COMMUNITY GUIDELINE

LIFELINES

GeoAI for Humanitarian Action

How is openly accessible GeoAI being used across the lifecycle of a humanitarian crisis?

What are the missed opportunities of not integrating the humanitarian action context into GeoAI development?

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EXECUTIVE SUMMARY

Geospatial AI (GeoAI) offers transformative potential to support **rapid disaster assessment**, **predictive modeling for early warning**, **population mapping in data-poor regions**, and **real-time tracking of displacement and infrastructure damage**. These capabilities promise to deliver the speed, scale, and accuracy that humanitarian decision-making needs under growing time and resource constraints. Yet despite rapid technical advances, GeoAI adoption in humanitarian contexts remains uneven and constrained by non-technical factors. This study reveals a persistent **mismatch between what is scientifically possible and what is operationally usable.** While researchers optimize for model accuracy and methodological rigor, humanitarian actors require tools that work offline, communicate uncertainty clearly, integrate with existing workflows, and earn trust through transparency and field validation.

300+

MILLION PEOPLE

worldwide face humanitarian emergencies

Drawing on literature review, expert focus groups, and a community survey, this report identifies distinct barriers and priorities for five stakeholder personas:

Data-Driven Humanitarians face operational challenges including poor connectivity, complex tools requiring extensive training, restrictive licensing, and fragmented platforms. They prioritize offline functionality, automated provenance tracking, uncertainty displays, and simple interfaces with preset workflows.

Technical Innovators struggle with competing tools, user-friendliness gaps, training deficits, and misaligned priorities between academic research, frontline responders, and affected communities. They need explainable outputs, robust documentation, community feedback mechanisms, and multi-lingual interfaces.

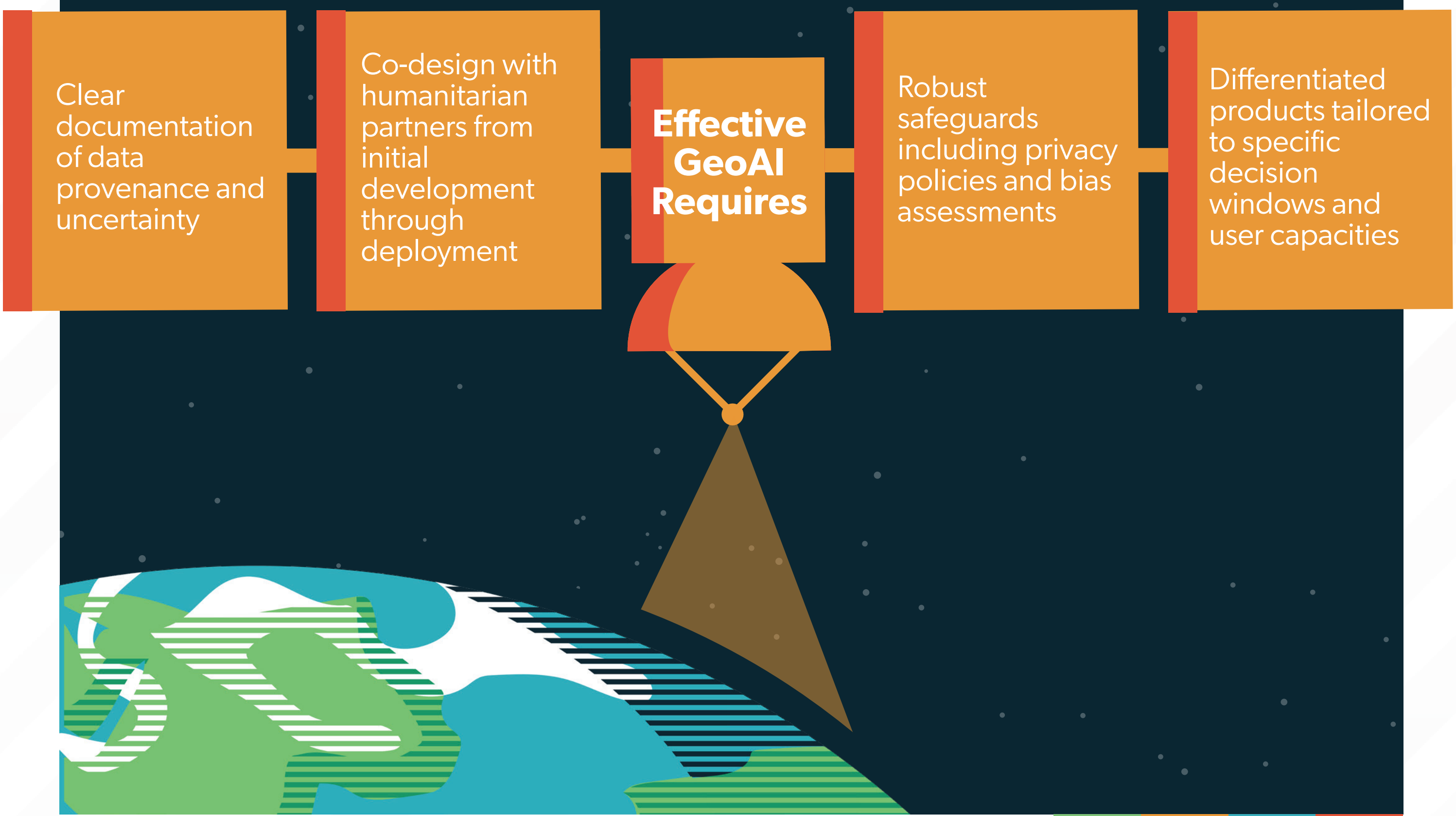
Strategic Decision Makers approach GeoAI through a risk management lens, concerned about ethical and privacy issues, reputational risks, misalignment with field needs, and lack of trust in model outputs. They require scalability, transparency, interoperability, adaptability to evolving crises, and clear evidence of field impact.

Ecosystem Enablers face structural barriers around costs, limited skilled personnel, and licensing constraints that hinder shared infrastructure development. They emphasize the need for confidence metrics, versioning and change logs, statements of known limitations, and interpretable outputs.

Crisis-Affected Individuals encounter fundamental access barriers: poor usability, language constraints, limited connectivity, and lack of awareness that GeoAI tools exist. They need early alerts, evacuation routes, shelter maps, and damage information in accessible, multi-lingual formats.

Beyond persona-specific barriers, the report identifies three systemic issues limiting GeoAI's humanitarian impact.

1. Open satellite data programs from commercial and public providers suffer from inconsistent policies, activation delays, and procedural barriers that slow emergency response.
2. Mechanisms like the International Charter on Space and Major Disasters face limitations including complex activation pathways and inability to operate in conflict settings where they're most needed.
3. Disaster frequency and cultural context shape risk perception and preparedness investments, with low-frequency hazard regions often undervaluing early warning systems until after disasters occur.



This report is an initiative of NASA Lifelines, a community driven program focused on improving the uptake and use of Earth observation data and tools to support more effective and equitable humanitarian action across the lifecycle of a crisis. This report was developed to better understand how open-source GeoAI is being used across the humanitarian crisis lifecycle, from anticipatory action and early warning to response, damage assessment, and long-term recovery. This report provides actionable recommendations for aligning scientific excellence with humanitarian realities, ensuring that advances in GeoAI translate into equitable, trustworthy, and effective support for the world's most vulnerable populations.

To learn more and get involved, visit **nasalifelines.org**

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Special thanks to **Rohini Sampoornam Swaminathan**, **Jeff Pituch**, and **Rhiannan Price** for their guidance and leadership in the development of this study.

Acknowledging the leaders from across the community who participated in this study and shared their experience and expertise:

Daniel Aderotoye, Shaimaa Ahmed, Fawad Akbari, Wesam Alnabki, Maheerah Anwar, Alexys Rodriguez Avellaneda, Amir Azimian, Liana Bernt, Sarah McLane Bryan, Tanmoy Chakraborty, Lauren Childs-Gleason, Margaret Chilinda, Oliver Cottray, Joe Flasher, Andreas Gros, Aryaana Khan, Patrick Kerwin, Hwa Saup Lee, Morgan Lehman, Vinithra Sudhakar, Avinash Mahech, Pietro Milillo, Nelson Mwova, Claudia Offner, Akintola Omowonuola, David Otoosakyi, Jessie Pechmann, Brian Perlman, Barira Rashid, Corey Scher, Andrew Schroeder, Ashim Babu Shrestha, Lucian Smith, Nishon Tandukar, Jamon Van Den Hoek, Roman Viatkin, Jim Volp, Yann, Lisa Marie Zammit, Andrew Zimmer, among others.

Recommended Citation
Rufai O. Balogun, Seamus Geraty (2026). GeoAI for Humanitarian Action, NASA Lifelines, USA, February, 2026

BACKGROUND

Introduction

Today, there are thousands of humanitarian organizations serving over 300 million people globally who are currently experiencing humanitarian emergencies.[1] The increasing number of humanitarian crises across the globe in the last two decades of the 21st century demands a quick, automated, and reliable information source for early responders, policymakers, and other actors in the crisis management lifecycle.[2] These crises, ranging from armed conflicts, public health emergencies, food insecurity, and environmental disasters, are varied in frequency of occurrence, scale of impact, and type, hence requiring varied approaches for monitoring, predicting, and responding to them. This has resulted in an evolving landscape of actors, who often require tailored information that adheres to ethical, transparent, and trustworthy frameworks during the evolution of these crises. The stage within the crisis management lifecycle also determines how quickly the respective actors would need the specific information to be provided. These dual needs for rapid and trustworthy information can be provided by the use of Earth observation and satellite-enabled technologies, coupled with the predictive capabilities of artificial intelligence, collectively referred to as GeoAI. GeoAI is considered as the application of AI, machine learning, and deep learning methods to geospatial data, GIS, and spatial problems and is used to extract features, detect patterns, make predictions, and scale spatial analysis. **The use of GeoAI for humanitarian action provides a unique opportunity for objective and trustworthy monitoring, forecasting, and situational analysis of humanitarian crises** in a scalable fashion, thereby aiding accountability of different actors in the crisis lifecycle.

It offers relevant information across the crisis lifecycle, from pre-event anticipatory action such as risk assessments and early warning systems, to post-event response and recovery efforts such as damage assessments.

Notwithstanding, these tools also come with their inherent challenges. In many resource-constrained areas, access to the expertise needed to set up these systems is often limited, and when available, it is applied too late. When combined with AI, they also pose the risk of false information being spread by malicious actors and false alarms that could erode humanitarian responders' trust.

NASA Lifelines has been exploring how openly accessible GeoAI is currently being used across the lifecycle of a humanitarian crisis and what the opportunity costs are when we don't integrate humanitarian contexts in the development of GeoAI tools. **This report sheds light on the current state of GeoAI applications in the humanitarian sector, and explores opportunities, challenges, risks and mitigation strategies around the use of the technology for transparent and trustworthy humanitarian action, that, above all, safeguards affected communities.** Drawing on interviews, questionnaires, and focus group discussions, this report incorporates perspectives from experts, users, and decision-makers across the humanitarian and GeoAI ecosystem to map the utility of GeoAI for real-world needs.

[1] The United Nations reported that in 2025, 305 million people needed urgent humanitarian aid due to escalating crises. Read more Here and Here

[2] International Rescue Committee. 2026 Emergency Watchlist: At a Glance

Humanitarian Action

Caribou Space defines humanitarian crises as **"Events or series of events that represent a critical threat to the health, safety, security, or well-being of a community or other large group of people. They are widely geographically distributed, often covering large areas and multiple populations. They are diverse and complex, and require coordinated efforts and resources across a variety of local, national, and international stakeholders ."** Building on that definition, humanitarian action is understood as a coordinated set of activities undertaken to prevent, mitigate, and alleviate human suffering, protect life and dignity, and safeguard fundamental rights of populations affected by acute or protracted crises. Humanitarian action can be taken at any phase of the crisis management cycle (**Figure 1**), which encompasses anticipatory action (risk reduction and early warning), rapid emergency response (search and rescue operations, restoration of essential services, and protection), and recovery and resilience-building, and is guided by the core humanitarian principles of humanity, neutrality, impartiality, and independence (UNHCR Humanitarian Principles).

The crisis management cycle is a conceptual framework that describes the temporal progression of a humanitarian emergency and the corresponding decision-making, coordination, and intervention phases undertaken by humanitarian actors to **reduce risk, save lives, and support recovery**. It spans pre-crisis, crisis, and post-crisis periods, while recognizing that humanitarian emergencies are dynamic, non-linear, and iterative, often overlapping, re-escalating, or transitioning unevenly across regions and populations, particularly in protracted or compound crises. In scientific and operational terms, the crisis management cycle comprises four interrelated phases:

- **Risk Reduction and Anticipatory Action (Pre-event):** This phase focuses on hazard monitoring, vulnerability assessment, exposure analysis, and early warning, aimed at preventing crises where possible or reducing their impacts before they occur. Activities include preparedness planning, anticipatory financing, and pre-positioning of resources based on probabilistic forecasts and risk indicators.
- **Emergency Response (Onset and Acute Phase):** Following crisis onset, this phase prioritizes life-saving interventions, rapid needs assessments, and protection of affected populations. Actions are characterized by high urgency, uncertainty, and the need for real-time situational awareness to guide decisions on aid delivery, access, and coordination among responders.
- **Stabilization and Early Recovery (Post-acute Phase):** As immediate life-threatening conditions subside, efforts shift toward restoring essential services, supporting livelihoods, and reducing secondary impacts. This phase bridges humanitarian relief and longer-term development, often occurring alongside ongoing response activities in complex emergencies.
- **Recovery, Reconstruction, and Resilience Building (Post-event):** The final phase emphasizes long-term recovery, reconstruction of physical and social systems, and strengthening community resilience to future shocks. Lessons learned from prior phases are integrated to improve preparedness, governance, and risk reduction strategies.

