Early Warnings for All

LEVERAGING AI TO ENHANCE MULTI-HAZARD EARLY WARNING SYSTEMS (MHEWS)

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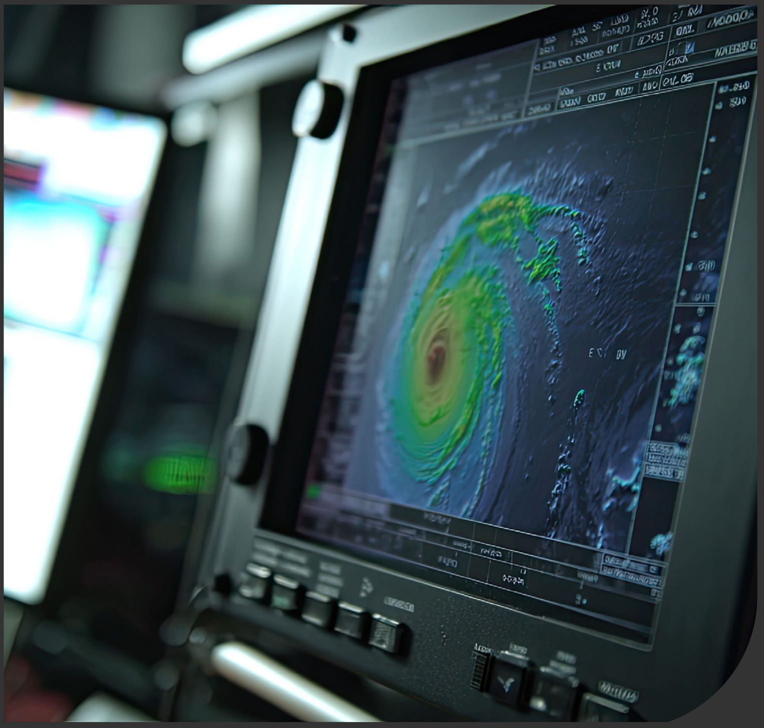

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Foreword

Disaster risks arising from the interaction of environmental hazards, exposure and vulnerability are increasing in frequency, intensity and complexity. They threaten lives, livelihoods and development gains worldwide, disproportionately affecting the most vulnerable communities. As climate risks intensify and exposure rises, the need for multi-hazard early warning systems (MHEWS) to reduce disaster losses and protect lives and livelihoods has become urgent. Yet significant gaps remain in coverage, quality and accessibility, particularly in the most vulnerable regions, underscoring the urgency of scaling up and strengthening early warning systems worldwide.

Recognising the growing risk of disasters and the proven value of early warnings, the United Nations Secretary-General launched the Early Warnings for All (EW4All) initiative in 2022 with a clear objective: to ensure that every person on Earth is protected by MHEWS. Co-led by the World Meteorological Organization (WMO) and the United Nations Office for Disaster Risk Reduction (UNDRR), and supported by the International Telecommunication Union (ITU) and the International Federation of Red Cross and Red Crescent Societies (IFRC), the initiative brings together governments, international organizations, scientific institutions, the private sector, donors and civil society to strengthen the full early warning value cycle.

At the same time, rapid advances in artificial intelligence (AI) are reshaping the way environmental risks are analysed, hazards are forecast, warnings are communicated, and early action is supported. This convergence of escalating disaster risk and accelerating technological innovation presents a critical opportunity to transform early warning systems, with AI offering new ways to address persistent gaps and expand their effectiveness and reach. Recognizing these opportunities, the initiative set up the AI for EW4All Group to bring together relevant stakeholders, identify practical applications, and develop concrete pilots to support countries in the use of AI for more inclusive and resilient early warning systems.

This report is an outcome of the AI for EW4All Group. Launched during the 2026 AI for Good Global Summit, it is a practical resource that provides an integrated analysis of how AI can contribute to the vision of EW4All. Its objective is to advance understanding of how AI is already being applied across the early warning system value cycle, highlighting opportunities for building more resilient and inclusive systems, and offering recommendations for advancing the responsible and effective use of AI. It is designed to support governments, practitioners and partners in identifying where AI can be applied today, what enabling conditions are required, and how to move from pilots to operational systems. Drawing on practical experiences from across the world, the report demonstrates how AI technologies can strengthen each of the four pillars of MHEWS: disaster risk knowledge; detection, observation, monitoring and forecasting; warning dissemination and communication; and preparedness to respond to warnings. It highlights where AI can address persistent operational gaps across the early warning value cycle - such as data limitations, forecasting capacity, and last-mile communication - while also examining the challenges associated with its integration. By bringing together evidence across all four pillars, the report provides one of the first end-to-end analyses of AI applications within MHEWS. Throughout, the report emphasizes that technological innovation should be accompanied by investments in human capabilities, institutional readiness, and solutions that respond to local needs and priorities.

The central message is clear: AI should augment human expertise, not replace it. Early warning systems ultimately depend on the dedication and judgment of meteorologists and other scientists, disaster managers, communication network providers, humanitarian workers, community leaders, and volunteers who transform scientific information into action that protects people and livelihoods. When deployed responsibly, AI can enhance these efforts – improving speed, scale, and precision – while helping to close persistent gaps, particularly in low- and middle-income countries where the need for expanded early warning coverage remains greatest.

By bringing together emerging practices, partner experiences and identifying strategic priority actions and recommendations, this report supports governments and partners in integrating AI into MHEWS in ways that are practical, responsible and people-centred. It provides guidance to decision-makers and financing partners to prioritize investments that strengthen and scale AI-enabled early warning capacity where gaps are widest. Realizing the full potential of AI for early warnings will also require shared standards, open data ecosystems, sustained investment in digital and observational infrastructure, and expanded capacity across countries and regions. Above all, it requires international cooperation to ensure that technological progress benefits those who are most vulnerable to disasters.

Together, we reaffirm our commitment to the vision of EW4All and to ensuring that innovation helps deliver life-saving protection to every person, everywhere. We call on governments, partners and investors to accelerate the responsible adoption of AI in early warning systems, strengthen collaboration, and ensure that innovation benefits those most at risk.

The future of early warning systems will be shaped not only by scientific breakthroughs, but by the strength of partnerships that connect science, technology, institutions, and communities. Together, we can ensure that early warning becomes early action, and that early action saves lives.

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Table of contents overview

Interactive elements
This report includes interactive navigation features to enhance the reading experience. Use the chapter icons at the top of each page to navigate between report sections. The highlighted icon shows your current location, and the Table of Contents provides quick access to all chapters and key content.

This report is structured around the four pillars of MHEWS, illustrating how AI can strengthen each stage of the early warning value cycle - from risk knowledge and forecasting to warning dissemination and preparedness. Each chapter can be read independently or as part of the broader end-to-end MHEWS framework, highlighting the interconnections between pillars and the role of AI in supporting more effective early action. Readers are encouraged to navigate between chapters, explore the case studies, and consult the AI Solutions Catalogue for additional examples.

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extended

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List of Abbreviations

Abbreviation	Spelled in full
AI	Artificial Intelligence
AOC	Areas of Concern
CAP	Common Alerting Protocol
CEOS	Committee on Earth Observation Satellites
CNN	Convolutional Neural Network
CREWS	Climate Risk and Early Warning Systems
DTE	Digital Twin Earth
EW4All	Early Warnings for All
EWS	Early Warning Systems
fAPAR	Fraction of Absorbed Photosynthetically Active Radiation
GEO	Group on Earth Observations
GIS	Geographic Information System
HLAB-AI	High-Level Advisory Body on Artificial Intelligence
IBF	Impact-Based Forecasting
IFRC	International Federation of Red Cross and Red Crescent Societies
INGC	National Institute for Disaster Management (Mozambique)
IPCC	Intergovernmental Panel on Climate Change
ITU	International Telecommunication Union
LLMs	Large Language Models
LMICs	Low- and Middle-Income Countries
LDCs	Least Developed Countries
LSTM	Long Short-Term Memory
MARS	Monitoring Agricultural ResourceS
MHEWS	Multi-Hazard Early Warning Systems
ML	Machine Learning
NMHSs	National Meteorological and Hydrological Services
NLP	Natural Language Processing
NWP	Numerical Weather Prediction
OECD	Organisation for Economic Co-operation and Development
PDC	Pacific Disaster Center
RSMC	Regional Specialized Meteorological Centre
SAR	Synthetic Aperture Radar
SEM	Socio-Economic Mapper
SIDS	Small Island Developing States
UN	United Nations
UNDRR	United Nations Office for Disaster Risk Reduction
UNGA	United Nations General Assembly
UNU-EHS	United Nations University – Institute for Environment and Human Security
UAV	Unmanned Aerial Vehicle
WFP	World Food Programme
WMO	World Meteorological Organization
xAI	Explainable Artificial Intelligence

Glossary

Artificial Intelligence (AI)
A set of technologies and techniques that enable machines to perform tasks requiring intelligence, including perception, reasoning, learning, and decision-making, complementing human capabilities.

Anticipatory Action
Acting ahead of predicted hazards to prevent or reduce acute humanitarian impacts before they fully unfold

Automated decision systems
Refers to a decision made by a system without human intervention, often based on analytics models and predefined strategies. These decisions can carry risks such as incorrect outcomes, missed opportunities, and wasted resources.

Common Alerting Protocol (CAP)
An international standard format for exchanging emergency alerts and public warnings across different communication systems.

Impact-Based Forecasting (IBF)
A forecasting approach that translates hazard information into expected impacts on people, infrastructure, and systems, enabling actionable decision-making.

Large Language Models (LLMs)
Very large deep learning models that are pre-trained on vast amounts of data, using transformer neural network architectures.

Machine Learning (ML)
Processes that enable computational systems to understand data and gain knowledge from it without necessarily being explicitly programmed.

Multi-Hazard Early Warning Systems (MHEWS)
An integrated system that enables the timely generation, dissemination, and use of warnings for multiple hazards, supporting informed action to reduce risks and impacts across the full early warning value chain.

Natural Language Processing (NLP)
A method that analyses text in natural languages through several processes such as part-of-speech recognition, syntactic analysis and semantic analysis.

Sentiment Analysis
Sentiment analysis (or opinion mining) is the automated process of using Natural Language Processing (NLP), AI, and machine learning to identify and classify emotional tones - positive, negative, or neutral - within text data

Nowcasting
Involves detailed forecasting of local weather, utilizing any method to predict conditions from the present to six hours ahead.

Numerical Weather Prediction (NWP)
Uses the current weather conditions as input into mathematical models describing the processes occurring in the atmosphere, aiming to forecast weather in a future period.

Executive summary

Disaster risks arising from the interaction of environmental hazards, exposure and vulnerability are increasing in frequency, intensity and complexity. At the same time, rapid advances in artificial intelligence (AI) are reshaping the way environmental risks are analysed, hazards are forecasted, and warnings are communicated. As climate risks grow and exposure rises in many regions, multi-hazard early warning systems (MHEWS) have become one of the most effective tools available to protect lives, livelihoods, and assets. Timely warnings enable governments, communities, and individuals to take protective action before hazards escalate into disasters.

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However, large gaps persist in global coverage and operational effectiveness. While 128 countries (as of 1 April 2026) now report some capacity for MHEWS, 72 more countries since reporting began in 2015, many communities remain unprotected or insufficiently reached by life-saving warnings. These gaps are particularly pronounced in low- and middle-income countries (LMICs), least developed countries (LDCs), and small island developing States (SIDS), where data limitations, infrastructure constraints, and capacity challenges continue to restrict system effectiveness.

MHEWS are structured around four interconnected pillars: disaster risk knowledge; detection, observation, monitoring, analysis and forecasting; warning dissemination and communication; and preparedness to respond to warnings.

The Early Warnings for All (EW4All) initiative builds on this established framework with the aim to ensure that every person on Earth is protected by early warning systems

This report assesses current applications of AI across all four MHEWS pillars, identifies operational gaps where AI can add value, and outlines the conditions required for responsible and effective implementation of AI. It builds on the work of the AI for EW4All Group by drawing on global case studies, partner experience, and emerging research. Across the report, AI is best understood as an enabling technology - one that enhances speed, scale, and analytical capacity, while remaining dependent on strong institutions, governance frameworks, and human expertise.

AI Opportunities Across the Early Warning Value Cycle

AI is contributing to the effectiveness of MHEWS across the four pillars:

Strengthening disaster risk knowledge (Chapter 2)

AI contributes to the discovery, integration, and usability of disaster risk data by enabling the processing of large and diverse datasets, including geospatial, socioeconomic, and historical loss and damage information. It supports the development and updating of exposure and vulnerability baselines - often through proxy indicators where conventional data are limited - and enhances the structuring and accessibility of risk information. AI also strengthens impact data tracking and learning by accelerating post-event damage and loss assessments and enabling more systematic analysis of observed impacts. These capabilities enable the operational use of both risk and disaster impact data within MHEWS, including to inform impact-based forecasting and the development and validation of anticipatory action triggers. However, these applications remain constrained by gaps in data availability, quality, and representativeness, particularly in data-scarce contexts, and require strong governance, validation, and sustained investment in foundational data systems to ensure reliability and equitable use.

Improved detection, observation, monitoring, analysis, and forecasting (Chapter 3)

AI is strengthening the full hazard information chain, with particularly strong advances in forecasting. In many cases, AI can now generate forecasts much faster, deliver additional skill gain, or at lower computational cost - enabling more frequent updates and improved prediction of high-impact events such as severe storms, floods, and tropical cyclones. Beyond hazard prediction, an emerging contribution of AI lies in impact forecasting, integrating hazard information with exposure and vulnerability data to better anticipate consequences for people, infrastructure, and systems. This represents a key bridge between risk information and forecast outputs, helping translate 'what the hazard will be' into 'what impact it will have'. At the same time, AI supports observational quality assurance, enables the integration of diverse data sources, and enhances real-time detection and monitoring. Together, these capabilities support earlier, more precise, and more reliable early warnings - while complementing existing forecasting and strengthening the human expertise needed in decision-making for preparedness and response. Gaps remain in observational data coverage, model generalisability across regions, and integration with existing operational forecasting systems. Data sparsity and bias, especially in underrepresented regions, continue to limit performance. There is a need for stronger integration between AI and traditional forecasting systems, investment in observational infrastructure, and frameworks to ensure transparency, validation, and human interpretability of AI generated forecasts.

Enhancing warning dissemination and communication (Chapter 4)

Even the most accurate forecast saves lives only if warnings reach people in time, are understood, and acted upon. AI is enhancing the ability to deliver timely, accessible and actionable warnings. Current AI applications can support the generation of multilingual warnings, enable more targeted and context-aware messaging, optimise communication channels, and real-time adaptation of dissemination strategies. Opportunities lie in scaling multi-channel, AI-enabled dissemination approaches that adapt to user context, counter misinformation, and personalise warnings without compromising consistency. These AI enabled approaches can make warnings more accessible to communities with diverse languages, literacy levels, and connectivity conditions. While AI offers large potential for personalization, its effectiveness is hindered by the offline status of 2.2 billion people. This connectivity gap limits AI from reaching the most vulnerable, and contributes toward skewed datasets that compromise AI accuracy. What is needed is a dual focus on strengthening communication infrastructure and adopting inclusive, multi-channel approaches that function across both high- and low-connectivity environments. To optimize AI-driven early warning systems, policy should focus on closing these digital gaps, thereby providing the infrastructure and data necessary for the technology to function equitably.

Supporting preparedness to respond to warnings (Chapter 5)

Preparedness and response mechanisms determine whether warnings translate into protective early action. AI is increasingly supporting preparedness and anticipatory action by enabling scenario modelling, identifying response capacity gaps, optimizing resource allocation, and helping to synthesis comparative analysis and evaluations to contribute to the development and improvement of anticipatory action frameworks where humanitarian assistance is triggered before disaster impacts occur. Additional opportunities include using AI to improve decision-support tools and enhancing evaluation and learning across response systems. However, since AI-driven scenarios often lack the inherent counterfactual 'what if' logic needed to simulate unprecedented events, these tools must be applied ethically to ensure that automated models do not overlook marginalized populations or reinforce historical biases. Emergency managers, meteorologists and other science professionals, and community leaders remain essential for interpreting forecasts and evaluating uncertainty, as they provide the critical oversight and accountability required when AI-driven outputs lack transparency. Ultimately, human decision-makers must remain responsible for ensuring that complex automated analyses translate into timely, reliable, and accountable action.

When deployed together across the early warning value cycle, these capabilities can transform fragmented technical systems into integrated, people-centred early warning ecosystems that translate knowledge and data into timely protective action.

Interpillar Challenges

Despite its potential, several cross-cutting challenges (Chapter 6) constrain the wider deployment of AI-enabled early warning systems:

Data interoperability and system integration: Early warning systems involve multiple institutions – disaster agencies, meteorological services, telecommunication providers, and humanitarian organizations - often using separate platforms and incompatible data formats and working across international or local borders. These silos limit the ability of AI tools to operate across the full early warning value cycle. At the same time, gaps in the availability and representativeness of data pose a systemic challenge across all pillars of early warning systems. Limited data coverage not only constrains risk analysis and forecasting, but also affects the relevance and reach of warning dissemination, and the effectiveness of preparedness, anticipatory action and response planning. These gaps increase the risk of bias in AI systems, potentially reinforcing existing inequalities in early warning coverage and outcomes. Addressing these challenges requires not only improved interoperability and integration across systems, but also targeted efforts to expand data collection, improve data sharing, and ensure that datasets are inclusive and representative. Bridging these divides is therefore a critical policy priority to enable equitable, end-to-end AI-enabled early warning systems.

Capacity, infrastructure and funding gaps: Many lack the computing infrastructure, technical expertise, and training required to deploy or scale AI-enabled systems. While AI-driven climate predictions can offset significant costs by leveraging global models to complement ground-based tools, this must be balanced against the high energy and water intensity of AI infrastructure, which can inadvertently exacerbate local environmental vulnerabilities. At the same time, insufficient and fragmented financing constraints sustained investment in early warning capabilities, limiting the ability to move from pilots to operational systems and to maintain long-term sustainability. The report also highlights emerging opportunities in the evolving AI financing landscape that can be leveraged to support scalable, sustainable, and resource-efficient implementation.

Governance, accountability and public trust: As early warning systems operate in life-safety contexts, AI deployment requires clear governance frameworks addressing transparency, accountability, bias mitigation, and data protection to maintain public trust and ensure decisions remain auditable. While the volume of data available to AI systems is increasing, data availability does not guarantee reliability or representativeness. Gaps in ground-based and local data, particularly in vulnerable regions, limit validation and can introduce bias into AI outputs.

This creates a direct link between data quality, governance, and trust. If data cannot be verified, and AI-driven decisions are not transparent or accountable, trust in early warning systems will erode. Governance frameworks must therefore ensure that data is validated and representative, AI outputs are explainable, decisions are traceable, and human oversight remains central. Strengthening these elements is critical to ensuring that AI-enabled early warning systems are both effective and trusted.

Equity and inclusion: Uneven access to connectivity, devices, and digital services means that data-intensive or internet-based warning systems may exclude vulnerable populations. In addition, underrepresentation of certain groups in datasets, as well as potential biases e.g., related to gender, ethnicity, or socioeconomic status) in the data and AI models, can lead to unequal outcomes. Addressing these challenges requires inclusive, multi-channel communication approaches and deliberate efforts to improve data representativeness and reduce bias in AI systems.

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Recommendations

To support responsible, transparent, and deeper integration of AI into early warning systems, the report identifies priority actions:

Invest in foundational infrastructure, including observation networks, digital infrastructure, data systems, computing capacity, and AI literacy within national agencies. Efforts should be grounded in an understanding of existing capacities and infrastructure, particularly in LDCs and SIDS, to ensure investments are targeted, appropriate, and effective.

Anchor AI deployment in governance and accountability frameworks, ensuring transparency, human oversight, and clear operational protocols for AI-supported decisions.

Prioritize human-centred and equity-driven AI design, ensuring systems serve marginalized populations and function effectively across diverse technological contexts.

Design AI-enabled early warning systems with interpillar integration from the outset, using interoperable architectures and shared data standards.

Mobilise sustained financing from diversified convention and non-conventional funding streams to support country-led AI projects as a foundation for testing and adapting solutions in local contexts - particularly in LDCs, SIDS and LMICs – while strengthening pathways to operationalisation, strengthening institutional capacity, and fostering partnerships to scale proven solutions and new technologies into nationally owned early warning systems.

Steer efforts on AI-based early warning systems towards those areas with the greatest gaps including: improving the availability, quality, and representativeness of foundational datasets, particularly in under-observed regions where data sparsity drives model bias; advancing impact-based forecasting that bridges hazard prediction and anticipated consequences for people and infrastructure; developing inclusive multi-channel dissemination approaches that function across high- and low-connectivity environments, strengthening integration of AI with operational forecasting and emergency management workflows in ways that preserve human oversight and accountability; and expanding AI applications in preparedness and anticipatory action while ensuring these tools do not reinforce existing biases or marginalise the populations least represented in training data.

From Innovation to Impact

The rapid evolution of AI presents a unique opportunity to strengthen early warning systems and accelerate progress toward universal coverage. However, technological innovation alone will not deliver protection. Effective early warning systems depend on the integration of scientific, local, indigenous, and traditional knowledge, supported by strong governance, resilient communication infrastructure, and community preparedness. AI can serve as a powerful force multiplier within these systems - enhancing data analysis, improving forecasts, and enabling more targeted warnings and anticipatory action. Ultimately, the success of AI-enabled early warning systems will be measured not by technological sophistication, but by their ability to save lives, protect livelihoods, and strengthen resilience in communities worldwide.

Chapter 1. Introduction

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1.1 Overview

The need for universal early warning coverage has never been more urgent as disasters triggered by extreme weather, climate variability and change, and other natural hazards are increasing in frequency, intensity, and complexity. Multi-hazard early warning systems (MHEWS) represent one of the most effective and cost-efficient risk reduction and climate adaptation measures. By providing timely information about impending hazards, these systems enable governments, communities, and individuals to take protective action before disaster strikes. Evidence consistently demonstrates that well-functioning early warning systems dramatically reduce mortality and economic loss. However, MHEWS are inherently complex, and gaps persist across their value chain - from disaster risk knowledge; detection, observation, monitoring, analysis, and forecasting; to warning dissemination and communication; and preparedness to respond.

Technological progress is opening opportunities to address some of these gaps and help build more resilient, inclusive and effective MHEWS. Recent advances in Artificial Intelligence (AI) have created new opportunities to address some of these gaps. The International Telecommunication Union (ITU) defines AI as "compris[ing] a rich set of methods and disciplines, including vision, perception, speech and dialogue, decisions and planning, problem-solving, robotics and other applications that enable self-learning. It is best viewed as a set of technologies and techniques used to complement traditional human attributes, such as intelligence, analytical ability and other capabilities" (ITU, n.d.).

In many countries, risk information is incomplete or outdated, hazard monitoring and forecasting capacity is uneven, warnings do not consistently reach those most at risk, and preparedness systems are not always able to translate warnings into early action. These gaps are especially pronounced in LMICs, LDCs and SIDS, where infrastructure, institutional capacity, and financing constraints remain significant. Identifying and addressing these challenges and opportunities, and driving progress, have been at the heart of the United Nations Early Warnings for All (EW4All) initiative. Launched in 2022, this initiative aims to ensure universal protection from hazardous hydrometeorological, climatological and related environmental events through life-saving MHEWS, anticipatory action, and resilience efforts. As of 1 April 2026, 128 countries report some capacity for MHEWS, 72 more countries since reporting began in 2015. While progress is underway, global coverage remains uneven, with AI-powered solutions offering a growing opportunity across the early warning system value cycle.

The central challenge is therefore not only to improve individual technical components of early warning systems, but to strengthen the connections between them so that risk knowledge, forecasts, communication, and preparedness function as an integrated, people-centred system. Bridging this gap between risk analytics and forecasting capability and effective decision-making with response represents one of the defining challenges of disaster risk reduction today. Here, technological progress is opening opportunities to address gaps and help build more resilient, inclusive and effective MHEWS.

AI is already being used in parts of the early warning value cycle to improve data integration, forecasting, translation, targeting, and anticipatory decision support. However, these applications remain uneven and context specific (Tiggeloven et al., 2025). In many cases, they are concentrated within particular stages of the value chain, often reflecting institutional mandates, available data, and resource constraints. This reflects both progress and current limitations. While AI adoption is advancing rapidly, its deployment is likely to remain incremental and tailored to specific contexts. A key question for the years ahead is therefore not only where AI can add value within individual pillars, but how it can progressively strengthen interoperability and coordination across the system, in ways that are practical, scalable, and resource-aware.

The developments in AI present a significant opportunity: if harnessed responsibly and inclusively, and where institutions, infrastructure and information systems function together across actors and operational domains, AI can help accelerate progress toward universal early warning coverage.

This report treats AI not as an objective in itself, but as an enabling set of methods and tools that can strengthen MHEWS when applied responsibly. Its value depends on the quality and representativeness of data, the resilience of infrastructure, the clarity of governance arrangements, and the continued role of human expertise and accountability. Throughout this report, the premise is that AI should augment - not replace - the scientific, institutional, and community capacities on which effective early warning systems depend.

1.2 Resource for action: purpose and applications of this report

This report provides a systematic review of AI's current role across the MHEWS value cycle. It identifies opportunities to build more resilient, inclusive, and impactful systems while offering practical recommendations for the efficient and safe integration of AI technologies. By examining AI's contribution to the four pillars of EW4All, the report explores how innovation can fill critical gaps in risk knowledge, forecasting, communication, and preparedness to create robust, end-to-end solutions.

The report is intended for a broad, multi-stakeholder audience, including policymakers and national governments responsible for MHEWS, including technical agencies such as meteorological and hydrological services and telecommunications authorities. It also targets private sector actors, particularly those involved in data, digital infrastructure, and AI solutions, to support collaboration and innovation across the early warning value cycle. It is also relevant to civil society organizations and community-based actors seeking to understand where AI may strengthen early warning practice and where caution, governance, and investment are required.

It emphasizes that while AI can enhance capacity, its application must remain grounded in human oversight and community needs. The report draws on global case studies to provide guidance for the practical and responsible adoption of AI in MHEWS.

Particular focus is given to LMICs, LDCs and SIDS. In these contexts - where data gaps, infrastructure and capacity constraints are most acute - AI-enabled solutions offer the greatest potential to bridge inequalities and strengthen disaster resilience. The report can support strategic planning by helping decision-makers identify where AI is already being applied across MHEWS, where gaps remain, and what enabling conditions are required for responsible implementation. In addition, it supports policy dialogue and coordination by highlighting cross-cutting issues - such as data quality, interoperability, inclusion, public trust, and governance - that need to be addressed jointly across institutions rather than within isolated technical domains. It can support learning and prioritisation by helping readers distinguish between AI applications that are already operational, those in advanced pilots, and those that remain promising but immature.

The report does not propose AI as a universal solution, nor does it assume that all countries should adopt the same tools or pathways. Instead, it aims to help readers make grounded decisions about where AI can realistically strengthen MHEWS in their own context, what risks need to be managed, and what investments are required for sustainable and equitable use. Ultimately, this work aims to empower policymakers, humanitarian partners, and local leaders to leverage emerging technology to protect lives and livelihoods.

1.3 The Early Warning for All (EW4All) initiative

The EW4All initiative supports countries in implementing people-centred, end-to-end MHEWS across four interconnected pillars (Figure 1):

- Disaster Risk Knowledge – led by UNDRR
- Detection, Observation, Monitoring, Analysis and Forecasting – led by WMO
- Warning Dissemination and Communication – led by ITU
- Preparedness to Respond to Warnings – led by IFRC

These pillars span the full early warning value cycle. Risk knowledge provides the foundation by identifying who and what is at risk, where vulnerabilities exist, and how hazards may translate into real-world consequences. Hazard monitoring and forecasting then generate timely information and predictions about when and where events may occur and how severe they may be. Dissemination and communication systems translate technical forecasts into timely, understandable warnings that reach at-risk populations. Preparedness and response mechanisms ensure that these warnings trigger effective protective actions. The pragmatic strength of MHEWS lies in synchronized action across these four pillars, supported by cross-cutting enablers such as governance, financing, and innovation in digital technologies, which includes AI.

Disaster risk knowledge

Systematically collect data and undertake risk assessments and analyses

- ➔ Are the hazard, exposure, and vulnerability well known by the communities?
- ➔ What are the patterns and trends in these factors?
- ➔ Are risk maps and data widely available?

Detection, observations, monitoring, analysing and forecasting of hazards

Develop hazard monitoring and early warning services

- ➔ Are the right parameters being monitored?
- ➔ Is there a sound scientific basis for making forecasts?
- ➔ Can accurate and timely warnings be generated?

Preparedness to respond to warnings

Build national and community response capabilities

- ➔ Are response plans up to date and tested?
- ➔ Are local capacities and knowledge made use of?
- ➔ Are people prepared and ready to react to warnings?

Warning dissemination and communication

Communicate risk information and early warnings

- ➔ Do warnings reach all of those at risk?
- ➔ Are the risks and warnings understood?
- ➔ Is the warning information clear and usable?

Figure 1. Overview of the 4 Pillars of MHEWS. Image adopted from World Meteorological Organization (2022). *Early Warnings for All Executive Action Plan 2023-2027*. https://library.wmo.int/records/item/58209-early-warnings-for-all

1.4 Global MHEWS and AI policy context

The EW4All initiative is anchored in broader international policy frameworks that establish both the urgency of universal warning coverage and the need for trustworthy digital innovation (Figure 2). These include the Paris Agreement's Global Goal on Adaptation (UNFCCC, 2015), the Sendai Framework's Target G on expanding multi-hazard early warning coverage (UNDRR, 2015), and the 2030 Agenda's emphasis on disaster risk reduction as a foundation for sustainable development (UN, 2015). At the same time, several recent UN General Assembly resolutions call for trustworthy, transparent, and inclusive AI for sustainable development (UNGA, 2024a, 2024b). The UN Secretary-General's High-Level Advisory Body on AI, established in October 2023 to frame the United Nations' approach to AI governance, provides crucial guidance for responsible innovation in this domain (High-Level Advisory Body on Artificial Intelligence, 2024). Together, these frameworks establish a clear international mandate for scaling early warning capabilities by 2030, where AI can be positioned as a strategic accelerator, but also highlight the need to address various challenges and risks posed by AI to ensure its benefits for all.

While the EW4All Executive Action Plan positioned AI as a strategic enabler in the early warning value cycle, leading to the establishment of the AI Group of EW4All by the Interpillar Technical Coordination Group (ITCG), early warning system policy frameworks and AI frameworks remain largely de-linked (WMO, 2022). This reflects the fractured organization of early warning systems, where different stakeholders contribute to distinct components of the value cycle. It also highlights the timeliness of this study in offering an integrated, interpillar analysis that situates AI within the broader MHEWS context.

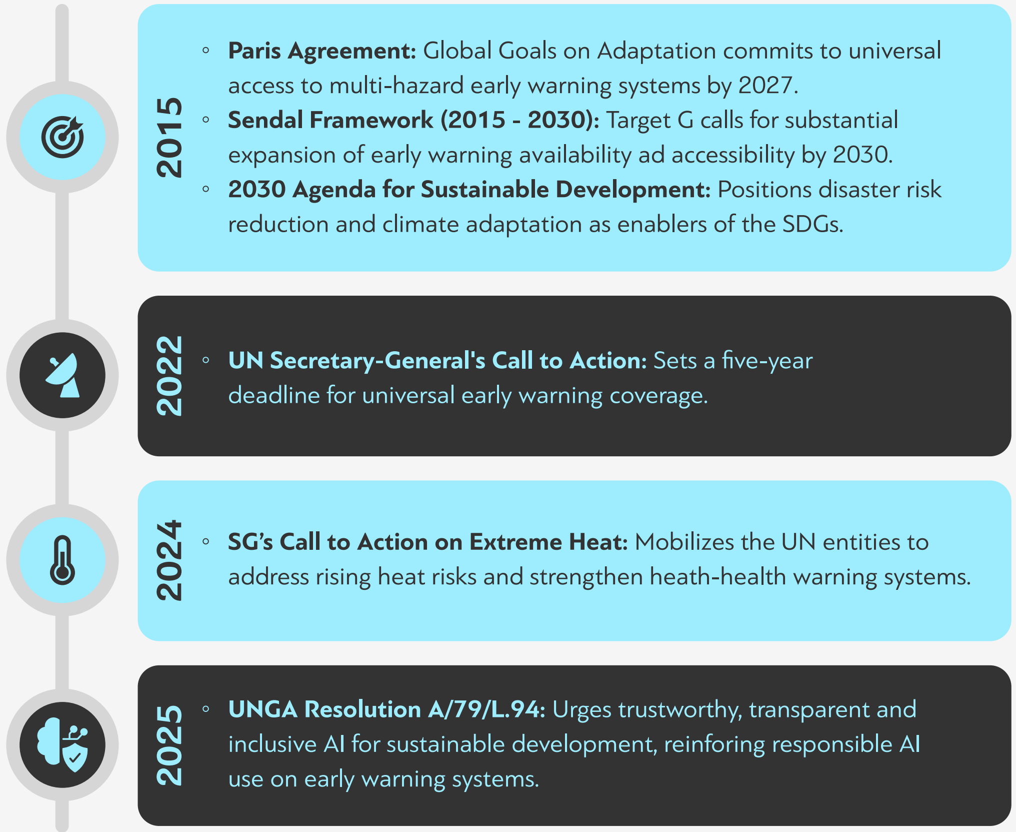

Figure 2. Overview of UN policy drivers relevant to EW4All.

1.5 Artificial intelligence: strategic role in MHEWS

AI is emerging as a strategic enabler for strengthening MHEWS, with potential to close persistent coverage and capability gaps. Its value lies not only in improving hazard forecasting, but also in advancing impact-based early warning, where hazard information is combined with data on exposure and vulnerability to anticipate consequences and support timely, targeted action. This shift enables early warning systems to evolve from static risk assessments toward dynamic, operational risk intelligence that is more responsive, adaptive, and people-centred. This section outlines how AI is currently applied across the four pillars of MHEWS, before examining the enabling conditions that determine whether these applications can be implemented effectively, equitably, and at scale.

The role of AI in disaster risk management builds on decades of research in Earth system science, remote sensing, and statistical modelling. Recent advances in machine learning, coupled with the rapid expansion of Earth observation data - such as high-resolution satellite imagery, geospatial datasets, drone imagery, and real-time remote sensing - and increased computational capacity, have created what may be described as an "AI moment" in environmental prediction and disaster risk management. These developments allow for improved analysis of complex, interconnected systems and support decision-making under uncertainty, particularly in data-scarce or operationally constrained contexts (Reichstein et al., 2019; Rolnick et al., 2022; World Bank, 2021a).

At the same time, AI introduces new risks that must be carefully managed. These include algorithmic bias that may disadvantage marginalized populations; privacy and data protection concerns; challenges related to the reliability, transparency, and accountability of automated systems; and the risk of over-dependence on technology at the expense of human expertise and local knowledge. Environmental impacts, such as the energy and water demands of large-scale computation, also warrant consideration (Rolnick et al., 2022). Addressing these risks requires robust governance frameworks, inclusive stakeholder engagement, and the integration of ethical safeguards throughout system design and deployment (European Commission, 2024b).

Within the context of MHEWS value cycle, AI is increasingly recognised as a potential strategic enabler, but its application remains unevenly distributed.

Pillar 1

Disaster risk knowledge (Chapter 2)

AI is used to collect, interpret and analyse complex disaster risk data and information to facilitate evidence-based, risk-informed decision-making within MHEWS. Advanced machine learning models can identify patterns in historical disaster data including losses and damages, predict future risk hotspots, and prioritize interventions for the most vulnerable populations.

Pillar 2

Detection, observation, monitoring, analysis, and forecasting (Chapter 3)

AI is strengthening the full hazard information chain, particularly in forecasting, by enabling faster, lower-cost predictions with competitive skill and more frequent updates for high-impact events. It also enhances observational data quality, integrates diverse data sources, and improves real-time detection and monitoring—supporting earlier, more precise, and more reliable early warnings while complementing existing approaches.

Pillar 3

Warning dissemination and communication (Chapter 4)

AI tools are being used to improve accessibility and targeting of warnings. Language and context-aware communication tools ensure that warnings are accessible to all communities, including those with linguistic diversity, limited literacy, or disabilities. AI-powered systems can generate multilingual alerts, adapt messaging to cultural contexts, select optimal communication channels based on user profiles, and personalize content to increase comprehension and trust.

Pillar 4

Preparedness to respond to warnings (Chapter 5)

AI contributes to preparedness by improving scenario modelling, identifying gaps in response capacity, and supporting the design of anticipatory action protocols. During response, AI can optimize resource allocation, coordinate multi-agency operations, and provide real-time situational awareness to decision-makers. Post-event, AI supports rapid damage assessment and recovery planning through automated analysis of satellite and drone imagery.

1.6 AI enabling environment: foundations for scalable and equitable MHEWS

AI-supported MHEWS depend on an enabling environment that spans digital infrastructure, data ecosystems, governance frameworks, human capacity, and inclusion. These conditions are interdependent and determine whether AI solutions can be deployed safely, equitably, and at scale in ways that are responsive to local contexts (Figure 3).

The AI Group of EW4All plays a central role in advancing these conditions and scaling AI solutions across all four pillars of MHEWS through country-focused pilots, capacity building, partner engagement, and knowledge sharing (ITU, 2026a). Working closely with governments, international organizations, and public- and private-sector partners, the Group identifies country needs and connects them with practical AI applications that can strengthen different stages of the early warning system value cycle. It mobilizes partnerships and resources to support the responsible deployment of AI to within MHEWS. A key contribution of the AI Group is the development of the AI Solutions Catalogue - an online repository of AI tools, platforms, and applications relevant to MHEWS. The catalogue brings together a growing set of solutions from across the global innovation ecosystem and serves as a practical resource for governments and practitioners seeking to identify and deploy appropriate AI technologies. Many of the AI applications referenced throughout this report are drawn from and can be explored further within the catalogue (ITU, 2026a). As AI capabilities continue to advance and extend into new domains, the catalogue will continue to evolve accordingly.

1.6.1 Digital infrastructure and data ecosystems

Data ecosystems form the foundation of AI-enabled early warning systems. AI applications depend on the availability, quality, interoperability, and governance of diverse datasets, including meteorological, environmental, geospatial, health, socio-economic, and community-generated data. AI's capacity to integrate these heterogeneous sources allows for a more comprehensive understanding of complex and cascading risks, supporting the development of interoperable and adaptive early warning systems (World Bank, 2021b). Recent work on impact-based, continental-scale monitoring systems - such as the African Multi-Hazard Early Warning and Action System (AMHEWAS) - demonstrates how pairing open hazard indicators with exposure and vulnerability layers can produce actionable advisories at scale, even in data-sparse environments (Isabellon et al., 2025).

At the same time, gaps in data availability also remain a major constraint, and biases in data, whether due to underrepresentation or historical inequalities, can also propagate through AI systems and affect outcomes. AI systems may unintentionally reinforce inequalities when certain groups are mis- or under-represented in the data or when relevant local knowledge is not reflected (Pagano et al., 2023). Addressing this requires sustained investment in open data initiatives, shared data standards, and inclusive data collection practices - particularly in LMICs, LDCs, and SIDS, where data infrastructure is often weakest.

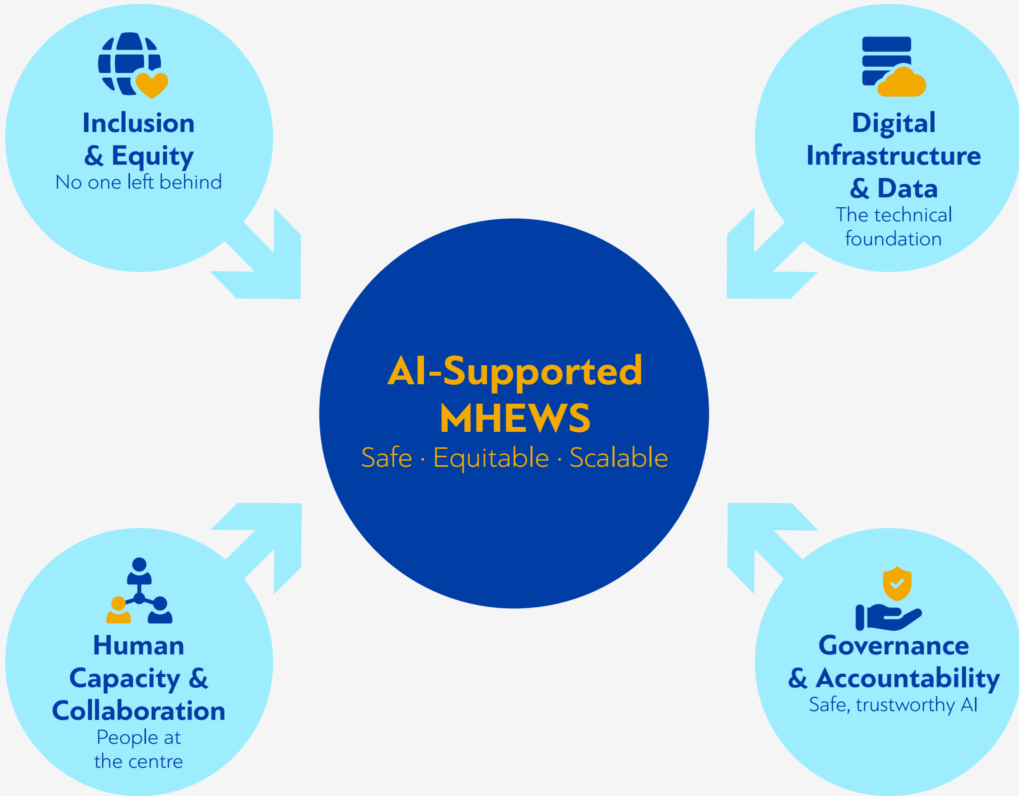

Figure 3. Overview of an AI enabled MHEWS.

Building on these data foundations, digital infrastructure is critical to operationalising AI-enabled MHEWS. Reliable connectivity, device access, power stability, and last-mile communication systems determine whether AI-supported early warning products and services can be produced, transmitted, and acted upon in time to save lives. Gaps in infrastructure, particularly in remote and low-resource settings, remain a primary constraint on the reach of MHEWS.

1.6.2 Institutional and governance frameworks

Building on these technical foundations are the institutional conditions required to ensure safe, effective, and coordinated deployment. Effective governance is required to address privacy, safety, data protection, transparency, accountability, and responsible innovation. AI systems used in early warning must be transparent, reliable, and aligned with ethical standards, particularly in life-safety contexts (OECD, 2021; UNESCO, 2021). Clear standards for interoperability and oversight are also necessary as AI systems become embedded in national warning infrastructures.

AI-enabled MHEWS also depend on coordination across a wide range of actors, including governments, meteorological services, disaster management agencies, telecommunication providers, humanitarian organizations, and community networks. Sustaining and scaling these capabilities will require a new generation of partnerships spanning UN agencies, governments, meteorological services, mobile network operators, technology companies, and local innovators - together bringing technological innovation, infrastructure investment, data access, and last-mile delivery within reach of all countries. Initiatives such as the EW4All AI Group illustrate how partnerships can support knowledge sharing, capacity building, and piloting.

1.6.3 Human capacity and operational readiness

The effectiveness of AI-enabled MHEWS ultimately depends on the people and institutions that use them. This includes digital literacy, technical skills, local expertise, and sustained investment in training and system maintenance. Research in human–automation interaction emphasize that AI systems are most effective when they augment rather than replace human expertise (Amershi et al., 2014; Parasuraman et al., 2000). Meteorologists, risk analysts, emergency managers, community leaders and members bring contextual knowledge, ethical judgment, and accountability that cannot be replicated by automated systems. AI systems can process vast amounts of data, identify patterns, and generate predictions rapidly. Human expertise can interpret and review these insights, evaluate uncertainties, and make decisions that consider broader social and political contexts. Designing systems that support effective human-AI collaboration is therefore critical.

1.6.4 Inclusion, ethics and equity

Inclusion, ethics, and equity considerations ensure that AI-enabled MHEWS serve all communities fairly and effectively. Persistent digital divides continue to exist across geography, income, gender, age, and ability. According to ITU estimates, nearly 2.2 billion people remain offline (equivalent to 26 per cent of the world's population), with the widest gaps concentrated in LMICs (ITU, 2025). For SIDS and other highly exposed, low-capacity contexts, the risks are particularly acute: without open regional data platforms, ethical AI governance, investment in local technical capacity, and climate-finance reform, AI-enabled tools risk deepening dependency on external providers rather than strengthening local resilience (Addison, 2025). These divides directly constrain the reach and effectiveness of AI-enabled MHEWS, risk creating new AI divides, limiting who can receive, understand, and act on life-saving information. Bridging these divides requires coordinated policy action and is further discussed in Chapter 5. Integrating digital inclusion and climate resilience into national development strategies can help ensure that MHEWS evolve in tandem with broader digital transformation efforts.

Without deliberate safeguards, AI may reinforce existing inequalities, for example, through biased datasets, exclusion of local knowledge, or unequal access to digital services (A. Kumar et al., 2025; Pagano et al., 2023). Addressing these risks requires inclusive design, accessible communication systems, participatory approaches, and strong oversight mechanisms.

1.7 The imperative for collective action

AI introduces new capabilities for MHEWS, but also new responsibilities. Its value will ultimately be measured not by technological sophistication, but by lives saved and resilience strengthened. Realising this potential requires coordinated action across governments, international organizations, the private sector, academia, and civil society. Strengthening each layer of the enabling environment - while ensuring alignment across them - will be critical to ensuring that AI enhances, rather than exacerbates, existing risk and inequality.

The chapters that follow examine how AI is already being applied across the four pillars of the early warning value cycle, what the evidence reveals about where integration is working and where critical gaps remain, and what a shared agenda for integrated AI investment should look like. The concluding chapter synthesises these insights into cross-cutting recommendations for governments, international organizations, technical partners, and donors.

