (2012). Help Me: Opportunistic smart rescue application and system. 2012 The 11th Annual Mediterranean Ad Hoc Networking Workshop (Med-Hoc-Net), 98–105. <https://doi.org/10.1109/MedHocNet.2012.6257129>
- Munang, R., Nkem, J. N., & Zhen, H. (2013). Using data digitalization to inform climate change adaptation policy: Informing the future using the present. *Weather and Climate Extremes*, 1, 17–18. <https://doi.org/10.1016/j.wace.2013.07.001>.
- Munawar, H. S., Mojtahedi, M., Hammad, A. W. A., Kouzani, A., & Mahmud, M. A. P. (2022). Disruptive technologies as a solution for disaster risk management: A review. *Science of The Total Environment*, 806, 151351. <https://doi.org/10.1016/j.scitotenv.2021.151351>
- Nevo, S., Elidan, G., Hassidim, A., Shalev, G., Gilon, O., Nearing, G., & Matias, Y. (2020). ML-based Flood Forecasting: Advances in Scale, Accuracy and Reach (arXiv:2012.00671). arXiv. <https://doi.org/10.48550/arXiv.2012.00671>
- Newman, P. A. (2007). Uninhabited Aerial Vehicles: Current and Future Use. In G. Visconti, P. D. Carlo, W. H. Brune, A. Wahner, & M. Schoeberl (Eds.), *Observing Systems for Atmospheric Composition* (pp. 106–118). Springer New York. https://doi.org/10.1007/978-0-387-35848-2_8
- Oh, C. (2022). Evaluation of the UNFCCC Technology Mechanism’s contribution to an international climate policy framework. *International Environmental Agreements: Politics, Law and Economics*, 22(3), 527–542. <https://doi.org/10.1007/s10784-021->

[09559-y](#)

- Owen, G. (2020). What makes climate change adaptation effective? A systematic review of the literature. *Global Environmental Change*, 62, 102071. <https://doi.org/10.1016/j.gloenvcha.2020.102071>
- Park, S., Oh, Y., & Hong, D. (2017). Disaster response and recovery from the perspective of robotics. *International Journal of Precision Engineering and Manufacturing*, 18(10), 1475–1482. <https://doi.org/10.1007/s12541-017-0175-4>
- Pantoja-Rosero, B. G., Achanta, R., & Beyer, K. (2023). Damage-augmented digital twins towards the automated inspection of buildings. *Automation in Construction*, 150, 104842. <https://doi.org/10.1016/j.autcon.2023.104842>
- Pelling, M. (2011). Urban Governance and Disaster Risk Reduction in the Caribbean: The Experiences of Oxfam GB. *Environment and Urbanization* 23(2): 383–400. doi: 10.1177/0956247811410012.
- Pilli-Sihvola K, Vaatainen-Chimpuku, S. (2016). Defining climate change adaptation and disaster risk reduction policy integration: Evidence and recommendations from Zambia. *International Journal of Disaster Risk Reduction*. 19: 461-473. <https://doi.org/10.1016/j.ijdrr.2016.07.010>
- Plank, S. (2014). Rapid Damage Assessment by Means of Multi-Temporal SAR — A Comprehensive Review and Outlook to Sentinel-1. *Remote Sensing*, 6(6), Article 6. <https://doi.org/10.3390/rs6064870>
- Pradhan, B. (2010). Flood susceptible mapping and risk area delineation using logistic regression, GIS and remote sensing. *Journal of Spatial Hydrology*. <https://www.semanticscholar.org/paper/Flood-susceptible-mapping-and-risk-area-delineation-Pradhan/bb91ff86700b46082c39cd580dfa74f419b49011>
- Radu, R. (2021). Steering the governance of artificial intelligence: National strategies in perspective. *Policy and Society*, 40(2), 178–193. <https://doi.org/10.1080/14494035.2021.1929728>
- Ravuri, S., Lenc, K., Willson, M., Kangin, D., Lam, R., Mirowski, P., Fitzsimons, M., Athanassiadou, M., Kashem, S., Madge, S., Prudden, R., Mandhane, A., Clark, A., Brock, A., Simonyan, K., Hadsell, R., Robinson, N., Clancy, E., Arribas, A., & Mohamed, S. (2021). Skilful precipitation nowcasting using deep generative models of radar. *Nature*, 597(7878), Article 7878. <https://doi.org/10.1038/s41586-021-03854-z>
- Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, 566(7743), Article 7743. <https://doi.org/10.1038/s41586-019-0912-1>