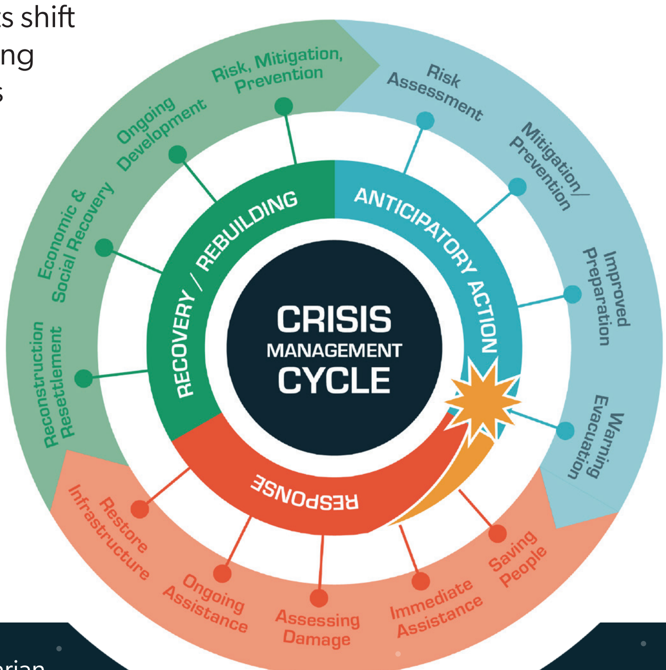


Figure 1: Diagrammatic description of the humanitarian crisis management cycle including Anticipatory Action; Response; Recovery and Rebuilding

GeoAI for Humanitarian Action

The crisis management cycle is governed by ethical, transparent, and accountable decision-making, and increasingly supported by GeoAI to enhance risk assessment, early warnings, exposure modelling, damage assessment, and timely response, particularly in data-scarce or resource-constrained contexts. Humanitarian decision-making is constrained by time, uncertainty, scale, and capacity gaps. While traditional spatial analysis remains foundational, GeoAI promises speed, accuracy, and scale that positions it as a unique enabler under humanitarian constraints. Traditional spatial analysis relies on established spatial statistics, manual interpretation, and workflows that are often limited by data volume and human capacity. GeoAI, on the other hand, uses machine learning and deep learning techniques to learn from data, automate feature engineering, build complex predictive models, and rapidly analyze large datasets. This value is demonstrated not only in its scientific novelty but also in the operational leverage over traditional methods. **Table 1** highlights some of these relative strengths of GeoAI building on traditional spatial analysis and its unique value-add to humanitarian action.

NOTE

GeoAI complements, not replaces, the geospatial analyst. While the geospatial analyst provides geographic logic, domain grounding, explainable reasoning, and contextual interpretation, GeoAI can enable pattern discovery at scale, automation under time pressure, and generalization across space and time. Humanitarian impact emerges when GeoAI is used by a geospatial analyst and embedded within sound spatial reasoning, not when it operates in isolation.

Table 1: Relative strengths and value of GeoAI in comparison to traditional spatial analytics within the humanitarian context. Note: Some of the listed benefits of GeoAI are not fully operational within the humanitarian context, but are included to highlight key areas of opportunity that technical innovators are working to realize. Learn More

Benefit	Spatial Analysis	GeoAI	Humanitarian Value
Speed of Processing (Learn More)	Sequential, manual workflows; processing slows rapidly as data volume increases	Near-real-time processing of large, multi-sensor EO datasets	Aligns analysis with disaster timelines, rapid response windows, and funding trigger
Scalable Experimentation	New questions require re-engineering workflows; limited by analyst time	Rapid hypothesis testing across regions, hazards, and scenarios [3]	Enables adaptive programming, continuous learning, and uncertainty-aware decisions
Reduced Redundant Work	Repeated preprocessing and baseline mapping across organizations	Reusable models, shared features, and pre-computed analytical products	Frees scarce expertise for interpretation and improves coordination across actors
Reduced Time to Interpretation (Learn More)	High expertise requirements; heavy cognitive load during crises	Complex analysis distilled into simple, decision-ready indicators	Expands access to insights and supports faster decisions by non-experts
Predictive Power	Primarily descriptive; slow, static, and assumption-driven forecasting	Predictive, probabilistic modeling using multi-temporal, multi-sensor data	Shifts action from reactive response to anticipatory and preventive strategies
Cost and Resource Optimization (Learn More)	Static planning; slow to update routes and logistics	Dynamic optimization using real-time spatial and temporal data	Improves efficiency, accountability, and delivery of aid under resource constraints

[3] An operational GeoAI system or tool can make it feasible to ask questions like: 1. What if rainfall intensity increases? Which areas are consistently misclassified? Where do vulnerabilities compound over time?

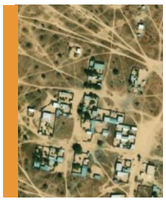
Practically, GeoAI is an enabler for humanitarian action, with compelling benefits in the following notable areas*:

Rapid Disaster Assessment and Response

GeoAI can quickly analyze satellite imagery and aerial data to assess damage from earthquakes, floods, or conflicts, identifying affected areas and populations much faster than manual methods. This enables responders to prioritize where help is needed most urgently.

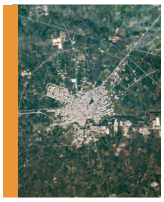
Predictive modeling for Anticipatory Action

Machine learning algorithms can analyze historical and real-time geographic data to predict where crises like famines, disease outbreaks, or displacement might occur, allowing humanitarian organizations to position resources proactively rather than reactively.



Population Mapping in Data-Poor Regions

GeoAI can help estimate population distributions in areas lacking census data by analyzing building footprints, settlement patterns, and other geographic features from satellite imagery. This is crucial for planning vaccination campaigns, food distribution, or infrastructure development.



Infrastructure and Access Mapping

GeoAI can identify roads, bridges, medical facilities, and other critical infrastructure, helping organizations understand access constraints and plan logistics for delivering aid in remote or conflict-affected areas.

Monitoring Displacement and Migration

By analyzing changes in settlement patterns over time, GeoAI can help track refugee movements and informal settlement growth, supporting camp management and resource allocation.

Environmental and Climate Risk Analysis

AI-powered geographic analysis can identify communities vulnerable to climate-related hazards like sea-level rise, drought, or extreme weather, informing both immediate humanitarian needs and longer-term resilience programming.

*This is not an exhaustive of all the practical areas where GeoAI is being used

NOTE ON GENERATIVE GEOAI

Generative GeoAI enables humanitarian responders to query complex geospatial data using natural language (e.g., "Which communities are most affected by flooding in the last 48 hours and how can we reach them?"), limiting the need for specialized GIS skills or time-intensive dashboard interaction. During emergencies, when cognitive bandwidth, time, and technical capacity are limited, this allows faster situational awareness, on-the-fly analysis, and decision-making directly in the field. Generative GeoAI can synthesize multi-sensor satellite data, models, and contextual knowledge into concise, actionable insights, explanations, and maps tailored to user intent, fundamentally lowering the barrier between geospatial data and humanitarian action.

METHODOLOGICAL DESIGN

This study uses a four-step approach to examine how GeoAI is currently used in humanitarian action, where it falls short, and where it holds the most promise. We gathered insights from experts, practitioners, and decision-makers across the humanitarian and GeoAI community through interviews, questionnaires, and focus group discussions. The study was conducted in these four phases: 1.) stakeholder profiling, 2.) desk research, 3.) focus group discussions, and 4.) a community survey.

Figure 2: High-level visual description of the research methodology used in this study.

Stakeholder Profiling

We developed five distinct stakeholder personas by building on existing NASA Lifelines community profiles and insights from expert interviews. These personas reflect the GeoAI for Humanitarian Action ecosystem (see **Figure 3**) and informed the design of the focus group discussions and the community survey.

Desktop Research

We synthesized white and grey literature on GeoAI for humanitarian action, with a primary focus on anticipatory action (risk assessment and early warning systems) and response and recovery (rapid emergency response and damage assessment). This body of work provided baseline knowledge to guide the analysis of these use cases. The results were compiled into research primers for the focus group discussions and are publicly accessible through the NASA Lifelines Gallery.

Community Survey

We designed a multi-stakeholder community survey to test and validate hypotheses related to the opportunities, challenges, and limitations of GeoAI for humanitarian action. Structured around the five identified stakeholder personas, the survey gathered perspectives on information needs, challenges, and the perceived utility of existing GeoAI tools and systems before, during, and after humanitarian emergencies.

Focus Group Discussion

We employed NASA Lifelines Supper Club approach to convene three virtual discussions, coined the GeoAI for Humanitarian Action Supper Club Series. Held over the course of two weeks, the series centered on the question: "How are openly accessible GeoAI tools and systems being used across the lifecycle of a humanitarian crisis?" To maintain focus, the discussions were organized around three core phases: Anticipatory Action (Risk Assessment and Early Warning Systems), Response (Rapid Emergency Response), and Recovery/ Rebuilding (Damage Assessment). Conversations drew upon current contexts, operational considerations, and working examples presented in the research primers on 1.) Risk Assessments and Early Warning, and 2.) Disaster Response and Recovery. The series engaged more than 25 experts from over 20 organizations across 5 regions with experience in geospatial intelligence, risk assessment, famine early warning systems, damage assessments, and humanitarian response.

STAKEHOLDER PERSONAS

This section introduces five stakeholder personas identified within the GeoAI for Humanitarian Action ecosystem.[4] Each persona reflects the distinct roles, contributions, and levels of influence that different actors play within the humanitarian action ecosystem as they relate to the development and use of GeoAI. For example, these actors may determine which GeoAI tools are most appropriate for strategic decision-making and coordination, invest in innovative technology development, build GeoAI tools, or use downstream products to aid their efforts in preparing and mitigating humanitarian emergencies. Together, the personas capture both the functional roles actors play in the GeoAI data value chain and how those roles can inform the design of scalable tools, as well as evaluation and learning metrics for assessing the uptake of GeoAI data and analytics. In humanitarian contexts, these data roles describe how each persona curates, shares, and uses open and proprietary datasets to meet their needs before, during, and after a crisis.

Identifying Stakeholder Personas

In tandem with the NASA Lifelines community profiles, Caribou Space's Beyond Borders report, and expert discussions, we identified five stakeholder profiles operating within the GeoAI for Humanitarian Action ecosystem:

- Technical Innovators
- Ecosystem Enablers
- Strategic Decision Makers
- Data Driven Humanitarians
- Crisis Affected Individuals

Building on these individual profiles, we identified each actor's specific and broad needs, roles, and contributions along the supply and demand functional spectrum proposed by Caribou Space. See **Figure 3.**

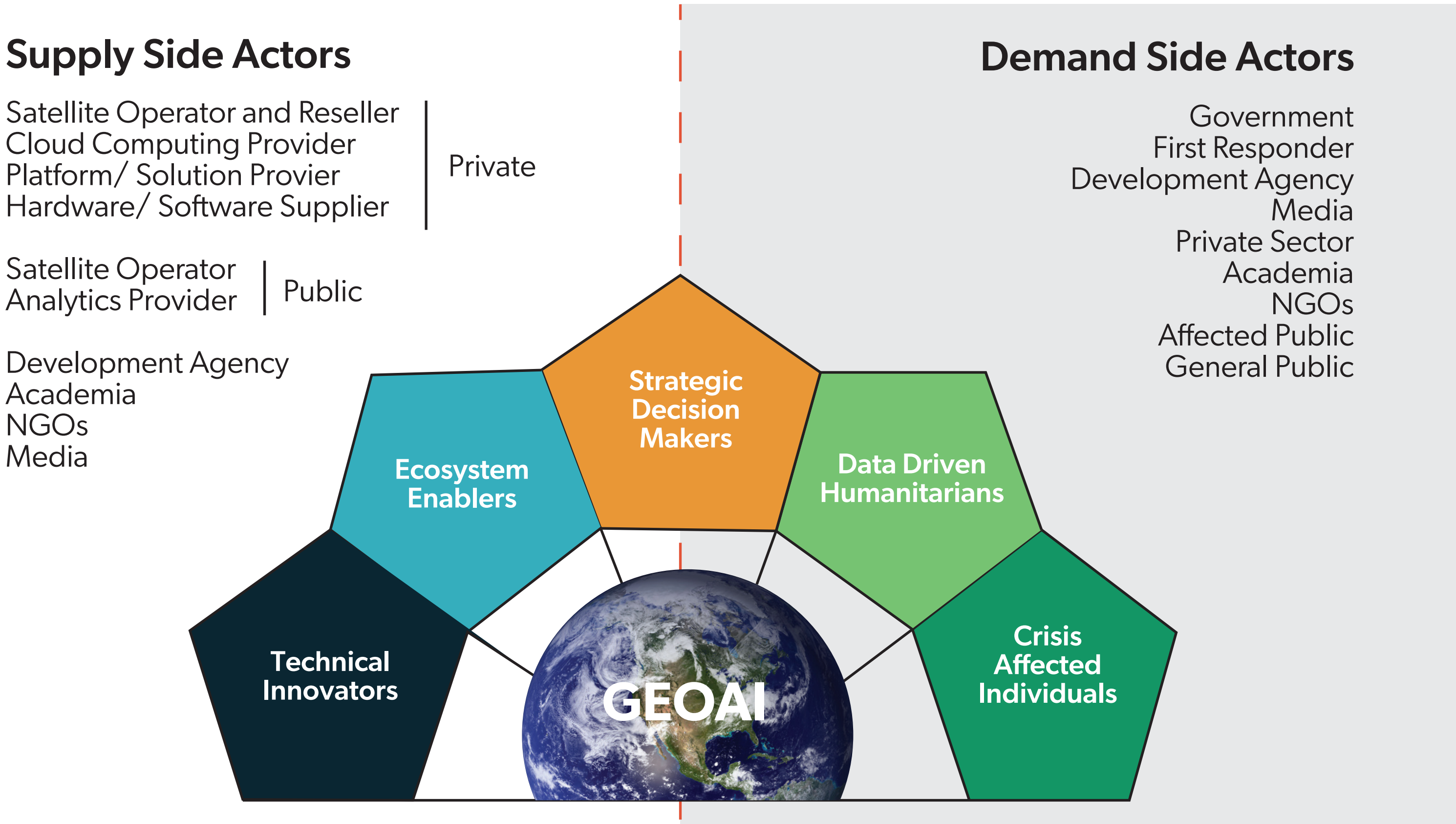


Figure 3 Diagrammatic description of actors within the GeoAI for Humanitarian Action ecosystem, highlighting supply and demand-side actors.