Chapter 2.
AI for strengthening disaster risk knowledge

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Pillar 1. Strengthening disaster risk knowledge

Early Warnings for All

ENABLES

- Quality risk data & baselines
- Enhanced understanding of impacts
- Operational use of risk information

CORE AI TECHNOLOGIES

- Machine Learning
- Natural Language Processing
- Computer Vision
- Neural Networks

Early Warnings for All

AI is improving the discovery, integration, and usability of disaster risk and impact data by enabling the processing of large and diverse datasets, including geospatial, socioeconomic, and historical loss and damage information. These capabilities help address persistent gaps in disaster risk knowledge, especially for countries with limited resources. Importantly, AI-enabled approaches can also strengthen the operational use of risk and impact data within MHEWS, helping translate risk information into decision-support products that inform impact-based forecasting and anticipatory action.

- AI can support the development and updating of exposure and vulnerability baselines, including through proxy indicators where conventional data is limited.
- AI strengthens impact tracking and learning by accelerating post-event damage and loss assessments and enabling more systematic analysis of observed impacts.
- AI can support the integration of hazard, exposure, vulnerability and impact information to strengthen the operational use of risk information within MHEWS, including to inform impact-based forecasting and anticipatory action triggers and thresholds.

These applications remain constrained by gaps in data availability, quality, representativeness, governance and interoperability, as well as institutional capacity to use AI appropriately and responsibly.

Sustained investment in foundational data systems, governance frameworks, validation mechanisms, and technical capacity to interpret and utilize the outputs will be critical to ensuring reliable and inclusive use of AI within disaster risk management systems.

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Within MHEWS, disaster risk knowledge (Pillar 1) is not a background analytical exercise undertaken in isolation from operations but a core operational imperative that underpins the entire early warning value cycle. It informs how hazards are prioritised, which variables have strong correlation with impacts and should be forecasted, how forecasts are interpreted, how warnings are framed and targeted, and how preparedness and early actions are triggered. In this sense, disaster risk knowledge is central to ensuring that early warning systems are people-centred, impact-based, and actionable.

Disaster risk knowledge encompasses both forward-looking risk information – describing the interaction of hazards, exposure and vulnerability, and providing estimates of the nature, level and distribution of disaster risk – and empirical (i.e., historical) disaster impact data, including loss and damage records, which provide observed evidence of how hazards translate into real-world consequences (UNDRR, 2015). Hazard monitoring and forecasting can indicate what may occur and when, but they do not, by themselves, explain what the consequences will be, who will be affected, or how severe impacts may be. Risk knowledge fills this gap by linking forecasts with exposure, vulnerability, and historical impact patterns, allowing hazard signals to be interpreted in terms of likely impacts, thereby supporting impact-based forecasting (IBF). In this way, it connects detection and forecasting with preparedness, anticipatory action and response, enabling early warning systems to function as integrated, impact-oriented systems rather than isolated technical components (UNDRR, 2024).

Conceptually, disaster risk is commonly understood as a function of hazard, exposure, and vulnerability, in line with internationally agreed terminology. Crucially, all components of risk are dynamic across time and spatial scales. For example, exposure changes as the spatial distribution and concentration of people, infrastructure, and other assets shift, including through urbanisation, and population movements such as displacement, migration and daily or seasonal mobility. Vulnerability evolves with livelihoods, health conditions, governance arrangements, and prior shocks. Some hazards themselves are increasingly non-stationary due to climate variability and climate change (IPCC, 2022). For early warning systems, this means that risk knowledge cannot remain static; it must be continually updated and interpreted in ways that reflect changing conditions on the ground.

Risk assessments have long supported land-use planning, infrastructure design, and disaster risk reduction strategies. While these assessments provide an essential baseline they are insufficient on their own to support impact-based warnings and anticipatory action. Both approaches require timely estimates of likely impacts under specific conditions, as well as the ability to link these to predefined thresholds for anticipatory action. Risk assessments produced primarily for planning purposes are rarely designed to interface directly with forecasting systems or operational decision points. As a result, risk knowledge products for MHEWS must evolve from static, planning-oriented outputs toward operationally relevant, decision-support information that is routinely used within early warning and preparedness processes. This shift does not imply abandoning traditional risk assessments. Rather, it involves repositioning them as reference inputs that inform ongoing operations and strengthen their value within the risk data chain. The process requires fit-for-purpose updating of exposure, vulnerability, and impact (EVI) indicators, together with data that underpin evidence-based risk avoidance and mitigation action. Increasingly, populations at risk need access not only to information on projected impacts of diverse hazards, but also to guidance on effective actions they can take to avoid or mitigate these impacts before, during and after these events. This also requires functional integration of EVI data with monitoring and forecasting systems; alignment with the spatial and temporal scales of decision-making; and presentation of risk and impact information in formats that support timely interpretation and informed action under uncertainty.

While progress in establishing MHEWS has accelerated in recent years, gaps remain in the use of risk knowledge, particularly in linking risk information and disaster impact data across the early warning value cycle (UNDRR, 2025). These challenges are most evident where risk information exists but is fragmented across organizations, outdated, poorly integrated into warning workflows, or disconnected from learning processes. It is within this context that artificial intelligence (AI) offers practical opportunities to strengthen risk knowledge for MHEWS. AI can support the integration of heterogeneous datasets across institutions, enable more frequent updating of exposure and vulnerability baselines, assist in translating risk information into decision-support products, and strengthen feedback loops between observed impacts and future warning thresholds.

At the same time, AI must be clearly positioned as an enabler rather than a substitute for building risk knowledge. It does not replace scientific modelling, co-production with communities, institutional mandates and accountability structures, or human judgement informed by local and contextual knowledge. Its value lies in augmenting existing capacities and systems, allowing countries to collect, interpret, and operationalise risk knowledge more effectively within MHEWS. This chapter therefore examines where and how AI can be leveraged to strengthen risk knowledge for MHEWS, grounded in country needs and operational realities. It is comprised of the following sections:

- Country needs and operational gaps in risk knowledge that AI could fill
- AI applications that strengthen risk knowledge
- Design principles, enabling conditions and priority actions for effective and responsible use of AI to strengthen disaster risk knowledge in MHEWS

2.1 Country needs and gaps in disaster risk knowledge

The global gap in risk knowledge generation and use does not primarily reflect a lack of data. In most countries, hazard observations, exposure datasets, vulnerability indicators and disaster loss records already exist in some form. The challenge lies in the ability to find, integrate, update, and operationalise this information in ways that directly support early warning functions particularly impact-based warnings, anticipatory action, and multi-hazard decision-making. Country experience consistently shows that risk knowledge is often produced for planning, reporting, or post-event analysis, but is not routinely embedded within the operational workflows that underpin early warning systems. As a result, available risk information does not consistently inform how forecasts are interpreted, how warnings are targeted, or how early actions are triggered. This section synthesises country needs into four recurrent operational gaps that constrain the effective use of risk knowledge in MHEWS.

2.1.1 Fragmented, incomplete, and inaccessible risk data and information

A widely documented gap is the fragmentation of risk-related data across institutions and sectors. Hazard data are often managed by meteorological, hydrological or geophysical services, exposure data by statistical or planning authorities, and disaster impact data by disaster management agencies, sectoral ministries or humanitarian actors. These datasets are rarely interoperable and frequently follow different standards, formats and access arrangements. As a result, risk information is often difficult to discover, access and combine during time-sensitive early warning operations. Weak or inconsistent metadata further limit users' ability to assess data quality and relevance. Differences in spatial resolution, temporal coverage and classification schemes complicate the alignment of hazard, exposure and impact datasets, particularly when forecast outputs do not correspond to the administrative or operational units used for preparedness and response (UNDRR, 2023).

2.1.2 Outdated and incomplete exposure and vulnerability baselines

A second major gap concerns the timeliness and completeness of exposure and vulnerability data used in early warning contexts. Population censuses, housing inventories, and asset registers are typically updated at multi-year intervals, making them poorly suited to reflect rapid changes in exposure that are highly relevant for MHEWS operations. Informal settlements, peri-urban growth areas, and locations hosting displaced or mobile populations are systematically under-represented. Internally displaced persons, refugees, seasonal migrants and pastoralist communities often fall outside formal statistical systems, creating significant blind spots in exposure mapping and risk estimation (IPCC, 2022; UNDRR, 2023).

Vulnerability information faces similar constraints. Socio-economic conditions, livelihood dependencies, health status, and access to basic services can change rapidly following shocks such as droughts, floods, conflict, or economic crises. However, vulnerability indicators and/or functions used in risk assessments are frequently static and insufficiently disaggregated by gender, age, disability, or livelihood group. This limits the ability of early warning systems to identify who is most at risk under current conditions and to account for differential impacts across population groups. As a result, early warnings may be poorly targeted both spatially and across different social groups, missing priority populations most at risk and undermining their ability to take anticipatory action.

2.1.3 Static risk information not designed for early warning system operations

A third gap arises from the continued reliance on risk information developed primarily for planning and policy purposes. National risk assessments and hazard maps provide important baseline information, but they are rarely designed to interface directly with forecasting systems, warning thresholds or operational decision points. As a result, they offer limited usability during unfolding events. Impact-based forecasting requires explicit linkage between hazard forecasts, exposure, vulnerability and expected consequences (WMO, 2021b), while anticipatory action mechanisms may depend on predefined triggers tied to forecasted impacts and agreed early actions. When risk information is not aligned with these workflows, translating hazard signals into timely decisions becomes challenging.

2.1.4 Weak loss and damage data tracking and learning loops

A fourth and distinct gap concerns the limited use of disaster impact data to support learning and continuous improvement. Loss and damage data are often collected slowly, inconsistently, and across multiple agencies, reports, and formats. Impact data is rarely consolidated or systematically analysed in ways that feed back into vulnerability characterisation, threshold calibration, or anticipatory action trigger refinement, limiting the ability of early warning systems (EWS) to adjust to changing impact patterns, including those influenced by climate change. As a result, early warning systems struggle to learn from experience. Confidence in impact-based warnings can erode over time when expected impacts do not align with observed outcomes. This gap is not primarily about access to existing datasets, but about post-event evidence, feedback, and institutional learning within MHEWS.

These four gaps illustrate that country needs in risk knowledge for MHEWS are not about the absence of data, but about persistent challenges in integrating, updating, and operationalising risk information and disaster impact data within early warning systems.

Each gap aligns with areas where AI-enabled approaches are already being applied or piloted to improve performance. Table 1 summarises where AI adds value, the associated AI functions, and techniques currently in use to strengthen the integration, updating, and usability of risk information and impact data, complementing existing systems by improving timeliness, granularity, and consistency. Section 2.2 builds on this foundation by examining specific AI applications that address each gap in practice.

Gap	Where AI adds value	Example AI functions	Representative techniques currently in use
Gap 1 **Fragmented, incomplete and inaccessible risk data and information**	Improves discoverability, structuring, and integration of dispersed risk, and impact information, enabling faster access and reuse during time-critical early warning operations, including through extraction and structuring of information from reports and other text-based sources, and translation across classification schemes	Language AI; semantic integration; data linkage	Natural language processing (NLP) (named entity recognition, relation extraction); document classification and clustering; embeddings and vector search; retrieval-augmented generation with human validation; probabilistic record linkage; schema and ontology matching; rules–machine learning hybrid reconciliation
Gap 2 **Outdated and incomplete exposure and vulnerability baselines**	Enhances the completeness, spatial resolution, and update frequency of exposure baselines for people, buildings, and assets; supports refinement of physical vulnerability where observed damage data are available; supports the extraction of remotely sensed proxies for social vulnerability	Computer vision; predictive spatial modelling; supervised (physical and social) vulnerability modelling	Object detection and segmentation; automated vectorisation; change detection; multi-temporal earth observation analysis; SAR (synthetic aperture radar)–optical feature learning; dasymetric population modelling; Random Forest and gradient boosting; supervised damage-state classification
Gap 3 **Static risk information not designed for EWS operations**	Increases the operational usability of risk information by enabling faster updating, harmonisation, and alignment of baseline layers with hazard forecasts and operational units used in MHEWS.	Data integration; baseline updating; spatial harmonisation	Automated feature extraction and updating; schema harmonisation at ingest; spatial resampling and aggregation; standardised gridded representations; machine learning-assisted quality control; versioning and change tracking
Gap 4 **Weak loss and damage data tracking and learning loops**	Accelerates consolidation and analysis of disaster impact and loss information, supporting calibration, learning, and incremental improvement of exposure and physical vulnerability assumptions.	Language AI; analytics for loss and impact estimation; evidence synthesis	NLP-based impact field extraction; document triage and summarisation; clustering of impact reports; probabilistic and machine learning-assisted regression-based loss estimation; uncertainty-aware analytics; social media mining (text and imagery) for impact signal extraction and severity classification

Table 1. AI contributions to addressing risk knowledge gaps

2.2 AI Applications that strengthen risk knowledge production and use

Artificial intelligence is increasingly applied to support the production and use of risk knowledge within the context of multi-hazard early warning systems. In practice, AI supports data integration, updating, and analysis tasks that would otherwise require substantial manual effort, particularly under time constraints. Its contribution is primarily technical and procedural, enabling earlier and more consistent use of risk and impact information in warning, preparedness, and anticipatory action processes.

The applications in this section are organised around four operational capability areas each corresponding to the risk knowledge gaps outlined in section 2.1 and illustrated in Figure 4. Each sub-section highlights where AI adds practical value and illustrates approaches already in use or advanced piloting. Figure 4 summarises how these applications collectively support progressive strengthening and operational use of disaster risk knowledge within MHEWS. Each sub-section highlights where AI adds practical value and illustrates approaches already in use or advanced piloting. Making risk data discoverable, interoperable and usable (2.2.1) provides the foundation for strengthening exposure and vulnerability baselines (2.2.2) as well as loss and damage data tracking and analysis (2.2.4). Together, these enable the operational use of integrated risk knowledge in MHEWS (2.2.3), informing warning, preparedness and anticipatory action. This framing is consistent with emerging evidence on AI applications in disaster risk reduction, as elaborated in the UNDRR Special Report on the Use of Technology for Disaster Risk Reduction (2025); namely, data detection and searches, near-real-time data processing, and simulations and risk modelling.

Across the four operational capability areas, AI contributes to data integration and analysis as a supporting tool within established institutional arrangements. It does not replace forecasting systems, define decision thresholds, or alter governance and accountability structures. Decision-making remains anchored in existing mandates and procedures. The design principles, enabling conditions and priority actions required for effective and responsible use are discussed further in section 2.3.

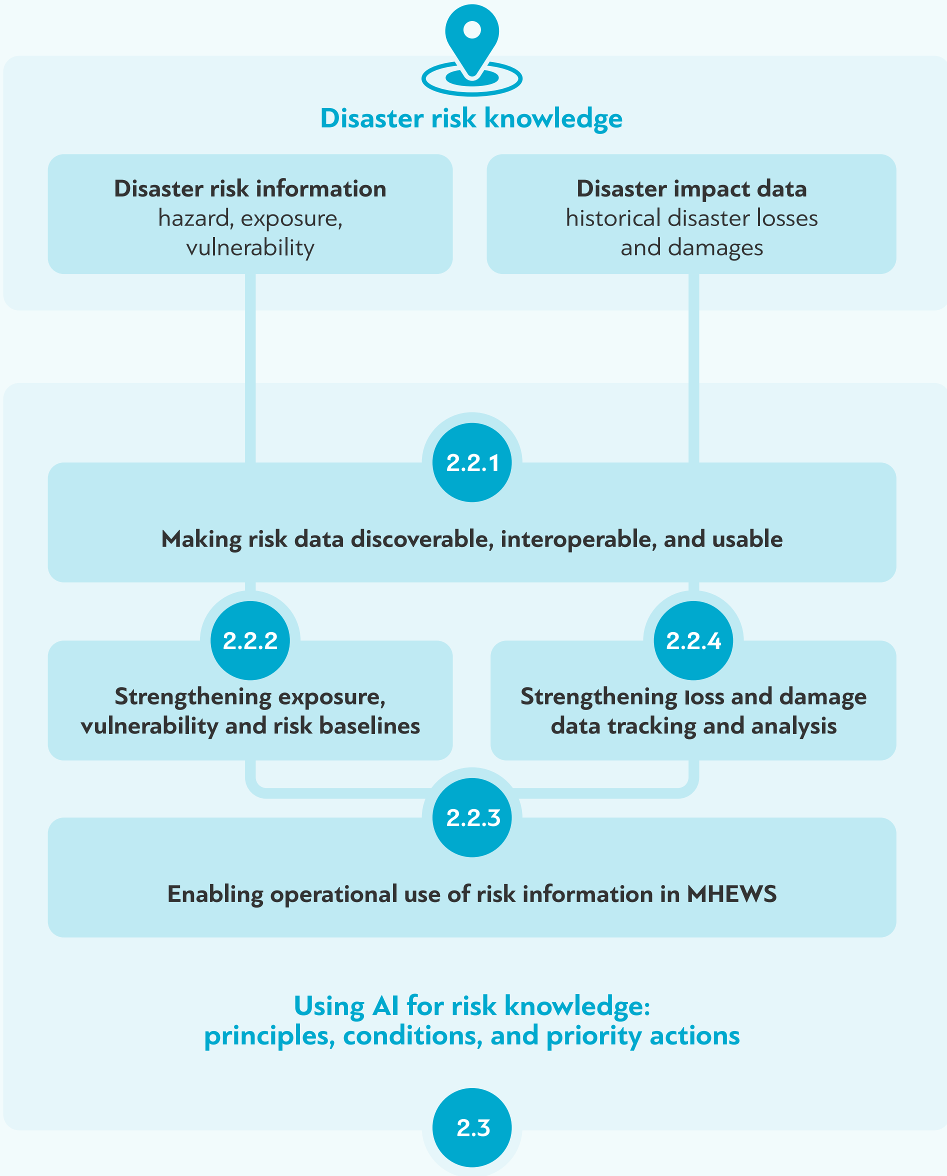


Figure 4. AI applications for strengthening disaster risk knowledge in MHEWS

2.2.1 Making risk data discoverable, interoperable, and usable

Many risk knowledge systems rely on datasets that sit across institutions and sectors, including disaster management authorities, National Meteorological and Hydrological Services (NMHSs), geological agencies, sectoral ministries, city authorities, utilities, and other custodians. Data and information are often stored in different formats or with different characteristics (e.g. coordinate systems) and have limited visibility outside the "home" institution. AI can reduce this friction by automating parts of the data integration and interoperability work required to make risk knowledge usable at scale. For hazards, this can include event inventories (e.g. historical flood extents, landslide catalogues), susceptibility and hazard maps, and related model outputs. For exposure, this includes population and settlement footprints as well as infrastructure layers. For vulnerability, this includes indicators drawn from household surveys, poverty mapping, critical infrastructure registries, or sectoral service coverage. For impacts, AI can support faster and more consistent aggregation by extracting losses and damages from narrative reports, reconciling duplicate or conflicting entries across agencies, flagging anomalies, and maintaining a traceable view of event impacts that analysts can review and validate. Gaps or biases in training data can affect results, underscoring the need for inclusive, high-quality data and human validation to ensure reliability.

In practice, dataset discovery is often constrained by weak metadata and fragmented catalogues. This is where machine learning (ML)–assisted metadata enrichment and natural language processing (NLP)–based information extraction can help identify, tag, and catalogue satellite products, climate and hydrological records, geospatial layers, census tables, and survey datasets, even when descriptions are incomplete or embedded in documents. A growing class of semantic approaches uses vector embeddings – numerical representations of meaning – to support dataset search by concepts rather than exact keywords, which is particularly useful when different institutions describe similar data using different terminology. For example, NASA researchers trained ML models to process large collections of Earth science dataset abstracts, where assigning keywords has traditionally been a manual process, and to suggest relevant metadata keywords (building on Word2Vec-style embeddings) to complement human curation and improve dataset discoverability at scale (NASA Earthdata, 2023). Box 1 provides a complementary operational example, illustrating how AI-enabled data integration can also support the incorporation of community-generated risk knowledge into formal geospatial and early warning data workflows.

Box 1. Sketch Map Tool: AI-enabled Integration of Community Risk Knowledge into Geospatial Data Pipelines

Advanced data-driven early warning models often miss critical local realities required for effective disaster preparedness, while traditional mapping methods are labour-intensive and slow to digitize, creating bottlenecks that prevent community insights from integrating into data pipelines before disasters strike. The Sketch Map Tool addresses this by enabling communities to spatially document local knowledge using pen-and-paper maps based on customizable base layers (OpenStreetMap, satellite imagery, or OpenAerialMap), which are then scanned and automatically georeferenced and digitized using Deep Learning models trained on extensive labelled datasets to detect markings and Computer Vision techniques for spatial alignment, producing immediate GeoJSON and GeoTIFF outputs for GIS analysis. Developed by Heidelberg Institute for Geoinformation Technology (HeiGIT), the tool achieved global scale in 2025 with over 30,000 maps created across 130+ countries, successfully integrating into the Enhanced Vulnerability and Capacity Assessment framework and operational workflows—notably in Colombia, where community insights were formally incorporated into Municipal Disaster Risk Management Plans. Key lessons emphasize the importance of training local staff for quality markings, maintaining manual validation using GeoTIFF "ground truth" references, and adapting map scales to specific contexts, though the generalized approach may not suit every community's aspirations. The successful urban adaptation and automated digitization demonstrate highly scalable potential for transforming community knowledge into actionable early warning data.

Further information:
https://sketch-map-tool.heigit.org/en

Another area where AI adds value in risk knowledge systems is data integration and harmonisation, enabling risk and impact data from different institutions to be combined and analysed. Even when relevant datasets are available, they often cannot be directly used together: administrative boundaries and coding schemes differ, place names are inconsistent, registries overlap imperfectly, attribute fields use different units and definitions, and spatial and temporal resolutions vary. AI can reduce this burden by assisting with entity matching (i.e., linking records that refer to the same location, asset, or institution across sources) and schema matching, which maps fields that represent the same concept. These approaches can be supported by anomaly detection to flag inconsistencies during data ingestion. Recent reviews of heterogeneous entity matching highlight this challenge explicitly: heterogeneous datasets differ widely in structure, schema, and semantics, and effective integration requires methods that can handle those differences rather than assuming standardised inputs (Moslemi et al., 2026). In practice, these AI-assisted workflows are most effective when paired with common standards and metadata practices, ensuring that harmonised datasets remain interoperable, traceable and maintained over time.

A related strand of work involves AI-based multimodal data fusion, which goes beyond aligning tables and schemas by learning how to combine different data modalities—such as radar and optical satellite imagery, elevation models, settlement layers, and administrative boundaries—into a single, consistent set of layers that can be analysed together and refreshed as inputs change. One example is the European Space Agency's WorldCover product, which builds features from Sentinel-2 multispectral time series, Sentinel-1 SAR (Synthetic Aperture Radar) backscatter time series, and digital elevation model–derived terrain variables, and uses a machine-learning model (CatBoost) to produce a globally consistent 10 m land-cover dataset in standardised tiles and formats (CEOS, 2024). A parallel direction extends multi-modality beyond geospatial layers into impact data harmonization, where NLP pipelines can extract structured information (e.g., who was affected, what was damaged, where impacts occurred, and the scale of losses) from post-event reports, including humanitarian needs assess-ments. These outputs can then be converted into formats that can be reconciled with geospatial inventories, supporting more consistent and queryable impact datasets even when source documents vary in structure and terminology. This approach has been demonstrated in methods designed to build and update large-scale impact databases of extreme climate events from textual sources using large language models (Li et al., 2024).

2.2.2 Strengthening exposure and vulnerability baselines

Accurate and up-to-date exposure and vulnerability baselines are essential for translating hazard forecasts into impact-based warnings. Updated risk baselines also enable the identification of critical areas, sectors and populations for which MHEWS need to be implemented and/or strengthened. For MHEWS, weaknesses in either component constrain the ability to produce credible, targeted, and actionable warnings. In most countries, exposure baselines are constructed from administrative asset registers, sector inventories, population censuses, and household surveys, combined through manual or semi-manual GIS workflows. These sources provide an essential foundation, but they are often constrained by coarse spatial resolution, infrequent update cycles, and limited coverage of fast-changing or informal environments (Georganos et al., 2022) Vulnerability information, in turn, is frequently represented through simplified proxies or static modifiers, reflecting long-standing challenges in data availability and empirical grounding. AI has demonstrated operational value in addressing some of these constraints, particularly in strengthening exposure baselines and the physical dimensions of vulnerability where observed impact data exist.

Strengthening exposure baselines
AI has shown clear operational value in improving the completeness, spatial resolution, and update frequency of exposure data used in early warning contexts. Three application areas are particularly relevant.

Automated mapping of built-up exposure. Computer vision and machine-learning techniques are increasingly used to detect and map buildings and other built structures from aerial and satellite imagery. These approaches support the production of more complete and up-to-date exposure layers than those derived solely from administra-tive registers or manual digitisation, particularly in rapidly urbanising areas and informal settlements where official records often lag behind physical development. A concrete operational example comes from Lusaka, Zambia, where the United Kingdom-based Ordnance Survey supported national partners in developing an automated digital base map using aerial imagery. Supervised machine-learning models were applied to detect, label, and vectorise features such as roofed structures, road networks, and land surface types, improving the consistency and completeness of urban exposure data (Ezechie, 2022). Similar approaches have been applied in contexts characterized by extensive informality. In eThekwini and Cape Town, South Africa, UNITAC supported municipal efforts to map informal settlements using the Building and Establishment Automated Mapper (BEAM). BEAM applies machine-learning models to automatically extract building footprints from aerial imagery, enabling cities to monitor settlement growth and improve the representation of exposed structures in areas that are poorly captured in official datasets (UNITAC, n.d.).

Automated exposure mapping reduces reliance on time-intensive manual digitisation and improves the spatial completeness of exposure layers used for impact estimation and warning targeting. These approaches are increasingly operationalised through publicly available global datasets and cloud-based geospatial platforms (e.g., Google Earth Engine) that integrate AI-based classification models with scalable data processing. Global building footprint datasets derived from ML models applied to high-resolution imagery now provide consistent and comparable representations of built-up exposure across countries (e.g., Google Open Buildings, Microsoft Global ML Building Footprints). Operationally, this integration supports more timely, scalable, and reproducible updating of exposure baselines, particularly in rapidly changing or data-scarce environments (Google Research, n.d.).

High-resolution population modelling. A second area where AI has demonstrated substantial operational value is population exposure modelling. The most widely used approach is top-down dasymetric disaggregation, which redistributes census population totals into high-resolution grid cells using machine-learning models trained on geospatial covariates such as built-up indicators, land cover, road networks, and night-time lights (Tuccillo et al., 2025). Random Forest and related models learn statistical relationships between population density and these covariates and apply them to allocate administrative totals in a systematic and reproducible manner. This enables the production of gridded population datasets that align more closely with hazard footprints than administrative-level counts. WorldPop, for example, operationalises this workflow through tools such as popRF, and its population grids are widely used in humanitarian, disaster risk, and early warning applications (WorldPop, n.d.). Complementary AI-enabled data sources further support the refinement and updating of these baselines. ML classification applied to medium-resolution satellite imagery (e.g., Sentinel-2) enables high-frequency land use and land cover mapping (C. F. Brown et al., 2022). These products support the detection of changes in settlements and built environments over time, providing proxy indicators to refine population distribution and update exposure baselines in dynamic or rapidly evolving contexts.

For MHEWS, high-resolution population grids support more consistent estimation of exposed populations under forecast scenarios, improve spatial targeting of warnings, and enable comparison of impacts across events. These approaches do not replace censuses or surveys; rather, they extend their operational usefulness by redistributing population totals in a transparent and reproducible way. Box 2 illustrates how the approaches are applied operationally to strengthen exposure baselines in data-poor and crisis-affected contexts.

Box 2. AI-Supported High-Resolution Population Mapping for Humanitarian and Early Warning Applications

In Tanzania, Zambia and Mozambique, the absence of accurate, up-to-date and granular population data poses a major constraint for crisis preparedness and response. Census information is often outdated, unavailable or disrupted by conflict and instability, forcing humanitarian actors to rely on indirect estimation methods such as counting rooftops in satellite imagery and applying average household sizes. To address this gap, the POMELO initiative generates population-density maps at a 100-by-100-metre resolution using open geospatial data, building footprints, road proximity, elevation and historical population trends. By integrating these diverse inputs, the model provides detailed and context-specific estimates of population distribution, offering a critical-evidence base for multi-hazard planning and emergency operations in data-poor environments. Developed through collaboration between the International Committee of the Red Cross, the Swiss Federal Institute of Technology Lausanne and the Swiss Federal Institute of Technology Zürich, POMELO has moved beyond pilot phase and is now operational. Once development was completed, the model was handed over to the International Committee of the Red Cross for maintenance and further improvement. However, the complexity of the codebase and the need for specialized technical expertise have posed challenges for long-term sustainability, requiring interim support from external contractors while options for more durable institutional arrangements are explored. Although the tool is technically scalable and could be adopted by other agencies, its deployment remains limited by the complexity of the underlying system and the need for specialist skills to implement and maintain it. Despite these constraints, POMELO demonstrates the value of AI-enabled population modelling in strengthening humanitarian decision-making where traditional census data are insufficient, offering a replicable approach for improving situational awareness and supporting more effective disaster risk reduction.

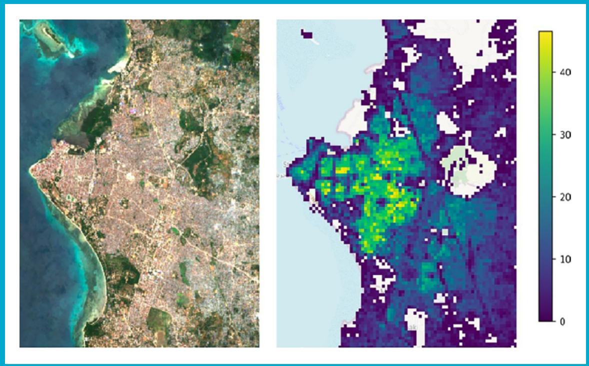


Figure 5. Visual comparison of Zanzibar City, Tanzania. Satellite image (left) and AI-derived population density map using Pomelo (right).

Source: ETH Zurich, AI enables more effective humanitarian action – Dept. of Civil, Environmental and Geomatic Engineering
Further information: https://nethope.org/case-studies/mapping-vulnerable-populations-with-ai-international-committee-of-the-red-cross/

The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by ITU, WMO, UNDRR and IFRC.

Dynamic exposure estimation. Beyond static exposure baselines, AI shows emerging operational value in estimating short-term changes in exposure, including diurnal patterns and population redistribution in response to hazardous events. These approaches identify deviations from baseline population distributions that signal increasing or decreasing exposure as people move. Operational examples include machine-learning models applied to anonymised mobile network operator data to infer near-real-time population movements and displacement. Organizations such as Flowminder have deployed these methods at national scale to analyse evacuation patterns and post-event population redistribution during cyclones and floods, supporting government and humanitarian decision-making by updating exposed population estimates (Flowminder Foundation, 2023). Complementary approaches use aggregated digital mobility data. Meta's Displacement Maps apply AI-based pattern recognition and bias correction to estimate population movement flows and temporary settlement patterns following major disasters, and have been used by humanitarian actors to support exposure assessment during flood and earthquake responses (Meta, 2023). These applications demonstrate how AI-enabled mobility analysis can enhance dynamic exposure estimation, particularly where census-based baselines become rapidly outdated. However, such indicators remain sensitive to data coverage, representativeness, and governance constraints, and should be treated as supplementary inputs alongside established exposure baselines.

Strengthening vulnerability characterisation. While AI has demonstrated strong and increasingly operational value in strengthening exposure baselines, its contribution to vulnerability characterisation remains more limited and uneven across vulnerability dimensions. To date, AI has contributed most clearly and operationally to physical vulnerability, where empirical damage data exists and can be systematically linked to hazard intensity. Contributions to social and economic vulnerability are more recent, context-specific, and largely analytical in nature, with limited uptake in MHEWS.

Generating and refining vulnerability and/or fragility curves. AI applications are most advanced in estimating physical vulnerability, particularly where observed damage data can be linked directly to hazard intensity. Machine-learning methods increasingly move beyond generic or expert-assigned fragility curves by learning vulnerability relationships directly from empirical observations. Several studies demonstrate this transition. ML-based frameworks have been developed to estimate building-level seismic vulnerability using observable structural characteristics derived from imagery and survey data. Supervised learning models predict vulnerability indices or damage states calibrated against post-event damage observations, enabling rapid, scalable assessment of existing building stocks without exhaustive field surveys (Ruggieri et al., 2021). Complementary work shows that artificial neural networks and ensemble models can derive seismic vulnerability indices directly from observed building performance, achieving higher classification accuracy than traditional empirical or regression-based approaches. These models explicitly link construction typology and structural attributes to observed damage outcomes, supporting data-driven refinement of vulnerability relationships (Elyasi et al., 2024). AI has also been applied to synthesise complex fragility relationships by learning from ensembles of physics-based simulations combined with empirical damage data. ML models can approximate multi-dimensional fragility surfaces for compound hazards, allowing vulnerability functions to be updated beyond purely analytical formulations (Harati & van de Lindt, 2025). Operationally, these approaches improve impact realism and enable iterative updating as new events occur, supporting validation and calibration of vulnerability relationships, while remaining sensitive to training data quality and primarily capturing structural damage rather than broader functional impacts.

Social vulnerability characterization. AI applications addressing social and differential vulnerability are considerably less mature from an operational perspective. Most uses of machine learning remain analytical, supporting exploration of how socio-demographic, infrastructural, and environmental factors shape observed impacts rather than informing routine early warning decisions. Recent studies show that ML models can capture non-linear relationships between demographic characteristics, built environment features, and flood impacts at neighbourhood and municipal scales, offering improved spatial differentiation compared to traditional composite indices (Kalaycıoğlu et al., 2023; Singha et al., 2024). Other work integrates census data, hazard exposure metrics, and remotely sensed proxy indicators (e.g., settlement density and built-form characteristics such as roofing materials, settlement morphology and proximity to road networks) to generate fine-scale socio-economic vulnerability maps, while emphasising the need for local calibration and validation (Dufitimana et al., 2025). Emerging operational platforms illustrate some pathways for use. The UN Global Pulse Socio-Economic Mapper (SEM) applies ML to integrate official statistics with alternative data sources to monitor socio-economic stress and vulnerability dynamics, primarily for situational awareness and policy analysis (UN Global Pulse, 2024).

Fairness-aware AI models further demonstrate analytical potential by explicitly addressing bias in vulnerability-related predictions (Yesmin & Akter, 2025). Despite these advances, AI-based social vulnerability models are rarely embedded in formal MHEWS workflows and should currently be treated as analytical support, not operational vulnerability baselines, given governance, ethical, and validation constraints.

Economic vulnerability analysis. Economic vulnerability reflects how hazard impacts translate into welfare losses, livelihood disruption, and constrained recovery. While conceptual and welfare-based frameworks exist, economic vulnerability assessments are not yet widely operationalised within early warning systems. Recent analysis by the OECD highlights how AI and advanced analytics can support disaster damage and economic cost estimation by integrating hazard data with economic statistics, sectoral information, and loss records. Machine-learning methods are used to interpolate missing loss data, classify damage categories, and explore relationships between hazard intensity and economic impacts, improving efficiency where traditional accounting methods are slow or incomplete (OECD, 2025). However, current applications are primarily focused on ex post damage assessment and scenario analysis, and do not yet provide forward-looking, operational economic vulnerability baselines suitable for early warning or anticipatory action.

Strengthening exposure and vulnerability baselines is essential to improving the relevance and effectiveness of MHEWS. AI has demonstrated clear operational value in enhancing exposure data and refining physical vulnerability relationships, supporting more credible translation of hazard forecasts into expected impacts. When applied within established institutional and data governance frameworks, these advances improve the timeliness, granularity, and consistency of baseline risk information needed for targeted warnings and anticipatory action.

2.2.3 Enabling operational use of risk information in MHEWS

MHEWS depend not only on the generation of hazard forecasts, but on the structured translation of those forecasts into decision-relevant risk information. Impact-based forecasting and anticipatory action require credible estimates of what is likely to happen, to whom, and with what potential consequences, alongside the identification of feasible actions to reduce or mitigate impacts, all under evolving forecast uncertainty (WMO, 2021b). Operational use of risk information therefore requires analytical processes that i) link hazard intensity projections with exposure and vulnerability data, ii) dynamically update expected impacts, coupled with recommended risk reduction actions, and iii) where feasible, explore systemic and cascading risk dynamics. AI contributes in this domain where it strengthens data integration, probabilistic estimation and scenario analysis within established institutional frameworks.

Linking hazard forecasts with exposure and vulnerability data. Operational MHEWS require systematic translation of hazard intensity forecasts into spatially explicit estimates of potential consequences. Forecast wind speeds, rainfall accumulations, inundation depths, or temperature anomalies must be combined with data on population, infrastructure, agricultural assets, and sector-specific sensitivity factors. This integration is operationally challenging and computationally demanding when datasets differ in resolution, format, and temporal frequency. AI contributes in this context where it supports harmonisation of heterogeneous geospatial datasets, probabilistic classification and scaling of expert-informed operational products. A documented operational example is provided by the European Commission Joint Research Centre's Monitoring Agricultural ResourceS (MARS) Crop Yield Forecasting System. In this case, expert-produced agricultural "Areas of Concern" (AOC) maps were used to train an explainable machine-learning model capable of probabilistically identifying agriculturally relevant climate hazard conditions (Box 3). In this context, AI supports the translation of hazard signals into information linking forecasts with sector-specific exposure and sensitivity factors.

Box 3. Expert-driven Explainable AI for Probabilistic Detection of Agricultural "Areas of Concern"

Concurrent climate extremes (e.g., heatwaves, drought, cold spells, rainfall deficit/surplus) can drive agricultural losses, but rapidly delineating at-risk areas is difficult as datasets grow. Researchers converted operational expert judgement into training data by compiling and digitising monthly "Areas of Concern" (AOC) maps produced for the European Commission Joint Research Centre's Monitoring Agricultural ResourceS (MARS) Crop Yield Forecasting System (2012–2022). An explainable AI (xAI) system—an ensemble of gradient-boosted decision trees (XGBoost with a logistic objective)—was trained to probabilistically detect multiple AOC hazard classes using gridded inputs from ERA5 reanalysis (means/anomalies over each ~30–45-day AOC analysis window) combined with Copernicus Global Drought Observatory indicators including Standardized Precipitation Index, soil-moisture anomaly, and vegetation stress via fAPAR anomaly. The system produces "first-guess" AOC maps with probabilities and ensemble-based uncertainty. AOC maps reflect expert judgement about where anomalies matter for agriculture sector, informed by crop conditions and impact signals such as crop model outputs/yield information as well as contextual factors such as agricultural land share and coping capacity like irrigation. The AI model learns an impact-relevant hazard signal calibrated to agricultural exposure/sensitivity. Overall, it demonstrates how expert-labelled operational products can be scaled with xAI to strengthen dynamic risk monitoring and feed downstream scenario and impact analysis.

Further information: Expert-driven explainable artificial intelligence models can detect multiple climate hazards relevant for agriculture | Communications Earth & Environment

Box 3 illustrates an operationally grounded application of AI in linking hazard signals to sectoral exposure and sensitivity. The model does not replace physical hazard forecasting; rather, it learns how hazard anomalies translate into agriculturally relevant concern zones, preserving uncertainty and interpretability. Its contribution lies in scaling expert judgement and enhancing consistency in risk monitoring.

Dynamic estimation of likely impacts supporting IBF and AA. Dynamic risk assessment differs from static risk profiling in its explicit use of evolving forecast information and iterative updating. As forecast lead times shorten and ensemble confidence changes, expected impacts must be recomputed. AI contributes where repeated spatial recomputation across large geographic domains and multiple ensemble members would otherwise be analytically intensive. Machine-learning components can integrate forecast hazard intensity fields with exposure datasets and empirically derived vulnerability relationships to estimate the probability of exceeding defined impact thresholds. Importantly, such systems preserve probabilistic information rather than collapsing outputs into binary hazard exceedance values. This supports structured decision-making under uncertainty (Bankes, 1993) and aligns with guidance on impact-based forecasting and warning services (WMO, 2021b). Dynamic impact estimation directly underpins impact-based forecasting and anticipatory action frameworks. IBF shifts the emphasis from hazard magnitude alone to projected consequences. Similarly, anticipatory action mechanisms rely on predefined trigger conditions linked to expected impacts rather than hazard-only thresholds (De Pérez et al., 2015; NLRC 510, 2021). AI strengthens this process by enhancing spatial targeting, improving calibration of probabilistic risk model inputs, and supporting transparent interpretation of model outputs.

Operational EWS generally rely on hybrid analytical approaches combining physics-based hazard models with statistical or machine-learning components alongside pre-defined rule-based trigger criteria. While advanced analytics enhance processing and integration of data, human oversight remains essential. Analysts review model outputs, interpret them in light of local context and operational realities, and determine whether established trigger conditions have been met, including decisions on whether and when to initiate early actions. An example of this approach in practice is provided by the Pacific Disaster Center's DisasterAWARE platform (Box 4).

Box 4. DisasterAWARE: AI-enabled Risk Intelligence and Analytics

DisasterAWARE, developed and operated by the Pacific Disaster Center (PDC), provides an operational example of how advanced analytics and AI-augmented components enhance multi-hazard risk intelligence at operational scale. The platform integrates a wide range of hazard monitoring and environmental datasets with exposure and vulnerability layers to support situational awareness and risk assessment for early warning and preparedness planning. PDC's AI for Humanity™ initiative underpins key analytical capabilities within DisasterAWARE. Machine learning algorithms are applied to identify patterns in incoming hazard data, support near real-time hazard detection and classification, and enhance exposure estimation by integrating diverse data sources automatically. AI components include natural language processing (NLP) and generative AI to curate and synthesise hazard information from hundreds of verified sources worldwide, reducing manual processing time and expanding global hazard coverage. These capabilities help identify hazard type, location and onset timing more rapidly and accurately than manual curation alone, supporting both the DisasterAWARE Pro platform and associated early warning products. Machine learning models also contribute to pattern recognition and temporal analysis over large datasets, enabling rapid identification of evolving risk signals and hidden relationships within hazard and exposure data. This enhances scalability and analytical depth for dynamic risk monitoring, allowing DisasterAWARE to update geospatial risk layers and hazard footprints as new information arrives. AI augments automated workflows that integrate continuous data feeds (e.g., satellite observations, forecast model outputs and media reports) into the platform's unified risk information ecosystem. While DisasterAWARE does not automate impact-based triggers, its AI-enabled architecture supports advanced hazard identification, accelerated data integration and enriched metadata generation. These components provide decision-makers with high-frequency insights and visual analytics, including hazard intensity projections and exposure overlays, which can inform preparedness actions such as resource pre-positioning, monitoring prioritisation, and community advisories. Operational users maintain responsibility for interpreting outputs and activating institutional response frameworks.

Further information: https://www.pdc.org/artificial-intelligence/

Scenario modelling for complex and systemic risk contexts. Disaster impacts increasingly occur within interconnected environmental, infrastructural and socio-economic systems. While the importance of systemic and cascading risk is well established in disaster risk scholarship (Pescaroli & Alexander, 2015), operational modelling of fully integrated multi-sector cascading dynamics remains limited in practice. Within MHEWS, artificial intelligence has instead demonstrated clearer operational value in strengthening scenario modelling and stress-testing under defined hazard assumptions. Scenario modelling supports preparedness planning, evacuation design, infrastructure stress-testing and medium- to long-term contingency analysis. Rather than dynamically simulating all cross-sector interdependencies in real time, scenario approaches explore plausible hazard conditions under defined assumptions. Their effectiveness depends on the quality and resolution of exposure datasets, environmental baselines and terrain representations that inform physics-based hazard simulations.

AI contributes in this space primarily by improving the quality, resolution and computational efficiency of these inputs. One prominent operational development is the Digital Twin Earth (DTE) initiative led by the European Space Agency (ESA). DTE and the broader Destination Earth (DestinE) programme of the European Union aim to create high-resolution digital replicas of Earth systems to support climate adaptation and disaster risk planning (European Commission, 2022; European Space Agency, 2023). Within these frameworks, machine-learning approaches, including neural operator architectures, are used to develop surrogate models that approximate complex physical simulations of ocean and coastal processes. Neural operators learn mappings between physical system states and can dramatically accelerate repeated scenario runs while remaining grounded in physics-based training data (Kovachki et al., 2024). This enables rapid exploration of multiple coastal flooding or sea-level rise scenarios for planning and uncertainty analysis. A complementary operational illustration is provided by the Tonga Disaster Preparedness Pilot Project (Box 5). The Tonga application demonstrates how AI strengthens scenario modelling by improving exposure inventories and environmental baseline datasets that feed into hazard simulations. Rather than modelling cascading system failures, the approach enhances the spatial realism and data completeness required for credible coastal inundation and evacuation planning scenarios.

Box 5. AI-Enabled Asset Mapping and Scenario Modelling for Coastal Risk Intelligence in Tonga

Figure 6. Digital Twin of Tongatapu, allowing sea level rise and flood scenario simulations.

Small island developing States (SIDS) such as Tonga are highly vulnerable to tsunamis, storm surges, and rising seas. Lack of detailed data on elements at risk such as buildings, mangroves, and critical assets such as coconut trees vital to local livelihoods have constrained comprehensive risk assessment and preparedness. To address the challenges, in Tongatapu Island, Tonga, an integrated suite of AI-driven tools were tested and introduced predictive analytics, automated mapping and 3D modelling capabilities. Automated asset mapping used a pre-trained FasterRCNN model on 15 cm imagery to identify and count coconut trees with 94.7% mAP50 accuracy, replacing months of manual fieldwork. Deep learning classification of Landsat data tracked mangrove changes from 2016–2021, strengthening understanding of natural coastal protection. This then feeds into scenario analysis using high-resolution 30 cm Pleiades Neo imagery enabled creation of a 3D digital twin using NeRF and 3D Gaussian Splatting. It supports realistic inundation simulations that pinpoint vulnerable "sank buildings" and improve evacuation planning. The 2024 Tonga Disaster Preparedness Pilot Project – delivered with the Tonga National Disaster Risk Management Office, United Nations Office for Disaster Risk Reduction, United Nations Office for Outer Space Affairs, the Committee on Earth Observation Satellites, Group on Earth Observations, and multiple technical partners – demonstrates how AI can convert fragmented datasets into actionable intelligence for ministries ranging from climate to statistics. This activity - implemented through the CEOS Working Group on Disasters - is part of the GEO Earth Observations for Disaster Risk Management Initiative (EO4DRM). Because the workflow relies on pretrained models and standardized satellite imagery, it offers high scalability for other Pacific SIDS seeking rapid, cost-efficient disaster-risk insights.