- Riaz, K., McAfee, M., & Gharbia, S. S. (2023). Management of Climate Resilience: Exploring the Potential of Digital Twin Technology, 3D City Modelling, and Early Warning Systems. *Sensors*, 23(5), Article 5. <https://doi.org/10.3390/s23052659>
- Roche, S., Propeck-Zimmermann, E., & Mericskay, B. (2013). GeoWeb and crisis management: Issues and perspectives of volunteered geographic information. *GeoJournal*, 78(1), 21–40. <https://doi.org/10.1007/s10708-011-9423-9>
- Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A. S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A. S., Maharaj, T., Sherwin, E. D., Mukkavilli, S. K., Kording, K. P., Gomes, C. P., Ng, A. Y., Hassabis, D., Platt, J. C., ... Bengio, Y. (2022). Tackling Climate Change with Machine Learning. *ACM Computing Surveys*, 55(2), 42:1-42:96. <https://doi.org/10.1145/3485128>
- Rotondi, C., Malandrino, F., Bianco, A., Chiasserini, C. F., & Stavrakakis, I. (2021). Scheduling of emergency tasks for multiservice UAVs in post-disaster scenarios. *Computer Networks*, 184, 107644. <https://doi.org/10.1016/j.comnet.2020.107644>
- Roztock, N., Strzelczyk, W., & Weistroffer, H. R. (2023). The role of e-government in disaster management: A review of the literature. *Journal of Economics & Management*, 45, 1-25. <https://doi.org/10.22367/jem.2023.45.01>
- Sarker, M. N. I., Yang, B., Yang, L., Huq, M. E., & Kamruzzaman, M. M. (2020). Climate change adaptation and resilience through big data. *International Journal of Advanced Computer Science and Applications*, 11(3).
- Sendai Framework for Disaster Risk Reduction 2015-2030, available: <https://www.undrr.org/publication/sendai-framework-disaster-risk-reduction-2015-2030>
- Şerban, A. C., & Lytras, M. D. (2020). Artificial Intelligence for Smart Renewable Energy Sector in Europe—Smart Energy Infrastructures for Next Generation Smart Cities. *IEEE Access*, 8, 77364–77377. <https://doi.org/10.1109/ACCESS.2020.2990123>
- Shiferaw, B., Tesfaye, K.,
- Kassie, M., Abate, T., Prasanna, B. M., & Menkir, A. (2014). Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: Technological, institutional and policy options. *Weather and Climate Extremes*, 3, 67–79. <https://doi.org/10.1016/j.wace.2014.04.004>
- Sivaram, V. (Ed.). (2018). Promoting digital innovations to advance clean energy systems. New York: Council on Foreign Relations <https://www.cfr.org/report/digitaldecarbonization>.
- Sun, W., Bocchini, P., & Davison, B. D. (2020). Applications of artificial intelligence for disaster management. *Natural Hazards*, 103(3), 2631–2689. <https://doi.org/10.1007/>

[s11069-020-04124-3](#).

- Syifa, M., Kadavi, P. R., & Lee, C. W. (2019). An artificial intelligence application for post-earthquake damage mapping in Palu, central Sulawesi, Indonesia. *Sensors*, 19(3), 542. <https://doi.org/10.3390/s19030542>
- Tadokoro, S. (2005). Special project on development of advanced robots for disaster response (DDT project). *IEEE Workshop on Advanced Robotics and Its Social Impacts*, 2005., 66–72. <https://doi.org/10.1109/ARSO.2005.1511621>
- Thüring, T., Schoch, M., van Herwijnen, A., & Schweizer, J. (2015). Robust snow avalanche detection using supervised machine learning with infrasonic sensor arrays. *Cold Regions Science and Technology*, 111, 60–66. <https://doi.org/10.1016/j.coldregions.2014.12.014>
- Torok, M. M., Golparvar-Fard, M., & Kochersberger, K. B. (2014). Image-Based Automated 3D Crack Detection for Post-disaster Building Assessment. *Journal of Computing in Civil Engineering*, 28(5), A4014004. [https://doi.org/10.1061/\(ASCE\)CP.1943-5487.0000334](https://doi.org/10.1061/(ASCE)CP.1943-5487.0000334)
- Torky, M., Gad, I., Darwish, A., & Hassanien, A. E. (2023). Artificial Intelligence for Predicting Floods: A Climatic Change Phenomenon. In A. E. Hassanien & A. Darwish (Eds.), *The Power of Data: Driving Climate Change with Data Science and Artificial Intelligence Innovations* (pp. 3–26). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-22456-0_1
- UNCCD. (1994). Convention to Combat Desertification in Those Countries Experiencing Serious Drought and/or Desertification, particularly in Africa. Available: https://catalogue.unccd.int/936_UNCCD_Convention_ENG.pdf
- UNDP. (2015). Multi-country Report. Available: <https://www.undp.org/publications/effective-law-regulation-disaster-risk-reduction>
- UNDRR. (2023). Early Warnings for All. Available: <https://www.undrr.org/early-warnings-for-all>
- UNDRR. (2010). Cancun Adaptation framework. Available: <https://www.preventionweb.net/publication/cancun-adaptation-framework-cancun-agreements-outcome-work-ad-hoc-working-group-long>
- UNDRR. (2023) GAR Special Report 2023: Mapping Resilience for the Sustainable Development Goals. Available: <https://www.undrr.org/gar/gar2023-special-report>
- UNISDR. (2005). Hyogo Framework for Action 2005-2015: Building the Resilience of Nations and Communities to Disaster (United Nations International Strategy for Disaster Reduction (UNISDR): 2005 see more at: <https://www.undrr.org/publication/>