"There is a complex network of stakeholders involved in satellite applications for humanitarian emergencies; … all stakeholders can be positioned along a spectrum from the supply-side to the demand-side, or both in a few cases. The supply-side provides the satellite applications, whereas the demand-side uses those applications to address their humanitarian emergencies. … Private Suppliers and Public Suppliers represent the majority of providers of satellite applications for humanitarian emergencies. "

from Caribou Space's Beyond Borders Report on the humanitarian data ecosystem

Mapping Personas to Data Roles

In assessing how to achieve effective data preparedness within the humanitarian data ecosystem, Haak et al. (2018) propose four data roles that support coordination and data sharing between humanitarian actors:

- Initiators / Coordinator
- Local Leads
- Data Suppliers
- Toolbox Users

These roles provide a useful framework for understanding how the identified stakeholder personas interact with data before, during, and after a crisis.

Initiators /Coordinators are typically well-recognized international agencies that are responsible for activating the humanitarian data ecosystem. They facilitate disaster and satellite tasking charters, open data programs for disaster response, support and invest in the development of downstream tools, where required, at the regional, national, and local levels. Some examples include the United Nations IOM, UNICEF, WFP, and UN OCHA.

Local Leads are the national body that coordinates with the initiator and facilitates participation, use, and implementation in their local context. Examples include the Department of Emergency Management, National Weather and Hydrological Services, Refugee Management, etc.

Data Suppliers are responsible for sharing relevant datasets with the ecosystem. These also include processed data from analytic tools that provide insights for the different use cases within the humanitarian action landscape. These roles often overlap between public and private organizations, such as EU CEMS, UNOSAT, and Microsoft AI for Good, which provide rapid mapping, and other Earth observation companies that provide open datasets during disasters.

Toolbox Users are either humanitarian or government agencies that use the processed data and outputs in their response coordination operations. This also includes data-driven humanitarians and tech-savvy crisis-affected individuals or community organizers.

From Page 10

[4] These personas do not capture every user type active in this space, they represent the scope selected for this study. We welcome feedback on additional personas that may warrant inclusion in future work.

Stakeholders Personas in Context

From left to right as depicted in Figure 3

Technical Innovators

This comprises the Social Impact Scientist and the Private Sector Technologist who are based in Academia, Government, or Private Technology Companies or startups with the drive to use their skillsets for the good of humanity. They are often the developers of faster and more efficient technologies and frameworks tailored for the humanitarian action context, either through the open source software community or within established tech companies with significant influence on the ecosystem. Due to their positioning within public and private sectors, their data roles often overlap those of Data Suppliers, Local Lead, or Toolbox users.

Ecosystem Enablers

This includes Data Providers, Educators, and Policy Makers who provide the enabling environment for the use and uptake of GeoAI in the humanitarian action ecosystem. Enabling the environment would include policy and regulations, education and skillsets, financial investments, and digital infrastructures. Data roles cross across Initiators/Coordinators, Local Lead, and/or Data Suppliers.

Strategic Decision Makers

This comprises the Humanitarian Decision Maker and the Philanthropic Funder, who are tasked to make strategic decisions on what tools or technologies get adopted, funded, and tested within the fragile environment of humanitarian action. Their data roles often involve serving as a Local Lead or Initiators/Coordinators.

Data Driven Humanitarians

Data-driven humanitarians are frontline technical coordinators, experts, or humanitarians who rely on geospatial technologies and artificial intelligence in their toolbox. They focus on tech, data, and innovation to improve their humanitarian work, response, and preparedness activities. Depending on the kind of organization they are working at, their data roles can vary between those of a Local Lead and Toolbox users.

Crisis Affected Individuals

Individuals in the affected community or members of the general public with a vested interest in the affected community. They can be considered as Toolbox Users, with questions on their awareness of the availability of these tools and the Disaster Assistance during humanitarian crises.

MAIN FINDINGS

This section synthesizes the main findings from the study, drawing on insights from the survey responses and facilitated discussion groups across the GeoAI and humanitarian ecosystem. Together, these inputs reveal a consistent pattern: **while GeoAI technologies are advancing rapidly in technical sophistication, their operational adoption in humanitarian contexts remains uneven and constrained by by both technical and non-technical factors.** It highlights a set of recurring tensions, between scientific innovation and operational reality, between data availability and equitable access, and between technical validation and social trust, that shape how, where, and by whom GeoAI is used in practice. Rather than pointing to a single bottleneck, the results illustrate a layered landscape of actors, expectations, and systemic constraints that collectively determine whether GeoAI tools become decision-relevant, trusted, and actionable during crises. The subsections that follow unpack these dynamics in detail, moving from the broader landscape of actors, to specific mismatches between scientific and operational needs, patterns of operational use and trust, systemic constraints in humanitarian contexts, and finally the emerging risks that accompany the growing deployment of GeoAI in high-stakes environments.

How Humanitarian Actors use GeoAI

Our study reveals that humanitarian actors GeoAI use clusters strongly around damage assessment, disaster response, flood hazards, urban resilience, and conflict/displacement (**Figure 4**), reflecting how GeoAI is operationalized across the crisis lifecycle.

Figure 4 Word Cloud highlighting the areas humanitarian actors use GeoAI for across different spectrum of the humanitarian crisis lifecycle. Font size represents frequency, with more current use focusing on damage assessment and disaster response

Risk Reduction and Anticipatory Action

In this phase, GeoAI is primarily used for risk scoring/hotspotting, hazard footprint mapping, and early warning/risk forecasting, particularly for recurrent hazards such as floods, cyclones, droughts, and heatwaves (**Figure 4**). In this phase, Technical Innovators provide these GeoAI products to support Data-Driven Humanitarians and Strategic Decision Makers to enable Anticipatory Action in the Crisis lifecycle. Notwithstanding, to be more effective amongst Data-Driven Humanitarians, these tools and systems need to prioritize uncertainty display, interpretable outputs, and low-bandwidth access to enable pre-crisis planning in data-constrained settings (**Table 2**). For Strategic Decision Makers, the emphasis lies on scalability, interoperability, and transparency, allowing GeoAI-derived risk insights to inform national preparedness plans, anticipatory financing, and cross-agency coordination. GeoAI at this stage functions as an enabler of anticipatory action, translating probabilistic forecasts into spatially explicit risk intelligence.

Emergency Response

During active crises, humanitarian actors could use GeoAI for damage assessment, need assessment, asset mapping/exposure, and situation reports, particularly in flood, earthquake/tsunami, wildfire, and conflict contexts. Here, GeoAI supports rapid situational awareness, enabling responders to map affected populations, damaged infrastructure, and accessible routes within reasonable timelines. In this phase, GeoAI for Crisis-Affected Individuals manifests through downstream products such as early alerts, evacuation routes, shelter maps, food and water access points, and damage maps, with emphasis on the timeliness, clarity, and simplicity of use over technical complexity. During the rapid response phase where stakes are high, Ecosystem Enablers recommend GeoAI systems to communicate confidence levels, known limitations, and versioned outputs to ensure responsible use. This phase highlights GeoAI's role as a force multiplier, reducing manual mapping workloads and accelerating time-to-interpretation under operational pressure.

NOTE

While many of the respondents identified as **Crisis Affected Individuals** highlighted little awareness of GeoAI enabled tools and systems during the crisis they had personally experienced, they demonstrated strong willingness to learn about them and use them. Our observation was that some of the well-used GeoAI enabled systems might already be modularized to abstract away the GeoAI components from the end-users. This is in fact a desired user design feature to keep the output simple and digestible to the end-user. However, it makes it difficult to clearly demonstrate the use and awareness of GeoAI as the underlying technology amongst this particular persona.

Recovery, Adaptation & Resilience Building:

In post-crisis and longer-term recovery phases, GeoAI usage shifts toward urban resilience, adaptation, food security, and conflict/displacement monitoring (**Figure 4**). GeoAI supports recovery monitoring, resource allocation planning, and exposure analysis, helping humanitarian and development actors track rebuilding progress, population returns, and evolving vulnerabilities. In this phase, GeoAI bridges humanitarian response and development planning, enabling data-driven transitions from relief to resilience.

Across the crisis lifecycle, **Strategic Decision Makers** and **Ecosystem Enablers**, recommends features such as **local ownership, adaptability to evolving crises, transparent change logs, and evidence of field impact** as vital components that can enable the uptake of GeoAI within the humanitarian context (**Table 2**).

Barriers Limiting the Uptake of GeoAI

Despite the growing maturity of GeoAI capabilities across the humanitarian crisis lifecycle, **uptake remains uneven, with varying constraints across persons in the humanitarian action ecosystem**. The barriers identified below reveal that challenges are not purely technical, but socio-technical, institutional, and contextual in nature. We provide a synthesis of the primary barriers, their implications, and recommendations for addressing them, and priority features to tackle these barriers in **Table 2 .**

Data-Driven Humanitarians

Data-driven humanitarians, often analysts embedded in NGOs, UN agencies, or government response units, face some of the most immediate operational barriers. Connectivity limitations and low-bandwidth environments constrain the use of cloud-based GeoAI tools, particularly during active emergencies. Policy and approval constraints, including procurement rules and data-sharing restrictions, slow adoption even when technical solutions exist. Additionally, many GeoAI systems are perceived as too complex, requiring long training times that are incompatible with rapid deployment cycles. High infrastructure costs, opaque model outputs, restrictive licensing, and the fragmentation of tools across platforms further reduce usability and trust. Together, these barriers limit the ability of data-driven humanitarians to translate GeoAI outputs into timely, actionable insights.

Technical Innovators

Technical innovators including researchers, developers, and GeoAI practitioners are constrained by a different set of challenges. The proliferation of competing tools and frameworks creates redundancy and slows convergence toward operational standards. Many tools lack sufficient user friendliness, making it difficult to transition prototypes into real-world deployments. Persistent training and skill gaps, combined with cost and computational resource constraints, further restrict experimentation and scaling. **Critically, innovators also face a mismatch of priorities between academic research incentives, frontline operational needs, and the lived realities of crisis-affected communities.** This disconnect often results in technically impressive systems that struggle to gain sustained humanitarian adoption.

NOTE

When Technical Innovators were asked what resource constraints most limit their innovation in the development of GeoAI for Humanitarian Action, they highlighted:

Figure 5 Resource constraints limiting the innovation of Technical Innovators within the GeoAI for Humanitarian Action ecosystem. Font size represents the frequency that the constraint is mentioned.

Strategic Decision Makers

Strategic decision makers such as agency leaders, donors, and policymakers tend to view GeoAI through a risk management lens. Key barriers include ethical and privacy concerns, particularly around sensitive population data, and reputational risks if GeoAI-driven decisions prove inaccurate or harmful. Additional challenges include misalignment with field needs, dependence on external technology suppliers, and the high cost of deployment and long-term maintenance. A cautious approach to trust in model outputs, compounded by weak data governance frameworks and unclear policies, limits institutional buy-in. For this persona, the absence of transparent, accountable, and field-validated GeoAI systems could potentially be a deal-breaker.

Ecosystem Enablers

Ecosystem enablers such as standards bodies, funders, open-data advocates, and platform builders face structural barriers related to costs, limited time and skilled personnel, and licensing or intellectual property constraints. These challenges hinder the development of shared infrastructure, open standards, and long-term maintenance models. Without sustained investment and coordination, GeoAI ecosystems risk fragmentation, duplication of effort, and limited interoperability across humanitarian actors.

Crisis-Affected Individuals

For crisis-affected individuals, barriers are fundamentally about access and relevance. Poor usability, language barriers, and limited connectivity prevent many from benefiting directly from GeoAI-enabled products. There is often a lack of awareness that such tools exist, and in many cases, GeoAI outputs are not designed around user needs, priorities, or cultural contexts. As a result, even well-intentioned GeoAI systems may fail to support last-mile decision-making and protective action.

Across personas, these barriers reveal a central tension: **GeoAI systems are frequently optimized for technical performance rather than operational trust, inclusivity, and governance.** Addressing these challenges requires not only better models, but co-designed workflows, transparent uncertainty communication, flexible licensing, and sustained capacity building tailored to each stakeholder group.

Table 2: Barriers limiting the adoption and use of GeoAI tools from the perspective of each persona within the humanitarian action ecosystem, along with the priority features expected in a GeoAI tool or system designed for humanitarian action for each persona.