Further information: https://www.un-spider.org/projects/TongaPilotProject

Across hazard domains, AI strengthens scenario modelling by enhancing inputs and accelerating analysis rather than replacing physical models. In flood risk, machine-learning surrogates approximate hydrodynamic simulations to rapidly test alternative rainfall or discharge scenarios (Mosavi et al., 2018). In wildfire modelling, AI generates high-resolution susceptibility and fuel maps from satellite data to improve fire spread simulations (Jain et al., 2020; Rodrigues & de la Riva, 2014). In infrastructure stress-testing, machine learning supports outage and recovery estimation under simulated extreme weather conditions (Fatima et al., 2024; Nateghi et al., 2011).These applications are operationally bounded but provide practical value for preparedness planning and risk-informed decision-making within MHEWS.

2.2.4 Strengthening loss and damage data tracking and analysis

Accurate, complete, disaggregated, and timely documentation of disaster impacts is essential for response, recovery planning, disaster risk financing and long-term risk reduction. For MHEWS, systematic tracking of observed impacts also strengthens the empirical basis for vulnerability calibration, trigger validation and anticipatory action design (UNDRR, 2024). Traditional damage and loss analyses typically based on field surveys, administrative reporting and manual imagery interpretation remain indispensable but are often time-intensive and delayed by access and coordination constraints. AI has demonstrated operational value in this context by accelerating damage detection, enabling faster aggregation of loss estimates and supporting structured extraction of impact information from diverse data sources, thereby improving the timeliness and analytical robustness of post-disaster impact tracking.

Automated damage detection from satellite and aerial imagery. The most mature AI applications in post-disaster impact assessment involve automated structural damage detection using remotely sensed imagery. Convolutional neural networks (CNNs) trained on labelled pre- and post-event satellite or aerial images can identify and classify building damage across multiple hazard types, including earthquakes, floods, windstorms and wildfires (Gupta et al., 2019; Xu et al., 2019). The development of benchmark datasets has significantly advanced this capability. The xBD dataset – one of the largest publicly available multi-hazard building damage datasets, includes annotated satellite imagery from diverse disaster events and has enabled systematic training and evaluation of deep learning models (Gupta et al., 2019). Empirical evaluations demonstrate that CNN-based architectures achieve high discrimination skill in identifying severely damaged structures when adequate image resolution and representative training data are available (Valentijn et al., 2020). Although performance varies depending on building typology, hazard characteristics geographic transferability and the representativeness of earth observation data – including image resolution and the extent to which training data reflect local conditions - AI-based workflows allow large spatial areas to be processed substantially faster than fully manual interpretation, with outputs requiring validation against complementary data sources in operational use. For instance, the WFP Innovation Accelerator, in partnership with InstaDeep's AI for Social Good team, and Google Research has developed SKAI, a machine learning based tool for performing automatic building damage assessments on aerial imagery of disaster sites (WFP, n.d.). Following the 2023 earthquake in Türkiye and Syria, the tool was deployed to identify damaged or destroyed structures and provided rapid damage estimates with an accuracy exceeding 81 percent. The solution has been tested across multiple recent natural emergencies and, on average, enabled expansion of the analysis area by a factor of seven while reducing the time required to produce initial (directional) damage assessments by a factor of six, bringing outputs to under one day (WFP, n.d.). This supports repeated assessments for evolving events and more continuous tracking of impact dynamics (UN Global Pulse, n.d.).

Operationally, satellite-based detection is increasingly complemented by drone-acquired imagery in access-constrained or rapidly evolving environments. UAV imagery provides high spatial resolution, and machine-learning classifiers can process large volumes of photographs to distinguish damaged from undamaged structures, generating georeferenced damage maps suitable for integration into response coordination platforms. However, effective post-disaster damage detection depends on the availability of reliable baseline exposure data. In many contexts, incomplete or outdated building inventories limit the accuracy of impact estimation. AI-assisted mapping tools are therefore being applied both before and after disasters to strengthen baseline exposure inventories (Box 6). By improving the completeness and spatial accuracy of building datasets, these approaches enhance comparability between pre- and post-event information and support more reliable damage assessments and impact tracking.

Box 6. OpenStreetMap's AI-assisted Pre- and Post-Disaster Mapping for Humanitarian Decision-Making

When disaster strikes, mapping the impacted areas to a high level of detail helps humanitarian responders to assess impact and make plans to support communities in need. The Humanitarian OpenStreetMap Team supports this work by enabling communities to collect geographic data, yet manual mapping of buildings and infrastructure remains labour-intensive. To address this challenge, the team has developed fAIr, an open-source AI-based tool designed to accelerate pre- and post-disaster mapping in resource-constrained settings. The system has been tested in Nepal, Liberia, Sierra Leone, Dominica, and Kenya, and is ready for broader deployment, with scale-up dependent on access to suitable open-source geographic imagery. The fAIr initiative applies machine-learning models trained on locally generated datasets, an approach shown to outperform global models in predicting buildings and roads. Community mappers first create a small training dataset by manually mapping features from imagery. The AI model then uses this dataset to generate mapping suggestions across a larger area. Users validate or reject these suggestions, and their feedback further improves model performance. This workflow significantly increases mapping efficiency while ensuring that local knowledge remains central to data quality. Development of fAIr has been informed by extensive experimentation, including an AI Innovation Challenge conducted with Omdena and a scientific evaluation with Masaryk University. Comparative "mapathons" demonstrated that AI-assisted mapping is most effective in areas where features are clearly identifiable, while complex informal settlements still require substantial human review. The project also highlighted the importance of user-centred interface design, leading to major usability improvements in version 2.0. As access to open imagery remains a constraint, fAIr is also testing the use of drone imagery collected by local mappers. Through its open-source design, community-driven workflow and emphasis on capacity strengthening, fAIr offers a scalable model for enhancing disaster preparedness and humanitarian decision-making in diverse geographic contexts.

Figure 7. FAIr prediction of buildings on open aerial imagery OAM.

Further information: https://nethope.org/case-studies/fair-humanitarian-open-street-map-team-hot/

Rapid aggregation of loss and damage estimates. Beyond detecting structural damage, AI contributes to the rapid aggregation and spatial synthesis of loss estimates. When AI-derived building damage classifications are combined with exposure inventories and replacement cost information, they enable accelerated estimation of direct physical losses. Traditional catastrophe modelling frameworks rely on predefined fragility or vulnerability functions to estimate expected damage given hazard intensity. AI-based detection introduces empirically observed spatial damage evidence that can complement or refine these modelling assumptions (Rudner et al., 2019). In hybrid workflows, CNN-generated damage layers are integrated into structured economic modelling systems to produce preliminary loss estimates within days of an event. Rapid aggregation is operationally significant. Faster availability of structured loss information supports early recovery planning, disaster risk financing mechanisms and reporting under international loss-and-damage frameworks. Importantly, AI does not replace established modelling frameworks such as the World Bank Global Rapid Post-Disaster Damage Estimation (GRADE) methodology (GFDRR, 2018); rather, it enhances the input data that feed into such systems. As additional imagery becomes available, AI-generated damage maps can be updated iteratively, supporting progressive refinement of loss estimates. Box 7 illustrates an operational example of AI-enabled rapid damage aggregation in Mozambique.

Extraction of impact information from post-event assessments. AI is also increasingly applied to extract structured impact information from textual situation reports, rapid needs assessments and other post-event documentation. NLP techniques can identify references to affected populations, damaged assets, service disruptions and economic impacts within unstructured reports, converting qualitative narratives into structured datasets (Imran et al., 2015). Humanitarian research has demonstrated that supervised machine-learning and NLP approaches can classify crisis-related information from situation reports and social media streams, supporting structured impact databases and situational awareness (Kersten et al., 2019). While such systems require careful validation and governance safeguards, they reduce manual coding burden and support longitudinal learning across events.

Box 7. AI-Enabled Post-Disaster Loss and Damage Estimation in Mozambique

Mozambique faces frequent cyclones, floods, and droughts that cause major damage to homes, infrastructure, and livelihoods. After events such as Cyclones Idai and Kenneth, rapid loss-and-damage estimates were difficult, especially in hard-to-reach and data-scarce areas. To improve speed, accuracy, and spatial coverage, World Food Programme (WFP) integrated AI-enabled methods into post-disaster assessments (Chojnacka, 2020; Wadland, 2021). Drones were used to capture high-resolution aerial imagery over affected zones, then processed the images with the Digital Engine for Emergency Photo-analysis (DEEP), WFP's open-source tool that applies machine learning and computer vision to automatically classify large volumes of photos, distinguish damaged from undamaged structures, and generate georeferenced damage maps. This shifted analysis from weeks of manual interpretation to hours, enabling near-real-time estimates of affected households and infrastructure impacts. The results supported operational decisions such as prioritizing food assistance, planning logistics, and identifying viable access routes when transport networks were disrupted (Chojnacka, 2020). The approach depended on multi-stakeholder partnerships. WFP worked with Mozambique's National Institute for Disaster Management (INGC) on training and preparedness activities related to drone deployment, and data interpretation so outputs are aligned with national emergency coordination mechanisms. Collaboration with private-sector and research partners also supported the development and refinement of the AI models, including geospatial analytics and cloud computing.

AI-enabled impact tracking strengthens MHEWS in three principal ways. First, it improves situational awareness during response. Automated damage detection and rapid aggregation reduce delays between hazard occurrence and structured impact estimation, enabling more timely targeting of humanitarian assistance and logistical planning. Second, it supports improved calibration of vulnerability models and impact thresholds.

Observed damage patterns can be compared with forecast hazard intensity and exposure datasets, enabling refinement of vulnerability functions and adjustment of thresholds used in impact-based forecasting and anticipatory action frameworks. Third, it contributes to a stronger empirical evidence base for future warnings and anticipatory action. Systematic accumulation of post-disaster damage data strengthens validation of forecast-based triggers and improves transparency in anticipatory financing mechanisms. Over time, this enhances credibility of impact-based early warning systems.

2.3 Using AI for risk knowledge: principles, conditions and priority actions

AI offers important opportunities to strengthen risk knowledge within MHEWS, particularly in analysing large, heterogeneous, and rapidly evolving datasets. Operational applications demonstrate value in exposure mapping, satellite imagery interpretation, environmental monitoring, infrastructure stress-testing, and post-disaster impact analysis. When embedded within structured risk assessment workflows, AI can improve the timeliness, spatial resolution, and scalability of risk information. However, AI does not substitute for foundational risk assessment methods. Its performance depends on data quality, institutional capacity, governance arrangements, and alignment with decision-making needs. Poorly designed or weakly governed AI systems can amplify existing data gaps, introduce bias, create false precision, or undermine accountability. Effective use of AI for risk knowledge therefore requires adherence to core principles, enabling institutional conditions, and clearly defined national priorities.

2.3.1 Core principles for responsible and operational AI use

The responsible and effective use of AI for risk knowledge depends on clear design principles that align technology with decision-making needs and institutional safeguards. The following principles provide a practical framework to ensure that AI applications strengthen, rather than undermine, the credibility and operational value of MHEWS.

Decision-centred design. AI applications in risk knowledge should be designed around specific operational decisions rather than technological possibility. The primary question is not what AI can model, but which risk management decision it supports: identifying populations and assets exposed to hazards, prioritizing vulnerability reduction measures, setting anticipatory action trigger thresholds, or guiding risk-informed investment in infrastructure and preparedness. AI outputs must correspond to clearly defined decision thresholds and institutional responsibilities. Tools that generate high-resolution maps without integration into decision workflows add limited operational value. Decision-centred design requires early engagement with end-users, including disaster management authorities, meteorological services, statistical offices, and sectoral agencies. Model outputs should be formatted in ways that align with established warning categories, contingency planning frameworks, and financing mechanisms.

Transparency and explainability. Risk knowledge outputs must be interpretable and auditable. Decision-makers need to understand which data inputs and assumptions underpin AI-generated results, what the main drivers are, and what uncertainties apply. Opaque "black box" models risk automation bias and reduced trust. In operational settings, transparency requires documentation of model architecture, training data sources, version control, and accuracy metrics. Explainable AI (xAI) techniques, interpretable feature importance summaries, and probabilistic outputs support validation against contextual knowledge and facilitate operational uptake. Beyond aggregate performance metrics, this includes explicit representation of model uncertainty to avoid false precision, ensuring that confidence levels in AI-derived proxy indicators and high-resolution outputs are clearly communicated and appropriately interpreted in decision-making. For AI-assisted synthesis tools, transparency requires traceable source references rather than unverified narrative outputs.

Human oversight and accountability. AI-enabled systems must operate within human-in-the-loop governance frameworks. Analysts and institutional authorities retain responsibility for the design of AI-enabled systems, interpreting outputs, validating anomalies, and authorising decision triggers. Automated outputs should inform structured judgement, not replace it. Clear lines of accountability are necessary regarding data stewardship, model updates, quality assurance, and release of derived risk products. This includes defining which institution is responsible for recalibration when hazard baselines shift or exposure data and vulnerability information are updated.

Inclusion, equity and "do no harm". Risk knowledge systems shape visibility. If informal settlements, displaced populations, or under-mapped rural areas are absent from training datasets or exposure layers, AI-derived outputs will systematically underestimate vulnerability. Inclusive design therefore requires deliberate attention to coverage gaps, representativeness, and disaggregation. Exposure and vulnerability data are often sensitive. Household locations, infrastructure vulnerabilities, and mobility patterns can create protection risks if mishandled. A "do no harm" approach requires minimising collection of sensitive data, applying strong access controls, conducting protection risk assessments before publication, and ensuring outputs do not inadvertently expose vulnerable groups. These safeguards are particularly critical in fragile, conflict and violence-affected contexts.

2.3.2 Enabling conditions for operational implementation

The effective application of AI for risk knowledge requires more than sound design principles; it depends on enabling institutional, technical and financial conditions. Without these foundations, even well-designed AI tools are unlikely to be sustainable or operationally integrated within MHEWS.

Institutional coordination across risk data holders. Risk knowledge typically integrates datasets held by multiple institutions, including meteorological services, disaster management authorities, statistical offices, land registries, infrastructure agencies and humanitarian partners. Effective AI deployment requires formal coordination mechanisms defining data stewardship roles, access permissions, update responsibilities and quality assurance processes. Coordination frameworks should include agreed identifiers (e.g., administrative codes, asset IDs, event identifiers) to ensure datasets can be linked consistently. Without such governance, AI applications risk producing fragmented outputs that cannot be integrated into national systems. Clear protocols for data ownership and sovereignty are essential. National data holders should retain ownership of raw data and ground-truth inputs, with defined arrangements for access, sharing and reuse. This helps prevent extractive practices and ensures that externally developed AI tools strengthen national capacity to govern risk data.

Interoperable data systems and standards. AI applications require consistent data structures, common formats and clear documentation. Risk datasets should follow minimum metadata standards, apply version control, and record the origin and processing history of data. National agreement on official administrative boundaries and standard place names is essential to avoid conflicting spatial interpretations. Interoperable systems allow hazard, exposure, vulnerability and impact datasets to be combined reliably. AI cannot compensate for fundamentally incompatible or poorly structured data systems.

Sustainable financing and system maintenance. AI-enabled risk knowledge is not a one-time investment. Sustained value requires predictable financing for data refresh cycles, satellite imagery access, model recalibration, system maintenance, cybersecurity, and user support. Many AI tools fail operationally when initial project funding ends and maintenance responsibilities are unclear. Lifecycle planning should include budgeting for hardware infrastructure, cloud services, data acquisition, validation exercises, and periodic performance review.

Capacity to interpret, validate and govern AI outputs. National and local institutions must have the capacity to interpret model outputs, understand uncertainty ranges, and challenge anomalous results. Capacity development should include training on data governance, probabilistic reasoning, validation techniques and ethical safeguards. Reliance solely on external technical partners limits sustainability and may weaken institutional ownership. Capacity strengthening is therefore a core enabling condition, not a secondary consideration.

2.3.3 Actions for countries

Countries seeking to use AI for risk knowledge should adopt a pragmatic, gap-driven approach.

Start from operational risk knowledge gaps, not AI ambition. The entry point should be clearly identified weaknesses in risk knowledge systems: incomplete exposure inventories, slow post-disaster impact estimation, outdated hazard and exposure baselines, or weak calibration of vulnerability functions. AI should be considered only where it demonstrably addresses these gaps more effectively than conventional approaches.

Use AI to strengthen existing MHEWS workflows, not create parallel systems. AI applications should be embedded within established national early warning architectures, statistical systems and disaster governance frameworks. Creating parallel AI platforms disconnected from official processes undermines sustainability and trust. Integration into existing data pipelines, reporting structures and decision triggers ensures operational relevance.

Prioritise hybrid and explainable approaches. Hybrid architectures combining physics-based hazard models, statistical analysis and machine-learning components offer greater robustness than fully automated systems. Explainable models and probabilistic outputs facilitate validation and institutional confidence. Where data are sparse, simpler, transparent methods may outperform complex models.

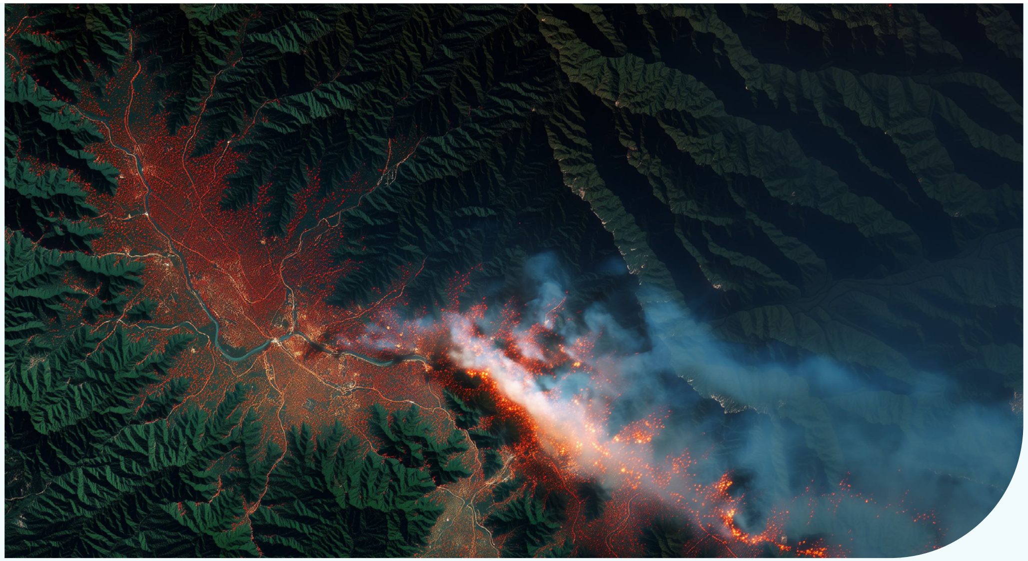
Systematically link impact data back into warning design. Post-disaster damage documentation and loss estimation should inform recalibration of vulnerability functions and refinement of impact-based warning thresholds. Institutional learning loops must be formalised so that observed impacts are systematically compared with forecast assumptions. AI can support this feedback process through automated damage detection and structured impact databases, but governance arrangements must ensure that lessons are incorporated into future warning design.

Invest equally in governance, capacity and safeguards alongside technology. Technological innovation must be matched by investment in governance frameworks, ethical safeguards, interoperability standards and human capacity. Without these foundations, AI risks amplifying inequities or generating outputs that lack credibility. Balanced investment ensures that AI strengthens, rather than undermines, national risk governance systems.

2.4 Conclusion

This chapter has argued that AI's value for disaster risk knowledge (Pillar 1) lies less in replacing existing risk assessment practice than in helping make risk knowledge usable across MHEWS value cycle. For Pillar 1, the central challenge is not simply producing more data, but ensuring that hazard, exposure, vulnerability and disaster impact data can be found, connected, updated and used for decisions in the context of MHEWS.

The examples presented in this chapter show how AI can support this shift. The Sketch Map Tool (Box 1) demonstrates how local and community knowledge can be digitised and connected to formal geospatial systems. POMELO (Box 2) shows how AI-supported population modelling can improve exposure estimates where census data are outdated or incomplete. The MARS Areas of Concern model (Box 3) illustrates how expert judgement can be scaled into probabilistic, sector-specific risk monitoring, while DisasterAWARE (Box 4) shows how AI-enabled analytics can support dynamic risk monitoring and insights. The Tonga pilot (Box 5) demonstrates the role of AI in improving asset mapping and scenario modelling for



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coastal risk planning. OpenStreetMap's fAIr tool (Box 6) highlights the importance of locally validated, AI-assisted mapping, and the Mozambique example (Box 7) shows how AI can accelerate post-disaster damage analysis and strengthen feedback into future risk understanding.

These cases point to a common lesson: AI's practical contribution is to reduce the time, labour and fragmentation involved in maintaining risk knowledge, while improving the granularity and consistency of the information available to decision-makers. This is especially relevant for impact-based forecasting and anticipatory action, where the critical question is not only what hazard may occur, but who and what is exposed, how vulnerability shapes likely impacts, and what evidence from past events should inform thresholds and action.

However, AI will only strengthen risk knowledge if it is embedded in accountable systems. It cannot compensate for weak data governance, unclear institutional mandates, poor interoperability, limited validation, or exclusion of communities and underrepresented populations from the data. Without these foundations, AI risks producing faster but not necessarily better risk information.

For countries and partners, the priority is therefore to apply AI selectively to well-defined operational gaps such as in improving exposure baselines, harmonising fragmented datasets, supporting scenario analysis, and strengthening impact tracking and learning loops. That way, AI can help transform static risk products into dynamic, decision-centred risk knowledge that supports more targeted, impact-based and actionable MHEWS.

Chapter 3.
AI for detection, observation, monitoring, analysis, and forecasting of hazards

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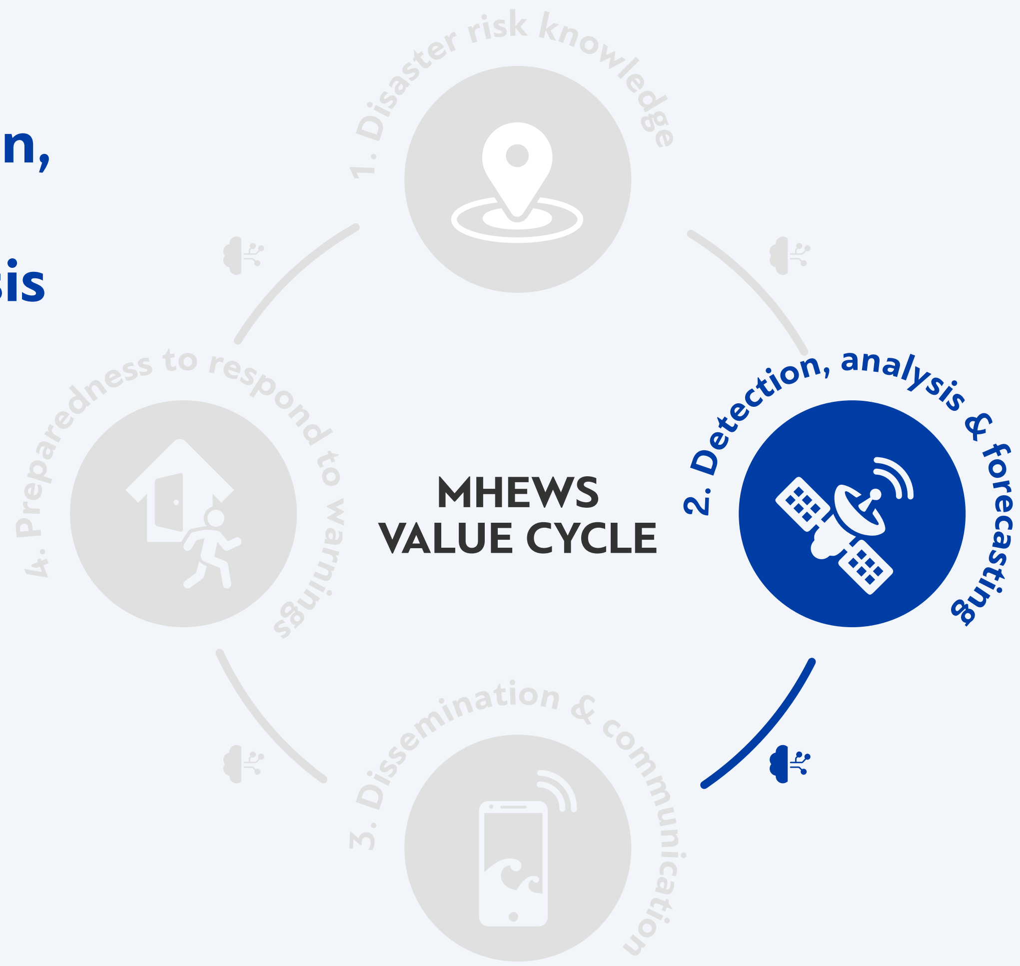
Pillar 2. Improved detection, observation, monitoring, analysis & forecasting



ENABLES

- More accurate forecasts
- Earlier & more reliable alerts
- Impact-based insights

CORE AI TECHNOLOGIES

- Machine Learning
- Neural Networks
- Physics-informed AI
- Deep Learning

AI is strengthening the full hazard information chain, with major advances in detection, observation, monitoring, analysis, and forecasting, while also enabling new applications in impact forecasting and anticipatory action.

- AI enhances observational quality assurance, real-time detection, and the integration of diverse data sources including satellite, radar, and in situ observations into operational systems.
- AI supports faster and more precise forecasting of high-impact weather and climate hazards across multiple timescales.
- AI has the potential to democratize access to advanced forecasting capabilities by reducing computational requirements and accelerating the transition from research to operational forecasting systems.
- AI is helping advance multi-hazard and Earth-system approaches by linking information across atmospheric, hydrological, oceanic, and other environmental domains.
- AI shows promise for supporting impact-based forecasting by helping link hazard forecasts with exposure and vulnerability data.

Together, these capabilities support earlier, more reliable, and more actionable warnings while complementing existing forecasting approaches and strengthening preparedness and response decision-making. However, challenges remain related to data sparsity, regional bias, limited observational coverage, model transparency and explainability, performance under extreme and changing climate conditions, and integration with operational forecasting systems. Continued investment in observational infrastructure, human capacity, governance frameworks, and robust validation processes will be essential to ensure trustworthy, equitable, and operationally relevant AI-enabled forecasting systems. International organizations, research community and operational institutions share responsibilities to ensure integration of AI into Early Warning Services.

Early Warnings for All

3.1 EW4All pillar 2: overview

Pillar 2 addresses the technical core of early warning systems (EWS) by ensuring that hazards are systematically detected, observed, monitored and analysed, and that their potential impacts are forecasted in a timely and reliable manner. This pillar aims to strengthen observation networks, promotes sustained data exchange, and enhances the capacity of NMHSs to generate accurate forecasts. In practical terms, Pillar 2 turns environmental data into robust, science-based predictions that inform decision-making. These forecasts underpin risk knowledge under Pillar 1, support effective warning dissemination under Pillar 3, and enable timely anticipatory action under Pillar 4 (WMO, 2022).

3.2 What has happened and why it matters? – The AI moment for detection, observation, monitoring, analysis and forecasting of hazards

Over the past decade, and with particularly rapid acceleration since the early 2020s, artificial intelligence (AI) and machine learning (ML) have begun to reshape how hazard-related information is generated, analysed, and interpreted. ML architectures have become increasingly capable of extracting patterns from large, heterogeneous datasets and representing complex, nonlinear relationships in the Earth system, which are key for modelling and prediction (Reichstein et al., 2019; Tiggeloven et al., 2025). These developments have occurred alongside major changes in Earth observation, including more satellites, better radar coverage, and expanded in situ networks (WMO et al., 2021). At the same time, advances in data assimilation and numerical modelling have enabled the creation of consistent global reanalysis datasets such as ERA5 (Hersbach et al., 2020), which are widely used to train and evaluate modern AI models.

Taken together, these developments mean that there are now a greater volume and diversity of environmental observations, and more advanced statistical techniques to extract meaningful information from this data rapidly and accurately. It is the convergence of these trends, and its promise for research and operational use, that has given rise to what can be described as an "AI moment" for hazard detection, observation, monitoring, analysis, and forecasting.

This AI moment is not defined by a single breakthrough, nor does it signal a replacement of established approaches. In fact, it is enabled by the cumulative effects of long-term investments in global observing systems, data assimilation, cloud computing and physical modelling of atmospheric and other environment processes, which are needed to train, benchmark, and physically dissect such data-driven models.

In the field of meteorology, in practical terms, this AI moment has been particularly marked by the rapid emergence of AI-based models for global weather prediction, trained on large historical datasets and forecast products (e.g. Pangu-Weather (Bi et al., 2023), Google's GraphCast (Lam et al., 2023), the European Centre for Medium-Range Weather Forecasts (ECMWF) AI Forecasting System (Lang et al., 2024a; Lang et al., 2024b). Within only a few years these statistical models have been developed and now rival, or surpass, the performance of leading numerical weather prediction (NWP) systems that are grounded in the explicit solution of physical equations and have been pioneered and developed by modelling centres around the world since the 1950s. These results indicate that data-driven approaches can reproduce key aspects of atmospheric evolution previously accessible mainly through physics-based modelling. Notably, these models achieve competitive forecast skill while requiring substantially lower computational resources with forecasts that previously required hours of supercomputer runtime now often generated in minutes or seconds.

In a significant milestone for the field, ECMWF, an intergovernmental organization that operates one of the world's leading global weather forecasting systems, has recently made its AI-based forecasting model operational alongside its traditional physics-based system, marking an important step in the transition from research to operations (ECMWF, 2025b), see Box 9).

Since the emergence of AI-based weather prediction, the scope of applications has expanded rapidly across timescales, spatial scales and components of the Earth system. AI methods are now being explored for tasks ranging from nowcasting through short-range to seasonal prediction, and even climate-scale simulations, and across spatial domains from global weather models to increasingly high-resolution regional and local applications. Their application extends beyond atmospheric forecasting to hydrological prediction, the analysis and attribution of extreme weather and climate events, and the development of AI models for the atmosphere, ocean, land surface, and sea ice, as well as increasingly coupled, multi-component Earth system models (WMO, 2025a).

For EWSs, these developments are substantial. AI methods can help extract patterns from large and heterogeneous datasets, integrate observations from satellites, radar, and in situ networks, and generate forecasts more rapidly and at lower computational cost. This has the potential to support more frequent forecast updates, improve the detection and prediction of extreme events, and strengthen multi-hazard and impact-based forecasting approaches. At the same time, important challenges remain. Many AI-based systems are still at the research or pilot stage, their performance varies across regions and hazards, and robust validation, transparency, physical consistency and careful operational integration are essential, consistent with existing practices for operational numerical weather prediction. Improvements in computational efficiency alone also do not address persistent disparities in data access, technical capacity, and institutional resources.

Within the framework of the EW4All initiative, AI should therefore be understood as an enabling technology rather than an objective in itself. The goal is to strengthen national EWSs to protect lives, livelihoods, and development gains. Like earlier transformative innovations in forecasting, AI will only deliver lasting impact if it is embedded within institutions, supported by sustained investment (balanced against continued investment in traditional modelling approaches), and aligned with operational realities.

Against this backdrop, this chapter examines selected domains in hazard detection, observation, monitoring, analysis, and forecasting where AI is already showing particular promise (section 3.3). It then discusses key challenges, requirements, and the role of the international community in supporting the responsible integration of AI into operational early warning systems (section 3.4). The chapter concludes with a summary and a brief historical reflection comparing AI with the early evolution of numerical weather prediction to reflect on its potential for early warning systems (section 3.5)

3.3 Where AI is already showing promise? – Use cases across hazard detection, observation, monitoring, analysis and forecasting

This section examines where AI is already demonstrating tangible added value across Pillar 2 value cycle, with focus on applications that are either operational, in advanced pilot phases, or technically mature and credible enough to inform near-term implementation. It focuses on 7 areas: data collection & quality control, severe event detection, nowcasting models, global weather prediction models, hazard forecast, post-processing, and climate modelling (Figure 8). We end by discussing a selection of overarching opportunities that apply across the case studies discussed.

3.3.1 Automated quality control of observational data

Reliable observation data is the starting point of every forecast. If errors or biases enter the system unnoticed, they can affect model performance and weaken early warning services. Maintaining observation data quality is therefore essential to ensuring trustworthy forecasts. In weather forecasting, quality control (QC) traditionally relies on rule-based checks and expert review. Observations are tested against fixed thresholds, compared with nearby stations, and manually examined when flagged as suspicious (WMO, 2023a). These methods require time and expertise, and they can struggle to keep pace with the rapid growth in data from satellites, radar networks, and automated stations.

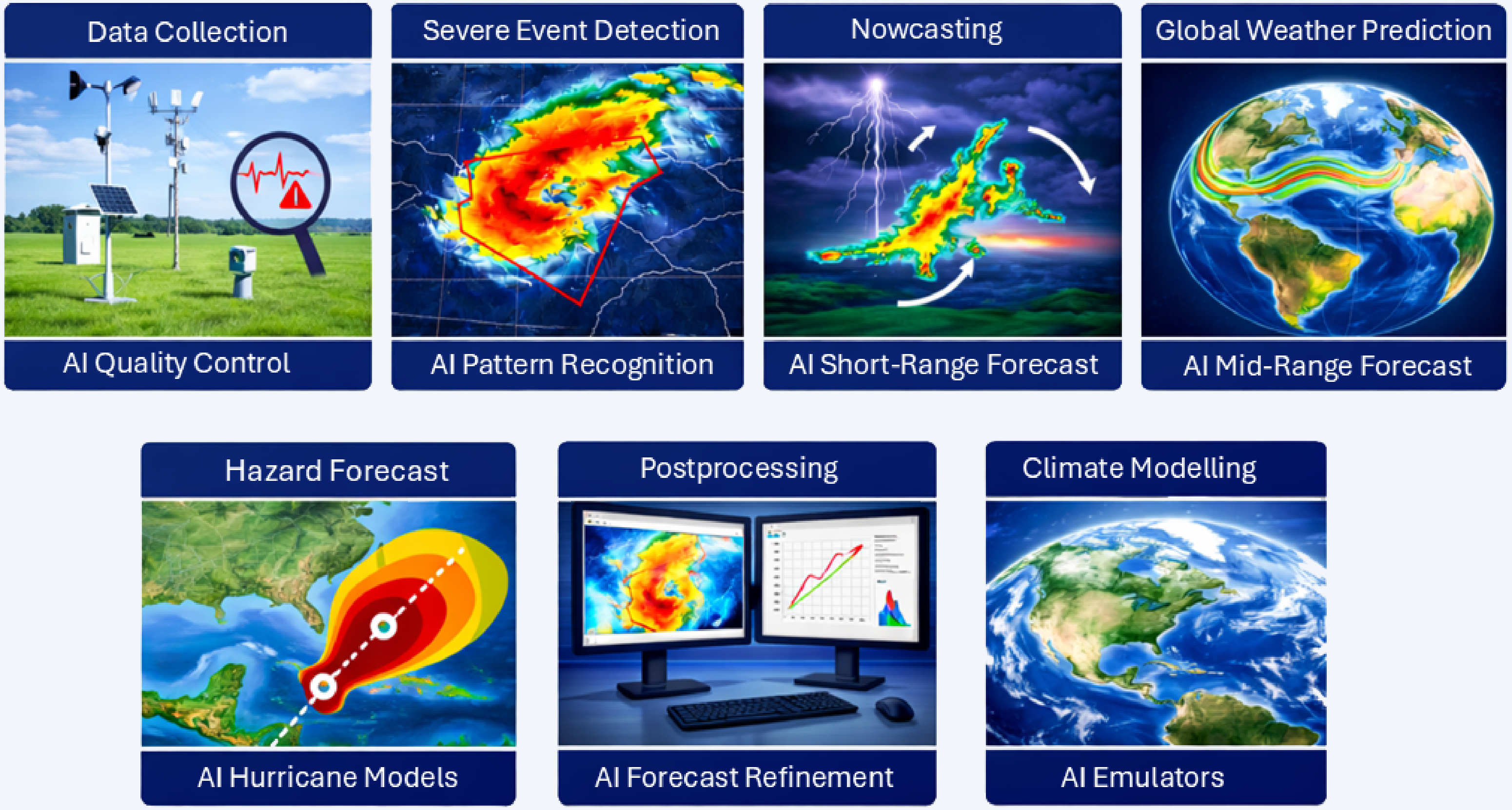


Figure 8. Each panel, identified by the top headers, illustrates a key focus area discussed in this chapter where AI shows particular promise. The bottom labels highlight example benefits AI can bring in each area.

ML strengthens this process by learning normal patterns for specific sensors and locations, allowing systems to detect unusual behaviour more quickly and consistently. When new observations deviate from these learned patterns, the system flags them as potential anomalies, allowing early detection of issues such as sudden instrument failures or gradual sensor drift. The approach reduces reliance on manually defined thresholds and helps identify problems across large volumes of observation data more efficiently, supporting faster monitoring of data quality in operational forecasting systems (Dahoui, 2023). This also improves downstream applications, such as weather prediction, and contributes to providing high-quality datasets for ML model training (Mohammed et al., 2025; Spohn et al., 2026).

Concrete implementations, which are well summarized in (Spohn et al., 2026), illustrate this progression. MeteoSwiss has developed a plausibility rating system that evaluates how reliable data are by comparing automated data quality checks with expert judgements and translating the results into confidence score, which can be used to select data according to the accuracy level desired by users (MeteoSwiss, 2024; Sigg et al., 2020). ECMWF has also implemented ML models, including Long Short-Term Memory (LSTM) autoencoders algorithm, to detect both short-term anomalies and long-term sensor drift in both satellite and in situ observation data. The system combines these outputs with a classification model to categorize the severity of detected data quality issues (Dahoui, 2023).

3.3.2 Real-time severe event detection

Many severe phenomena, such as tornadoes, severe storm, and flooding develop rapidly and occur at spatial scales that remain difficult to predict accurately in advance, highlighting the importance of real-time or near real-time detection of hazard signatures for warnings, rather than direct prediction. Real-time severe event detection focuses on identifying hazardous weather as it develops, providing critical situational awareness on which timely warnings depend. Traditionally, forecasters monitor radar and satellite imagery alongside surface observations, supported by rule-based algorithms that flag predefined thresholds. These include features such as strong radar reflectivity cores, echo-top structures, and rapid cooling of cloud-top temperatures observed from geostationary satellites, which indicate strong convective updrafts and storm intensification (Murillo & Homeyer, 2019; Rosenfeld et al., 2008).

ML enhances this process by identifying characteristic signatures of severe weather directly from high-volume observational data and by automating this process for operation in real-time. Rather than relying solely on preset thresholds, ML models can learn complex relationships among various data sources such as radar and satellite, allowing them to recognize combinations of patterns associated with hazardous conditions (McGovern et al., 2023). By extracting relevant features from large observational datasets and continuously analysing incoming data streams, these approaches enable near-real-time identification of developing severe weather systems. This supports faster and more consistent detection of emerging threats, helping early warning services issue alerts with greater confidence and timeliness.

Operational and near-operational examples span multiple severe weather types. In the United States, NOAA's National Severe Storms Laboratory (NSSL) is developing and testing the New Tornado Detection Algorithm (NTDA), which applies ML techniques trained on historical Doppler radar observations and confirmed tornado events to estimating probability of tornado presence by identifying complex storm-rotation signatures, helping forecasters identify tornado-producing storms and associated severe weather signatures more effectively (NOAA National Severe Storm Laboratory, n.d.; Sandmæl et al., 2023). Moreover, NASA has published an open-source software that uses ML methods to automatically detect severe convective storm cloud-top features—such as overshooting tops and above-anvil cirrus plumes—from geostationary satellite (Cooney et al., 2025). In a similar manner, flood detection from earth observation is supported by ML workflows that classify water and inundation extent from satellite imagery to enable timely rescue operations, as documented by UN-SPIDER in its compilation of flood detection and mapping ML applications (UNOOSA, n.d.).

3.3.3 Weather nowcasting

Nowcasting refers to very short-range weather forecasting, typically covering the period from 0 to 2 hours (WMO, 2024b). This specialized field provides a high-resolution description of the atmosphere's current state and its evolution over the immediate term. Because hazardous phenomena—such as intense convective rainfall, severe thunderstorms, and flash floods—can develop with extreme speed, robust nowcasting capabilities are considered a critical component of integrated EWS to support real-time protective actions and decision-making (Sun et al., 2014). Traditionally, weather nowcasting combines radar-based extrapolation with statistical modelling techniques. Radar observations are used to track the motion of precipitation systems, often through object tracking or motion-vector estimation, after which these movements are projected forward in time (Germann & Zawadzki, 2002; Seed, 2003). Statistical relationships derived from past events may also be applied to estimate short-term growth or decay, providing a baseline for short-range guidance. While effective for steady, organized systems, these approaches are less effective when storms intensify quickly, initiate suddenly, or interact in complex ways that exceed the assumption of simple extrapolation methods (Sun et al., 2014).

ML approaches treat weather nowcasting as a spatiotemporal sequence prediction task, learning the evolution of precipitation systems directly from sequences of observational data such as radar imagery. Deep learning architectures such as Trajectory-based Recurrent Neural Networks have been developed to model the motion and transformation of precipitation structures in time and space (Shi et al., 2017). Rather than relying solely on motion-based extrapolation, ML systems can better anticipate structural changes and nonlinear development in storms, improving representation of processes such as convective initiation and rapid storm intensification (Ravuri et al., 2021). It should be noted that many of the same analytical and ML techniques used for severe weather detection in observations can also be applied to nowcast or forecast fields to identify hazardous conditions expected to develop in the near future (Guastavino et al., 2022).

The following example cases demonstrate promising added values of ML application in nowcasting. MeteoSwiss has developed COALITION-4 algorithm, which integrates ML into an operationally oriented setting to improve thunderstorm nowcasting by combining satellite, radar, and lightning data (MeteoSwiss, 2024). The Hong Kong Observatory (HKO) has pioneered the use of ML for precipitation nowcasting, with its research on TrajGRU and the HKO-7 dataset setting international benchmarks for radar-based ML models (Hong Kong Observatory (HKO), n.d.; Wong, 2025). HKO, which also serves as a WMO Regional Specialized Meteorological Centre (RSMC), also operates ML-driven nowcasting and provides the product on their web-portal under the WMO framework (see Box 8). Similarly, The Korean Meteorological Administration (KMA) has been operating NowAlpha, which is a radar-only precipitation nowcasting system, since May 2025 (WMO, 2025c). Furthermore, Met Office of the United Kingdom has collaborated with Google to develop AI models for precipitation nowcasting using radar observations. Evaluated by forecasters, these models have demonstrated promising ability to capture realistic storm intensity and structure compared with traditional nowcasting methods (Ravuri et al., 2021). Finally, Google's recent operational global machine learning nowcasting model, leverages the Global Precipitation Mission's CORRA dataset, geostationary satellite data, and global NWP data to predict precipitation for the next 12 hours (Agrawal et al., 2025).

Box 8. AI-Enabled Nowcasting and Capacity Development in Southeast Asia

Developing countries in Southeast Asia, as well as Least Developed Countries (LDCs) and Small Island Developing States (SIDS), face persistent gaps in severe-weather monitoring and forecasting due to limited observational networks, constrained data-exchange capacity, and insufficient computational infrastructure, making it difficult to capture rapidly evolving convective storms, monsoonal heavy rainfall, and tropical cyclones that drive flash floods and coastal inundation. To address these challenges, the Regional Specialized Meteorological Centre for Nowcasting hosted by the Hong Kong Observatory provides an integrated suite of artificial-intelligence and machine-learning nowcasting products, open-source tools, and capacity-building support. The platform combines operational AI nowcasting products delivered through the RSMC web portal, an upgraded community version of the Hong Kong Observatory's nowcasting system (Community-Short-range Warning and Integrated Radar Likelihood System, Com-SWIRLS) featuring deep-learning precipitation modules, and extensive training through programmes such as the World Meteorological Organization Severe Weather Forecasting Programme for Southeast Asia. Newly launched AI satellite-based convective nowcasting and automatic tropical cyclone analysis (updated every ten minutes) represent the first deep-learning nowcast products available from World Meteorological Organization Integrated Processing and Prediction System (WIPPS) designated centres, offering guidance up to eight hours ahead and demonstrating clear skill improvements over traditional extrapolation methods. Importantly useful guidance can still be provided in radar sparse regions. The community version of HKO nowcasting software is available for free to facilitate development of a nowcasting system in other NMHSs and several NMHSs have already been using the software modules. Training workshops or in-house attachment programme have been organized on technical and training supports that they would continue to facilitate adapting the nowcast techniques including the AI nowcasting algorithms for enhancing forecast and warning operation for EW4All development.