[hyogo-framework-action-2005-2015-building-resilience-nations-and-communities-0](#)

- UN-ISDR (2005). Platform for the Promotion of Early Warning, Four Elements of People Centered Early Warning Systems, presented at the Virtual Symposium, Public Entity Risk Institute: Early Warning Systems – Interdisciplinary Observations and Policies from a Local Government Perspective. April 18-22, 2005.
- Van Niekerk D. Disaster risk governance in Africa (2015). A retrospective assessment of progress against the Hyogo Framework for Action (2000-2012). *Disaster Prevention and Management: An International Journal*. 24(3): 397-416. <https://doi.org/10.1108/DPM-08-2014-0168>
- Venier, S. & Capone, F. (2019). Speaking with one or multiple voices in multi-hazard early warning systems? A survey of international and national legal and policy frameworks. In Samuel, K.L.H., Aronsson-Storrier, M., Nakjavani Bookmiller, K. (eds.) *The Cambridge handbook of disaster risk reduction and international law*. Cambridge University Press.
- Walsh, T., Evatt, A., & de Witt, C. S. (2020). *Artificial Intelligence & Climate Change: Supplementary Impact Report*. Oxford, 1, 1-15.
- Warner, J. 2008. “Emergency River Storage in the Ooij Polder - A Bridge Too Far? Forms of Participation in Flood Preparedness Policy.” *International Journal of Water Resources Development* 24(4): 567–582. doi:10.1080/07900620801923153.
- Wu, D., & Cui, Y. (2018). Disaster early warning and damage assessment analysis using social media data and geo-location information. *Decision Support Systems*, 111, 48–59. <https://doi.org/10.1016/j.dss.2018.04.005>
- Wu, Z., Yin, H., He, H., & Li, Y. (2022). Dynamic-LSTM hybrid models to improve seasonal drought predictions over China. *Journal of Hydrology*, 615, 128706. <https://doi.org/10.1016/j.jhydrol.2022.128706>
- Yamazaki, F., & Liu, W. (2016). Remote sensing technologies for post-earthquake damage assessment: A case study on the 2016 Kumamoto earthquake. 6th Asia Conf. on Earthquake Engg.
- Yano, J.-I., Ziemiański, M. Z., Cullen, M., Termonia, P., Onvlee, J., Bengtsson, L., Carrassi, A., Davy, R., Deluca, A., Gray, S. L., Homar, V., Köhler, M., Krichak, S., Michaelides, S., Phillips, V. T. J., Soares, P. M. M., & Wyszogrodzki, A. A. (2018). Scientific Challenges of Convective-Scale Numerical Weather Prediction. *Bulletin of the American Meteorological Society*, 99(4), 699–710. <https://doi.org/10.1175/BAMS-D-17-0125.1>
- Ybañez, R. L., Ybañez, A. A. B., Lagmay, A. M. F. A., & Aurelio, M. A. (2021). Imaging

ground surface deformations in post-disaster settings via small UAVs. *Geoscience Letters*, 8(1), 23. <https://doi.org/10.1186/s40562-021-00194-8>

Yilmaz, I. (2010). Comparison of landslide susceptibility mapping methodologies for Koyulhisar, Turkey: Conditional probability, logistic regression, artificial neural networks, and support vector machine. *Environmental Earth Sciences*, 61(4), 821–836. <https://doi.org/10.1007/s12665-009-0394-9>

Yoshikane, T., [Link to external site, this link will open in a new tab](#), Yoshimura, K., & [Link to external site, this link will open in a new tab](#). (2021). A machine learning bias correction method for precipitation corresponding to weather conditions using simple input data. *Earth and Space Science Open Archive ESSOAr*. <https://doi.org/10.1002/essoar.10507695.1>

Yu, M., Yang, C., & Li, Y. (2018). Big Data in Natural Disaster Management: A Review. *Geosciences*, 8(5), Article 5. <https://doi.org/10.3390/geosciences8050165>

Yusoff, A., Din, N. M., Yusof, S., & Khan, S. U. (2015). Big data analytics for Flood Information Management in Kelantan, Malaysia. 2015 IEEE Student Conference on Research and Development (SCORED), 311–316. <https://doi.org/10.1109/SCORED.2015.7449346>

Zellou, B., El Moçayd, N., & Bergou, E. H. (2023). Review article: Towards Improved Drought Prediction in the Mediterranean Region – Modelling Approaches and Future Directions. *Natural Hazards and Earth System Sciences Discussions*, 1–53. <https://doi.org/10.5194/nhess-2023-63>

Zeng, Q.-C. (2018). Monitoring, Predicting and Managing Meteorological Disasters. *World Meteorological Organization Bulletin*, 67(2). <https://public.wmo.int/en/resources/bulletin/monitoring-predicting-and-managing-meteorological-disasters>