Persona	Primary Barriers	Priority features in GeoAI
Data-Driven Humanitarians	1. Connectivity limits 2. Policy/ Approval Constraints 3. Too complex/ Long training time, 4. Cost and infrastructural requirements 5. Opaque outputs with limited interpretability 6. Licensing 7. Fragmentation of tools	1. Offline/ low bandwidth modes 2. Automated provenance 3. Uncertainty display 4. Simple user Interface with preset workflows 5. Open licensing 6. Local data integration 7. Micro trainings
Technical Innovators	1. Competing tools 2. User friendliness 3. Training/ skill gaps 4. Cost/ resource constraints 5. Mismatch of priorities from academia, frontline responders, and affected Communities	1. Explainable/ interpretable outputs 2. Clear documentations with metadata on provenance and uncertainty 3. Rapid technical or community forums for sharing feedbacks 4. Multi-lingual interface 5. Low-bandwidth modes
Strategic Decision Makers	1. Ethical and privacy risks 2. Reputation risks if tools fail 3. Misalignment with fields needs 4. Dependence on external technology suppliers 5. High cost of deployment and maintenance 6. Lack of trust in outputs 7. Data governance and policy issues	1. Scalability of the GeoAI tools, 2. Transparency of the data, models, and outputs 3. Interoperability with other established tools and data formats for humanitarian operations 4. Adaptability to evolving crises 5. Evidence of Field Impact 6. Local Ownership 7. Ability to interact using natural language

Ecosystem Enablers	1. Costs of building GeoAI systems 2. Skills/ time of training 3. Licensing/ IP	1. Confidence/ Uncertainty of the GeoAI derived predictions 2. Versioning/ Change log of datasets and outputs 3. Statements of known limitations and safe use 4. Interpretability of outputs
Crisis-Affected Individuals	1. Usability 2. Language barriers 3. Connectivity 4. Lack of Awareness of GeoAI tools 5. Unavailability of GeoAI tools for user needs	1. Confidence/ Uncertainty of the GeoAI derived predictions 2. Versioning/ Change log of datasets and outputs 3. Statements of known limitations and safe use 4. Interpretability of outputs

Scientific versus Operational Needs Mismatch

The ecosystem of GeoAI for humanitarian action is faced with the persistent challenge of reconciling scientific needs with the operational realities of humanitarian actors, especially during rapid crisis response. While scientific advances continue to push the boundaries of accuracy, model sophistication, and methodological rigor, humanitarian operations are constrained by time, access, trust, and institutional capacity, resulting in a divergence between what is technically possible and what is operationally usable. This mismatch is not primarily a technological gap but a socio-technical alignment challenge. Scientific GeoAI advances tend to be accuracy-driven, data-intensive, and method-centric whereas humanitarian operations are time-critical, resource-constrained, trust- and mandate-driven. **Bridging this gap requires reframing GeoAI development around clear use cases, explicit decision windows, differentiated audiences, and equitable data access, ensuring that scientific excellence translates into operational relevance. Without this alignment, even the most advanced GeoAI systems risk remaining scientifically impressive but operationally marginal.**

Table 3 reveals a scientific–operational mismatch in the use of GeoAI for humanitarian action by showing that **different user personas require fundamentally different forms of value from the same technologies**. Technical innovators emphasize scientific needs, such as access to compute resources, representative benchmarks, peer-reviewed validation metrics, and interpretable models, reflecting incentives rooted in research rigor, generalizability, and methodological advancement. In contrast, data-driven humanitarians and crisis-affected individuals prioritize operational reliability: low-bandwidth or offline functionality, micro-trainings, continual field validation, local language accessibility, and seamless integration with real-world response timelines. Strategic decision makers further widen this gap by focusing on trust, scalability, interoperability, and evidence of field impact, rather than model performance alone, while ecosystem enablers emphasize standards, certification, and governance mechanisms needed to sustain responsible deployment. Collectively, this reflects that **GeoAI systems optimized for scientific excellence do not automatically translate into operational utility**, and that humanitarian adoption depends on reconciling research-driven validation paradigms with context-specific, trust-centered, and resource-constrained operational realities.

Table 3: Respective needs of different user personas from a GeoAI system designed for humanitarian action

Persona	Infrastructure	Capacity Building	Trust and Validation	Tool Design	Recommendations
Data-Driven Humanitarian	Low-bandwidth or Offline Modes	Micro-trainings on tool usage	Continual field validation to capture evolving crises.	Integration with Local Humanitarian Operations workflow and timeline	**Constant exchange of information through forums like ITUs GeoAI discovery series to address emerging and existing gaps. Most data driven humanitarians could use serious upskilling to understand and adopt geoAI tools**
Technical Innovators	Compute Resources to develop models and representative datasets	Data Benchmarks that captures Humanitarian Contexts (esp. Armed Conflicts)	Peer reviewed validation metrics. Detailed metadata on data provenance	Interpretable models to facilitate continual learning after the emergency	**A global geoAI humanitarian forum could reduce duplication - we can take advantage of existing forums like the UN geospatial network to advocate for improving the available tools, models and their transparency; but might be helpful to have a strong group with people from academia, private and public sector and UN/NGOs**
Strategic Decision Maker	Dashboards, decision ready data, generative GeoAI and natural language querying	Briefings on evidence of field impact, interoperability, and scalability	Transparency on model and data bias, and known limitations of the GeoAI tools. Impact Assessment on Humanitarian Operations	Adaptability to evolving crises and interoperability with other tools	**High level policy and research papers on geoAI ethical and governance framework could be useful to consider here**
Ecosystem Enabler	Technical Standards for Data Sharing and Provenance in the Humanitarian Context	Self-paced micro-modules targeted at training the trainers. Certifications to develop GeoAI for humanitarian contexts	Quality Metadata on Data Uncertainty, Changelog, and Safe use	Standardized, open source, and interoperable tools	**More awareness raising with donors on the importance of integrating GeoAI tools**
Crisis-Affected Individuals	Low-bandwidth or Offline Modes	Outputs shared in accessible local language (multi-lingual)	Validation by Authoritative Agencies or Community Leaders	Simple and Accessible User Interface to facilitate user experience	**Use of generative geo AI could be an option to reduce existing language barriers**

What Makes GeoAI Trustworthy for Humanitarian Actors?

Trust in GeoAI outputs for humanitarian action extends beyond the technical quality of maps, models, and statistical metrics, and is fundamentally shaped by socio-cultural context, institutional credibility, and operational relevance, which vary across regions and crisis settings. **Establishing trust begins with due diligence in data handling, including careful verification, validation, and ethical review before information is shared or acted upon**. Equally important is the engagement of trusted local voices, such as community leaders, local responders, and national institutions, who can contextualize GeoAI outputs and mediate their acceptance among affected populations and frontline responders.

Explainability plays a differentiated role in this trust-building process. While model explainability and interpretability are essential for scientists to assess performance, diagnose errors, and iteratively improve GeoAI systems, decision-makers and first responders operating under time pressure may not require detailed explanations of model internals at the moment of action. This distinction **highlights the need to separate explainability for system development from interpretability for operational use**, recognizing that trust among first responders, who must act on the information under high uncertainty, is often the most difficult to establish.

More broadly, trust in GeoAI systems is strengthened through transparent and open workflows that allow stakeholders to understand how data products are generated, including clear documentation of data provenance, uncertainty, and security safeguards. Involving local communities in data collection and validation processes, where feasible, can further enhance legitimacy and acceptance. Ultimately, trust in GeoAI for humanitarian action emerges from the interaction of technological robustness and social dynamics, with different stakeholders, scientists, decision-makers, responders, and affected communities, operating within distinct hierarchies of trust that must be acknowledged and actively managed for responsible and effective deployment.

NOTE

GeoAI for humanitarian action should be **transparent, explainable**, and **community-centered**. It should **strengthen local agency** rather than replace human judgment, operate **offline in low-resource settings**, communicate **uncertainty clearly**, and be governed by **ethical standards** that protect vulnerable populations. Success means tools that are **trusted, accessible, and proven** to save lives; not just technically impressive.

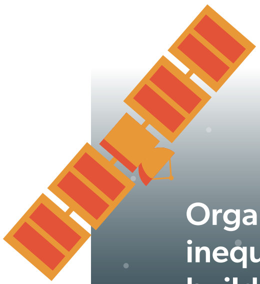
Systematic Issues in the Humanitarian Context

Despite rapid advances in Earth observation, artificial intelligence, and geospatial analytics, the application of GeoAI in humanitarian action remains constrained by a set of persistent systemic challenges. **These challenges extend beyond algorithmic performance and data availability, reflecting deeper issues related to data governance, institutional activation mechanisms, and socio-cultural perceptions of risk and preparedness.** In practice, such constraints shape when, where, and how GeoAI-derived information can be accessed, trusted, and operationalized by humanitarian actors. The following sections examine three interrelated issues: **open satellite data programs, the operational limitations of the International Charter on Space and Major Disasters, and the influence of disaster frequency and cultural context**, that collectively limit the effective and equitable deployment of GeoAI across humanitarian contexts.

Open Satellite Data Programs

Open data programs from commercial and public satellite imagery providers represent a foundational pillar for GeoAI-enabled humanitarian action. However, their impact is currently constrained by inconsistent policies and coverage across providers, delays between crisis onset and data release, technical and procedural barriers that make accessing the imagery difficult. First, data stewardship remains uneven. Providers that aim to generate social and humanitarian impact often lack clear, reliable commitments regarding when and how philanthropic or emergency data releases occur. **Uncertainty around release timing, licensing terms, processing levels (e.g., raw vs. analysis-ready data), and API access creates friction precisely when humanitarian response teams require predictability and speed.** Second, although many providers participate in activation protocols aligned with frameworks such as the International Charter on Space and Major Disasters, operational access is frequently slowed by: complex request pathways, manual approval steps, fragmented data portals, misalignment between released data formats and humanitarian workflows. These delays erode the value of GeoAI systems that depend on rapid ingestion and automation.

A key opportunity for GeoAI lies in tiered data-access strategies. Open, lower-resolution, and more frequently available EO data can be used for rapid risk screening and anomaly detection, enabling GeoAI systems to trigger targeted requests for higher-resolution, temporally precise commercial imagery only when and where it is most needed. This approach reduces cost, accelerates response, and aligns commercial incentives with humanitarian priorities. Finally, the humanitarian community itself has a role to play. Through collective demand signaling, coordination platforms, and evidence of impact, humanitarian actors can exert pressure on commercial providers to standardize, streamline, and operationalize open data programs, ensuring they are fit for crisis response rather than symbolic commitments.



Organizations like Common Space are working to address the challenge of data access inequities in crisis affected regions. Common Space is a nonprofit initiative that aims to build and operate an independent, community-owned high-resolution satellite constellation dedicated to humanitarian aid, public good, and open data access.

The International Charter on Space and Major Disasters

The International Charter on Space and Major Disasters, supported by entities such as the United Nations Office for Outer Space Affairs and UN-SPIDER, represents one of the most established mechanisms for mobilizing satellite data during disasters. Yet, despite its longevity and institutional legitimacy, its uptake and measurable impact remain uneven.

One limitation is that Charter activation is not straightforward. Requests must be formally invoked by authorized entities (e.g., national governments or approved intermediaries), which introduces delays and excludes certain contexts. Critically, the Charter cannot be activated in conflict settings, rendering it ineffective in many of today's most severe humanitarian crises, including civil wars and state-perpetrated violence. In such contexts, governments are unlikely, or unwilling, to request damage mapping of actions affecting their own populations (e.g., Tigray, Sudan). Even when activated, another challenge is information overload without operational alignment. Charter activations often result in:

- Large volumes of heterogeneous data products
- Rapidly produced maps using off-the-shelf methods
- Limited validation or uncertainty quantification
- Insufficient engagement with local actors

As a result, end users, particularly humanitarian practitioners, frequently default to tools and datasets they already trust, regardless of whether Charter-derived products are more comprehensive or timely. This explains why the impact of Charter contributions is difficult to trace across humanitarian outcomes: outputs are produced, but rarely embedded into decision-making pipelines.

GeoAI could help address this gap by:

- Standardizing analytical outputs
- Encoding uncertainty explicitly
- Prioritizing decision-relevant indicators rather than generic damage layers
- Enabling impact attribution by tracking how data products inform downstream actions

Moreover, partnerships with civil society organizations and UN-adjacent entities, such as UNOSAT, offer a viable pathway for extending Charter-like capabilities into politically sensitive or conflict-affected settings, where traditional activation mechanisms fail.

Disaster Frequency, Cultural Context, and Perceived Value of Preparedness

A third, often underappreciated, constraint on GeoAI for humanitarian action is socio-cultural perception of risk, particularly in regions where disasters occur infrequently. In high-frequency hazard environments, such as hurricane or wildfire-prone regions, disaster preparedness is normalized through seasonal calendars, drills, and institutional memory. In contrast, in regions with low-frequency but high-impact hazards, disasters are often perceived as exceptional or unavoidable, reducing incentives for anticipatory planning and early warning investments. This has direct implications for GeoAI:

- Early warning systems may be ignored or undervalued
- Predictive insights may be met with skepticism
- Investments in preparedness-oriented analytics may appear unjustified until after a disaster occurs

Without sustained engagement, GeoAI risks being seen as reactive technology, deployed only post-event, rather than as a tool for anticipatory action. Bridging this gap requires coupling GeoAI outputs with risk communication strategies, localized narratives, and culturally grounded explanations of probabilistic forecasting and climate change impacts. In this sense, the effectiveness of GeoAI is not solely determined by model performance, but by its integration into social systems of meaning, trust, and preparedness.