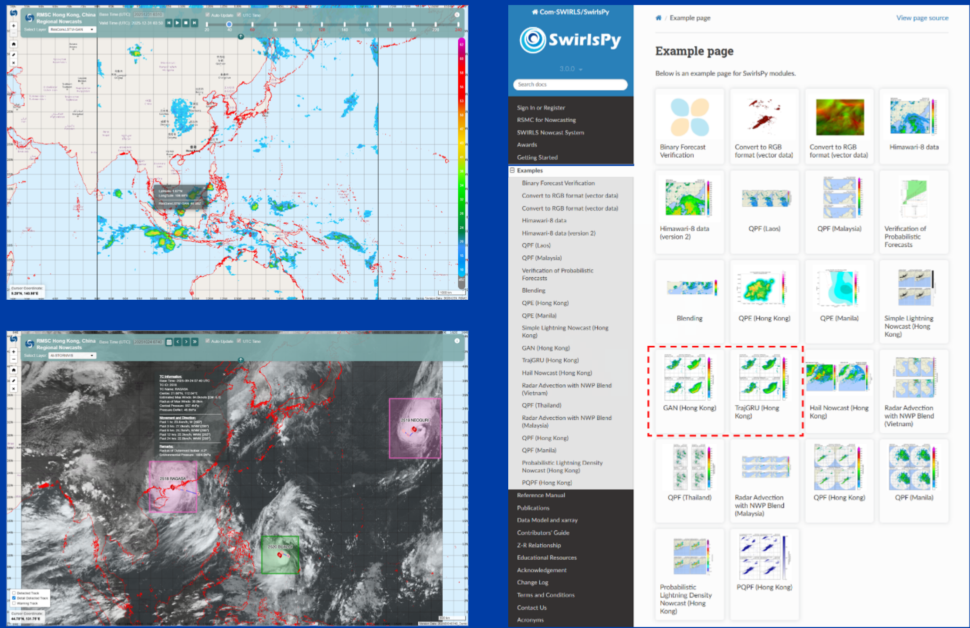


Figure 9. (Upper left) AI-based nowcasting products on RSMC Hong Kong website: deep learning nowcast of satellite derived reflectivity (upper); and automatic tropical cyclone location and intensity analysis (lower left). (Right) New release of the community version of HKO nowcasting software featuring the two deep learning nowcast modules (box in red dashed line).

Further information: https://rsmc.hko.gov.hk
The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by ITU, WMO, UNDRR and IFRC.

3.3.4 Numerical weather prediction

Numerical weather prediction (NWP) is the foundation of modern weather forecasting and underpins most early warning systems worldwide. Developed and progressively refined since the 1950s, NWP combines observations from satellites, radar, and surface stations through data assimilation to produce a physically consistent estimate of the atmospheric state. This initial condition is then integrated forward in time using the governing equations of atmospheric physics to simulate how weather systems evolve. The approach provides the basis for daily forecasts, hazard outlooks, and severe weather guidance. However, running these models is extremely computationally demanding: high-resolution simulations and ensemble forecasts require powerful supercomputing infrastructure, meaning that operating a full NWP system remains feasible only for a limited number of countries and major forecasting centres.

Recent advances in ML are beginning to complement this framework. Instead of solving the governing physical equations directly, ML models learn statistical relationships governing atmospheric evolution from large historical reanalysis datasets, spanning decades of observation. Once trained, these models can generate global forecasts in seconds rather than hours, dramatically reducing computational cost and enabling more frequent updates (e.g. AI Forecasting System (European Centre for Medium-Range Weather Forecasts, 2024, GraphCast (Lam et al., 2023), and Pangu-Weather (Bi et al., 2023). Operational deployments are now emerging: ECMWF has made its AI model AIFS operational alongside its traditional Integrated Forecasting System, using the same physics-based initial conditions while delivering significant efficiency gains (see Box 9). Similarly, the Israel Meteorological Service reports operational use of NVIDIA's Earth-2 (NVIDIA, 2024). Finally, NOAA has also introduced Project EAGLE (Experimental AI Global and Limited-area Ensemble forecast system), an initiative designed to help both NOAA and the wider weather community quickly evaluate, refine, and showcase AI models for global and regional ensemble forecasting in near real time to identify the most promising AI advances efficiently (NOAA, 2025).

It is important to note that the reanalysis datasets on which most current AI forecasting models are trained blend observational data with physics-based numerical weather prediction through data assimilation, a process used to produce a spatially complete and physically consistent reconstruction of the atmosphere despite gaps and inconsistencies in raw observations. As a result, these models retain a latent dependence on traditional modelling frameworks. Emerging research is exploring new paradigms that train AI systems more directly on observational datasets (for example through initiatives such as ECMWF's Artificial Intelligence–Direct Observation Prediction (AI-DOP), see (McNally et al., 2025) aiming to reduce reliance on physics-based pipelines while maintaining physically consistent forecasts. At the same time, recent literature highlights that purely data-driven approaches remain fundamentally constrained by the information content of historical observations and may struggle to generalise to unprecedented conditions, reinforcing the continued importance of physically based modelling frameworks for robust forecasting (Smith & Thorpe, 2026).

Box 9. Operational AI Weather Forecasting at ECMWF

Recent advances in machine learning have enabled the development of data-driven weather forecasting models that complement traditional numerical weather prediction. The Artificial Intelligence Forecasting System (AIFS) developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) represents one of the first operational implementations of this approach. Unlike physics-based models such as ECMWF's Integrated Forecasting System (IFS), which explicitly solve the governing equations of atmospheric dynamics, AIFS learns the evolution of atmospheric states directly from historical datasets, including ERA5 reanalysis and operational analyses. The model uses a hybrid deep-learning architecture combining graph neural networks and transformer attention mechanisms to represent spatial relationships across the global atmosphere and produce forecasts at six-hour intervals that can be rolled forward to generate medium-range predictions. Evaluations show that AIFS produces highly competitive forecasts for upper-air circulation and surface variables while requiring far less computational power than traditional NWP systems, enabling a 10-day global forecast to be generated within minutes on a single GPU (Lang et al. 2024a; Lang et al., 2024b)

Building on these developments, ECMWF reached a significant milestone in 2025 by introducing AI-based forecasts into its operational forecasting suite, running alongside the traditional physics-based models used by meteorological services worldwide. The first operational configuration, AIFS Single, provides deterministic global forecasts that complement existing guidance for medium-range weather prediction and hazard monitoring (ECMWF, 2025a). ECMWF has subsequently extended this approach toward probabilistic ensemble forecasting through AIFS-ENS, which generates multiple forecast realizations to quantify uncertainty and improve risk-based decision-making (Lang & Magnusson, 2025). The operational deployment of both deterministic and ensemble AI forecasts marks an important step in integrating machine-learning models into real-world forecasting workflows and highlights the growing role of hybrid AI–physics approaches in global weather prediction.

Further information:
https://www. .int/en/about/media-centre/news/2025/ecmwfs-ai-forecasts-become-operational
https://www.ecmwf.int/en/newsletter/185/earth-system-science/aifs-ens-becomes-operational

3.3.5 Example Hazard 1: Tropical cyclone track and intensity forecasting

Tropical cyclones, also known as hurricanes in the Atlantic and eastern Pacific and typhoons in the northwestern Pacific, are among the most destructive weather hazards globally. These large rotating storm systems form over warm ocean waters and can produce extreme winds, heavy rainfall, storm surges, and coastal flooding. Each year they cause significant loss of life and economic damage, particularly in coastal regions and small island developing States (SIDS). Accurate forecasts of cyclone track and intensity are therefore critical for early warning, evacuation planning, and disaster preparedness. While NWP models have steadily improved track forecasts, predicting storm intensity, especially rapid intensification, remains a major operational challenge because it depends on complex air–sea interactions and small-scale storm dynamics that global models struggle to resolve.

Two main machine-learning approaches exist: global AI weather models that predict hurricanes as part of a full atmospheric forecast, and specialized AI models built specifically to predict cyclone behaviour.

Global AI weather models, such as those discussed in the previous section, also simulate tropical cyclones as part of their full atmospheric forecasts. This approach retains the advantages described earlier, including the rapid generation of forecasts and the ability to produce large ensembles at comparatively low computational cost. Because tropical cyclone movement is largely controlled by large-scale atmospheric steering flows, global AI models can reproduce storm tracks with high accuracy while producing forecasts much faster than conventional numerical models. However, predicting storm intensity remains more challenging, as the small-scale processes that govern intensification, such as eyewall dynamics and air–sea heat exchange, are harder for global AI models to capture. Recent evaluations with AIFS confirm that while track forecasts are strong, intensity prediction still lags behind physics-based models (Philippé et al., 2026).

A second approach develops machine-learning models built specifically for tropical cyclone forecasting, using satellite observations, environmental variables, and historical storm datasets to directly predict cyclone track, intensity, and rapid intensification probabilities. Recent experimental work by Google and has demonstrated AI systems capable of jointly predicting tropical cyclone track and intensity with skill often outperforming leading operational models (Google DeepMind and Google Research, 2025), see Box 10). This specialized model shows particular promise for detecting precursors of rapid intensification and generating probabilistic forecasts that complement traditional NWP guidance. For example, during Hurricane Melissa in October 2025, AI-driven predictions provided early indications of rapid intensification that helped refine operational forecasts alongside conventional models (NOAA, 2025).

Box 10. AI-Supported Probabilistic Forecasting for Tropical Cyclone Hazards

The National Hurricane Center (NHC) of the United States routinely evaluates new forecasting guidance to improve tropical cyclone track and intensity predictions. Official forecasts are produced by synthesizing multiple NWP models together with observational data, and verification analyses show that consensus guidance derived from multiple models generally performs better than individual model forecasts. As part of the ongoing evaluation of emerging forecasting approaches, NHC has examined experimental ML–based guidance alongside conventional dynamical models. One example is an experimental ML tropical cyclone ensemble forecasting system developed by Google, which generates probabilistic predictions of storm track and intensity by producing up to 50 ensemble forecast scenarios. The model is based on the methodology introduced in (Alet et al., 2025) and trained on global reanalysis data and fine-tuned on key historical information about the track, intensity, size and wind radii of nearly 5,000 observed cyclones from the past 45 years.

During Hurricane Melissa in October 2025, this experimental guidance included forecasts from a ML tropical cyclone ensemble model developed by Google. The model's ensemble predictions were evaluated alongside conventional dynamical forecast models. Forecast discussions and subsequent analyses indicated that a large portion of the Google ensemble members projected that Melissa could intensify to Category 5 strength, highlighting the possibility of extreme intensification and providing additional probabilistic guidance on storm evolution. While these results are promising, operational experience during the season highlighted important limitations; many experimental systems, including emerging AI-based guidance, remain under active development and were not consistently available in time for routine operational use, indicating that further development is needed before full operational integration.

Further information:
https://www.nhc.noaa.gov/pdf/NHC_Verification_Report_2025_Preview.pdf
https://www.nhc.noaa.gov/data/tcr/AL132025_Melissa.pdf
https://deepmind.google/blog/how-were-supporting-better-tropical-cyclone-prediction-with-ai/
https://www.brightband.com/blog/how-did-google-deepmind-perform-for-hurricane-melissa

3.3.6 Example hazard 2: flood forecasting

Floods are among the most widespread and recurrent natural hazards, affecting river basins, urban areas, and coastal zones across all regions. Accurate and timely flood forecasts are central to effective early warning services, particularly in densely populated or low-lying regions and in mountain environments where exposure is high and lead times may be limited. Similar to weather forecasting, flood forecasting has traditionally relied on physically based hydrological and hydraulic models driven by meteorological inputs (WMO, 2018). While these models provide important process understanding, they can be computationally demanding and sensitive to calibration and data availability, particularly in data-sparse or ungauged basins. It should also be noted that compared with global weather forecasting, physics model-based global flood forecasting remains more challenging due to the complexity and diversity of hydrological processes, limited observations of river basins, and uncertainties in representing runoff generation and flood mechanisms across different landscapes (Brunner et al., 2021; Samadi et al., 2025).

ML is increasingly used to complement these systems by learning rainfall–runoff relationships directly from large observational archives and regional datasets. Large-sample hydrology studies have shown that deep learning models such as LSTMs can match or outperform traditional conceptual rainfall–runoff models across diverse catchments (Kratzert, et al., 2019a; Kratzert, et al., 2019b). This work explored how integrating basin attributes and additional hydrological information can improve robustness and provide insight into the internal behaviour of these models, suggesting that LSTMs can learn representations consistent with key processes such as storage and hydrological memory (Kratzert, et al., 2019b; Lees et al., 2021). By the time of writing, versions of these LSTM models adapted for operational environments have been integrated into Google's Flood Hub which provides 7-day forecasts for 150+ countries (Google Research, 2025), see Box 11).

Box 11. AI Driven Flood Forecasting for Anticipatory Action

Floods are the world's most common disaster stemming from natural hazards, causing thousands of fatalities and disrupting millions of lives annually. Timely predictions are essential to empower governments and humanitarian organizations to strengthen early warning systems and implement Anticipatory Action programmes—taking protective measures before disaster strikes to save lives and livelihoods.

Google Research has used AI to develop scalable flood forecasting models that provide riverine flood predictions up to seven days in advance. A key breakthrough is the ability to support data-scarce regions, by using virtual gauges to infer flood risk where physical data is unavailable (Nearing et al., 2024). Today, Google's system provides coverage for over two billion people during major riverine flood events, with forecasts accessible via Google's Flood Hub and API.

In Kogi State, Nigeria, GiveDirectly partnered with Google to pilot an anticipatory cash transfer program. AI-generated flood forecasts triggered payments 48–72 hours before expected flooding, enabling over 3,250 households to evacuate safely and protect their assets. The result was a 90% reduction in food insecurity and significantly improved household resilience.

In a major step towards national disaster resilience, Nigeria launched its first large-scale AI-driven Flood Anticipatory Action Program (OCHA, 2025), led by the United Nations Office for the Coordination of Humanitarian Affairs and the UN Country Team in collaboration with the national government. The programme integrated multiple data sources into a unified trigger mechanism. When flood risk thresholds were met, pre-defined actions were automatically activated, such as aid distribution, shelter preparation, and livestock support.

Together, these advancements show how AI-driven flood forecasting, when combined with strong local partnerships, can transform disaster preparedness—shifting the focus from reactive response to proactive, life-saving action.

More information:
https://sites.research.google/gr/floodforecasting/

3.3.7 Example hazard 3: geophysical hazards

Although the primary focus has been on hydrometeorological hazards, we make a brief reference here to AI related developments within the monitoring of geological and other environmental hazards in the spirit of advancing towards fully Multi-Hazard Early Warning Systems (MHEWS). In the geophysical realm, the primary challenge lies in detecting precursor signals, such as millimetre-scale ground deformation or micro-seismic tremors, within massive, high-dimensional datasets characterized by significant environmental and instrumental noise. Satellite-based Interferometric Synthetic Aperture Radar (InSAR) can measure millimetre-scale surface deformation associated with earthquakes, volcanoes, and landslides, but the analysis of large volumes of interferometric data is computationally demanding and historically relied on labour-intensive manual interpretation (Anantrasirichai et al., 2018; Gaddes et al., 2018). Similarly, modern seismic monitoring networks generate continuous streams of waveform data, and the rapid detection and characterization of earthquake signals within these large datasets is challenging for traditional detection approaches, motivating the development of automated analysis methods (Perol et al., 2018).

Increasingly, ML techniques are being explored to complement traditional physics-based and statistical approaches across this geophysical hazard spectrum, in particular earthquakes and landslides. For example, deep learning models are used for seismic phase detection, enabling rapid magnitude estimation from noisy continuous data (Kubo et al., 2024). For landslides monitoring and forecasting, ML classifiers have been applied to integrate environmental predictors such as rainfall, terrain characteristics, and soil moisture conditions to estimate landslide susceptibility or generate rapid hazard assessments following triggering events (Kuradusenge et al., 2020; Mondini et al., 2023; Singh & Tyagi, 2024). Similar to hydrometeorological applications, ML approaches do not replace established methods but rather complement them by extracting patterns from large, heterogeneous observational datasets, improving anomaly detection, and supporting probabilistic risk assessment in near-real time (Mousavi & Beroza, 2023).

Operational examples include the use of ML operational seismic monitoring. The Southern California Seismic Network has implemented the deep-learning phase picker PhaseNet within its near-real-time event processing pipeline. The system replaces traditional phase-picking algorithms, producing two to three times more phase picks and improving earthquake location accuracy while reducing analyst workload in operational monitoring (Tepp et al., 2025). Another operational use is for landslide identification. During Hurricane Melissa in 2025, NASA and the U.S. Geological Survey used the Landslide Hazard Assessment for Situational Awareness (LHASA) system to estimate landslide risk across Jamaica. LHASA applies machine-learning models, trained on historical landslide inventories and environmental predictors to combine satellite-derived rainfall with terrain information. The system generated near-real-time hazard maps that supported rapid identification of areas likely affected by rainfall-triggered landslides (NASA, 2025; Stanley et al., 2021).

3.3.8 Post-processing and guidance

Post-processing is the stage where raw model forecasts are translated into products that can be directly used by forecasters, emergency managers, and the public (Vannitsem et al., 2018). Post-processing ensures that forecasts are consistent, calibrated, and relevant for decision-making. Traditionally, this work has relied on statistical techniques such as Model Output Statistics (MOS), regression methods, and ensemble calibration. These approaches correct systematic model biases, adjust forecast probabilities, and adapt coarse model output to specific locations. However, many traditional statistical post-processing techniques rely on relatively simple relationships between predictors and observations and may struggle to capture complex or nonlinear error patterns, particularly for extreme events or long-range forecasts (Vannitsem et al., 2018, 2021).

Machine learning can enhance forecast post-processing. (Chantry et al., 2021) describe such applications as examples of "Medium AI," where machine learning methods augment rather than replace NWP systems. In this context, ML can learn relationships between historical forecasts and observations to support tasks such as bias correction, downscaling model output to specific locations, improving the representation of forecast uncertainty, and automating feature detection for severe events. These applications extend traditional statistical post-processing approaches while allowing more flexible use of large meteorological datasets.

Operational implementation is becoming part of the activities of major meteorological centres. At the Met Office in the United Kingdom, ML is already used operationally within the BestData post-processing system to improve site-specific temperature forecasts (Met Office, n.d., 2022). At Germany's Deutscher Wetterdienst (DWD), machine-learning post-processing is being explored to correct biases and blend forecasts from two regional models, ICON-RUC (optimized for very short-range convection forecasts up to about 14 hours) and ICON-D2 (providing forecasts up to about 48 hours), into a seamless probabilistic precipitation forecast (Schubert & Primo, 2025). The Bureau of Meteorology in Australia also casts RainForests, a ML technique for calibrating ensemble rainfall forecasts in their operation (Trotta et al., 2024). At longer forecast horizons, machine learning has also been applied to the post-processing of global ensemble forecasts from the ECMWF Integrated Forecasting System at medium-range lead times of several days, improving the calibration and probabilistic skill of ensemble predictions (Bouallègue et al., 2024). At the subseasonal-to-seasonal scale (weeks to months), the WMO S2S AI Challenge further demonstrated that machine-learning post-processing of numerical model forecasts can outperform standard bias-corrected reference forecasts for temperature and precipitation at weeks 3–4 and 5–6 (Vitart et al., 2022).

3.3.9 Climate model parameterization and emulation

Climate change is altering the frequency and intensity of many hazards, making robust climate projections essential for interpreting changing hazard baselines in forecasting and warning systems and for supporting adaptation planning. While comprehensive Earth system models provide physically grounded projections, they are computationally expensive and rely on parameterizations to represent processes that occur at scales smaller than the model grid. AI/ML is addressing these limitations through two primary pathways: improving the representation of unresolved physical processes and emulating broader aspects of full climate model behaviour.

The first pathway concerns AI-based parameterization of subgrid processes. Many important atmospheric and oceanic phenomena, such as convection, cloud microphysics, and turbulent mixing, cannot be resolved explicitly in global climate models and must instead be approximated. In this approach, ML models are trained on high-resolution simulations or observational datasets to learn these process relationships and are then embedded within physically based general circulation models to replace or augment traditional parameterization schemes. Studies have demonstrated that neural networks can reproduce key aspects of convection and cloud processes within climate models (Brenowitz & Bretherton, 2018; Gentine et al., 2018). These hybrid approaches aim to improve physical fidelity while potentially reducing computational cost, though careful validation is required to ensure stability and physical consistency.

The second pathway involves climate model emulation, in which AI systems are trained on outputs from physically based models to approximate their large-scale behaviour at much lower computational cost. Such emulators can reproduce patterns of temperature and precipitation across scenarios and are particularly useful for expanding ensemble size, accelerating scenario testing, and supporting probabilistic risk analysis (Watson-Parris, 2021). Recent work has demonstrated probabilistic and lightweight emulators capable of reproducing key climate variables and enabling very large ensembles at substantially reduced computational cost (Cachay et al., 2024; Duncan et al., 2024; Guan et al., 2025). While emulators do not replace comprehensive Earth system models, they offer a complementary tool for exploring uncertainty and enabling more rapid assessment of long-term hazard risk.

Taken together, these approaches illustrate how AI is currently being integrated into climate modelling primarily through hybrid methods and model emulation. However, it is important to emphasize that, despite these advances, fully AI-based climate simulation systems capable of replacing comprehensive Earth system models do not yet exist (see Box 12).

3.3.10 Overarching opportunities

The following are a selection of overarching opportunities that apply across the individual case studies discussed previously, highlighting systemic ways AI can strengthen hazard monitoring and forecasting.

Accelerated research-to-operations cycles
AI-based systems have demonstrated a markedly shorter research-to-operations cycle than traditional models. Global models such as GraphCast, Pangu-Weather and ECMWF's AIFS progressed rapidly from research and development-based demonstration to real-time evaluation within a few years.

Box 12. AI-based Climate Simulation – The Grand Challenge

Climate simulation aims to reproduce the long-term behaviour of the Earth system by numerically solving the physical equations governing atmospheric and ocean circulation and their interactions with land, ice, and biogeochemical processes. Modern Earth System Models integrate these components to simulate climate variability and change over decades to centuries. Unlike weather forecasting models, which aim to predict the specific state of the atmosphere over hours to days, climate simulation seeks to reproduce the statistical behaviour of the climate system over decades or longer and must represent many additional physical processes, such as ocean circulation, land–atmosphere interactions, and biogeochemical cycles, that are not typically included in weather forecasting models (Pan et al., 2025).

At present, no fully AI-based climate simulation system exists that can replace comprehensive, physically based Earth system models. The complexity of the climate system poses major challenges for purely data-driven approaches. Climate models must remain numerically stable over very long integrations, respect physical conservation laws, and represent feedback processes, such as cloud–radiation interactions, that may only become apparent over decades (Reichstein et al., 2019). In addition, training data for climate applications are limited. While the observational record contains hundreds of thousands of individual weather samples that can be used to train AI weather models, it spans only a few decades in total, yet many crucial climate phenomena, such as ocean circulation variability or long-term climate trends, only become apparent over several decades.

Nevertheless, an emerging line of research is exploring whether neural networks can learn aspects of climate dynamics directly from data. One recent example is NeuralGCM (Kochkov et al., 2024), a hybrid modelling framework that combines a differentiable atmospheric dynamical core with neural-network representations of unresolved physical processes. Trained using reanalysis data, the model can generate skilful weather forecasts and simulate aspects of atmospheric climate behaviour, including seasonal cycles and storm statistics, while using substantially less computational power than traditional models.

Despite these promising results, important limitations remain. Current AI-based models typically simulate only the atmosphere rather than the full Earth system, rely on prescribed boundary conditions such as sea-surface temperatures, and struggle to generalize to substantially different climate states, particularly when responding to external forcings not represented in the training data (e.g. large CO_2 changes or volcanic perturbations), for which robust evaluation and verification frameworks remain an open challenge.[1] Even hybrid approaches can exhibit numerical instability or climate drift during long simulations, and key feedback processes remain difficult to learn from relatively short training datasets. As such, AI-driven climate simulation remains a research frontier rather than an operational alternative to established Earth system modelling frameworks.

[1] *The field is rapidly evolving, with emerging efforts toward fully coupled AI-based Earth system models, such as SamudrACE, which simulate both the atmosphere and ocean but are currently trained on climate model output rather than reanalysis data (Duncan et al., 2026). Generalizability across climate states is explored with AI atmosphere models such as LUCIE-3D, which can reproduce responses to prescribed warming ocean conditions, although their performance degrades outside the range of ocean temperatures represented in reanalysis data (Guan et al., 2025).*

Within WMO, this accelerated pathway is reflected in the use of dedicated WIPPS pilot projects designed to test AI-based Earth System Prediction tools in operational environments. One example is the AI for Nowcasting Pilot Project (AINPP), which evaluates the skill of AI-based nowcasting products through international intercomparison and explores pathways for real-time dissemination and technology transfer to operational services (see Box 13). Additional initiatives extend this approach to longer forecasting timescales. The ECMWF–WMO AI Weather Quest project aims to establish an open, standardized framework for evaluating AI-based sub-seasonal to seasonal forecasting systems while fostering collaboration between NMHSs, researchers, and the private sector (Loegel et al., 2025; ECMWF, n.d.). Complementary work is underway in hydrology, where pilot projects on global riverine flood prediction are examining how hybrid physics–AI systems can be integrated into operational workflows and EWSs. Together, these pilots provide structured environments for real-time experimentation with AI forecasting technologies without requiring immediate replacement of existing operational systems.

Box 13. AI-Enabled Nowcasting for High-Impact Weather in Developing Countries

Across many developing countries, rising losses from extreme weather coincide with limited observation networks and constrained computational capacity, making traditional numerical weather prediction difficult to operate and sustain. To address the need for accurate, affordable, and operationally feasible short-term forecasting, the WMO-led AI for Nowcasting Pilot Project (AINPP) is advancing deployable AI-based systems designed for 0–6-hour prediction of rapidly evolving hazards such as intense rainfall, lightning, dust storms, flash floods, and severe convection. Regional intercomparisons conducted across Africa, Asia, and Latin America have evaluated multiple AI nowcasting algorithms, identifying models with proven skill and operational value; these validated systems are now being deployed in selected target countries. The approach uses deep learning trained on historical radar, satellite, and lightning observations to detect storm development and predict convective hazards in the next minutes to hours. Because these models operate with lower computational requirements and make efficient use of satellite data, they are well suited to data-sparse and resource-limited environments. AINPP aims to integrate AI outputs directly into NMHS workflows, providing near-real-time guidance on storm evolution, intensity, and location. An open-source “nowcasting-in-a-box” toolkit is under development to enable countries to deploy validated AI capabilities using locally available data. The initiative is supported by WMO, participating NMHSs, research institutions such as NCAR, the University of Leeds, RIKEN, and INPE, and selected private-sector partners including Microsoft, Google, and NVIDIA. Early results demonstrate validated AI models, standardized verification methods, and strengthened national capacity through pilot deployments and training. Designed for scalability, AINPP's open-source tools, operational guidelines, and emerging Standard Operating Procedures—such as those developed in Southern Africa under WISER-EWSA—provide a pathway for national and regional replication aligned with the Early Warnings for All initiative.

Further Information:
WMO AI for Nowcasting Pilot Project (AINPP): https://www.ainpp.org/
WMO AINPP Asian Nowcasting Intercomparison: https://www.wmc-bj.net/ainpp/evaluation/objective_metrics/index.html
AINPP Intercomparison for Africa https://ml-env-for.leeds.ac.uk/ainpp/

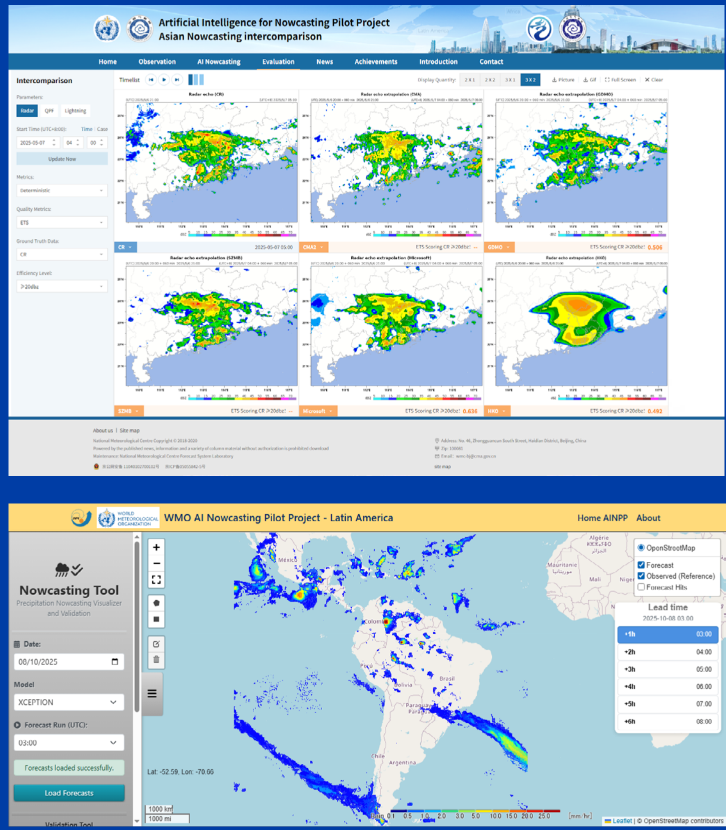


Figure 10. Artificial Intelligence for Nowcasting Pilot Project. (Top) Regional intercomparison in Asia for radar. (Bottom) Regional product in Latin America.

The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by ITU, WMO, UNDRR and IFRC.

Democratizing access to advanced forecasting capabilities
One of the most significant opportunities associated with AI is its potential to democratize access to advanced forecasting capabilities. Operating high-resolution NWP systems requires substantial scientific expertise, sustained institutional capacity, and access to high-performance computing infrastructure. As a result, the ability to develop, run, and continuously upgrade national forecasting models remains concentrated in a relatively small number of well-resourced countries. Many NMHSs, particularly in lower-income countries, therefore rely primarily on guidance products generated by global or regional centres to support their operational forecasting activities (WMO, 2025a, 2025b).

AI-based forecasting systems may help reduce some of these barriers. While training such models requires large datasets and significant computational resources, once trained they can generate forecasts rapidly and at much lower computational cost. This creates the possibility that advanced forecasting guidance could be distributed and run locally by NMHSs without the need for large national high-performance computing facilities, potentially enabling countries to leapfrog directly to more advanced forecasting capabilities (WMO, 2025a, 2025b).

A concrete example is the WMO CREWS pilot project in Malawi, Africa, where the Bris AI weather prediction model, developed between Met Norway and ECMWF (Nipen et al., 2026), was deployed and being demonstrated by the Malawi Department of Climate Change and Meteorological Services (DCCMS) through the Forecast-in-a-Box framework to enable the national weather service to run AI-based forecasts on modest infrastructure (WMO, 2025c). While still at the pilot stage, the initiative demonstrates that AI-based systems can be adapted to national contexts and operated locally, offering a practical pathway toward strengthening national forecasting capabilities. Further evaluation and scaling will determine how such approaches can be expanded more broadly.

Faster and more frequent forecasts
As discussed, AI enables rapid generation of forecasting guidance, often producing multi-day forecasts in minutes rather than the hours typically required for high-resolution NWP. This reduced runtime creates opportunities for more frequent forecast cycles, rapid re-initialization when new observations become available, and larger exploratory ensemble generation to assess uncertainty.

For operational services, such capabilities can be particularly valuable during rapidly evolving events such as tropical cyclones, severe convective outbreaks, or flash floods. Faster model turnaround allows forecasters to compare updated scenarios, monitor shifts in track or intensity guidance, and assess uncertainty more dynamically. In time-critical situations, this can support earlier identification of risk escalation and more timely warning updates.

Integration across heterogeneous datasets and its promise for MHEWS and impact-based forecasting
AI is helping integrate heterogeneous observational datasets that differ in spatial coverage, resolution, and uncertainty. Several of the operational examples discussed earlier such as MeteoSwiss's COALITION-5 and HKO's AI nowcasting framework illustrate this capability. Similar data-fusion approaches underpin AI flood forecasting systems, which combine satellite imagery, meteorological inputs, and hydrological data to generate predictions even in basins with limited ground observations. In the geophysical domain, this integration involves combining fundamentally different data types, including satellite-based InSAR measurements of surface deformation, continuous seismic waveform data, and environmental predictors such as rainfall, terrain, and soil moisture used for landslide monitoring.

Looking ahead, these developments point toward a broader promise: the emergence of AI systems that learn directly from and integrate across the full spectrum of Earth observations, representing an important step toward more unified Earth system modelling (Reichstein et al., 2025) and the realization of truly integrated multi-hazard early warning systems (MHEWS). This observation-first paradigm is beginning to emerge for example in meteorology, where models are increasingly trained directly on observations rather than on reanalysis products that blend observations with physical modelling through data assimilation. For example, ECMWF's Data-driven Observation Prediction initiative explores learning forecast relationships directly from raw observational datasets such as satellite radiances, radar measurements, and surface observations (McNally et al., 2025). This is particularly relevant for forecasting across longer timescales, such as sub-seasonal prediction, where predictability depends on interactions across Earth system components including soil moisture, ocean conditions, snow cover, and land–atmosphere coupling, requiring models that can synthesize information across these disparate observations (Robertson & Vitart, 2018). Extending such approaches to incorporate a broader range of observations, including oceanic and geophysical datasets, will be an important step toward fully integrated Earth system models.

At the same time, the evolution toward impact-based forecasting and warning services will require combining geophysical hazard predictions with socioeconomic exposure and vulnerability information in order to translate forecasts into actionable risk information for decision-makers (WMO, 2015, 2021a), and discussions in Chapter 2 AI for Disaster Risk Knowledge). AI methods are promising for these tasks because they can learn relationships across diverse data streams. An interesting emerging trend in this direction extracts signals from non-traditional data streams such as social media posts, which can act as "geo-sensors" providing real-time observations during disasters and helping fill gaps where traditional monitoring systems are limited (Hameed et al., 2025; Saengtabtim et al., 2025). Similarly, approaches such as Groundsource show how large-scale analysis of news data can generate high-resolution records of flood impacts, providing complementary ground-based evidence for model training and validation in contexts where such systematic global records are currently lacking (Mayo et al., 2026).

3.4 Where do we go from here? - From research & development to action: requirements and challenges, and the role of the international community

The recent advances in AI for hazard detection, observation, monitoring, analysis, and forecasting mark an important moment for EWSs. However, the transition from research and development progress to sustained operational impact is neither automatic nor guaranteed. Experience across meteorological, hydrological, and other hazard-monitoring communities demonstrates that technological capability alone is insufficient to deliver better early warnings. Instead, meaningful impact depends on how AI is integrated into operational systems, supported by appropriate data and infrastructure, governed responsibly, and aligned with national capacities and priorities.

This section focuses on the pathway from science to action. It outlines the key cross-cutting requirements and challenges that must be addressed for responsible implementation, and the critical role of the international community in enabling equitable, sustainable, and operationally relevant use of AI across countries with diverse levels of technical capacity.

3.4.1 Requirements and challenges

The effective integration of artificial intelligence into hazard detection, monitoring, analysis, and forecasting requires more than technical innovation; it depends on a clear set of operational requirements. Defining these requirements helps clarify the conditions under which AI can move from experimental applications to becoming a trusted and durable component of hazard monitoring and warning services. The considerations outlined here broadly track discussions in recent World Meteorological Organization assessments of artificial intelligence for Earth system prediction, including the Research Board Task Team on Artificial Intelligence for Weather Final Report (WMO, 2025a) and *AI Exploration Roadmap for WIPPS - Issues and Challenges for Incorporating Artificial Intelligence-Based Earth System Prediction Technologies into WIPPS* (WMO, 2025b).

Establishing and maintaining strong data foundations (data availability, quality, and continuity)
AI systems depend on observational data not only for training, but also for validation, calibration, bias correction, and real-time application. In fact, it is the availability of well-curated global reanalysis datasets, which integrate diverse observations into physically consistent historical records, that has been a key enabler of the recent generation of AI-based forecasting models. In practice, this means that NMHSs and other hazard monitoring agencies must continue prioritizing the continuity and quality of core observation networks, including surface stations, radar systems, satellite data access, and hydrological measurements.

Implementation guidance is clear: AI should not be introduced as a substitute for strengthening observation systems. Instead, NMHSs should view AI as a tool that increases the value of existing observations when data are consistent and well documented. Actions such as improving metadata management, documenting changes in observing systems, and systematically archiving historical data directly improve the effectiveness of AI-based applications.

Ensuring operationally realistic infrastructure
Although AI-based systems can reduce the computational burden associated with traditional numerical modelling, NMHSs still require reliable digital infrastructure to support operational use. This includes stable data ingestion pipelines, sufficient storage, secure processing environments, and reliable connectivity to access externally generated AI-based guidance.

For many NMHSs, particularly in lower-income countries, full-scale local infrastructure may not be realistic. In such cases, implementation should focus on ensuring reliable access to regional or global AI-based products and on integrating these products into national workflows. Practical implementation therefore involves choosing solutions that are sustainable over the long term, rather than pilot systems that depend on short-term project funding or specialized hardware.

Building institutional capacity to interpret, evaluate and use AI outputs
AI implementation does not require NMHSs and other hazard monitoring agencies to develop advanced AI models internally (e.g. the CREWS Forecast-in-a-Box project in Malawi described in the previous section) However, it does require sufficient institutional capacity to interpret AI-supported outputs responsibly. Forecasters and analysts must understand what AI products can and cannot provide, how uncertainty is represented, and how AI guidance should be weighed relative to traditional methods and expert judgement.

In addition to interpretation, institutions must also be able to critically evaluate AI outputs in their operational context. This includes ground-truthing forecasts against observations, assessing performance across different regions and timescales, particularly in data-scarce environment, and testing products with user communities. Such evaluation is essential to avoid assumptions that AI-based products are inherently superior, and to ensure that they are fit for purpose in local decision-making contexts.

This implies targeted training focused on interpretation rather than model development, development of internal guidance documents on AI use, integration of AI outputs into existing decision-support systems rather than parallel workflows, and strengthening institutional capacity for ongoing evaluation and validation of AI outputs. Without such preparation, there is a risk of either over-reliance on automated outputs or rejection of AI tools due to lack of confidence.

Defining governance and accountability for AI supported decisions
Operational implementation also requires clear governance arrangements. NMHSs and other hazard monitoring agencies must explicitly define how AI-supported information contributes to hazard monitoring and warning decisions, who is responsible for interpreting AI outputs, and how decisions are documented to ensure transparency and accountability. This is particularly important in multi-hazard and multi-agency contexts, where responsibilities for monitoring, forecasting, and warning dissemination may be distributed across institutions.

Safeguarding sovereignty and managing strategic dependence
Frontier AI-based forecasting systems are currently developed by a relatively small number of global research centres and private actors. While shared global models can broaden access to advanced capabilities, they may also increase dependence on external providers for updates, maintenance, and long-term support. For many NMHSs, particularly in resource-constrained settings, reliance on externally developed AI systems could shape national forecasting autonomy in new ways.

Operational implementation therefore requires clarity regarding licensing, data governance, model access, update cycles, and continuity arrangements. Ensuring that AI integration strengthens rather than diminishes national ownership of forecasting capability is an important strategic consideration, particularly within the framework of Early Warnings for All.

Ensuring reliable generalization for high-impact events and a changing climate
AI systems are trained on historical data and tend to perform best under conditions similar to the past. Yet early warning systems are most critical during rare, extreme, or unprecedented events including rapidly intensifying storms, compound hazards, and extremes unfolding under climate change. As warming alters hazard frequency, intensity, and location, AI models may be required to operate outside the conditions represented in their training data.

Ensuring robust performance under such non-stationary conditions remains a central challenge. Models must be systematically evaluated for high-impact extremes and stress-tested under unfamiliar scenarios. Without careful attention to generalization limits, AI systems may perform well on average conditions while underperforming during the events that matter most for protecting lives and livelihoods.

Addressing bias and uneven performance explicitly
Closely related to generalization is the challenge of bias. AI systems may also perform unevenly across regions. Models trained predominantly on data-rich environments can show stronger performance in well-observed areas and weaker results in data-sparse or climatically distinct regions. If not explicitly assessed, such disparities risk reinforcing existing inequalities in forecasting capability.

Transparent regional evaluation and clear communication of performance limitations are therefore essential. Without deliberate attention to geographical equity, there is a risk that AI systems perform well in well-observed regions while underperforming precisely in the regions where vulnerability and adaptive capacity are lowest, reinforcing rather than addressing service inequities. As stated earlier, a strong local database plays a key role in bias correction.

Improving transparency and explainability

Many high-performing AI models operate as black boxes, offering limited insight into how outputs are generated. While full interpretability is not always feasible, operational use requires a minimum level of transparency. Developers must therefore provide documentation, diagnostics, and guidance that allow forecasters to understand how outputs should be interpreted and under what conditions they may fail.

Beyond transparency, explainability is essential, particularly during model development and evaluation. AI systems should be assessed to ensure their behaviour is scientifically coherent and physically plausible. This may include tracing outputs to recognizable physical processes, checking closure of key physical budgets, conducting ablation studies to understand the contribution of individual components, and adopting modular designs that allow specific processes to be switched on and off for testing and analysis.

Both transparency and explainability are essential for underpinning the accountability processes required for early warning systems.

Strengthening verification and validation of AI outputs

AI-based prediction systems require verification approaches that go beyond those used for traditional numerical models. Unlike physics-based systems, AI models may produce plausible outputs even when affected by input errors or internal inconsistencies, creating a risk of undetected or “silent” failures, such as precipitation occurring without clouds, persistent imprints of tropical cyclones tied to initial conditions, or outputs generated from misaligned geospatial inputs (e.g. incorrect longitude conventions).

A key requirement is therefore the systematic identification and correction of such AI-specific failure modes. Because these issues may not trigger model failure, verification frameworks must include targeted diagnostics, automated input and consistency checks, and operational safeguards to ensure their detection before outputs are used in decision-making.

Strengthening verification frameworks to include these checks, alongside conventional skill metrics, is critical to ensure that AI-based systems are robust, physically consistent, and reliable for operational use, particularly in contexts where forecast information directly triggers decisions, such as evacuations, the activation of anticipatory action frameworks or the allocation of humanitarian resources.

Breaking silos and building partnerships to realize integrated early warning systems

The capabilities of AI to integrate across heterogeneous datasets underpin its promise for both the development of MHEWS, and impact-based forecasting. However, this potential remains significantly underexplored both in research and operational practice.
A key constraint is the persistence of disciplinary and institutional silos. Forecasting systems are often designed around individual hazards rather than as multi-hazard systems, and hazard prediction and impact assessment are typically developed as separate components rather than as part of a comprehensive, integrated modelling framework. As a result, forecasting systems, hazard monitoring, and impact assessment are often developed and operated separately, limiting the ability to fully exploit cross-domain data integration.
Addressing this requires fostering partnerships to break down silos across and within scientific and operational communities, strengthening data exchange and developing shared data bases across domains, and designing integrated systems from the outset rather than linking separate components.

Bridging the research-to-operations gap

Operational early warning systems require tools that function reliably on a continuous basis. Many AI applications remain at research stage and lack the robustness, version control, and maintenance arrangements required for 24/7 operations. Developers face the challenge of moving beyond prototypes toward systems that can be maintained, updated, and supported over time.

For AI developers, this implies designing with operational constraints in mind from the outset and co-developing with operational users. For NMHSs and other hazard monitoring agencies, it requires openness to experimentation within controlled and well-governed frameworks, and accelerating the transition from pilots to scale by defining clear operationalisation pathways, including validation standards, institutional ownership, long-term financing, and integration into existing workflows, alongside a clear pathway to integration into national operational systems. Bridging this gap is essential if AI is to move from research-stage capability or experimental system to reliable component of early warning systems.

3.4.2 Role of the international community

The transition from scientific advances in AI to sustained operational impact in hazard monitoring and forecasting cannot be achieved by individual countries acting alone. The international community has a critical role to play in ensuring that AI contributes to EW4All in an equitable, responsible, and operationally meaningful manner. The operational requirements outlined in the previous section define conditions necessary for AI to function effectively. The accompanying table (Table 2) clarifies how these requirements can translate into possible differentiated responsibilities across WMO and international organizations, the research and AI community (including academia and the private sector), and NMHSs as operational agencies.

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Challenge Area	WMO and International Organizations	Research & AI Community	NMHSs (Operational Agencies)
Strong Data Foundations	Promote global data-sharing standards; safeguard open data exchange; support metadata and continuity standards.	Develop models robust to heterogeneous datasets; document training data sources and limitations.	Maintain observation networks; ensure data continuity, metadata quality, and systematic archiving.
Operational Infrastructure	Facilitate shared infrastructure solutions (e.g., WIPPS, regional centres); promote sustainable access models.	Design computationally efficient and adaptable models suitable for different infrastructure contexts.	Ensure reliable data ingestion, storage, secure processing, and integration into operational workflows.
Institutional Capacity and Education	Support global training initiatives and competency frameworks; foster peer learning and regional cooperation.	Develop documentation, training materials, and collaborative research–operations engagement.	Build AI literacy; train staff in interpretation and uncertainty; integrate AI into decision-support systems.
Governance and Accountability	Develop guidance on AI governance in forecasting; clarify accountability principles across agencies.	Provide version control, documentation, and clear communication of model limitations.	Define how AI informs warning decisions; ensure human oversight and documentation of use.
Sovereignty and Strategic Dependence	Promote equitable access to AI capabilities; encourage transparent model governance and long-term continuity.	Promote open-source solutions; avoid opaque dependencies; ensuring clear and consistent licensing of model code, weights, and outputs	Assess reliance risks; ensure continuity; maintain national ownership of final warning decisions.
Robustness under extremes and climate change	Establish evaluation standards for extreme events and warming scenarios; support global benchmarking efforts.	Stress-test models under out-of-distribution and climate-shift conditions; publish performance boundaries.	Evaluate and document performance for high-impact events and evolving local risk patterns.
Geographical Bias & Equity	Encourage regional performance assessments, particularly in LDCs and SIDS; encourage equitable model performance in research community; embed equity into pilot frameworks.	Provide transparent diagnostics across regions and hazard types.	Interpret regional limitations; incorporate awareness of bias into operational judgement.
Transparency and Explainability	Promote explainability in collaborative AI forecasting initiatives.	Prioritize mechanistic understanding of AI model behaviour alongside predictive skill.	Perform validation, testing, and interpretation of model behaviour against physical understanding
AI Verification and Validation	Integrate AI-specific verification standards within WIPPS, including diagnostics for non-physical outputs and silent failures; support shared benchmarking and intercomparison frameworks.	Identify and document AI-specific failure modes; develop diagnostics for non-physical behaviour and input sensitivity;	Critically evaluate AI outputs in operational contexts, including ground-truthing against observations, assessing performance across regions and timescales
Breaking silos and strengthening partnerships for AI for MHEWS and impact-based forecasting	Foster collaboration across hazard-specific agencies under EW4All; promote data sharing and interoperable data frameworks across disciplines.	Develop integrated models across hazards and impacts; collaborate across disciplines and contribute to shared data bases.	Build partnerships across hazard, disaster management, and humanitarian actors; support data exchange and adopt integrated workflows across hazard and impact systems.
Bridging Research to Operations	Facilitate co-development between research community and operational users; provide structured pilot mechanisms and phased integration pathways.	Co-develop model with users; design systems with operational constraints in mind; ensure maintainability and long-term support.	Test AI tools in pilot mode; prioritise operational deployment, with clearly defined integration pathways into national systems; ensure long-term financing and national ownership

Table 2. Key Challenges for different members of the International Community (WMO and international organizations, research and AI community, NMHS and operational agencies) to ensure responsible integration of AI into Early Warning Services.

The requirement specific roles are left as challenges in the table for the reader to consider and will not be further discussed in the text for sake of brevity. Across all actors, transparency, documentation, and human oversight function together as a continuous accountability chain, rather than isolated responsibilities.

In conclusion, it is important to also stress that international support, as much as it is vital, must respect and be anchored in nationally defined priorities, operational realities, and institutional capacities. Within EW4All, the objective is not uniform technological adoption, but meaningful strengthening of national hazard monitoring and forecasting capabilities and tailoring to their needs. Respecting national ownership of forecasting processes and final warning decisions is essential to long-term sustainability and accountability.

The national EW4All roadmaps developed by countries as part of the EW4All initiative reflect this principle. References to AI and machine learning are not uniform across roadmaps and are generally not framed as standalone gaps requiring universal adoption. Instead, where AI appears, it is typically articulated at the level of specific activities aimed at addressing operational needs, such as the use of machine learning for forecast post-processing and bias correction, the development of AI-supported nowcasting tools, or the integration of AI to enhance forecasting workflows (often as pilot activities). These activity-level proposals illustrate how countries are selectively exploring AI where it aligns with existing priorities and capacities.

By directly supporting such initiatives, the international community can help ensure that AI contributes to strengthening operational forecasting capabilities while remaining aligned with national priorities and institutional ownership.

3.5 Conclusion

As this chapter has shown, the rapid maturation of AI and ML offers clear opportunities to strengthen Pillar 2 by improving the speed, frequency, and in some contexts the skill of hazard monitoring and forecasting, while lowering some computational barriers that constrain operational services. The case studies presented illustrate these advances across timescales—from AI-enabled nowcasting and nowcasting intercomparison (Box 8; Box 13), to global weather forecasting with ECMWF's AIFS (Box 9), and emerging applications in climate modelling (Box 12)—as well as across hazards, including cyclone forecasting (Box 10) and flood forecasting (Box 11). At the same time, these developments introduce new operational and governance challenges, including uneven performance across regions and extremes, dependence on data continuity and quality, limited transparency in some model classes, and the need for robust uncertainty quantification and validation.

Taken together this chapter has highlighted where AI is already adding value in operational or near-operational workflows, where it shows credible promise across hazards and timescales, and what requirements must be met for responsible and equitable integration within early warning systems.

In closing, the central question for EW4All is not whether AI will influence hazard detection, observation, monitoring, and forecasting, but how it can be integrated in ways that strengthen national systems and protect lives under strong national ownership and leadership.

The history of numerical weather prediction offers a useful parallel. Pioneered during a similarly rapid burst of scientific innovation in the late 1940s and early 1950s, particularly through the collaboration between meteorologists, mathematicians, and computer scientists, numerical forecasting initially faced scepticism from both theoretical scientists and operational forecasters. Yet the combination of improved observations, emerging electronic computers, and advances in atmospheric dynamics gradually demonstrated the feasibility of objective, model-based prediction (Lynch, 2006). Early numerical forecasts were limited in resolution and scope and were not immediately capable of replacing traditional forecasting methods, but they provided a foundation upon which operational systems could be built and refined.

Translating these scientific advances into routine operational forecasting services, however, took decades of continued development, operational testing, and sustained investment in observing networks, computing infrastructure, data assimilation techniques, and collaboration between research and operational communities (Harper et al., 2007). In the process, numerical weather prediction fundamentally transformed forecasting practice and became the backbone of modern weather forecasting and early warning services. AI-based approaches may follow a similar trajectory. While recent advances suggest the potential for substantial gains in forecast efficiency and capability, their long-term value will depend on how they are integrated with existing forecasting infrastructure, combined with physical understanding and observational systems, and translated into operational tools that NMHSs can deploy reliably.

The experience of NWP also demonstrates that technological breakthroughs do not automatically translate into universal operational capacity. Even after more than seventy years of development, the ability to run advanced numerical models remains unevenly distributed, requiring significant computing infrastructure, data systems, and specialized expertise. In this sense, operational forecasting capacity remains, in many contexts, a privilege rather than a universal capability.

At the same time, the technical maturity of NWP has also not eliminated the central role of human expertise in forecasting. Despite decades of operational use and continuous improvement, numerical forecasts are rarely relied upon without human interpretation and contextual judgement, particularly when high-impact decisions are involved. NWP did not replace human forecasters; rather, it transformed their role, embedding numerical guidance within a broader forecasting process that depends on expert interpretation and institutional trust, and retains organizational accountability.

As with earlier transformations, the challenge is therefore not only technological but institutional and ethical. It involves ensuring that emerging AI capabilities contribute to reducing, rather than reinforcing, existing inequalities in access to forecasting capacity and early warning services, particularly in regions where such capabilities remain most constrained. At the same time, their integration must sustain the trust on which operational forecasting and warning decisions ultimately depend. Only then can these advances be fully considered a gain for EW4All.

Chapter 4.
AI for warning dissemination and communication

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Early Warnings for All

Pillar 3. Enhancing warning dissemination & communication

ENABLES

- Clear, relevant messages
- Reach every community
- Action through trusted channels

CORE AI TECHNOLOGIES

- Natural Language Processing (NLP)
- Large Language Models (LLMs)
- Computer Vision & Geospatial AI
- Speech Technologies
- Automated Decision Systems

Early Warnings for All

Even the most accurate forecasts only save lives if warnings reach people in time, are understood, and lead to action. AI is enhancing the delivery of timely, accessible, and actionable warnings by supporting multilingual communication, targeted messaging, optimized dissemination channels, and real-time adaptation of communication strategies.

- AI can support the generation of multilingual and context-aware warning messages tailored to different communities and risk scenarios.
- AI-enabled dissemination approaches can optimize communication channels and adapt warnings in real time to improve accessibility and response.
- Inclusive, multi-channel warning systems are essential to ensure warnings reach populations with varying literacy levels, languages, and connectivity conditions

AI also presents opportunities to counter misinformation and personalise warnings without compromising consistency or trust in official communication. However, the effectiveness of AI-enabled early warning systems is constrained by persistent digital and connectivity gaps. Around 2.2 billion people remain offline, limiting access to digital warnings and reducing the representativeness of datasets used to train AI systems.

To fully realise the benefits of AI-driven warning dissemination, greater investment is needed in resilient communication infrastructure and inclusive dissemination approaches that function across both high- and low-connectivity environments. Strengthening connectivity and closing digital divides will be critical to ensuring AI-enabled early warning systems operate effectively, equitably, and leave no one behind.

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4.1 AI enabled warning dissemination and communication

MHEWS reduce disaster losses when warnings are received, understood, trusted, and acted upon. Their value therefore lies not only in forecasting hazards accurately, but in ensuring that alerts reach people at risk in time to enable action. This requires translating complex hazard information into timely, understandable, and actionable communication and alerts delivered across multiple channels, languages, and social contexts. This part of the early warning value chain is often referred to as the last mile, to ensure that connectivity gaps are addressed to reach every person.

ITU research shows that 97.9 per cent of the world's population is covered by a mobile network - 173 million people (2.1 per cent) are beyond the reach of 2G+ coverage, 362 million people (4.4 per cent) are beyond the reach of 3G+ coverage - and 4 in 5 people own a mobile phone (ITU, 2025). Around 140 countries have no inclusive mobile early warning systems, with these gaps being most pronounced in low- and middle-income countries (LMICs). Warning dissemination and communication - the focus of Pillar 3 of the EW4All initiative, led by ITU - represents an interface between technical early warning capabilities and life-saving community action. Pillar 3 encompasses the entire communication pathway from authoritative warning sources to individual and community action. This includes message formulation (translating technical hazard information into actionable guidance), channel selection and optimisation (choosing appropriate dissemination technologies and media), targeting and personalisation (ensuring messages reach specific at-risk populations), infrastructure resilience (maintaining communication capabilities during disasters), and feedback mechanisms (enabling two-way communication and verification) (ITU, 2026b; Sutton et al., 2014). Each component presents distinct technical, institutional, and social challenges that AI technologies can help address.

Despite its importance, warning dissemination and communication remains one of the least studied components of AI-enabled early warning systems. A 2025 systematic review covering 324 studies on AI in early warning systems found an imbalance: while 55 per cent of research focused on risk knowledge (Pillar 1), 38 per cent on monitoring and forecasting (Pillar 2), only 6 per cent were relevant to Pillar 3 and 1 per cent to Pillar 4 (Tiggeloven et al., 2025). During storm Daniel which caused flooding in Libya in 2023, forecasts were available days in advance but failures in communication contributed to thousands of deaths and people displaced (Reichstein et al., 2025). This highlights how technical forecasting excellence alone cannot prevent loss of life when communication systems fail to reach vulnerable populations with timely, understandable, and actionable information. AI holds promise for addressing such challenges in Pillar 3 to enable adaptive, multilingual, and increasingly personalised communication at scale while optimising dissemination across diverse channels - including mobile networks, radio, television, sirens, satellite systems, and social media platforms. Rather than replacing human judgment, AI should augment existing dissemination and communication mechanisms by improving speed, consistency, situational awareness, and inclusivity in warning delivery.

The growing complexity of disaster risk, as highlighted in Chapter 2, further increases the importance of effective communication. Urbanisation and population growth have created dense, heterogeneous communities with diverse communication needs, language preferences, digital literacy, and technological access levels (Martelo et al., 2024; Zajac et al., 2025). Climate change is intensifying hazard frequency and generating compound and cascading disaster scenarios that require multi-hazard warning approaches (R. Kumar & Rani, 2025). At the same time, the proliferation of communication technologies - from traditional broadcast media to mobile phones, social media, and Internet-of-Things (IoT) devices - has both expanded dissemination opportunities while complicating coordination and message consistency across multiple channels and stakeholders .

Multi-hazard environments introduce additional challenges as different hazards require different lead times, message formats, and communication strategies. For example, fast-onset events such as flash floods, earthquakes, tornadoes, or tsunamis require near-instantaneous alerts with clear, simple instructions, whereas slow-onset hazards such as tropical storms, droughts, or heatwaves require more sustained and adaptive communication campaigns (Abid et al., 2025; Aboualola et al., 2023; Narmatha B. et al., 2025; Ouaissa et al., 2024; Peña-Cáceres et al., 2025). Effective warning systems must therefore tailor message content, timing, and delivery channels to different hazard characteristics while maintaining public trust and institutional credibility (Dalela et al., 2022; Tsichrintzi et al., 2024). Digital platforms and standardised frameworks - including the Common Alerting Protocol (CAP), Filtered Alert Hub, MeteoAlarm, Google Public Alerts, and the IFRC Alert Hub - have already expanded the reach and interoperability of warning systems globally. AI can further strengthen these infrastructures by enhancing localisation, personalisation, and real-time situational awareness while supporting inclusive, people-centred communication strategies. Given the rapidly evolving technological and communication demands, ITU is uniquely positioned to guide the application of AI to warning dissemination and communication by leveraging global standards, public-private partnerships, and inclusive digital innovation.

This chapter synthesises research evidence and operational practice to show how AI can enhance message generation and translation, targeting and personalisation, communication network resilience and channel optimisation, public response, feedback and misinformation (Figure 11), while also addressing gaps and challenges relevant to Pillar 3. Drawing on Pillar 3 partner cases and research evidence, it provides guidance for governments, regulators, telecommunication operators, and partners to enable practical uptake and responsible integration of AI to support warning dissemination and communication. The chapter focuses specifically on AI applications that support dissemination during the warning phase. The chapter explicitly excludes AI applications primarily focused on hazard detection and forecasting (Pillar 2) unless they directly inform dissemination strategies. Similarly, while acknowledging the importance of response preparedness (Pillar 4), the review focuses on communication during the warning phase rather than post-impact coordination. Particular attention is given to LMIC contexts, recognising that these contexts face the most significant challenges in warning dissemination and communication, and stand to benefit increased investment in AI-enabled solutions.

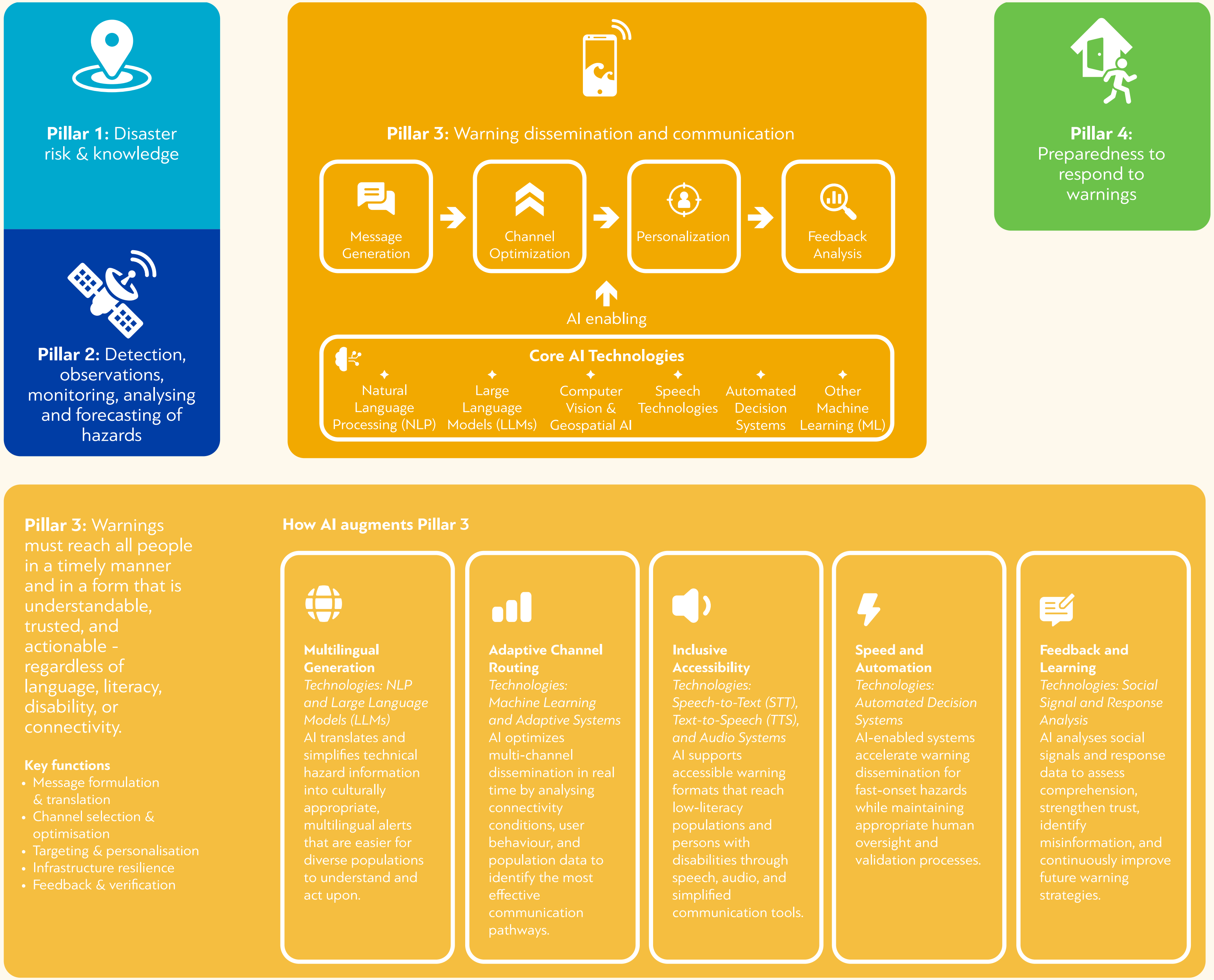

Figure 11. AI Value Cycle for Warning Dissemination: From Hazard Data to Community Action.

4.2 AI applications for warning dissemination and communication: opportunities and challenges

Effective warning dissemination and communication is a critical component of end-to-end early warning systems, linking hazard detection with protective action by at-risk populations. The EW4All initiative emphasises that early warning systems must be people-centred, recognising that effectiveness depends not only on technical accuracy and speed but on whether warnings are trusted, understood, and actionable for diverse populations. AI can support these principles by enabling culturally appropriate communication, accessible formats for persons with disabilities, multilingual translation, personalised messaging aligned with literacy levels and vulnerabilities, clear attribution of information from trusted sources, and adaptive learning from community feedback. Aligned with the Sendai Framework for Disaster Risk Reduction and the Sustainable Development Goals, AI-enhanced EWS can support warnings that are timely, understandable, accessible, and actionable - helping translate early warnings into early action for all. However, without careful attention to context, participation, and equity, AI deployment may also risk undermining people-centred approaches.

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Within EW4All, Pillar 3 is structured around four interconnected outcomes that define the enabling environment for effective warning systems: i) **governance** - establishes who has authority to issue warnings, through which channels, following what protocols, and with what institutional backing; ii) **infrastructure** - the technical systems and platforms required to deliver warnings across multi-channels, encompassing both national-scale systems and local solutions; iii) **inclusion** - emphasises equity and accessibility, ensuring warnings reach marginalised populations including persons with disabilities, linguistic minorities, remote communities, displaced populations, and those with limited connectivity or literacy; and iv) **quality and trust** - addresses message quality, standardisation in relation to CAP, interoperability, and institutional credibility (GSMA, 2026b; IFRC, 2026a; ITU, 2026a; UNDRR, 2021). These four outcomes are mutually reinforcing: governance provides the institutional foundation for infrastructure investment; infrastructure enables inclusive reach; and quality standards build the trust necessary for effective warning response. Across this chapter, AI is treated both as an enabling technology and, in some applications, as a force multiplier: it can strengthen each Pillar 3 outcome, but its practical contribution is best understood through the operational stages of warning dissemination and communication discussed below. Table 3 summarises examples of key AI functions, their applications, the benefits they provide for warning dissemination and communication.

AI function	Primary applications	Example Pillar 3 benefits	Example technologies and approaches
Natural Language Processing (NLP)	Multilingual message generation and translation; text simplification; sentiment and misinformation analysis	Rapid multilingual content creation; improves clarity and accessibility to diverse literacy levels; enables monitoring of public risk perception and detection of misinformation	Neural machine translation, text simplification algorithms, named entity recognition, sentiment analysis
Large Language Models (LLMs)	Contextual message generation; conversational chatbot interfaces; information synthesis; tone and cultural adaptation	Human-like, context-aware communication; transforms one-way alerts into interactive dialogue; converts complex hazard information into actionable guidance; localized adaptation	ChatGPT, Claude, Gemini, domain-specific fine-tuned models, AI advisory chatbots
Computer Vision & Geospatial AI	Hazard visualisation; damage assessment and infrastructure monitoring; visual content generation	Rapid situational awareness through visual and geospatial representations; visual alerts support understanding for low-literacy populations; monitoring critical infrastructure; improve risk communication and public engagement	Convolutional neural networks, object detection, image segmentation, satellite imagery analysis, generative adversarial networks
Speech Technologies	Text-to-speech (TTS); automatic speech recognition (ASR); voice alerts and audio message delivery	Accessible warnings for low-literate populations and persons with disabilities; hands-free, auditory delivery; multilingual audio warnings and two-way communication via voice channels	Neural TTS, ASR models, voice synthesis systems
Automated Decision Systems	Real-time alert triggering; routing across channels; workflow automation; CAP-aligned dissemination	Matches decision speed to fast-onset hazards; ensures consistent, standardized warnings; reduces operational burden while maintaining human oversight	Rule-based systems, expert systems, hybrid AI-human workflows, CAP-integrated alert automation
Other Machine Learning (ML)	Channel optimization, targeting and routing; pattern recognition and behavioural analysis; predictive response modelling	Data-driven dissemination strategies; real-time optimisation; improves targeting of vulnerable populations; learns from historical response patterns to refine warning effectiveness	Neural networks, random forests, reinforcement learning, predictive analytics models

Table 3. Summarizes examples of key AI functions, their applications, and the benefits they provide for warning dissemination and communication (Pillar 3).

Effective warning dissemination and communication also involves interconnected operational stages: message generation and translation; targeting and personalisation; communication network resilience and channel optimisation; and public response, feedback and misinformation management. Each presents distinct opportunities and challenges for AI technologies - including natural language processing, large language models, speech technologies, computer vision, geospatial AI, and automated decision systems - to enhance speed, inclusivity, and effectiveness of warning delivery.

- **Message generation and translation:** Requires transforming technical hazard information from meteorological services, seismological networks, or other monitoring systems into clear, actionable warnings appropriate for different audiences and channels. Challenges include maintaining accuracy while ensuring accessibility, adapting content for diverse literacy levels and languages, and generating messages rapidly enough for fast-onset hazards (Miller, 2024; Peña-Cáceres et al., 2025). Traditional approaches rely on pre-scripted templates and manual translation, which can be slow, inflexible, and resource-intensive. AI-enabled natural language processing and large language models can automate multilingual translation, simplify technical terminology, and dynamically generate context-specific warning messages while preserving scientific accuracy (Faiaz & Nawar, 2024; Ogie et al., 2018, Chapter 1).

- **Targeting and personalisation:** Generic warnings broadcast to entire populations often fail to motivate appropriate action, because recipients cannot assess their personal risk or determine what specific actions they should take (Demuth et al., 2016; Lindell et al., 2016). Effective warnings are tailored to specific populations based on location, vulnerability, language, literacy, and other characteristics. Personalisation increases relevance and trust but requires balancing individual targeting with privacy protection and avoiding overreliance on digital channels that exclude offline populations (Ogie et al., 2018; Zhao et al., 2025). AI-driven analytics can help tailor message content and formats to population characteristics while applying privacy-preserving methods that safeguard sensitive data. AI enabled geospatial analysis can also identify who is at risk, demographic and vulnerability data to understand population characteristics, and technical capabilities to deliver differentiated messages to specific groups (Cutter & Finch, 2008).

- **Communication network resilience and channel optimisation:** Warnings must be delivered through appropriate channels - including mobile networks such as cell-broadcast and location-based SMS, broadcast media, sirens, community networks, social media, and other digital platforms - based on population characteristics, infrastructure availability, and hazard urgence (GSMA, 2024c; ITU, 2026b). Optimal channel selection requires understanding which populations have access to which technologies, how to reach marginalised groups, and how to ensure redundancy when primary channels fail (Ogie et al., 2018; Shaik et al., 2025). This also depends on the urgency of the alert as a cell-broadcast message can reach many in seconds, while broadcasting platforms such as the radio or TV, may take more time to spread the message. Multi-channel approaches are essential for redundancy and to reach diverse populations, but require coordination to ensure message consistency (Rossi & Frisiello, 2024). AI can support adaptive dissemination by analysing connectivity data, population reach, and historical performance to recommend the most effective combination of communication channels in real time.

- **Public response, Feedback and misinformation management:** Understanding whether warnings were received, understood, trusted, and acted upon is essential for system improvement. Poorly designed or overly frequent alerts can erode trust and lead to warning fatigue, reducing the likelihood that people will take action when it matters most. Feedback mechanisms therefore play a critical role in enabling real-time adjustment of messaging strategies, identifying communication gaps, and documenting lessons learned (Abid et al., 2025; Aboualola et al., 2023; Shaik et al., 2025). AI can enhance this by analysing feedback signals from surveys, social media, and operational data, to assess behavioural response patterns, detect risks of over-alerting, and support clearer, more targeted messaging (GSMA, 2024b, 2025a, 2026a). Individuals often rely on multiple channels to verify warnings – e.g., receiving an alert on a mobile phone and confirming it via radio broadcast or trusted community sources - highlighting the importance of coordinated, multi-channel communication strategies.

The following subsections dive deeper into the core stages of warning dissemination and communication introduced above. The preceding section presented these stages as high-level summaries of key functions; the sections that follow expand on each in detail. Each subsection synthesises research evidence, presents relevant Pillar 3 partner case studies, and examines how AI technologies can be applied in practice within each stage. This includes discussion of specific AI-enabled approaches, operational benefits, and associated implementation considerations within the EW4All framework. Together, these sections illustrate how AI can support end-to-end improvements across the full communication chain, from the generation of warning messages through to how they are received, interpreted, and acted upon by at-risk populations (Figure 12).

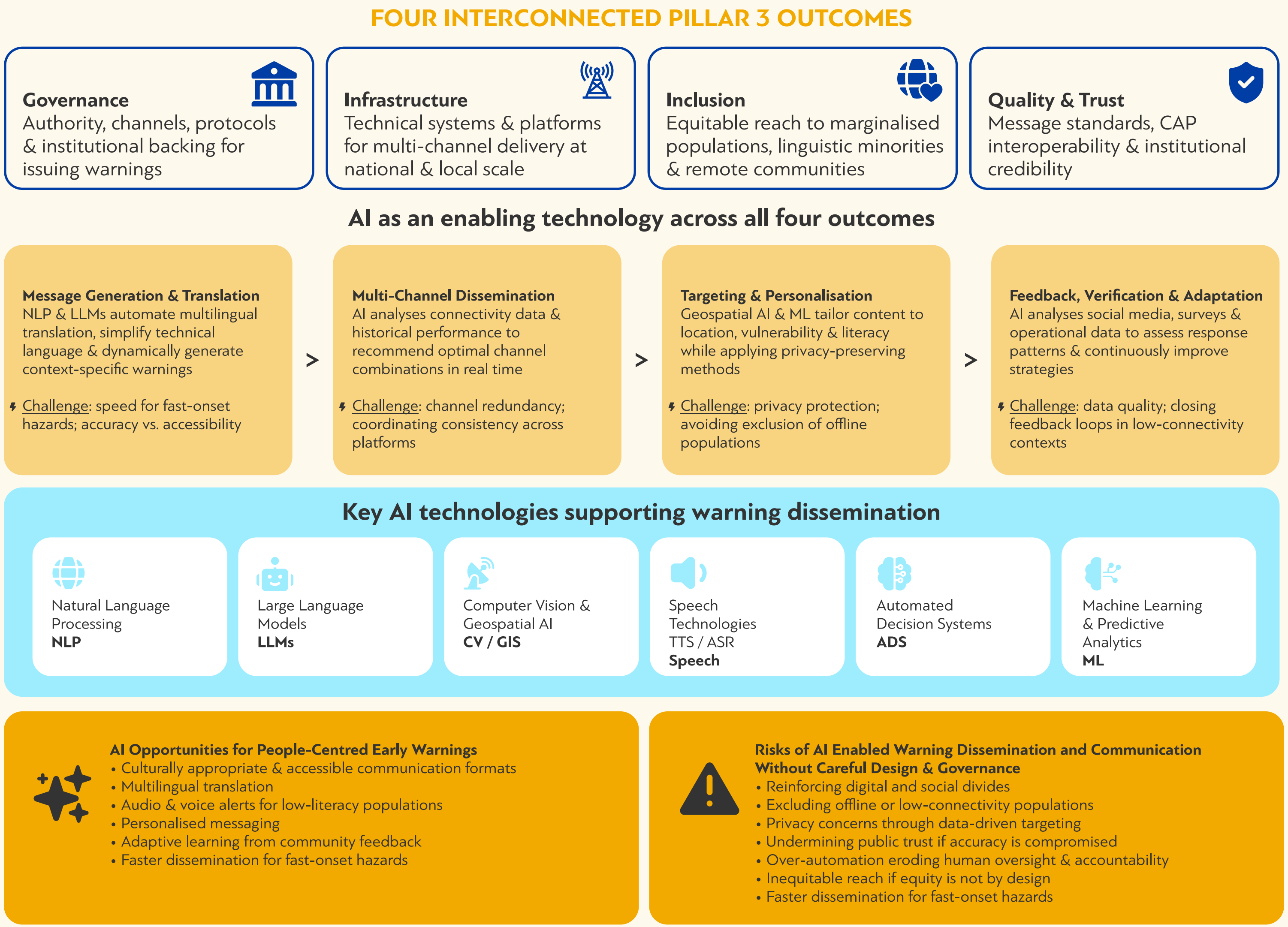

Figure 12. Overview of AI applications for warning dissemination and communication (Pillar 3), illustrating the four interconnected outcomes, key stages in the warning process, supporting AI technologies, and the opportunities and risks of AI deployment.

4.2.1 AI for automated message generation and translation

Translating technical hazard information into clear, actionable public warnings is time-intensive and requires specialised expertise. During fast-onset events, delays in message formulation can cost lives (Tsichrintzi et al., 2024). Messages must be adapted for multiple channels (SMS, radio and social media, amongst others), translated into multiple languages, and tailored for different audiences - tasks that strain the capacity of even well-resourced warning agencies (Shaik et al., 2025). Traditional approaches rely on trained forecasters and communication specialists manually drafting warnings, often using templates that provide structure but require significant customisation (Ogie et al., 2018). For multilingual countries or regions, translation adds further delays and requires specialised linguistic expertise. The result is often a trade-off between speed (issuing generic warnings quickly) and quality (crafting tailored, accessible, actionable messages).

Automated text warning message generation

LLMs like ChatGPT, Gemini and Claude, as well as domain-specific variants, can generate human-like warning messages from technical bulletins, adapting content for different audiences, channels, and literacy levels. LLMs can incorporate contextual information - including prior warnings, local geography, and cultural factors - to produce more relevant and actionable messages (Shaik et al., 2025). However, LLMs require careful validation to prevent errors, inappropriate content, or 'hallucinations' (generating plausible but false information) (UNDRR, 2025). For instance, (Lütjens et al., 2024) in July 2025, after an 8.8 magnitude earthquake off Russia's Kamchatka Peninsula. Grok, an AI chatbot on X, falsely told users that Hawaii's tsunami warning had been cancelled, citing incorrect sources. The Pacific Tsunami Warning Center kept the warning active but Grok's misinformation caused confusion, leading to traffic congestion in Waikiki (Beaty, E., 2025). AI hallucinations embedded can directly undermine the warning dissemination function by supplanting official alerts with plausible but false information.

Template-based approaches are an important complementary method to fully generative, free-text outputs produced by LLMs. NLP systems can use predefined templates that are automatically populated from structured data inputs. NLP algorithms can analyse incoming data about extreme weather, including its nature, severity, and geographical scope, and use these messages to generate precise and actionable messages (IEEE Public Safety Technology, n.d.). While less flexible than generative AI, template-based systems offer greater reliability, transparency, and lower computational resources (Al Mamun et al., 2024). China has implemented a national-scale AI-driven early warning system that integrates automated message generation with multi-channel dissemination. The system, operated by the China Meteorological Administration (CMA), in coordination with the Ministry of Emergency Management, uses NLP and machine learning to automatically generate public warnings from technical meteorological bulletins (Box 14). This implementation enhances dissemination capacities and demonstrates how AI can operate at a national scale within appropriate governance frameworks.

Box 14. China's AI-Driven Full-Process Early Warning Dissemination System

Traditional early warnings face fragmented multi-source data, poor forecast-historical record coordination, single-format dissemination, high user access barriers, incomprehensible terminology, and language barriers - resulting in inadequate "last-mile" coverage for rural areas, ethnic minorities, elderly groups, and cross-border populations. China's operational AI-driven system addresses rapid-onset (floods, typhoons, severe convection) and slow-onset disasters (droughts, extreme heat) through five core applications: risk perception empowerment integrating meteorological forecasts, real-time monitoring, and historical records using algorithmic analysis to rank current disaster magnitude historically and generate differentiated products for government, enterprises, and public users; multi-modal product generation automatically converting warnings into videos, infographics, text, and voice broadcasts across multiple channels; a vertical meteorological large language model enabling voice/text Q&A for warning details; intelligent language conversion automatically translating warnings for cross-border workers and tourists; and AI quality control achieving 99.99% accuracy. Operational results demonstrate 99.68% national coverage, 1-minute delivery to emergency managers, and 3-minute-20-second average public delivery, fundamentally reshaping early warning efficiency through data fragmentation elimination, precise risk quantification, and multi-modal cross-language accessibility.

Further information: https://gmas.asia/

AI can also support the operational workflow of alert creation and dissemination, helping authorities produce and distribute consistent messages more efficiently. England's national flood warning system illustrates how rule-based AI can be embedded directly into duty officer workflows to standardise and accelerate message generation while preserving human oversight (Box 15).

Box 15. Smart Alert System in England, United Kingdom

Flooding is a significant and persistent natural hazard in England, where more than 5.5 million homes and businesses face ongoing flood risk. The Environment Agency (EA), the national authority responsible for flood forecasting and warning, manages a large-scale communication system serving approximately 2.6 million registered users and issuing nearly 3,000 flood alerts each year. This operational scale places considerable pressure on the roughly 200 Flood Warning Duty Officers responsible for issuing timely, accurate, and actionable alerts. Historically, warning workflows relied heavily on manual processes that varied across operators and regions, creating operational bottlenecks during emergencies. Officers had to rapidly draft and format messages while ensuring accuracy, consistency, and compliance with strict safety standards. During fast-onset flooding events, even minor delays or inconsistencies could reduce warning effectiveness and increase risk to communities. A further challenge was bridging the 'last-mile' communication gap - ensuring that warnings reached residents through multiple delivery channels, while maintaining clarity and avoiding information overload for both the public and technical staff. The EA therefore sought a modernized system capable of accelerating alert creation while preserving human oversight and public trust.

To address these challenges, the EA deployed the Smart Alert Assistant developed by Intersec. The solution introduces a rule-based alert creation tool that helps emergency responders produce clear, consistent, and rapid warning messages. Rather than drafting alerts from scratch during crises, duty officers use a guided digital interface that standardizes message creation while allowing flexibility for local expertise. The system supports the full range of warning categories used in England, covering both slow-rising river floods and rapid flash flooding events.

The Smart Alert Assistant applies rule-based AI to streamline communication workflows in a practical, human-centred way. The system functions as an interactive "wizard" guiding officers through structured steps. Users first select the appropriate alert model based on flood type and the geographic area at risk. The system then automatically populates message templates with standardized headlines, forecast information, and recommended safety guidance drawn from approved datasets. All alerts must still be reviewed and approved by a Flood Warning Duty Officer before dissemination, ensuring professional judgment and local knowledge remain central to the process. This approach reduces cognitive load during emergencies while maintaining strict operational control and accountability.

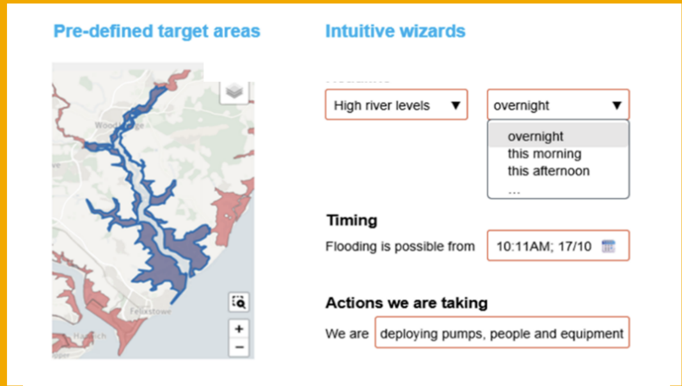

Figure 13. Smart Alert Assistant

The Smart Alert Assistant has improved operational efficiency and communication consistency within England's flood warning system. Automated formatting and data entry allow officers to issue alerts more quickly. Standardised templates also ensure consistent life-saving instructions across communication channels, reducing confusion among recipients and minimizing variation between operators under high-pressure conditions. A key lesson from the system's deployment is that AI tools are most effective when they augment rather than replace human expertise; mandatory human validation has been essential for maintaining institutional trust.

The Smart Alert Assistant represents an early step toward a broader AI-enabled crisis communication ecosystem. The platform is designed to evolve from rule-based automation toward advanced capabilities, including LLM assisted drafting, dynamic geographic targeting, and AI-supported training tools that reinforce compliance with safety protocols. Technically, the system is highly adaptable. It provides a unified interface capable of disseminating alerts across multiple channels, including Cell Broadcast, Location-Based SMS, and traditional broadcast and digital platforms. This flexibility makes the approach transferable to other countries, particularly where communication infrastructure varies widely.

Further information: https://intersec.com/blog/ai-for-good-summit-key-takeaways-on-advancing-early-warning-systems

AI enabled voice and multimodal warning communication

AI can also generate warning content in multiple formats, improving accessibility and reach across diverse populations. In traditional early warning systems, there is a critical gap in enabling asynchronous, multilingual voice communication. Advances in AI-driven text-to-speech (TTS) and automatic speech recognition (ASR) have expanded the feasibility of voice-based early warning communication (Behravan et al., 2024). TTS systems can automatically convert warning messages into spoken alerts, improving accessibility for visually impaired and low-literacy populations. ASR technologies allow incoming crowd-sourced voice reports to be converted into structured data and enable users to interact with warning systems via voice interfaces. When integrated, these technologies support multilingual voice communication during emergencies, reducing barriers for communities speaking diverse languages and dialects (Behravan et al., 2024).

AI-supported voice systems can also help incorporate community perspectives into warning systems. For example, the NetHope Voices project in refugee settlements in Northern Uganda and Nigeria collects community voices through storytelling and reporting tools such as SMS and WhatsApp. By combining traditional analytics with generative AI, the project provides community insights for policymakers and strengthens links between lived experience and government climate preparedness efforts (NetHope, 2023). AI-powered voice technologies are also being deployed to overcome language and literacy barriers in operational warning systems. In Sudan, the DARAJA + AI initiative converts official weather alerts into audio messages in local languages and disseminates them through trusted channels such as WhatsApp, community radio stations, and local information networks (Box 16).

Voice-based AI systems are also emerging in contexts with limited internet connectivity. For example, Pakistan faces challenges in early warning dissemination due to low literacy rates, linguistic diversity, and limited internet connectivity in rural areas. Communities most vulnerable to climate-related disasters often lack access to timely early warning information, as national emergency hotlines become

Box 16. AI-Powered Voice Alerts Bridge Language Gaps in Sudan's Early Warning System

In Sudan, language and literacy barriers prevent many communities from receiving and understanding early warning messages, placing lives at risk during extreme weather events. Official forecasts and alerts are typically issued in Arabic or English text, excluding populations who cannot read or speak these languages. As a result, warnings for floods, extreme heat, storms, and droughts often fail to reach vulnerable groups in a form they can understand, turning otherwise manageable hazards into humanitarian emergencies. DARAJA + AI addresses this gap by transforming text-based weather alerts into audio messages in local languages. The AI-powered system converts official forecasts into clear voice messages delivered through familiar and trusted channels such as WhatsApp, local radio stations, and community networks. Currently in pilot stage, the system is being tested with three initial languages: Sudanese Arabic, Bedawit, and Dongolawi, with plans for national scaling and regional expansion to Ethiopia and other East African countries. The solution covers floods/flash floods, heavy rainfall, extreme heat, sand and dust storms, dry spells and droughts. Implementation partners include Resurgence, Ethiopian Meteorological Institute, Sudan Meteorological Authority, Sudan Urban Development Think Tank, and Andariya, with dissemination supported by Zain Sudan, MTN Sudan, Sudanese Red Crescent Society, and media partners. Funding comes from the TECH4Resilience Challenge, UK International Development, and German Federal Foreign Office. Key outcomes include increased reach to non-literate communities and minority language speakers, enabling early protective action and improved resilience across vulnerable areas. The adaptable model is designed for global expansion to other DARAJA programme countries and regions, where language barriers limit access to critical information.

Further information: https://www.resurgence.io/daraja/

overwhelmed during crises, low literacy rates limit text-based warnings, and uneven Internet access renders app-based alerts inaccessible. Existing systems rely on generic SMS broadcasts or static messages that lack localization and responsiveness to people's specific circumstances. To address these gaps, Viamo developed the Generative AI Voice Companion, known as Noor, which provides real-time, spoken disaster guidance in Urdu through a toll-free number accessible via basic mobile phones on Ufone and Zong networks. Operational since April 2025, this solution requires neither Internet connectivity nor literacy. Unlike conventional systems, Noor draws from trusted disaster guidance developed by national authorities and humanitarian organizations, listening to users; spoken questions and generating tailored responses within seconds. Securely deployed using Microsoft Azure and OpenAI infrastructure, the solution is owned and implemented by Viamo with funding from the GSMA Innovation Fund and has reached over 100,000 users, with significant potential for scalability and expansion plans underway (Viamo, 2025).

Beyond voice communication, AI can also generate visual and geospatial communication products that enhance situational awareness. By integrating multimodal datasets - including meteorological observations, sensor networks, satellite imagery, and social media - AI systems can automatically generate maps, infographics, and videos showing hazard intensity, exposure, and vulnerability in near real time. For example, generative vision models have also been used to simulate potential hazard impacts, such as generating physically consistent satellite imagery depicting expected flood damage, helping improve risk awareness and preparedness (Luccioni et al., 2021; Lütjens et al., 2024).

AI enabled multilingual translation of warning messages

Language barriers represent a major obstacle to effective early warning communication, particularly in multilingual and culturally diverse societies. Individuals who speak marginalized or minority languages are often disproportionately vulnerable because they lack access to warnings they can understand. AI-powered translation systems offer a solution by enabling real-time, or rapid dissemination of warnings into minority languages that would otherwise be delayed or omitted.

Recent advances in multilingual LLMs and neural machine translation models have expanded the ability to translate emergency messages into low resource languages (Lankford & Way, 2024; Trujillo-Falcon et al., 2025). However, inaccurate translation and lack of information in certain languages remain a challenge (Villarreal et al., 2025). In particular, meteorological and hazard specific terminology can be difficult to translate with accuracy and timeliness. Recognising these barriers, researchers and practitioners are continuously trying to use AI technologies to improve the translation and dissemination of early warning communication.

Operational applications are already emerging. For example, the National Weather Service in the United States has collaborated with the AI translation platform Lilt to develop an automated emergency-weather translation programme that adapts neural machine translation tools to specialized weather terminology through a patented training process. The system enables large language models to generate more accurate and context-sensitive translations of weather alerts in languages such as Chinese, Spanish, and Vietnamese (Khurana et al., 2023). Similarly, Canada's national public alerting system Alert Ready integrates AI-powered translation directly into alert-authoring software to enable real-time bilingual alerts across hazard types (Box 17).

Box 17. AI-Powered Translation for Bilingual Emergency Alerts

Alert Ready, Canada's national public alerting system operated by Pelmorex Corp., in partnership with federal and provincial emergency management agencies, integrates AI-powered neural machine translation within CAP-enabled alerting infrastructure to enable real-time bilingual alerts in English and French. Many regional authorities lack the capacity to translate alerts rapidly during fast-moving emergencies, but this AI translation tool is embedded directly in alert-authoring software. The system uses machine learning-powered language models to instantly translate alert content between English and French, enabling authorities to issue bilingual alerts for all hazard types—including AMBER alerts, floods, wildfires, earthquakes, extreme weather events, and public safety threats. Alert distributors such as radio stations, television services, and wireless providers can then extract content in the language relevant to their audience. The AI-based tool generates translations significantly faster than human translators, which is especially valuable during emergencies outside normal business hours. Implementation requires comprehensive testing and validation to ensure accuracy, and some jurisdictions have specific Official Languages requirements that must be incorporated. Looking ahead, Pelmorex is exploring extending the tool to support selected Indigenous languages and piloting integration into its public-facing mobile application, which would allow users to view emergency messages in their preferred language, beyond Canada's two official languages.

Further information: https://www.pelmorex.com/en/products-and-solutions/alerting/alerting-system/

The importance of remaining CAP compliant and interoperable in AI-enabled alerts

While CAP provides a standardised framework for structuring and distribution of emergency warnings across multiple channels, ensuring that AI-generated warnings comply with this standard presents a technical and governance challenge. AI systems trained primarily for natural language generation may produce outputs that are fluent and contextually appropriate but structurally non-compliant with CAP's required fields, metadata schemas, and validation rules. Non-compliant outputs risk failing to integrate with existing early warning infrastructures - including broadcast media, mobile networks, and digital platforms - thereby breaking the chain of dissemination at a critical moment. Achieving CAP compliance in AI-generated alerts will require deliberate model training on CAP structure and validation requirements, robust automated checking mechanisms, and human oversight workflows to catch errors before distribution. Without such, the speed advantages that AI offers in automated warning generation may be offset by interoperability failures that undermine message quality and public trust.

Effective deployment of AI-generated warning systems depends on robust data and governance frameworks. High-quality training data - including historical alerts, technical bulletins, and user feedback - are essential to ensure accurate and reliable message generation. Multilingual systems additionally require parallel language datasets, and in low-resource contexts may depend on transfer learning or community-based data collection to address gaps. Human oversight remains essential across operational deployments to detect errors, ensure contextual appropriateness, and maintain accountability, with review intensity potentially decreasing as system reliability improves. Quality assurance should combine automated checks - such as readability assessment, consistency testing, and CAP validation - with human review, supported by systematic logging of generated messages and edits to enable continuous improvement. Cultural and linguistic appropriateness must be addressed through local model fine-tuning and community validation processes, particularly where training data are dominated by Western or English-language sources. Transparent communication that alerts may be AI-generated, combined with clear validation processes and human oversight, is essential to strengthen public confidence and support responsible AI use.