Emerging Risks of GeoAI

While GeoAI holds remarkable promise for scaling and fast-tracking humanitarian action, it also poses significant risks. These risks, when not adequately managed, can have unintended downstream impact in the high-stake environment of humanitarian action. Even more, malign actors can take advantage of some of the capabilities of GeoAI to influence public opinion and escalate civic actions. This section highlights some of the emerging risks of using GeoAI within the humanitarian action contexts, some example downstream impact, and potential mitigation strategies for humanitarian actors (See **Table 4**).

Table 4: Risks of using GeoAI for Humanitarian Action, potential downstream impact, and recommended mitigation strategy.

Risks	Downstream Impact	Mitigation Strategy
Incorrect predictions from GeoAI leading to false alarms	Erosion of trust in GeoAI systems; humanitarian actors may disregard or underutilize GeoAI even when it is beneficial	Provide uncertainty-aware predictions, confidence scores, and validation summaries; maintain human-in-the-loop decision-making
Growing trends of satellite data privatization in the Global North	Inequitable access to high-quality data for training, validating, and deploying GeoAI models in humanitarian contexts, particularly in the Global South	Support and expand open data programs; promote public–private partnerships with humanitarian access clauses
Fear-mongering around AI technologies	Resistance to GeoAI adoption among humanitarian actors and the general public	Responsible communication on the benefits, limitations, and appropriate use of AI and GeoAI technologies
Misrepresentation or misuse of satellite imagery	Public misinformation, misinterpretation of crises, and erosion of institutional credibility	Data providers should supply indicators of uncertainty, provenance, and potential manipulation; media literacy and clear contextual annotations
Algorithmic and datasets bias	Reinforcement of existing spatial, social, or political inequities when models rely on incomplete or unevenly distributed data	Conduct bias and impact assessments; diversify training datasets; transparently document known biases and limitations
Failure to represent local crisis contexts	GeoAI outputs that are misaligned with on-the-ground realities, reducing operational relevance and effectiveness	Co-design tools with local humanitarian actors; integrate local data sources and contextual knowledge
Use of GeoAI without safeguards in conflict-affected zones	Misuse by hostile actors, exposure of vulnerable populations, or targeting of critical infrastructure	Apply security-by-design principles; restrict sensitive outputs; enforce clear standards on permissible use of geospatial intelligence
Lack of transparency or explainability	Incorrect prioritization of aid, misallocation of resources, or inappropriate infrastructure investments	Develop interpretable models; provide clear documentation, model cards, and decision rationales tailored to non-technical users

NOTE: MISREPRESENTATION OF SATELLITE IMAGES IN CONFLICT SETTINGS

There is growing concern about the deliberate misrepresentation of satellite imagery, including the use of deepfakes, to spread misinformation in conflict settings. This emerging form of information or **cognitive warfare** involves digitally altered, AI generated, or out of context images used to exaggerate military successes or fabricate humanitarian impacts. For example, during **Ukraine's Operation SpiderWeb** and reporting around **U.S. and Israeli airstrikes on Iran's nuclear program**, fake or misleading imagery circulated to shape public narratives and undermine trust in the information ecosystem. Potential mitigation strategies include improving public awareness of indicators of manipulation and increasing transparency from governments, media outlets, and satellite imagery providers about how data are verified. While third party tools are being developed to detect AI generated imagery, they remain in an ongoing arms race with increasingly sophisticated generative models. Approaches such as using historical satellite archives to cross check imagery can help, but verification is more difficult with very high resolution proprietary data that are costly, less accessible, and often lack the long temporal records available in open archives such as Landsat.

Hopes for GeoAI

In our focus group discussions, we highlighted some of the hopes of experts, humanitarian actors, and users for GeoAI as an enabling technology in humanitarian action. These are grounded in the expectation that advances in GeoAI can meaningfully improve how risks are anticipated, communicated, and acted upon across the crisis lifecycle. **GeoAI experts and humanitarian actors envision GeoAI as a catalyst for earlier action, faster and more targeted response, clearer risk communication, and more equitable access to critical information.** These hopes extend beyond operational efficiency to include strengthened trust, improved coordination across preparedness, response, and recovery, and greater empowerment of local communities.

Table 5: Hopes and aspirations for the use of GeoAI technology for humanitarian action

Dimension	Hopes	Potential Impact[5]
Anticipatory Action & Early Warning	GeoAI enables the saving of lives by identifying risk before disasters occur.	Reduced mortality and morbidity through earlier evacuations, pre-positioning of resources, and protective actions informed by forecast-based intelligence.
Rapid Emergency Response	People receive accurate and actionable information at the appropriate time.	Faster and more targeted response operations, improved allocation of limited resources, and reduced delays in reaching affected populations.
Cross-Phase Coordination (Preparedness–Response–Recovery)	GeoAI brings together experts from multiple disciplines (engineering, medicine, geography, emergency services, technology).	More holistic situational awareness, reduced disciplinary silos, and integrated decision-making that accounts for physical, social, and health impacts of crises.
Risk Communication & Preparedness	Risk information is communicated in the native languages of affected populations, acknowledging varying levels of disaster literacy.	Improved comprehension of hazards, greater trust in warnings, increased compliance with protective actions, and enhanced public understanding of climate change and disaster predictability.

[5] Potential impact refer to benefits of realizing the stated hope within the humanitarian context

Preparedness & Risk Reduction	Disaster-related data and analytics are openly shared, even when acquisition and processing are costly.	Greater equity in access to information, enabling low- and middle-income countries to conduct risk assessments, preparedness planning, and independent analyses.
Last-Mile Delivery & Community Engagement	GeoAI-derived insights reach affected communities directly, beyond national agencies and centralized institutions.	Empowered local responders and communities, improved last-mile decision-making, and reduced dependency on delayed top-down information flows.
Institutional Adoption & Innovation	More humanitarian organizations are willing to experiment with and adopt AI-enabled tools.	Increased organizational learning, gradual normalization of GeoAI in operations, and the emergence of evidence-based best practices for responsible deployment.

SHARING GEOAI PRODUCTS WITHIN THE HUMANITARIAN CONTEXT

Safeguards and Recommendations

Effective sharing of GeoAI models, datasets, and tools in humanitarian contexts requires safeguards that prioritize trust, accountability, and operational safety over raw technical performance. Suresh and Guttag identified seven distinct upstream sources of biases throughout a machine learning pipeline that could potentially lead to unintended downstream harms when an ML model, tool, or system is used (**Figure 6**). These sources include historical bias, representation bias, measurement bias, aggregation bias, evaluation bias, learning bias, and deployment bias. In humanitarian operations, these sources of bias could translate into allocative harms (misdirecting or withholding assistance) and representational harms (erasing or stigmatizing communities), especially when datasets and models are reused beyond their valid spatial, temporal, or sociopolitical scope. Hence, a case for providing safeguards for deploying GeoAI models, tools, and systems within the humanitarian context. **Table 6** highlights the different dimensions of safeguards and recommendations that humanitarian actors would prioritize in a ML system.

Prior to deployment, humanitarian actors emphasize the need for formal safeguards, including data protection and privacy policies, human-in-the-loop review processes, bias assessments, and clearly defined incident or rollback plans should tools fail in the field. Approval by authoritative agencies or humanitarian clusters, alongside community feedback mechanisms, provides additional social and institutional validation, anchoring GeoAI systems within trusted governance structures. Together, these measures shift GeoAI from a "black-box" analytical product toward a transparent, auditable, and socially accountable decision-support system, which is essential for responsible adoption in high-stakes humanitarian operations. More so, to enable uptake of GeoAI within the humanitarian context, data-driven humanitarians express a strong preference for open licensing coupled with simple user experiences and micro-trainings, enabling rapid uptake without deep technical expertise. Trust is further reinforced through robust metadata that clearly documents temporal validity windows, spatial coverage and scale, data sources and licensing, methodological summaries, accuracy metrics, and explicit representations of uncertainty and confidence. Critically, the inclusion of known limitations and safe-use notes helps prevent misuse of GeoAI outputs beyond their intended operational scope.

Seven Distinct Upstream Sources of Biases Throughout a Machine Learning Pipeline

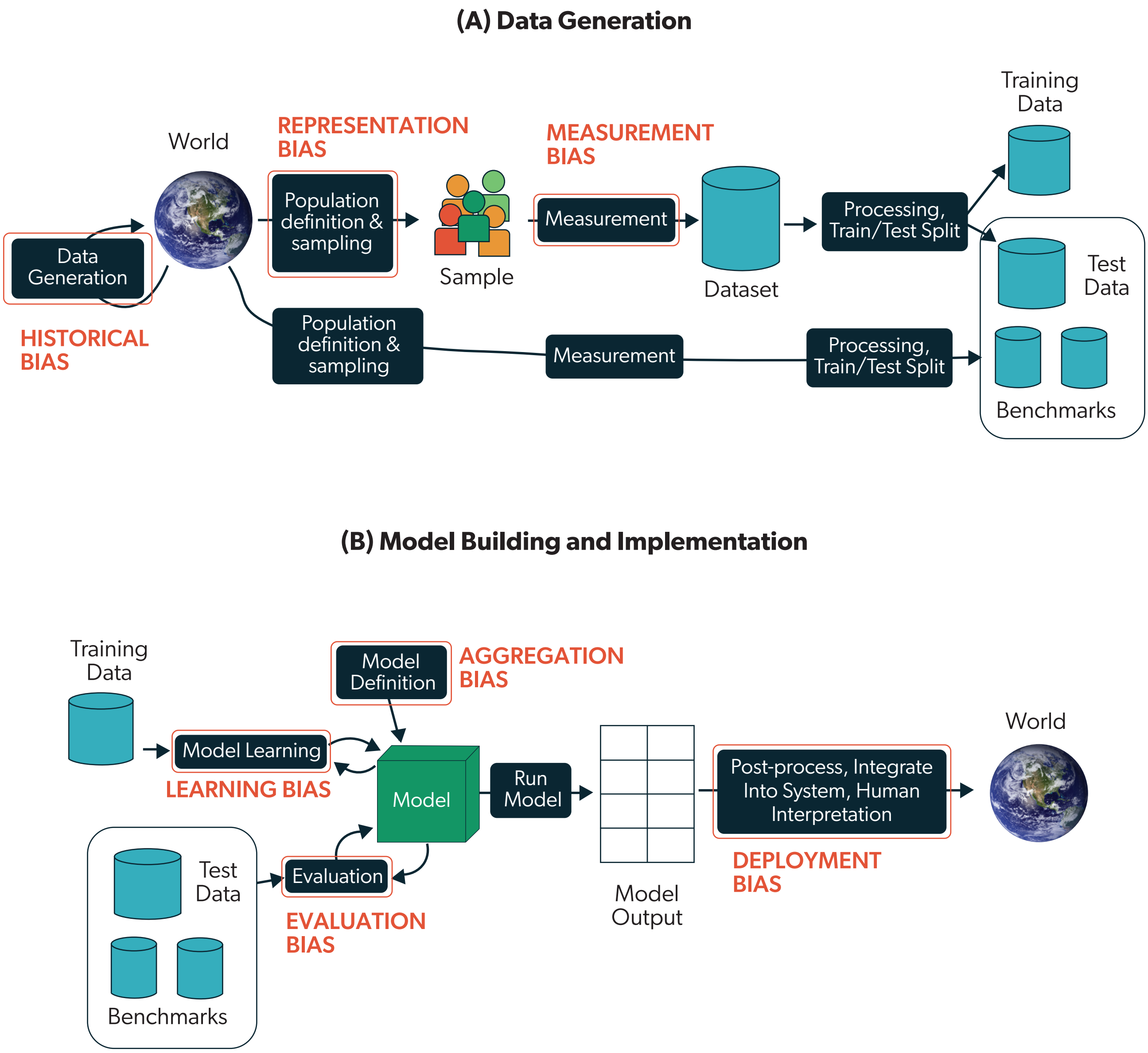


Figure 6: Sources of harms in an ML model, tool, or systems across the ML pipeline from data generation to model building, implementation, and deployment. Source: Harini Suresh and John Guttag. 2021. A Framework for Understanding Sources of Harm throughout the Machine Learning Life Cycle. In Proceedings of EAAMO '21:

Table 6: Summary of safeguards and recommendations for sharing GeoAI models, systems, and tools in ways that elicits trust within the Humanitarian Context.