4.2.2 AI for targeting and personalisation of warnings

Generic, untargeted warnings often fail to motivate protective action, particularly among populations experiencing warning fatigue from frequent false alarms or warnings for hazards they perceive as low-risk. AI powered targeting and personalisation can improve warning effectiveness by tailoring messages to specific audiences and contexts. By analysing behavioural, demographic, and environmental data, machine learning systems can segment populations according to vulnerability, exposure, and likely response patterns. Research in epidemic surveillance and climate risk monitoring highlights the value of combining technical risk indicators with social data (search queries, microblogs, or mobility patterns) to understand behavioural responses and refine models (Reichstein et al., 2025). AI-driven platforms are increasingly being used to translate early warning signals into targeted operational responses.

Spatial targeting of populations at risk

AI can further improve warning targeting through advanced geospatial analysis. Geographic information systems (GIS) combined with machine learning enable precise identification of populations located in hazard-affected areas. These systems can analyse hazard exposure, population distribution, connectivity infrastructure, and transportation networks to determine where warnings should be delivered and which channels are most likely to reach affected communities. Computer vision analysis of satellite imagery can also detect vulnerable structures, informal settlements, and evacuation routes, strengthening situational awareness during emergencies.

High-resolution connectivity and population mapping can further refine spatial targeting. Box 18 illustrates the Early Warning Connectivity Map (EWCM) applied in Liberia, which combines AI-derived population data with telecommunications coverage mapping to identify communities that may not receive alerts due to connectivity gaps. Similar approaches are being explored in hazard monitoring systems; for example, an AI-driven forest fire early warning system developed by Developed by LUMS National Centre of Robotics & Automation in partnership with UK Aid, Frontier Technologies, WWF-Pakistan, and Pakistan Forest Department, and deployed in Pakistan's Khyber Pakhtunkhwa province uses computer vision and IoT sensors to detect fires and analyse spatial spread patterns in remote mountainous terrain, supporting targeted alerts and response planning in areas with limited monitoring infrastructure [(Shahid & White, L., 2024)].

Box 18. Applying the Early Warning Connectivity Map to strengthen warning dissemination in Liberia

Under the AI Group of EW4All, ITU, in collaboration with Microsoft AI for Good Lab, the Institute for Health Metrics and Evaluation (IHME) at the University of Washington, and Planet Labs, developed the Early Warning Connectivity Map (EWCM). This tool builds on the Disaster Connectivity Map platform - a joint initiative of ITU, GSMA and the Emergency Telecommunications Cluster of the World Food Programme - by layering connectivity data, high-resolution population data, and hazard risk information to identify "connectivity coldspots" which leaves populations vulnerable to hazards as they cannot receive emergency notifications because they live beyond the reach fixed broadband, 2G and 3G+ networks. A central innovation is the integration of a 100-metre resolution population dataset generated using AI applied to satellite imagery.

Liberia served as an early operational application of the tool. Liberia faces significant exposure to multiple natural hazards, including river and urban flooding, landslides, and wildfires, alongside medium risks from coastal flooding and extreme heat. Effective early warning systems depend on reliable communication infrastructure to deliver alerts to at-risk populations. In November 2024, ITU produced an initial connectivity dataset for Liberia and shared it with the Liberia Telecommunications Authority (LTA) for validation. In December 2024, LTA and mobile network operators MTN and Orange provided detailed cell site data to improve the accuracy of national coverage maps. Using the Mobile Coverage Platform subsystem of the DCM, developed by Masae Analytics and CloudRF, ITU generated updated high-resolution cellular coverage maps and returned refined datasets to LTA for operational use.

The Liberia deployment generated several operational and institutional benefits. The dataset supported LTA in strengthening cell broadcast implementation by identifying flood-prone areas where warning messages could not currently be delivered. ITU provided technical assistance throughout 2025, including training on calculating coverage statistics at county and district levels to support evidence-based planning. LTA conducted pilot verification tests in Sinoe County in December 2025 using the Speedchecker Android application. Although heavy rains and flooding limited access to some communities, the exercise highlighted the importance of validating connectivity data under real disaster conditions.

Beyond early warning applications, the EWCM produced wider policy and institutional impacts. The analysis informed Universal Access strategies by identifying priority connectivity gaps, leading to targeted ground-truthing and drive tests in four counties - Lofa, Rivercess, Sinoe, and Grand Bassa. The project also improved coordination within LTA by strengthening collaboration between engineering, universal access, and data divisions. Stakeholders reported that visual connectivity maps were particularly effective for communicating results. Spatial representations of coverage gaps proved easier to understand than traditional national statistics, improving decision-maker engagement and supporting investment prioritisation.

Further information: https://s41721.pcdn.co/wp-content/uploads/2022/04/AI4G_EW4All_Discovery_EWCM_2026.01.20.pdf

The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by ITU, WMO, UNDRR and IFRC.

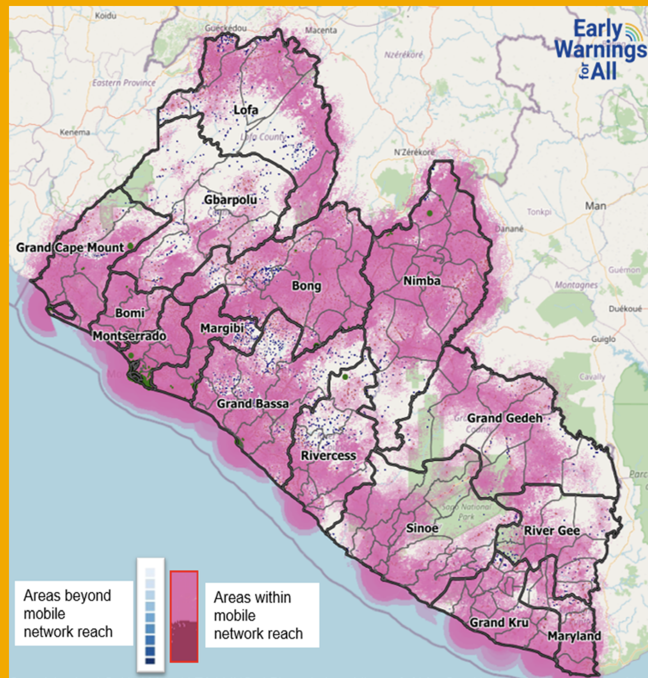

Figure 14. Early Warning Connectivity Map (EWCM)

AI can also improve targeting by analysing population mobility patterns, which influence exposure to hazards and the effectiveness of warning dissemination. For example, research in Senegal used anonymised mobile phone data to analyse seasonal population mobility patterns across livelihood zones. By examining changes in the locations of cell towers used during calls, researchers identified characteristic movement patterns associated with fishing, agro-pastoralism, and seasonal migration. Deviations from these patterns can signal emerging shocks - such as flooding or livelihood disruption - providing early indicators of vulnerability. The project, conducted by Global Pulse, WFP, and Universidad Politécnica de Madrid, demonstrated how machine learning techniques such as unsupervised clustering can help detect changes in mobility patterns and support earlier humanitarian response (Montjoye et al., 2014).

Geo-targeting is already core to the CAP through polygon and geocode fields; AI could enhance this further by using high resolution geospatial and population data to ensure spatially precise alerts that avoid over warning or under warning (Codyre et al., 2025). These capabilities support highly localised warning dissemination, allowing alerts to be directed to specific neighbourhoods, buildings, or populations based on real-time exposure and location.

Channel personalisation

Personalisation can also extend beyond message content to choice of channel, format and timing of alerts. AI systems can learn from historical communication and behavioural data to identify which channels (such as SMS, mobile applications, voice call, or broadcast radio) are most effective for different demographic groups and locations, as evidence shows that communication effectiveness and engagement vary by channel, age, and socio-economic context (Khan et al., 2024; Kwak et al., 2025; Miller, 2024). When combined with user preference data (where available and ethically collected), this enables: i) delivery of alerts in a recipient's preferred language and modality (text, audio, and sign language video); ii) channel selection tuned to device type and connectivity (e.g. SMS for basic phones, app push for smartphones, and robocall for landlines); and iii) timing adjustments that account for local practices (e.g., radio usage patterns, and night time phone muting). For example, the Crisis Learning, Early-Warning, Anticipation and Response (CLEAR) initiative (Box 19)integrates multiple hazard and humanitarian data streams to generate actionable insights for frontline responders (GSMA, & CLEAR Global, 2024). By combining climate indicators, conflict monitoring, displacement data, and field reports, CLEAR supports anticipatory decision-making and helps bridge the persistent 'last-mile' gap between early warning information and timely humanitarian action.

Box 19. CLEAR: AI-Powered Early Warning and Early Action

The Crisis Learning, Early-Warning, Anticipation and Response (CLEAR) initiative, led by the Norwegian Refugee Council (NRC) with support from Twilio, is an AI-powered ecosystem designed to operationalize early warning signals into field-level humanitarian action, directly complementing the Early Warning for All (EW4All) framework. CLEAR addresses the critical "last mile" gap between early warning data and effective response by unifying disparate data streams; including conflict monitors, climate data, displacement tracking, and field reports, into an integrated information platform that delivers actionable, sub-national level insights to frontline responders within hours of crisis onset and with the aim to use historical knowledge to enable proactive action. Through its four core components: a Crisis Detection and Alert Engine, a Situation Analysis Generator, a Field Response Console, and a Rapid Cash Decision Support system, CLEAR translates multi-hazard early warning signals into operational triggers, enabling anticipatory action before crises reach peak humanitarian impact. Built on principles of collaboration and shared infrastructure, CLEAR is designed to integrate with EW4All/MHEWS technical standards and the CREWS Initiative, pooling resources across 8+ humanitarian partner organizations to break down the data silos and platform fragmentation that currently undermine timely, coordinated response across the sector. CREWS serves as a primary early warning data source for CLEAR's Crisis Detection Engine.

Further information: https://clearinitiative.io/

Conversational AI and interactive public engagement

AI-powered chatbots can further strengthen individual-level personalisation by providing interactive access to risk information. Rather than passively receiving alerts, users can query their risk levels and proactive actions based on their own situations. AI-enabled multi-turn conversations can deliver intermediate, context-specific explanations of risks and recommended protective actions, significantly improving personalized interpretation and understanding of warning messages (Urbanelli et al., 2024). Furthermore, chatbots can provide multilinguistic and multimodal information (voice, images, or video), adjust conversational tone and cultural tailoring for diverse communities to improve the inclusivity and the acceptance of risk information (Zhao et al., 2025). Building on this, conversational AI systems can continuously enhance personalisation through reinforcement learning. They can analyse historical conversations and real-time feedback (response time, sentiment, and language complexity) to adapt future interactions (Makridis et al., 2025).

Several emerging applications demonstrate this potential. In Bangladesh, AI advisory systems are being developed using ITU's GENIE.AI framework, which aims to provide open-source, scalable chatbot solutions that integrate climate data and early warning information to strengthen community resilience (IEEE Humanitarian Technologies, 2026). Conversational AI is also being applied directly to public warning dissemination. Everbridge's one2many are developing a Public Warning Chatbot, which provides access to official emergency alerts using data structured through the CAP. The system uses large language models to respond to user questions based on CAP alert content, including event type, urgency, severity, affected locations, and recommended protective actions (CrisisChat, 2026). Similar approaches are being developed to support highly vulnerable populations. The Signpost AI initiative, implemented by the International Rescue Committee and Mercy Corps, developed SignpostChat, a generative AI assistant designed to provide displaced populations with trusted information and personalised early warning alerts. Operating in countries including Greece, Italy, Kenya, and El Salvador, the system offers multilingual and voice-enabled interfaces and is designed through a community-led approach to ensure culturally appropriate communication. Pilot testing completed in 2025 demonstrated improvements in chatbot performance (51.68% pass rate to 76.81% over approximately 2,000 evaluations) and staff productivity, while highlighting the continued importance of human-in-the-loop oversight and staff training in AI literacy (Signpost AI, 2026).

Integrated machine translation enables multilingual interaction, automatically delivering responses in the user's preferred language. By combining predefined responses to common queries with AI-generated answers grounded in official alert data, such systems can expand access to warning information while reducing pressure on emergency services and enabling feedback loops between authorities and affected populations.

4.2.3 AI for communication network resilience and channel optimisation

Reliable communication networks are the backbone of effective early warning systems. Even the most advanced forecasting and decision-support systems cannot save lives if warnings cannot reach people in time. AI is increasingly being applied to optimising dissemination channels and strengthening the resilience of communication infrastructure, ensuring that messages generated upstream (Section 4.2.1) and tailored to populations (Section 4.2.2) can be effectively delivered.

Strengthening telecommunications resilience during disasters

Early warning dissemination systems are highly dependent on telecommunications infrastructure, which is itself vulnerable to disruption during disasters. Even advanced AI enhanced warning systems can fail when disasters damage telecommunications infrastructure. Earthquakes, floods, and storms routinely disrupt dissemination channels by destroying infrastructure components, cutting power, or overwhelming networks through sudden surges in usage.

AI can strengthen telecommunications resilience through several complementary strategies. Predictive maintenance applies machine learning to network performance data to anticipate failures before they occur (Microsoft, 2025). As extreme heat becomes a frequent hazard, some operators now utilize AI models that synthesize cell site sensors with local weather data to predict site temperatures; this allows for the automated adjustment of cooling mechanisms more efficiently than fixed thermostats. Intelligent traffic management predicts congestion, dynamically allocates bandwidth, and prioritizes emergency alerts over non-essential traffic (GSMA, 2023). MNOs are further leveraging AI-powered weather analytics to inform physical infrastructure protection; for example, operators can use these insights to time the removal of large antennae before predicted high-wind events, such as cyclones, to minimize equipment damage and service interruptions (GSMA, 2025b). AI simulation tools further support hazard-specific infrastructure design, while adaptive rerouting systems identify alternative communication paths when networks degrade (IBM Research, 2023). Stress testing further enables proactive reinforcement of infrastructure by modelling network performance under disaster scenarios.

Hybrid communication architectures are increasingly recognised as an important resilience strategy. By integrating terrestrial mobile networks with satellite links, mesh networks, and emergency communication systems, operators can maintain redundancy when primary infrastructure fails. Research from the GSMA highlights that mobile networks frequently serve as a critical information lifeline during disasters, enabling affected populations and emergency responders to access real-time information and coordinate response activities (GSMA, 2024a). Strengthening redundancy, business continuity planning, and rapid restoration capabilities is therefore essential for maintaining communication services during crises.

AI enabled channel optimisation for warning dissemination

Beyond infrastructure resilience, AI can improve the effectiveness of warning dissemination by optimising how alerts are routed across multiple communication channels. Effective dissemination requires selecting the right combination of channels based on population characteristics, infrastructure availability, and the urgency of the hazard.

Machine learning models trained on historical warning performance data can identify which channel combinations are most effective in different scenarios. These models may incorporate variables such as hazard severity, time of day, demographic characteristics, infrastructure conditions, and previous public response patterns. By analysing these factors, AI systems can recommend dissemination strategies that maximise reach, timeliness, and effectiveness.

Network analysis techniques further support channel optimisation by identifying vulnerabilities, forecasting potential failure points, and optimising routing to maintain connectivity. AI-enabled network management systems can monitor communication infrastructure and adapt dissemination routes in real time. During disasters, these systems can anticipate network congestion and pre-allocate bandwidth for alerts, dynamically switch between channels (e.g., cell broadcast, SMS, satellite, radio) when networks degrade, and support operators in prioritising emergency traffic in line with policy and regulatory frameworks (Ajayi et al., 2025). In Senegal, an initiative combining mobile network data, satellite information, and census data used AI analysis of cell-tower activity to detect flood-related evacuation movements up to 36 hours before official alerts were issued, enabling earlier humanitarian response and aid deployment (UNDRR, 2025). While primarily a response-oriented application, such insights reveal where populations are moving, which towers are overloaded, and where connectivity is degrading - illustrating how AI can inform more targeted and timely dissemination strategies in near real time.

The potential of AI-enabled network management to maintain warning dissemination under disaster conditions is illustrated by an industry initiative to develop AI-powered virtual command centres capable of dynamically rerouting alerts as infrastructure degrades (Box 20).

Box 20. AI-Powered Virtual Command Centres for Disaster Communication Resilience

Disasters and climate variability place acute stress on the telecommunications infrastructure that early warning systems depend on. When networks degrade or fragment, maintaining situational awareness and routing alerts across available channels becomes a critical operational challenge. In response to this challenge, fourteen telecommunications companies - including MTN, NTT, Orange, Verizon, TIM, and Intersec - collaborated under the TM Forum's Catalysts programme to develop a Virtual Command Center (VCC) for disaster recovery. Launched as a minimum viable product in 2024, the VCC integrates AI, autonomous networks, and digital twin technology into a single operational interface for emergency management.

The platform's AI capabilities serve two core functions relevant to warning dissemination. First, predictive analytics process real-time data from across network infrastructure to forecast failure points and guide pre-emptive resource allocation before and during disasters. Second, autonomous network capabilities allow the system to self-heal, reconfigure, and reroute communications when physical infrastructure is damaged - maintaining connectivity for alert dissemination without requiring manual intervention. Digital twins of network infrastructure enable operators to simulate disruption scenarios and test rerouting strategies before deploying changes to live networks. Intersec's contribution to the platform directly connects these capabilities to warning dissemination: real-time population heatmaps and geotargeted mass notification tools allow emergency managers to direct alerts through whichever combination of channels remains viable as disaster conditions evolve.

Further information: https://www.tmforum.org/catalysts/projects/C24.0.651/autonomous-networks-hyperloops-phase-v
https://intersec.com/blog/ai-for-good-summit-key-takeaways-on-advancing-early-warning-systems

4.2.4 AI for public response, feedback and misinformation management

The most effective early warning systems rely on two-way communication between authorities and the public, allowing affected populations to share feedback, report local conditions, seek clarification, and verify information. Such mechanisms enhance situational awareness, confirm message receipt and understanding, and build trust through responsive engagement. During disasters, authorities face overwhelming volumes of information from social media, emergency calls, public messages, sensors, and media reports. At the same time, misinformation and rumours can spread rapidly and undermine response efforts. For example, during the 2023 wildfires in Maui (United States of America), inaccurate reports about evacuation routes circulated online, creating confusion among residents and tourists (Stimpson et al., 2025). Managing such information flows requires the ability to rapidly process large volumes of unstructured data, identify credible and urgent signals, filter misinformation, and respond effectively to public concerns. Increasingly, AI is being deployed to support this process by automating data analysis, detecting patterns, and prioritising information for human decision-makers.

AI enables public feedback, situation awareness and response to warnings

While many emergency notification systems currently rely on the direct aggregation of official data, AI is increasingly seen as a tool to enhance public feedback and situational awareness. Platforms like Google Public Alerts currently aggregate official emergency warnings and distribute them through services such as Google Search and Google Maps. These systems prioritize authoritative alerts when users search for disaster-related terms - like the name of a storm or wildfire - ensuring that verified information reaches the public quickly. While these platforms are primarily data-distribution hubs today, there is significant potential to integrate AI-enabled verification and feedback mechanisms in the future to further improve information quality.

By applying NLP, future systems could validate the accuracy of alerts and better match complex user queries to specific warnings or analyse crowdsourced reports - such as mentions of flooding or blocked roads—to map real-time conditions more accurately for authorities.

AI also shows the potential to measure and predict public behavioural responses to warning messages, helping assess early warning effectiveness by linking communication with evacuation and mobility patterns. This can support both public awareness and policymaking for disaster preparedness. Machine learning methods and approaches, such as reinforcement learning, have been used to simulate how natural hazards such as floods, wildfires and hurricanes influence human mobility patterns, including movement predictability, evacuate destination, and trajectory patterns (Fan et al., 2021; Gunkel et al., 2025). However, the use of trajectory and mobility data raises privacy concerns and requires strong safeguards to prevent surveillance-based misuse. While research in this area is expanding, operational applications remain limited. As a result, this field represents an important area for further research and pilot implementation to better understand and evaluate public behaviour during natural hazards.

Social media analytics and risk perception monitoring
AI can analyse historical compliance and response patterns to improve warning design and effectiveness. Understanding public situational awareness of hazards and impacts is essential for assessing early warning performance. A persistent gap exists between perceived and actual risk, which can weaken warning communication. Low risk perception may reduce preparedness and worsen impacts, as seen during the 2021 floods in Germany, where analysis of 5,800 Twitter messages showed widespread surprise at the event's severity, revealing limited hazard awareness and communication gaps (Zander et al., 2023)

Advances in NLP and machine learning enable analysis of crowdsourced social media data to assess situational awareness, risk perception, and communication effectiveness (Ogie et al., 2018).

Techniques such as text mining, topic modelling, and Named Entity Recognition are widely used for sentiment and emotion analysis across disasters including floods, hurricanes, typhoons, and snowstorms. Although research is extensive, operational application in early warning systems remains limited. NLP-based sentiment analysis can reveal when warning messages lack clarity or empathy, affecting communication effectiveness, and help authorities refine future messaging and communication strategies (Salley et al., 2025).

AI for detecting and mitigating disaster misinformation
Misinformation is a significant challenge during disasters. False or misleading information may include rumours, unverified reports, exaggerated hazard impacts (such as false earthquake predictions), or fraudulent aid claims (Komendantova & Erokhin, 2025). Such misinformation can generate confusion and panic, discourage affected populations from seeking assistance, and disrupt relief and rescue operations. To address this, NLP and machine-learning approaches are being developed to detect and mitigate false information. For example, sentiment analysis can identify sudden surges in negative discourse linked to misinformation spread (Komendantova & Erokhin, 2025), while deep learning models, including convolutional neural networks, are used to detect manipulated or fake images (Hamid et al., 2023).

The effectiveness of AI-based misinformation management relies on digital data. Many AI approaches rely on large volumes of information from online platforms such as social media, messaging services, and digital news sources. In regions where internet access is limited, where digital literacy is low, or where communities rely primarily on offline communication channels, these systems may provide only partial visibility into the information environment. As a result, misinformation circulating through offline networks - such as word of mouth, community radio, or informal messaging groups- may remain undetected. Unequal and limited access to digital channels may cause uneven protection against misinformation. Although fake news detection research is advancing from early development toward maturity, real-world deployment of AI-based false-alert detection within early warning systems remains limited, indicating significant potential for operational application (Alonso et al., 2021). In Japan, for example, AI-based systems are already being used to help filter misinformation from social media during disasters. The crisis intelligence platform Spectee Pro (Box 21) analyses social media posts, images, and other data sources to identify credible reports while filtering misleading or false content; verified information can be distributed to authorities within minutes to support emergency response (JapanGov, 2025).

4.2.5 Gaps and challenges for AI-enabled warning dissemination and communication

Despite growing interest in the application of AI to early warning systems, gaps and challenges remain in its use for warning dissemination and communication (Table 4). Current research is concentrated on hazard detection, forecasting and impact modelling. By contrast, comparatively limited research examines how AI can support the communication stage of early warning systems, including message comprehension, accessibility for diverse populations, trust in automated alerts, or behavioural responses (El Morr et al., 2024; Tiggeloven et al., 2025). Research in disaster risk communication consistently shows that warning effectiveness depends not only on the accuracy of forecasts, but also on how messages are understood, trusted, and acted upon by the public.

Persistent digital divides present an additional challenge, which are particularly pronounced in LMIC contexts. Many emerging AI enabled dissemination approaches rely heavily on Internet connectivity, smartphones, social media platforms, or data-intensive digital infrastructures (Reichstein et al., 2025).

Box 21. Using AI to Detect and Mitigate Disaster Misinformation

Spectee Pro is an AI-powered crisis intelligence platform developed in Japan that enhances real-time situational awareness by analysing diverse data sources, including social media posts, weather data, traffic information, and public camera feeds.

The platform analyses large volumes of user-generated content from social media, alongside images, videos, and other open data sources, to identify credible reports of incidents such as flooding, fires, and infrastructure damage. Using techniques such as natural language processing and image recognition, Spectee Pro filters out irrelevant or potentially false content and prioritises posts that are likely to reflect real-world events. This helps reduce noise and limits the amplification of misinformation during fast-moving crises.

A key feature of the system is its hybrid verification approach. AI is used to flag relevant events - such as flooding, fires, or infrastructure damage -based on text, images, and geolocation data, while a 24/7 human verification team validates critical information before dissemination. Verified insights are then visualised on a geospatial dashboard and delivered to authorities within minutes, significantly improving response times compared to traditional reporting methods.

Spectee Pro has been widely adopted across Japan, with over 1,000 organizations - including local governments and emergency responders - using the platform to support disaster management and risk response. In pilot deployments in countries such as the Philippines, the platform has reduced situational awareness gaps from hours to minutes, enabling faster and more targeted emergency action.

Further information: https://www.japan.go.jp/kizuna/2025/03/next-gen_disaster_tech.html; https://digitalx.undp.org/SpecteePro_dx3.html

However, access to these technologies remains uneven, both between and within countries. Populations most vulnerable to disaster risk - including rural communities, older persons, migrants, and low-income households - often have lower levels of connectivity or digital literacy (World Bank, 2021b). If AI-enabled dissemination relies primarily on online platforms or data-intensive services, these disparities risk excluding precisely those populations most in need of timely warnings. Multi-channel communication strategies remain essential to reach diverse audiences and ensure redundancy in warning delivery (WMO, 2023b). In many LMICs, early warning communication continues to rely on radio, community networks, or local authorities, which may not easily integrate with advanced data-driven platforms. Ensuring that AI applications complement - rather than replace - existing community-based and low-technology communication channels is therefore essential to avoid widening existing risk and information inequalities.

Data limitations further constrain the effectiveness and equity of AI systems in warning dissemination. AI models rely on large datasets for training and validation, yet data related to communication effectiveness, behavioural response, accessibility needs, and local information ecosystems are often incomplete or biased toward digitally connected populations. This is particularly evident in automated translation, which requires high-quality, localized glossaries to produce understandable warnings. While AI translation is proficient in predominant languages, many regions lack standardized terminology for less dominant or indigenous languages, where direct "word-for-word" equivalents for concepts like "risk," "probability," or specific weather phenomena often do not exist. Consequently, the rigorous co-creation of meaningful EWS glossaries is an essential prerequisite to automation to ensure alerts remain culturally and linguistically relevant (Khan et al., 2024; Kwak et al., 2025; Miller, 2024). Some efforts are underway, for example by CLEAR (Box 19). Addressing these risks requires equity-by-design approaches, including diversified data sources, participatory design processes, and continuous auditing to identify and mitigate algorithmic bias (UNESCO, 2021).

Issues of trust, transparency, and accountability also remain central, as many high-performing AI models remain opaque 'black boxes', limiting explainability and raising concerns about transparency, institutional responsibility, and public acceptance (Park et al., 2025). In safety-critical contexts such as disaster warnings, limited explainability can undermine public confidence and complicate institutional accountability for automated recommendations or decisions (OECD, 2022). Transparent governance frameworks, explainable AI methods, and clearly defined human oversight mechanisms are essential to ensure that AI-supported warning systems remain aligned with established emergency management responsibilities.

Legal and ethical requirements - including data protection, bias mitigation, and compliance with emerging regulatory frameworks for high-risk AI systems - introduce additional operational complexity (Shaik et al., 2025). The deployment of AI in public warning systems must comply with data protection regulations, safeguards against algorithmic discrimination, and emerging regulatory frameworks governing high-risk AI applications. Within the European Union, for example, the European Union Artificial Intelligence Act establishes obligations for transparency, risk management, and human oversight in AI systems used in critical public-sector functions (European Commission, 2024a). While these regulatory frameworks are essential for responsible and trustworthy AI, they also introduce additional institutional and technical requirements for authorities implementing AI-enabled warning systems.

At the system level, structural and institutional barriers can further constrain integration and scaling. Early warning systems typically involve complex governance arrangements across meteorological services, disaster management authorities, telecommunications providers, and local governments. Fragmented institutional responsibilities and uneven adoption of interoperability standards - such as the CAP - can limit the integration of AI-enabled dissemination tools across platforms and jurisdictions. In addition, many countries continue to rely on legacy warning infrastructure that was not designed to support advanced analytics or real-time AI integration, making modernisation technically and financially challenging.

Collectively, these challenges highlight that realising AI's potential in warning dissemination and communication requires not only technical innovation, but also strengthened governance, inclusive design, human oversight, and sustained institutional capacity aligned with responsible and people-centred AI principles.

Challenge	Key limitations/risks in relation to Pillar 3	Implications for EWS in relation to Pillar 3	Mitigation measures
Data availability and access	Limited high-quality datasets for underrepresented languages and dialects; lack of parallel corpora and annotated speech data; restricted access to telecommunication and communication platform data.	Reduced accuracy of multilingual alerts, voice messaging, personalization, and audience targeting; some populations may not receive understandable warnings.	Invest in multilingual data collection, community-based datasets, transfer learning, and improved data-sharing agreements; integrate data assessments into dissemination gap analyses.
Explainability and interpretability	AI models often operate as 'black boxes', making decisions difficult to understand or verify. Generative AI struggles to explain outputs or uncertainties, reducing institutional acceptance and public confidence.	Difficulty validating AI generated warning messages or dissemination decisions, reduced accountability, and hesitation to act on warnings.	Apply explainable AI approaches, include uncertainty indicators, maintain human oversight for warning approval, and establish governance and audit frameworks.
AI hallucinations and reliability	Generative AI may produce incorrect or fabricated outputs, including false hazard information or misleading imagery.	Inaccurate warning messages or supporting information could trigger unnecessary panic, reduce credibility of alerts, or undermine trust in official communication channels.	Require human validation of AI-generated warning content, implement automated verification checks, and restrict AI autonomy in life-critical communication stages.
Standardisation and system integration	Ensuring AI-generated multilingual messages comply with Common Alerting Protocol (CAP) requirements across channels is technically complex. Legacy systems may lack interoperability.	Inconsistent messaging across channels (e.g., cell broadcast, SMS, broadcast media, apps), reduced interoperability, and integration barriers within national early warning infrastructures.	Train AI systems on CAP standards, implement validation workflows, and provide technical assistance and phased integration aligned with Pillar 3 implementation.
Institutionalisation and governance	Fragmented institutional mandates, weak coordination among authorities and telecommunication operators, limited data-sharing, and insufficient technical capacity hinder adoption.	Delays in warning approval and dissemination, fragmented communication workflows, and sustainability risks for AI-enabled alerting systems.	Strengthen governance frameworks, clarify institutional roles, invest in capacity building, and establish long-term operational ownership.
Privacy and data protection	Behavioural modelling, location-based alerts, and personalisation require sensitive data (e.g., device location or mobility patterns), raising privacy and surveillance concerns.	Privacy concerns may reduce public acceptance of targeted alerts and create legal risks for authorities operating dissemination systems.	Apply data minimization, anonymization, transparent data governance, and compliance with data-protection regulations, especially when using location-based dissemination.
Misinformation and deepfakes	AI both combats and enables misinformation, including realistic fake alerts, manipulated images, and deepfakes during disasters.	Confusion and erosion of trust in official warning channels; people may ignore authentic alerts if credibility is undermined.	Strengthen verification systems, rapid rumor tracking, clear source authentication, and proactive risk communication strategies.
Infrastructure and connectivity gaps	AI-enabled dissemination systems depend on computing resources, mobile connectivity, and communication infrastructure that may be limited in high-risk regions.	Risk of widening the digital divide and system failure during disasters when connectivity is disrupted.	Use appropriate-technology approaches, edge computing, offline functionality, hybrid cloud-local deployment models; expand mobile network, and broadband coverage and ensure equitable access to infrastructure.
Algorithmic bias and equity risks	AI trained on historical or incomplete data may overlook inequalities and underserved populations.	Unequal reach or effectiveness of warning messages across demographic groups, languages, or geographic areas.	Use representative datasets, fairness metrics, bias auditing, and community participation in system design and evaluation.
Context sensitivity and false alarms	AI systems may struggle with cultural nuance or rapidly evolving disaster contexts.	Poorly contextualised warnings, excessive false alarms, or missed alerts can reduce public trust and response effectiveness.	Maintain human-in-the-loop decision-making, localise models for national contexts, and conduct continuous monitoring and evaluation of warning performance.
Capacity, sustainability, and vendor dependence	Limited local expertise to operate AI-enabled dissemination systems; risk of vendor lock-in and dependence on proprietary platforms.	Systems may degrade over time, become difficult to maintain, or fail to integrate with national alerting infrastructure.	Invest in national capacity building, knowledge transfer, open standards, and sustainable procurement strategies for EWS.

Table 4. Overview of key challenges and mitigation strategies for AI-enabled warning dissemination and communication in the Pillar 3 context.

4.3 From innovation to impact: guidance for action

This section provides guidance for organizations considering AI deployment to strengthen warning dissemination and communication within early warning systems. Drawing on research evidence, and lessons from the global case studies (Boxes 14-21), it identifies interdependent areas for action: strategic planning; technical implementation; institutional governance; community engagement and equity; and monitoring, evaluation, and learning.

Strengthening warning dissemination and communication through AI requires translating technological innovation into operational systems that are trusted, sustainable, and people-centred. Effective implementation begins with clearly defining the problem AI is intended to address - such as improving dissemination speed for fast-onset hazards, expanding coverage, enabling multilingual communication, or increasing resilience of communication systems (Faiaz & Nawar, 2024; R. Kumar & Rani, 2025). Baseline assessments of existing warning performance – e.g., message generation time, population coverage, channel availability, and language support - help identify priority gaps where AI can add value and establish measurable benchmarks, while realistic resource planning ensures longer term sustainability (Shaik et al., 2025).

Determining appropriate levels of AI autonomy is a critical consideration. Effective systems adopt tiered approaches in which AI manages routine, high-confidence tasks, humans review moderate-confidence decisions, and full human control is retained for critical situations (Blunier, 2024). For example, England's Smart Alert Assistant (Box 15) standardises message creation through rule-based AI while requiring Flood Warning Duty Officers to review and approve all alerts before dissemination, preserving accountability while reducing cognitive burden during emergencies. Similarly, large-scale systems such as China's AI-enabled dissemination platform (Box 14) demonstrate how automated processes can accelerate message production and delivery while maintaining rigorous quality control mechanisms.

Successful deployment also depends on integration with existing warning infrastructure (meteorological systems, communication networks, emergency platforms), institutional processes, and community-based feedback mechanisms (Miller, 2024). For example, the CLEAR Initiative (Box 19) demonstrated effective multi-stakeholder coordination, by bringing together humanitarian organizations, data providers, and technology companies to combine multiple early warning data streams into a unified operational platform. AI integration should also be supported by interoperability standards and strong data governance frameworks that safeguard privacy, ensure data quality, and enable secure information sharing (Shaik et al., 2025). Testing, including community validation across hazard scenarios and user groups, can help improve reliability, usability, and cultural appropriateness before wider implementation (Ogie et al., 2018). The EWCM deployment in Liberia (Box 18) demonstrates the value of field validation and collaboration with national telecommunication authorities and mobile network operators to verify data. Such testing helps improve technical reliability while ensuring systems are usable and appropriate for the operational context. Clear institutional roles, transparency measures, and accountability mechanisms can help build public confidence and sustain systems over time. Investments in technical, operational, and institutional capacities are necessary to sustain systems beyond pilot phases. In Liberia (Box 18), technical implementation was combined with training for national authorities, strengthening institutional capacity to manage and apply connectivity data for early warning planning.

People-centred design and continuous engagement ensure warnings are understandable, accessible relevant, actionable, and trusted, particularly for marginalised and vulnerable populations (Shaik et al., 2025; Zhao et al., 2025). Several case studies highlight how AI can support more inclusive communication approaches. For example, voice-based alerting in Sudan (Box 16) converts text warnings into audio messages in local languages to reach non-literate communities, while AI-enabled translation tools in Canada's national Alert Ready system (Box 17) support rapid bilingual dissemination.

These approaches illustrate how AI can help address language, literacy, and accessibility barriers when designed with equity considerations in mind.

Monitoring and evaluation frameworks are important to ensure AI deployments achieve meaningful outcomes, and should link technical performance indicators - such as speed, coverage, and delivery reliability - with social outcomes including comprehension, trust, protective action, and equitable reach (Shaik et al., 2025). For example, China's AI driven early warning system (Box 14) demonstrated the impacts of comprehensive monitoring achieving higher national coverage, 1-minute delivery to emergency managers, and 3 minute 20 second average public delivery. Whilst Spectee Pro's (Box 21) near-real-time performance data - including verification accuracy, response latency, and user adoption across government agencies - illustrates how operational metrics can drive iterative improvement in AI-assisted warning systems.

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Together, these lessons highlight that effective AI deployment requires more than technological innovation alone. Strategic planning, institutional coordination, inclusive design, and continuous learning are all necessary to translate emerging AI capabilities into operational early warning systems that protect people and communities at scale.

4.3.1 Enabling conditions and stakeholder roles for AI implementation across pillar 3

Successful implementation of AI in warning dissemination depends not only on technological capability, but on how systems are planned, governed, tested, and continuously improved in real-world contexts (Table 5). Evidence across this chapter shows that AI deployments are most effective when embedded within strong institutional coordination, sustainable resourcing, and user-centred design.

In practice, countries that have made progress with AI-enabled dissemination systems have followed a collaborative and iterative approach. This typically begins with joint needs assessments across forecasting agencies, disaster management authorities, and communication regulators, followed by pilot initiatives that test AI applications in controlled settings before scaling. These processes are often supported by peer exchange and structured feedback loops. Such sequencing would mean that when AI-generated impact forecasts improved lead times, the institutional infrastructure to act on them already existed. Where governance design lagged behind AI ambition, improved forecasts may not reliably translate into faster or more effective warnings.

Effective implementations define clear roles and responsibilities across the warning value cycle - from forecast validation to message authorization and dissemination. Where coordination mechanisms are weak or fragmented, delays, duplication, and accountability gaps can undermine system performance, regardless of the underlying technology.

Sustained financial resources are essential to move beyond pilot initiatives toward long-term operation, maintenance, and system evolution. While many AI applications have been successfully demonstrated, scaling requires long-term financing, integration into operational workflows, and local capacity development. Multi-year operational funding commitments should be treated as a prerequisite for responsible deployment at scale. Technology providers, for their part, should be evaluated not only on technical capability but on whether their partnership models build local capacity to operate and maintain systems independently.

In addition, AI-supported systems perform best when trained analysts remain actively engaged in validating outputs and making final decisions, and when communities trust both the source and content of warnings. Systems that fail to build trust, risk excluding vulnerable populations and reducing the effectiveness of warnings.

Across emerging and more mature systems, effective AI-enabled warning dissemination shares several practical characteristics:

- AI tools are embedded within existing operational chains, linking forecasting, decision-making, and dissemination, rather than functioning as standalone applications.
- Roles are well-defined across agencies, with explicit protocols for message approval, escalation, and cancellation.
- AI supports, but does not replace, expert judgement; analysts validate outputs and retain authority over final decisions.
- Multi-channel, inclusive dissemination where systems combine digital (e.g. cell broadcast, apps) and non-digital channels (e.g. radio, community networks) to ensure reach across all populations.
- User-centred message design, where warnings are tested to ensure they are understandable, actionable, and tailored to different audiences, including marginalized groups.
- Systems are continuously improved through monitoring, drills, pilot testing, and peer review across countries and agencies.
- Sustainable institutionalisation will allow AI capabilities to be integrated into national systems with dedicated funding, trained personnel, and long-term maintenance plans.

Insights also shows that even technically advanced systems can fail if enabling conditions are not adequately addressed, this can be from the technology itself, but also from system design, governance, and human factors. Systems that have performed under operational stress - including during the events they were designed to address - invested in redundant connectivity, backup power, and network resilience assessments prior to AI procurement. Warnings frequently fail not because they were not transmitted, but because they were not trusted (lack of credibility or prior experience with false alarms), not understood (unclear or overly technical messaging), not accessible (language barriers, disability, or lack of connectivity), not actionable (lack of clear guidance or capacity to respond). These challenges are particularly pronounced for marginalised and vulnerable populations. AI systems that rely heavily on digital data or channels risk reinforcing these gaps if equity and inclusion are not explicitly addressed. Emerging risks specific to AI include data bias, model opacity, over-reliance on automation, and interoperability challenges, all of which require ongoing monitoring and governance - even in mature systems. These lessons reinforce a critical distinction: success in early warning systems is not the transmission of a message, but the ability of individuals and communities to take timely and appropriate protective action.

Building on these insights, several cross-cutting conditions underpin effective implementation:

- Interoperability and standards, including adoption of the Common Alerting Protocol (CAP), cross-platform integration, and regional and international cooperation.
- Data governance frameworks that address privacy protection, responsible data sharing, and quality assurance.
- Equity and inclusion commitments that ensure multi-channel delivery, accessibility for persons with disabilities, linguistic diversity, and reach to underserved populations.
- Public-private partnerships that enable resource mobilization, technology transfer, and collaborative innovation.
- Capacity ecosystems that combine formal training, mentoring, peer learning networks, and sustained institutional support.
- Adaptive management approaches that enable continuous learning, iteration, and context-specific adaptation.

Stakeholder	Key roles and responsibilities	Critical enabling conditions	Example actions
National governments, including regulators	Needs assessment; Policy and regulatory frameworks; funding and resource allocation; coordination across agencies; sustainability planning	Political commitment; adequate funding; inter-agency coordination mechanisms; long-term planning	Establish national AI strategies for DRR; allocate sustained funding; create coordination bodies; develop regulatory frameworks
Disaster Management Agencies	Needs assessment; technical implementation; system operation; message generation and dissemination; public communication; performance monitoring	Technical capacity; operational procedures; institutional mandates; inter-agency coordination	Deploy AI systems; train staff; operate systems; monitor performance; coordinate with partners
Forecasting agencies e.g., NMHSs	Generate and validate hazard information; translate forecasts into actionable warnings; collaborate with communication authorities to ensure timely and accurate dissemination; integrate AI into forecasting and impact-based warning processes.	Access to historical and real-time data; technical capacity and infrastructure for AI integration; interoperability with dissemination systems; clear mandates and institutional coordination frameworks	Deploy AI models to improve impact-based forecasting; use ML to refine warning thresholds and reduce false alarms; collaborate with telecommunication operators to align forecast outputs with dissemination triggers
Telecommunication operators	Infrastructure provision; message delivery; network resilience; cell broadcast implementation	Infrastructure investment; regulatory support; public-private partnerships; technical standards; emergency protocols	Provide network access; integrate with warning systems; track delivery; invest in resilience
Technology providers	AI system development; technical support; capacity building; knowledge transfer	Technical expertise; sustainable business models; commitment to local capacity building; ethical practices	Develop appropriate technologies; provide training; transfer knowledge; ensure ethical design
Industry associations e.g., GSMA; Global Satellite Operators Association	Facilitate industry-wide standards and coordination; promote adoption of AI-enabled dissemination technologies; conduct research and support knowledge sharing and best practices across members; advocate for enabling regulatory environments	Strong collaboration between public and private sectors; data-sharing frameworks; incentives for innovation and investment in AI-driven communication systems.	Conduct research and develop guidelines for AI-enabled mobile and satellite alerting; support pilots; convene stakeholders to share lessons on multi-channel and AI-enhanced dissemination
Research & academic institutions	Research and innovation; evaluation and learning; capacity building; knowledge generation	Research funding; academic freedom; partnerships with implementers; commitment to applied research	Conduct research; evaluate systems; train professionals; generate evidence
International organizations	Technical assistance; funding; knowledge sharing; standards development	Sustained commitment; flexible funding; coordination with national governments; respect for local ownership	Provide technical assistance; fund implementation; facilitate knowledge sharing; develop standards
Civil society	Community engagement; feedback and advocacy; trust building; equity monitoring	Community trust; organizational capacity; funding; inclusion in decision-making	Engage communities; provide feedback; advocate for equity; monitor implementation
Communities & individuals	Feedback and input; system testing; trust and adoption; protective action	Access to information; mechanisms for input; trust in institutions; capacity to respond	Provide feedback; participate in testing; adopt protective actions; share experiences

Table 5. Stakeholder roles and enabling conditions for AI implementation in warning dissemination and communication

4.4 Conclusions and recommendations

This chapter highlighted that AI offers significant potential to strengthen warning dissemination and communication - Pillar 3 of the EW4All initiative. AI technologies enable capabilities previously difficult to achieve at scale: generating multilingual, context-appropriate messages within seconds; optimizing dissemination channels in real time; tailoring and targeting communication to diverse audiences; and analysing feedback to continuously improve warning effectiveness. These functions directly address persistent challenges of speed, scale, accessibility, and personalisation that constrain traditional warning approaches.

Evidence from research and the case studies presented in this chapter shows that these benefits are already emerging in operational systems. China's AI-enabled national dissemination platform (Box 14) demonstrates how automation can support near-universal warning coverage with rapid nationwide delivery. Voice-based alerts in Sudan (Box 16) show how AI can expand accessibility for non-literate communities, while AI-powered translation in Canada's national alerting system (Box 17) illustrates how multilingual communication can be integrated directly into alerting infrastructure. EWCM deployment in Liberia (Box 18) demonstrates how AI-generated connectivity and population data can help identify communication coverage gaps and inform national early warning planning. Multi-organizational platforms such as the CLEAR initiative (Box 19) illustrate how AI can integrate diverse data sources to support anticipatory humanitarian action. Operational alerting tools such as the Smart Alert Assistant in England (Box 15) show how AI can streamline message creation while maintaining human oversight. Finally, Spectee Pro (Box 21) demonstrates how the systematic collection and analysis of user feedback, alongside near-real-time performance metrics - such as verification accuracy, response latency, and user adoption - can support continuous, iterative improvement in AI-assisted warning systems. Taken together, these examples confirm that AI is no longer a theoretical concept in early warning systems but an emerging operational tool delivering measurable improvements in dissemination speed, coverage, accessibility, and coordination.

At the same time, AI is not a panacea. Infrastructure gaps, limited data availability, institutional capacity constraints, and digital divides risk reinforcing inequalities if deployment is uneven, especially in LMIC contexts. Challenges - including privacy protection, algorithmic bias, misinformation risks, and trust - require strong governance and accountability frameworks. AI should augment rather than replace human judgment and institutional responsibility. Decisions regarding warning issuance, communication of uncertainty, and adaptation to local cultural contexts require human oversight and validation, while AI supports speed, consistency, and analytical scale. Progress therefore depends on balanced implementation, and continued research and innovation. Investments in connectivity, local technical capacity, co-creation methods, and governance must accompany technological adoption, engaging communities in system design, testing, and refinement, alongside continued reliance on multi-channel dissemination that reaches offline or hard to reach populations.

The experiences highlighted across the chapter illustrate several pathways for progress. Strategic partnerships between technology providers, humanitarian organizations, governments, and research institutions can help align technical innovation with real-world operational needs. AI can also support evidence-based planning for communication infrastructure by identifying coverage gaps and strengthening dissemination networks. At the same time, inclusive communication tools - such as voice-based alerts and multilingual translation systems - demonstrate how AI can help ensure warnings are accessible to diverse populations, including those facing language, literacy, or connectivity barriers. A central challenge ahead is implementation and scaling: translating proven technological potential into early warning systems capable of delivering universal, actionable alerts that protect all communities.

Chapter 5.
AI for preparedness to respond to warnings

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Pillar 4. Where warnings become action

Early Warnings for All

ENABLES

- Better preparedness & resource allocation
- Timely early action
- Continuous learning & improvement

CORE AI TECHNOLOGIES

- Machine Learning
- Optimization Algorithms
- Simulation & AI Planning
- Decision Intelligence

Preparedness and response systems determine whether warnings translate into effective early action. AI can strengthen four critical decision domains: analyzing institutional frameworks to surface governance gaps; integrating fragmented data to identify local capacity needs; calibrating financing triggers to optimize resource allocation; and synthesizing multi-source information to improve coordination across institutions.

- AI can support enabling environment analysis by identifying gaps in legal frameworks, institutional mandates, and financing mechanisms that prevent anticipatory action.
- AI can strengthen local preparedness by integrating dispersed data to surface capacity gaps, generate training scenarios, and adapt warning messages for vulnerable communities.
- AI-enabled decisions can improve anticipatory financing by calibrating probabilistic triggers, optimizing resource allocation, and simulating trade-offs between false alarms and missed events.
- AI can enhance stakeholder coordination by synthesizing real-time information into tailored decision-support products and extracting lessons across operations.

However, AI systems reflect the data they are trained on and may underperform in data-scarce contexts, reinforce existing inequities, or obscure uncertainty in ways that erode trust. Human judgment therefore remains indispensable. Emergency managers, humanitarian practitioners, and community leaders play an irreplaceable role in interpreting outputs, exercising contextual judgment, and maintaining accountability.

Ultimately, AI should complement rather than replace human decision-making, with clear governance structures established before deployment to ensure oversight, equity, and accountability to the most vulnerable populations.

Early Warnings for All

5.1 Pillar 4: where warnings become action

The basis of a successful early warning system rests on the successful integration of all EW4All pillars and its ability to deliver on *timely action*. A forecast that does not reach the right audience, or a warning that prompts no response, or a risk assessment filed away will not service the populations that early warnings should protect. Early warning systems are mechanisms that convert information into protection (Šakić Trogrlić et al., 2022).

The critical element of protection is embedded in Pillar 4 of the EW4All initiative: preparedness to respond to warnings. Pillar 4 is where the value of disaster risk knowledge (Pillar 1), observations and forecasting capacities (Pillar 2) and dissemination of early warnings (Pillar 3) materialize into saving lives, livelihoods and assets (Hermans et al., 2022). Pillar 4 encompasses the plans that define what individuals, communities, government agencies, and humanitarian practitioners should do when warnings arrive, the protocols that determine when action begins, the pre-positioned resources that enable anticipatory action and rapid response, and the coordination mechanisms that align efforts across organizations (UNDRR & WMO, 2024). In other words, Pillar 4 is about protection: the timely reduction of disaster risk to life, health, livelihoods, assets, and essential services through anticipatory and response actions triggered by early warning information.

The evidence for Pillar 4's significance is unambiguous. Evidence suggests that anticipatory cash transfers enabled by early warning improve food security outcomes (up to 18 percent additional households report acceptable food consumption scores compared to control groups (WFP, 2024). Further, anticipatory actions have proven to be more cost-effective than traditional, post-shock responses, often achieving returns on investment 1.5-2 times greater (H. Brown et al., 2025). Yet fewer than one third of countries globally report having local-level plans to act on early warnings (IFRC, 2023a). This gap between warning and action represents the central challenge Pillar 4 exists to address.

Artificial intelligence does not close this gap on its own. But AI offers capabilities, pattern detection at unprecedented scale, rapid synthesis of complex data, and capabilities to support decision-making under uncertainty, that are increasingly relevant to the specific constraints anticipatory action and preparedness systems face. Most analyses of the role of artificial intelligence for early warning systems focus on forecasting accuracy or hazard detection; but, so far, there is limited analysis on the use of AI in preparedness and anticipatory action, or on how artificial intelligence can help communities identify the most appropriate actions to take. This chapter explores where AI can meaningfully reduce delays, decision-making noise, blind spots, and coordination failures that prevent warnings from delivering protection.

The chapter is organized around the decision architecture that defines Pillar 4, rather than around AI capabilities. Section 5.2 highlights the four domains through which preparedness decisions are made: enabling environments, local preparedness capacity, financing connected to action, and stakeholder collaboration. For each, it asks where AI genuinely helps, where it falls short, and where it should not be used at all. Section 5.3 addresses the trust imperative, examining why opacity, data inequality, and accountability gaps represent fundamental constraints on AI integration in high-stakes preparedness contexts. Section 5.4 translates this analysis into guiding principles for responsible integration, grounded in humanitarian principles. The chapter concludes by drawing together the conditions under which AI can strengthen preparedness and response to warnings.

5.2 The Pillar 4 framework: how decisions define protection

Protection is not produced by forecasts alone. It depends on the quality of decisions taken under time pressure, uncertainty, institutional misalignment, and resource constraints. Pillar 4 can therefore be understood not simply as a set of implementation activities, but as a decision architecture composed of four interrelated domains, which are evaluated in greater detail in this section: the enabling environment, local preparedness, pre-agreed financing and coordination. Each domain represents a category of high-stakes choices that determine whether information becomes protection. In this chapter, artificial intelligence is evaluated not by its technical sophistication, but by whether it improves the timeliness, coherence, equity, and legitimacy of those decisions (WMO, 2026).

5.2.1 Enabling environments: governance coherence as a decision problem

The key to preparedness to respond to warnings is whether institutions are legally and financially able to act on specific forecasts or credible risk analysis. Under Pillar 4, strengthening enabling environments requires ensuring that legal frameworks permit anticipatory action; establishing institutional mandates and coordination structures; securing financial mechanisms for rapid response; and achieving coherence across disaster risk management, climate adaptation, and humanitarian systems (IFRC, 2024a). In practice, these systems frequently operate in silos (Zembe et al., 2023). To illustrate: disaster risk management laws may authorize response only after impact, and agricultural or social protection policies may reference forecasts without specifying decision thresholds, roles, or budget lines. The result is a governance gap between information and authorization.

The enabling environment challenge in Pillar 4 is not primarily one of locating legal gaps, as practitioners typically know whether frameworks authorize anticipatory action or not. The harder problem is building the analytical foundation for stakeholder dialogue: identifying which specific provisions require revision, where contradictions across ministries create operational blockages for anticipatory action, and what precedents from other jurisdictions might be transferable. In multi-level governance systems, where disaster risk management, climate adaptation, and humanitarian mandates are distributed across different administrative tiers, such inconsistencies may be genuinely invisible without systematic cross-referencing. Natural language processing can support this diagnostic function, surfacing gaps such as preparedness plans referencing forecast thresholds without an associated anticipatory action, or responsibilities assigned without corresponding budget lines (Lensing et al., 2025). The value lies not in replacing stakeholder engagement, but in sharpening the evidence base that informs it.

Comparative analysis further expands this contribution. Humanitarian networks have operational presence across various countries, creating opportunities for cross-context learning. Legal provisions enabling forecast-based financing in one country may offer replicable models elsewhere (Jin & Mihalcea, 2023). NLP tools can identify analogous clauses across jurisdictions, accelerating policy learning. Evidence from anticipatory action programmes is often concentrated in a small number of well-documented country contexts, and the challenge for reform advocates is not access but contextualization: identifying which findings are transferable, under what conditions, and how they map onto the specific legal and institutional landscape where reform is being sought. AI-supported synthesis tools can help bridge this gap by drawing connections between documented programme outcomes and the specific provisions or gaps identified in a target country's frameworks (WFP, 2025). In this way, AI can reduce the informational burden that often slows reform processes and strengthen the analytical basis for advocacy. These systems can rapidly diagnose gaps that would otherwise require extensive manual review (Planas et al., 2022).

Yet the limits are equally clear. Identifying legal gaps does not close them. Revising frameworks requires navigating institutional incentives, competing mandates, and political risk. Governance reform is inherently political. AI cannot negotiate trade-offs between ministries, reconcile power asymmetries, or generate political will. Legal traditions vary in ways automated systems may struggle to interpret fully, and informal norms that shape implementation often lie beyond textual analysis (Bressan & Bergmaier, 2021).

5.2.2 Local preparedness: the local capacity challenge

If enabling environments determine whether action is authorized, local preparedness capacity determines whether action is feasible. Under Pillar 4, local capacity determines whether responders and communities possess the knowledge, resources, and systems required to act effectively when warnings arrive (Syed et al., 2021). The decision challenge is practical and operational: where to prioritize training; which communities require evacuation planning most urgently; what early actions are operationally feasible within the short time window between warning and impact, how to adapt warnings and associated anticipatory actions and preparedness protocols to different contexts; how to allocate limited equipment and personnel; and how to learn systematically from exercises and real events (Fant & Adelman, 2022).

These decisions are difficult because preparedness capacity is uneven, dynamic, and often poorly documented. Training records, equipment inventories, and infrastructure data are frequently fragmented across agencies. Informal settlements and remote communities may not be well mapped. Further, after-action reviews are labor-intensive and vary in quality, making cross-event learning inconsistent. Here, AI can play a role in developing tailored capacity building material. For instance, a preparedness expert responsible for protocol design needs a conceptual grasp of anticipatory action frameworks, while a finance officer needs to understand trigger logic and accountability requirements, and a community volunteer needs clear, actionable guidance relevant to their specific context. AI-supported learning tools, if trained on relevant operational content, can tailor both the substance and framing of training to specific roles and responsibilities, making capacity building more targeted and ultimately more effective (Box 22).

Box 22. AI-Driven Impact-Based Cyclone Preparedness Guidance for Bangladesh

Coastal Bangladesh, particularly the southern region, faces recurrent cyclonic storms and cascading hazards at least annually, yet despite advances in forecasting and the Cyclone Preparedness Programme (CPP), significant gaps persist in impact-based, location-specific early warning guidelines, limiting anticipatory action at the local level. To address this, a tool in development employs generative AI to bridge the gap between forecast and landfall by producing contextualized, impact-based preparedness guidance for rapid-onset cyclonic storms associated with wind, rainfall, and storm surge. Its core innovation is a localized guideline-generation module built on a Retrieval-Augmented Generation (RAG) framework that integrates real-time meteorological forecasts with hyper-local vulnerability and exposure information. A cyclone damage classifier predicts probable impacts based on wind speed, rainfall, and surge, enabling the system to recommend specific anticipatory actions, while multi-layer risk maps visualize spatial risk patterns and highlight areas requiring early or intensified preparedness. The retrieval layer dynamically selects relevant exposure data, and the generation model produces tailored preparedness guidance that reflects anticipated impacts and underlying vulnerabilities, translating technical weather signals into clear, actionable instructions in Bangla to support socially responsive disaster communication. The initiative involves the Storm Warning Centre of the Bangladesh Meteorological Department and members of the FOREWARN Disaster Hackathon Team—Md. Abrar Faiaz, Alphy Shaharin, and Nowshin Nawar—within the broader Start Network FOREWARN Bangladesh network. Early results indicate improved clarity and operational relevance of localized advisories, enabling earlier identification of high-risk areas for prioritizing anticipatory actions. High-quality local data and culturally appropriate messaging remain essential, and AI functions most effectively as a decision-support tool that complements local expertise. The model is designed for scalability across forecasting systems, institutional capacities, and multiple hazards beyond cyclones.

Further information: https://doi.org/10.1145/3704522.3704549

Artificial intelligence becomes relevant where fragmentation and scale constrain human analysis. Machine learning can integrate dispersed training records, logistics inventories, hazard exposure data, and demographic indicators to identify recurring capability gaps or areas of heightened vulnerability (Saravi et al., 2019). Natural language processing can extract structured insights from large numbers of after-action reports, identifying repeated bottlenecks such as communications failures, medical supply gaps, or delays in evacuation decision-making. These techniques allow organizations to move from anecdotal learning to systematic pattern recognition across operations (Alam et al., 2018; Imran et al., 2016).

Computer vision techniques have been applied to accelerate emergency response. For example, satellite and drone imagery can provide rapid assessments of vulnerability to disasters (Braik & Koliou, 2024; NVIDIA, 2022). This information can then be used to train risk models and inform preparedness and anticipatory action protocols to better anticipate and respond early (see also Chapter 2). Having these systems in place ahead of hazard events is an important preparedness activity that could be triggered by a warning, and ultimately reduce the time required to mount an emergency response. For example, following Cyclone Idai in Mozambique (2019), automated damage classification significantly reduced the time required to map affected structures, influencing operational targeting (UNITAR UNOSAT, 2019). Generative AI models can also expand the range of training scenarios used in preparedness exercises, simulating variations in hazard timing, severity, and geographic impact that may not be represented in recent experience. For example, an End-to-End Simulation Exercise Manual for Early Warning systems being developed by IFRC introduces, for the first time, a pioneering model for developing MHEWS simulations fully supported by the integration of Generative Artificial Intelligence (GenAI) which will help the user to generate substantial texts that would otherwise have to be described in detail in this manual. The approach also provides users with responsible and ethical guidance on leveraging GenAI as a support tool to accelerate their work, without replacing expert judgment. AI-supported language processing further enables adaptation of early warning and associated anticipatory actions to different contexts, supporting services such as IFRC's WhatNow platform, which helps translate technical risk information into locally actionable guidance (IFRC, 2023b).

Contingency plans and anticipatory action protocols represent significant preparedness tools in humanitarian operations, yet they typically function as static documents reviewed annually and updated manually (R. Choularton, 2007). This creates a structural gap: the plans that are supposed to guide response are rarely calibrated to current forecast conditions or updated impact estimations. AI offers a practical opportunity here. By connecting contingency plans to live forecast outputs, impact models, and evolving exposure data, agencies can move from fixed response scripts toward adaptive planning tools that reflect actual risk conditions at the moment of decision. For agencies where contingency planning is a core institutional practice, this kind of dynamic integration could meaningfully shorten the distance between a forecast and an operationally ready response. The technical precedent exists, as Box 23 illustrates for Early Action Protocols, and the same logic applies at the broader level of contingency planning frameworks (Box 23).

However, AI has structural limitations: AI systems cannot build the trust that determines whether communities will take early actions such as complying with evacuation orders (Das & Wegmann, 2022). After-action reports reflect what institutions choose to document, not necessarily what communities experience. Preparedness ultimately depends on judgment developed through mentorship, lived experience, and repeated practice. These are capacities that cannot be automated (Lamsal et al., 2025).

AI has a potential role in enhancing learning, accelerating analysis, and supporting prioritization (Lin et al., 2018). Critically, the capabilities of AI systems to detect patterns very rapidly can help identify blind spots.

Such blind spots may arise, for example, due to incomplete data: inventories that do not take into account last-mile delivery capacities, unrecorded training gaps, or communities not assessed in official records. AI can surface these gaps by cross-referencing multiple fragmented data sources, thereby flagging inconsistencies that human analysts may not have the bandwidth to detect.

Box 23. AI-Enabled Anticipatory Action Protocol Digitization

Early Action Protocols (EAPs) are locked in static PDF documents containing complex conditional logic (e.g., "Activate if wind >100km/h AND 500 homes exposed") requiring manual interpretation for monitoring systems—a process that is slow, error-prone, and lacks immediate validation against historical impact data, risking false alarms and delayed funding release. Piloted in Philippines and Guatemala, this Generative AI system serves as an intelligent ingestion engine for IFRC's GO platform, using LLMs to read unstructured EAP documents and identify hazard triggers (e.g., "Rainfall >100mm") and impact justifications (e.g., "Expect >25% crop loss"), handling complex dependencies while instantly converting narrative rules into standardized machine-readable JSON code. Future generative capabilities will assist National Societies in drafting new protocols by analyzing successful trigger databases to suggest optimized thresholds reducing false alarms based on historical success rates. Developed by IFRC, National Societies, Togglecorp, Yellow Umbrella, and Development Seed for hydro-meteorological (floods, typhoons, droughts, heatwaves) and geophysical hazards (earthquakes), the prototype achieves zero-latency configuration reducing setup time from days to seconds with high accuracy. Impact-based validation is enabled by cross-checking the Montandon Global Crisis Data Bank to verify thresholds actually caused past humanitarian crises, enabled by Montandon's event correlation allowing for cross-country protocol comparison. The language-agnostic LLM processes protocols in multiple languages providing scalability to integrate with global platforms.

Further information: https://github.com/IFRCGo/EAP_Trigger_Analysis

5.2.3 Finance connected to action: the trigger decision

Financing is critical: availability of funding determines whether early action is feasible and readiness can be sustained (Linnerooth-Bayer & Hochrainer-Stigler, 2015). Linking early warnings to pre-arranged financial mechanisms is critical to ensure that action can begin before impacts escalate (Thalheimer et al., 2022). The central decision challenge is defining when to release resources based on probabilistic forecasts. This requires calibrating trigger thresholds that balance competing objectives: minimizing missed events that result in preventable harm, limiting costly false alarms that erode trust, allocating scarce resources across multiple risks, and demonstrating cost-effectiveness to sustain donor and government support (Anticipation Hub, 2022).

This challenge is inherently difficult because forecasts express probabilities, not certainties. A 60 percent probability of severe flooding implies a 40 percent chance that a severe flood may not take place (and that impacts would be less extreme than anticipated). Acting too early or too often risks financial inefficiency and political criticism (Sawada et al., 2022). Conversely, acting too conservatively risks delayed response and higher humanitarian costs (R. J. Choularton & Krishnamurthy, 2019). Moreover, meteorological probabilities must be translated into impact probabilities, which vary across geographies. Identical rainfall forecasts can produce vastly different consequences depending on local vulnerability.

AI can be used to assess the historical relationships between hazards and impacts in ways that humans may miss, which can ultimately inform how thresholds are designed. Machine learning models trained on past forecasts and observed outcomes can translate meteorological predictions into probabilistic impact forecasts, enabling graduated response strategies. For example, models can provide inputs for pre-positioning supplies at lower probability and intensity levels and activating evacuation protocols at higher ones. Systems such as Google's flood forecasting platform demonstrate the feasibility of combining hydrological modelling with machine learning to generate probabilistic forecasts with uncertainty quantification across multiple countries, which could help calibrate thresholds for anticipatory action (Price et al., 2025). By connecting to the forecast data via the platform's API, governments and humanitarian actors can integrate AI-based triggers directly into their internal dashboards. This can accelerate human-in-the-loop processes and reduce the time between a forecast and anticipatory actions like cash disbursements.

AI can also support threshold optimization. In Somalia, the World Food Programme linked seasonal drought forecasts to pre-arranged financing, reaching over 117,000 individuals before acute food insecurity peaks by leveraging AI techniques to calibrate the trigger levels (WFP, 2023). By simulating alternative trigger levels against historical data, models can estimate trade-offs between false alarms and missed events under different policy objectives. Optimization algorithms can identify resource allocation strategies that maximize expected lives protected per dollar spent or that prioritize highly vulnerable populations under explicit equity constraints (Ocal & Torun, 2025), see also Box 24).

Box 24. Hybrid AI Post-Processing for Extreme Rainfall Early Warning in East Africa

In Eastern Africa, the bottleneck for anticipatory action is often not forecast availability but forecast usability: whether probabilistic outputs are calibrated to impact thresholds that financing mechanisms can act on. NHMSs face additional constraints, as limited supercomputing infrastructure restricts their ability to produce the high-resolution ensemble forecasts that anticipatory triggers require. This system addresses both constraints. Deployed operationally in Kenya, Ethiopia, Rwanda, and Uganda, it post-processes global weather prediction outputs using AI to generate high-resolution probabilistic rainfall forecasts at low computational cost, with calibration explicitly converting outputs into probabilities aligned with impact thresholds used for anticipatory financing decisions. Developed through partnerships between national meteorological departments, IGAD Climate Prediction and Applications Centre, University of Oxford, ECMWF, and WFP, the system reduces forecast generation time from three hours to 40 minutes, enabling frequent updates with 30-54 hour lead times and achieving 5-10% skill improvements for high rainfall thresholds. Critically for preparedness and response, the lead times achieved are sufficient to trigger pre-arranged financing and early action before impact. The key lesson is not technical: translating AI outputs into calibrated probabilities aligned to agreed trigger thresholds is what makes forecasts actionable for anticipatory decision-making. National forecasters trained to operate the system strengthen local ownership of that translation process, with expansion underway to additional IGAD states.

Further information: https://medium.com/@ifrcgoproject/from-forecast-to-action-building-the-mvp-for-automated-eap-trigger-monitoring-655147cb7b2b

Despite these advantages, AI has fundamental limits. It cannot and should not make critical decisions, such as determining acceptable levels of risk or defining normative trade-offs between fiscal prudence and humanitarian precaution. It cannot eliminate, and may even hide, uncertainty inherent in probabilistic forecasts. Optimization models may concentrate resources where impacts are easiest to identify and prevent rather than where need is greatest unless equity constraints are explicitly embedded. Institutional barriers remain regardless of model sophistication (Slater et al., 2023).

There is significant potential to use AI tools for calibration of triggers and optimization of resources to support priority populations (Box 25). AI can strengthen the analytical basis for anticipatory financing and improve transparency around trade-offs. As across other aspects of Pillar 4, AI augments financial decision-making by clarifying risk and consequence, but responsibility for acting on that information remains human and institutional.

Box 25. AI-Driven Anticipatory Cash Aid for Flood Resilience in Bangladesh

Farmers on Jamira, an unelectrified island on Bangladesh's Jamuna River, face increasingly erratic and devastating floods due to climate change. Historically, these farmers relied on fragmentary warning systems, such as observing river currents, receiving word-of-mouth updates, or watching a neighbour's television. In August 2024 alone, unpredictable floods affected 6 million people in Bangladesh and caused an estimated $1.67 billion in economic damages, leaving vulnerable farmers deeply in debt from submerged, ruined harvests. Standard government warnings provide a three-day notice, leaving families with minimal time to secure their crops and livestock.

To combat the climate risks, the international nonprofit GiveDirectly is partnering with Google.org and Google Research to shift the traditional humanitarian model from reactive to proactive. The initiative utilizes Google's AI-based Flood Hub, which analyses historical and current data to provide accurate flood warnings up to seven days in advance, even in river basins lacking streamflow gauges. Leveraging this extended warning window, GiveDirectly identifies highly vulnerable villages using combined flood and socioeconomic data, and delivers unconditional cash transfers of 10,375 Bangladeshi taka ($85) days before a flood strikes.

To generate evidence on this approach, GiveDirectly is launching a randomized trial in 2026 that will cover over 100,000 families in northern Bangladesh. Similar previous pilots in Nigeria demonstrated that anticipatory cash allowed farmers to successfully purchase agricultural inputs, protect animals, and diversify their incomes. For the farmers in Jamira, receiving unconditional funds ahead of a disaster will empower them to hire labourers for rapid early harvests, purchase vital animal medicine, and reinforce their homes—demonstrating that timely financial autonomy is a critical tool for building climate resilience.

Learn more: https://restofworld.org/2025/google-flood-hub-cash-aid/
https://nethope.org/case-studies/ai-supported-triggers-for-cash-transfers-givedirectly-2

5.2.4 Stakeholder collaboration: the coordination imperative

Preparedness and anticipatory action ultimately depend on coordination among diverse actors. In order to be successful, preparedness to respond to warnings requires collaboration across meteorological services, disaster management authorities, humanitarian organizations, local governments, and communities. The decision challenge lies in maintaining shared situational awareness and aligned action under time pressure, when information is incomplete, evolving, and interpreted differently by different institutions.

This challenge is created by the siloed nature of the different elements of early warning systems. Meteorologists typically work with ensemble forecasts and probabilistic outputs. Disaster managers require impact-based projections to guide operational planning. Humanitarian actors need estimates of population exposure and logistical access constraints. Communities require clear, actionable guidance expressed in locally meaningful terms. Each actor relies on different information systems, terminologies, and mandates. During rapid-onset disasters, translating across these epistemic and institutional boundaries can exceed human processing capacity, particularly when data streams update continuously.

Artificial intelligence provides an opportunity where fragmentation and scale overwhelm manual coordination. Machine learning can automate the integration of meteorological observations, satellite imagery, vulnerability assessments, and demographic data into unified analytical products (Mohanty et al., 2021). AI-enabled dashboards can present differentiated views of the same underlying data: technical forecast layers for specialists, impact maps for planners, exposure summaries for humanitarian coordinators, and simplified action messages for public communication (R. Kumar & Rani, 2025). Natural language generation tools can assist in drafting structured situation reports by synthesizing multiple inputs in near real time, reducing reporting delays during fast-moving crises (IFRC, 2026b; Rocca et al., 2023). Based on these AI capabilities, there is an opportunity to develop shared operational chatbots, where multiple organizations input situation reports, field data, and assessments into a common system, and a generative AI model produces tailored responses depending on the user's role and query. For example, a logistics coordinator asking about access constraints would receive a different output than a communications officer asking about affected population estimates, even from the same underlying data pool. This kind of role-responsive synthesis remains nascent but represents a plausible near-term development of the dashboard and situation reporting tools already being piloted across humanitarian operations.

AI can also support cross-event learning. Natural language processing applied to after-action reviews across countries can identify patterns in what types of interventions perform well under particular hazard conditions and institutional settings (IFRC, 2024b). Such meta-learning approaches can surface transferable lessons, for example, under what lead times forecast-based cash transfers are most effective, or which coordination mechanisms consistently reduce response delays .

Coordination is not a purely informational problem. Even with accurate and timely data integration, actors may not coordinate if mandates conflict, resources are contested, or trust is weak (Pantiris et al., 2025). Automated dashboards risk creating false impressions of consensus by masking underlying uncertainties or power asymmetries. If certain populations are underrepresented in data streams they will also be underrepresented in synthesized outputs. AI systems cannot substitute for leadership, negotiation, or the relational infrastructure built through repeated joint exercises and shared experience (Upadhyaya et al., 2025).

AI can be used to enhance information coherence, but it can never automate coordination efforts. AI has a role in reducing delays in data synthesis, tailoring outputs to diverse audiences, and strengthening institutional memory across operations. But effective collaboration ultimately depends on trust, clarity of roles, and sustained investment in relationships which take time to develop.

5.2.5 Where AI becomes relevant in Pillar 4

Artificial intelligence contributes most clearly where preparedness and anticipatory action decisions are constrained by scale, fragmentation, and computational complexity. AI excels at detecting patterns across dispersed data, synthesizing heterogeneous information streams, calibrating probabilistic thresholds, and optimizing resource allocation under defined objectives. AI has the potential to strengthen the foundations of preparedness by expanding what institutions can know, compare, and simulate.

However, the role of AI must be understood in the context of humanitarian operations. Governance reform requires political negotiation. Local preparedness depends on trust relationships. Financing anticipatory action based on pre-agreed triggers involves normative judgments about acceptable risk of future impacts. Coordination requires authority, mandate clarity, and sustained inter-institutional confidence. These are not primarily computational problems; they are political and social ones. The more AI systems influence high-stakes choices, the more questions of trust, transparency, equity, and accountability become central rather than peripheral. For this reason, any assessment of AI in preparedness to respond to warnings must move beyond technical capability toward governance conditions. The following section examines why trust becomes the decisive constraint in the integration of AI into early warning systems.

Preparedness and anticipatory action decision (Pillar 4)	What the decision involves in practice	How AI can support the decision	What AI must not do
Strengthening Enabling Environments	Ensuring legal frameworks permit anticipatory action; achieving policy coherence across disaster risk management, climate adaptation, and humanitarian systems	Analyze frameworks to identify gaps and inconsistencies; comparative analysis across countries to identify transferable provisions; synthesize evidence to support advocacy for policy reform	Replace political processes required for policy reform; recommend policy changes without understanding institutional capacity to implement
Building Local Preparedness Capacity	Assessing capability gaps; training responders and communities; ensuring warnings lead to reduced human suffering; learning from exercises and real events	Integrate data to identify recurring capacity gaps; generate synthetic scenarios; adapt warning messages to local capacities	Build trust between communities and authorities; replace human judgment about culturally appropriate action; ignore local knowledge and community preferences
Connecting Finance to Action	Defining objective triggers linking forecasts to financing releases; calibrating thresholds balancing false alarm costs against missed events; allocating scarce resources across competing priorities	Translate forecasts into probabilistic impact predictions; optimize triggers balancing multiple objectives; simulate outcomes under alternative strategies to compare cost-effectiveness	Bypass human authorization before releasing financing; make normative decisions about acceptable risk; optimize purely for efficiency without explicit equity constraints
Strengthening Stakeholder Collaboration	Coordinating among actors with different information needs and mandates; learning which interventions transfer across contexts; maintaining shared situational awareness	Integrate meteorological observations, satellite data, vulnerability assessments, and social media into unified situation reports; generate tailored dashboards; analyze after-action reviews to identify transferrable lessons	Replace human coordination and negotiation, ignore power asymmetries affecting whose information is considered authoritative

Table 6. The role (and limits) of AI in preparedness to respond to warnings decisions under Pillar 4.

5.3 The trust imperative: why full automation cannot work

Early warning systems do not function solely through technical accuracy. They function through collective acceptance by officials who authorize action, by institutions that commit resources, and by communities that bear the costs of compliance. Decisions determine anticipatory actions, financing release, and operational mobilization, trust is not optional. It is the mechanism through which probabilistic information becomes legitimate collective action.

The integration of AI into these processes introduces new forms of opacity, data dependency, and distributed responsibility. Systems that operate through complex model architectures, rely on uneven data coverage, or are developed across institutional boundaries alter how reliability is understood and how accountability is assigned. Even when performance metrics indicate high accuracy, users may struggle to interpret model outputs, diagnose failures, or determine who is responsible when decisions informed by AI prove inadequate. These dynamics do not negate AI's potential contributions, but they fundamentally shape the conditions under which those contributions are accepted and acted upon.

For this reason, the question is not only whether AI improves decision quality, but whether it operates within governance arrangements capable of sustaining trust over time. The following analysis examines four interrelated dimensions of this challenge: opacity and explainability, data inequality and representational bias, technical and ethical boundaries, and the allocation of accountability in high-stakes decision systems.

5.3.1 The black box problem: opacity and explainability

Many AI systems used in early warning systems rely on nonlinear architectures in which predictions emerge from complex interactions across multiple hidden layers or ensemble components. While such structures enable strong predictive performance, they make it difficult to trace how specific inputs influence outputs. Even technically trained operators may therefore struggle to explain why a system assigned a particular risk probability or altered its assessment between updates (Doshi-Velez & Kim, 2017).

Opacity becomes consequential in high-stakes preparedness and anticipatory action contexts (Molnar, 2020). When evacuation orders are issued, financing is activated, or resources are mobilized, decision-makers must justify their actions to superiors, political authorities, and affected communities. Traditional forecasting systems often allow experts to identify the source of error, whether it is related to incorrect input data, model assumptions, or anomalous environmental conditions. This traceability supports institutional learning and enables users to develop calibrated expectations about system reliability. When AI systems produce unexpected or inaccurate outputs, however, identifying the source of failure may be far more difficult. Without diagnostic clarity, confidence in system reliability becomes fragile.

With AI-based early warning systems, the difficulty of tracing back the error (and therefore improving the model output) can result in repeated false alarms. Research has documented "cry wolf" effects: recurring false alarms lead to warning fatigue, where communities become skeptical and less likely to take protective action (Breznitz, 2013). Each false alarm imposes costs on those who comply (Krishnamurthy R et al., 2020). On the other extreme, a false negative whereby an early warning system fails to predict a crisis would result in mistrust of systems. After multiple false alarms or false negatives, early warning systems lose credibility, and relevant actors may stop responding to warnings (Simmons & Sutter, 2009).

Efforts to improve interpretability, including feature attribution methods, surrogate models, and uncertainty visualization, can illuminate aspects of model behavior (Materia et al., 2024). Yet such tools often provide partial approximations rather than full transparency into internal reasoning. Moreover, preparedness and anticipatory action decisions depend not only on overall accuracy but on calibration: whether predicted probabilities correspond to observed outcomes over time.

5.3.2 Data gaps and inequity

AI systems derive their predictive capacity from the data on which they are trained and validated. Where those data are incomplete, unevenly distributed, or systematically biased, model performance will reflect those limitations. In the context of preparedness and anticipatory action, this creates a critical limitation: the regions where early warning has the greatest life-saving potential are often those where the operational, institutional, and community-level data needed to support Pillar 4 decisions are most limited (Quinn et al., 2018). This is precisely where humanitarian workers operate. Fragile and conflict-affected states, remote rural areas, and rapidly urbanizing informal settlements are also the environments where baseline data and observation networks are most scarce. The result is a structural mismatch: without sufficient data, AI systems could be weakest where the humanitarian system needs them most.

The first challenge concerns preparedness capacity data. AI systems supporting Pillar 4 decisions require granular, current information on what response capacity actually exists and where: training records, equipment inventories, warehouse stock levels, and community-level responder networks. In practice, this data is fragmented across agencies, inconsistently recorded, and rarely digitised to a standard that enables machine-readable integration. Where informal or community-based response capacity goes undocumented entirely, AI-supported readiness assessments will systematically underestimate what is available, and misallocate pre-positioned resources as a result (Jackson et al., 2019).

The second challenge concerns last-mile community data. Anticipatory action depends on reaching the right people, through the right channels, in time to act. Yet data on who is reachable, via which communication pathways, in which languages, and with what level of trust in official warning systems is largely absent from national preparedness databases. Where such data exists, it is typically held by local NGOs or community organizations rather than integrated into national systems. AI systems cannot optimise dissemination or targeting without this information, and the gap is sharpest in the communities facing the highest exposure (Dang et al., 2019).

The third challenge concerns response effectiveness records. AI systems supporting anticipatory financing or resource deployment decisions require historical evidence of what interventions worked, under what conditions, and for whom. After-action reviews, activation timelines, and outcome data are systematically under-documented across humanitarian operations. Where records exist, they are rarely structured in formats amenable to computational analysis. Without this evidence base, trigger calibration and resource allocation models rest on assumption rather than demonstrated performance (Huynh & Kiang, 2023).

Transfer learning offers partial mitigation by adapting models trained in data-rich environments for use in data-scarce contexts. For example, the RapiD (MapWithAI) model – developed by Meta and integrated into OpenStreetMap – uses Earth observation imagery to generate roads and other infrastructure features which can then be validated through user input. Such technologies offer an opportunity to fill in critical information gaps in highly vulnerable settings at unprecedented speed (Fila et al., 2023). However, while certain physical relationships may generalize, many drivers of impact are locally specific: drainage conditions, construction practices, social coping mechanisms, institutional response capacity. Models trained in well-monitored regions may therefore perform poorly in rapidly urbanizing or infrastructure-constrained environments, particularly where informal settlement growth has altered exposure patterns. Transferability cannot fully compensate for absence of locally grounded data (Haqiqi et al., 2021).

These dynamics are compounded by concentration of technical capacity. Development of advanced AI systems requires computational resources, specialized expertise, and sustained investment that remain disproportionately located in wealthier countries (Hwang, 2018). Even when tools are made available through open-source platforms or partnerships, effective deployment requires local capacity to curate data, validate outputs, monitor performance, and retrain models as conditions change. Where such capacity is limited, AI systems risk reinforcing existing disparities rather than narrowing them (Montgomery, 2024).

The equity implications are clear. If AI systems perform best in contexts where data are abundant and institutional capacity is strong, while underperforming where vulnerability is highest, the global expansion of AI-enabled early warning is likely to widen protection gaps. Ensuring that AI strengthens rather than undermines EW4All's equity objectives therefore requires deliberate investment in common standards for preparedness data collection, after-action documentation, and community-level response records, alongside local expertise, and performance evaluation across diverse population groups.

5.3.3 Technical and ethical boundaries

The performance of AI systems in preparedness and anticipatory action is constrained not only by governance conditions, but by inherent technical and ethical limits. These boundaries arise from three sources: the model uncertainties associated with hazard and impact prediction; the distributional properties of training data; and the sociotechnical contexts in which models operate.

Inherent predictive limits
AI models are most effective where hazards exhibit detectable precursors and where extensive historical data exist. Strong performance has been demonstrated for certain slow-onset or seasonally patterned risks, such as drought and riverine flooding in well-monitored basins (Krishnamurthy et al., 2020). However, predictive performance varies substantially across hazard types and temporal scales. Rapid-onset events such as flash floods, landslides, or severe convective storms remain difficult to forecast with long lead times due to the chaotic dynamics of atmospheric systems (Nanding et al., 2015). Earthquakes present an even more profound constraint: stress accumulation and rupture processes occur at scales that remain poorly observed, and no reliable short-term prediction method has emerged despite decades of research (Dascher-Cousineau et al., 2023).

Compound hazards further complicate modelling efforts. Tropical cyclones that generate both storm surge and inland flooding, or cascading failures across infrastructure systems, involve interacting processes where small changes in initial conditions can produce divergent outcomes. In many locations, such complex events are too rare to provide robust training datasets (Kruczkiewicz et al., 2021).

Climate change introduces an additional source of complexity. Most AI systems are trained on historical data under the implicit assumption that past relationships between hazards and impacts remain informative and relevant for future conditions. As warming intensifies, hazard magnitudes and combinations increasingly exceed historical experience (Armstrong McKay et al., 2022). Models trained on past distributions may therefore underestimate unprecedented extremes or fail to recognize emerging risk patterns. No increase in computational power can fully compensate for the absence of historical analogues (Wunderling et al., 2024).

Socio-technical limits
AI systems operate within linguistic, cultural, and institutional environments that shape how outputs are interpreted and acted upon. Natural language processing tools remain unevenly developed across languages, particularly for minority or low-resource languages. Even where translation is possible, cultural framing and locally meaningful communication cannot be reduced to lexical equivalence (Naik et al., 2024). More fundamentally, AI systems designed without meaningful community participation may marginalize local knowledge and weaken collective ownership of early warning processes (Birhane et al., 2022).

Together, these technical and ethical boundaries underscore that AI performance is context-dependent. Model capability is shaped not only by algorithm design, but by hazard physics, data representativeness, institutional capacity, and social legitimacy. Recognizing these limits is not a rejection of AI, but a prerequisite for responsible integration within preparedness and anticipatory action systems (Section 5.4 explores responsible integration in greater detail).

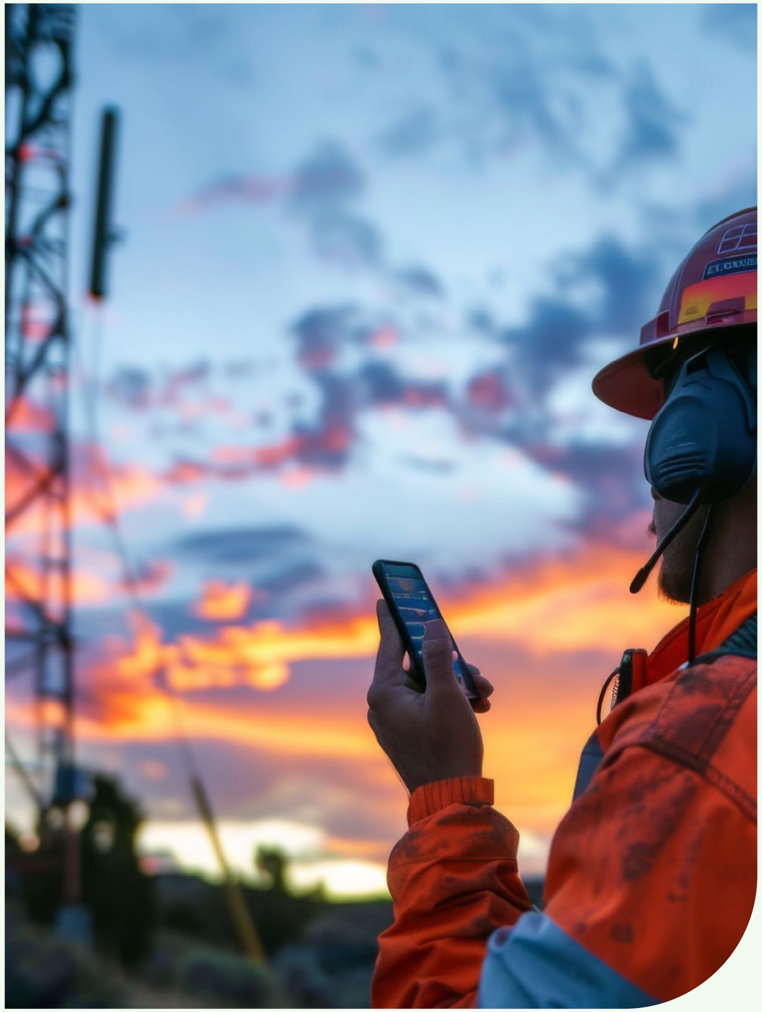
5.3.4 The accountability question

When AI-informed preparedness and anticipatory action decisions lead to harm (either due to underestimation of impacts, delayed activation, or misallocation of resources), determining responsibility is rarely straightforward (Neri et al., 2020). Unlike traditional decision processes in which lines of authority and causation are more clearly defined, AI systems introduce additional layers between input data, analytical processing, and operational action. This can create three distinct accountability challenges: attribution, authority, and redress.

Attribution challenges arise from the distributed chain of actors involved in any AI-informed decision. Responsibility may span data providers, model developers, deploying agencies, and operational decision-makers, with no single actor having full visibility into the system as a whole. Assigning liability across this chain, absent explicit contractual or regulatory frameworks, leaves accountability diffuse and contestable (Liang et al., 2025).

Authority challenges concern who ultimately authorizes AI-informed decisions. If evacuation orders or anticipatory financing releases are based in part on algorithmic outputs, responsibility must remain clearly located with identifiable decision-makers. The presence of a human reviewer is insufficient if authority is ambiguous or if institutional incentives encourage automatic reliance on model recommendations. Accountability requires that decision authority be explicit, documented, and subject to oversight (Cath, 2018).

Redress challenges emerge when affected communities seek explanation or remedy following harm. Vulnerable populations often lack the technical expertise, institutional access, or legal standing required to contest AI-informed decisions (Pi & Proctor, 2025). When commercial software providers are involved, contractual liability limitations may further complicate avenues for recourse. If accountability mechanisms are unclear or inaccessible, trust in early warning systems may erode regardless of average performance levels (Fanni et al., 2023).



5.4 Guiding principles for responsible integration

Artificial intelligence will not strengthen preparedness to respond to warnings by default. Its impact will depend on how it is embedded within the institutional, legal, and operational structures that govern Pillar 4 decisions. For the humanitarian community, this embedding must be consistent with humanitarian principles that underpin acceptance, access, and legitimacy in crisis contexts. Because anticipatory action involves high-stakes actions, the integration of AI must be deliberate, conditional, and anchored in clear humanitarian-centred principles. The following principles translate the preceding analysis into institutional requirements, building on existing principles and practices including those originally defined in International Humanitarian Law. They are therefore not abstract ethical aspirations, but practical conditions under which AI can enhance preparedness and anticipatory action without undermining trust, equity, or accountability. For EW4All partners, these principles provide a framework for determining when, where, and how AI should be deployed and equally, when it should not.

5.4.1 Humanity: preserving human responsibility in life-saving decisions

The principle of humanity places human life, dignity, and well-being at the centre of all humanitarian action. This principle recognizes that saving lives and alleviating suffering are not merely technical exercises, but moral imperatives that require human judgment, compassion, and accountability. In preparedness to respond to warnings, decisions about early actions including evacuation, resource allocation, and anticipatory financing carry consequences measured in lives and livelihoods. The principle of humanity demands that such decisions remain grounded in human moral responsibility, not delegated to technical systems. Artificial intelligence systems operate through computational processes that can appear autonomous and authoritative. When AI tools generate probabilistic forecasts, impact estimates, or resource allocation recommendations, there is a risk that these outputs could be treated as definitive rather than advisory. However, these decisions must remain under identifiable human authority (Shneiderman, 2020).

Human oversight must therefore be substantive rather than symbolic. Decision-makers require both the authority and the capacity to interrogate model outputs, understand uncertainty ranges, and override automated recommendations when contextual knowledge warrants caution. Interfaces should present uncertainty transparently, and organizational culture must guard against the tendency to treat algorithmic outputs as definitive (Wilson & Daugherty, 2018).

Transparency is another non-optional requirement. Explainability of AI models should be proportional to decision stakes. Where AI outputs directly influence high-consequence actions, interpretability and auditability become governance requirements rather than technical preferences. Trade-offs between accuracy and interpretability should be documented and subject to institutional review (Haresamudram et al., 2023).

Equally important is the establishment of accountability frameworks prior to deployment. Institutions must define who validates models before operational use, who monitors performance over time, who has authority to suspend use if reliability degrades, and what mechanisms exist for affected communities to seek explanation and redress. Without clearly assigned responsibility, the diffusion of authority inherent in complex AI systems risks eroding institutional legitimacy (Green & Chen, 2019).

5.4.2 Impartiality: ensuring AI serves the most vulnerable

Impartiality is embedded in humanitarian principles. In the context of early warning systems, this means that protection must reach those most at risk, regardless of their location, wealth, religion, or social conditions. Preparedness systems are judged not by average performance, but by whether they protect the most vulnerable populations.

AI systems optimized for overall predictive accuracy may perform unevenly across population groups and geographies. Underrepresentation of informal settlements, rural communities, or minority language groups in training data can lead to systematic underestimation of risk (Stirling, 2008).