Recommended Ways to Share GeoAI Outputs

Dimension	Description
Open Licensing	Enables reuse, adaptation, and rapid dissemination across humanitarian organizations without restrictive legal barriers
Micro-Trainings	Short, targeted training (e.g., videos, walkthroughs, quick-start guides) that support rapid onboarding during crises
Simple User Experience	Intuitive interfaces with preset workflows that minimize technical burden and reduce training time
Robust Metadata	Comprehensive documentation accompanying datasets and tools to ensure transparency and correct interpretation. Metadata that signals high data quality contains the following: Timestamp/ Validity Window, Spatial Coverage/ Scale, Source and Licensing, Method Summary, Accuracy and Validation , Uncertainty/ Confidence, Know Limitations/ Safe use notes
Timestamp / Validity Window	Clear indication of when the data or model outputs are valid, accounting for rapidly evolving crisis conditions
Spatial Coverage / Scale	Explicit description of geographic extent and spatial resolution to avoid misuse beyond intended scales
Source and Licensing Information	Clear attribution of data sources and licensing terms to support ethical and legal use
Method Summary	Plain-language explanation of how the GeoAI model or dataset was generated
Accuracy and Validation	Quantitative performance metrics and validation approaches relevant to humanitarian contexts
Uncertainty / Confidence	Explicit communication of prediction confidence, uncertainty ranges, or reliability indicators
Known Limitations / Safe-Use Notes	Clear statements on appropriate use cases, constraints, and scenarios where outputs should not be applied

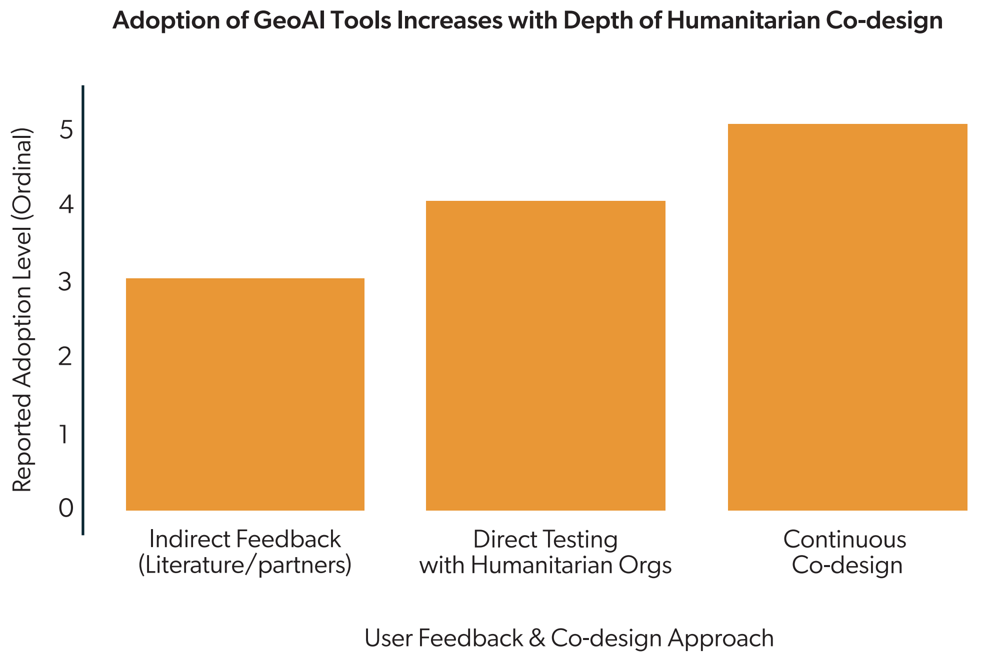
Safeguards Required Prior to Deployment

Dimension	Description
Data Protection and Privacy Policy	Measures to protect sensitive population data and comply with humanitarian data responsibility principles

Human-in-the-Loop Review	Mandatory expert or field-based review before GeoAI outputs inform operational decisions
Incident / Rollback Plan	Predefined procedures to halt or retract GeoAI tools if errors, harm, or misuse are identified
Community Feedback Mechanisms	Channels for field staff or affected communities to report issues, errors, or contextual mismatches
Approval by an Authoritative Agency (Humanitarian Cluster / Agency)	Endorsement by trusted institutions (e.g., UN agencies, national authorities) to legitimize use, including alignment with sectoral coordination mechanisms (e.g., Shelter, WASH, Protection clusters) prior to operational use
Bias Assessment	Evaluation of potential biases in data, models, or outputs that could disadvantage vulnerable populations

The community survey data amongst Technical Innovators show that tools developed through continuous co-design or direct testing with humanitarian organizations are more frequently associated with faster uptake, compared to tools relying primarily on indirect feedback from literature or partners (**See Figure 7**). At the same time, respondents who include model cards, data provenance and licensing notes, uncertainty or confidence scores, bias and impact assessments, and ethical use statements demonstrate a clearer alignment with humanitarian expectations around trust, accountability, and safe use. In contrast, tools released with "none of the above" supporting information reflect weaker signals of operational readiness and are less likely to inspire confidence among humanitarian actors. Taken together, **these patterns suggest that adoption is driven not only by technical capability, but by the combination of continual co-design and explicit disclosure of model assumptions, limitations, and risks, reinforcing the idea that GeoAI tools gain legitimacy and uptake when they are treated as shared humanitarian infrastructure rather than standalone scientific products.**

Figure 7: Co-design approach by Technical Innovators for GeoAI tools and systems and the corresponding rate of adoption by other humanitarian actors. X-axis (Co-design Approach) progresses from Indirect feedback ⇢ Direct testing ⇢ Continuous co-design, Y-axis (Reported adoption level). This demonstrates that the more directly and continuously humanitarian actors are involved in GeoAI tool development, the higher the reported adoption.



APPLICATIONS

This section presents a set of illustrative applications that ground the preceding analysis in real-world applications of GeoAI across the crisis management cycle, with a particular focus on anticipatory action, early warning, response, and recovery. Rather than offering an exhaustive review, these cases are intended to surface examples of GeoAI tools currently being used to address information needs for humanitarian actors and the accompanying challenges of using this technology within the humanitarian context. Together, they highlight the conditions under which GeoAI adds tangible value, the constraints that limit its adoption or impact, and the trade-offs faced by humanitarian actors working under time, resource, and trust constraints.

Anticipatory Action

Geospatial AI (GeoAI) provides a unique opportunity to strengthen risk analytics and early warning systems (EWS) in the humanitarian action context, particularly in areas with scarce datasets, enabling effective disaster risk preparedness and anticipatory action. Losses and damages due to extreme weather and climate events between 1970 and 2021 have been reported to reach at least $4.3 trillion. These extreme events are growing in magnitude, frequency, and reaching an unprecedented scale of impact that requires fast, reliable, and effective disaster management practices. Science suggests that the devastation caused by these disasters can be mitigated by conducting risk assessments and developing effective EWS. For example, increasing the availability and access to well-designed and effective Multi-Hazard Early Warning Systems (MHEWS) could provide nearly tenfold return on investments by significantly reducing ensuing damage by at least 30%. More specifically, countries with less comprehensive MHEWS could experience up to six times higher disaster mortality ratios and four times more affected people compared to countries with a comprehensive system. Despite the growing efforts for comprehensive MHEWS across the globe, significant gaps still exist, particularly in least developed countries.

Early Warning Systems (EWS)

The United Nations Office for Disaster Risk Reduction defines an EWS as “an integrated system of hazard monitoring, forecasting and prediction, disaster risk assessment, communication and preparedness activities, systems and processes that enables individuals, communities, governments, businesses and others to take timely action to reduce disaster risks in advance of hazardous events.” It is a series of coordinated information channels by which people receive timely information about an impending disaster to make informed decisions and act. This could take the form of an alert or bulletins before the occurrence of a disaster. Hence, an EWS is considered a core component of comprehensive disaster preparedness plans. MHEWS is an end-to-end, people-centered system designed to detect different hazards that occur alone, simultaneously, or cascading, including the risk of a hazard and ensuring at-risk people take early action, while capturing the unique challenges and vulnerabilities of each community. The United Nations called for the Early Warnings for All, a goal to ensure that everyone is protected from hazardous weather, water, or climate events through early warning systems by the end of 2027. Since the call, only 55% of World Meteorological Organization (WMO) member states have indicated having a fully functioning MHEWS. This goal is built on four pillars, serving as the core component of an effective EWS. These pillars include: 1.) Disaster risk knowledge and management, 2.) Detection, observation, monitoring, analysis, and forecasting, 3.) Warning dissemination and communication, and 4.) Preparedness and response capabilities.

Disaster Risk Assessment

In the framing above, WMO considers Disaster Risk Assessment as a sub-component of an EWS. However, in many technical and operational deployments of risk analytics using GeoAI, it is considered an independent portion of the pipeline. Risk is often framed in terms of the specific hazard, exposure, and vulnerability of people or assets in a location, together with their adaptive capacity when a hazard happens. This framework often disentangles vulnerability from risk, supposing an ensuing hazard becomes a disaster when it hits the element at risk. This framework has been a core approach for designing many disaster risk assessment frameworks that informs preparedness and anticipatory action, and consequent disaster mitigation. It helps to clarify where and how to direct disaster interventions, such as lowering hazard exposure through relocations, reducing vulnerability through social protections, or investing in early warning. This technically places Risk Assessment as a first step in many preparedness and anticipatory action plans. For example, the INFORM Risk Index profiles 190+ countries across hazards, exposure, vulnerability, and lack of coping capacity to support hazard prevention, preparedness, and anticipatory action.

Bank of Examples

GeoAI plays a central role in anticipatory action and disaster risk reduction by integrating EO, numerical models, and AI-driven forecasting systems. Operational early warning systems increasingly fuse numerical weather prediction (NWP) and AI-based weather models with EO data and impact models across hazards such as floods, landslides, droughts, wildfires, food insecurity, and volcanic activity. Prominent examples include GDACS, GloFAS / EFAS, FEWS NET, NASA FIRMS, NASA LHASA, ShakeAlert, and Volcanic Ash Advisory Centers (VAACs). Recent advances in AI-based global weather models such as GraphCast, ECMWF AIFS, FourCastNet, and MetNet-3 have improved lead times and predictive skill for extreme rainfall, tropical cyclones, and heat stress precursors. Basin-scale flood forecasting platforms such as Google Flood Hub operationalize these advances to support governments and humanitarian partners, particularly in flood-prone regions of the Global South.

Risk modeling frameworks further integrate hazards, exposure, vulnerability, and coping capacity, exemplified by the INFORM Risk Model, which supports national and sub-national resource allocation. In food security, GeoAI-driven systems enhance anticipatory action by assessing risks related to agricultural production, market access, and climate shocks, although the open dissemination of such datasets in conflict settings raises ethical and protection concerns. Conflict early warning efforts, such as ACLED, provide event-level intelligence but remain constrained by reporting biases and limited local contextualization.

Building on early warning signals, GeoAI supports forecast-based financing and anticipatory interventions. Initiatives such as DASTAA demonstrate how household- and community-level flood risk assessments can trigger early actions; though such granularity remains expensive and difficult to scale. Similar approaches are applied to precipitation-triggered landslide risk assessments, combining EO time series with hydrological and terrain models. These systems illustrate how GeoAI can move beyond alerts toward decision-triggered action, while also highlighting persistent gaps in data availability, validation, and equity.

Challenges and Opportunities

Targeted efforts are being made to integrate digital technologies, including GeoAI, to develop more effective risk analytics tools and early warning systems. GeoAI, together with historical and forecast hazard layers, exposure layers, vulnerability, and adaptive capacity from socio-economic indicators, governance, and other coping proxies such as social protection coverages and shelters, can be used to provide rapid and scalable risk assessment. These datasets are combined with performant models to carry out hazard modelling and simulation, exposure estimation (population, assets, and critical lifelines such as road networks), vulnerability, and capacity modelling. These are then aggregated or fused to estimate hazard likelihood and the intensity of hazard exposure. On the other hand, operational early warning systems increasingly fuse numerical weather prediction (NWP) and AI weather models with EO data and impact models (hydrology, food security, landslides, fire, locusts). Flagship systems include GDACS, GloFAS/EFAS, FEWS NET, NASA FIRMS/GWIS, NASA LHASA, ShakeAlert, and VAACs for volcanic ash. AI-based global weather models like GraphCast, ECMWF AIFS, FourCastNet, and MetNet-3 improve lead-times/skill for heavy rainfall, tropical cyclones, and extreme heat precursors. The Google Flood Hub operationalizes basin-scale river flood forecasts to support governments and NGOs.

Although these Open Source GeoAI tools provide enormous benefit for the humanitarian context, they are not immediately adopted by humanitarian decision makers as they require collaboration and trust building, and local ownership and integration. In addition, the two communities – Technical Innovator and Data-driven Humanitarian – focus on different evaluation metrics. Technical Innovators often evaluate the performance of a GeoAI system based on technical metrics such as AUROC, IoU, F1, etc. However, Data Driven Humanitarians and Strategic Decision Makers often measure success by the lead time gained, false-alarm rate, missed event rates, lives saved or livelihoods protected, cost per avoided loss, time-to-cash for anticipatory actions, coverage of at-risk groups, and geographic bias checks. These two metrics are not particularly easy to harmonize and would require concerted efforts to meet the design and use needs of both communities. Our aim in this research is to identify the gaps, challenges, and opportunities for learning and improvement in using Open Source GeoAI tools for Risk Assessments and Early Warning Systems in the humanitarian context.

Table 7: Challenges of using GeoAI for Risk Assessment and Anticipatory Action within the Crisis Lifecycle

Challenge	Context
Granularity–Cost Trade-off in Household-Level Risk Assessment	Household-level risk modeling holds significant promise for targeted preparedness and anticipatory action, but remains **prohibitively expensive and technically demanding**. Open-source datasets rarely support household-scale localization, necessitating **ground-level imagery (e.g., drones)** and intensive field surveys, which are difficult to scale and sustain, particularly in low-resource settings.
Hydrological Data Scarcity and Access Restrictions	In many regions of the Global South, **flood gauge networks are sparse or absent**, limiting calibration and validation of flood risk models. While satellite- and model-based products (**e.g., Google FloodHub)** partially address this gap, restricted access and governance arrangements—often limited to governmental entities—constrain broader use by researchers, NGOs, and local responders.
Inequitable Distribution of High-Quality Data	High-resolution, high-frequency EO data frequently **do not reach preparedness or response teams**, nor the research community that could adapt them into operational tools. These inequities in access, prioritization, and licensing undermine the effectiveness of GeoAI for early warning and risk reduction where it is most needed.