AI systems that improve aggregate efficiency but underperform for vulnerable populations fail to uphold the humanitarian principle of impartiality. For this reason, equity must be treated as a performance requirement rather than merely an aspiration. Model validation should assess disaggregated outcomes and explicitly examine performance for vulnerable populations. Where disparities are identified, they should be treated as system failures requiring urgent correction (Wang et al., 2025).

Impartiality should be achieved through two related actions. First, sustained investment in data infrastructure, observation networks, and local technical capacity in underserved regions is indispensable to ensuring AI strengthens rather than undermines equitable protection. Second, meaningful community participation should be embedded in AI decisions. Local knowledge can reveal contextual factors absent from formal datasets, inform acceptable error tolerances, and improve communication strategies. Participation is therefore not a nice-to-have, but a functional component of system reliability (Raji et al., 2020).

Box 26. Participatory Mapping for Conservation in Colombia's Río Atrato Basin

Despite legal recognition granting community personhood to protect Colombia's Río Atrato Basin, data sources remain scarce and fail to incorporate ancestral knowledge and traditional conservation practices required for consultation and territorial project understanding. This participatory mapping methodology deployed in Chocó's Río Atrato Basin digitizes community data through maps that overlay with authoritative sources for integrated conservation analysis. Using the AI-embedded Sketch Map Tool, communities lead workshops where participants draw conservation project locations on paper maps, with AI automatically detecting sketches to generate digital datasets integral to consultation processes—addressing environmental degradation, heavy metal pollution, floods, and altered water courses. Developed through partnership between SIEMBRA (legal representatives), Río Atrato Basin communities, University of Glasgow researchers, and Caritas Scotland-SCIAF, the validated methodology has been integrated within national government agency conservation strategies. With strong adaptation potential across Latin America's indigenous communities, the open-source tool enables low-cost reproducibility alongside published mapping guides.

Further information: https://eprints.gla.ac.uk/376242/

5.4.3 Do no harm: technical integrity as a protective standard

Humanitarian interventions can cause unexpected harm when poorly designed or implemented. In early warning systems, inadequate technical performance can create false confidence, generate warning fatigue through repeated false alarms, or miss critical threats entirely. Poor AI performance can have catastrophic consequences by endangering the people that the systems are designed to serve. Part of the risk arises because AI tools are not static: they degrade, drift, and require ongoing recalibration as hazards evolve and exposure patterns change. Validation must extend beyond average accuracy to include stress-testing under rare high-impact events, compound hazards, and shifting climate conditions. Calibration of models is especially critical in systems influencing financing triggers and resource allocation (Eche et al., 2021).

Transparency requirements should be proportional to decision stakes: where AI outputs directly influence high-consequence actions, interpretability becomes a governance requirement. Sustained investment in common and open data infrastructure, observation networks, and local technical capacity is essential for ongoing monitoring, validation, and model retraining as conditions change (Montgomery, 2024).

5.4.4 Accountability to vulnerable populations

Humanitarian organizations are fundamentally accountable to the people they serve. Affected populations have the right to understand how decisions affecting their safety are made, to question those decisions, and to seek redress when harm occurs. Accountability in AI-informed preparedness does not begin or end with deployment. It must be sustained throughout the lifecycle of system use. Institutions integrating AI into Pillar 4 decision processes should ensure that responsibility for decisions remains clearly attributable, that performance is subject to ongoing independent review, and that affected communities have access to explanation and redress mechanisms where harm is alleged (Novelli et al., 2024).

Operational accountability requires transparency proportional to decision stakes. Where AI outputs influence evacuation orders, financing activation, or resource allocation, institutions should be able to document how system outputs were interpreted, who authorized resulting actions, and what safeguards were in place. Performance audits should be periodic rather than reactive, and oversight bodies should have authority to mandate corrective measures where deficiencies are identified (Lechterman, 2024).

Public legitimacy ultimately depends not on technical sophistication, but on visible institutional responsibility. AI systems that cannot be explained, reviewed, or challenged risk weakening trust in early warning systems, even when average predictive performance appears strong. Therefore, before integrating AI into operational decisions, institutions must establish clear frameworks specifying who validates system readiness, who monitors ongoing performance, who has authority to suspend or modify use, and what mechanisms exist for communities to raise concerns and seek redress.

5.4.5 Operationalizing these principles

Translating these principles into practice requires embedding them within institutional procedures before deployment, not retrofitting them after harm occurs. Institutions responsible for humanitarian response are ultimately responsible for how AI is integrated into decision-making processes. These organizations should establish pre-deployment validation protocols that assess model performance across geographic, demographic, and hazard-type dimensions, not solely on aggregate accuracy. Oversight committees with genuine authority to interrogate, pause, or override AI outputs should be constituted in advance, with clear terms of reference specifying who validates models and training data, who authorizes operational use, who monitors ongoing performance, and who holds responsibility when outputs contribute to harm. Procurement frameworks and operational contracts should specify explainability requirements, data governance standards, and performance thresholds as binding conditions rather than aspirational guidance. These obligations cannot, however, be uniform across actors or contexts: NHMSs bear primary responsibility for model validation and technical performance; disaster management authorities for authorization and resource mobilization; humanitarian organizations for last-mile communication and community accountability; and donors and technical agencies for resourcing capacity transfer in lower-income settings, including support for local data infrastructure, training, and institutional readiness.

Governance structures alone are insufficient if the people operating within them lack the capacity or incentive to apply them. Building AI literacy among humanitarian decision-makers, so that they can meaningfully interrogate model outputs, recognize distributional limitations, and exercise informed override, is as important as the technical design of the systems themselves. This requirement is most acute in low- and middle-income countries, where technical capacity is frequently concentrated in a small number of institutions and where the gap between AI system developers and operational end-users is widest; donors and international technical agencies bear a particular obligation to resource AI literacy programmes in these contexts, rather than treating capacity transfer as secondary to system deployment. Participatory processes that engage affected communities in system development and validation can surface local knowledge that improves model relevance while strengthening the social legitimacy on which warning compliance depends. Structured feedback mechanisms that systematically capture false alarms, missed events, and near-misses and feed them directly into model review cycles ensure that accountability to affected populations is reflected not only in governance documents but in how systems are continuously improved. Operationalizing the principles of humanity, impartiality, do no harm, and accountability ultimately depends on building institutions that learn.

5.5 Conclusion: from potential to protection

This chapter examined AI as it relates to the decision-making challenges embedded within Pillar 4 of EW4All. Preparedness to respond to warnings succeeds not when predictions are generated, but when decisions are authorized, trusted, and acted upon. AI offers powerful tools for processing complex data, calibrating probabilistic thresholds, accelerating assessment, and supporting coordination across fragmented systems. These capabilities can strengthen the analytical foundations of preparedness and anticipatory action.

However, preparedness and early action decisions are not governed by information alone. These decisions depend on trust, legitimacy, equity, and accountability. The same features that give AI strength (scale, complexity, automation, and probabilistic reasoning) also introduce opacity, uneven representation, and diffusion of responsibility. Without deliberate governance design, these dynamics risk weakening the very trust on which early warning systems depend.

The central question, therefore, is not whether AI can improve preparedness performance, but under what conditions it can do so while preserving public confidence and institutional responsibility. This requires human oversight as a design principle, explicit equity safeguards, transparent validation and audit mechanisms, sustained investment in local capacity, and clear allocation of accountability before deployment. Pillar 4 is the point where early warnings result in people and livelihoods being protected. If AI is to strengthen that transformation, it must operate within systems that are not only technically capable, but socially legitimate. The measure of success will not be model sophistication, but whether the integration of AI enables more timely, equitable, and trusted protection for those most vulnerable to disaster.

The trajectory of AI in humanitarian preparedness will be shaped less by technological breakthroughs than by governance choices made prior to AI integration. Whether AI narrows or widens protection gaps will depend on whose risks are prioritized, whose knowledge is incorporated, and who remains accountable when systems fail. The responsibility for those choices rests with the institutions implementing EW4All today.

Chapter 6.
Integrating AI across the MHEWS value cycle: interpillar insights and recommendations

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6.1 AI and the need for end-to-end integration

Building on the enabling conditions set out in Chapter 1, this chapter synthesises key insights from across the report to provide an integrated perspective on AI's role in MHEWS. The preceding chapters have shown how AI is already transforming technical capabilities across the early warning value cycle - enabling faster hazard detection, improved forecasting, more targeted warning dissemination, and more informed anticipatory action. However, a critical structural observation emerges from this review: only a handful of the case studies examined cover the full MHEWS value cycle. AI applications remain largely driven by the institutional mandate of the organization leading on a particular pillar, producing innovations that strengthen individual components without necessarily reinforcing the system as a whole. For AI to be truly transformative in the context of EW4All, it must move beyond siloed interventions to address the full end-to-end value chain.

Several common lessons emerge from the case studies reviewed: the importance of high-quality local data, culturally and linguistically tailored communication, modular architectures that scale across hazards and regions, and a consistent human-in-the-loop approach ensuring AI remains a decision-support tool. Together, these cases show how next-generation AI systems can reduce the cognitive burden on disaster managers, improve the timeliness and specificity of warnings, and make preparedness more inclusive - from river basins in the Caribbean to cyclone-exposed deltas and coastal regions in Bangladesh.

Additional use cases in Annex 1 and the AI Solutions Catalogue span multiple hazards, geographies, and operational contexts - including meteorological forecasting, tsunami detection, flood risk monitoring, wildfire identification, logistics planning, and humanitarian information management. They further demonstrate how governable, human-centred AI is strengthening the MHEWS value cycle, from agentic systems combining space- and ground-based observations for crisis decision support, to multi-agent platforms tailored for SIDS, and generative AI tools translating forecasts into localised preparedness guidance.

This chapter therefore focuses on how AI can be better integrated across the MHEWS value cycle - identifying opportunities and challenges that cut across pillars and require coordinated investment and governance. It puts forward recommendations for a shared agenda for governments, international organizations, technical partners, and donors to ensure that AI strengthens early warning systems as a whole.

6.2 AI across the MHEWS value cycle: how the Pillars connect

The preceding section established that AI's transformative potential lies in strengthening the early warning system as a whole, not only its individual parts. This section examines how that integration works in practice - tracing the causal chain through which information must flow to convert hazard detection into protective action, and identifying where AI can most effectively accelerate, augment, or bridge those flows.

MHEWS are mechanisms that convert information into protection outcomes. Their effectiveness depends on the integrity of a continuous causal chain - from hazard detection and risk assessment, through forecasting, message generation, and dissemination, to the ultimate response by at-risk populations. A forecast that does not reach the right audience, a warning that prompts no response, or a risk assessment that remains unused will fail to deliver protection, regardless of technical quality.

Understanding where AI can accelerate, augment, or bridge those flows is critical to identifying where integrated AI investment will deliver the greatest returns. AI creates new opportunities to move beyond improving individual components toward strengthening the system as a whole - including its diagnostic capabilities. By integrating data across the value cycle - including forecast accuracy, warning reach, response patterns, and outcomes - AI can help answer key operational questions: which communities are not receiving warnings in time, where warnings are not acted upon, and what barriers prevent protective action. This diagnostic capability could enable AI to not only enhance outputs, but to reveal weak links between forecast and action, and to inform targeted interventions that strengthen those links.

The central challenge for AI in MHEWS is not simply technological deployment, but its integration across the early warning cycle in ways that strengthen operational systems, reinforce institutional coordination, and ultimately deliver people-centred protection outcomes.

6.2.1 Interpillar data flows and cross-cutting conditions for AI integration

The following section details how AI enhances each of the four pillars and, crucially, how their value is realised through interpillar connectivity.

Risk knowledge is the foundational input upon which all other pillars depend. As the report highlights, AI can accelerate the production and updating of risk information - from exposure mapping using satellite imagery, to vulnerability characterisation drawing on assets, populations and socioeconomic data, to AI-enabled disaster impact estimation. Risk knowledge is more valuable if it is operationally connected to the rest of the system: to the monitoring thresholds that trigger forecasts in Pillar 2, to the warning targeting parameters that determine who receives an alert and in what form in Pillar 3, and to the preparedness protocols and anticipatory action triggers that determine whether warnings result in protection in Pillar 4. Risk knowledge that remains siloed within a single agency, or disconnected from operational decision processes, cannot fulfil its protective function, regardless of its technical quality.

Monitoring and forecasting generate the time-critical hazard intelligence on which the rest of the system acts. AI has already transformed the speed, resolution, and cost of hazard prediction, with operational AI weather forecasting systems now deployed at major meteorological centres. However, as this report makes clear, the value of improved forecast skill is only realised when forecasts are correctly interpreted, communicated, and acted upon downstream: warning messages are only useful if their content is accurate and probabilistic estimates are well-calibrated; disaster financing mechanisms are only actionable if the forecasts underpinning them are reliable. The connection to Pillar 3 is therefore not only about technical outputs, but about how those outputs are operationalised – ensuring that forecast information is translated into warning messages that are timely, targeted, and comprehensible to the communities and decision-makers who receive them.

Warning dissemination and communication is the critical interface between technical warning capability and life-saving community action, the part most directly responsible for whether a warning reaches and can motivate the people at risk to take the recommended action. The report showed how AI can enable multilingual, multi-channel, personalised communication at scale, increasing the likelihood that warnings are received and understood across diverse populations. The functional value of this pillar, however, depends significantly on the accuracy and timeliness of the forecasts it conveys from Pillar 2: a warning that communicates an inaccurate forecast, or one that arrives too late to allow protective action, cannot fulfil its purpose. Equally, the effectiveness of Pillar 3 is contingent on whether the preparedness measures it calls for - evacuation routes, early action protocols, and community response plans for instance - are in place through Pillar 4.

Preparedness to respond to warnings is where the entire upstream investment in risk knowledge, forecasting, and communication should translate into protection through early and anticipatory action. AI has the most to offer here as a tool to reduce informational blind spots, accelerate analysis, and support decision-making under uncertainty - for example, by integrating forecast data with vulnerability profiles to trigger anticipatory financing, or by analysing historical response data to identify where protective action has failed to materialise. The value of this pillar is, however, fundamentally dependent on what precedes it: disaster financing can be activated if the forecasts from Pillar 2 are reliable and probability estimates are accurate; early action protocols can only be effective if the warnings from Pillar 3 reach the right actors in time; and preparedness planning is only meaningful if it is grounded in the risk knowledge produced in Pillar 1.

Across all pillars, AI's greatest value lies in strengthening these connections. It depends on enabling conditions that support coordination across institutions, data systems, and operational processes. These conditions have been identified across the pillar chapters of this report; they are consolidated here as cross-cutting challenges and corresponding design principles for the responsible, integrated deployment of AI in MHEWS (Table 7).

Theme	Key interpillar challenges	Considerations for AI integration
Data interoperability and system architecture	Risk, hazard, and response data are often siloed across institutions with incompatible formats, limiting system-wide AI integration.	AI integration requires interoperable data ecosystems, including common standards (e.g., CAP), shared metadata frameworks, and institutional data-sharing agreements. AI applications should align with existing operational infrastructures and national early warning platforms to enable integration across the full MHEWS value cycle.
Capacity and equity gaps	AI uptake remains concentrated in well-resourced contexts; LMICs, LDCs, and SIDS face compounding constraints in data, connectivity, and technical capacity.	Addressing these gaps requires targeted investment in capacity development, data access, and computing infrastructure. International cooperation is needed to expand open tools, shared models, and support for locally adapted AI solutions.
Institutional coordination	Effective MHEWS require coordination across meteorological services, disaster management agencies, telecommunications operators, social protection systems, and community networks. AI pilots are often developed within institutional silos, limiting operational integration across the four pillars. Governance arrangements within EW4All must therefore support interpillar coordination among the four lead agencies.	AI integration requires clear institutional mandates, coordinated operational procedures, and shared governance frameworks. The AI Group of EW4All can provide a platform to align AI strategy across the pillars, strengthen coordination between global initiatives and national implementation, and promote sustained partnerships among public, private, and humanitarian stakeholders.
Human oversight, accountability and trust	In life-safety contexts, expanding AI automation raises accountability questions about who is responsible when systems fail. Limited visibility into how AI systems function can undermine confidence among both institutions and affected communities.	AI must augment, not replace, human expertise. Systems must be transparent, explainable, and auditable, with clear accountability across three dimensions: attribution (who is responsible), authority (who can review and override AI outputs), and redress (what mechanisms exist for affected communities to seek explanation or remedy). This applies especially to high-impact decisions such as warnings, evacuations, and financial triggers.
Decision-centre AI design	AI tools are sometimes developed around technological capabilities rather than operational needs, resulting in limited integration into real-world workflows and decision processes.	AI systems should be designed around specific operational decisions and user needs across the early warning cycle. A central design question should be: which decision does this AI system support, and for whom? Decision-centred design ensures that AI strengthens operational effectiveness rather than adding technical complexity.

Table 7. Summary of cross-cutting challenges and implications for AI integration across the MHEWS value cycle.

6.2.2 Evidence from practice: an interpillar application

Among the case studies presented in this report, the MAZU (Multi-hazard, Alert, Zero-gap, Universal) framework in China stands out as one of the most comprehensive operational implementation of an integrated approach to the MHEWS value cycle. Rather than focusing on a single technological innovation, MAZU demonstrates how governance, infrastructure, and AI technologies can be aligned across the entire early warning value cycle (Box 27). The operational test of this system was demonstrated during Super Typhoon Yagi (2024). AI-enhanced forecasting identified high-risk zones three days in advance, the unified platform disseminated targeted alerts across sectors, and the Call-and-Response Protocol enabled the orderly evacuation of over one million people with zero fatalities in high-impact zones (Chen, 2025).

Across the cases reviewed, several common lessons emerge. Future investment in AI for early warning systems should prioritise systems that strengthen interoperability across the early warning value cycle. AI's effectiveness depends on governance arrangements, validation mechanisms, trusted delivery channels and community-centred design. The strongest examples demonstrate that AI has the greatest value when it helps transform fragmented warning components into integrated, actionable and inclusive early warning systems for all.

Box 27. An Integrated End-to-End Approach to MHEWS

The MAZU model represents China's integrated, governance-driven approach to the early warning system value cycle and how they can function as an integrated system linking risk knowledge, hazard detection, warning dissemination, and mandated response actions.

1. First mile: risk knowledge
MAZU is built on a strong risk knowledge foundation, supported by China's first national comprehensive disaster risk survey (2020-2022) covering 23 disaster types. These data are integrated with meteorological, geographic, and socioeconomic information to produce dynamic AI-enabled risk maps that guide planning and preparedness.

2. Monitoring and forecasting
China's monitoring and forecasting capacity is built on an integrated land-sea-air-space observation network and advanced AI models. The system also incorporates "Observation as a Service", where algorithms are deployed directly at observation sites to extract hazard features in near real time, gaining crucial minutes for fast on-set events. AI-enhanced ensemble forecasting models improve prediction accuracy and help identify high-risk zones several days in advance.

3. Unified warning dissemination
A national unified warning release system connects agencies vertically from national to county level and horizontally across 22 ministries. Covering more than 220 hazard types and using the CAP, the platform emphasizes people-centred dissemination through multichannel alerting, geolocated targeting, sector-specific services and community-level mobilization. Traditional methods — door-to-door notification, loudspeakers and drills — ensure that vulnerable groups are not left behind.

4. Mandated response through governance
China's Call and Response (C&R) protocol links alerts directly to predefined emergency actions. High-level warnings trigger measures such as evacuations, infrastructure protection, and resource mobilization across sectors. This governance mechanism ensures that warnings translate into timely, coordinated response.

Together, these elements operationalize the MHEWS value cycle, forming a closed-loop early warning ecosystem (Figure 15). The MAZU model demonstrates how AI and strong governance can transform fragmented systems into coherent national resilience infrastructure. Through the MAZU International Cooperation Initiative, China is sharing this model as a practical example of how integrated governance and AI-enabled technologies can help accelerate global progress toward universal early warning coverage.

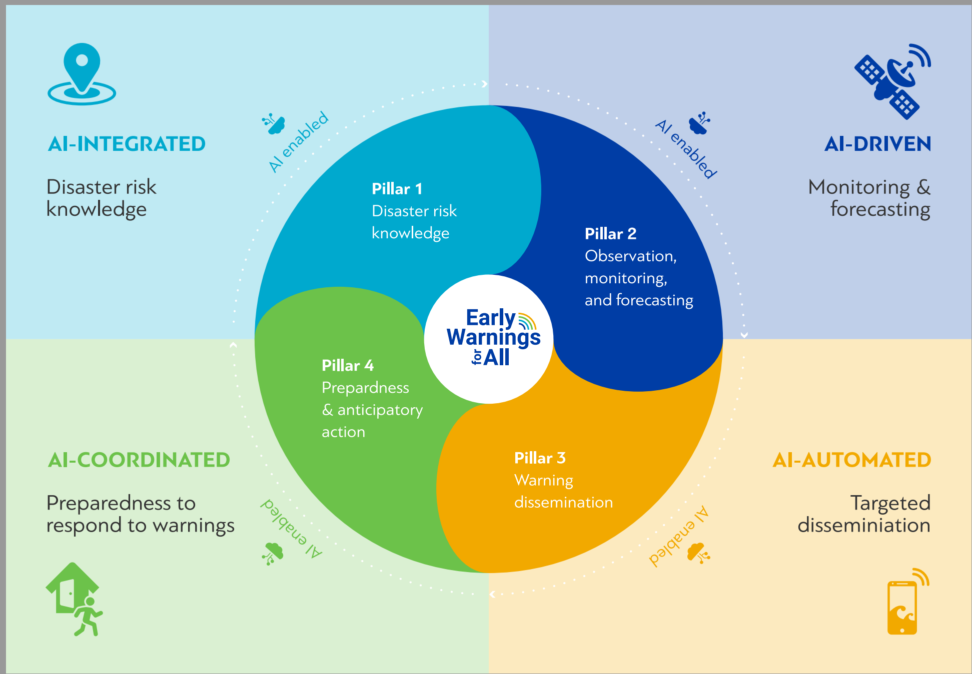

Figure 15. The whole process of AI-enabled early warning as a closed-loop.
Adapted from: https://wmo.int/media/magazine-article/governance-and-artificial-intelligence-keys-integrated-end-end-approach-early-warnings-all

6.2.3 AI integration in national MHEWS roadmaps: progress, gaps, and implementation challenges

International support for AI in EW4All must be grounded in national priorities and capacities, focusing on strengthening country-owned systems rather than promoting uniform technological adoption for its own sake. A MHEWS roadmap provides a strategic framework for strengthening people-centred EWS at national and local levels (WMO, 2024). Developed through national gap analyses and stakeholder consultations, the roadmaps outline priority actions, investments, and institutional responsibilities to advance disaster risk reduction. Actions are structured around the four pillars, alongside cross-cutting enablers such as governance, coordination, financing, and monitoring.

A systematic review of 27 national MHEWS roadmaps developed since 2022 shows that AI integration remains at an exploratory and nascent stage across the assessed countries.[1] Only 10 countries explicitly reference AI technologies such as machine learning or natural language processing (Figure 16). Where AI is mentioned, it is not framed as a gap in itself, but rather appears as a set of enabling activities proposed to address existing operational gaps. The distribution of references to AI is notably uneven across the four Pillars indicating the differential readiness and maturity of AI applications across national entities and early warning systems in LMICs, LDCs and SIDS. AI references are most concentrated in Pillar 2, with eight countries proposing AI applications primarily for model calibration and improved forecasting. AI integration is largely absent from Pillar 1, with only one country referencing plans to increase AI adoption, alongside capacity building in natural language processing and big data analytics. Only two countries reference AI applications under Pillar 3, despite AI's significant potential to translate forecasts into personalised and actionable public warnings, and the availability of tools such as the ITU EWCM (Box 18). No explicit AI references appear under Pillar 4 in the roadmaps. This pattern may partly reflect the nature of Pillar 4, where decision-making is often political, institutional, and relational, and therefore less amenable to direct AI application. At the same time, it highlights an opportunity to explore how AI can better support decision-making processes in preparedness and anticipatory action. In terms of cross pillar activities, only one country, addresses AI governance, proposing a framework for the socially responsible use of AI as an output indicator.

These findings suggest that AI applications are currently being considered primarily as technical enhancements to forecasting systems rather than as transformative tools across the full early warning value cycle by national stakeholders, primarily based in LMICs, LDCs and SIDS. This pattern reflects not a lack of recognition of AI's broader potential, but likely constraints related to limited resources, technical capacity, and enabling governance frameworks required to support system-wide integration. Addressing these barriers represents a key opportunity for future roadmaps and implementation plans to expand AI adoption across all pillars.

The assessment also identifies three bottlenecks that will shape the feasibility of AI integration and deployment across the early warning system value cycle. First, many national MHEWS roadmaps highlight the demand for high-performance and cloud computing, indicating that foundational data and computing infrastructure required for AI deployment remain underdeveloped. Second, AI-related capacity building and training are identified as needs, reflecting the challenge of transitioning from conceptual AI planning to operational implementation. Third, the mobilization of dedicated and sustainable financing mechanisms remains a prerequisite for scaling AI-enabled early warning capabilities. Operationally, addressing these constraints will require targeted investments in national digital infrastructure,

1 Search terms used to identify AI-related references in MHEWS roadmaps included: Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), Big Data analytics, and Early Warning Connectivity Map (EWCM).

expanded training and capacity development programmes, and strengthened financing and technical partnerships to support long-term implementation within national EW4All partner agencies.

The current 'AI moment' coincides with a shift in the climate and development finance landscape, creating new opportunities to strengthen early warning systems. This creates an opportunity for aligning national roadmaps and investments with emerging AI financing streams. Major climate funds - including the Green Climate Fund (GCF) and the Adaptation Fund - along with bilateral donors, are increasingly exploring how AI can support climate adaptation and resilience. Multilateral initiatives, including the World Bank's Climate and Disaster Risk Platform and the Global Risk Financing Facility, are also expanding support for technology-enabled early warning. Initiatives such as the Climate Risk and Early Warning Systems (CREWS) also illustrate this emerging direction. Under the CREWS 2030 Strategy, one of the three strategic priorities focuses on driving next-generation early warning systems through innovation, integration and strategic partnerships, explicitly highlighting the role of emerging technologies, including AI. The strategy aims to support at least 15 pilot projects testing solutions such as AI-based forecasting, next-generation satellite systems, cell broadcast, and mobile alert platforms, with an emphasis on scalable and context-appropriate approaches (CREWS, 2025). The strategy converges on the view that AI can help bridge persistent early warning coverage gaps when implemented through responsible, people-centred, and institutionally integrated approaches. Complementary initiatives from the private and nonprofit sectors are also expanding the AI funding landscape, including programmes such as the Google.org Impact Challenges and the GSMA Innovation Fund.

Realizing AI funding potential will require coordinated action: governments must establish enabling policies and invest in national data and computing infrastructure, while UN agencies and international organizations can provide guidance and technical assistance for responsible AI deployment. Research and technical communities can advance context-appropriate innovation, and donors and financing institutions can channel resources toward scalable, country-owned solutions. Together, these efforts are essential to enable AI-supported, end-to-end early warning systems across the value cycle.

Countries referring to AI in national MHEWS roadmaps (n=27)

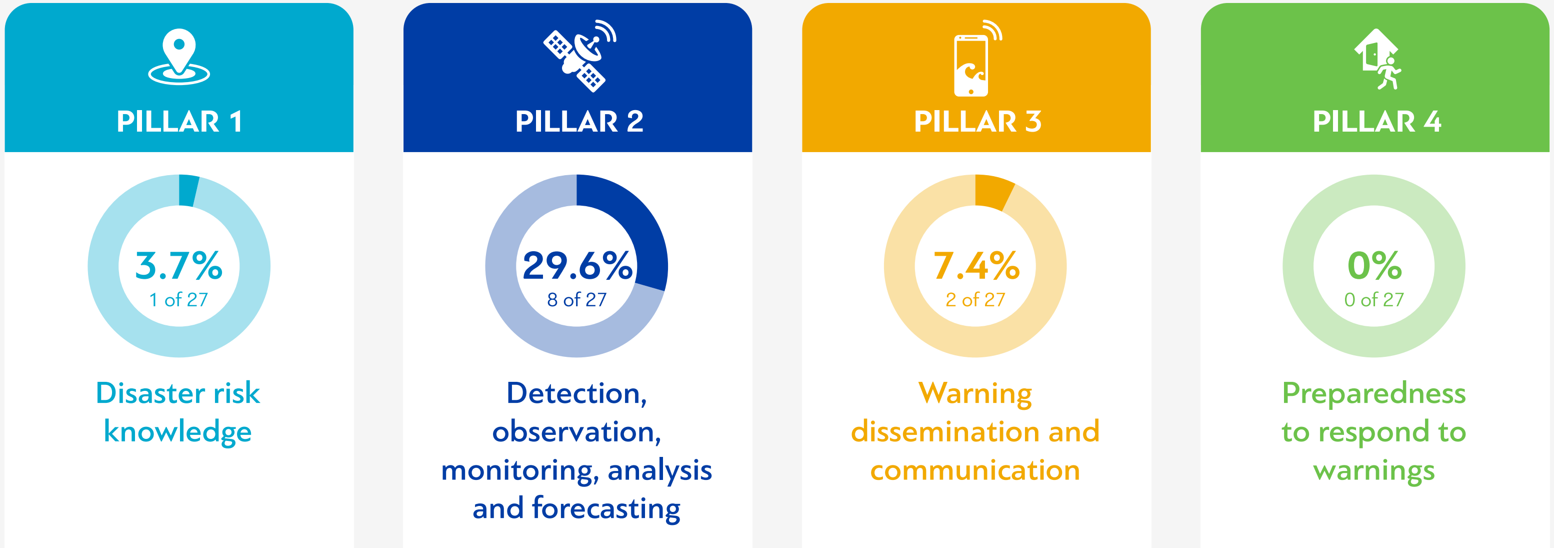

Figure 16. Across 27 national MHEWS roadmaps, countries reference AI unevenly: 8 in relation to Pillar 2, 2 to Pillar 3, 1 to Pillar 1, and none to Pillar 4.

6.3 Overall recommendations for integrated AI enabled MHEWS

The following recommendations (Table 8) are organised around four implementation imperatives that emerge from the interpillar analysis above. They are addressed to different stakeholder groups (Table 8) and are structured to reinforce one another. They aim to complement the specific actions identified in individual pillar chapters, and provide the integrating framework within which pillar-level action delivers maximum early warning system-wide benefit.

Recommendation 1: Invest in observational infrastructure as the foundation for AI performance	**Recommendation 2:** Anchor AI integration in governance and accountability frameworks, not only technology	**Recommendation 3:** Prioritise human-centred, equity-driven and principled AI design	**Recommendation 4:** Design AI enabled EWS with interpillar integration from the outset	**Recommendation 5:** Mobilise funding to support AI pilots and accelerate transition to operational scale
• Strengthen observation systems, such as ground networks, satellite access, and in-situ sensors, since AI performance depends on the quality of underlying data. • Support NMHSs in SIDS, LDCs, and LLDCs to upgrade data collection, assimilation, and operational computing infrastructure. • Expand access to shared datasets, such as historical reforecasts, satellite imagery archives, and global hazard databases, for AI training, especially in data-poor regions. • Establish quality-assurance frameworks for AI-generated data products to ensure reliability and accountability in operational early warning systems.	• Designate a national focal point to consider integration of AI in early warning systems and coordinate governance across the agencies responsible for each MHEWS pillar, while also ensuring alignment with regional and global frameworks addressing AI governance and cross-border risks. • Maintain human oversight for life-safety decisions, with defined levels of review that can evolve as systems are validated. • Adopt national accountability frameworks for AI in EWS specifying which systems are used, what decisions they influence, how performance is monitored, and what recourse exists if systems fail.	• Embed humanitarian principles in AI design - including humanity, impartiality, 'do no harm' and accountability to affected populations - while ensuring systems improve access for marginalised and high-risk groups. • Ensure multilingual and low-connectivity compatibility, recognising that populations beyond 2G coverage and linguistic minority communities remain central to EW4All's people-centred mandate. • Co-design AI tools with affected communities to ensure trust, build accountability, and develop locally relevant systems. • Ensure AI forecasting models are carefully evaluated for how they generalise across regions, avoiding performance disparities. • Strengthen AI literacy at national level so people can provide feedback to improve EWS over time.	• Adopt modular, interoperable architectures and adaptable AI systems that can be tailored to local hazards, languages, and institutional contexts, enabling systems focused on one pillar that can integrate effectively with others. • Invest in shared data and infrastructure to support all pillars and avoid siloed platforms. • Embed feedback loops across the early warning cycle and encourage data sharing: impact data should improve risk models (Pillar 1), observations and forecast performance should refine hazard models (Pillar 2), communication data should improve targeting (Pillar 3), and response outcomes should inform preparedness protocols (Pillar 4).	• Support country led AI pilot projects as a first step to test, validate, and adapt solutions to local contexts, especially in LDCs, SIDS, LMICs. • Establish clear pathways from pilots to operationalisation, ensuring successful solutions are systematically scaled and embedded within national early warning systems. • Strengthen institutional capacity to integrate AI into operational workflows, such as forecasting, dissemination, and decision-making processes. • Mobilise sustained, long-term financing and partnerships to scale proven piloted AI solutions. • Foster collaboration between governments, the private sector, and research institutions to accelerate innovation while ensuring national ownership and sustainability.

Table 8. Overall recommendations to improve AI integration in MHEWS.

Translating the above recommendations into action requires specific commitments from different stakeholders across the EWS value cycle, as outlined in Table 9.

Stakeholder group	Priority actions	Enabling conditions
Governments and National Agencies	• Develop national AI enabled EWS integration strategies aligned with national MHEWSEW4All roadmaps • Establish interpillar AI governance focal points, e.g. through the Prime Minister's Office • Enable anticipatory action triggered by AI-supported alerts • Invest in shared data infrastructure and observation systems • Move towards interoperability standards (e.g., CAP, open data formats) for EWS systems	• Political commitment to interpillar coordination • Sustained multi-year financing for EWS infrastructure and AI integration • Clear inter-agency coordination mechanisms with clear accountability • Technical capacity within NMHSs, DMAs, MNOs, and humanitarian agencies
UN agencies and international organizations	• Strengthen coordination of national AI strategies for MHEWS through effective governance, cross-sector collaboration, and sustained resourcing • Develop global benchmarks for AI in early warning, drawing on examples in the case studies e.g. MAZU, China (Box 14). • Provide technical support for national AI-EWS strategies, especially for alignment in EW4All roadmaps • Facilitate matchmaking with the private sector and expand open data access for AI development, especially through the AI for EW4All Group	• Strengthened mandate and resources for the EW4All AI Group • Sustained member-state funding • Cross-agency knowledge sharing and co-fundraising for AI country pilot projects
Technical Partners and Research Communities	• Continue to advance AI integration • Focus on adapting, transferring, and operationalising proven AI solutions, particularly in LMICs, through partnerships with national operational agencies • Improve validation frameworks for low-data contexts • Develop open-source AI tools and support national capacity transfer, especially in LMICs	• Research funding aligned with operational needs • Partnerships with national operational agencies • Open data and models
Donors and Financing Institutions	• Align climate and development finance to support AI-enabled EWS investments • Fund interpillar AI projects • Invest in AI capacity building in LMIC agencies	• Flexible multi-year financing that supports iterative technology development • Coordination across climate, technology, humanitarian and development funding • Monitoring frameworks focused on system-level impact, not just project outputs

Table 9. Recommendations for MHEWS stakeholders to improve AI integration in EWS.

The vision of EW4All is clear: to ensure that every person on Earth is protected by effective multi-hazard early warning systems. The rapid evolution of AI offers a powerful opportunity to accelerate this effort. Early warning systems are more effective when risk knowledge, hazard monitoring, communication, and preparedness function together as an integrated chain that turns scientific and contextual information into timely decisions. Realising the potential of AI therefore depends not only on technical innovation, but also on system design, institutional capacity, and governance. Countries must invest in interoperable data systems, strengthen national early warning capabilities, and establish frameworks that ensure transparency, traceability, and human oversight. AI should augment human expertise - supporting analysis and decision-making while preserving clear human accountability.

Progress will require coordinated action across governments, international organizations, research institutions, the private sector, and civil society as they all play essential roles in building resilient early warning ecosystems. Collaboration can expand access to data, share technological advances, and ensure that AI-enabled tools reach regions where early warning coverage remains limited. When deployed responsibly, AI can act as a force multiplier within early warning systems - integrating diverse data sources, detecting emerging risks earlier, and enabling more targeted warnings and anticipatory action. In doing so, it can help close long-standing gaps between technical capability and operational response.

The evidence presented in this report demonstrates that AI can strengthen every stage of the early warning value cycle when embedded within well-governed, integrated systems. To date, the greatest impact has been observed in forecasting and data integration functions, where AI is already enhancing the speed, accuracy, and scalability of early warning systems. By contrast, applications in warning dissemination and anticipatory action remain less mature but represent a critical frontier for achieving end-to-end early warning effectiveness. In many LMICs, however, AI adoption remains largely at the pilot stage, highlighting a key transition challenge - from isolated technical innovations to sustained, scalable, and nationally owned systems that deliver protection at scale. The current global momentum around AI presents an opportunity to mobilize innovation, partnerships, and investment at a scale consistent with the ambition of EW4All, which can be supported through the AI for EW4All Group. The greatest impact comes not from technology alone, but from trusted systems that connect science, institutions, and communities. When these elements work together, early warning becomes early action, and early action saves lives.

Annex. Additional examples of partner AI use cases supporting the EWS value cycle

Use case	Location	Application	Overview
AI4SIDS Multi-Agent Flood Warning System	Trinidad and Tobago / Caribbean SIDS	Flood early warning	A modular multi-agent system integrates weather stations, river gauges, and social media observations to generate dynamic flood risk assessments. A conversational interface allows disaster managers to query conditions in natural language while maintaining human oversight of alerts, strengthening situational awareness and last-mile decision support for small island contexts. By combining data analysis (Pillar 2), dynamic risk synthesis (Pillar 1), decision support for disaster managers (Pillar 4), and improved alert interpretation for public communication (Pillar 3), the system strengthens the full early warning cycle in SIDS. Further information: https://doi.org/10.1109/ICTMOD63116.2024.10878134; https://youtu.be/PDYJY_ITYns
ECHO Governable Agentic AI System	Europe	Flood crisis decision-making	The ECHO "live-twinning" platform orchestrates specialized AI agents that retrieve Earth observation data, run hydrological models, and map vulnerable populations. This strengthens situational awareness (Pillar 1) and hazard modelling (Pillar 2) while supporting expert-validated decision pathways for emergency management (Pillar 4), significantly accelerating crisis assessment timelines. Further information: https://trillium.tech/echo
AI-Based Tidal Surge Forecasting	Bangladesh	Coastal surge and embankment failure	This system integrates AI water-level forecasting with embankment vulnerability mapping derived from drone surveys, soil testing, and community knowledge. It generates location-specific surge and overtopping predictions (Pillar 2) linked to risk mapping (Pillar 1) and supports targeted early warnings (Pillar 3) and anticipatory preparedness planning (Pillar 4) for vulnerable coastal communities. Further information: https://clareprogramme.org/update/ai-driven-surge-prediction-safeguarding-bangladeshs-coastal-communities/

Use case	Location	Application	Overview
FireSat Satellite Wildfire Detection	Global	Early wildfire detection	FireSat uses a constellation of AI-enabled satellites to detect fires as small as 5x5 meters by comparing new multispectral imagery with historical observations. The system dramatically improves early hazard detection (Pillar 2) and enables faster alerting and coordination of firefighting responses (Pillars 3-4) before fires escalate into large disasters. Building on the successful Protoflight launched in March 2025, Earth Fire Alliance and Muon Space will deploy the first three operational FireSats in mid-2026, which will deliver twice-daily global observation. The full constellation will comprise 50+ satellites in the coming years. Further information: https://earthfirealliance.org/
AI-Generated Weather Articles and Alerts	Canada	Multi-hazard public warning	AI editorial tools automatically generate localized weather and hazard articles tailored to hundreds of communities. This strengthens warning dissemination (Pillar 3) by providing timely, location-specific information while enabling editorial teams to focus on severe events, ultimately improving preparedness messaging and public protective action (Pillar 4). Further information: https://www.pelmorex.com/
AI Avatars for Localised Emergency Communication	Canada	Preparedness and crisis communication	AI-generated avatars deliver trusted government safety messages in more than 170 languages using video communication. By automating multilingual messaging and localized preparedness guidance, the system enhances accessible warning dissemination (Pillar 3) and supports public awareness and protective action during emergencies (Pillar 4). Further information: https://www.pelmorex.com/en/media-hub/the-weather-network-launches-its-first-advertising-campaign-using-an-ai-assisted-avatar/

Use case	Location	Application	Overview
Night-Time Light Disaster Monitoring	Global	Disaster impact assessment	Satellite night-time light observations detect sudden changes in illumination patterns that signal infrastructure damage, power outages, or displacement. These insights support rapid impact assessment (Pillar 1), complement hazard monitoring (Pillar 2), and guide humanitarian response planning and resource allocation (Pillar 4) during disasters. Further information: https://earthobservations.org/about-us/news/when-the-lights-go-out-using-night-time-data-to-understand-disaster-impacts
AI-Assisted Damage Assessment	Global	Post-disaster analysis	AI models detect building footprints and identify damaged structures from satellite imagery. When combined with expert review, this approach accelerates large-scale disaster impact assessments (Pillar 1) while supporting rapid situational awareness (Pillar 2) and enabling humanitarian actors to prioritize response operations (Pillar 4). Further information: https://disha.unglobalpulse.org/our-products/#Product-DA
AILAS Weather-Adaptive Routing	Madagascar / Africa	Humanitarian logistics	The AI Logistics Awareness System analyses street-level imagery and weather forecasts to predict passability of unpaved roads during storms. These forecasts strengthen hazard monitoring related to accessibility (Pillar 2) and enable humanitarian agencies to plan safe logistics routes and reach vulnerable communities during emergencies (Pillar 4). Further information: https://heigit.org/ailas

Use case	Location	Application	Overview
AIRA Infodemic Monitoring	Africa	Public health crisis communication	The AI-powered Infodemic Response for Africa platform scans large volumes of social media and news content to identify misinformation trends during health emergencies. It supports risk analysis (Pillar 1), information monitoring (Pillar 2), targeted communication strategies (Pillar 3), and improved preparedness messaging for communities (Pillar 4). Further information: https://www.afro.who.int/aira
GREAT Multi-Sensor Tsunami Detection	Multi-basin global pilots	Tsunami early detection	The GREAT initiative integrates hydroacoustic, infrasound, and sea-level data with AI models to detect tsunami-generating events faster than traditional seismic-only systems. Earlier hazard confirmation strengthens monitoring (Pillar 2), supports faster alert issuance (Pillar 3), and enables earlier evacuation decisions (Pillar 4). Further information: https://doi.org/10.5194/gmd-18-3487-2025
AI Nowcasting Platform (RSMC Hong Kong)	Southeast Asia	Severe storm monitoring	Deep learning models analyse satellite imagery to detect and track convective storms and tropical cyclones, producing nowcasts updated every ten minutes. The system strengthens monitoring and forecasting (Pillar 2) while supporting early alerts (Pillar 3) and operational preparedness across NHMSs (Pillar 4). Further information: https://rsmc.hko.gov.hk/
Noor GenAI Voice Assistant	Pakistan	Disaster preparedness information	A generative AI voice assistant accessible through basic mobile phones provides spoken disaster guidance in Urdu via a toll-free number. The offline design ensures that early warning information remains accessible in low-connectivity and low-literacy environments. By enabling conversational access to trusted guidance, the system strengthens last-mile warning communication (Pillar 3) and supports community preparedness and protective decision-making (Pillar 4). Further information: https://viamo.io/

Use case	Location	Application	Overview
SignpostChat AI Assistant	Global displaced populations	Humanitarian information access	A generative AI chatbot delivers personalized information about hazards, services, and preparedness for displaced communities. The system combines multilingual translation with human oversight to ensure culturally appropriate guidance. It strengthens vulnerability awareness (Pillar 1), delivers multilingual guidance and alerts (Pillar 3), and supports informed decision-making for affected populations during crises (Pillar 4). Further information: https://www.signpostai.org/
RealTime Mobility Insights for Early Warning	Senegal	Livelihood disruption monitoring	AI analysis of anonymised mobile phone data identifies abnormal mobility patterns that may signal emerging shocks such as floods or livelihood disruptions. This approach provides near-real-time insights into population vulnerability and displacement risk. These insights strengthen vulnerability monitoring (Pillar 1), provide early indicators of emerging crises (Pillar 2), and inform humanitarian preparedness and response planning (Pillar 4). More information: https://arxiv.org/abs/1904.08525
Google Groundsource	Global (150+ countries)	Flash flood prediction for Urban Areas	An AI-powered methodology developed by Google as part of its Crisis Resilience efforts, transforms decades of public reports into high-quality historical disaster datasets. Using Gemini to analyse millions of public reports, the system identified over 2.6 million historical flood events and combined them with geospatial mapping to create a global urban flash flood dataset. This dataset enables AI models to forecast flash floods in urban areas up to 24 hours in advance. The approach strengthens historical risk and hazard data for vulnerability analysis (Pillar 1) and improves short-term hazard forecasting and monitoring through the Google Flood Hub (Pillar 2). Further information: https://research.google/blog/introducing-groundsource-turning-news-reports-into-data-with-gemini/

Use case	Location	Application	Overview
Ignitia's AI-powered virtual radar	15+ countries - tropical regions and West Africa	Hyper-local storm warning (nowcasting)	AI is used to improve the localisation of weather warnings in regions with limited conventional observation infrastructure. Ignitia's AI-powered "virtual radar" system generates hyper-local storm forecasts using remote sensing data and machine learning, providing nowcasts up to three hours in advance. Storm alerts are delivered through accessible channels such as WhatsApp using the WhatsApp Weather Chatbot and SMS, using local dialects and co-designed formats to ensure comprehension in low-bandwidth or low-literacy environments. By enabling warnings for smallholder farmers and rural communities that often lack radar coverage, the system strengthens risk monitoring (Pillar 1), forecasting and data analysis (Pillar 2), and communication of warnings to end users (Pillar 3). Further information: https://www.ignitia.info/

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