Redundant and Costly Analytical Efforts	Disaster risk analyses are often **repeated independently by multiple organizations** over the same geographic areas using cloud-based infrastructures, resulting in duplicated costs and inconsistent outputs. There is substantial unrealized potential for **centralized assessment and preprocessing**, with shared, analysis-ready products disseminated to first responders and researchers to improve efficiency and coherence.
Opacity in GeoAI Use for Early Warning Thresholds	It is frequently unclear **when and how GeoAI systems are operationally used** to trigger early warnings, particularly regarding risk thresholds and decision rules. While use cases are relatively well-defined for predictable hazards (e.g., recurrent hydrometeorological risks in Mozambique), they are far less transparent for complex or compound hazards.
Dual Data Scarcity: Hazards and Vulnerability	Risk assessment is constrained not only by limited hazard data, but also by **insufficient information on vulnerability and adaptive capacity**. This twofold scarcity includes: (i) unequal access to high-quality satellite imagery and derived products, (ii) limited, inconsistent ground-level data on exposure, vulnerability, and mitigation efforts—both of which are essential for holistic risk characterization.
Strategic Alignment Across Scales	Finally, discrepancies between **international and local disaster risk management approaches** raise questions about strategic coherence. GeoAI systems developed at global scales often lack alignment with local priorities, capacities, and decision contexts, limiting their practical utility for preparedness and response on the ground.

Response and Recovery

Disasters often have a far-reaching impact on public and private communications, transportation, and utility structures. This inadvertently disrupts housing, health, migration, and education, often escalating in areas with ongoing conflicts. For disaster response and recovery, humanitarians need reliable, current information that fits into their workflows and is accurate enough to inform decision-making. The continued advancement in GeoAI provides a remarkable opportunity to offer fit-for-purpose tools for rapid assessments and provide timely insights to response teams and humanitarian decision makers.

Response, Relief and Reconstruction

Some examples of Response, Relief, and Reconstruction efforts within the Disaster Management Cycle include, but are not limited to Rapid Emergency Response and Needs Assessment, Damage Assessment, and Post-Disaster Economic Assessments. Rapid emergency response involves actions taken during or immediately after a disaster to save lives, reduce damage, and restore essential services. This typically includes activities like evacuation, search and rescue, medical relief, and food provision within the first 72 hours after the start of a disaster. This also involves a preliminary needs assessment by a response team or local disaster management organization. Damage assessment involves the estimation of the degree and distribution of destruction in the aftermath of a disaster. This typically captures the hazard footprints, exposed or affected elements (infrastructure, agriculture, people), and their corresponding economic costs. Post-disaster economic Assessments are often used during large-scale disasters for coordinated assessments of sectoral and economic post-disaster damages, losses, and recovery needs. For example, the Post Disaster Needs Assessments (PDNAs), Damage and Loss Assessments (DaLAs), and the Global Rapid Post-Disaster Damage Estimation (GRADE) are used for high-impact government-led damage assessment, particularly in developing countries. These approaches are known to effectively provide well-calibrated estimates of the direct economic damages to residential buildings, non-residential buildings, infrastructure, agriculture, and others. They are a vital component of Disaster Financing and Recovery Planning that takes place over a longer timeframe.

NOTE

In rapid emergency response and search-and-rescue operations, logistics account for an estimated 80% of operational activity, making access to critical infrastructure a primary determinant of response effectiveness. When logistics fail, humanitarian operations are fundamentally compromised, regardless of the availability of personnel or relief supplies. In this context, **logistics is synonymous with access, specifically, access to streets, bridges, transport corridors, and essential facilities that enable the movement of people, heavy equipment, and aid**. Timely information on the functional status of infrastructure, such as whether bridges can safely support large trucks or whether key road segments remain passable, is therefore crucial for effective resource allocation and operational planning. However, relying solely on local or manual reporting can introduce significant delays, particularly in large-scale or rapidly evolving disasters. **This operational reality underpins the central role of coordination mechanisms such as the Logistics Cluster, which emphasizes the need for rapid, reliable, and spatially explicit information to support access-driven decision-making during emergency response.**

Applications of GeoAI in Disaster Response and Recovery

Geospatial technologies, field intel, and artificial intelligence can be leveraged to quickly assess who and what is affected, what is urgently needed (shelter, water, power, medical supplies), and where to focus efforts, particularly in conflict-affected contexts. More specifically, GeoAI can enhance:

Rapid Emergency Response

by providing models for faster and scalable extraction of disaster footprints, hazard exposure, and at-risk elements, accessibility constraints, including road blockage, debris zones, and safe routes to shelters and care centers. In parallel, support Rapid Needs Assessment triangulated by field reports from the operational response team to assess human movements, accessibility, shelter capability, WASH facilities, and dispatch routes for supplying aid. An often-unspoken expectation for these kinds of models is the ability to provide a platform to map fast and verify continuously in the field. This way, early outputs are indicative of where to direct actions and can be rapidly validated to improve the on-field fidelity.

Damage Assessment

by providing faster, scalable, and precise models and datasets for change detection, including assessing the structural damage to buildings and infrastructure, and extracting damage proxy maps.

Recovery and Reconstruction

by providing frameworks that enable the seamless translation of damage assessments into sectors, while identifying the relative degree of confidence (uncertainty), loss ranges, and assessment of recovery progress. Providing future projections of hazard risk exposures and potential damage from varying hazard scenarios can also inform long-term programming efforts.

NOTE

In conflict zones, datasets on damage are in exceptionally high demand, yet existing damage assessment efforts remain highly siloed and methodologically fragmented. In practice, assessments are often conducted independently, with limited reuse of prior analyses, leading to redundancies and a lack of complementarity across products. Moreover, current damage assessment methodologies vary substantially in definitions, spatial units of analysis, sensors, and validation practices, complicating cross-comparison and integrated use. This fragmentation is particularly problematic in conflict settings, where damage is multi-sectoral, affecting housing, WASH infrastructure, agriculture, electricity, and other critical systems, and evolves progressively over time. Addressing these challenges requires moving beyond parallel, non-interoperable mapping efforts toward approaches that explicitly identify the unique contributions of different analytical methods, including AI-driven techniques, and integrate them within a coherent, multi-sectoral damage assessment framework capable of supporting coordinated humanitarian decision-making.

Currently, established actors in the GeoAI and humanitarian action ecosystem provide tools, operational maps, open datasets, and models for disaster response and recovery. For example, UN organizations like the UNOSAT/ OCHA, UN IOM, UNDP, The World Bank (GRADE), and the Copernicus Emergency Management Service (EMS) provide operational mapping of varying types of disasters, footprints, and damage. The open-source communities contribute open models, datasets, and tools for developing more precise damage assessment AI models and benchmarking them with state-of-the-art performance. International Charters enables the provision of expedited satellite tasking and open data mechanisms from public and private organizations with medium to high-resolution datasets for more precise mapping of hazards. Together with well-established open licensing, several baseline geospatial layers, such as Building Footprint, Road Networks, Hospital/ Clinic Network, Population Grids, and Critical Facilities, enabling the development of these tools, are being provided by the ecosystem.

Additionally, these data foundations are supported by an active ecosystem of volunteers from the Humanitarian OpenStreetMap Team (HOTOSM), MapAction, Missing Maps, and others. These platforms and communities, collectively called Volunteered Geographic Information (VGI), supply rapid spatial data layers and analysis of infrastructural damage during disasters, particularly in areas where authoritative datasets are outdated, incomplete, or non-existent. These efforts often provide essential spatial layers such as building footprints, road networks, bridges, schools, and health facilities that can aid the development of rapid disaster assessment, exposure analysis, and response coordination. In sum, VGI provides a dual function: 1.) it provides the training and validation data for developing machine learning models, and 2.) acts as an operational data source for situational awareness during crises. More so, the community also provides practical examples of how to develop GeoAI tools for meeting humanitarian needs, with similar constraints on the lack of open Very High Resolution Data. For example, HOT is leading efforts for using fAIR, an AI-assisted mapping tool, and localizing open-source AI models like RAMP in partnership with local communities and volunteer mappers. Complementary tools such as MapWithAI, an OSM-friendly platform for evaluating AI-generated road predictions against satellite imagery, further exemplify how to use AI to meet the humanitarian need for scale and speed while embracing key quality control ethos.

Bank of Examples

During the acute response phase, GeoAI supports search and rescue, logistics, and situational awareness, where time is critical. Population exposure and displacement modeling tools such as LandScan provide gridded population estimates and rapid population updates, often combined with damage assessments to infer potential displacement patterns. Mobility-based approaches such as aggregated movement data from Meta AI for Good initiatives offer insights into population movements during crises, but require careful consideration of representativeness, particularly in low-income contexts where device ownership is uneven. Auxiliary datasets, such as open shelter locations, can help mitigate these biases. Logistics and access mapping are equally critical. The Logistics Cluster provides field-validated information on road and infrastructure accessibility, where delays in assessing access can directly translate into lost lives during the "golden hours" of rescue. GeoAI has potential to accelerate these assessments, particularly through flood-extent–aware routing and rerouting, where traditional algorithms fail under dynamic conditions. Unmanned Aircraft Systems (drones) are increasingly used to inspect bridges and critical infrastructure when satellite resolution or revisit times are insufficient. However, their effectiveness depends on pre-existing local capacity, including trained pilots, regulatory clearance, and workflows for rapid processing, highlighting that drones introduce new operational constraints even as they fill critical data gaps.

Damage assessment represents one of the most mature GeoAI application areas in humanitarian action. Within the geospatial community, platforms such as Copernicus Emergency Management Service (EMS) Rapid Mapping provide standardized workflows for producing event footprints, damage grading layers, and change-detection products within hours to days of an event, using categories derived from EMS-98 and openly published product manuals. Organizations such as UNOSAT / OCHA, UNDP, and the World Bank actively operationalize EO-based damage assessments across hazard contexts. The World Bank's GRADE initiative uses EO exposure models to estimate direct economic losses within days to weeks after major disasters, supporting Post-Disaster Needs Assessments (PDNAs) and recovery frameworks.

Recent efforts by Google Research and Microsoft AI for Good Lab have introduced AI-assisted damage mapping across multiple hazards, including building damage mapping in crises such as Myanmar (2025). In conflict settings, open-source tools increasingly leverage Sentinel-1 SAR time series combined with open building footprints to map damage progression (e.g., Ukraine), addressing cloud cover and revisit limitations. These efforts are underpinned by open datasets and benchmarks (e.g., xBD/xView2, SpaceNet, EBD, BRIGHT), international satellite tasking charters, and rapid validation by global volunteer networks such as HOT OSM, which provide contextual infrastructure and accessibility maps.

In the recovery phase, damage and exposure products feed into economic loss estimation, infrastructure reconstruction planning, and resilience building. EO-based damage assessments support longer-term investment decisions, insurance mechanisms, and monitoring of reconstruction progress, while also informing updated risk models for future preparedness. At this stage, the emphasis shifts from speed to completeness, validation, and integration with socio-economic data, reinforcing the need for interoperable, multi-sectoral GeoAI systems.

Challenges and Opportunities

Despite this growing body of work within the ecosystem, the use of **GeoAI for humanitarian actions still faces many bottlenecks that limit its adoption and wide-scale use**. Some of these are well-known challenges with developing vision models for geospatial datasets, while others are unique to the humanitarian response community.

GeoAI tools and platforms, while powerful, are often plagued with bias, transferability, and scalability challenges with many humanitarian implications. These issues stem not only from domain shifts in sensors, seasonality, geographies, and building typologies, but also from systemic issues like limited availability of open data for training and inadequate incentives for data sharing. **Because most open datasets are heavily represented in the Global North, models frequently struggle to generalize to local contexts in the Global South, where disasters and humanitarian crises are most acute.** This leads to common misclassifications such as underdetecting damage in low-rise or non-engineered structures, misidentifying informal settlements, or overlooking context-specific features like unpaved roads or vernacular housing. Over time, these biases reinforce a cycle in which regions most in need of GeoAI-enabled insights remain the least represented in the datasets and models designed to support them.

Investments in open data initiatives, context-aware model adaptation, and inclusive partnerships that enable capacity building and equitable participation from researchers, institutions, and volunteers in the Global South can help bridge this gap. Equally important is the integration of reliable uncertainty quantification metrics, such as calibrated probabilities and confidence layers at different scales of maps or data aggregation, to transparently communicate the limits of model predictions. Without this kind of design approach for GeoAI development, the trust in using GeoAI for humanitarian response can be eroded, particularly in the context where a good balance of scalable assessment and acceptable precision is critical for high-stakes decision making.

More so, GeoAI for Humanitarian Action is equally challenged by the need for ethical tools that can safeguard people in fragile and conflict-affected zones. These include designing tools that adopt a do-no-harm framework by redacting sensitive features, deploying tools that respect the data rights and privacy of hazard-affected communities. These frameworks are not often at the forefront of open-source GeoAI development. These challenges also make the need for scalable validation difficult in this context, where providing reliable ground truth is equally subject to access and safety constraints. Additionally, maintaining open models, tools, and datasets often requires concerted efforts and funding to continuously expand, validate, and release the most up-to-date and representative datasets, benchmarks, and models. Finally, reaching last-mile responders in low-resource settings in fragile contexts often requires a significant design for resource efficiency, which is often not central to many GeoAI deployment approaches. Without these considerations, GeoAI risks widening existing divides rather than closing them.

Table 8: Challenges of using GeoAI for rapid response, long-term recovery and reconstruction within the crisis Lifecycle

Challenge	Context
Timeliness and Information Latency in Early Response	A persistent challenge in humanitarian response is that r**esponse teams often operate with delayed or outdated information** during the most critical early phases of a disaster. Search and rescue teams, typically the first actors on the ground, frequently rely on low-bandwidth satellite communications to relay situational updates, limiting the volume and richness of information that can be shared. At the same time, organizations such as UNITAR and MapAction, which support crisis mapping and damage assessment, do not consistently receive access to the most recent or highest-quality satellite imagery (RGB, SAR, hyperspectral). **This disconnect reduces the operational value of GeoAI systems that depend on timely, high-fidelity inputs.**

Data Availability Constraints and Sensor Trade-offs	Access to up-to-date optical imagery is often **constrained by cloud cover, revisit frequency, and licensing, particularly in rapidly evolving disasters**. While Synthetic Aperture Radar (SAR) offers a partial solution by enabling cloud- and night-independent observations, its integration into humanitarian workflows remains uneven due to: • Higher technical complexity • Limited interpretability for non-expert users • Scarcity of SAR-specific damage benchmarks • As a result, many GeoAI pipelines remain overly dependent on multispectral data, increasing vulnerability to missing or degraded observations
Unique Challenges in Conflict and Complex Emergency Settings	Damage mapping in conflict-affected areas introduces additional complexities not typically present in natural disasters: • Repeat and progressive damage over space and time complicates snapshot-based assessments • Sustained access for field validation is often impossible, particularly in active conflict zones • Automated AI approaches become increasingly fragile when verification and ground truth are absent, raising the risk of compounding errors • Advanced SAR techniques, including interferometric SAR (InSAR), offer promise for tracking progressive damage across both war and disaster settings, but remain underutilized in operational humanitarian systems
Overpromising and Methodological Fragility in GeoAI	A growing concern within the GeoAI ecosystem is the attribution of unfounded or exaggerated performance claims, often based on accuracy metrics derived from non-independent or weakly validated datasets. In humanitarian contexts, **available datasets are frequently incomplete, noisy, or biased toward extreme cases**. Moreover, a significant portion of GeoAI development is conducted without sufficient thematic expertise in natural hazards or armed conflict, leading to: • Overreliance on aggregate metrics (e.g., accuracy, F1-score) • Inadequate treatment of fringe or moderate damage cases • Limited consideration of sampling design and statistical representativeness The absence of sustained collaboration with structural engineers, affected communities, and spatial statisticians further exacerbates these issues.
Automation Pressures and the Risk of Humans-Out-of-the-Loop Systems	Chronic constraints in humanitarian settings, limited funding, staffing shortages, and restricted technical capacity, are pushing the ecosystem toward increasing automation. **While automation can improve scalability, it also incentivizes humans-out-of-the-loop decision-making, reducing opportunities for expert review and contextual interpretation. In high-stakes humanitarian applications, this trend poses significant risks to responsible, accountable decision-making, particularly when uncertainty is poorly communicated.**
Fragmented Information Systems and Missed Opportunities for Integration	Finally, the lack of a coordinated, real-time humanitarian information system remains a major structural gap. **Crisis information is often scattered across satellite products, situation reports, social media, and ad hoc field updates.** There is growing potential for GeoAI, large language models (LLMs), and conversational systems to help integrate heterogeneous inputs, photos, videos, text reports, and geolocations, into coherent situational awareness products like HOTOSMs ChatMaps. Recent disaster responses have demonstrated that informal, community-driven information sharing (e.g., via messaging platforms and social media) can save lives, yet these signals are rarely integrated into formal GeoAI pipelines.

NOTE: THE NUANCES OF DAMAGE ASSESSMENT

Damage assessment following disasters is inherently shaped by the vantage point from which damage is observed and interpreted. EO scientists typically characterize damage from an overhead perspective, relying on features visible from rooftops or building envelopes, such as roof collapse, debris fields, or spectral and textural anomalies. In contrast, structural engineers assess damage through in-situ, gradation-based methodologies, drawing on established field protocols to determine building serviceability, repairability, or the need for demolition. These assessments incorporate structural components that are often not observable from space, including foundation integrity, load-bearing elements, internal cracking, and material fatigue.

This epistemic mismatch has important implications for how "damage" is defined, annotated, and modeled within GeoAI systems. From an EO vantage point, damage classification is constrained to what is externally visible, whereas structural engineering assessments reflect what can be meaningfully detected on the ground and linked to actionable decisions. Nevertheless, in the computer vision and remote sensing communities, many datasets labeled as "validation" data remain entirely remotely observed, lacking systematic field-based engineering verification. Prominent rapid mapping efforts, such as those produced by international humanitarian mapping initiatives, have historically conducted limited structural field validation of their damage annotations. Empirical evidence illustrates the consequences of this gap. Following the 2010 Port-au-Prince earthquake, overhead damage annotation approaches exhibited omission errors on the order of 26%, indicating that a substantial fraction of damaged structures were not captured in remote assessments. Such errors risk propagating through downstream AI models, particularly as these datasets are increasingly reused for training, benchmarking, and operational deployment. Yet, the rapid mapping ecosystem, designed to deliver timely products across successive disasters, offers limited opportunities for iterative refinement, re-annotation, or methodological improvement between events.

Recent efforts have attempted to partially address this limitation through historical validation, for example by comparing damage maps against Damage Proxy Maps derived from independent data sources. However, these approaches still rely predominantly on remote sensing and proxy indicators, with very limited integration of field engineering surveys. In this context, "field work" refers specifically to systematic post-event engineering assessments that evaluate how well remote damage classifications correspond to actual on-the-ground structural conditions; a practice that remains rare due to cost, access constraints, and safety considerations. A fundamental challenge underlying these limitations is that damage is an ephemeral landscape process. Immediately after a disaster, damage patterns evolve rapidly as emergency response, debris removal, temporary repairs, and reconstruction begin. This temporal transience severely constrains the window for meaningful validation of remotely sensed damage snapshots. Consequently, GeoAI systems must operate within an environment where opportunities for ground-truth verification are scarce and temporally misaligned with data acquisition.

Given these constraints, the critical question is not whether remote sensing–based damage maps can achieve perfect building-level accuracy, but how they can best support decision-making within known limitations. In humanitarian contexts, damage assessments can serve multiple, distinct purposes: (i) rapidly directing response teams and affected communities to hotspots of damage, (ii) supporting block-by-block or building-level evaluations when combined with field inspections, and (iii) informing longer-term processes such as resource mobilization for recovery and insurance claims. Importantly, the unit of analysis and tolerance for uncertainty vary across these use cases. For example, moderate damage, such as broken windows, façade failures, or partial roof loss, may be more operationally relevant for early humanitarian response than severe or total destruction, particularly when the goal is to restore habitability and facilitate rapid returns to housing. Fully destroyed structures, by contrast, often require months or years for resolution and may be less actionable in the immediate response phase. Thus, the utility of remote sensing–based damage assessments should be evaluated not solely in terms of per-building accuracy, but in terms of their ability to reduce response times, prioritize interventions, and allocate resources effectively.

In this light, GeoAI-enabled damage mapping should be reframed as a decision-support tool, rather than a substitute for field-based engineering assessments. Aligning scientific development with operational realities requires acknowledging the epistemic limits of overhead observations, explicitly communicating uncertainty, and designing damage products that are fit for purpose across diverse humanitarian and recovery contexts.

CONCLUSIONS

The promise of GeoAI for humanitarian action is clear. Across the crisis management cycle, from early warning and anticipatory action to emergency response, damage assessment, and recovery, **GeoAI enables rapid analysis of large Earth observation datasets and supports decision-making under severe time constraints.** These capabilities can transform how humanitarian actors assess risk, allocate resources, and protect vulnerable populations.

Yet this study reveals a persistent gap between technical potential and operational reality. **Many GeoAI systems are optimized for scientific performance rather than for trust, accessibility, and governance in humanitarian settings**. The barriers identified across stakeholder personas are primarily socio-technical and institutional, not technological. Data-Driven Humanitarians need simple, offline-capable tools, not just accurate models. Strategic Decision Makers require transparency and evidence of real-world impact, not only statistical performance. Crisis-Affected Individuals need accessible, multilingual tools they can actually use, not platforms designed for technical experts. This mismatch stems from misaligned incentives, fragmented ecosystems, and limited co-design. Academic research prioritizes novelty and publication, while humanitarian operations demand speed, reliability, and contextual relevance. Commercial satellite data are often released philanthropically, yet inconsistent policies and activation delays reduce their usefulness during crises. Coordination mechanisms exist but frequently fail in conflict and politically sensitive settings. **Despite growing technical sophistication, many GeoAI tools still lack transparency, uncertainty communication, and ethical safeguards required for responsible use in high-stakes environments.**

Closing this gap requires a fundamental shift in how GeoAI is developed, validated, and deployed. Technical excellence must be paired with continuous co-design involving humanitarian practitioners, affected communities, and local responders from the outset. **Transparency should encompass data provenance, limitations, bias, and uncertainty, not just model architecture. Validation must move beyond benchmark metrics to include field impact, humanitarian outcomes, and input from local and sectoral experts who understand on-the-ground realities.** Addressing systemic inequities is equally critical. High-quality data, compute, and expertise remain concentrated in the Global North, while crises disproportionately affect the Global South. Open data, capacity building, and equitable partnerships are essential to prevent GeoAI from reinforcing existing divides.

Overall, GeoAI's success in humanitarian contexts will be judged not by algorithmic sophistication, but by lives saved, resources better allocated, and communities empowered to prepare for, respond to, and recover from crises. **GeoAI must be treated not as a standalone technology, but as shared humanitarian infrastructure embedded in trusted governance, ethical frameworks, and local decision-making systems.** Prioritizing operational trust, equity, transparency, and impact is essential if GeoAI is to fulfill its promise of enabling more effective, accountable, and just humanitarian action worldwide.

COMMUNITY SURVEY DATASETS

The outcome of the community survey is publicly accessible. Note, the data contains all the survey responses under the main response sheet, and respective stakeholder persona responses under separate individual sheets named accordingly.

Access the Survey Results Here

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GLOSSARY

Geospatial AI (GeoAI): The application of AI, machine learning, and deep learning methods to geospatial data, GIS, and spatial problems and is used to extract features, detect patterns, make predictions, and scale spatial analysis. (ESRI)

Humanitarian Contexts: Operational, social, and environmental settings characterized by acute or protracted crises that threaten human life, dignity, safety, and livelihoods, including natural disasters, armed conflict, public health emergencies, and food insecurity. These contexts are marked by high uncertainty, resource constraints, ethical sensitivities, and the need for rapid, coordinated decision-making among diverse actors.

Crisis Management Cycle: A conceptual framework describing the temporal progression of a humanitarian emergency and associated interventions, typically comprising:

> **Risk Reduction and Preparedness** – hazard monitoring, vulnerability assessment, and early warning;
>
> **Anticipatory Action** – pre-emptive interventions triggered by forecast-based risk thresholds;
>
> **Rapid Emergency Response** – life-saving actions immediately following crisis onset;
>
> **Stabilization and Early Recovery** – restoration of essential services and livelihoods;
>
> **Recovery and Resilience Building** – long-term reconstruction and risk reduction to mitigate future crises.
>
> The lifecycle is iterative and non-linear, with phases often overlapping in complex or protracted emergencies.

Humanitarian Action: Coordinated, principled activities undertaken to prevent, mitigate, and alleviate human suffering; protect life and dignity; and uphold fundamental rights of populations affected by crises, across all phases of the crisis management cycle. Humanitarian action is guided by the principles of humanity, neutrality, impartiality, and independence, and increasingly relies on timely, trustworthy, and ethically governed information systems.

Humanitarian Crisis: Events or series of events that represent a critical threat to the health, safety, security, or well-being of a community or other large group of people. They are widely geographically distributed, often covering large areas and multiple populations. They are diverse and complex, and require coordinated efforts and resources across a variety of local, national, and international stakeholders. (Caribou Space)

Damage Assessment: The systematic estimation of the degree, type, and spatial distribution of destruction following a disaster or conflict event. Damage assessment typically integrates information on hazard footprints, exposed and affected elements (e.g., buildings, infrastructure, agriculture, populations), and associated economic or functional losses, often derived from Earth observation, field surveys, or hybrid approaches.

Risk Assessment: The process of evaluating the likelihood and potential consequences of harmful events by integrating information on hazards, exposure, vulnerability, and adaptive capacity. In humanitarian contexts, risk assessment supports preparedness, anticipatory action, and prioritization of interventions under uncertainty.

Earth Observation (E.O.): The collection of information about the Earth's surface, atmosphere, and oceans using satellite- and airborne-based sensors, including optical, multispectral, hyperspectral, thermal, and radar systems. EO provides spatially explicit, repeatable, and scalable data for monitoring environmental processes and human activities.

Early Warning Systems: Integrated systems that monitor hazards, assess risks, and disseminate timely and actionable warnings to enable individuals, communities, and institutions to take preventive or protective actions before a hazardous event occurs. EWS combines scientific forecasting, communication mechanisms, and institutional response capacity.

Anticipatory Action: Pre-emptive humanitarian interventions implemented before a crisis fully unfolds, based on forecast-based risk thresholds and probabilistic early warnings. Anticipatory action aims to reduce impacts, protect lives and livelihoods, and lower the cost of response by acting ahead of disaster onset.

Rapid Emergency Response: The immediate, life-saving phase of humanitarian action following crisis onset, focused on search and rescue, emergency medical care, shelter, logistics, and access to essential services. This phase is highly time-sensitive and dependent on rapid situational awareness and access to critical infrastructure.

Recovery: The phase of humanitarian and development action focused on restoring and improving livelihoods, infrastructure, services, and social systems following a crisis. Recovery seeks not only to return communities to pre-crisis conditions but also to enhance resilience and reduce future risk through reconstruction and capacity building.